How Quickly do Equity Prices Converge to Intrinsic Value?

Dennis R. Capozza
Ross School of Business
University of Michigan
Ann Arbor, MI 48109
Capozza@umich.edu
734 764 1269

Ryan D. Israelsen
Ross School of Business
University of Michigan
Ann Arbor, MI 48109
risraels@umich.edu

March 11, 2009

The helpful comments of the participants in seminars are gratefully acknowledged. The usual disclaimer applies.

How Quickly do Equity Prices Converge to Intrinsic Value?

Abstract

This research hypothesizes that in markets where information costs, transactions costs and the economic impact of information can vary widely, we should expect both significant predictability and systematic variation in the predictability. Controlling for other factors, we find that on average, 15-30% of the difference between the stock price and the estimated intrinsic value is removed in a year. We document that levels of predictability vary with firm characteristics like leverage, size and number of analysts. Momentum is stronger for larger firms with more analysts. Reversion to the intrinsic value is greater for smaller firms with more analysts.

How fast do equity prices adjust to new information? Is there an equilibrium level of predictability in asset markets? Numerous studies in real estate, equity and currency markets have documented significant momentum and reversion in these asset markets that varies over time and space and with the characteristics of the asset. Is this variation in predictability systematic? In this research we hypothesize that in markets where information costs, transactions costs and the economic impact of information can vary widely, we should expect predictability to vary systematically. We test this hypothesis with a unique data set that includes estimates of "intrinsic value" based on the discounted present value of future earnings. We document that there is a high degree of predictability in equity prices relative to the estimates and this predictability varies with firm characteristics like leverage, size, liquidity and number of analysts that proxy for information costs, transactions costs and valuation precision. We find that on average, 15-30% of the difference between the stock price and the estimated intrinsic value is removed in a year.

It has long been accepted that financial markets, in particular equity markets, are at least weak-form "efficient" so that excess returns can not be earned by using investment strategies based on historical share prices or other public financial data. "Efficiency", however, does not rule out predictability if information is costly to obtain. Theorists have modeled situations where predictability is consistent with rational expectations equilibrium or Bayesian Nash equilibrium (Brunnermeier, 2001).[1]

Although information is a zero marginal cost good once produced, there are incentives to conceal rather than share information for strategic reasons until positions have been secured in financial markets. The estimates that information traders use for the "fundamental" values of traded assets are not costlessly revealed in public data; but rather must be produced at a cost by firms that specialize in collecting and analyzing the necessary information. These information producers may then trade profitably for their own accounts or sell the information to specialized trading firms like hedge funds. In equilibrium with free entry we should expect that the marginal producer/trader will break even; but intra marginal low cost producers will continue to earn abnormal returns.

For example, an article on hedge funds in the Wall St. Journal provides evidence on the effects of equilibrating entry and exit from this industry:

> Fat returns are becoming more elusive. In 2005, the average hedge fund returned

[1] At least four situations can produce predictability in models that are consistent with equilibrium: (1) asymmetric information and slow diffusion of the information (Hong and Stein, 2000), (2) strategic behavior (Kyle, 1985), (3) inventory effects arising from regular patterns of demand, e.g., payday effects and (4) liquidity and margin interactions: Brunnermeier (2006) outlines how volatility shocks can result in margin increases that eventually mean revert.

> 9.3%, below the 11.4% average for the past decade, according to Hedge Fund Research Inc., a Chicago consultant. By comparison, the S&P 500 index returned 7.7% last year. A record 848 hedge funds closed up shop in 2005, many of them hobbled by poor performance, according to Hedge Fund Research. Susan Pulliam WSJ, 9/16/2006; Page A1

In frictionless markets predictable components of prices like correlation and reversion can be arbitraged and eliminated. While there may not be any completely frictionless markets, there are varying degrees of frictions like information costs and transactions costs among assets. In earlier research, we (Capozza and Israelsen, 2007) studied the pricing of real estate investment trusts (REITs) relative to the net asset value of the REITs based on the value of the underlying real properties. We found strong evidence that REIT prices converge to the underlying net asset value in a one year holding period but only weak evidence of momentum in returns at that horizon. The advantage of using REITs for this experiment is the availability of net asset values as a metric for "fundamental value" and the homogeneous sample that arises from including securities from a single industry. The disadvantage is the relatively small samples (only 75 REITs).

