Dependence in Commodity Prices

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INTRODUCTION

In recent years, the time-series properties of speculative prices have been given renewed attention. Two key issues involve the shape of the distribution that generates price changes and the relationship of price changes across time. The random walk hypothesis incorporates both of these elements by specifying that price changes in all nonoverlapping periods be independent and possess the same stationary distribution. Moreover, the concept of market rationality, which is consistent with the random walk theory, asserts that assets are priced by traders who use all available information to make unbiased predictions of future prices. The collective wisdom from earlier studies [Working (1934); Kendall (1953); Roberts (1959); Alexander (1961); Fama (1965)] generally supports the notion that speculative prices do follow a random walk, based on tests of serial correlation between successive price changes. Recent studies, however, reveal contradictory evidence regarding the nature of asset price changes over different time horizons. In particular, monthly and annual security returns have been shown to exhibit negative serial correlation [Fama and French (1988); Lehmann (1988); Poterba and Summers (1987); Cecchetti, Lam, and Mark (1989)]. Daily and weekly *individual* security returns appear to be negatively autocorrelated [French and Roll (1986); Lo and MacKinlay (1988)], while weekly *portfolio* returns reflect positive serial correlation [Conrad and Kaul (1988); Lo and MacKinlay (1988)]. The common conclusion from this evidence suggests a violation of the random walk hypothesis in many financial markets, implying that there are information components in past prices, beyond a general trend, that can be used by the technical analyst to predict future prices.

Perhaps more interesting is the attempt recent studies have made to suggest economic rationales either supporting or refuting the random walk hypothesis. These studies include "memory" in speculative prices caused by fads [Lehmann (1988);

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De Long et al. (1987, 1988, 1989)], rational bubbles [Behzad and Grossman (1987)], overreactions [DeBondt and Thaler (1985)], preference reversals [Slovic and Lichtenstein (1983)], production smoothing [Fair (1989)], consumption smoothing [Black (1989)], dividend smoothing [Shiller (1989)], market learning [Turner, Startz, and Nelson (1989)], time-varying risk perceptions [Friedman and Kuttner (1988)], small sample bias [Kim, Nelson, and Startz (1988)], and nonsynchronous trading [Lo and MacKinlay (1989)].

The relevance of time-series properties of speculative price movements is intensified by the recent debate on market volatility. Shiller (1981) argues that nonrandom stock price movements may be causing return volatility which is "excessive" in that it cannot be fully explained by volatility of the underlying fundamentals. French and Roll (1986) also show that the return variance in trading time periods is significantly higher than that in nontrading time periods. They argue that this phenomenon is at least partially due to noise from traders' overreaction to previous trades.

Compared with the financial markets literature, limited evidence exists on price behavior in real asset markets. Pindyck and Rotemberg (1988) show that prices of largely unrelated raw commodities have a tendency to move together. The excess comovement among commodity prices is puzzling since the correlation of prices cannot be fully accounted for by correlation of underlying common fundamentals. It has been hypothesized that the excess cross-sectional correlation is due to "herd" behavior, or fads, in markets—either bullish or bearish trading on all commodities for no explainable economic reason. Moreover, this seemingly irrational behavior could be explained if excess correlation is attributed to pooling of the aggregate fundamentals, thereby providing more information than the fundamental price determinants for each individual asset analyzed separately. The commonality among movements in raw commodity prices is further supported by evidence that the changes in commodity prices are often indicators of future inflation [Boughton and Branson (1988)].

Ma (1989) shows that daily cash commodity prices often exhibit reversals immediately following the arrival of significant information. While this evidence is consistent with the overreaction hypothesis, his findings cannot be generalized since they apply only to price behavior after significant events. Similarly, as Frankel (1986) points out, if commodity prices are flexible but other goods prices are sticky, a decline in the nominal money supply will raise the real interest rate and depress real commodity prices in the short run. Commodity prices would then overshoot their equilibrium levels to generate an expectation of future appreciation sufficient to offset the higher interest rate. When the real rate effects eventually vanish, the price will revert to its true long-run equilibrium.

This study seeks to test directly the random walk hypothesis in the cash prices of 17 commodities. Three theoretical components of commodity price series are identified: a systematic component reflecting price drift or the expected arrival of information, a negatively autocorrelated component which is attributed to the bid–ask spread of marketmakers, and a noise term which represents the pricing of unexpected information. Using the variance ratio test of Lo and MacKinlay (1988), the random walk hypothesis is rejected for daily commodity prices since many short-term realized returns exhibit either positive or negative persistence over different time horizons. Furthermore, the positive serial correlation between successive price changes goes beyond the structure of the underlying fundamentals. For many commodities, particularly grains and other crops, there is some evidence that positive serial correlation exists in price changes over short and intermediate time horizons.

