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# Stock price dynamics: nonlinear trend, volume, volatility, resistance and money supply

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We present a methodology to study a data set of 119 260 daily closed-end fund prices using mixed-effects regressions with the objective of understanding price dynamics. There is strong statistical support that relative price change depends significantly on (i) the recent trend in a nonlinear manner, (ii) recent changes in valuation, (iii) recent changes in money supply (M2), (iv) longer-term trend, (v) recent volume changes and (vi) proximity to a recent high price. The dependence on the volatility is more subtle, as short-term volatility has a positive influence, while the longer term is negative. The cubic nonlinearity in the weighted price trend shows that a percentage daily gain of up to 2.78% tends to yield higher prices, but larger gains lead to lower prices. Thus, the nonlinearity of price trend establishes an empirical and quantitative basis for both underreaction and overreaction within one large data set, facilitating an understanding of these competing motivations in markets. Increasing money supply is found to have a significant positive effect on stock price, while proximity to recent high prices has a negative effect. The data set consists of daily prices during the period 26 October 1998 to 30 January 2008.

*Keywords:* Asset price dynamics; Momentum; Price trend; Money supply; Liquidity; Volume

## 1. Introduction

A basic tenet of classical finance is that prices reflect the collective public information available to the market, and information influencing the value of securities is immediately incorporated into asset prices. However, the process whereby investors and traders react to new announcements, as well as new supplies of investment capital or cash, leads to a complicated dynamical problem beyond mere valuation. Traders are also aware of the reactions of others' assessments through price and volume changes. The question of whether a significant portion of traders are influenced by these factors is an empirical one. If the investors who base their decisions solely on valuations constitute the vast majority – measured through the percentage of the assets owned by this group – then statistical methods should confirm this to be the case. If, on the other hand, a significant fraction base decisions partly on the reactions of others, then it should be possible, in principle, to extract some results that reveal the strategy in their decisions. For example, concepts such as underreaction and overreaction have been utilised in

discussing investor behaviour. Without a clear quantitative methodology for distinguishing these two opposing modes, it is very difficult, if not impossible, to utilise these concepts in finance. In other words, knowing only that the market dynamics sometimes exhibit overreaction and sometimes underreaction does not provide much insight into trader motivation nor is it useful in trading decisions.

Our goal in this paper is to provide some quantitative answers to these questions. Such a task has always faced a key obstacle, namely noise, which can be defined as the randomness in the stream of information updating the valuation of an asset. From the perspective of an investor or trader this information is stochastic. As Fischer Black (1986) noted, 'noise makes it very difficult to test either practical or academic theories about the way economic or financial markets work'. In addition, he states that markets are efficient at least 90% of the time, defining efficiency as a market price that is 'more than half of value and less than twice value'. This means that even when the market is 'efficient', a security valued at \$100 can have a market price anywhere between \$50 and \$200. This point is consistent with frequent assertions by practitioners that there are important issues beyond valuation. However, the attempts to uncover these

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issues are often stymied by the presence of noise, as Black has noted. This leads to the question of whether there are methodologies whereby this noise can be greatly reduced to permit additional analysis of price dynamics.

One way to overcome this obstacle has been to perform a large-scale statistical study in the hope of extracting a result that may be too small to be useful to traders, but establishes the effect through statistical significance. Toward this end, Poterba and Summers (1988) established that stock returns display small positive serial correlations for short time periods and are negatively autocorrelated over long time periods.

To study the concepts of underreaction and overreaction, Madura and Richie (2004) performed a statistical study on the daily opening and closing prices of exchange traded funds (ETFs) during the time period August 1998 to August 2002. They define underreaction as positive (alternatively, negative) cumulative abnormal returns following large positive (alternatively, negative) price movements. Similarly, overreaction is defined as the reversal of returns following large price movements. They found evidence of overreaction after extreme price changes of greater than 5% in either direction within normal or after-hours trading periods. If stocks are more likely to increase on a particular day if they had increased the previous day, then one can claim that there is evidence of underreaction. In other words, investors are not reacting fully on the first day. For instance, a group of investors may remain unconvinced of the new information and are waiting for further confirmation as manifested in higher prices. Once confirmed, these investors submit their buy order, further increasing demand and thereby driving prices higher. On the other hand, if price increases tend to be followed by price declines, then one can classify this as part of overreaction. In aggregate, they found some evidence for overreaction.

In an effort to quantify overreactions, Sturm (2003) showed that a stock with either positive fundamentals or price trend tends to rebound after a large drop of 10%. However, a stock already on a downtrend or suffering from certain negative fundamentals (e.g. declining book value per share) exhibits no such rebound. Further bolstering the empirical evidence for overreaction, Duran and Caginalp (2007) studied 134 406 data points representing daily closing prices for a set of closed-end funds. Focusing on the deviation between the market price and the 'net asset value' (NAV), they examined changes in this deviation, which they divided into several distinct threshold levels (e.g. 5 to 7.5%). With a large statistical significance they found that large deviations from the net asset value led to a significant price movement in the opposite direction. More surprisingly, they found precursors to large deviations. In addition, Caginalp and Ilieva (2008), using hybrid difference equations and regressions, found that the recent price trend is a statistically significant factor (with positive coefficient) in predicting tomorrow's price change.

The objective of this paper is to provide quantitative answers to the questions of whether and to what extent

investors are influenced by the following factors: (a) recent price trend, (b) recent valuation, (c) changes in money supply, (d) volatility, (e) long-term price trend, (f) recent changes in volume, (g) resistance (i.e. proximity to yearly highs), and (h) effects of time (during the data period). A primary goal of this paper is to identify when over- and underreaction occur and to determine a quantitative methodology for distinguishing between the two using nonlinearity in the price trend. Also, we are able to confirm reversion to the mean, a Poterba and Summers (1988) finding, by including the longer-term trend. The claim that an influx of money bolsters trading prices is supported by experimental (Caginalp *et al.* 1998, 2001), theoretical (Caginalp and Balenovich 1999), and empirical (Caginalp and Ilieva 2008) studies. Thus, it is reasonable to incorporate a variable which represents the amount of available money. Volatility is identified with risk in classical finance. As such, we consider this factor in order to test the effect of volatility on trading prices. Traders often observe the volume, and believe that an uptrend is more likely to continue if it is accompanied by rising volume, and that gradual price rise with declining volume is a sign that the uptrend is likely to falter. Smith *et al.* (1988) noted that bids (and thereby volume) tend to diminish shortly before the peak of an experimental bubble. Resistance is included to test the relationship between the current price and a recent high price. The effect of time is considered to ensure our results are not the artefacts of a particular time period. For a more detailed discussion of the motivation behind the inclusion of these factors, see section 3.