In this research we extend the research to a large sample of firms across many industries. We estimate the relevant correlation and reversion parameters using a unique panel data set for 8,845 securities from 1997 to 2006. An important variable in the data set is the intrinsic value of each firm for each year. The intrinsic values are constructed by AFG Research from estimates of future earnings based on growth rates and the decay of "economic margin," i.e., the spread of return on equity above or below the cost of capital. The decay rate is based on individual characteristics of the firm that capture its competitive advantages. "When the economic margin decays to zero, all incremental investments are zero NPV proposition, thus, ending the wealth creation of the firm."[2]

In studies of mean reversion one must ask what the values are that the assets revert toward. In most cases[3] reversion is simply defined as price reversal at some horizon. A more meaningful economic basis for reversion is reversion to a suitably defined "fundamental" or "intrinsic" value. If fundamental values can be obtained, more powerful tests of reversion become possible. Reversion can then be observed not only when prices reverse direction but anytime prices converge to the fundamental value. By contrast, using price reversals to define reversion is fraught with both Type I and Type II errors, which are mitigated by having a metric for fundamental value. For example, if fundamentals improve at the same time that a stock is reverting down, we will not see a price reversal if the improving fundamentals exceed the reversion. In this study, we use the intrinsic value as our metric for fundamental value.

---

[2] The Applied Financial Group, 2004.

[3] For example see De Bondt and Thaler (1985), Jegadeesh (1990), Jegadeesh and Titman (1995) and Lo and MacKinlay (1990).

In the absence of conditioning on fundamental value, estimates of momentum will be biased since a relevant variable is being excluded. For example, consider an asset whose price and value are initially $20. If the fundamental value increases to $30 and the price does not adjust fully and immediately to this new level, the price must "revert" towards $30 over time. This reversion to the new fundamental value will be mis-identified as serial correlation if fundamental value and a reversion parameter are not included in the estimates.

Our analytical framework is closely related to the story and analysis in Hong and Stein (1999), HS henceforth. In HS two types of boundedly rational traders interact in financial markets, "newswatchers" or information traders and "momentum" traders. Information traders trade on new information. If information diffuses slowly to the risk-averse information traders, equity prices under react to new information and revert slowly and predictably to the new fundamental values. The under reaction implies that momentum traders can profit by trend chasing since they are able to analyze price movements and infer future price movements from the price patterns caused by the slow diffusion of information. The presence of momentum traders whose forecasts are simple functions of past prices, accelerates prices in the direction of fundamentals; "but this comes at the expense of creating an eventual overreaction to any news. " (HS, 1999) Notice that the actions of momentum traders directly impact the momentum or autocorrelation while those of the information traders determine the speed of reversion.[4]

In the next section we review the difference equation that characterizes the dynamic properties. The third section describes the panel data set we use for our estimates and the fourth section discusses the empirical results. The fitted values for the coefficients indicate the wide variation in possible dynamics. The final section summarizes and concludes.

[4] Black (1989) provides an alternative construct for equilibrium momentum and reversion in stock prices based on the net demand for portfolio insurance. He points out that since portfolio insurance involves increasing positions when prices rise and reducing as prices fall:

> Mean reversion is what balances supply and demand for portfolio insurance. High mean reversion will discourage portfolio insurers because it will mean they are selling when expected return is higher and buying when expected return is lower. For the same reason, high mean reversion will attract "value investors" or "tactical asset allocators," who buy after a decline and sell after a rise. Value investors use indicators like price-earnings ratios and dividend yields to decide when to buy and sell. They act as sellers of portfolio insurance.
>
> If mean reversion were zero, I think that more investors would want to buy portfolio insurance than to sell it. People have a natural desire to try to limit their losses. But, on balance, there must be as many sellers as buyers of insurance. What makes this happen is a positive normal level of mean reversion.

Dynamics in a Simple Model of Correlation and Reversion[5]

The economics of mean reversion is the basic notion that, in the long run, markets converge towards equilibrium. In financial markets, long run equilibrium implies that there are no arbitrage opportunities within the limits of transactions costs.

In each time period, *t,* and for each firm, we assume there is a long-run equilibrium value, P_t^*, for the stock price that is determined by the value of the underlying property assets and other variables.