These results indicate that many daily commodity prices appear not to react to unexpected information in a rational fashion in that either the adjustment process to new information is not instantaneous, possibly because of transaction costs, or because new information is revealed in a serially correlated fashion that is not properly anticipated. In other markets, such as livestock and gold, evidence of short-term price reversals appears. Such price reversals may occur because farmers and ranchers alter their near-term marketing plans in response to recent price changes, or because central banks try to stabilize gold price markets in the short run. Longer-term positive price trends (possibly due to inflation changes) are apparent in gold prices, while price reversals (possibly due to cobweb cycle effects) appear in livestock markets. Finally, in some markets such as silver and soybeans, no significant violations of random walk assumptions are observed.

EMPIRICAL DESIGN

Variance Ratio Tests

Before investigating the nature of random walks, Working (1934) and Larson (1960) make the distinction between anticipatory and random elements in a price series. As pointed out by Houthakker (1934), the randomness of a process can only be defined as the absence of any systematic pattern. The importance of the distinction between the anticipatory component and the random component is also empirically demonstrated by Conrad, Kaul, and Nimalendran (1989), who show that the individual components in the stock return series exhibit different time-series properties. As the short-horizon realized return shows negative dependence due to the bid–ask spread, an incorrect conclusion may be reached with respect to the time-series property of the true underlying return process. Others argue that the systematic structure of the time series, if expected, should be deterministic. Therefore, the testing of the random walk hypothesis should only be relevant with respect to the random component in the price series.[1]

The basic idea behind variance ratio tests is that price changes following a stable random walk will have a random variance component that increases linearly with time. Thus, if a commodity price series tends to vary up or down with a random variance of 0.1 over a one-day interval, the random variance component of price changes would, on average, be 0.2 over a two-day interval and 0.5 over a five-day interval, etc. Of course, estimates of variances over each interval would not be precise if they were made from random samples of data. For instance, the one-day random price change might be computed to be 0.09 and the five-day random price change variance might be computed to be 0.475. Thus, it is necessary to use a test-statistic to determine whether ratios of variances computed over different intervals are consistent with the linear variance characteristics of a random walk process or differ significantly from the results that would ordinarily be generated by a random walk process. Lo and MacKinlay (1988) have developed appropriate "variance ratio" test statistics for investigating the random walk properties of price series. Their test statistics are used to analyze the random walk properties of commodity price data. The procedures are described in Appendix A.

[1]The serial correlation computed over the original price series may reflect mainly the time-series property of the underlying systematic structure expected by the market.

The variance ratio test in Appendix A is conducted over q-day intervals versus one-day intervals. However, the test is robust for various interval length combinations. For instance, if q is designated as the number of lags and the basic interval length is designated i, variance ratio tests can be conducted for various combinations of q and i. Thus, for values of $i = 1$, i.e., for one-day price changes, variance ratio tests are run for (lag) values of $q = 2$, i.e., for price changes over two days, 4, i.e., for price changes over four consecutive trading days, or one trading week, 8, and 16. Values for i of 4 are used also (to measure the variance of price changes over approximately one week) and of 16 (to measure the variance of price changes over approximately a one-month, or four-week, period). When, for instance, variance ratio tests are computed for $i = 16$ and $q = 2$, the variance of price changes over 32 trading days is compared to the variance of price changes over 16 days.

All price changes are measured as log price relatives, i.e., as $\ln(P_t/P_{t-qi})$ where P_t is the closing price on day t and P_{t-qi} is the closing price of qi days earlier. If a stable random walk process holds, once the price change series is detrended and other regularities in price movements are taken into account, the random variance of the price change series should grow linearly with the length of the time over which the price changes are computed.

However, if the error component of price changes tends to cumulate rather than to vary randomly over some specific time interval, then the variance of the price change over large intervals would be greater than expected. The expected long interval price change variance should equal the variance of the short-interval price change multiplied by q (the number of short intervals in the long interval). However, if random price movements are positively correlated so prices move continuously in the same direction, the price change would cumulate in that direction, and would not be systematically offset by random walk movements in the opposite direction. One factor that could cause cumulative price movements would be a failure of the market to incorporate all new information in current prices instantaneously. Thus, prices might move in the same direction for several days or weeks in a row. Another factor generating price trends could be the sequential release of information that is not fully anticipated. For instance, in a drought, it may rain on any given day, yet, each day that goes by without rain will cause escalating crop damage at some point. As the next day comes and goes without rain, prices may continue to adjust to the ever increasing possibility that crop damage will be severe. Conversely, every day in the fall that goes by without frost may increase the chances for obtaining a bumper crop. As the weather information is revealed day-by-day, crop prices may continue to adjust in the same direction to reflect new supply possibilities.