We present a quantitative study of 119 260 daily prices for a set of closed-end funds. Studying such funds presents an opportunity to subtract out the random changes in valuation appropriately, and thereby eliminate a large part of the 'noise' discussed above. Since closed-end funds regularly report their NAV based upon the current value of the investments, they offer a substantial advantage in this regard compared with stocks of most corporations. The set of closed-end funds we consider are those that report their NAV on a daily (rather than weekly) basis. Thus the 125 equity closed-end funds we study have assets that are sufficiently liquid, and there is a sound basis for daily evaluation of the underlying assets. However, for our purposes the liquidity of the underlying assets is not as important as the trading volume of the actual stock (i.e. the closed-end fund). After all, the underlying assets of a large company such as GE or IBM are usually not very liquid, but the stock is very active, and traders are interested in knowing the direction of the stock price. While the discount (defined as the percentage that the trading price of the closed-end fund is below its NAV) has been the subject of many papers (see Anderson and Born 2002 for a survey), almost all of these focus on reasons that are essentially steady-state issues, e.g. tax liability, corporate structure or liquidity of underlying assets. In other words, even if the discount is larger due to tax liability or the underlying illiquidity of

the assets, this situation does not change from one day to the next.

Studying the daily price changes circumvents many of these steady-state issues that do not change on a daily basis. If valuation were the only factor in price movements, then the volatility of the trading price of closed-end funds would be similar to that of the NAV. However, Pontiff (1997) finds that even though closed-end funds underreact to changes in NAV, their prices are on average 64% more volatile than their assets. So the volatility of closed-end funds cannot be completely attributed to changes in the NAV. Thus the questions posed by market dynamics can be addressed effectively through the study of daily price changes of closed-end funds while compensating for changes in valuation.

We note that while the data set involves closed-end funds, there is little reason to believe that the market price dynamics of these stocks differ significantly from the average stock on the exchanges. Key daily trading features such as trading volume, market capitalization, and ratio of institutional to individual ownership are similar to most mid-cap stocks. The average weekly volume of the set of closed-end funds we consider is about 400 000 shares traded. Hence, the group of stocks we consider is comparable in activity to many ordinary stocks, bonds and options. Our methods can be applied to a broad range of stocks upon the adoption of a valuation model that is already well understood in finance. However, from a scientific perspective, the ability to use an unambiguous quantity such as the net asset value provided by closed-end funds enhances the credibility of the methodology. Analogously, our methods are not restricted to daily changes, and one can implement them on different time scales of interest. Once again, however, the daily changes minimise the 'noise' that is present so that the dynamics of asset prices can be determined more precisely. For example, an analysis of yearly changes in the US not only involves fewer data points, but also suffers from diminished credibility since the statistical results may simply be artefacts of particular eras such as the depression of the 1930s or the high-tech bubble of the late 1990s. The analysis of daily data minimises such possibilities. Furthermore, using data involving 1000 trading days, for example, instead of 20 yearly data points enhances the statistical power of the tests.

Our basic approach is to determine the fractional change in the price of a stock as a regression on a set of variables, including an appropriate valuation variable that effectively subtracts out much of the stochastic noise due to changes in valuation. The set of variables is discussed in sections 2 and 3. The definitions of the valuation, recent price trend, and volume trend variables include a weighting so that the most recent changes have the greatest effect. In addition to the use of related terms in mathematical modelling (Caginalp and Balenovich 1999) there is both experimental (Grether 1980) and empirical (Sturm 2003) evidence that individuals tend to

emphasise recent events more heavily than earlier events in their decisions. Furthermore, we consider both the square and cubic price change terms, and obtain a nonlinear function indicating that a daily gain of up to 2.78% tends to yield higher prices, but larger gains lead to lower prices. The analogous crossover point for price drops is 2.1%. There is a negative coefficient of smaller magnitude for the long-term trend, consistent with mean reversion on this time scale. Further evidence that traders are influenced by the evidence of others' strategies through price patterns is the fact that the price representing the recent quarterly high is associated with a slightly negative coefficient, providing 'resistance' to a stock's upward movement. Positive changes in the money supply are associated with increases in the fractional price, consistent with a liquidity (excess cash) perspective of markets (Caginalp *et al.* 1998 and 2001).

Our regressions indicate an ambiguous role for volatility, indicating that the classical concept of associating volatility with risk is oversimplified. In fact, the sign is positive for the short term, suggesting that volatility has a tendency to boost trading prices. However, in the longer-term, volatility is a negative factor. The recent change in volume is a slightly positive factor, indicating that positive (negative) changes in volume correspond to positive (negative) changes in price. Finally, we utilise a time variable defined as the number of months since the earliest data point. By using regressions that include up to the cubic power in this variable, we can largely extract and eliminate any effects due to a particular time period. The Price Trend, Valuation, M2 Money Supply, Short-Term Volatility, and Volume Trend coefficients are essentially unchanged upon introduction of this variable, suggesting that our results for these factors are not artefacts of the changes during this time period.

This paper's primary contributions to the literature are summarized by the following.

- (1) Identification of the nonlinearity in the price trend provides a method for distinguishing between over- and underreaction. Without such a method it is difficult to argue that a systematic bias exists or that the study of these concepts would be helpful for trading.
- (2) The key concept behind these regressions is the inclusion of Valuation as an independent variable. By including in the regression a function based on the NAV, a significant portion of the price's volatility is eliminated, thereby removing (or explaining) a great deal of 'noise' from the data. Thus, the effects of other factors are no longer camouflaged by the valuation.
- (3) The M2 money supply is also a significant factor in price changes, which supports the findings of theoretical, experimental and empirical studies.
- (4) The volatility results are quite intriguing as short-term volatility actually boosts prices while long-term volatility has a small negative effect on price changes.

**2. Data and variables**

We use data on 125 closed-end funds (28 Generalized, 66 Specialized and 31 World funds) consisting of 119 260 daily prices during the time period 26 October 1998 through 30 January 2008. As noted in the introduction, we consider these funds because their NAV is reported on a daily basis. Thus, estimating the value of an asset is not necessary, as it would be for most corporate stocks, thereby eliminating additional error.

We discuss first the independent variables utilised in the regressions.

**2.1. Valuation**

As noted above, although the value (NAV) of a closed-end fund is known, it seldom trades at that price. In fact, these funds may trade at a persistent premium or discount. So, if a fund has been consistently trading at a discount of 10% and subsequently trades at a 5% discount, value investors are not likely to regard it as a bargain despite the discount. Thus, we define the relative premium (or discount) as

$$\frac{NAV(t) - P(t)}{NAV(t)}$$

and then subtract the weighted average of the relative premium/discount over the past 10 days from this value as

$$D(t) = \frac{NAV(t) - P(t)}{NAV(t)} - \frac{1}{3.2318} \sum_{k=1}^{10} \frac{NAV(t-k) - P(t-k)}{NAV(t-k)} e^{-0.25k},$$

where NAV(*t*) is the net asset value of the fund on day *t* and *P*(*t*) is the fund's share price on day *t*. The  $e^{-0.25k}$  factor is a smoothing factor that (i) emphasises more recent deviations between the NAV and share price and (ii) gradually reduces the impact of large deviations in the past. Large relative deviations between NAV and price (that occur with non-trivial frequency) will therefore not drop out of this Valuation variable abruptly, but rather fade slowly from the equation. The coefficient  $(3.2318)^{-1} = (\sum_{k=1}^{10} e^{-0.25k})^{-1}$  is used to normalize the variable.