Value changes are governed by reversion to the fundamental value and by serial correlation according to

$$\Delta P_t = \alpha \Delta P_{t-1} + \beta (P_{t-1}^* - P_{t-1}) + \gamma \Delta P_t^* \qquad (1)$$

where Δ is the difference operator. If we define P_t to be the stock price at time *t,* then equation (1) represents a "dollar" return formulation. Alternatively, we can define P_i to be the log of the dividend-adjusted stock price to obtain the more common percentage return formulation. The first term on the right in (1) is the serial correlation or momentum term, where α is the serial correlation coefficient. The second term is an error correction or reversion term that provides reversion to the equilibrium value. β ($0<\beta<1$) is the rate of reversion or adjustment to equilibrium. The third term captures the contemporaneous adjustment to fundamentals. Partial adjustment implies that $0\leq \gamma \leq 1$. For a detailed discussion of the equation (1), please see Capozza, Hendershott and Mack (2004).

The Data

We use annual data for equities from January 1997 to November 2006. A unique feature of the database is estimates of the intrinsic values of the firms estimated by AFG Research. To create the intrinsic values, AFG creates a "percent to target" for each firm, each month. The percent to target

> measures the deviation between a stock's current market price and AFG's price target. For example, a stock with a $10 price with a $12 target would carry a 20% upside, or 20% to Target. AFG target prices utilize a discounted cash flow analysis to arrive at an equity value for each company. The terminal value of this DCF is determined by a *decay* of Economic Margins (spread above the cost of capital). Each company's EMs are decayed to 0 over a certain number of years based on the individual characteristics and competitive advantages of that firm. When a company's EM reaches a value of 0, all incremental investments are zero NPV propositions, thus ending the wealth creation of the firm. (AFG Research 2004)

To account for the possibility of data errors, we eliminate from our sample any observations for which the absolute change from the previous month in "percent-to-target" is greater than 100%.

---

[5] This section is based on the model in Capozza, Hendershott and Mack, 2004.

Of 560,027 observations only 14,944, or about 2.7%, fall into this category.

Summary statistics for these intrinsic values and for market prices are presented in the first two rows of Table 1. Fundamental value, P*, is the current market price plus the percent to target as described above. It is defined as the current target price using a discounted cash flow (DCF) analysis to arrive at an equity value for each company. The terminal values of the DCF analysis are determined by a decay of the spread that the firm earns above the cost of capital. This decay is based on the individual characteristics and competitive advantages of each firm.

Returns, Size and Volume are taken from the monthly file of the Center for Research in Security Prices (CRSP). Size is defined as the log of the market value of equity (price time shares outstanding). Volume is the log of dollar volume (price times volume) over the period. Prices and returns are adjusted for splits and dividends.

Leverage is taken from the Standard & Poor's Compustat Annual file. We measure leverage as Total Liabilities (item #181) over Total Assets (item #6). We adjust the timing in order to ensure that the data were publicly available at the beginning of the period.

From the I/B/E/S file, we measure Analysts at the log of 1 plus the number of unique analysts making earnings forecasts during the 12 previous months.

All variables are Winsorized at 1% and 99%. There are 321,341 monthly firm observations with no missing data. There are a total of 8845 distinct firms in our sample with an average of 3872 per month, and between 3301 and 4873 firms in any given month. Where indicated, we at times delete the smallest decile of stocks and/or stocks selling for under $5.

Table 1. Summary Statistics

This table reports means, standard deviations and extreme values for a number of summary statistics calculated across our sample of 321,341 monthly observations for 8,845 firms from 1997 to 2006. Returns are dividend and split adjusted CRSP returns. Intrinsic Value and Percent to Target are supplied by Applied Financial Group (AFG).

