Selectivity, Information And The Return To Futures Trading

Dr. John L. Trimble, Finance, University of Central Florida
Dr. M. Wayne Marr, Finance, Clemson University

Abstract

One of the more controversial issues in modern financial economics and in futures trading in particular is whether traders have the ability to earn returns above what they could with a buy-and-hold strategy. The weight of evidence in support of Martingale price movements generally has been considered to be evidence that the expected value of "trading returns" is zero. This paper shows, however, that, when the contingent claims in a futures contract are taken into account in defining return, expected trading returns may not be zero, even if prices follow the Martingale pattern. We also point out that, if a sample of trades is representative of some trading strategy with its corresponding trading information, the impact of that strategy on a trader's expected return can be represented by a probability model of the strategy's success. This results because, to be successful, a trading strategy must select trades nonrandomly. Using these results, the paper specifies a model of the expected return of an arbitrary trading strategy. As an illustration, the model is estimated for an artificially constructed strategy in gold futures that imitates what the industry claims is the epitome of futures trading performance -- many small losses more than offset by a few big gains. Statistical tests based on the estimation of this model support the characterization of returns being due to the trading strategy using information to nonrandomly select trades.

1. Introduction

One of the more controversial issues in modern financial economics and in futures trading in particular has to do with the ability to traders to earn returns above what they could with a buy-and-hold strategy. Central to this controversy, is the substantial empirical support for Martingale price movements and the belief that this means that traders cannot possess information that would lead to long-run profit. Such a conclusion may not be universally true.

This paper presents, in an environment of repeated trading and zero expected price changes, an empirically tractable model of expected returns that can accommodate the possibility of long-run profits due to timely information. The plan of the paper is as follows. Section 2 introduces and challenges the established Bachelier-Osborne paradigm. Section 3 outlines the importance of a trading strategy and its related information. Section 4 distinguishes the contingent claims in a trade and specifies a definition of return that takes them into account. Section 5 uses the modified definition to specify a model of expected return that incorporates

repeated trading. Section 6 presents an illustrative estimate of the model for an artificially constructed strategy in gold futures that imitates what the industry claims is the epitome of futures trading performance -- many small losses more than offset by a few big gains. The last section discusses the conclusions and implications of the paper.

2. The Private Reward in Trading

Being motivated by the possibility of private rewards, future traders think in terms of trading strategies, the potential success of a strategy and the financial management problems involved in implementing a strategy. Much of their viewpoint is stated or can be gleaned from a list of speculator's trading rules.(2) In regard to financial management problems, the rules stress, for example, the importance of accurately estimating the capital needed to implement a strategy and "staying the course." Otherwise, it is suggested, one will have difficulty dealing with the fact that successful trading is the result of many small losses offset by a few big

gains.

The essence of this viewpoint is that the reward for investing in trading information is a private reward. Differences in beliefs stemming from the possibility of private reward of course make trading possible in the first place. Nonetheless, a common empirical approach is to attempt to measure futures trading returns without accounting for private rewards by using periodic returns data such as daily, weekly, or monthly returns.

The problem created by inappropriately relying on periodic returns may be behind the conflicting evidence in some studies of futures trading: On the one hand are those studies showing that expected returns to futures trading are zero.(3) On the other hand, are studies which show that large professional traders consistently earn abnormal returns [Teweles, Harlow, and Stone (1977)]. If one represents the zero-sum-game nature of future trading by Martingale price movements (i.e., zero expected prices changes) then on average there are zero expected returns to futures trading. Any randomly selected sample of price changes thus will have an average of zero. Yet the essence of trading decisions is to "select" price changes from transaction to transaction that are nonrandom. A trader who exhibits this skill of "selectivity" -- nonrandomly choosing price changes from transaction to transaction -- can earn abnormal returns. Thus, to evaluate such a trader's expected return, one must take account of this selectivity skill. Such is the approach we take in this paper.

3. Trading Strategies and Information

Futures markets are composed of speculators and hedgers. Uncertainty about future spot prices and a desire to limit risks motivate hedgers to trade futures securities, while speculators believe that they know something about where prices are likely to go. Speculators, presumably, are in the information gathering business and represent those most knowledgeable -- albeit with considerably uncertainty -- about future price directions. Speculators, moreover, cannot be simply a continuous procession of new entrants replacing those exiting the industry. Instead, if returns to information gathering really exist, there is at least a cadre of knowledgeable speculators who are able to evaluate their expected return to continued speculation and judge it superior to the alternatives.(5) Both hedgers and speculators, moreover, will be interested in trading to profit from relevant trading information. But the speculator is distinct in that he is attracted by a per-

ceived potential to profit by investing in information gathering. This paper addresses trading based on this profit-seeking motivation, although the model that will be presented later can also be applied to hedging-motivated trading.