**2.2. Price trend**

The Price Trend, *T*(*t*), is defined as

$$T(t) = \frac{1}{3.2318} \sum_{k=1}^{10} \frac{P(t-k+1) - P(t-k)}{P(t-k)} e^{-0.25k},$$

where *P*(*t*) is the fund's price on day *t* and the value 1/3.2318 is again used as a normalization factor to account for the weighting term of  $e^{-0.25k}$ . This definition represents a weighted average of the past 10 days of the

asset's price change that places greater emphasis on more recent days.

**2.3. Money supply**

Theoretical (Caginalp and Balenovich 1999), experimental (Caginalp *et al.* 1998) and empirical observations (Caginalp and Ilieva 2008) have indicated a role for increased money supply in bolstering trading prices. We use the M2 (not seasonally adjusted) statistic† obtained from the Federal Reserve website in weekly units and linearly interpolate for daily data. For consistency, the relative change in this statistic,  $[M(t) - M(t-1)]/M(t-1)$  is utilised in our model.

**2.4. Volatility**

The volatility in the model is computed as the standard deviation of the relative price change,  $R(t) = [P(t) - P(t-1)]/P(t-1)$ , for the past *X* number of days including the current day. If *t* represents today, then we define today's volatility as the standard deviation of the relative price change values over the past *X*+1 days, i.e.

$$Volatility(t) = \{\text{variance}(R[t - X, t])\}^{1/2},$$

where  $R[t - X, t]$  represents a column vector containing the relative price change values over the past *X*+1 days. We set *X*=10 for Short-Term Volatility or *X*=251 for 52-Week Volatility, i.e. we compute the standard deviation of the past 11 (or 252) days (including today). We use the unbiased estimator of the variance:

$$\frac{1}{X} \sum_{i=t-X}^{t-1} (R(i) - \text{Mean}(R[t - X, t]))^2.$$

This definition determines the deviation of the relative price change about the growth curve of the share price. If the relative price change is constant, then the price is an exponential function of time. Indeed, representing the relative price change in a limiting form such as

$$\frac{1}{P} \frac{dP}{dt}$$

yields the differential equation

$$\frac{1}{P} \frac{dP}{dt} = C,$$

which implies  $P(t) = Ke^{Ct}$  via separation of variables where *K* and *C* are constants. For example, if the stock price follows the pattern  $e^{0.02t}$  (i.e. *K*=1 and *C*=0.02), then the relative price change would be constant ( $e^{0.02} - 1 \simeq 0.02$ ) and the Volatility would be zero. Thus, with the above definition the trend in price would not contribute to the volatility.

†M2 includes: Currency, Traveller's checks, demand and other checkable deposits, retail MMMFs (money market mutual funds), savings, and small-time deposits. M2 is measured in trillions for this paper.

**2.5. 52-Week price trend**

To determine the 52-Week Price Trend a straight line is fitted to the relative price change,  $[P(t) - P(t - 1)] / P(t - 1)$ , over the past 252 days (including the current day,  $t$ ). The slope of this line is then multiplied by 252 (to convert to annual units) and utilised as the 52-Week Price Trend variable.

**2.6. Volume trend**

We incorporate the trading volume for each fund into the model by considering the trend of the volume in the same manner as the Price Trend. The Volume Trend,  $VT(t)$ , is defined as

$$VT(t) = \frac{1}{3.2318} \sum_{k=1}^{10} \frac{Vol(t - k + 1) - Vol(t - k)}{Vol(t - k)} e^{-0.25k}$$

where  $Vol(t)$  represents the trading volume† for day  $t$ .

**2.7. Time**

The Time variable,  $Time(t)$ , is defined as the approximate number of months since 26 October 1998 (the earliest date included in the data set). More precisely, this variable is calculated by determining the number of days from date  $t$  to 26 October 1998, dividing this number by the average number of working days per month (i.e.  $252/12 = 21$ ), and then rounding down to the closest integer (i.e. if the resulting number is 15.8, then the variable is assigned a value of 15). Finally, the variable is normalized by dividing by the total approximate number of months in the data set, 143 (this number corresponds to regression 5 which includes this variable). Also,  $Time^2(t)$  and  $Time^3(t)$  are considered to determine the nature of the relationship (e.g. linear, quadratic or cubic).

**2.8. Resistance**

The possibility that stock prices tend to decline after approaching a recent (in this case quarterly) high is called Resistance which we identify by an indicator variable and use as an independent variable in a regression. The recent quarterly high is defined by  $H(t) := \max\{P(s)\}$  for  $s \in [t - 63, t - 16]$ . The Resistance Indicator,  $Q(t)$ , is set if the following conditions are satisfied: (1) for  $s$  in  $[t - 15, t - 10]$ ,  $P(s) \leq 0.85H(t)$  and (2)  $0.85H(t) \leq P(t) \leq H(t)$  (note that there is no condition on  $P(s)$  for  $s$  in  $[t - 9, t - 1]$ ). Thus, we interpret Resistance as having occurred on day  $t$  if the share price on day  $t$  is within 85–100% of the recent quarterly high.

**3. Discussion of variables**

The variables defined above are chosen due to their role in theory, investment practice or experimental settings, rather than as a consequence of data mining. We discuss

below the motivation for the inclusion of each of these variables.

**3.1. Price trend**

The influence of price trend on future price changes has been of interest from many perspectives. Traders often express their belief in momentum. For example the phrases ‘the trend is your friend’ or ‘don’t fight the tape’ are old sayings on Wall Street. The apparent persistence of a trend provides some support for the hypothesis of underreaction. Yet the hypothesis of overreaction also receives much attention. A quantitative methodology for distinguishing these two competing motivations is necessary to transform these philosophical ideas into finance. We are able to accomplish this in several ways using a single set of large data.

Various theories such as the ‘affect heuristic’ have suggested that prices rise excessively as investors focus on a salient feature of a company or its product (Slovic *et al.* 2004). As more investors are attracted to the stock, one expects a positive trend term in the short run, consistent with our findings. However, when viewed on a longer time scale, it is clear that, at some point, the fundamentals will become more evident, resulting in a return to more modest prices. This perspective can be regarded as a basis for overreaction on a longer time horizon, and has some statistical backing from the DeBondt and Thaler (1985) study. Our results, which encompass the effects of both long- and short-term trends, are consistent with this study and with that of Poterba and Summers (1988).