Conversely, price changes may also move inversely over various time intervals. For instance, high hog prices one year may cause farmers to breed more hogs for the next marketing season, at which point prices are likely to fall. Similarly, high cattle prices one day may induce more farmers to ship their cattle to market in the next day or two so cattle prices will fall. Corn–hog cycles and cobweb cycles are well known in agriculture, and cause large price changes over one interval to be offset by significant reversals over longer intervals. Such processes also violate random walk assumptions since random price changes in one period are inversely correlated with price changes over a longer interval rather than being independent. If such phenomena exist, the variance of price changes over long intervals will be less than would be expected if short interval price changes are merely extrapolated to the longer period. Thus, if the variance ratio tests are significantly negative, evidence exists that the random walk hypothesis is rejected in a manner that would be expected if price reversals occurred. However, if variance ratio tests are significantly positive, this will be consistent with the evidence of persistence in price movements.

Return Adjustments for Holidays, Weekends, and Nontrading Periods

Before performing the variance ratio tests as described in the previous section, the sample must be examined to determine the transaction type of the daily prices (bid, ask, or variable transaction prices), thin trading, and the impact of nontrading periods. Each of these issues are relevant for the current topic. For example, if actual transaction prices are used, a seemingly negative autocorrelation may be produced since actual transaction prices often fluctuate between bid and ask prices. For this reason, the daily prices in the sample are obtained from dealer's offering quotes or ask prices. The selection of prices of the same type allows elimination of the bias on variance ratios from the negatively correlated component in the transaction price series—if the process of the bid–ask spread is stationary. A further bias in estimates of serial correlation can be introduced if the prices are taken from thin or nonsynchronized trading. This is mainly attributed to the fact that for a less actively traded instrument, the price may reflect new information after a lag. However, the slower adjustment speed to information, while it may exhibit nonrandom walks, does not suggest opportunities for profit since the instrument is not often traded. Lehmann (1980), recognizing both the problem of bid–ask spreads and of thin trading, suggests that using weekly returns from Thursday to Thursday may significantly reduce both biases. This is due to the fact that the impact of bid–ask spreads or infrequent trading will be insignificant when returns are computed over a longer time horizon. Therefore, to reduce the possible biases, the variance ratios over price changes are measured on longer time horizons as well as short horizons.

Since the variance ratio test is used to compare return variances, computed over periods of different lengths of time, the ratio will be biased if the time-series used is not homogeneous in terms of time periods covered for every price change. Whenever there are many types of institutional nontrading periods, such as holidays and weekends, the price change will cover more than the standard daily period, i.e., one-day trading session and one evening nontrading session. Thus, the variance ratio specified by equation (4) will be biased. Another subtle but significant issue with respect to uneven lengths of time periods over which price changes are computed results from the fact that return variances are higher in the trading session than in the nontrading session [French and Roll (1986)]. For instance, the Friday close to Monday close seemingly does not cover three standard daily periods, since there is only one day trading session and two day nontrading sessions in that period.

Therefore, it is important to adjust for both the uneven length of time and the uneven mix of trading and nontrading periods over a given interval. This can be conducted by first computing the daily return series, R_t, by the difference of logarithms of the original daily price series, P_t, i.e.,

$$R_t = \mathrm{Log}(P_t/P_{t-1}) \tag{1}$$

Note that while the time horizon of R_t generally covers one day trading session and one night nontrading session, it may also include more than one trading and nontrading periods if day t is a day following a nontrading day session, e.g., weekday holidays or Monday. To assure that the price series being tested is homogeneous in terms of the length of trading/nontrading periods, the daily returns immediately following a nontrading day session are excluded from the sample. That is, all Monday returns and returns following holidays are discarded. Using the rest of the sample, the revised price series, P_t' can be generated by

$$P_t' = P_O\left(1 + \exp \prod_{i=0}^{t} (1 + R_i) - 1\right) \tag{2}$$

where P_O is the base price on the first day of the sample. Equation (2) computes a revised price based on the continuously compounded daily returns from a base price. This way, daily prices are generated based on daily returns which all have the same length of trading and nontrading periods. Thus, the simulated time series of daily prices, P_t', has the property that each price change from the previous one covers the same number of trading and nontrading hours. Since all Monday returns are taken from the sample, the weekly return (Tuesday to Tuesday return) measured over the P_t' series is equivalent to Lehmann's (1988) weekly return adjusted for bid–ask spreads and thin trading, and four trading days comprise one week.