Trading in futures markets is often heavy. Holding periods average only three months and often are much shorter. The sometimes swiftness of price movement can create profit opportunities in short holding periods. As a consequence, traders often must decide on trades very quickly. This makes it unlikely that anyone could trade profitably without a preconceived strategy -- which may manifest itself as "skill," "instinct," or both. Rational traders, moreover, like other economic agents, must weigh the expected return to trading against the alternatives. Such a decision usually cannot be made sensibly on the basis of a trade or two but instead must consider a strategy's performance in using trading information in a variety of market conditions over the population of potential trades. In this paper, therefore, the trading strategy will be taken to be the vehicle through which a trader's information influences his expected return.

4. Futures Prices and the Definition of Trading Return

We assume that the distribution of futures prices for a single contract by described by the following Martingale process:

$$p_t = p_{t-1} + \varepsilon_t \tag{1}$$

where the ps designate today's and yesterday's prices; and the ε are symmetrically distributed random variables with zero means and heteroscedastistic standard deviations ϕ.(6) That is, the standard deviation of price changes is assumed to vary from one day to the next. In this form then, the Martingale model above is consistent with previous studies of future price movements. For example, if statistical tests conclude that, in some period, the ϕ are all equal, then prices follow a random walk in that period. On the other hand, if the tests conclude otherwise, then prices may follow a Martingale.

Price movements, of course, may not follow a Martingale when the ϕ are unequal in a some specified period. Given the data, it seems reasonable to expect that this would be true some of the time, even under the more stringent assumptions favoring the Martingale process.

Thus, in practice, one might expect prices to follow the process in equation (1) only approximately.

Turning now to the definition of trading return, note that, since expected price changes in the above Martingale model are zero, the expected value of return, as defined traditionally, is also zero. Examining the futures contract more carefully, however, reveals that the traditional definition of return is inappropriate.

4.2. The definition of trading return

The traditional definition of return is an inappropriate measure of the return to an individual trader because it ignores the contingent claims in a futures contract. Every contract lays a claim to a profit or to a loss contingent upon the position taken relative to the direction of price movement. If, for example, a trader has a long position, then he has a claim to a gross profit if he can close the trade at a price above his entry price during the life of the contract; otherwise he has a claim to a loss. To take account of these contingent claims, the definition of return must take account of the sign and magnitude of the price change in trade.

The most common definition of return is the ratio of the difference in ending and beginning prices and the beginning price. However, there are a number of unresolved questions about what is the actual investment in a futures contract [Figlewski (1984)]. To avoid dealing with this issue here, we focus only on nominal returns. The return for a typical trade, r^*, which commences at price and terminates at the price prevailing k periods later, therefore, would be defined traditionally as:

$$r^* = p_{t+k} - p_t \qquad (2)$$

Based on the price model in equation (2), the expected value of r^* is zero. This zero expectation should not be taken as an implication of the efficient market model -- it appears that the model of return given by equations (1)-(2) is incomplete. In a subtle way, any role for information in earning an excess return is defined away in that model. What is needed, therefore, is an extension of equations (1)-(2) that leaves open the possibility for an investor to make money.

Toward this end, consider the possible claim in a trade where the trader enters at today's price and closes the trade at the price prevailing k periods later. If he takes a long position and the closing trade price is

greater than or equal to then his gross expected return is $+E(r^* \mid r^* \geq 0)$ -- i.e., the expected value of r^* in equation (2) given that $r^* \geq 0$ -- where the "+" sign signs the expected value of the trade and also designates a "long" position. On the other hand, if he takes a short position and the closing trade price is less than or equal to today's price, then his gross expected return is $-E(r^* \mid r^* \leq 0)$ where the "-" sign signs the expected value of the trade and also designates a "short" position. In either case, he claims a profit because price moved favorably to his claim. Now, if he takes a long position and the closing trade price is less than or equal to today's price then his gross expected return is $+E(r^* \mid r^* \leq 0)$. On the other hand, if he takes a short position and the closing trade price is greater than or equal to today's price, his gross expected return is $-E(r^* \mid r^* \geq 0)$. He claims a loss in either case because price moved unfavorably to his claim. Thus, there are four possible outcomes -- two contingent claims for each of the positions that can be taken in a futures contract.