**3.2. Money supply**

When applied to any consumer good, the law of supply and demand clearly stipulates that an increase in demand will raise prices. An investment vehicle differs from a consumer good in that there is typically no consumer at the end of the trading chain, and purchase of the asset is solely for the purpose of re-selling at a higher price (or obtaining a stream of dividends). As such, it is not clear that an increase in the money available for possible investment in that asset (analogous to demand for a consumer good) will lead to higher asset prices, as it would for a consumer good. Furthermore, the methods of classical finance (e.g. the no-arbitrage hypothesis) would cast doubt on the concept that a larger money supply should lead to higher prices. However, experimental asset markets have provided considerable evidence (Caginalp *et al.* 1998) that a larger ratio of cash to asset leads to higher prices. Mathematical models (Caginalp and Balenovich 1999) have indicated that a greater cash supply leads to higher prices. There is also a belief in some investment circles that ‘cheap money fuels market prices’, so that when there is an increase in money supply the increase in available investment funds tends to push up prices.

†Note that the Volume may be zero on certain days. This would cause the Volume Trend to be infinite on those days. As such, any records in the data set with a volume of zero are excluded.

### 3.3. Volatility

A basic idea in finance is that risk and reward are inversely correlated so that investors seeking higher return must tolerate higher risk (Bodie *et al.* 2008). In the classical literature, risk is identified with volatility in the asset's price. The measure of volatility, however, depends crucially on the time scale for measurement. We consider both short-term and long-term volatility. Volatility has been studied by other researchers (see Duran 2009 and the references therein).

### 3.4. Volume trend

As with the price trend, volume provides an indication to traders about the beliefs and resources of other traders. In the process of price discovery, a trader who believes that the asset is undervalued will nevertheless strive to purchase it at the lowest possible price. Since he does not know the strategies and assessments of the other traders, his only recourse is to examine the earliest manifestations of their trading decisions which are exhibited in the changes in price and the volume of trading. Rising prices on low volume provide an indication to traders that the buying interest is not as strong as one might believe by examining price changes alone.

### 3.5. Resistance

A concept that is frequently used by traders involves resistance, or the tendency for prices to pull back when approaching a yearly or recent high. Traders are then aware that all other traders know that a higher price could not be attained during that time period. This could be viewed as a manifestation of 'anchoring' whereby observers focus on a particular value and neglect to consider other possibilities. Traders have explained the concept of resistance by stating that investors who held the stock through the recent high may experience regret at not having reaped a profit. Thus, as the shares again approach this recent high, these investors seek to recover their perceived 'losses' by selling, thereby lowering the stock price and preventing it from breaking through this price barrier. A yearly high, for example, also provides information to traders by setting a price at which supply and demand for the asset were equal after a period of rising prices. Recently, the concept of resistance has received academic attention in a study that indicates that the yearly return is influenced by the stock's proximity to the yearly high (George and Hwang 2004), although another study (Sturm 2008) demonstrates some limitations of these findings and obtains more mixed results.†

## 4. Methodology

To determine the influence of the variables defined above on investor decisions, we consider their effect on the relative price change. This is accomplished by performing regressions with the next day's relative price change,  $R(t+1) = [P(t+1) - P(t)]/P(t)$ , as the dependent variable and various subsets of the above factors (using the data of day  $t$  and earlier) as the independent variables. For each variable the regression provides a coefficient and its corresponding statistical significance ( $t$ - and  $p$ -values). The relative changes in the above variables can be adjusted for the fact that some variables have a much larger range than others in order to facilitate comparison of the magnitudes. For example, the average of the absolute value of the Price Trend variable is 0.003 698 796, while the absolute value of the Volume Trend average is 0.248 292, or approximately 67 times larger. To facilitate comparisons of coefficients, the Volume Trend coefficient should be multiplied by a factor of 67. Note that this scaling is essentially a matter of convenience from our perspective, as it does not alter the statistical significance indicators. Whether scaled or not, one can use the computed coefficient of the regression multiplied by the average magnitude of the variable to determine whether it is large enough to be of value to trading or investing (see table 4).

Our data set consists of closing prices from different funds. An ordinary linear regression is an example of a classical modelling technique that assumes that observations, in our case closing prices, are independent and identically distributed. However, as our data set consists of closing prices from different funds, this assumption is not necessarily valid. Thus, we need to utilise a method that accounts for the variation within funds and between different funds. To accomplish this, we utilise a mixed-effects model, i.e. a model with both fixed and random effects. A fixed effect is a parameter 'associated with an entire population or with certain repeatable levels of experimental factors', while random effects 'are associated with individual experimental units drawn at random from a population' (Pinheiro and Bates 2000). As we wish to draw inferences regarding all closed-end funds based upon our sample, fund is utilised as a random effect in our model, while the other independent variables (see section 2) are fixed effects. While an ordinary linear regression would estimate parameters using expected mean squares, our mixed-effects regression utilises the restricted maximum likelihood method to obtain unbiased estimates of the variance components of the random effects. Thus this procedure implements a methodology that accounts for the grouped (by fund) data, while still providing coefficients and significance values that are representative of the entire data set.

†The Resistance variable can be explored more fully by augmenting this variable within the context of our methodology. In particular, Sturm (2008) finds that investors are influenced differently based on how recently the high price was attained (i.e. last month, two months ago, three months ago, etc.). Thus, one could define a variable, or variables, representing this time difference and include it as an additional independent variable in our regressions.

We execute linear regressions of the form

$$R(t + 1) = \alpha_0 + \alpha_1 \text{Variable}_1(t) + \alpha_2 \text{Variable}_2(t) + \dots + \alpha_n \text{Variable}_n(t),$$

where  $t$  represents the current day,  $R(t + 1) = [P(t + 1) - P(t)]/P(t)$  represents the following day's relative price change, or return, and  $\text{Variable}_i(t)$  represents one of the above independent variables. Each regression includes an intercept term ( $\alpha_0$ ), which may be interpreted as the 'drift' term of classical finance. Retaining this intercept term in the regressions adjusts for the average return so that non-zero coefficients for any of the variables demonstrate 'abnormal return', i.e. return beyond the small daily average return of a stock within a particular class.

## 5. Results

### 5.1. Linear regressions

**Regression 1.** As a baseline, we perform a linear mixed-effects regression with only the independent variable Price Trend. The regression has the form

$$R(t + 1) = \alpha_0 + \alpha_1 T(t).$$

Although Price Trend is statistically significant, its value is negative and small (see table 1). In quantitative terms a 1% per day increase during the recent time period, on average, yields a 0.04% decrease today. A significant, small (and most likely not tradeable) Price Trend term is consistent with the Poterba and Summers (1988) findings. However, the sign is negative, whereas Poterba and Summers found a positive trend term.