EMPIRICAL RESULTS

The sample includes daily cash prices for 17 commodity prices. The data used in the sample are described in Appendix B. All commodities have futures contracts traded during the same sample periods. Most commodities have more than 4000 daily observations which range over at least 15 years. To eliminate weekend and holiday effects, all price series are modified, as shown in equation (2), to eliminate returns ascribable to trading days that immediately follow a trading halt. Thus, each daily return represents only one full day's return. Based on the procedure described in the previous section, the variance ratios and their test statistics for various trading intervals and lags 2 through 60 (q = 2 to 60) are computed for each price series. For the sake of brevity, only the variance ratios of daily returns for selected lags with representative values are reported in Table I.[2]

The intervals over which returns are calculated for Table I include daily returns, with lags approximately equal to one week (four trading days), two weeks (eight trading days), and four weeks (16 days). Because holidays also are omitted, a month of trading contains approximately 16 trading days, and a year of trading contains between 12 and 13 such "months." The use of lags and intervals of approximately one week, one month, etc., in length should help reduce or eliminate possible systematic price patterns that recur on regular calendar-day intervals. Regarding the variance ratios presented in Table I, for all commodity price series combined, more than half of the variance ratios are significantly different from one at the 10% level or better as indicated by the Z values in parentheses. The data suggest that the random walk hypothesis is rejected for the daily price movements of most commodities since at least one variance ratio is significantly different from zero at the 10% confidence level for every commodity except silver and soybeans. The variance ratio for lag 2 can be approximated by 1-γ, where γ is the first-order autocorrelation. For example, a variance ratio of 1.014 for soybean oil implies a 1.4% positive serial correlation between successive daily prices. Therefore, based on the one-to two-day variance

[2]Only a few variance ratios of the 59 are reported for each of the commodities. The other results may be obtained from the authors upon request.

ratios, with an interval of one day and a lag of 2 reported in Table I, the (log-) prices of soybean meal, oats, coffee, sugar, heating oil, pork bellies, and copper are positively autocorrelated, and the day-to-day price changes of corn, feeder cattle, live hogs, and gold are negatively autocorrelated.

Over longer periods of time, from one week to one month, most of the commodity price changes exhibit positive persistence. For instance, when price changes are compared over one- to four-day intervals, thereby roughly comparing weekly to monthly price changes, price changes for soybean oil, wheat, cotton, coffee, sugar, heating oil, live cattle, live hogs, and copper all exhibit significantly positive serial correlation, while only pork bellies exhibit significantly negative serial correlation. A large proportion of the 17 commodities analyzed also show positive serial correlation when the variance of daily price changes is compared over four-, eight-, or 16-day intervals, or when four-day price changes are compared over two consecutive four-day periods. These results suggest that trending prices frequently occur in commodity markets; thus, there may be some validity to using trend-following technical analysis techniques in various commodity markets.

However, several commodities exhibit significantly negative serial correlation. Feeder cattle price changes usually exhibit significantly negative correlation patterns, while pork belly prices also exhibit decreasing variance ratio patterns except for very short intervals. In addition, gold exhibits negative serial correlation over relatively short intervals but positive serial correlation over longer periods, as variances computed over two to 12 lags are compared for 16-day return intervals. A possible explanation for these results might be that there might still be some systematic component remaining when the price series are differenced using small q's. Thus, variance ratios different from unity, observed at the shorter lags, may only reflect the serial correlation of the underlying systematic process of the commodity prices rather than the structure of the noise component per se. However, if the noise component, ε_t, truly follows a random walk, the variance ratio should follow a U (or a reversed U) shape as the level of q increases.[3] That is, $\lambda(q)^* = 1$ when $q = 1$ and q^*, and that does not appear to be the case. Thus, it is also possible that some markets do not respond efficiently to short-run random price shocks. For instance, farmers may bring more or less livestock to market with a lag, in response to past price increases or decreases, respectively, thereby causing negative correlation in price changes. Also, central banks may move to stablilize gold prices after sharp short-run price changes occur in gold's dollar price, etc.

Overall, in the cash price series of most of 17 commodities analyzed, most series exhibit autocorrelated random components. A few commodities exhibit a negatively correlated component over some variance intervals. Positive trends may reflect serially correlated releases of unexpected information— such as the unanticipated worsening of potential supply shortages or of droughts over time. Negative serial correlation might reflect the unanticipated lagged effect of supply adjustments or storage adjustments in response to previous price changes as, for instance, when more feeder cattle are sent to the meat packer rather than being kept on feed if prices are temporarily high, and the market does not anticipate the increased supply.

The findings of this study sharply contrast with other evidence in financial markets. Conrad, Kaul, and Nimalendran (1989); Ma (1989); Fama and French (1987);

[3]As pointed out by Fama and French (1986), the variance ratios would follow a U-shape if the underlying return generating process is composed of a random process and a mean-reverting process. The duration of the U-curve depends on the relative magnitude of each process.

