The Interval of Observation

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Abstract

We revisit Kendall's (1953) conclusion that "the interval of observation may be very important". Contrary to his other conclusions on return predictability, this conclusion has received surprisingly little attention. Most tests in finance and economics routinely regress daily, weekly and monthly observations on daily, weekly and monthly observations, respectively. This is especially surprising because, while convenient, this convention lacks economic reasoning in many applications. For instance in the case of return predictability, if markets are - almost - efficient one would expect that - if anything - specifically new information in the last trading days in the previous months should be most informative. Then using all information in the full last month might be a crude approach to test for predictability in the shorter run. We revisit Kendall's study; use commodity returns to predict stock returns and find that the interval of observation is indeed very important. It strongly affects conclusions regarding economic and statistical significance. For instance, we find - after adjusting for potential data mining - the conventional approach can strongly underestimate actual return predictability.

Key words: observation interval, return predictability tests, market efficiency

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We revisit Kendall's (1953) conclusion that "the interval of observation may be very important". Contrary to his other conclusions on return predictability, this conclusion has received surprisingly little attention. Most tests in finance and economics routinely regress daily, weekly and monthly observations on daily, weekly and monthly observations, respectively. This is especially surprising because, while convenient, this convention lacks economic reasoning in many applications. For instance in the case of return predictability, if markets are - almost - efficient one would expect that - if anything - specifically new information in the last trading days in the previous months should be most informative. Then using all information in the full last month might be a crude approach to test for predictability in the shorter run. We revisit Kendall's study; use commodity returns to predict stock returns and find that the interval of observation is indeed very important. It strongly affects conclusions regarding economic and statistical significance. For instance, we find - after adjusting for potential data mining - the conventional approach can strongly underestimate actual return predictability.

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1. Introduction

"The series looks like a "wandering" one as if once a week the Demon of Chance drew a random number (...) and added it to the current price to determine next week's price."

Many textbooks in finance use this famous quote of Sir Maurice Kendall (1953).[1] This is not surprising, as Kendall's study provided the empirical basis for theoretical developments that ultimately lead to the efficient market hypothesis. Kendall tested for autocorrelation in weekly and monthly price changes using past weekly and monthly price changes, but found no relation. His study led him to three main conclusions. Whereas, the last two conclusions are well known[2], his first conclusion has attracted little attention: "The interval of observation may be very important."

Just as in Kendall's earliest return predictability tests, researchers today still regress daily data on daily data, weekly data on weekly data, monthly data on monthly data almost everywhere in economics and finance. The convention of using past information of the previous day, week or month is a long-standing tradition in finance. This seems strange because apart from the convenience of having data available at a specific frequency, this convention lacks a clear economic motivation. For instance, in the case of market efficiency: if markets aggregate information not instantaneously but still fairly quickly, and an investor wants to predict next month's return, it makes more sense intuitively to use shorter intervals (i.e. the last trading week of the previous month) than the conventional approach of using a full month of past information to test whether predictability is present. Using all information in the full last month might decrease signal to noise levels and underestimate true predictability.

As an illustration of what happens if we relax this convention, we revisit Kendall's original 1953 study and test the ability of past commodity returns to predict future stock returns. Our result show that results can be drastically different once we deviate

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[1] For instance Brealey and Meyers: Principles of Corporte Finance (5th international edition, pg. 324).

[2] These conclusions are: "it seems a waste of time to isolate a trend in data such as these;" and "the best estimate of the change in price between now and next week is that there is no change," respectively.

from this convention and predict monthly stock returns using commodity returns over the last trading days in the previous month. We not only find strong return predictability based on changes in commodity prices but many other important differences: we find significance results where results were insignificant before; we find no significance where the normal convention indicates significance; we find changes in significance levels; and last but not least our results show large difference in parameter estimates with strong implications for the economic significance of trading strategies based on this predictability.

This paper makes several contributions. Probably the most important contribution is that we show how variation in a fairly innocuous assumption can have drastic consequences on conclusions of empirical results in economics and more specifically finance. While we illustrate our point using a similar approach as in Kendall's original study we see no reason why the convention might not similarly affect other conclusions in the literature.

More specifically, our study shows that returns might be more predictable than previously thought. We find strong predictability in monthly stock market returns based on the normal convention of predicting using past monthly changes in commodity prices, particularly fuels and metals. Although the predictability of stock returns based on oil price changes is well known (see Driesprong, Jacobsen, Maat 2005) evidence that also other commodity returns predict stock returns is new. We appear to be the first to show that monthly changes in other commodities quite unrelated to Oil, such as Copper, Aluminum, and Nickel also predict monthly S&P 500, monthly UK, and monthly World index returns. We also show that these predictability results become stronger if we relax the normal convention and study regressions of information based on the last trading day of the previous month only and add a maximum of 22 trading days (which is the average number of trading days in any month in our sample) after correcting our test statistics for the potential effects of data mining.

Apart from statistical significance our results also show drastic changes in economic significance. Sharpe ratios of trading strategies using short term information in commodity price changes to predict stock market returns are substantially higher than buy and hold strategies but also in comparison with the conventional trading strategies. We find increases in Sharpe ratios up to 26 percent. This should make our study interesting to practitioners as well.

Taken together we propose that our results provide strong evidence that the interval of observation is indeed important and conclusions may drastically vary with the interval of observation. It seems that the question what the proper interval of observation is, deserves more attention than it has received over the last fifty years of research in finance and economics.

Apart from Kendall (1953) our work also relates to more recent studies linking commodity prices and stock returns. There are several reasons why commodity returns may predict stock returns. Commodities prices drive many of the input costs in the production process and therefore affect the profitability of firms if they do not pass the cost increases on to consumers. Alternatively, if firms do increase the prices of finished goods in response to commodity price rises then inflation increases throughout the economy. The passing on of cost increases (rather than absorbing them) is more common (Bloch et al, 2004) so researchers (e.g. Boughton and Branson, 1988) have suggested that commodity price increases are a leading indicator of inflation. Given that inflation typically has a negative impact on stock returns (see Fama and Schwert, 1977; and Barnes et al., 1999) it seems reasonable to expect rational market participants to begin marking down the price of stocks as commodity prices increase. Other commodities have a direct impact on the disposable income of consumers. If the price of the likes of Heating Oil and Unleaded Gas increase, consumers have less money to spend on other items. This downturn in demand can be expected to undermine the profitability of major sectors of the stock market such as the consumer discretionary sector.

While oil prices rises are typically the first commodity prices to come to mind from an economic perspective, many other commodities play important roles. Sommer (2006) reports that non-fuel commodities constituted a higher share of world trade (14 percent) during in the 2000–04 period than their fuel commodity equivalents (7 percent). Driesprong, Jacobsen and Maat (2006) show that changes in monthly oil prices predict stock market returns over the world. However, to the best of knowledge there have been no papers devoted to the predictive power of other commodities.

Our work also relates to the delayed reaction of stock markets to information. This literature is becoming more and more established in the literature. Hong and Stein (1999) develop a theoretical model where boundedly rational agents "newswatchers" observe some private information but fail to extract other newswatchers' private information. This leads to the gradual diffusion of information across investors, which, in turn leads to under-reaction and stock return predictability. Recent empirical evidence supports this proposition. Hong, Torous, and Valkanov (2004) show that 14 of the 34 U.S. industries can predict the U.S. stock market by one month, while Driesprong, Jacobsen and Maat (2006) find that the gradual diffusion of information hypothesis may explain why oil price changes predict stock returns with a one month lag. What is not clear however, is whether a full monthly return is required to predict future returns. If markets aggregate information not instantaneously but still fairly quickly, and an investor wants to predict next month's return, it makes more sense to use shorter intervals than the conventional approach of using a full month. To the best of our knowledge, we are the first to investigate this.[3]

Criticism of data snooping is ever present in empirical analysis so we are careful to structure our study in such a way as to minimize this. Rather than basing our tests on theory based on patterns in current data we test a theory which was formulated over fifty years ago. Consistent with Kendall (1953) we study commodity data albeit for a more recent time period. He adopted the practice of the time and simply selected some commodity series from the universe of all possible series with no justification. In contrast, we select 20 commodities (to keep our statistical analysis manageable) based on their relative importance to the global economy and diversity. We choose the commodities with the largest world production over the last five years, as measured by the Goldman Sachs Commodity Index which have daily data available

[3]Campbell, Lo and McKinlay (1997) argue that *"a proper comparison of observed returns across distinct sampling intervals must allow for nontrading at the finest time interval, after which the implications for coarser-sampled returns may be developed"* (see page 90.) They show that time aggregation affects the autocorrelation of observed portfolio returns in a highly nonlinear fashion. (see equation 3.1.40 page 97).

for a reasonable time period. This results in a sample of West Texas Crude Oil, Heating Oil, Copper, Aluminum, Gold, Silver, Wheat, Corn, Live Cattle, Hogs, Brent Crude Oil, Cocoa, Coffee, Lead, Natural Gas, Nickel, Soybeans, Sugar, Unleaded Gas, and Zinc. Finally, we use the Bonferroni adjustment formally account for any data snooping bias in our tests. We also apply the bootstrapping approach of Rapach and Wohar (2005) but these results are almost identical the Bonferroni-adjustment results so we do not report them.