For symmetrically distributed price changes, the conditional expected values of return for each of these four possible outcomes all have the same absolute value. This is made more evident by noting the following relations among the expected return outcomes that follow from our assumed symmetry of price changes:

$$+E(r^* \mid r^* \geq 0) = -E(r^* \mid r^* \leq 0) \qquad (3a)$$

$$+E(r^* \mid r^* \leq 0) = -E(r^* \mid r^* \geq 0) \qquad (3b)$$

$$+E(r^* \mid r^* \geq 0) = -[+E(r^* \mid r^* \leq 0)] \qquad (3c)$$

Equation (3a) simply says that for a single trade the expected value of either of the winning outcomes is the same regardless of the position taken -- long or short. Equation (3b) says that the expected value of either of the losing outcomes is the same regardless of the position taken. And equation (3c) implies in conjunction with the others that the expected value of a winning outcome equals the negative of the expected value of a losing outcome. Thus, the absolute value of expected return is the same for any of the four possible outcomes.

Turning now to the definition of the return in a trade, suppose that the price distribution is stable under addition and subtraction, then it is straightforward to show that $+E(r^* \mid r^* \geq 0) = E(\mid r^* \mid)$. This relation, moreover, obviously holds with the expectation operators removed. As a result, the following definition of

return may be specified. For this definition the expected value of return incorporates all of the above expected returns of the contingent claims in a trade:

$$
r = \begin{cases} |r^*| & \text{if the trade is successful} \\ -|r^*| & \text{if the trade is unsuccessful} \end{cases} \tag{4}
$$

4.3. Expected value of the return in a trade

Returns calculated from sample price data using either equation (2) or (4) will always yield the same results. Yet when applied to the Martingale price modeling equation (1), the return defined in equation (2) has an expected value that is always zero while the return defined in equation (4) has an expected valued for a single trade that is zero only if the probability of success equals probability of failure.

To state the calculation of the expected value of the return in a trade more clearly, let $g(\varepsilon)$ designate the symmetrical distribution of daily price changes for equation (1). Supposing that this distribution is stable for sums and differences, then the distribution of price changes in a trade [as defined in equation (3)] is $g(r^*)$ which has a mean of zero. Applying the revised definition of return in equation (4) yields an expected return, $E(r)$, for a single trade of:

$$
E(r) = P \int_{-\infty}^{\infty} |r^*| g(r^*) dr^* - (1-P) \int_{-\infty}^{\infty} |r^*| g(r^*) dr^* \tag{5}
$$

where P is the probability that a trade is successful. Note that, in a given successful trade, then P=1 and $E(r) = C\theta$, where C is a constant the value of which varies with the exact form of the distribution of price changes.(7) Equation (5) says that the expected return in a trade is proportional to the standard deviation of the sum of daily price changes enclosed by the beginning and ending trade prices is not necessarily equal to the expected value of market price changes.

Note once more that the definition of trading return in equation (4) and its corresponding expected value in equation (5) apply only to a single hypothetical trade. One may think, however, of a "population" of trades for a given trading strategy as a countably infinite set of trading returns with a population proportion of successful trades and expected returns. At the moment, we have no such model of the expected returns from one trade to the next. Nor is there as yet any specific relation between expected return and trading information. These will be the subjects of the next section.

5. The Expected Return of a Trading Strategy

This section specifies a model of expected return incorporating repeated trading. It incorporates, furthermore, the impact of a trading strategy through the strategy's probability of success -- allowing the probability to vary from trade to trade as influenced by ex ante trading information.

Since the remainder of the paper deals with repeated trading, all subsequent equations will carry trade subscripts. To keep the notation simple, however, the trade subscripts will be suppressed. In particular, hereinafter the following parameters and variables should be thought of as carrying an s-subscript designating the sth trade:

$$P, E, \sigma, Z, r, R, \theta, r^*, \eta, \zeta.$$

5.1. A strategy's probability of success

Success in trading involves correctly selecting the direction and magnitude of the price change in a trade frequently

enough to earn a profit. Potentially, there is an infinity of combinations of direction and magnitude prediction hat could lead to profit. If the industry claim is correct, however, the most likely trading pattern is where trading is successful because, like a "clutch hitter," the trader often enough, has correctly selected the direction of price change whenever the magnitude of price change is large enough on average to more than offset his losses. This of course is the practitioner's description of successful trading mentioned in the introduction: successful trading involves making big enough gains on a few trades to more than offset most trades which are losses or small gains. This latter case will be seen to admit to statistical testing in the model of expected return that follows later.