Variable	Mean	Standard Deviation	Minimum	Maximum
Monthly Log Return for Price (log((P+div)/P_{-1})	0.00	0.14	-0.52	0.43
Monthly Log Return for Intrinsic Value (P*)	0.00	0.26	-1.35	1.14
Percent to Target (log(P*/P))	0.20	0.72	-1.27	3.23
Liquidity (Log of Dollar Volume)	12.63	2.34	7.30	17.84
Size (Log of Market Capitalization)	12.99	1.84	8.98	20.18
Leverage (Total Liabilities / Total Assets)	0.54	0.27	0.00	1.26
Analysts (Log of 1 plus the Number of Analysts)	1.58	1.09	0.00	4.25

The Initial Estimates of the Base Model Decomposition

In this section we take advantage of the metric for intrinsic value in our data set and begin to impose structure on the data by estimating the relation in Equation 1. Equation 1 splits price movements into three components: 1) correlation with previous price changes, 2) reversion to fundamental value and 3) changes arising from coincident changes in fundamental value. Any one of these can be the source of price momentum. For example, if price traders use high past price changes to predict future positive price changes in their decisions to trade as in Hong and Stein (1999), then the first component may be positive and significant. If information is impounded slowly into prices then we should observe a positive reversion coefficient (beta) that is less than one. If the process for fundamentals has persistence that is unanticipated, then momentum could partly arise from contemporaneous adjustment to changes in fundamentals. The standard approach to momentum, of course, combines all three into a composite estimate of momentum

Table 2 summarizes our initial results. The four models vary the fixed effects as defined in the fourth row. All the estimates use Roll (1984) returns to avoid well-known issues arising from bid/ask bounce. Model 3 is closest to the standard momentum estimates because it uses time fixed effects which control for market fluctuations. The use of deciles in momentum studies plays a similar role.

At this one year horizon, the lagged return enters negatively rather than positively. That is, there is reversal rather than momentum at this horizon once we control for reversion to fundamentals.

This is consistent with the momentum literature where researcher find momentum is significant at shorter horizons and morphs into reversal at longer horizons. The reversion (beta) and coincident adjustment (gamma) coefficients are positive and highly significant as might be expected.

In model 4 of Table 2 we include firm fixed effects as well as time fixed effects. Fixed effects help to control for differences in risk levels among securities and possible measurement error in our metric for fundamental value.6 The inclusion of firm fixed effects considerably strengthens the reversion and coincident adjustment coefficients both statistically and economically. For example, we now find that 25% of the change in intrinsic value is incorporated into prices within one year. 19% of the gap between actual and intrinsic value is removed in a year.

Since the correlation parameter is significantly negative at the annual horizon, when we control for firm fixed effects, past relative strength actually reduces future performance.

These results are consistent with the interpretation that much of what we observe as momentum is actually slow reversion towards a changing fundamental value. Adjustment to changes in fundamental value is partial in any time period, i.e., information about fundamental value diffuses slowly into prices. As a result unconditional past returns are correlated with the gap between actual and fundamental value and provide a path, albeit an inefficient one, for divining future returns. As more precise metrics for fundamental value become available, we may observe faster adjustment to new information.

[6] JT test for differences in risk among momentum deciles as embodied in size and market correlation and find that momentum results are affected by but robust to controls for these variables.

Table 2: Estimates of the Base Model by Holding Periods with Time and/or Firm Fixed Effects

The dependent variable is the 11 month (end of January to end of December) Roll (1986) percentage return. All models estimated by panel regression. Year fixed effects included in models 2 and 4. Firm fixed effects are included in Models 3 and 4. Significant coefficients are in boldface type.

	Model 1		Model 2		Model 3		Model 4	
	Coefficient	T-Statistic	Coefficient	T-Statistic	Coefficient	T-Statistic	Coefficient	T-Statistic
Correlation (alpha)	**-13.5%**	-17.6	**-19.7%**	-22.6	**-10.9%**	-14.5	**-17.9%**	-20.8
Reversion (beta)	**11.4%**	20.1	**27.4%**	31.3	**10.4%**	19.0	**24.6%**	29.1
Coincident Adj. (gamma)	**13.3%**	29.0	**20.9%**	36.5	**12.4%**	27.9	**19.2%**	34.6
Firm /Time Fixed Effects	No	No	Yes	No	No	Yes	Yes	Yes
R^2/Degrees of Freedom	7.9%	17,642	36.7%	13,478	15.1%	17,634	42.0%	13,470

The Determinants of Equilibrium Correlation and Reversion

Our goal in this section is to explore the causes of differences in the dynamic response of equity prices to shocks. In the context of the model, these differences will appear as different estimates of α and β.Therefore we rewrite (1) as

$$\Delta P_{kt} = (\sum_i \alpha_i (Y_{kit} - \overline{Y}_i))\Delta P_{k,t-1} + (\sum_i \beta_i (Y_{kit} - \overline{Y}_i))(P^*_{k,t-1} - P_{k,t-1}) + \gamma \Delta P^*_{kt} \qquad (2)$$

where i indexes the variables and k indexes firms. The Yi , which may include a subset of the X and a unit vector, are independent variables, and $\overline{Y}_i$ represents the mean value of Yi in the sample7.