While it is well known that monthly lagged oil price changes predict monthly stock returns (Driesprong, Jacobsen and Maat, 2005), We also find evidence to support Kendall's (1953) proposition. The conventional approach can indeed strongly underestimate the size and strength of return predictability. Commodities that have a statistically significant relationship with the S&P 500 when monthly commodity data is used often have a stronger statistically significant relationship when cumulative daily data is used. The economic significance under the cumulative daily approach is also consistently higher. We also find evidence of robust return predictability using cumulative daily data that is not evident in the monthly data and evidence of return predictability in the monthly data that is not evident in the cumulative daily data.

The rest of the paper is structured as follows: Section 2 contains our data and methodology. We present and discuss the results in Section 3. Section 4 concludes the paper.

2. Data and Methodology

We follow Kendall (1953) and study commodity data but we focus on a more recent period for which daily data is available. Kendall (1953) adopted the practice of the time and selected some commodity series from the universe of all possible series. We choose the 20 commodities with the largest world production over the last five years, as measured by the Goldman Sachs Commodity Index, which have daily data available for a reasonable time period. This results in a sample of West Texas Crude Oil, Heating Oil, Copper, Aluminum, Gold, Silver, Wheat, Corn, Live Cattle, Hogs, Brent Crude Oil, Cocoa, Coffee, Lead, Natural Gas, Nickel, Soybeans, Sugar, Unleaded Gas, and Zinc. We are confident these 20 commodities give us a good representation of the entire commodity universe as they are also well represented in the Dow Jones / AIG and IMF commodity indices. Moreover, we feel that if stock markets will respond to past changes in commodity prices the effect should be strongest for the most important commodities in an economic sense.

The summary statistics of our data are presented in Table 1. Our longest commodity series, Corn, commences in 1946. We have approximately ten years of data for our shortest commodity series, Natural Gas, with most series starting in the 1990s or earlier. Heating Oil has had the biggest gains, with a mean monthly return of 0.68%, while Coffee has been the worst performer with a mean monthly return of -0.58%. By way of comparison, the mean monthly return of the S&P 500 is 0.59%. All commodity series are more risky than the three equity series. Live Cattle have the lowest standard deviation at 4.51%, but this is still higher than the standard deviation of the S&P 500 (4.09%). The most risky commodity series is Natural Gas, which has a standard deviation of 22.09%. Extreme returns are reasonable common in commodity series, with the distribution of Silver returns having particularly fat tails (kurtosis = 26.00).

Please insert Table 1 around here.

We use the simple random walk model as starting point and add one explanatory variable. The traditional regression equation is as follows:

$$r_T^m = \mu + \alpha x_{T-1}^m + \varepsilon_t \qquad (1)$$

We estimate the following additional models of the form:

$$r_T^m = \mu + \alpha x_{t-1}^d + \varepsilon_t \qquad (2)$$

Where x_{t-1}^d denotes the last trading day of the previous month, the last two trading days of the previous month and so on up to 22 trading days. We use log returns and log changes so alpha measures the total net response of investors with respect to the sum of all daily changes up to 22 trading days. We stop at 22 days as this is the average number of trading days in a month. We expect that if the market is not fully efficient the reaction in the first few days of the past month should have the strongest effect on this month stock returns.

We recognize that our cumulative daily regression results could show significance by chance. We increase the number of models from 1 (monthly returns) to 22, although these models are partially overlapping. Just to be sure we adjust our test statistics for the fact that we use multiple models. More precisely, we use the Bonferroni adjustment to adjust our significance levels for the fact we are testing 22 'different' daily periods. (Bonferroni t-values with 22 searches are 10%: t = 2.61, 5%: t = 2.84 and 1%: t = 3.32, respectively). We also apply the data snooping bootstrapping approach of Rapach and Wohar (2005) but these results are almost identical the Bonferroni-adjustment results so we do not report them.

3. Results

In this section we present our results and discuss their implications. Our key contribution is that the interval of observation is very important. We use the ability of commodity series to predict stock series to illustrate this. We find evidence that some commodity series predict equity markets when monthly data is used but not when cumulative daily data is used, other commodity series predict equity series when cumulative daily data are used but not when monthly series is used. Even when there is evidence of predictability in both cumulative daily and monthly series, the statistical and economic significance varies considerably.

In Table 2 we report the regression results of the traditional method of monthly regressions based on equation 1. It is well known that lagged oil price changes predict stock returns (Driesprong, Jacobsen and Maat, 2005), however this paper appears to be the first to show that changes in other commodities, such as Copper, Aluminum, Heating Oil, Live Cattle, Nickel, Unleaded Gas, and Live Cattle also predict movements in the S&P 500.

As each of these commodities increase in price, the S&P 500, on average, declines the following month. While this finding appears to be new it is not surprising given the importance of many of these commodities to the production process for many companies and their link to inflation. Increases in the price of Copper, Aluminum, and Nickel lead to profit erosion if the prices of finished good are not increased and to general inflation if they are increased, and both of these tend to be negative for the stock market. It is also likely that increases in the price of other commodities like Heating Oil and Unleaded Gas reduce consumer's disposable income which reduces the demand for the products of many listed companies leading to profit declines.

Please insert Table 2 around here.

The statistical significance is especially strong (significant at the 1% level) for West Texas Crude Oil, Heating Oil, Aluminum, Brent Crude Oil and Nickel. The economic significance is also large. Of the eight statistically significant commodities, the coefficients range from -0.065 for Live Cattle to -0.137 for Aluminum. This implies that a 1% increase in the price of Aluminum, which is a frequent occurrence in this volatile commodity, in any given month results in a 0.14% decline in the value of the S&P 500 on average. This is a non-trivial decline given that by the end of sample period (30 June 2006), the S&P 500 had a market capitalization of US$12,020 billion.

In Panel B we present the equivalent results for the World Index. A similar trend is evident to the S&P 500 results, although the World results are slightly weaker. Changes in a selection of Industrial Metals and Energy related commodities have a negative relationship with changes in the World equity index. The statistical significance is moderately lower than the corresponding results for the S&P 500, although West Texas Crude Oil, Aluminum, Brent Crude Oil remain statistically significant at the 1% level.

The results of the monthly regressions testing the ability of monthly commodity price changes to predict monthly changes in the UK stock index are presented in Panel C. The results are consistent with the S&P 500 and World Index results, in that Industrial Metals (Aluminum and Nickel) and Energy Related commodities (West Texas Crude Oil and Brent Crude Oil) are the main predictors (they have a negative relationship) with the equity index. These results are to be expected given that these two categories of commodities are given the biggest weights in commodity indices (such as the Goldman Sachs Commodity Index) because they have the biggest world production. They are also the commodities that feed most directly into input costs in the production process. They are therefore the commodities that are most likely to affect the profitability of firms if they increase and the firms do not pass the cost increases on to consumers. The UK results indicate one relationship that was not evident in the previous results. Changes in sugar prices appear to have a positive relationship with changes in the UK stock index.