In the meantime, to allow for the possibility that a trader may be able to use trading information to earn a profit, suppose that an individual's trading does note affect the market price and that the probability of success for a trading strategy can be expressed in the form of a binary selection model based upon the trader's rational expectation of the profit in a trade. This rational expectation of profit forms a continuous latent variable, p, that predicts trading success for a given strategy. The latent variable p is unobserved but the outcome of a trade -- success or failure -- is observed. To develop this model, suppose that p depends on a linear combination of <u>ex ante</u> observable trading information variables plus a random error, ζ. Let the vector of information variables be designated as Z with a corresponding vector of parameters γ. Then, in terms of this index, success and failure can be expressed in terms of p crossing an arbitrary threshold such as zero:

$$p = \begin{cases} Z\gamma + \zeta_t \leq 0 & \text{if the trade is successful} \\ Z\gamma + \zeta_t \geq 0 & \text{if the trade is unsuccessful.} \end{cases} \tag{6}$$

The probability of success for each trade, P, can be expressed, therefore, as a function of the information variables, Z, as follows:

$$P = Pr[\zeta_t \leq -Z\gamma] = \int_{-\infty}^{-Z\gamma} h(\zeta_t) d\zeta_t \tag{7}$$

where $h(\zeta)$ is the distribution of ζ.

With this model of the probability of success specified and measuring the effect of an arbitrary strategy, the desired model of expected trading return influenced by trading information also can be specified. In variant forms similar models in other applications appear elsewhere in the literature(9) as noted earlier. It will be necessary therefore to specify only the minimum essentials of the model.

5.2 Expected trading return

To reflect that the expected return to trading is a private return to the strategy (with its associated information), we need a model of returns based on the definition in equation (4) needs to be specified first. To do this, suppose that the population of returns mentioned at the end of section 4.3 is divided into two groups: successful (i.e., gaining) returns and unsuccessful (i.e., losing) returns. Let the value of the gaining returns have g-subscripts and be designated $|r^*|$ -- that is, for returns with price changes of r^*, their value will be $|r^*|$ if the trades are successful ones. Similarly, let the value of the losing returns have l-subscripts and be designated $-|r^*|$. In addition, let the expected values of the Rs be designated as $\beta\sigma$ and $-\beta\sigma$ with g-subscripts for gaining trades and l-subscripts for losing trades.

One can think of the values of the Rs as composed of their respective expected values plus random components that have means of zero and constant variances. Thus, for repeated trading the definition of return in equation (4) may be modified as follows:

$$r = \begin{cases} R_g = \beta_g\sigma_g + \zeta_g, & \text{if } \zeta_g \leq -Z\gamma \\ R_l = \beta_l\sigma_l + \zeta_l, & \text{if } \zeta_l \geq -Z\gamma \end{cases} \tag{8}$$

where the ζs, are the random components. In this form, the value of return can deviate form its expected value. But more important, a trader's return now depends on the probability of success of his trading strategy with its related information.(10)

Expected trading return for the trading strategy, E, therefore is simply the expected value of r in equation (8) modified for repeated trading. This expected value can be written as:

$$E = P\beta_g\sigma_g + (1-P)\beta_l\sigma_l + P\delta_gI_g(Z) + (1-P)\delta_lI_l(Z) \tag{9}$$

where βs, and δs are coefficients to be estimated. $I(Z)$ for gaining trades is the positive statistical bias (11) induced by the trading strategy's probability of success. It can therefore be thought of as a productivity measure of the strategy and its corresponding information; the exact form of I will depend on the statistical assumptions for equation (8). $I(Z)$ for losing trades, on the other hand, is then the negative statistical bias induced by the strategy's probability of failure, which, therefore, can be thought of as a sterility measure of the strategy and its corresponding information; the exact form of I also depends on the statistical assumptions for equation (8).

5.3 Evaluating a trading strategy's performance

The value of a strategy depends on the relative magnitudes of the last two terms in equation (9) since the first two will sum to zero, if the distribution of price changes is symmetrical as we have assumed. This is so because the coefficient-weighted values of the Is sort out the bias in the βs that would be caused if one ignored the strategy's nonrandom selection of trades from the population of price changes. Thus, one should find that the first two terms of equation (9) recover the mean of the distribution of price changes. And the mean of this distribution, both theoretically and in this sample, is zero.