An important issue is the choice of the Yi, which affect the predictability coefficients alpha and beta. Many stories, both behavioral8 and rational9 are consistent with predictability. For example, all the estimates of gamma in Table 4 are much less than one. This means that less than the full change in fundamentals is incorporated into prices contemporaneously. If investors under react to changes in fundamentals in one period, then prices must mean revert towards fundamental value in the future if equilibrium is ever to be attained. A behavioral explanation would emphasize psychological studies that document “under reaction” or “over reaction” to new information.10 Rational approaches, on the other hand, might focus on costly information that diffuses slowly (Heaton and Brav, 2002; Hong and Stein, 1999).

Econometrically, if we believe equation (2) is the correct model, then exclusion of one of the variables will bias the remaining coefficients, i.e., the standard bias arising from exclusion of a relevant variable. For example, suppose only lagged price changes are included and mean reversion is excluded. If mean reversion is partial each time period, i.e., if beta is less than one, then successive price change realizations will tend to have the same sign as prices revert to fundamental value. The estimated statistical serial correlation, then, will be biased upward. Thus the serial correlation, or alpha, as defined in equation (2) is not identical to “momentum” as typically defined in the finance literature. Since metrics for fundamental value are generally not available in studies of price predictability in financial markets, most estimates of momentum are biased upward.

---

[7] In equation (2) we have assumed that γ is not endogenous. Allowing for endogeneity affects the amplitude but not the frequency (CHM, 2004).

[8] See Odean (1998), Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Barberis and Huang (2001).

[9] See Conrad and Kaul (1998), Berk, Green and Naik (1999), and Johnson (2002).

[10] See Bern (1965) and Tversky and Kahneman (1974),

Among the research on equity markets, the most closely related model to our Equation (2) is the work by Hong and Stein (1999). In the HS world there are two types of boundedly rational stock traders, information traders or news watchers and price traders. Information traders follow information events and conditionally reassess their estimate of the value of the equity based on the new information. Information, especially non-public information, is not impounded immediately into prices but diffuses slowly to the information traders. Information traders might include insiders who would clearly have access to accurate and timely information and "value investors" who have a comparative advantage at processing the new information. As the information diffuses the stock price will tend to move in one direction over a period of time.

Price traders, on the other hand, follow the stock price movements but not the "news. "When they observe one sided movements, i.e., "trends" or "momentum," they piggyback on the information traders and make trades that reinforce the trend. If returns are correlated, then "price" traders (technicians/momentum traders) can use price history to trade profitably provided they identify the trends early enough.

In equation (1) or (2), implicitly, the α arises from the actions of the price traders while the β emerges from the optimization of the information traders. Although both types of traders are constrained to specific types of information, they are nevertheless rational optimizers within the bounds of the constraints. We expect the following stylized facts to apply:

Impact—Companies where the information event will have more impact will be preferred. For example, macroeconomic or industry events will be magnified for highly levered firms, making them more efficient trading vehicles.

Precision—Companies and events with more precise information (higher signal to noise ratios) will be preferred trading vehicles. Price traders should be more active in securities that have stronger trends relative to their volatility. Information traders should be more active among companies where financials are more transparent, thus making it easier to assess the impact of any new information.

Costs—Since revenue from trading must more than cover transactions costs, securities with lower transactions costs will be preferred.

Economic Impact

Any given "unit" of information will have more impact on asset prices when the security is leveraged to the information. Both operating and financial leverage will affect economic impact; but we expect financial leverage to be the more important since financial leverage varies widely (see Table 1).

Information and Transactions Costs

Most of the research on predictability has focused on the role of information and transactions costs. First consider the role of information dissemination.

Hong, Lim, and Stein (2000) test the implication of Hong and Stein (1999) that stocks for which information travels slowly have more momentum. They find that the profitability of momentum strategies declines with firm size after a point and with analyst coverage. Furthermore, the analyst coverage effect is stronger for stocks that are past losers than for stocks that are past winners.