We present our cumulative daily regression results in Table 3. In each instance we regress the cumulative daily return (from the previous month) of each commodity series on the monthly return of the equity index. We start with the daily return of the last day of the previous month, then move to the cumulative two day return from the previous month and so on until we arrive at the cumulative 22 day return. We stop here because 22 is the average number of trading days in any given month. We run results based on our one day and all subsequent cumulative returns beginning at the last day from the previous month and beginning with a one day lag. This latter approach is adopted to check whether the different closing times of the equity and commodity markets are driving the results. We find no major differences in the results between these two approaches so we present the results beginning on the last day of the previous month. Panel A contains the results for the S&P 500, Panel B for the World Index, and Panel C for the UK Index. We recognize that our cumulative daily regression results could show significance by chance so we use the Bonferroni adjustment to adjust our significance levels for the fact we are testing 22 different daily periods.

Please insert Table 3 around here.

Turning to the S&P 500 results in Panel A, we can clearly see that many periods shorter than one month predict the next months return in the S&P 500 for the majority of Industrial Metal and Energy related commodities. Changes in West Texas Crude Oil, Heating Oil, Copper, Aluminum, Brent Crude Oil, and Nickel all show consistent ability to predict movements in the S&P 500. Changes over periods ranging from 10-22 days, 10-22 days, 2-15 days, 1-22 days, 10-22 days, and 15-18 days are statistically significant for West Texas Crude Oil, Heating Oil, Copper, Aluminum, Brent Crude Oil, and Nickel respectively. This suggests that individuals and money managers alike need not use a full month's commodity return but can rather use as the last days return of month for Brent Crude Oil and the last two days return of a month for Copper to predict how the S&P 500 is going to move in the coming month. There is evidence that the two day change in the price of Hogs has a positive relationship with S&P 500 monthly returns. This provides further evidence that the interval of observation is important as someone using monthly changes in the price of Hogs to predict monthly returns in the S&P 500 would conclude that no relationship exists.

Considering all the commodity series for any given interval of observation gives added insight into change how important this choice is. Kendall (1953) used weekly data in his paper when he concluded that commodity series had little predictive power. Researchers investigating commodity data for a more recent time period would arrive at precisely the same conclusion if they used weekly data. Neither the 5 nor 6 day cumulative periods generate statistically significant results for any of the commodity series when regressed against the S&P 500. However, a series such as Copper is statistically significant for periods slightly shorter than a trading day week (2-4 days) and periods slightly longer than a trading day week (7-9 days). As another example, a researcher who arbitrary uses three-weekly or 15 days of data, without giving consideration to other intervals would conclude that commodity series have strong predictability. Over this interval five of the commodity series generate statistically significant results.

The World results, displayed in Panel B, show a similar trend as their S&P 500 counterparts, but as with the Monthly results in Table 2, are not quite as strong. There is evidence of cumulative daily movements of Industrial Metals (Copper, Aluminum, and Nickel) of periods much shorter then a month predicting monthly movements in the World Index, but there is less evidence of this for the Energy related commodities. Only price changes in Heating Oil is statistically significant (for a 15 day period). Unlike the monthly results for the World Index, changes in the price of Sugar have a positive relationship with movements in the World Index. This holds for cumulative daily periods of 6 to 9 days. Other cumulative daily results also show that a six day change in the price of Gold and a one day change in the price of Zinc have positive relationship with movements in the World Index. Nether of these commodities had any relationship in the monthly data.

The UK results displayed in Panel C are as expected given the monthly UK results in Table 2 and the relationship between the cumulative daily and monthly results for the other two equity indices. Changes in the price of Aluminum for a range of periods between 4 and 17 days and changes in the price of Nickel for periods of 13 to 15 days have a negative relationship with the UK equity index. The positive relationship between Sugar and the UK Index documented in the monthly data is also evident in the cumulative daily data for periods of 9 and 13 days. Movements in the price of Hogs, Natural Gas, and Zinc over 1 or two days each have a positive relationship with movements in the UK Index. No relationship is evident in the monthly data for these commodities.

We present results which compare the statistical and economic significance of the monthly and cumulative daily approaches in Table 4. To mitigate the possibility that our cumulative daily results are being driven by chance we adjust these results for data snooping bias using the Bonferroni technique. There is a lot of consistency between commodities that are statistically significant in the monthly regressions and the daily regressions after the Bonferroni adjustment so we focus on these results first as they enable us to make meaningful conclusions about differences in the economic and statistical significance for the same commodity where only the interval of observation varies.

Please insert Table 4 around here.

West Texas Crude Oil, Heating Oil, Copper, Aluminum, Brent Crude Oil, and Nickel are all statistically significant at the 10% level or above under both monthly and cumulative daily approaches. It is clearly evident that the economic significance (beta coefficient) is consistently higher for each of the cumulative daily S&P 500 regressions than their monthly equivalents. This difference is sometimes relatively minor. For Brent Crude Oil the monthly coefficient is -0.08 and the cumulative daily coefficient is -0.09, but there is also instances of it being different by an order of magnitude. For instance, the monthly coefficient for Copper is -0.072, yet the cumulative daily coefficient is -0.393.

The strong predictive power of periods of less than one month is also evident in the t-statistics. The statistical significance of Copper, Aluminum, Nickel, West Texas Crude Oil, and Heating Oil is either at the same level (e.g. West Texas Crude Oil at 1%) or stronger (e.g. Copper 1% versus 10%) under the cumulative daily approach versus the monthly approach. The power of the cumulative daily approach is also indicated by the R-squared for the respective regressions. Each cumulative daily R-squared is higher than its monthly equivalent and this difference is sometimes large (e.g. Copper 5.86% versus 1.60%). The optimal cumulative daily period (based on statistical significance) is 3 days for Copper. This indicates that the S&P 500 is particularly sensitive to movements in the price of Copper. Other Energy and Industrial Metal commodities have a longer optimal cumulative daily period, ranging from 15 days for Heating Oil, to 22 days for Aluminum.

Taken together, these results provide strong evidence that movement in the prices of several Energy and Industrial Metal commodities predict changes in the S&P 500. Both the economic and statistical significance of this predictive power increases when data from periods less than a month is used, which indicates that markets aggregate information more quickly than a month. Individuals and money managers alike can add value to their investment decisions by using the information contained in price movements in these commodities over shorter horizons than a month.

The statistical significance of Live Cattle and Unleaded Gas in the monthly framework is not evident in the cumulative daily regressions after the Bonferroni adjustment. On the other hand, cumulative two-day movements in the price of Hogs and Soybeans have a statistically significant relationship (positive and negative respectively) with movements in the S&P 500 that was not evident in monthly approach. This is further evidence that the interval of observation is important.

The World Index results displayed in Panel B are similar to their S&P 500 counterparts in that monthly and cumulative daily movement in a range of Energy and Industrial Metal commodities (Heating Oil, Aluminum, and Nickel predict the World

Index. The Bonferroni adjustment removes the statistical significance in the cumulative daily West Texas Crude and Brent Crude Oil results, while Copper is not statistically significant using monthly data. The economic significance of Heating Oil, Aluminum, and Nickel is larger in the cumulative daily results, with the beta coefficient of Aluminum being -0.226 for the cumulative daily versus -0.133 for the monthly. Consistent with the S&P 500 results, the statistical significance and R-squareds are also larger under the cumulative daily approaches. The optimal number of days for the cumulative daily results is also similar to their S&P 500 counterparts. Heating Oil has an optimal number of 15 days in both instances, while Nickel is 15 days for the World Index versus 16 days for the S&P 500. The optimal number of days for Aluminum, at 11, is lower in the World Index results.

Changes in Copper have a negative relationship with the World Index, while Gold, Sugar, and Zinc changes have positive relationships in the cumulative daily data that do not exist in the monthly data. Unsurprisingly, the optimal number of days for each of these is low (e.g. Zinc 1 day), indicating that the significance at these short horizons is being cancelled out by other effects as the horizon tends towards one month. Changes in the price of West Texas Crude and Brent Crude Oil both have a statistically significant negative relationship with the World Index in the monthly data which does not exist in the cumulative daily data. A strong negative relationship is prevalent but the significance does not survive the Bonferroni adjustment.

The UK results displayed in Panel C also display a similar trend to the S&P 500 and World Index results. Aluminum, Nickel, and Sugar are statistically significant under both the cumulative daily and monthly approaches and this statistical significance is stronger under the cumulative daily approach. The economic significance and R-squareds are also higher under the cumulative daily approach. Unlike the Industrial Metals, movements in the price of Sugar have a positive relationship with movements in the UK index. Consistent with the World Index results, changes in the price of West Texas Crude and Brent Crude Oil both have a statistically significant negative relationship with the in the monthly data but this significance does not survive the Bonferroni adjustment in the cumulative daily results. Movements in the price of Zinc and Hogs both display a positive relationship with movements in the UK Index over 2 and 1 day periods respectively.