Thus, a successful trading strategy (measured as a positive gross return) is one where the gaining and losing effects (i.e., the last two terms in equation (9)) sum to a positive value. In addition one would want a positive δI for gaining trades. (This ensures a positive correlation between the probability of success and the level of profit in a successful trade. One also would want the gaining effect to overshadow the losing effect on average. Thus, for a strategy to be classified as successful, one would want $\delta>0$ for gaining trades and on average δI for gaining trades must be greater than δI for losing trades.

Estimates of the parameters in equation (9) can be calculated for specific assumptions about the distributions of the random components in the definition of trading return in equation (8).

6. An Illustration: Expected Return of an Artificial Strategy that Imitates the Pattern of Professional Trading

This section estimates the return that can be attributed to the information in the artificially constructed trading strategy mentioned earlier that imitates the pattern of professional trading -- many small losses more than offset by a few big gains. The first part of the section discusses the construction of the strategy's trades. The second presents the statistical assumptions used in estimating the model of expected trading return. The third describes of the data series used. And the last part presents and interprets the estimates.

6.1. The artificial strategy

For this task, we construct a set of trades that mimic the descriptive pattern of successful futures trading -- "many small losses more than offset by a few big gains." We do not, however, specify a specific strategy but rather create a relationship between the trades and the information on which they are based. We evaluate the relationship as if it were that of an underlying strategy -- a strategy that we call the artificial strategy.

To construct this relationship, we artificially imbue a filter rule with "real" trading information. Since in markets

favorable to them, filter rules have the successful-trading property of "many small losses more than offset by a few big gains," they are a useful point of departure. In fact, were it not for their lacking adaptability, filter rules would be successful trading strategies anyhow. But they lack the adaptability to deal with "unfavorable" markets. That is, they cannot adjust to changing market conditions, and the particular market conditions under which a particular filter rule works are fortuitous. Yet, if a filter rule could be enhanced to give it "adaptability," the enhanced rule would be a successful strategy fitting the descriptive pattern of successful trading.

We choose to enhance a known filter rule, one studied by Stevenson and Bear by using ex post information as if it were known ex ante (12). Knowing this ex post information does not guarantee success in a particular trade, but it does shift the chances for success relatively in favor of the investor. What we want to do, therefore, is to measure the value of this information in terms of its contribution to expected return.

Since the Stevenson and Bear filter rule is designed to terminate if price moves "too far" against the investor's position, longer lasting trades tend to be (but are not always) winning trades. About eighty-five percent of the time, if a trade lasts three or more days, it is a winning trade. Only twenty-three percent of all trades last three or more days. Thus, we construct a variable, Z, that equals the number of days in a trade if that number exceeds two and is zero otherwise. We use this variable as if it were ex ante trading information. The contribution of this variable Z to expected return is then measured in the estimation.

A subtlety in this strategy that is also a subtlety in the descriptive pattern of successful trading is that the artificial strategy always has a position in the market. This means that, to realize the winning trades, an investor must also realize the losing trades. Having a position continuously -- or almost continuously -- is an integral part of the strategy. Thus the ex ante information is not information that the investor can use to select only the profitable trades. Rather it is information about the relationship between the size of the profit and the chance of success on average. To realize the value of this relationship, the investor must have a continuous position in the market and, as a consequence, suffer many small losses.

6.2 Statistical assumptions

In order to estimate the model of expected trading return in the previous section and, subsequently, to draw inferences about the results, it is necessary to make some assumptions about the distributions of the random components, the ζs, in equation (12). For the return equations, the ζs are assumed to be identically and independently distributed with the following specifications:

$$E(\zeta_j) = 0, \quad j = g, \, l \tag{10}$$

$$E(\zeta_j \zeta_r) = \begin{cases} \sigma^2, & j = r \\ 0, & \text{otherwise} \end{cases}$$

Estimation is accomplished by using a variant of the instrumental-variables technique discussed by Olsen (1980). For, this method, we assume that the ϕ for the trading strategy are independently and logistically distributed and that the ζs for the returns equations each are linearly related to the trading strategy's. This leads to the following relations:

$$I_g(Z) = E(\zeta_T | \zeta_T \leq - Z\gamma) = -\log P - [(1-P)/P] \log (1-P) \tag{11a}$$

$$I_l(Z) = E(\zeta_T | \zeta_T \geq - Z\gamma) = \log (1-P) + [P/(P-1)] \log P \tag{11b}$$

$$P = Pr(\zeta_T \leq - Z\gamma) = 1/(1 + e^{-Z\gamma}). \tag{11c}$$

where γ is a vector of coefficients to be estimated in the logistic probability model of equation (11c).