The existence of transaction costs may prevent prices from reverting if the costs are large enough relative to the mispricing. Lesmond, Schill and Zhou (2004) show that stocks that generate persistent momentum returns are also those with high transaction costs. This result can arise when metrics for fundamental value are not available and are excluded. The measured momentum may actually be reversion to new fundamentals as described above. High transactions costs can slow adjustment and may increase persistence.

Lee and Swaminathan (2000) form 30 portfolios based on past returns and volume using data from all firms listed on NYSE and AMEX from 1965 to 1995. They find that eventually, the momentum effect reported by Jegadeesh and Titman (1993) reverses. Furthermore, this reversal is predictable using past volume data. In their sample, the prices of high (low) volume stocks that have performed well (poorly) tend to mean revert more quickly (slowly). Inasmuch as volume is a proxy for transaction costs, this is consistent with Hong and Stein (1999). By contrast, we find that, conditional on size, higher dollar volume reduces correlation and increases momentum.

Valuation Precision

Because we are interested in momentum and mean reversion with respect to the fundamental value, variables related to ease of valuation are of interest. Mispricing is likely to be more significant in complex firms which are difficult to evaluate than in more focused firms.

The intrinsic value of more highly leveraged firms may be less precisely measured even if debt is easier to value than equity. For example, consider the case where the value of liabilities is known but the assets are measured imprecisely. In this situation, the uncertainty about the fundamental or intrinsic value of the equity will be magnified in percentage terms for more levered firms.

In addition, highly levered firms face possible bankruptcy costs that are difficult to measure (Andrade & Kaplan, 1998). As debt increases, bankruptcy becomes more likely. Additionally, market values of debt are also difficult to estimate. On the other hand, if firms have to go to the debt market often, more information may actually be available about the firm and mean reversion may occur more quickly.

To summarize this section, in asset markets, efficiency arises from the actions and trading of rational information gatherers. The interaction of boundedly rational traders can result in predictable momentum and reversion in prices. Mean reversion to fundamental value proceeds slowly as information about fundamentals is disseminated to information traders. Momentum in prices arises when price traders, who process only past price movements, identify that prices are trending to a new fundamental value.

These two types of traders are both information producers who evaluate the price impact, the precision and the associated transactions costs before trading on their information. High impact, low cost information events and firms should attract more information producers and result in faster convergence to equilibrium. The price path, however, may be characterized by overshooting when price traders add sufficient momentum to the dynamics.

In equilibrium, with free entry of information producers, the marginal producer will break even; but intra-marginal (low-cost) producers may earn abnormal returns. More lucrative events and/or securities will attract more information producers who can precipitate faster price adjustments.

Empirical Estimates

A number of variables are available in the data set that relate to the production of information.

- *Log of Size (i.e., market capitalization)*—Larger firms tend to be more actively traded and more widely followed by analysts. With better information and lower transactions costs, larger firms should attract more information producers. Adjustment to new information should evolve at a faster pace.
- *Log of Dollar Volume*—As with size, more actively traded firms, i.e., more liquid firms, will have lower effective trading costs.
- *Debt to Asset Ratio*—The ratio of debt to assets measures the degree of financial leverage for the firm. We expect that information will have more impact on more highly levered firms. Thus, leverage should attract more information producers. On the other hand leverage reduces the precision of metrics for intrinsic value. Adjustment speeds will be faster for more levered firms if the impact effect dominates the precision effect.
- *Number of Analysts*—To the extent that analysts are information producers, more analysts should improve the dissemination of information and speed the adjustment process.

Endogenous Dynamic Adjustment

Estimates for equation (2) are presented in Table 3. The pattern of coefficients for alpha, beta and gamma is similar to that for the base model in Table 2. We focus here on the cross product terms. The pattern of the coefficients across models is quite consistent and highly statistically significant for all except those for leverage. To simplify the exposition we concentrate on the model 4 results with both fixed effects. The other models can be viewed as robustness checks.

Analysts – An increase in the number of analysts increases both the reversion and the correlation coefficients. The former is consistent with faster information flow to information traders and faster convergence to the equilibrium. The faster rate of reversion may make it easier for trend following price traders to detect (higher signal to noise ratio) the trend. The implication then is more correlated prices conditional on the reversion.