We now turn our consideration to the economic significance of our results from the perspective of a trading rule. More specifically, we apply a monthly trading rule which involves using the prior 60 months to generate our regression parameters. We then use these parameters, together with the latest commodity return, to predict whether S&P 500 will out perform the T-bill rate in the next month. If the model suggests it will, we go long the S&P 500, if not we invest in T-bills. We continue this each month and generate a return to our trading rule based on the assumption of 0.1% trading costs. We then apply an equivalent cumulative daily trading rule which uses 60 past observations of cumulative daily data for each interval. We compare the monthly and cumulative daily approaches to a buy and hold approach based on their means, standard deviations and Sharpe Ratios. We present cumulative daily results based for the period that gives the highest t-value, as reported in Table 4, and for the period that generates the highest Sharpe Ratio.

Please insert Table 5 around here.

As expected, the buy-and-hold approach is more risky than each of the trading rule approaches. The buy-and-hold approach is continually in the market so the standard deviation of the S&P 500 based on each of the commodity series start dates is larger than the standard deviation of each trading rules. Despite, the lower standard deviations, the monthly trading rule does not generate Sharpe Ratios that are consistently better than the buy-and-hold approach as the trading rule means tend to be lower than their buy-and-hold counterparts. Only 7 of the 20 commodity series generate Sharpe Ratios under the monthly trading rule that are greater than their buy-and-hold equivalents.

However, the trading rule performance improves dramatically when the cumulative daily data is used. The cumulative daily intervals that produce the highest Sharpe Ratios result in 15 of the 20 commodity series generating superior Sharpe Ratios to the buy-and-hold approach. Many of the Sharpe Ratio improvements are dramatic, with those of Copper, Silver, and Soybeans more than doubling. The poor performance of the S&P 500 equating to the start dates of the Coffee and Natural Gas series is expected once the start dates are considered. The Coffee data starts July 1994 that means the first out-of-sample performance is August 1999 onwards, just prior to the onset of the bear market, while the Natural Gas first out-of-sample performance is February 2002, which is part way through the bear market.

These trading rule results provide further evidence on the importance of the interval of observation. A trader using these rules to determine that predictive ability of commodity series for equity series would make quite different conclusions depending on the interval of observation they choose. If they used monthly data they would conclude little value could be added across all the commodities, but if they choose to use cumulative daily data with certain frequencies they would conclude there was a lot of predictability that could be profitably exploited.

In summary, we propose that our results provide strong evidence that the interval of observation is indeed important. Where statistically significant results occur under monthly and cumulative daily approaches we find that level of significance is consistently higher under the cumulative daily approach, even after the Bonferroni adjustment. The R-squared and economic significance are always higher under the cumulative daily approach. We also show that robust relationships exist in the data as shown in the cumulative daily results that someone using monthly data would not pick up. Alternatively, several monthly results do not stand up to the Bonferroni adjustment in the cumulative daily framework.

4. Conclusions

We investigate the observation of Sir Maurice Kendall (1953) that "the interval of observation may be very important" that he made in his seminal paper on return predictability Just as in Kendall's earliest return predictability tests, researchers still regress daily data on daily data, weekly data on weekly data, monthly data on monthly data almost everywhere in economics and finance. The convention of using past information of the previous day, week or month is a long-standing tradition in finance. This seems strange because apart from the convenience of having data available at a specific frequency, this convention lacks a clear economic motivation. If markets aggregate information not instantaneously but still fairly quickly, and an investor wants to predict next month's return, it makes more sense to use shorter intervals than the conventional approach of using a full month of past information to test whether predictability is present.

We assume that if there is any predictability, the market will most likely be nearly efficient and respond faster to new information than a full month. Therefore we start with a regression of information based on the last trading day of the previous month only and add a maximum of 22 trading days (which is the average number of trading days in any month in our sample).

We find evidence to support Kendall's (1953) proposition. The conventional approach can indeed strongly affect conclusion regarding size, strength and even sign of return predictability. Commodities that have a statistically significant relationship with the equity indices when monthly commodity data is used often have a stronger statistically significant relationship when cumulative daily data is used. The economic significance under the cumulative daily approach is also consistently higher. We also find evidence of robust return predictability using cumulative daily data that is not evident in the monthly data and evidence of return predictability in the monthly data that is not evident in the cumulative daily data. Taken together we propose that our results provide strong evidence that the interval of observation is important and conclusions may drastically vary with the interval of observation. The question what the proper interval of observation deserves more attention than it has received over the last fifty years of research in finance and economics.

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Table 1: Summary Statistics

Monthly	Start Date	Obs	Mean (%)	Std Dev (%)	Skewness	Kurtosis	rho(1)	Price as of 30 June 2006
sp500	194607	720	0.590%	4.09%	-0.522	5.164	0.024	1270.200
World	198002	317	0.711%	4.153%	-0.632	4.516	0.043	1319.930
UK	196901	450	0.572%	6.327%	0.285	8.677	0.082	5482.600
WT Crude Oil	198304	279	0.328%	9.320%	0.012	5.462	0.127	73.93 $/barrel
Heating Oil	198606	241	0.680%	11.02%	-0.175	7.190	-0.087	205.66 cents/gallon
Copper	198901	210	0.332%	6.882%	0.172	4.997	0.030	353.75 cents/pound
Aluminum	198901	210	-0.009%	5.657%	-0.427	4.561	-0.008	2550.50 $/ton
Gold	196906	445	0.594%	5.767%	0.612	7.097	0.109	612.60 $/oz
Silver	196801	462	0.359%	9.076%	-1.540	26.083	0.039	11.01 $/oz
Wheat	196201	534	0.093%	7.372%	-0.042	4.869	0.072	3.41 $/bushel
Corn	194607	720	0.001%	6.773%	-0.014	5.893	0.055	2.16 $/bushel
Live Cattle	197609	358	0.309%	4.513%	-0.076	4.213	0.107	113.16 cents/pound
Hogs	198001	318	0.233%	10.013%	0.714	9.413	-0.053	78.45 cents/pound
Brent Crude Oil	198706	229	0.600%	10.684%	0.221	4.491	-0.025	73.70 $/barrel
Cocoa	198301	282	0.031%	7.338%	0.360	3.751	-0.093	1914.00 $/ton
Coffee	199407	144	-0.567%	9.163%	0.433	6.418	-0.036	64.56 cents/pound
Lead	198901	210	0.140%	6.913%	0.442	3.938	-0.032	955.00 $/ton
Natural Gas	199701	114	0.214%	22.086%	-0.184	4.829	-0.194	5.13 $/mcf
Nickel	198901	210	0.081%	9.264%	0.045	3.769	0.044	22275 $/ton
Soybeans	195109	658	0.094%	7.469%	0.151	9.862	-0.025	5.41 $/bushel
Sugar	197909	322	0.183%	11.292%	0.813	5.643	0.084	17.03 cents/pound
Unleaded Gas	198606	241	0.603%	12.688%	0.652	6.859	-0.095	218.68 cents/gallon
Zinc	198901	210	0.315%	6.892%	0.082	3.398	0.028	3260.00 $/ton

Note: Summary statistics are based on equity market and commodity data from Global Financial Data (GFD).

