Fusion Investing

Charles M.C. Lee
Henrietta J. Louis Professor of Accounting and Finance
Johnson Graduate School of Management
Cornell University
Ithaca, New York

Although fundamental valuation and behavioral finance are often viewed as divergent approaches, some research suggests important connections between the two. For example, indicators of investor sentiment may provide important clues about the transitional dynamics between long-term reversals and short-term momentum. Fusion investing is a relatively new approach that attempts to integrate traditional and behavioral paradigms to create more robust investment models.

In this presentation, I will lay the groundwork for a better understanding of the relationship between fundamental value and investor sentiment. The integration of these two elements of investing is called "fusion investing." I will discuss an integrative framework that can be used by value investors who also wish to think in behavioral terms. My thesis is that even a pure value investor needs to consider investor sentiment in formulating his or her strategy.

Efficient Market Hypothesis

In the traditional view of markets, the intrinsic value of a company is defined as the present value (PV) of its expected payoffs to shareholders. This PV is conditional on the information set available at time t, δ, such that

$$V_t = \sum_{i=1}^{\infty} \frac{E_t(D_{t+i} \mid \delta')}{(1+r)}.$$

Operationally, the efficient market hypothesis (EMH) is often interpreted as meaning that the price of a stock at time t equals the value at time t for all t, or $P_t = V_t$, $\forall t$. In other words, because the PV of future dividends cannot be known with certainty, the current price of the stock is the best proxy for V_t. For investors who subscribe to the EMH, the market is viewed as being extremely quick to reflect information relevant to future dividends.

At first, all the empirical evidence seemed to support the EMH. Researchers found that stock prices are hard to predict, and event studies indicated that prices adjust quickly to new information. In fact, in a 1978 article, Michael Jensen wrote, "I believe there is no proposition in economics which has more solid empirical evidence supporting it than the Efficient Market Hypothesis."[1]

But now, researchers are finding that even though returns are difficult to predict, prediction is not an impossible task; systematic patterns in returns can be observed. Researchers are also finding that prices adjust quickly but not in an unbiased manner. For example, a positive earnings surprise precedes a positive price drift. Furthermore, beta is not nearly as useful in explaining expected returns as theory suggests it should be. If beta is not already dead, it is surely comatose. Increasingly, the EMH—at least the proposition that stock prices reflect a company's fundamental value—appears too simplistic.[2]

The Behavioral Model

The behavioral finance literature has suggested an alternative to the traditional view of markets. In a relatively early study, Shiller (1984) introduced a simple model that illustrates the key dynamics in the

[1] Michael C. Jensen, "Some Anomalous Evidence regarding Market Efficiency," *Journal of Financial Economics* (June 1978):95–101.

[2] Charles M.C. Lee, "Market Efficiency and Accounting Research," *Journal of Accounting and Economics* (September 2001):233–253.

behavioral view of the world versus the traditional view.[3] In this model, only two types of trader exist: the informed trader (or smart money) and the noise trader. Smart money performs valuation analysis, such as discounted cash flow (DCF) computations, to calculate the PV of future dividends, whereas the demands of noise traders are motivated by whims, rather than serious valuation analysis. Noise traders have time-varying demands that are not based on an optimal forecast of expected returns for a stock.

In equilibrium, Shiller's model provides the following formula for price:

$$P_t = \sum_{k=0}^{\infty} \frac{E_t(D_{t+k}) + \phi E_t(Y_{t+k})}{(1 + \rho + \phi)^{k+1}},$$

where ρ is the expected real return such that there is no demand for shares by smart money and ϕ is the risk premium that would induce smart money to hold all the shares. This risk premium can be thought of as an arbitrage cost to eliminate market noise.

In short, the model says that price at time t is the PV of expected dividends discounted to infinity ("V"), plus an additional term. The first term, $E_t(D_{t+k})$, denotes fundamental value, the stream of expected future dividends. The second term, $E_t(Y_{t+k})$, represents the expected demand from noise traders, which is also known as investor sentiment. So, when noise traders are bullish, the second term will be positive and price will be higher. I think of ϕ as arbitrage costs. If arbitrage costs are zero, the second term drops out and price is only the PV of future dividends. In other words, if arbitrage costs are extremely low, $P = V$ and the EMH holds as a special case. If arbitrage costs are extremely high, the second term dominates and price is largely set by noise-trader demand.