Leverage – When significant, higher leverage (Debt to Assets) tends to reduce reversion and increase correlation. This suggests that the precision effect dominates for information traders while the economic impact effect dominates for price traders.

Size and Volume—Size and volume are highly correlated and give mixed results in tests of robustness across horizons (not reported). The one-year result is that volume decreases correlation but increase the rate of reversion. Firms that trade at higher volumes for any given size have lower implied transactions costs. Size on the other hand has a positive effect on correlation and a negative effect on reversion. We can conjecture that the largest firms, because they are so well followed, may be unattractive vehicles for information traders.

Table 3: Estimates of the Interaction Model in Equation 2

The dependent variable is the 11 month (end of January to end of December) Roll (1984) percentage return. All models estimated by panel regression. Year fixed effects included in models 2 and 4. Firm fixed effects are included in Models 3 and 4. Significant coefficients are in boldface type.

	Model 1 No Fixed Effects		Model 2 Firm Fixed Effects		Model 3 Time Fixed Effects		Model 4 Both Fixed Effects	
	Coefficient	T-Statistic	Coefficient	T-Statistic	Coefficient	T-Statistic	Coefficient	T-Statistic
Correlation (alpha)	**-1.5%**	-2.4	**-12.3%**	-17.4	0.3%	0.5	**-10.4%**	-15.2
Alpha times volume	**-5.6%**	-9.2	**-6.1%**	-9.1	**-5.7%**	-9.8	**-6.2%**	-9.6
Alpha times size	**1.8%**	2.4	**4.8%**	5.6	**2.6%**	3.6	**5.5%**	6.8
Alpha times number of analysts	**2.3%**	3.7	**5.0%**	7.4	**2.8%**	4.7	**4.9%**	7.5
Alpha times leverage	1.4%	0.6	-1.2%	-0.4	2.7%	1.2	3.0%	1.2
Reversion (beta)	**16.2%**	36.5	**29.5%**	44.5	**14.9%**	35.2	**26.8%**	42.2
Beta times dollar volume	**1.3%**	3.2	**1.4%**	2.8	**1.3%**	3.4	**1.6%**	3.3
Beta times size	**-7.0%**	-13.6	**-7.4%**	-11.3	**-6.8%**	-13.9	**-7.5%**	-12.1
Beta times number of analysts	**5.7%**	13.9	**6.7%**	14.0	**4.7%**	12.0	**5.6%**	12.3
Beta times leverage	-1.2%	-0.8	**-9.2%**	-4.6	-0.2%	-0.1	**-5.6%**	-3.0
Contemporaneous adjustment (gamma)	**19.2%**	56.9	**23.7%**	56.1	**18.0%**	55.6	**22.1%**	54.6
Firm FE/Time FE	No	No	Yes	No	No	Yes	Yes	Yes
R^2 / Degress of Freedom	12.9%	31,238	39.0%	24,501	21.6%	31,229	45.1%	24,492

Conclusion

In a world where information is costly to acquire, the structure of the investment industry that supplies and trades on the information can have an impact on the predictability of security prices. Our stylized investment industry is one where fundamental value changes exogenously. The investment industry produces information about the changing fundamental values and trades towards the "efficient" prices. Information is produced using scarce resources, including labor or talent and capital. With fixed costs and free entry into the industry, equilibrium arises when entry of new firms reduces the profits of the marginal firm to "normal" but intra-marginal producers may still earn abnormal profits.

The interaction of boundedly rational information and momentum traders results in both momentum and mean reversion. Empirically, estimates of reversion require a metric for fundamental value, which is typically not available. In the absence of a metric for reversion, we have argued that estimates of momentum are biased upward.

In this stylized world

- The value of information is the net payoff from trading on the information
- Information is less costly to acquire for some securities, especially large firms and widely followed firms
- Net revenue from information is higher for more levered firms and more liquid firms
- Private information is more valuable than public information so that corporate insiders have an information advantage
- Barriers to entry increase the value of information, e.g. for market makers and specialists.

We exploit the power of estimates of intrinsic values calculated from discounted values of future cash flows with decay in the economic margin over time. We use the intrinsic values as a metric for fundamental value. Following the framework in Capozza, Hendershott and Mack (2004) and Capozza and Israelsen (2007), we estimate the momentum and reversion parameters for all available equities. Like the earlier estimates for REITs, this large sample of equities exhibits significant mean reversion. There is evidence of negative correlation during the sample period at long horizons (yearly) once we control for reversion and contemporaneous adjustment.