TABLE I
VARIANCE RATIOS FOR DIFFERENT INTERVAL LENGTHS AND LAGS

Length of interval	1	1	1	1	4	4	16	16
Number of lags	2	4	8	16	2	4	2	12
Corn	0.970[a]	0.990	1.048	1.111	1.030	1.070	1.174[b]	1.203
	(−1.884)	(−0.376)	(1.074)	(1.598)	(0.930)	(1.265)	(2.742)	(0.856)
Oats	1.120[b]	1.274[b]	1.395[b]	1.486[b]	1.027	1.094	0.968	0.681
	(6.545)	(8.579)	(7.594)	(6.053)	(0.735)	(1.480)	(−0.429)	(−1.158)
Wheat	0.983	0.959	0.982	1.102	0.986	1.125[b]	1.059	1.008
	(−1.090)	(−1.505)	(−0.409)	(1.478)	(−0.447)	(2.268)	(0.929)	(0.035)
Soybeans	0.984	0.993	0.939	0.937	1.041	1.024	0.951	0.711
	(−1.014)	(−0.256)	(−1.350)	(−0.912)	(1.275)	(0.442)	(−0.776)	(−1.215)
Bean oil	1.014	1.079[b]	1.147[b]	1.239[b]	1.066[b]	1.142[b]	1.129[a]	1.088
	(0.872)	(2.874)	(3.282)	(3.453)	(2.079)	(2.582)	(2.031)	(0.370)
Soybean meal	1.072[b]	1.139[b]	1.104[b]	1.095	1.032	1.034	0.932	0.754
	(4.511)	(5.068)	(2.319)	(1.373)	(1.017)	(0.622)	(−1.074)	(−1.035)
Cotton	0.974	0.971	0.999	1.087	1.069	1.168[b]	1.067	0.938
	(−1.521)	(−0.953)	(−0.016)	(1.145)	(0.137)	(2.796)	(0.970)	(−0.239)
Heating oil	1.043[a]	1.080[b]	1.184[b]	1.265[b]	1.081[a]	1.158[b]	0.953	0.695
	(1.892)	(2.033)	(2.864)	(2.668)	(1.773)	(2.008)	(−0.517)	(−0.892)

Coffee	1.093[b]	1.284[b]	1.590[b]	1.992[b]	1.190[b]	1.475[b]	1.143[a]	1.641[b]
	(5.181)	(9.120)	(11.619)	(12.670)	(5.286)	(7.630)	(1.990)	(2.381)
Sugar	1.056[b]	1.085[b]	1.137[b]	1.251[b]	1.049	1.147[b]	1.014	1.292
	(3.229)	(2.812)	(2.785)	(3.314)	(1.404)	(2.450)	(0.197)	(1.123)
Gold	0.889[b]	0.908[b]	0.910[a]	1.019	0.918[b]	1.045	1.125[a]	1.595[b]
	(−5.925)	(−2.835)	(−1.708)	(0.233)	(−2.193)	(0.595)	(1.666)	(2.122)
Silver	0.989	1.036	1.026	1.115	0.949	1.058	1.013	0.998
	(−0.644)	(1.240)	(0.555)	(1.571)	(−1.521)	(0.859)	(0.192)	(0.007)
Copper	1.100[b]	1.220[b]	1.343[b]	1.511[b]	1.094[b]	1.274[b]	1.082	0.749
	(5.793)	(7.318)	(6.987)	(6.757)	(2.706)	(3.956)	(1.178)	(0.965)
Feeder cattle	0.908[b]	0.841[b]	0.787[b]	0.723[b]	0.941	0.871	0.847[a]	0.464
	(−4.115)	(−4.089)	(−3.355)	(−2.830)	(−1.304)	(−1.437)	(−1.695)	(−1.588)
Live cattle	0.974	0.960	1.038	1.212[b]	1.032	1.231[b]	0.990	0.413[b]
	(−1.638)	(−1.468)	(0.834)	(3.061)	(1.002)	(3.633)	(−0.164)	(−2.467)
Live hogs	0.850[b]	0.742[b]	0.821[b]	0.992	1.061[a]	1.354[b]	1.044	0.616
	(−9.399)	(−9.357)	(−3.984)	(−0.121)	(1.922)	(5.563)	(0.684)	(−1.610)
Pork bellies	1.046[b]	1.018	1.012	0.871[a]	1.009	0.816[b]	0.855[b]	0.523[a]
	(2.930)	(0.672)	(0.262)	(−1.867)	(0.282)	(−2.903)	(−2.281)	(−2.007)

[a] Significant at the 10% level.
[b] Significant at the 5% level.

Lehmann (1987); and Lo and MacKinlay (1987) all show that the daily, weekly, and monthly realized returns for stocks are negatively serially correlated. However, Conrad et al. (1989) find that while the bid–ask spread exhibits negative serial correlation, the expected return component is positively autocorrelated. To the contrary, this study suggests that the noise term, which represents the price reaction to unexpected information, exhibits positive long-term serial correlation for many commodities, particularly for most agricultural crops, heating oil, and gold and silver.