Table 2: Monthly Regression Results

Panel A: Commodities Predicting S&P 500	alpha	t(alpha)	beta	t(beta)	R^2
WT Crude Oil	0.008	3.27***	-0.087	-3.47***	3.70%
Heating Oil	0.007	2.81***	-0.083	-3.59***	4.43%
Copper	0.007	2.70***	-0.072	-1.85***	1.60%
Aluminum	0.007	2.67***	-0.137	-3.04***	3.94%
Gold	0.006	2.82***	-0.021	-0.82	0.08%
Silver	0.006	2.77***	0.005	0.27	0.01%
Wheat	0.005	2.93***	0.006	0.25	0.01%
Corn	0.006	3.77***	-0.010	-0.41	0.03%
Live Cattle	0.007	3.31***	-0.075	-1.75*	0.65%
Hogs	0.008	3.20***	0.020	0.67	0.23%
Brent Crude Oil	0.007	2.55***	-0.080	-3.40***	4.07%
Cocoa	0.008	3.26***	-0.033	-0.92	0.33%
Coffee	0.007	2.09**	0.013	0.48	0.08%
Lead	0.007	2.64**	-0.026	-0.93	0.21%
Natural Gas	0.004	1.03	0.025	1.06	1.61%
Nickel	0.007	2.61***	-0.065	-2.46**	2.38%
Soybeans	0.006	3.69***	-0.012	-0.64	0.05%
Sugar	0.008	3.28***	0.016	0.75	0.18%
Unleaded Gas	0.007	2.66***	-0.044	-1.91*	1.64%
Zinc	0.007	2.58***	0.000	0.00	0.00%

Panel B: Commodities Predicting World	alpha	t(alpha)	beta	t(beta)	R^2
WT Crude Oil	0.007	3.09***	-0.080	-3.01***	3.29%
Heating Oil	0.006	2.34***	-0.047	-1.85*	1.53%
Copper	0.005	1.77*	-0.041	-1.14	0.48%
Aluminum	0.005	1.71*	-0.133	-2.95***	3.43%
Gold	0.007	3.09***	0.022	0.63	0.07%
Silver	0.007	3.09***	0.001	0.06	0.00%
Wheat	0.007	3.08***	0.013	0.40	0.05%
Corn	0.007	3.07***	-0.013	-0.38	0.06%
Live Cattle	0.007	3.12***	-0.057	-1.23	0.32%
Hogs	0.007	2.97***	0.005	0.20	0.01%
Brent Crude Oil	0.005	1.97**	-0.061	-2.47***	2.40%
Cocoa	0.008	3.09***	-0.026	-0.76	0.21%
Coffee	0.005	1.62	0.036	1.51	0.72%
Lead	0.005	1.75*	-0.043	-1.23	0.53%
Natural Gas	0.004	0.97	0.024	0.96	1.53%
Nickel	0.005	1.70*	-0.058	-2.22**	1.78%
Soybeans	0.007	3.09***	0.015	0.56	0.06%
Sugar	0.007	3.12***	0.031	1.60	0.72%
Unleaded Gas	0.006	2.30**	-0.026	-1.11	0.63%
Zinc	0.005	1.73*	-0.008	-0.21	0.02%

Panel C: Commodities Predicting UK					
	alpha	t(alpha)	beta	t(beta)	R^2
WT Crude Oil	0.008	2.84***	-0.092	-2.80***	3.00%
Heating Oil	0.006	2.21**	-0.037	-1.21	0.72%
Copper	0.005	1.99**	-0.035	-0.92	0.30%
Aluminum	0.005	1.92*	-0.106	-2.14**	1.86%
Gold	0.006	2.12**	-0.034	-0.76	0.10%
Silver	0.006	1.90*	-0.042	-1.29	0.36%
Wheat	0.006	1.85*	-0.002	-0.05	0.00%
Corn	0.006	1.87*	-0.012	-0.32	0.02%
Live Cattle	0.009	3.47***	-0.045	-0.68	0.14%
Hogs	0.007	2.70***	0.019	0.70	0.13%
Brent Crude Oil	0.005	1.92**	-0.057	-2.20**	1.65%
Cocoa	0.008	2.89***	-0.03	-0.72	0.19%
Coffee	0.006	1.82*	0.033	1.02	0.65%
Lead	0.005	1.97**	-0.034	-1.03	0.29%
Natural Gas	0.004	1.07	0.009	0.40	0.27%
Nickel	0.005	1.93*	-0.052	-1.91*	1.23%
Soybeans	0.006	1.84*	0.021	0.60	0.08%
Sugar	0.007	2.75***	0.056	1.92*	1.46%
Unleaded Gas	0.006	2.16**	-0.017	-0.72	0.20%
Zinc	0.005	1.94*	0.03	0.71	0.22%

Note: Estimation results of regression (1) $r_T^m = \mu + \alpha x_{T-1}^m + \varepsilon_t$ in the text, where r_T^m is the monthly return on the equity market index in month *T* and x_{T-1}^m is the return on the commodity series in month *T-1*. t-values are based on Newey-West heteroskedasticity and autocorrelation consistent (HAC) standard errors and t-values denoted *, **, and *** are statistically significant at the 10%, 5%, and 1% levels respectively.

Table 3: Cumulative Daily Regression Results

Panel A: Commodities Predicting S&P 500

Day	W Oil	H Oil	Copp	Alum	Gold	Silv	Whea	Corn	Catt	Hogs	B Oil	Coco	Coff	Lead	N Gas	Nick	Soyb	Suga	UL Gas	Zinc
1	-0.07	0.55	-2.52	1.08	1.42	-0.35	0.61	0.49	0.88	1.49	-2.62*	-0.01	-1.09	0.27	1.67	-0.36	-1.93	0.09	-0.19	2.54
2	-0.21	0.25	-3.33***	-1.42	0.47	-2.18	0.03	0.12	-0.22	3.60***	-1.64	1.63	-1.85	-0.16	1.65	-1.07	-2.72*	-0.40	1.05	1.25
3	-0.35	0.10	-3.94***	-1.24	0.49	-0.85	0.25	0.41	0.78	2.59	-1.55	-0.09	-2.43	-0.78	1.63	-1.12	-1.62	-0.19	0.74	0.44
4	0.31	0.01	-3.17**	-1.04	0.18	-1.02	1.23	0.34	0.31	1.97	-1.27	-0.03	-1.27	-0.40	1.40	0.13	-0.61	0.01	0.74	1.35
5	1.21	-0.28	-2.59	-1.22	0.99	-0.08	0.44	0.69	0.24	1.61	-0.88	-0.25	-1.70	-0.17	1.45	0.23	-1.11	1.26	0.40	1.63
6	0.37	-0.58	-1.94	-1.28	0.68	-1.62	0.17	0.17	-0.20	1.10	-0.87	-0.58	-1.69	0.22	1.43	0.40	-1.19	1.57	0.38	1.02
7	-0.27	-1.51	-2.64*	-2.21	0.35	-0.80	-0.20	0.73	-0.09	0.97	-1.26	-0.93	-1.92	-0.01	1.27	-0.16	-0.50	1.62	0.10	0.64
8	-1.13	-2.12	-3.06**	-2.49	0.47	-0.49	0.00	0.31	0.17	1.51	-1.97	-0.88	-2.08	0.14	1.76	-0.79	-0.77	1.57	-0.12	0.04
9	-1.51	-2.33	-3.00**	-2.58	0.19	-1.57	0.43	0.59	-0.12	1.46	-2.57	-1.06	-1.25	-0.45	1.48	-1.88	-0.52	1.74	0.02	-0.61
10	-2.81*	-3.01**	-2.02	-2.53	-0.64	-1.56	0.31	0.28	-0.26	1.40	-3.07**	-0.96	-0.75	-0.38	1.50	-1.63	-0.71	1.41	-0.79	0.14
11	-2.08	-2.49	-2.13	-3.20**	-0.65	-1.06	0.37	-0.10	-0.15	1.42	-3.22**	-1.45	-0.11	-0.78	1.39	-2.14	-0.86	0.90	-0.20	-0.41
12	-1.81	-2.58	-2.53	-2.81*	-1.48	-1.23	0.32	-0.39	-0.12	1.17	-3.09**	-1.63	0.38	-0.62	1.18	-2.24	-0.66	1.06	-0.29	-0.08
13	-1.98	-3.23**	-2.15	-3.02**	-1.07	-0.96	0.41	-0.09	0.05	1.10	-2.88**	-1.45	0.57	-0.80	1.06	-2.57	-0.39	1.29	-0.68	-0.18
14	-2.15	-3.66***	-1.88	-3.36***	-1.30	-1.11	0.28	-0.64	-0.60	1.20	-3.11**	-1.26	0.50	-0.71	0.96	-2.70*	-0.25	1.27	-0.76	-0.04
15	-2.56	-4.32***	-3.27**	-3.20**	-1.26	-0.80	0.62	-0.66	-0.55	1.26	-3.11**	-0.76	0.26	-1.22	0.76	-2.89**	-0.27	0.78	-1.22	0.06
16	-2.81*	-3.89***	-2.01	-3.52***	-1.03	-0.35	1.17	-0.16	-0.93	1.32	-2.75*	-0.77	1.42	-1.37	1.03	-3.24**	-0.26	0.66	-1.44	-0.07
17	-2.70*	-4.23***	-2.00	-3.52***	-0.80	-0.25	0.48	-0.19	-1.17	1.66	-3.29**	-0.85	1.16	-1.23	1.07	-2.97**	-0.38	0.94	-1.55	-0.20
18	-3.30**	-4.26***	-2.10	-3.51***	-0.49	0.33	0.53	-0.68	-1.01	1.30	-3.46***	-0.90	1.29	-0.66	1.26	-2.83**	-0.59	0.94	-1.87	-0.17
19	-3.53***	-3.62***	-1.94	-3.13**	-0.47	0.17	0.54	-0.41	-1.46	1.11	-3.51***	-0.90	1.24	-0.20	1.25	-2.30	-0.47	0.74	-2.22	0.05
20	-3.07**	-3.71***	-2.12	-3.58***	-0.46	0.23	0.41	-0.31	-1.48	1.17	-3.17**	-1.09	0.39	-0.47	0.67	-2.15	-0.77	0.55	-2.01	-0.21
21	-2.70*	-3.57***	-2.07	-3.55***	-0.37	0.50	-0.05	-0.34	-1.68	0.87	-3.35***	-0.73	-0.04	-0.97	0.91	-1.96	-0.43	0.44	-1.76	-0.22
22	-2.81*	-3.56***	-1.73	-3.70***	-0.45	0.45	0.22	-0.12	-1.53	0.75	-3.43***	-0.66	0.32	-0.92	0.74	-1.87	0.05	0.53	-2.06	-0.35