**Regression 2.** This baseline regression above is a standard treatment of such data, and as such, does not circumvent the key issue of 'noise' due to changes in valuation (i.e. fundamentals). The inclusion of our Valuation variable in the regression above removes much of this noise and dramatically identifies the role of Price Trend as shown below for the regression

$$R(t + 1) = \alpha_0 + \alpha_1 T(t) + \alpha_2 D(t).$$

The results in table 2 show that by 'subtracting out' the valuation, i.e. including the Valuation in the regression, the Price Trend is not only statistically significant but has a positive coefficient comparable in magnitude to the Valuation coefficient.

**Regression 3.** Regression 2 shows the significance of the Price Trend variable. To explore the nonlinearities in the relationship between Price Trend and Relative Price Change, the quadratic and cubic factors of the Price Trend and Valuation variables are added to regression 2. In addition, the cross terms, e.g. Price Trend multiplied by Valuation, are also included. This regression has

Table 1. Regression 1 results.

Term	Value	Std. error	t-value	p-value
Intercept	0.00043484	0.000039850	10.91202	<0.0001
Price trend	-0.03787525	0.007761571	-4.87984	<0.0001

Observations: 117760; Groups: 125; Degrees of Freedom: 117634. We list the number of observations, groups and degrees of freedom for each regression, because these may vary depending upon the included independent variables. The calculation of the Price Trend, Valuation and Volume Trend variables requires the previous ten days' data. Thus, these variables cannot be computed for the first ten days for each fund. Accordingly, the first ten days of data are excluded from the regressions. Similarly, the first 63 days of data for each fund are excluded due to the Resistance and Breakout variables, while the first 251 records of each fund from the regression data set are ignored due to the formulas for 52-Week Volatility and 52-Week Price Trend.

Table 2. Regression 2 results.

Term	Value	Std. error	t-value	p-value
(Intercept)	0.0004893	0.000039393	12.42070	<0.0001
Price Trend	0.2270024	0.009145194	24.82204	<0.0001
Valuation	0.1988558	0.003739072	53.18320	<0.0001

Observations: 117760; Groups: 125; Degrees of Freedom: 117633.

Table 3. Regression 3 results.

Term	Value	Std. error	t-value	p-value
(Intercept)	0.0002	0.00004	5.61263	<0.0001
Price Trend	0.3581	0.01085	33.00490	<0.0001
Valuation	0.2304	0.00422	54.62312	<0.0001
(Price Trend) <sup>2</sup>	3.8716	0.88137	4.39271	<0.0001
(Price Trend) <sup>3</sup>	-610.7741	40.74653	-14.98960	<0.0001
(Valuation) <sup>2</sup>	0.3529	0.05692	6.19928	<0.0001
(Valuation) <sup>3</sup>	-1.3587	0.11411	-11.90712	<0.0001
(Price Trend)(Valuation)	-1.2234	0.44093	-2.77467	0.0055
(Price Trend) <sup>2</sup> (Valuation)	-139.8894	27.18508	-5.14581	<0.0001
(Price Trend)(Valuation) <sup>2</sup>	9.3560	5.39400	1.73452	0.0828

Observations: 117760; Groups: 125; Degrees of Freedom: 117626.

the form

$$R(t + 1) = \alpha_0 + \alpha_1 T(t) + \alpha_2 D(t) + \alpha_3 T^2(t) + \alpha_4 T^3(t) + \alpha_5 D^2(t) + \alpha_6 D^3(t) + \alpha_7 T(t)D(t) + \alpha_8 T^2(t)D(t) + \alpha_9 T(t)D^2(t).$$

The inclusion of the additional terms does not appear to affect the significance of the Price Trend and Valuation terms (see table 3); however, it does increase the magnitudes of their respective coefficients. The relationship between Price Trend and the Relative Price Change can be visualized using the three-dimensional graph (see figure 1) of Relative Price Change, Valuation and Price Trend with the coefficients

Table 4. Regression 4 results.

Term	Value	Std. Error	t-value	p-value
(Intercept)	0.000099	0.000124	0.80097	0.4231
Price Trend	0.234642	0.010836	21.65396	<0.0001
Valuation	0.206172	0.004232	48.71275	<0.0001
M2 Money Supply	0.385010	0.040603	9.48238	<0.0001
Short-Term Volatility	0.071211	0.008063	8.83150	<0.0001
52-Week Volatility	-0.043829	0.011562	-3.79074	0.0002
52-Week Price Trend	-0.031533	0.019147	-1.64683	0.0996
Volume Trend	0.000267	0.000087	3.08137	0.0021
	Value	Mean( Var )	(Value)(Mean( Var ))	
(Intercept)	0.000099	N/A	N/A	
Price Trend	0.234642	0.003698796	0.000868	
Valuation	0.206172	0.008276127	0.001706	
M2 Money Supply	0.385010	0.0008950968	0.000345	
Short-Term Volatility	0.071211	0.01183092	0.000842	
52-Week Volatility	-0.043829	0.0121939	-0.000534	
52-Week Price Trend	-0.031533	0.001934814	-0.000061	
Volume Trend	0.000267	0.248292	0.000066	

Observations: 88 127; Groups: 114; Degrees of Freedom: 88 006.

Table 5. Regression 5 results.

Term	Value	Std. Error	t-value	p-value
(Intercept)	0.00015	0.000371	0.41238	0.6801
Price Trend	0.22643	0.010867	20.83641	<0.0001
Valuation	0.20262	0.004247	47.70291	<0.0001
M2 Money Supply	0.38763	0.040588	9.55020	<0.0001
Short-Term Volatility	0.08290	0.008206	10.10215	<0.0001
52-Week Volatility	-0.02654	0.012917	-2.05492	0.0399
52-Week Price Trend	-0.06216	0.019528	-3.18314	0.0015
Volume Trend	0.00025	0.000087	2.81859	0.0048
Time	-0.00961	0.002518	-3.81704	0.0001
(Time) <sup>2</sup>	0.02821	0.005146	5.48264	<0.0001
(Time) <sup>3</sup>	-0.02011	0.003068	-6.55358	<0.0001

Observations: 88 127; Groups: 114; Degrees of Freedom: 88 003.

Table 6. Regression 6 results.

Term	Value	Std. Error	t-value	p-value
(Intercept)	0.0005491	0.000040813	13.45485	<0.0001
Price Trend	0.2248558	0.009401159	23.91788	<0.0001
Valuation	0.2021202	0.003837561	52.66893	<0.0001
Resistance	-0.0011975	0.000520305	-2.30156	0.0214

Observations: 111 135; Groups: 125; Degrees of Freedom: 111 007.

Table 7. Regression 7 results.