Four implications are present when examining the market from the point of view of Shiller's model. First, price is not simply the PV of future dividends. Price is the weighted average of a stock's fundamental value and noise-trader demand. As long as arbitrage involves a cost, price will not typically equal value. Second, fundamental analysis (i.e., valuation and cash flow projection) is only one component of investing in stocks. In other words, the study of a company's fundamental value is only one part of the investment decision. Third, the other part of the investment decision (beyond fundamental value), particularly for smart money, is the demand from noise traders, which can have a substantial impact on the market. Thus, in addition to fundamentals, rational investors need to consider "fads" and "fashions." John Maynard Keynes articulated this concept when he compared the market to a beauty contest.[4] The objective is to decide not only who you think has the prettiest face but also who you think everyone else will think has the prettiest face. In other words, the goal is to determine not only what you think the PV of future dividends will be but also what other investors think the PV of future dividends will be.

Fourth, the time-series behavior of noise-trader demand, or investor sentiment, matters. A value investor has to assume that Y_t is mean-reverting over a defined investment horizon. If Y_t is a random walk and today's Y_t is an unbiased forecast of tomorrow's Y_t, then price equals value plus a random walk, which, by definition, is not mean-reverting. If that is true, value could go in any direction—and value investors have a problem. The problem arises because, under these circumstances, the value investor cannot actually make money using fundamental value, particularly within a relatively short investment horizon. If the holding period is three days or three weeks, throw away your accounting book! If the holding period is three years, maybe fundamental value matters more. The success of value investing largely depends on how long it takes for the price to revert to the mean.

Investor sentiment can be measured two ways. One way is to focus on fundamental value by estimating the PV of a company's future cash flows, V, and comparing that value with the price of the company's stock. The difference can be thought of as a measure of investor sentiment. Another way to measure investor sentiment is to focus on noise-trader demand by identifying sentiment indicators that can help predict the direction of such demand.

Improving Valuation Models

First, consider the fundamental approach to valuation. In recent years, I have written a number of papers that have been aimed at improving the valuation model.[5] Taken together, the evidence appears to support the notion that a better estimation of V leads

[3] Robert J. Shiller, "Stock Prices and Social Dynamics," *The Brookings Papers on Economic Activity*, vol. 2 (1984):457–510.

[4] John M. Keynes, *The General Theory of Employment, Interest and Money* (New York: Harcourt, Brace & World, Inc., 1935), chapter 12.

[5] Richard Frankel and Charles M.C. Lee, "Accounting Valuation, Market Expectation, and Cross-Sectional Stock Returns," *Journal of Accounting and Economics* (June 1998):283–320; Charles M.C. Lee, James N. Myers, and Bhaskaran Swaminathan, "What Is the Intrinsic Value of the Dow?" *Journal of Finance* (October 1999):1693–1741; William R. Gebhardt, Charles M.C. Lee, and Bhaskaran Swaminathan, "Toward an Implied Cost of Capital," *Journal of Accounting Research* (June 2001):135–176; Sanjeev Bhojraj and Charles M.C. Lee, "Who Is My Peer? A Valuation-Based Approach to the Selection of Comparable Firms," *Journal of Accounting Research* (May 2002):407–439.

to better investment management performance. For example, in Frankel and Lee (1998), we used analyst earnings forecasts to compute a *V* estimate based on the residual income model and examined the usefulness of the resulting value-to-price (V/P) ratio in predicting future returns.

Table 1 is taken from that study. Our sample included all companies with analyst coverage between 1977 and 1991 (we stopped in 1991 to allow for three years of subsequent returns). To construct this table, we grouped companies into 25 portfolios as of 30 June of each year based on their V/P and book-to-market (B/M) ratios. The lowest-B/M companies are in Quintile 1 (Q1) and the highest-B/M companies are in Q5. Companies are also independently sorted based on V/P, with the low-V/P companies in Q1 and high-V/P companies in Q5. Table values represent the average buy-and-hold return for the companies in each portfolio over the next 36 months. The numbers in parentheses indicate the total number of observations (company years) in each cell.