The empirical evidence also suggests that the long-term price dependence between successive daily commodity prices is significant enough to reject the random walk hypothesis. The level of serial correlation indicates that there is a component in prior prices which can be used to predict future prices. If asset returns reflect the arrival of information, the systematic component represents market pricing with respect to the expected component of the information set, and the noise term represents the reaction to the unexpected information arrival. Consequently, the evidence of a positively autocorrelated random component for most commodities, and negatively correlated price changes for some others, suggest that the dependence between successive prices goes beyond the level expected by the market.

Under the current structure, one can only speculate on the sources of the nonrandom walks. One possibility is that information may arrive sequentially, so that market participants are not equally informed at the same point of time [Copeland (1976)]; or, given the same information set, the analytical ability differs among market participants [Heiner (1983); DeLong et al. (1987)]. Either explanation, while seriously challenging the basic assumption of market efficiency, does not necessarily reject economic efficiency because trading costs are not considered. The findings also provide a strong argument for the possibility of market irrationality, since the market price does not fully adjust to unexpected information instantaneously. This may be a result of fads or trading noises, as suggested by previous authors. Undoubtedly, the design of this study is unable to provide a direct test on the causes of nonrandomness in commodity prices.

Potential traders may be able to use random walk tests to determine which commodities tend to exhibit random walk behavior, and which do not. More intensive studies using trend following trading rules may be justified for markets that exhibit positive price change persistence over some intervals, while trading systems that try to exploit price reversals might be usefully investigated if negative price persistence (significantly low variance ratios) are found to exist. However, even if random walk conditions are violated, it is possible that no trading rules will be able to exploit such "inefficiencies" profitably if market monitoring (information) and trading costs are high. This may particularly be the case with cash markets, which are investigated here. The findings only suggest that market inefficiencies exist, but evidence is not sufficient to show that excess profits can be earned as a result.

In particular, caution should be exercised in concluding that significant statistical relationships necessarily imply significant excess economic profit. Predictable relationships in time series can be stable and significant by some statistical criteria, but not meaningful in obtaining economic profit. The necessary requirements to achieve significant economic profit depend on more than the identification of predictable and repetitive patterns. Further, the statistical relationship needs to be specific enough to suggest operational trading rules and the profit generated must be high enough to cover both transaction costs and the risk premium associated with trading. Therefore, the mere evidence of serially correlated price changes does not guarantee the existence of excess economic profit.

CONCLUSIONS

In this study, the random walk hypothesis in the cash prices of 17 commodities is tested. Using variance ratio tests, it is found that the time-variance relationship generally does *not* hold for returns of short- and longer-term holding periods, as expected by the random walk hypothesis. This implies that the returns are not independent and intertemporally uncorrelated. The evidence further indicates that there is a positively autocorrelated random component over intermediate time intervals for many commodities. In the short run, a negative serial correlation may result from price overreactions that cause realized daily returns to exhibit a mean-reverting process for some of the commodities. However, when the holding horizon is longer, the realized returns exhibit positive serial correlation for almost all commodities except some livestock-related commodities.

The implication from the findings suggests that in the price series there is a component, independent of the underlying fundamentals, that can be used to predict future prices. This implies the possibility of market irrationality since positive dependence of prices may be a result of fads in the market. This may also reflect some type of market rigidity in the form of traders' noninstantaneous adjustment to unexpected information, the speed of information releases, serial correlation in information disclosures that are not fully anticipated, or institutional restrictions which prevent the market from being cleared immediately. The sources of the nonrandom walks is left for future research.

Practical implications of non-random walks are not absent, however. In particular, in a market characterized by positive serial correlation in price movements, trend-following technical analysis may provide traders with useful insights into future market direction. Also, in such a market, option prices may need to be increased for more distant options to allow for the possibility that accelerating price trends may develop over time. Conversely, in markets characterized by overreaction in daily price changes or long-term negative serial correlation, fair prices for long-term options may be somewhat lower than prices determined by employing a variance measure calculated from the standard deviation of log price changes over daily intervals or other short-term (weekly) intervals—as is commonly done.

Appendix A

VARIANCE RATIO TESTS

To separate the random component in the price change from the systematic component reflecting the changes of an underlying economic model, the variance ratio test first developed by Tintner (1940) is used, as well as the corresponding test statistics developed by Lo and Mackinlay (1988). Specifically, let P_t represent the asset price at time t, and L_t be the natural logarithm of price. The continuously compounded return, R_t, which is the difference in successive log-prices, should contain two components: a systematic component, ϕ_t, which is differentiable with respect to time and determined by the underlying price trend and systematic price movement fundamental of the asset, and a random innovation ε_t, generated by unexpected random causes. Therefore,

$$\text{Log}(P_t/P_{t-1}) = \phi_t + \varepsilon_t \tag{A1}$$

where $\text{cov}(\phi_t, \varepsilon_t) = 0$, and $\text{E}(\varepsilon_t) = 0$. In equation (A1), it should be noted, however, that the systematic component can be serially correlated due to the nature of the economic determinants which may be time-path dependent. That is, $\text{cov}(\phi_t, \phi_{t-1})$ is not necessarily equal to zero. Based on the specification in equation (A1), the ε_t are said to follow a Gaussian *random walk* if and only if the noise component is independent of time, and normally distributed with an expected value of zero and variance equal to σ^2.