Term	Value	Std. Error	t-value	p-value
(Intercept)	0.0000844	0.00012428	0.67890	0.4972
Price Trend	0.2357864	0.01084270	21.74610	<0.0001
Valuation	0.2060078	0.00423260	48.67172	<0.0001
M2 Money Supply	0.3852189	0.04060101	9.48791	<0.0001
Short-Term Volatility	0.0717047	0.00806476	8.89111	<0.0001
52-Week Volatility	-0.0427853	0.01156665	-3.69902	0.0002
52-Week Price Trend	-0.0308970	0.01914791	-1.61360	0.1066
Volume Trend	0.0002703	0.00008667	3.11880	0.0018
Resistance	-0.0038353	0.00132225	-2.90056	0.0037

Observations: 88 127; Groups: 114; Degrees of Freedom: 88 005.

Table 8. Comparison of individual funds to entire population.

Term	Price Trend	Valuation	M2 Money Supply
Average Value	0.298753	0.227028	0.26835
Regression 4 Coefficient	0.234642	0.206172	0.38501
	Short-Term Volatility	52-Week Volatility	
Average Value	0.086857	1.6558247	
Regression 4 Coefficient	0.071211	-0.043829	
	52-Week Price Trend	Volume Trend	
Average Value	-1.248058	0.003503	
Regression 4 Coefficient	-0.031533	0.000267	

Ordinary linear regressions were run on each individual fund. The coefficient values for the short- and long-term Price Trend, Valuation, M2 Money Supply, short- and long-term Volatility, and Volume Trend were averaged over all of the funds. These average values are compared to the corresponding coefficient values resulting from the mixed-effects linear regression run for all funds.

obtained from table 3:

$$R(T, D) = 0.0002 + 0.3581T + 0.2304D + 3.8716T^2 - 610.7741T^3 + 0.3529D^2 - 1.3587D^3 - 1.2234TD - 139.8894T^2D + 9.3560TD^2$$

with  $T$  representing Price Trend and  $D$  representing Valuation.

From this three-dimensional surface, it is clear that the relationship between the Relative Price Change and Price Trend is highly nonlinear. Taking the cross-section of this surface when the Valuation is zero yields the function

$$R(T, 0) = 0.0002 + 0.3581T + 3.8716T^2 - 610.7741T^3$$

plotted in figure 2.

This regression involving nonlinear terms shows the complex nature of underreaction and overreaction. Small changes in price tend to continue, indicating that there is underreaction, while large changes tend to be reversed, indicating overreaction. One of the problems in utilising the concepts of underreaction and overreaction has been the difficulty in distinguishing between the two. In any particular situation, if one cannot determine in advance, using a scientific method, whether there will be overreaction or underreaction, then an efficient market advocate can claim the market is free of bias. A methodology to delineate between these concepts can render them into practical tools rather than philosophical insights.

Note that if the terms with higher (>1) powers of the Valuation variable are excluded from the regression, then there is still a cubic relationship between Price Trend and Relative Price Change. However, instead of a change greater than 2.78% producing a negative Relative Price Change, the necessary change is 8.37%, which is not as significant in practical terms. Inclusion of the additional Valuation terms provides a more complete picture of the

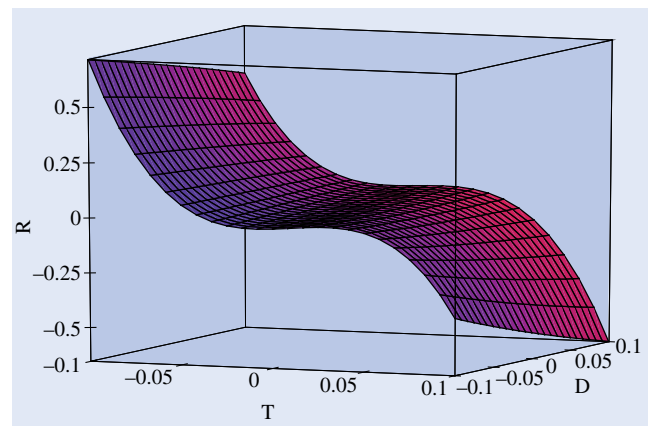


Figure 1. The coefficients of the Price Trend variable,  $T$ , and the Valuation variable,  $D$ , together with all terms up to cubic order (namely,  $D, T, D^2, T^2, DT, D^3, T^3, D^2T, DT^2$ ) are used as the independent variables in a regression for the Relative Price Change,  $R$ . The coefficients of these terms define a cubic polynomial in  $D$  and  $T$  that is plotted above. The surface describes the effect on the Relative Price Change on the following day, exhibiting the nonlinear relationship between  $D, T$  and  $R$ . In particular, a positive trend that is large can influence the following day's Relative Price Change in the opposite direction (analogously for a negative trend). The precise point at which the magnitude changes sign depends nonlinearly on the valuation.

dynamics between Price Trend and Relative Price Change.

**Regression 4.** This regression examines the effects of the M2 Money Supply (M2), Short-Term Volatility (STVol), 52-Week Volatility (Vol), 52-Week (Long-Term) Price Trend (LTT), and Volume Trend (VT) (in addition to the Valuation and Price Trend) on the Relative Price Change:†

$$R(t + 1) = \alpha_0 + \alpha_1T(t) + \alpha_2D(t) + \alpha_3M2(t) + \alpha_4STVol(t) + \alpha_5Vol(t) + \alpha_6LTT(t) + \alpha_7VT(t).$$

†Note that as previously mentioned, with the inclusion of the 52-Week Volatility, 52-Week Price Trend and Volume Trend, more records are excluded from each fund. The total number of records used is decreased from 117 760 to 88 127 and the number of funds dropped from 125 to 114. The 11 excluded funds had fewer than 253 days' data.

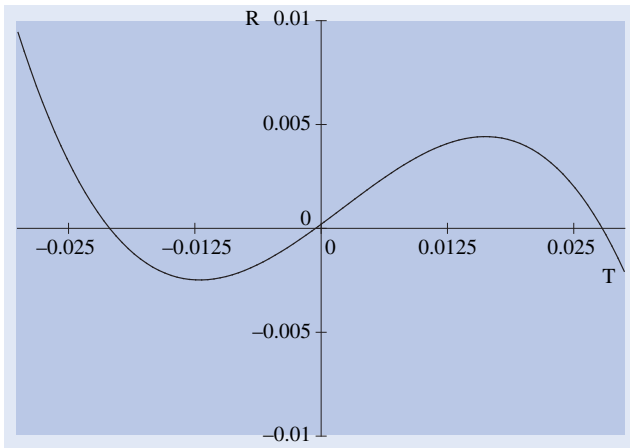


Figure 2. The cross-section of the surface in figure 1 obtained by setting the Valuation variable,  $D$ , to zero is plotted with the Price Trend variable,  $T$ , on the horizontal axis and the Relative Price Change variable,  $R$ , on the vertical. The coefficients of the regression terms define a cubic polynomial in  $D$  and  $T$  that is plotted above. The  $T$  intercepts of the above graph are  $-0.021$ ,  $-0.000562$  and  $0.0278$  indicating that if the Price Trend is between  $-2.1$  and  $2.78\%$ , then the Relative Price Change and Price Trend have the same sign. Thus, smaller changes in the Price Trend tend to push the Relative Price Change in the same direction. However, if the Price Trend is less than  $-2.1\%$  or greater than  $2.78\%$ , then tomorrow's price change is more likely to be opposite today's.