To estimate the βs, and the δs, consider equation (9) which is the mean over all trades, successful and unsuccessful. Each real trade however is conditional on having been successful or unsuccessful. Equation (9) can be modified to take account of these conditional expectations and still be estimable by ordinary least squares by dropping P and by setting the g-subscripted σ and I equal to zero for losing trades; and by setting the l-subscripted σ and I equal to zero for gaining trades. Adding a stochastic error, η, gives the following stacked regression:

$$E = \beta_g \sigma_g + \beta_l \sigma_l + \delta_g I_g + \delta_l I_l + \eta. \tag{12}$$

The η in equation (12) is assumed to be identically and independently distributed random variables each with a zero means and constant variance. The model in equation (12) can be estimated using instrumental variables regression. First the logistic probability model in equation (11c) is estimated and predicted values (i.e., and instrumental variable) for P calculated.(13) These are then used to calculate predicted values (i.e., instrumental variables) for the Is. The instruments for the Is are then substituted in the model of equation (12) and the remaining parameters estimated by ordinary least squares.

Recall that, if there is a relationship between success in trading and the level of gain in a trade, then Iδ for gaining trades should be positive and statistically significant at some reasonable level. In addition, the gaining effect on average should be greater in magnitude than the losing effect.

Note that the first two terms in equation (12) represent the mean of the underlying distribution of price changes from which the trades are drawn. For futures price data the expected price change is zero. Thus, when averaged over the entire sample of data, the sum of the first two terms in equation (12) should be zero.

To check the implications of the model from equation (12) in a situation simulating real trading, an estimate of this model is presented for the artificial strategy after the data for gold futures are discussed in the next section. The results fit well with the above expectations.

6.3. Gold futures prices

The data used in this study are gold futures prices from the COMEX in New York. On the COMEX, gold futures traded in contracts of 100 troy ounces. Prices consist of daily open, high, low and close prices from June 1, 1978, through March 31, 1982. The price series is constructed for the June and December contracts. Prices are for the most "current" (i.e., June or December) or "nearby" contract. And one contract is "rolled over" into the other contract on the first day of the delivery month. For example, on June 1, the series is rolled into the December contract from June contract. As such, the price series is (approximately) a continuous contract.

It is possible to pick many price series from the various contracts that are active at any time by using different rollover points. But some contracts are more heavily traded than others and thus provide greater assurance that the desired trades can be executed. These contracts are more "liquid." The June and December contracts provide the greatest liquidity.

The returns observations used in estimating the model are the actual trading returns for the artificial strategy described earlier and are calculated as indicated in equation (4). Also calculated from the price data, and associated with each return observation, are the standard deviations of gaining trades and losing trades. The standard deviation of a gaining trade, for example, is calculated by first calculating for each day in the trade, the deviations in the open, high, low and close prices from the average of these four prices in the preceding day and then by calculating the variance for that day using those four deviations. These daily variances are then summed for the days in the trade. And finally, the standard deviation of the gain is the square root of this sum of variances. The standard deviation of losses is calculated similarly. The standard deviation of losses is zero for a gaining trade and vice versa.

6.4 Return to trading the artificial strategy

The instrument for P and hence for the Is replace those corresponding variables in the model of equation (12). They are calculated by first estimating the probability model of equation (11c) which gives an estimate of the parameter vector γ. The vector of ex ante trading information variables, Z, consists of only the information variable (i.e., number of days) defined above in the description of the artificial strategy plus a dummy variable designating the rollover points.

Mean statistics for the sample appear in Table 1. A total of 321 trades were made over the nearly four-year period. The average profit in winning trades was $1482.77 per trade and 34.6 percent of the trades were winning trades. Corresponding to this were losing trades of $590.57 loss per trade which accounts for the balance of 65.4 percent of the trades. The average variance of prices in winning trades was $980.24 while in losing trades it was $482.69. Overall, the average profit per trade was $126.38.

Table 2 presents the estimate of the probability model of trading success. One can see quickly that the information variable is indeed the driving force. It is by far the most significant of the variables in Table 2. It thus will be interesting to see what effect this has on the expected return to trading the strategy. Table 3 presents the estimates for the expected trading return model in equation (12). The first matter of interest is whether the trading loss term, is significant. If the coefficient for that variable is significant and positive, it is a clear indication of some superiority in the trading information. It means that the information in the trading strategy is directly related to trading gains. For the estimates in Table 3, the instrumental variable (IV) test statistic developed by Godfrey (1983) is used to test the statistical significance of δ for gaining trades. The value of the test statistic is 6.23. And, being asymptotically t-distributed with one degree of freedom, it indicates that δ is significantly different from zero at the ten-percent level. When the δs for gaining and losing trades are restricted to be equal in estimation, the δ-coefficient is positive. From this we conclude using Godfrey's test that $\delta > O$ for gaining trades. A simple t-test for differences in means concludes that δI for gaining trades is greater than δI for losing trades on average. As a result, one can reasonably accept the hypothesis that the artificial strategy increases the trader's return above the market average expected return of zero.