Panel B: Commodities Predicting World

Day	W Oil	H Oil	Copp	Alum	Gold	Silv	Whea	Corn	Catt	Hogs	B Oil	Coco	Coff	Lead	N Gas	Nick	Soyb	Suga	UL Gas	Zinc
1	-0.46	-0.19	-2.18	-0.70	1.39	0.14	-0.19	-1.40	-0.43	0.26	-1.86	-0.51	-0.77	-0.84	1.69	-0.53	-2.03	0.58	0.06	2.84**
2	-0.72	-0.28	-2.10	-1.88	0.96	-0.78	-1.25	-1.63	-0.83	2.48	-1.23	1.95	-1.68	-0.95	2.05	-0.94	-1.70	0.05	0.64	1.47
3	-1.02	-0.27	-2.58	-1.78	1.01	-0.07	-0.94	-0.86	0.29	1.50	-1.05	-0.41	-2.33	-0.71	1.56	-1.09	-1.17	1.00	0.22	0.61
4	0.09	-0.09	-3.05**	-2.39	1.06	-0.06	0.34	-0.61	0.30	1.42	-0.34	-0.38	-0.94	-0.93	1.05	-0.44	-0.92	1.31	0.51	1.07
5	0.68	-0.33	-2.82**	-2.75*	2.13	0.42	0.51	-0.43	0.06	1.11	-0.12	-0.17	-1.22	-1.18	1.05	-0.63	-1.24	2.53	0.38	0.87
6	0.06	-0.81	-1.71	-2.66*	2.67*	-0.16	0.51	-0.57	0.21	0.52	-0.34	-0.58	-1.34	-0.84	1.10	-0.25	-1.28	2.92**	0.56	0.24
7	-0.10	-1.00	-2.49	-2.15	1.99	0.22	0.31	-0.10	0.27	0.24	-0.37	-0.81	-1.24	-0.82	0.99	-0.28	-0.67	2.65*	0.50	0.04
8	-0.59	-0.99	-3.33***	-2.56	2.09	0.55	0.32	0.08	0.89	1.07	-0.46	-0.91	-2.36	-0.59	1.33	-0.89	-0.67	2.72*	0.54	-0.70
9	-1.09	-1.25	-3.60***	-2.97**	1.71	-0.15	0.98	0.20	0.34	0.87	-1.31	-1.19	-1.56	-1.08	1.11	-2.12	-0.29	2.84**	0.66	-1.03
10	-2.19	-1.95	-2.33	-3.11**	0.70	-0.61	0.54	-0.23	0.07	0.92	-1.77	-1.69	-0.85	-1.12	1.13	-2.04	-0.53	2.49	-0.18	-0.14
11	-1.70	-1.36	-2.13	-3.40***	0.79	-0.46	0.44	-0.39	0.29	0.95	-1.94	-1.93	-0.02	-1.87	1.10	-2.63*	-0.50	1.90	0.24	-0.71
12	-1.18	-1.39	-2.29	-3.13**	0.21	-0.92	-0.01	-0.84	0.50	0.89	-1.91	-1.85	0.47	-1.62	0.95	-2.71*	0.00	1.99	0.31	-0.47
13	-1.33	-1.79	-2.26	-3.04**	0.49	-0.65	0.31	-0.48	0.48	0.74	-1.68	-1.77	0.85	-1.88	0.79	-3.04**	0.48	2.42	0.17	-0.69
14	-1.51	-2.41	-1.78	-3.15**	0.53	-0.92	0.34	-0.63	0.03	0.73	-2.03	-1.66	0.78	-1.52	0.77	-3.11**	0.81	2.32	-0.18	-0.46
15	-1.94	-2.81*	-2.67*	-3.05**	0.34	-0.43	0.53	-0.93	0.28	0.86	-2.10	-1.23	0.69	-2.02	0.54	-3.21**	0.53	1.55	-0.58	-0.01
16	-1.76	-1.98	-1.43	-3.12**	0.57	-0.13	1.30	-0.37	-0.23	0.99	-1.64	-1.10	1.70	-1.82	0.73	-3.16**	0.84	1.35	-0.74	-0.05
17	-1.58	-2.20	-1.54	-3.16**	0.70	-0.24	0.88	-0.39	-0.25	1.37	-1.81	-0.92	1.61	-1.79	0.83	-2.90**	0.67	1.56	-0.76	-0.20
18	-2.29	-2.10	-1.54	-3.36***	0.96	0.34	0.99	-0.60	-0.27	0.93	-2.40	-0.78	1.96	-1.24	1.03	-2.85**	-0.13	1.65	-1.07	-0.43
19	-2.30	-1.62	-1.24	-3.08**	0.74	0.08	1.10	-0.50	-0.83	0.66	-2.18	-0.70	1.91	-0.94	1.05	-2.46	-0.02	1.34	-1.21	-0.14
20	-2.35	-1.76	-1.32	-2.99**	0.53	0.06	1.03	-0.41	-0.92	0.77	-2.11	-1.02	1.37	-0.96	0.51	-2.17	0.17	1.18	-1.18	-0.38
21	-2.15	-1.87	-1.14	-2.76*	0.81	0.42	0.48	-0.46	-1.20	0.48	-2.29	-0.56	1.07	-1.04	0.72	-1.70	0.19	1.35	-0.81	-0.20
22	-2.52	-2.05	-0.88	-2.62*	0.65	0.57	0.89	-0.06	-1.29	0.24	-2.45	-0.70	1.26	-1.01	0.54	-1.53	0.55	1.20	-1.24	-0.30