The Price Trend and Valuation variables are still statistically significant (see table 4) and of approximately the same magnitude with slightly smaller positive coefficients than in regression 3, while the Intercept term is only marginally significant. The M2 Money Supply has a positive coefficient (a  $t$ -value of 9.5). This confirms the experimental findings of Caginalp *et al.* (1998) that the money supply is a significant factor in the price change and that an infusion of money into the market should cause prices to rise.

The Short-Term Volatility coefficient is statistically significant and comparable in magnitude (when scaled with respect to the average magnitude, as discussed above) to the Price Trend, Valuation, and M2 Money Supply variables. The Short-Term Volatility typically contributes 0.000842 (the product of the coefficient with the average magnitude of the volatility) compared with 0.0017 for the Valuation.

In addition, it is surprising to find that the coefficient of the Short-Term Volatility is positive, indicating that a short uptrend that has high variance leads to higher prices than a steady uptrend. This may indicate that some large spikes in prices tend to attract the attention of buyers, and, analogously, sharp drops tend to induce more selling compared with the same magnitude of change that is more evenly distributed.

In contrast to this evidence that Short-Term Volatility actually boosts the Relative Price Change, we find that the coefficient of the 52-Week Volatility is negative and statistically significant (a  $t$ -value of  $-3.79$ ), indicating that an increase in the annual volatility of a fund forces the Relative Price Change down. Thus, while short-term

volatility does not appear to discourage buying, we find evidence that longer-term volatility does make funds less attractive to investors.

The 52-Week Price Trend is marginally significant with a  $t$ -value of  $-1.64$ , yielding limited support for mean reversion over longer time periods as noted by Poterba and Summers (1988) using different methods. It is also consistent with the findings of DeBondt and Thaler (1985), who found that those portfolios that performed poorly the previous year tended to outperform the market on average the following year, and vice versa.

We find evidence that the Volume Trend is statistically significant. Its  $t$ -value of 3.08 implies strong statistical support for the positivity of this coefficient. This is consistent with trader beliefs that rising volume in an uptrend is a positive sign for the direction of prices. However, the impact as measured in the product of the coefficient with the average magnitude of the variable is one order of magnitude smaller than for most of the other variables.

**Regression 5.** In any regression spanning several years there is the possibility that the results are influenced by events or characteristics of a particular era or time period. For example, momentum trading may have been popular when the market was rising. In order to discount this possibility we include the time variables (up to third order) in the list of variables in regression 4. These variables represent the number of months, the square of the number of months, and the cube of the number of months since 26 October 1998. In this way if prices are rising then falling and rising again during the time period considered, the cubic polynomial in time generated by the regression will account for this. For example, if the Price Trend coefficient is entirely due to this time issue, then the coefficient of Price Trend in this new regression would be statistically zero. Hence, this new regression is of the form:

$$R(t + 1) = \alpha_0 + \alpha_1 T(t) + \alpha_2 D(t) + \alpha_3 M2(t) + \alpha_4 STVol(t) + \alpha_5 Vol(t) + \alpha_6 LTT(t) + \alpha_7 VT(t) + \alpha_8 Time(t) + \alpha_9 Time^2(t) + \alpha_{10} Time^3(t).$$

The results in table 5 show that all three Time terms are statistically significant. In addition, the absolute value of the relative percentage changes of the Price Trend, Valuation, M2 Money Supply and Volume Trend coefficients from regression 4 to regression 5 are less than 6.5%, while the percentage change of the Short-Term Volatility is 16%. This leads to the conclusion that our results for these variables are not significantly influenced by the particular time period included in this study. The magnitude of the relative percentage changes for the 52-Week Volatility and 52-Week Price Trend are 40 and 97%, respectively. Since these variables involve data for an entire year, they are most strongly influenced by inclusion of the time variables.

To determine whether the hypothesized phenomenon of resistance is statistically significant we perform two regressions, the first involving only the basic two variables, the second involving all of the factors we have found to be significant.

**Regression 6.** This regression includes the Resistance along with the Price Trend and Valuation as independent variables. It has the form

$$R(t+1) = \alpha_0 + \alpha_1 T(t) + \alpha_2 D(t) + \alpha_3 Q(t).$$

Although the Resistance variable appears to be small in magnitude (see table 6), its impact is comparable to the other variables since the indicator variable is one when the criteria are met compared with relatively small magnitudes for the other variables (see the discussion after regression 4). Since the criteria for resistance are met infrequently compared to all data points (namely 687 of 111 135), one does not obtain the overwhelming  $p$ -values as in the other variables. However, one still has 98% confidence that the coefficient is negative.

**Regression 7.** Augmenting regression 6 with the remaining independent variables (M2 Money Supply, Short-Term Volatility, 52-Week Volatility, 52-Week Price Trend, and Volume Trend) yields a regression of the form

$$R(t+1) = \alpha_0 + \alpha_1 T(t) + \alpha_2 D(t) + \alpha_3 M2(t) + \alpha_4 STVol(t) + \alpha_5 Vol(t) + \alpha_6 LTT(t) + \alpha_7 VT(t) + \alpha_8 Q(t).$$

The statistical significance of the Resistance variable (see table 7) increases from regression 6 to regression 7 (the  $p$ -value decreases from 0.0214 to 0.0037) and remains negative (a  $t$ -value of  $-2.90056$ ). In addition, the magnitude of the coefficient increases three-fold from regression 6 to regression 7. The fact that the significance of Resistance in regression 7 is much stronger than in regression 6 demonstrates the importance of including variables that are known to have an effect on the dependent variable. The percentage relative changes in the other coefficients (excluding Intercept) from regression 4 (which does not include Resistance) to regression 7 are less than 2.4%.

Note that the inclusion of the Time variables has little effect on the Resistance (a coefficient of  $-0.0039525$  with a  $p$ -value equal to 0.0028) with negligible differences between the results for the other variables and regression 5. While the  $p$ -value of 0.0037 does not yield the same overwhelming degree of confidence as with some of the other variables, it is nevertheless very significant, attaining the 99.5% level. The reason for the difference (i.e. three standard deviations for Resistance instead of 21 for Price Trend) is probably attributable to the fact that only 687 points satisfied our criteria for Resistance. The impact of Resistance, when it does occur, is large, as one can see by multiplying the coefficient  $-0.0038353$  by the value (namely one) when the criteria are met. Comparing this with the analogous product for valuation, namely 0.001706, we see that Resistance asserts a negative influence that is twice as large as a typical positive

Valuation change. Stated otherwise, if one is within the Resistance criterion, as we have defined it, the Valuation variable needs to be twice the typical magnitude in the positive direction just to neutralize the effect of Resistance. Valuation aside, the Price Trend needs to be 4.4 times the average magnitude of 0.000868 in order to counteract the Resistance.