It is necessary, therefore, to isolate the noise component from the entire series. This can be accomplished by taking finite differences of the price series. When a lag, q, is used to finite difference the log of the price series, any systematic pattern of ϕ_t that exists between P_t and P_{t-q} should be irrelevant in determining the variance ratios. For instance, a constant geometric (percentage) drift at rate ρt will merely cause the mean of the log relative, $\log(P_t/P_{t-q})$, to be adjusted by a constant term equal to $q^* \ln \rho$, but will not affect the variance of the log relative. Furthermore, for systematic price behavior that follows a regular cyclical pattern, as the time interval, q, lengthens, regular harmonic processes such as day of the week effects will tend to net out and, therefore, have less effect on variance measures. Thus, the finite differencing of a lagged price series will eliminate drift effects and either eliminate or, at least, reduce the importance of other systematic components without also eliminating the random component (Powers, 1971). On the other hand, the random component of a price series over various differencing intervals cannot be reduced by finite differencing since it is not ordered in time.

Variance ratio tests are often considered superior to traditional white-noise tests or autocorrelation tests for random walks, since they do not require that the underlying economic model, ex ante, be specific. The traditional autocorrelation method assumes either that there is no systematic component in the underlying process (martingale), or that the economic model be specified ad hoc to distinguish the random component ε_t for testing. In either case, the hypothesis is always a joint test for both the validity of the model and the independence of the ε_t.

However, the finite difference method can effectively eliminate a large number of functional forms as possible candidates for the underlying systematic component without actually specifying the true relationship.[4] Equation (A1) produces the familiar stochastic differential equation:

$$dL(t) = \mu_\phi dt + (\sigma + \sigma_\phi) dZ(t) \tag{A2}$$

where $dZ(t)$ is a Wiener process with mean of zero and variance equal to t. μ_ϕ and $\sigma^2{}_\phi$ are the mean and variance of the systematic component, ϕ_t. Two important properties of equation (A2) are first, that the "drift" in log-price over a given time interval is proportional to the length of the interval, i.e., a drift of $\mu_\phi \Delta t$, and second, that the variance of the random error term, $\sigma^2\Delta t$, is also proportional to the elapsed time. The variance ratio test will facilitate the testing of the time-variance property implied by a random walk—if the elapsed time between observations is Δt and the variance of the associated noise term is σ^2, then doubling the time between observations will imply a variance equal to $2\sigma^2$, tripling, a variance of $3\sigma^2$, and so on. This can be demonstrated by the qth differencing of equation (A1) where there

[4]The finite difference method cannot eliminate all possible forms of the systematic structure. For example, if S_t follows a recurring format, such as a sin or cosine function, the variance ratios will also follow a U-shape repetitively with respect to the lags for the differences. However, typical patterns (daily, weekly, monthly, seasonalities or trends), that are related to fundamentals or institutional arrangements, can be removed by finite differences.

exists a strictly positive integer, q, such that the ϕ_t systematic component vanishes from the variance calculation after the differencing. Since the bid–ask spread is not time additive over longer time periods, the left-hand side becomes $\mathrm{Log}(P_j/P_{j-q})$, which represents the holding period return over q periods, and is equal to the sum of the random component, ε_t, from $t = j - q$ to $t = j$, the net drift components at time t and $t - q$ that is,

$$\mathrm{Log}(P_t/P_{t-q}) \approx \sum_{k=0}^{q} \varepsilon_{t-k} + q \ln \mu_\phi$$

and the variance of the q-period return is:

$$V(R_q) \approx \sum_{k=0}^{q} V(\varepsilon_{t-k}) + \sum_{i=0}^{q} \sum_{j=0}^{q} \mathrm{Cov}(\varepsilon_{t-i}, \varepsilon_{t-j})$$

$$\text{where } i \neq j .$$

The random walk hypothesis would require that the ε_t be independent and identically distributed (i.i.d.). Therefore,

$$V(R_q) = qV(\varepsilon_t) \tag{A3}$$

which reduces to $V(R_q) \approx qV(\varepsilon_t) \approx q\sigma^2$. Thus, the familiar unit-root variance ratio, and the following necessary condition for random walks must hold:

$$\lambda(q) = V(q)/[V(1)q] = 1 \tag{A4}$$

where $\lambda(q)$ represents the variance ratio of the finite difference log-price series, $V(q)$ equals the variance over an interval of length, q, and $V(1)$ represents the variance over an interval of unit length. The variance ratio test compares the variance of a q-period return to that of the product of q and the variance of a one-period turn.