Panel C: Commodities Predicting UK

Day	W Oil	H Oil	Copp	Alum	Gold	Silv	Whea	Corn	Catt	Hogs	B Oil	Coco	Coff	Lead	N Gas	Nick	Soyb	Suga	UL Gas	Zinc
1	0.55	1.14	-1.63	-0.74	2.17	0.65	0.41	-1.14	-0.45	0.61	0.62	0.49	0.28	0.14	1.50	-0.31	-0.52	0.88	1.00	2.86**
2	0.21	0.77	-1.32	-2.11	0.32	-0.41	0.04	-0.63	-0.61	2.84**	0.35	0.88	-1.28	0.15	2.23*	-0.60	-0.79	0.41	1.52	2.43
3	-0.68	0.22	-0.88	-2.09	0.05	-0.23	0.78	0.34	-0.06	2.29	0.07	-0.43	-1.52	0.29	1.36	-0.64	0.19	1.53	0.60	1.02
4	0.16	0.06	-1.51	-2.75*	-0.36	-0.20	1.11	0.18	0.56	1.95	0.38	-0.04	-0.60	0.37	0.87	-0.41	0.22	1.61	1.02	1.86
5	1.08	-0.14	-1.24	-2.93**	0.79	0.76	1.50	0.61	0.74	2.12	0.49	-0.11	-0.53	0.19	0.75	-0.56	0.20	2.26	0.97	1.40
6	-0.13	-0.46	-0.48	-2.86**	0.56	-0.33	1.22	0.37	0.65	1.45	0.14	-0.65	-0.58	0.53	0.76	-0.06	0.34	2.54	1.14	1.05
7	-0.50	-1.09	-1.48	-2.14	0.17	-0.29	0.84	0.31	0.78	1.07	-0.51	-0.66	-0.48	0.49	0.58	0.16	0.23	2.33	0.79	0.93
8	-0.79	-0.84	-1.98	-2.39	0.56	-0.21	0.95	0.40	0.91	1.68	-0.34	-0.48	-1.32	0.79	0.89	-0.54	0.53	2.44	0.99	0.39
9	-1.29	-0.96	-2.24	-2.44	0.22	-0.76	1.05	0.15	0.73	1.64	-1.37	-0.73	-1.18	0.42	0.72	-1.79	0.39	2.71*	1.03	0.41
10	-2.38	-1.75	-1.29	-2.59	-0.29	-0.70	1.04	-0.15	0.37	1.63	-1.98	-0.85	-1.07	0.52	0.44	-1.55	0.33	2.53	0.11	1.11
11	-2.27	-1.37	-1.63	-2.99**	-0.17	-0.72	0.65	-0.47	0.25	1.50	-2.00	-1.19	-0.12	-0.40	0.36	-2.15	0.52	2.08	0.31	0.37
12	-1.79	-1.28	-1.81	-2.82*	-0.38	-1.08	0.08	-0.79	0.18	1.49	-1.96	-1.27	-0.01	-0.93	0.29	-2.46	0.62	2.30	0.12	0.48
13	-1.72	-1.35	-2.00	-2.65*	0.02	-0.84	0.19	-0.70	0.36	1.32	-1.71	-1.37	0.40	-1.15	0.15	-2.94**	0.48	2.79*	-0.08	0.15
14	-1.83	-1.58	-1.56	-2.77*	-0.12	-0.60	0.28	-0.86	0.02	1.36	-1.98	-1.23	0.39	-0.43	0.09	-3.00**	0.63	2.59	-0.32	0.55
15	-2.03	-1.77	-1.68	-2.60	-0.42	-0.61	0.46	-0.96	0.28	1.19	-1.62	-0.74	0.46	-1.00	-0.03	-2.83*	0.39	2.15	-0.45	1.18
16	-1.68	-1.10	-0.94	-2.54	-0.27	-0.56	0.89	-0.58	-0.25	1.43	-1.24	-0.62	1.14	-1.01	0.04	-2.52	0.38	1.97	-0.41	0.99
17	-1.43	-1.27	-1.09	-2.64*	-0.19	-0.94	0.49	-0.32	-0.05	1.43	-1.42	-0.55	1.03	-1.11	0.16	-2.40	0.26	2.10	-0.31	0.79
18	-2.18	-1.25	-1.02	-2.57	-0.23	-0.54	0.54	-0.71	-0.06	1.27	-2.05	-0.40	1.38	-0.88	0.56	-2.25	-0.03	1.89	-0.82	0.64
19	-2.16	-1.01	-0.76	-2.37	-0.59	-1.20	0.44	-0.42	-0.58	1.14	-1.80	-0.61	1.44	-0.84	0.72	-2.00	0.53	1.74	-0.90	1.13
20	-1.95	-1.01	-0.75	-2.15	-0.36	-1.13	0.16	-0.39	-0.59	1.12	-1.72	-0.84	1.07	-0.75	0.11	-1.78	0.30	1.78	-0.67	0.79
21	-1.93	-1.09	-0.70	-1.86	-0.50	-0.90	-0.11	-0.28	-0.82	0.95	-1.96	-0.50	0.67	-0.99	0.28	-1.48	0.40	1.94	-0.51	0.90
22	-2.34	-1.36	-0.64	-1.91	-0.63	-0.77	0.32	-0.12	-0.65	0.65	-2.17	-0.33	0.89	-1.20	0.13	-1.45	0.67	1.60	-1.01	0.73

Note: Estimation results of regression (2) $r_T^m = \mu + \alpha x_{t-1}^d + \varepsilon_t$ in the text, where r_T^m is the monthly return on the equity market index in month T and $x_{t-1_t}^d$ is the return on the commodity series on the last day of month *T-1*, the last two days of month *T-1* etc. t-values are based on Newey-West heteroskedasticity and autocorrelation consistent (HAC) standard errors and t-values in t-values denoted *, **, and *** are statistically significant at the 10%, 5%, and 1% levels respectively. These are based on the Bonferroni correction, which based on 22 different alternatives has critical t-statistics of 2.60, 2.84, and 3.32 for 10%, 5%, and 1% levels of significance respectively.

Table 4: Monthly and Cumulative Daily Regression Results Comparison

	Beta Monthly	Optimal Beta Cum. Daily	t(beta) Monthly	Optimal t(beta) Cum. Daily	Optimal Number of Days	Monthly R^2	Daily R^2
Panel A: Commodities Predicting S&P 500							
WT Crude Oil	-0.087	-0.094	-3.47***	-3.53***	19	3.70%	3.84%
Heating Oil	-0.083	-0.096	-3.59***	-4.32***	15	4.43%	5.05%
Copper	-0.072	-0.393	-1.85*	-3.94***	3	1.60%	5.86%
Aluminum	-0.137	-0.141	-3.04***	-3.70***	22	3.94%	3.94%
Gold	-0.021	-0.061	-0.82	-1.48	12	0.08%	0.39%
Silver	0.005	-0.109	0.27	-2.18	2	0.01%	0.48%
Wheat	0.006	0.069	0.25	1.23	4	0.01%	0.31%
Corn	-0.010	-0.018	-0.41	-0.68	18	0.03%	0.07%
Live Cattle	-0.075	-0.075	-1.75*	-1.68	21	0.65%	0.60%
Hogs	0.020	0.214	0.67	3.60***	2	0.23%	2.40%
Brent Crude Oil	-0.080	-0.090	-3.40***	-3.46***	18	4.07%	4.14%
Cocoa	-0.033	-0.076	-0.92	-1.63	12	0.33%	0.91%
Coffee	0.013	-0.113	0.48	-2.43	3	0.08%	1.42%
Lead	-0.026	-0.048	-0.93	-1.37	16	0.21%	0.60%
Natural Gas	0.025	0.044	1.06	1.76	8	1.61%	2.86%
Nickel	-0.065	-0.090	-2.46***	-3.24**	16	2.38%	3.37%
Soybeans	-0.012	-0.171	-0.64	-2.72*	2	0.05%	0.92%
Sugar	0.016	0.055	0.75	1.74	9	0.18%	0.96%
Unleaded Gas	-0.044	-0.057	-1.91*	-2.23	19	1.64%	2.10%
Zinc	0.000	0.328	0.00	2.54	1	0.00%	2.15%
Panel B: Commodities Predicting World							
WT Crude Oil	-0.080	-0.071	-3.01***	-2.52	22	3.29%	2.83%
Heating Oil	-0.047	-0.063	-1.85*	-2.81*	15	1.53%	2.28%
Copper	-0.041	-0.168	-1.14	-3.33**	8	0.48%	3.05%
Aluminum	-0.133	-0.226	-2.95***	-3.40***	11	3.43%	5.41%
Gold	0.022	0.170	0.63	2.67*	6	0.07%	1.47%
Silver	0.001	-0.020	0.06	-0.92	14	0.00%	0.14%
Wheat	0.013	0.045	0.40	1.30	16	0.05%	0.50%
Corn	-0.013	-0.166	-0.38	-1.63	2	0.06%	0.91%
Live Cattle	-0.057	-0.059	-1.23	-1.29	22	0.32%	0.33%
Hogs	0.005	0.160	0.20	2.48	2	0.01%	1.41%
Brent Crude Oil	-0.061	-0.061	-2.47***	-2.45	22	2.40%	2.57%
Cocoa	-0.026	-0.098	-0.76	-1.94	11	0.21%	1.48%
Coffee	0.036	-0.072	1.51	-2.36	8	0.72%	1.20%
Lead	-0.043	-0.076	-1.23	-2.02	15	0.53%	1.37%
Natural Gas	0.024	0.120	0.96	2.05	2	1.53%	5.21%
Nickel	-0.058	-0.087	-2.22**	-3.21**	15	1.78%	2.67%
Soybeans	0.015	-0.234	0.56	-2.03	1	0.06%	1.09%
Sugar	0.031	0.096	1.60	2.92**	6	0.72%	2.02%
Unleaded Gas	-0.026	-0.029	-1.11	-1.24	22	0.63%	0.70%
Zinc	-0.008	0.349	-0.21	2.84**	1	0.02%	2.27%