Since the rollover effect is insignificant and the βs are not equal across the return equations, the remaining effect to consider is whether the estimates indicate that the underlying distribution of price changes has a mean of zero as the earlier discussion indicates that it should. Using sample estimates, we calculate the sum of the first two terms in equation (9) to be $39.33, a value which is not significantly different from zero. (Note that the artificial strategy trades on average every three trading days. The average three-day holding return for the sample is $23.18 and is not significantly different from zero). Thus, the estimated model is consistent with an underlying price-changes distribution having a zero mean.

Looking again at equation (9), one would expect that, using sample estimates, the sum of the last two terms should be approximately equal to the sample's average profit of $126.38. This is the fact the case. The calculated value is $121.51 and is well within the statistical bounds of $126.38 at standard levels of confidence.

Although the estimation finds a statistically significant relationship between the trading information in the artificial strategy and the level of profit, one would want to consider whether the results might be due to occurrences in the sample period that are unlikely to be repeated out of the sample period. To explore how different the estimates in another sample might be, note that it was during the period spanned by this data that the spot price of gold rose to over $800 an ounce. Conceivably, with such a wild surge in gold prices, it is likely that a few returns could account for the trading strategy's profit. In fact, if two trades were eliminated, net profit for the nearly four-year period would drop form $40,568 to $13,028. Assuming an investment of $10,000 (i.e., good faith deposit to cover margin calls from possible draw-downs) and transactions costs of $9,630 (i.e., a volume-trading rate of $30 a trade), the compound annual rate of return drops from 34.3 percent to -24.6 percent.

Is this a telling indictment of the strategy? It is if these two trades are sample-specific occurrences unlikely to be repeated in other samples. On the other hand, if the strategy positions the trader to capture profit in such opportunities, then these two trades are a realization of what can be expected in other trading. For the artificial strategy, the estimated probability of success is nearly 100 percent for each of these two trades.

Table I.
Sample Averages for the Artificial Strategy

Profit (in winning trades)	$1482.77
Loss (in losing trades)	-590.57
Profit per trade	126.38
Std. Deviation (winning trades)	980.24
Std. Deviation (losing trades)	482.69
Percent of winning trades	34.60
Number of winning trades	111.00
Number of trades	321.00

Table II.
Binary Logit Estimate of the Probability
of Trading Success

Variable	Estimate
Information variable (No. days)	2.317
	(0.260)
Rollover	-0.002
	(0.036)
Intercept	-5.054
	(0.514)

Sample Size 321
Likelihood ratio test against intercept only = 204.86.
(2 degrees of freedom)

Notes: Maximum likelihood estimation using zero-one dummy variable designating profitable trades as the dependent variable. The estimated dependent variable is the probability of success. Standard errors are in parentheses.

Table III.
Expected Trading Return

Determinants	Gains Regime	Losses Regime
Std. Deviation (gains)	1.833	
	(0.083)	
Trading gain	352.794	
	(91.190)	
Std. Deviation (losses)		-0.848
		(0.164)
Trading loss		-57.889
		(28.900)
Rollover	0.039	0.039
	(1.400)	(1.400)

Sample Size 321
R2 .67

Notes: Instrumental variables estimation using ordinary least squares. Unadjusted standard errors are in parentheses.

Thus, it may be true that such a strategy simply places a trader in a position to win when the right opportunity comes along. The descriptive pattern of successful trading indicates after all that most successful traders earn their returns on a few big trades. It is important moreover to bear in mind the advantage of a strategy that keeps the trader in the market continuously; the timing problem of getting into the market whenever a "big" move comes may be obviated. For such a strategy, the question boils down to whether a trader believes enough in his strategy to commit the requisite capital to stay in the market during the losing periods and whether he ultimately earns an above-average return. This is something that, in real-life trading, one would not want to judge from a single sample.