To test the null hypothesis that the time-variance relationship in equation A4 holds, finding $\lambda(q)$ significantly different from unity is sufficient to reject the random walk hypothesis. Lo and MacKinlay (1988) derive efficient estimators for $V(q)$ as well as the asymptotic distribution of $\lambda(q)$. Their test is more powerful than similar previous tests since they allow the use of overlapping data, which results in significantly larger sample sizes, particularly for large q*. Therefore, consider the observed log-price series $L_0, L_1, \ldots L_n$, where the total number of observations equals $n + 1$. Define the unbiased estimators of μ, $V(1)$, and $V(q)$ as $u, v(1)$, and $v(q)$, respectively. Then

$$u = 1/(n - 1)\sum_{k=1}^{n} (L_k - L_{k-1})$$

$$v(1) = 1/(n - 1) \sum_{k=1}^{n} (L_k - L_{k-1} - u)^2$$

$$v(q) = 1/[(n - q + 1)(1 - q/n)] \sum_{k=1}^{n} (L_k - L_{k-q} - qu)^2$$

As shown by Lo and MacKinlay (1988), the test statistic, $z(q)$, is asymptotically normal with a mean of zero and variance of unity with the following:

$$z(q) = n^{1/2}(\lambda(q) - 1)(2(2q - 1)(q - 1)/3q)^{-1/2}$$

where the variance ratio is estimated by

$$\lambda^*(q) = v(q)/[v(1)q]$$

The estimations on the variance ratios of different lags, $\lambda(q)$, and their associated test statistics $z(q)$ allows one to determine whether the variance ratios are significantly different from unity. The random walk hypothesis will be rejected if $\lambda^*(q)$ is significantly different from unity. Furthermore, an estimate of $\lambda(q)$ greater (less) than 1 for $q = 2$ would suggest significantly positive (negative) serial correlation between prices.[5]

To determine whether a nondrift systematic component in the original price series is contributing to the price dependence measured by the variance ratios, the length of the differencing interval, q, may need to be large. However, the variance ratio would start from one ($q = 1$) and exhibit deviations from one as q becomes larger, and eventually resolutes back to one when q equals q^*, where q^* is the number of differences needed to eliminate all systematic effects and randomize the original series. As q^* is unknown if the underlying model is not first estimated, the evidence of deviations from unity for a given q only indicates the rejection of random walks *relative to* the holding period being investigated.

The variance ratio tests can also be modified by altering the "unit" interval over which price changes are calculated. Then, q refers to the number of such intervals used in the analysis. For instance, this study uses the "unit" interval lengths of one day, four days, and 16 days. Thus, when $q = 12$, for a 16-day interval, the variance of price changes over 192 trading days is compared to the variance of price changes over a 16-trading-day interval.

[5]Lo and MacKinlay (1988) demonstrate the relationship between variance ratios and n-order serial correlations.

Appendix B

SAMPLE DESCRIPTION: DAILY SPOT COMMODITY PRICES

Spot Commodity	Description	Unit	Sample Period	Daily Obs.
Pork bellies	12–14 lb., mid-U.S.	lb.	Jun. 69/Dec. 87	4706
Soybeans	No. 1 yellow, cent. Ill.	bu.	Jun. 69/Dec. 87	4706
Live cattle	Tex.–Okla.	cwt.	Jun. 69/Dec. 87	4706
Coffee	Brazilian, N.Y.	lb.	Jun. 69/Dec. 87	4706
Sugar	Cane, raw, world	lb.	Jun. 69/Dec. 87	4706
Corn	No. 2 yellow, cent. Ill.	bu.	Jun. 69/Dec. 87	4706
Cotton	1 1–16 in. str. lw.-md., Memphis	lb.	Jun. 69/Dec. 87	4706
Feeder cattle	Feeder, Okla. City avg.	cwt.	Jun. 69/Dec. 87	4706
Heating oil	No. 2 N.Y.	gal.	Sep. 79/Dec. 87	3104
Hogs	Omaha avg.	cwt.	Jun. 69/Dec. 87	4706
Wheat	No. 2 hard, Kansas City	bu.	Jun. 69/Dec. 87	4706
Soymeal	Decatur, Ill.	ton.	Jun. 69/Dec. 87	4706
Oats	No. 2 milling, Minneapolis	bu.	Jun. 69/Dec. 87	4706
Soybean oil	Crd., Decatur, Ill.	lb.	Jun. 69/Dec. 87	4706
Gold	London fixing AM	oz.	Jun. 69/Dec. 87	4706
Silver	London fixing AM	oz.	Jun. 69/Dec. 87	4706
Copper	Cathodes	lb.	Jun. 69/Dec. 87	4706

Source: *The Wall Street Journal*, provided by MJK Commodity Data Services.

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