In the far-right column and along the bottom row of Table 1 are the buy-and-hold returns for the three-year period following the formation of the portfolios. The bottom line of Table 1 reports the difference in return for extreme quintiles—that is, the return differential between the high-B/M (Q5) and low-B/M (Q1) portfolios, controlling for V/P. The far-right column in Table 1 shows the difference in return for the high-V/P (Q5) and low-V/P (Q1) portfolios, controlling for B/M.

For the B/M portfolios, the difference between Q5 and Q1 is minimal, meaning that B/M has little predictive ability for future returns over the following three years once we control for V/P. When B/M is controlled for, however, the V/P portfolios still have significant predictive ability for returns. In fact, the right-most column shows that the difference in return between high-V/P and low-V/P portfolios is between 15 and 47 percent for the following three years. This outcome indicates that a better valuation model can yield higher returns over the next three years. This is the good news.

The bad news is that, in the same study, we show that the price convergence to fundamental value is a long-term phenomenon. **Figure 1**, also based on the Frankel and Lee study, illustrates the cumulative monthly buy-and-hold return over 36 months for a long-minus-short B/M strategy and a long-minus-short V/P strategy. In other words, this graph plots the cumulative return for the Q5–Q1 strategy in the 36 months after portfolio formation.

Notice that in the first 12 months, both strategies return about 5 percent. After 24 months, the B/M strategy has earned a cumulative return of approximately 5 percent while the V/P strategy has earned a cumulative return of 17 percent. At the end of 36 months, the divergence in the return of the two strategies is quite striking. The V/P strategy has a cumulative return of about 35 percent, compared with a return of roughly 15 percent for the B/M strategy.

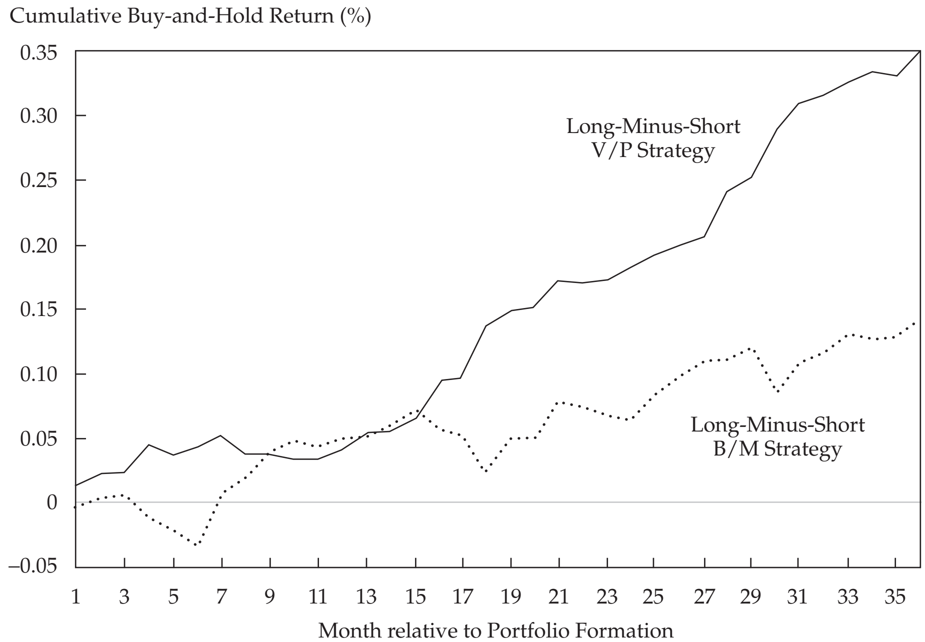
Table 1. Average 36-Month Buy-and-Hold Returns for B/M and V/P Portfolios, 1977–1991