7. Conclusion

The principal contention of this paper is that the focus of traditional methods on the "average" investor is inappropriate for evaluating the return to futures trading. It argues that, if traders have profitable trading information, the existence of such information will not be revealed necessarily by examining periodic returns formed from "aggregate" market prices. In fact, if markets are "relatively efficient," it is unlikely that the existence of such information will be revealed, in this way. Instead, the existence of profitable trading information will be revealed in terms of its contribution to the performance of the trading strategy in which it is used. Thus, we argue that the judgement of whether trading information is profitable must be made in the context of the private reward involved.

By accounting for the contingent claims in a futures contract moreover one can measure, using market prices, the private return to a trade as a nonrandom selection of a price change. In addition, given a sample of trades that represents the performance of a strategy, one can evaluate the performance of that strategy and the performance of specific information variables within it in the context of the model of expected returns developed in this paper. Moreover, performance can be measured in terms of focused statistical tests that are less likely to reject a good strategy than previously used tests. We have shown how this can be done in an illustrating application with an artificial strategy. In addition, this shows how to evaluate information content of the type fitting the descriptive pattern of successful trading (i.e., large returns on a few trades).

An important idea in this paper is the generic relating of specific market information to a trader's expected return. One obvious implication of this is that, if an investor plans to trade, he should consider the trading strategy in selecting securities because, if the mean return (i.e., expected trading return) is affected by the trading strategy, so will be the variances, covariances, and hence correlations of returns. It suggests that, to be a successful trader, one must anticipate what sorts of information might surface, have a strategy for trading on these various kinds of information, and know what the average effect the trading will have on his expected portfolio return.

Another important implication of the paper is that, for certain questions, the application of the Bachelier-Osborne paradigm is inappropriate. For example, since returns may not necessarily be the result of price changes deviating from the Martingale pattern, not much can be learned in these situations of the value of information in trading decisions by examining the behavior of periodic returns. Since matters such as this are central to markets being efficient, evidence of Martingale price movements by itself, as Lucas (1978) suggests, may have little to do with market efficiency.

Notes

1   Dusak (1973) is an example of work based on the "average investor" focus of the Bachelier-Osborne paradigm.
2   As an example, see the rules given in Reilly (1982, pp. 511-512).
3   This is a conclusion in Dusak (1973).
4   The term "selectivity" has been used in the investment literature to mean skill in selecting profitable securities. The term is also used in the econometrics literature to refer to a nonrandom sample selected from the parent population. In this paper the term is used simultaneously in both senses, except that, on the financial side, skill in selecting securities is skill in selecting trades.
5   Silber (1984) describes the activities of scalpers who must trade in fast-paced markets. He refers to scalpers as market makers; however, since they typically trade only their own account, it seems equally valid to refer to them simply as traders. As such, scalpers are traders in possession of specialized information but who otherwise are no different than any other trader.
6   For convenience, the distribution of price changes is assumed to have a variance. This is not a necessary assumption however.
7   The expected absolute value of a symmetrically distributed random variable is proportional to its variance (assuming it exists). This

can be seen, intuitively, by recognizing first that there is only one parameter in the distribution of the price change for a single trade and that its expected value will not be zero since the distribution of the absolute value is formed by folding the probability distribution to the left of zero onto the probability distribution to the right. Now, since the mean is not zero and since both the mean and the variance are constants in the distribution, they must be proportional to one another.

8   Heckman (1979) discusses the model generally. Hausman and Trimble (1984) use a switching regression with selectivity bias in analyzing appliance investment choices.

9   Ibid.

10   The σ^s could be dependent upon a market rate of return. In this case, the model in equation (9) might be thought of as a single index model that includes the effects of specific trading information.

11   The statistical bias caused by nonrandom selection procedure is called selectivity bias. The I(Z)s in equations (11) are called Mill's ratios.

12   The filter rule take directly from Stevenson and Bear (1970) is: Starting with the closing price on the first day of trading, wait for the closing price of the future to move up or down z percent and then establish a position with the market by buying if the future has gone up z percent and by selling if the future has gone down z percent ... Place a stop-loss order z percent from the price of the established position. If the price moves in the favorable direction, establish a new stop-loss order each day z percent from the close on the preceding day. When the price moves in the unfavorable direction, maintain the stop-loss order until it is executed. The closing price on the day that a stop-loss order is executed becomes the same base as the closing quotation was on the first day of trading in the process of establishing a new position. The value of z used for this paper is 1.

13   Technically, equations (11c) and (12) are a nonlinear simultaneous system. The estimation procedure we use here is an instrumental variables procedure; see Hausman (1985) and Heckman (1979).

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