The inclusion of the same variable(s) in various regressions can be viewed as a test of robustness. As demonstrated by the results above, once the Valuation variable has been added to the regression, the coefficients and significance values of the other independent variables do not vary significantly from one regression to another.

In analysing daily closing prices there is always the issue of the bid/ask spread at the end of the trading day. In other words, the close may occur at either the asking price or the bidding price. This tends to introduce some noise into the analysis of trading prices. However, the large statistical significance attained in our linear regressions suggests that this randomness is not a dominating factor. Moreover, if there is a non-random bias for the closing price to be at the asking price, for example, under particular conditions, then it has the same effect as rising prices. The bid/ask spread is usually not very significant for active stocks, as it is often about one cent for a \$30 stock so it is an effect that is about  $(3000)^{-1}$  but could be much larger for less active stocks.

## 5.2. Forecasting

One advantage of a linear regression is that if it models the dynamics of the dependent variable well, it can be utilised to obtain predictions of that variable's behaviour. The S-Plus statistics package provides forecasting functionality. As the entire data set was used to obtain the above results, we perform an in-sample forecast utilising regression 4. This forecast predicts the Relative Price Change for the 88 127 data points included in the regression. We compare the sign (i.e. positive or negative) of the predicted Relative Price Change with that of the actual observed Relative Price Change and find that the model successfully predicts the sign of the Relative Price Change 57% of the time (50 641 correctly predicted signs out of 88 127 observations) attaining a statistical significance of 40 standard deviations. This provides some evidence that the variables used in this regression play a key role in market price dynamics. Another approach to forecasting using trend and valuation has been implemented in Duran and Caginalp (2008) where the coefficients of these terms are optimised using market data.

## 5.3. Regression per fund

We perform a linear regression individually for each of the 125 funds with dependent variable Relative Price Change and the independent variables from regression 4.

A regression is of the form

$$R(t+1) = \alpha_0 + \alpha_1 T(t) + \alpha_2 D(t) + \alpha_3 M2(t) + \alpha_4 STVol(t) + \alpha_5 Vol(t) + \alpha_6 LTT(t) + \alpha_7 VT(t).$$

We found that only 17 of the 125 funds have a negative Price Trend coefficient, supporting the above evidence of a positive trend effect. Of these 17 funds, five are related to the Energy industry. In addition, these individual regressions confirm the mixed-effects linear regression results and show that the coefficients are not distorted by a small number of funds. The average values of the coefficients are close to the regression 4 results for all variables except the 52-Week Volatility, 52-Week Price Trend and Volume Trend (see table 8). Thus, it appears that these variables are more dependent upon the characteristics of the individual funds than the others.

## 6. Conclusion

Using a methodology that compensates for the randomness of changing valuation, we find strong evidence that the Price Trend, M2 Money Supply, Volatility and Volume Trend influence investor decisions. Unlike some previous studies, the near elimination of the noise associated with changing fundamentals yields results that are significant in magnitude. Of particular interest, we find that the dependence of (today's) Relative Price Change on (yesterday's) Price Trend is nonlinear, thus supporting both of the ideas of underreaction and overreaction, in a way that distinguishes between them quantitatively. Roughly speaking, when the Price Trend is not large, the price tends to continue in the same direction; but when the Price Trend is large it moves in the opposite direction. This suggests that investors and traders view a gradual trend as information that the asset's value is increasing and are thereby willing to pay more for it. However, when there is a large change, they tend to view the price change as excessive and implement a strategy of capitalizing on the overreaction, consistent with the findings of Duran and Caginalp (2007).

Using the weekly changes in the M2 Money Supply (interpolated for daily changes) as one of the independent variables, in addition to the others that we have already established, we have implemented a regression analysis to demonstrate the positive effect of money supply on asset price changes. There is very clear statistical evidence ( $t$ -values greater than 9) that an increase in money supply is a positive factor in price changes. For this variable in particular, there is the possibility that an increasing money supply is associated with a particular time period during our ten-year data period. The inclusion of a time variable with terms up to (Time)<sup>3</sup> essentially eliminates this possibility, as the coefficient and the statistical significance are virtually unchanged.

Short-term and long-term volatility both have a statistically significant effect on trading price. Volatility that is

persistent appears to deter investors, consistent with the concept of risk aversion. Surprisingly, short-term volatility has a positive effect on trading price. This may suggest that volatility may be associated with increased attention on the stock that draws more investors, and hence, increases the demand for the stock, boosting prices.

In our study we find definitive statistical support for the hypothesis that rising volume has a positive influence on price changes, thereby confirming the experimental and practitioner ideas.

We formulate a reasonable mathematical criterion for resistance, the phenomenon by which stock prices tend to decline after approaching a recent high, and find strong support for the assertion that prices are less likely to rise when they are just below the recent highs.

Looking beyond the particular variables (e.g. Price Trend, Money Supply, etc.) studied in this paper, we note that our method is quite general and is capable of addressing other hypotheses that can be formulated quantitatively. The use of assets in which one can objectively define a valuation enables one to compensate for the random noise that is inherent in fundamentals, as illustrated by the first two regressions. Without addressing the issue of changes in valuation, statistical methods will often show that the null hypothesis of no effect cannot be eliminated. For some variables, there may be nonlinearity which can also be understood (as with Price Trend and Valuation in regression 3) using this methodology. Nonlinearity can provide an explanation for phenomena that influence the dependent variable in competing directions, e.g. underreactions and overreactions. An important nonlinear term can also appear as a zero coefficient in a linear regression as a consequence of having a positive effect for part of the variable domain and negative on the remainder.

While our study has focused on closed-end funds and daily price changes, the methods can be applied to any particular time horizon, and to more general stocks once a method for valuation is chosen. From the perspective of establishing the methodology and effects of key variables, closed-end funds have the advantage that there is no ambiguity in their valuation. More generally, one would need to use a method of valuation (which is available from classical finance) together with our methodology in order to obtain predictions on relative price changes.

A major challenge in the analysis of financial markets has been the development of methodology that can establish and quantify the effect of various forces that move prices. Our study has taken a step in this direction, and provides considerable statistical evidence for the implementation of the asset flow differential equations utilising these concepts. Through optimisation of parameters relating to trend, for example, one can use these equations to predict price dynamics (see Duran and Caginalp 2008 for the differential equations and Caginalp and Ilieva 2008 for the difference equations).

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