We then interact the estimates of the correlation and reversion parameters with size, dollar trading volume, leverage, and number of analysts. We find that correlation is stronger when there are more analysts, more leverage and larger size. Reversion is faster for less levered firms with more analysts. These results are consistent with the hypothesis that predictability of equity prices during this period arose from the production of costly information by traders studying both fundamentals (information traders) and price history (price traders).

We view our result as preliminary since much data collection and research will be needed before we can fully understand how the structure of the investment industry and its diverse participants interact to create the observed predictability in equilibrium. Nevertheless these results do provide important evidence on the adjustment process in equity markets.

References

Andrade, G., and S. Kaplan, 1998, "How Costly Is Financial (Not Economic) Distress? Evidence from Highly Leveraged Transactions that Became Distressed," *Journal of Finance*, 53, 1443-1494.

Barberis, Nicholas, and Ming Huang, 2000, Mental Accounting, Loss Aversion, and Individual Stock Returns, *Journal of Finance* 54 1247-1292.

Barberis, Nicholas, A. Shleifer, and R. Vishny, 1998, A Model of Investor Sentiment, *Journal of Financial Economics* 49, 307-343.

Berk, J.B., Green, R.C., Naik, V., 1999. Optimal investment, growth options, and security return, *Journal of Finance* 44, 1553-1608.

Brunnermeier, M.K., 2001, Asset Pricing under Asymmetric Information, Oxford University Press, Oxford.

Brunnermeier, M.K. and L.H. Pedersen, 2006, Market Liquidity and Funding Liquidity, Working paper, Princeton University.

Capozza, Dennis R., Patric Hendershott and Charlotte. Mack, 2004, "An Anatomy of Price Dynamics in Illiquid Markets: Analysis and Evidence from Local Housing Markets," *Real Estate Economics*, 2004, 32:1, 1-32.

Capozza, Dennis R. and Ryan Israelsen, 2007, Predictability in Equilibrium: Price Dynamics for REITS," *Real Estate Economics*, 2007, 35:4

Conrad, Jennifer, and Gautam Kaul, 1998, An Anatomy of Trading Strategies, *Review of Financial Studies*, 11, 489-519.

Daniel, K., D. Hirshleifer, and A. Subrahmanyam, 1998, Investor Psychology and Security Market Under- and Overreactions, *Journal of Finance*, 53, 1839-1886.

De Bondt, Werner F.M.; Thaler, Richard H., 1985, Does the Stock Market Overreact? The Journal of Finance,Vol. 40, p793-808, 16p.

Heaton, J, and A. Brav, "Competing Theories of Financial Anomalies", *Review of Financial Studies* 15 no. 2, 2002.

Hong, Harrison, and Jeremy Stein, 1999, A Unified Theory of Underreaction, Momentum Trading and Overreaction in Asset Markets, *Journal of Finance* 54, 2143-2184.

Hong, Harrison, Terence Lim and Jeremy Stein, 2000, Bad News Travels Slowly:Size, Analyst Coverage and the Profitability of Momentum Strategies, *Journal of Finance* 55, 265-295.

Jegadeesh, Narasimhan, 1990, Evidence of Predictable Behavior of Security Returns, Journal of Finance 25, 881-898.

Jegadeesh, Narasimhan, and Sheridan Titman, 1995, Short-Horizon Return Reversals and the Bid-Ask Spread, Journal of Financial Intermediation 4, 116-132.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to Buying Winners and Selling Losers:Implications for Stock Market Efficiency, *Journal of Finance* 48, 65-91.

Johnson, Timothy C., 2002, Rational Momentum Effects, *Journal of Finance* 57, 585-608.

Lo, Andrew and Craig MacKinlay, 1990, When Are Contrarian Profits Due to Stock Market Overreaction?, Review of Financial Studies 3, 175-205.

Roll, R., 1984, A Simple Implicit Measure of the Effective Bid-Ask Spread in an Efficient Market, *Journal of Finance* 39, 1127-1139

Tversky, A., and D. Kahneman, 1974, Judgement under Uncertainty:Heuristics and Biases", *Science* 185, 1124-1131.