	Beta Monthly	Optimal Beta Cum. Daily	t(beta) Monthly	Optimal t(beta) Cum. Daily	Optimal Number of Days	Monthly R^2	Daily R^2
Panel C: Commodities Predicting UK							
WT Crude Oil	-0.092	-0.106	-2.80***	-2.38	10	3.00%	1.87%
Heating Oil	-0.037	-0.046	-1.21	-1.77	15	0.72%	0.94%
Copper	-0.035	-0.110	-0.92	-2.24	9	0.30%	1.28%
Aluminum	-0.106	-0.192	-2.14**	-2.99**	11	1.86%	3.31%
Gold	-0.034	0.586	-0.76	2.17	1	0.10%	1.15%
Silver	-0.042	-0.039	-1.29	-1.20	19	0.36%	0.29%
Wheat	-0.002	0.124	-0.05	1.50	5	0.00%	0.56%
Corn	-0.012	-0.174	-0.32	-1.14	1	0.02%	0.22%
Live Cattle	-0.045	-0.056	-0.68	-0.83	21	0.14%	0.20%
Hogs	0.019	0.250	0.70	2.84*	2	0.13%	2.21%
Brent Crude Oil	-0.057	-0.056	-2.20**	-2.17	22	1.65%	1.69%
Cocoa	-0.030	-0.069	-0.72	-1.37	13	0.19%	0.55%
Coffee	0.033	-0.070	1.02	-1.52	3	0.65%	0.62%
Lead	-0.034	-0.042	-1.03	-1.21	22	0.29%	0.48%
Natural Gas	0.009	0.109	0.40	2.23	2	0.27%	4.80%
Nickel	-0.052	-0.080	-1.91*	-3.00**	14	1.23%	1.79%
Soybeans	0.021	-0.107	0.60	-0.79	2	0.08%	0.20%
Sugar	0.056	0.089	1.92*	2.79*	13	1.46%	2.45%
Unleaded Gas	-0.017	0.097	-0.72	1.52	2	0.20%	0.60%
Zinc	0.030	0.292	0.71	2.86**	1	0.22%	1.35%

Note: Columns 2, 4, and 7 contain monthly estimation results of regression (1) $r_T^m = \mu + \alpha x_{T-1}^m + \varepsilon_t$ in the text, where r_T^m is the monthly return on the equity market index in month T and x_{T-1}^m is the return on the commodity series in month *T-1*. Columns 3, 5, 6 and 8 contain daily estimation results of regression (2) $r_T^m = \mu + \alpha x_{t-1}^d + \varepsilon_t$ in the text, where r_T^m is the monthly return on the equity market index in month T and $x_{t-1_t}^d$ is the return on the commodity series on the last day of month *T-1*, the last two days of month *T-1* etc. t-values are based on Newey-West heteroskedasticity and autocorrelation consistent (HAC) standard errors. The monthly t-values are based on traditional levels of significance. t-values denoted *, **, and *** are statistically significant at the 10%, 5%, and 1% levels respectively. The optimal number of days is the number of days that generates the highest t-value after applying the Bonferroni correction. The optimal t-value for the cumulative daily approach use the Bonferroni correction, which based on 22 different alternatives has critical t-statistics of 2.60, 2.84, and 3.32 for 10%, 5%, and 1% levels of significance respectively. t-values denoted *, **, and *** are statistically significant at the 10%, 5%, and 1% levels respectively.

Table 5: Economic Significance

	Buy and Hold			Monthly				Highest t-value				Highest Sharpe Ratio		
	Mean	Std Dev	Sharpe	Mean	Std Dev	Sharpe	Days	Mean	Std Dev	Sharpe	Days	Mean	Std Dev	Sharpe
WT Crude Oil	8.70%	13.43%	0.32	8.49%	11.74%	0.35	19	8.97%	11.44%	0.40	18	9.15%	11.39%	0.42
Heating Oil	8.20%	13.28%	0.33	8.52%	11.57%	0.41	15	8.14%	11.43%	0.38	9	8.93%	11.74%	0.44
Copper	7.81%	13.94%	0.28	8.76%	11.85%	0.42	3	9.66%	11.51%	0.51	12	10.52%	11.98%	0.56
Aluminum	7.81%	13.94%	0.28	7.15%	11.92%	0.28	22	8.30%	11.42%	0.39	20	8.82%	11.35%	0.44
Gold	8.41%	15.26%	0.16	7.53%	11.62%	0.13	12	5.99%	11.79%	0.00	1	9.05%	11.95%	0.26
Silver	7.16%	15.24%	0.07	6.75%	11.46%	0.06	2	6.59%	11.61%	0.05	22	7.85%	11.36%	0.16
Wheat	6.81%	14.94%	0.06	6.19%	10.99%	0.02	4	6.25%	11.30%	0.03	3	7.57%	11.35%	0.15
Corn	7.35%	14.15%	0.17	6.97%	10.83%	0.18	18	7.42%	10.98%	0.22	3	8.53%	10.63%	0.33
Live Cattle	9.66%	14.70%	0.29	7.17%	12.86%	0.14	21	7.57%	13.09%	0.17	2	9.01%	12.84%	0.29
Hogs	9.13%	14.79%	0.30	6.48%	13.47%	0.13	2	9.17%	13.06%	0.34	3	9.57%	13.18%	0.37
Brent Crude Oil	8.11%	13.29%	0.33	8.26%	11.59%	0.39	18	9.12%	11.43%	0.47	18	9.12%	11.43%	0.47
Cocoa	8.67%	13.39%	0.32	6.52%	12.21%	0.17	12	6.64%	11.70%	0.19	19	7.98%	11.98%	0.30
Coffee	-0.65%	14.76%	-0.25	-6.27%	12.81%	-0.72	3	-1.85%	10.88%	-0.45	3	-1.85%	10.88%	-0.45
Lead	7.81%	13.94%	0.28	6.52%	12.11%	0.22	16	6.63%	12.51%	0.22	13	7.83%	12.54%	0.32
Natural Gas	2.64%	13.09%	0.04	3.75%	7.90%	0.20	8	-0.39%	10.01%	-0.25	3	4.95%	7.56%	0.37
Nickel	7.81%	13.94%	0.28	6.49%	11.01%	0.24	16	6.86%	11.15%	0.27	12	9.65%	11.63%	0.50
Soybeans	6.70%	14.30%	0.09	6.71%	10.54%	0.13	2	6.74%	10.71%	0.13	22	7.95%	10.68%	0.24
Sugar	9.35%	14.75%	0.31	7.10%	13.32%	0.18	9	7.10%	13.22%	0.18	1	8.78%	12.75%	0.32
Unleaded Gas	8.20%	13.28%	0.33	7.10%	11.42%	0.29	19	6.80%	11.35%	0.27	18	7.44%	11.23%	0.33
Zinc	7.81%	13.94%	0.28	6.93%	12.39%	0.25	1	5.42%	11.93%	0.13	11	7.15%	12.46%	0.27

Note: Buy and Hold results are annualized mean, standard deviation and Sharpe Ratios for buying and holding the S&P 500 from the start date of each commodity series until the end of our sample period (30 June 2006). Monthly results refer to those generated by a trading rule which uses rolling monthly regression of 60 observations each to predict whether the trader should invest in the S&P 500 or T-bill the next month. Highest t-value results are the equivalent trading rule results when cumulative daily rather than monthly results are used. We report the cumulative daily period that gave the highest t-value in Table 4. Highest Sharpe Ratio results are cumulative daily trading rule results which produce the highest Sharpe Ratio.