	V/P						
B/M	Q1 (low V/P)	Q2	Q3	Q4	Q5 (high V/P)	All Companies	Q5–Q1 Difference
Q1	0.316	0.468	0.342	0.457	0.634	0.407	
	(998)	(592)	(296)	(264)	(269)	(2,419)	0.318**
Q2	0.366	0.461	0.489	0.415	0.516	0.450	
	(495)	(694)	(573)	(333)	(344)	(2,439)	0.150**
Q3	0.396	0.440	0.530	0.576	0.566	0.513	
	(295)	(515)	(660)	(565)	(453)	(2,488)	0.170*
Q4	0.350	0.422	0.484	0.589	0.630	0.535	
	(210)	(341)	(533)	(866)	(600)	(2,550)	0.280**
Q5	0.263	0.442	0.544	0.588	0.732	0.558	
	(386)	(328)	(433)	(510)	(824)	(2,481)	0.469**
All companies	0.331	0.450	0.491	0.549	0.637	0.493	
	(2,384)	(2,470)	(2,495)	(2,538)	(2,490)	(12,377)	—
Q5–Q1 difference	–0.053	0.026	0.202**	0.131	0.098	—	—

* Significant at 1 percent level.
** Significant at 10 percent level.

Source: Based on data from Richard Frankel and Charles M.C. Lee, "Accounting Valuation, Market Expectation, and Cross-Sectional Stock Returns," *Journal of Accounting and Economics* (June 1998):283–320.

Figure 1. Cumulative Monthly Buy-and-Hold Return for a Long-Minus-Short B/M Strategy and a Long-Minus-Short V/P Strategy



Note that the improvement in the valuation model yields higher returns only in the long run; after one year, the models produce approximately the same return. Clearly, the long-term nature of value convergence requires patience for an investor using a value-type strategy.

Another consideration regarding value plays is that they can be quite risky. Piotroski (2000) examined the returns of the top quintile of B/M companies—that is, the 20 percent of companies with the highest-B/M values, or value stocks.[6] **Table 2** presents the results of his study, which is based on data from 1976 to 1996. The market-adjusted mean return for this collection of high-B/M companies is 5.95 percent over a one-year period. Thus, value stocks as a group outperformed the market by about almost 6 percent a year.

But notice that the median of the return distribution is negative. In other words, the typical value company in this population underperformed the market by 6 percent. The reason value companies, as a group, outperformed the market is that the top 10 percent of companies have an average market-adjusted return of 71 percent. In fact, only about 44 percent of the value stocks actually outperformed the market (i.e., had positive market-adjusted returns in the one- or two-year period after portfolio formation).

Limitations of Value Investing. In short, value investing has its risks. It requires patience; abnormal returns are typically realized only over a two- to four-year investment horizon. Value plays can be

[6] Joseph D. Piotroski, "Value Investing: The Use of Historical Financial Statement Information to Separate Winners from Losers," *Journal of Accounting Research* (Supplement) (2000):1–41.

Table 2. Buy-and-Hold Returns for a High-B/M Strategy, 1976–1996

Return	Mean	10th Percentile	25th Percentile	Median	75th Percentile	90th Percentile	Percent Positive
One-year return							
Raw	0.2394	–0.3913	–0.1500	0.1053	0.4381	0.9017	0.6100
Market adjusted	0.0595	–0.5597	–0.3170	–0.0605	0.2550	0.7082	0.4369
Two-year return							
Raw	0.4788	–0.5172	–0.1786	0.2307	0.7500	1.5793	0.6457
Market adjusted	0.1271	–0.8715	–0.5174	–0.1112	0.3943	1.2054	0.4322

risky because the median value stock is no bargain; it underperforms. And buying value stocks typically means buying negative momentum because value-based signals and momentum-based signals are negatively correlated. Thus, picking value stocks usually entails running against a headwind, at least over the first 3–12 months, because value stocks tend to trend down over the short run. As a forecasting tool, value-based signals are more successful over longer holding periods.

Another limitation of value investing is that often an improvement in the valuation model contributes only marginally to return prediction. If a stock is extremely overvalued, it is overvalued based on practically every criterion—price to sales, price to book, price to earnings, and so on—and the same is true for an extremely undervalued stock. If the stock, however, is only marginally over- or undervalued, it will not revert back to fundamental value quickly.

What exactly is the problem with value investing? Fischer Black, in his 1986 presidential address to the American Finance Association, provided a key insight into this puzzle.[7] In this address, he discussed the role of noise in financial markets. In particular, he made the following observation:

> All estimates of value are noisy, so we can never know how far away price is from value. However, we might define an efficient market as one in which price is within a factor of 2 of value, i.e., the price is more than half of value and less than twice value. . . . By this definition, I think almost all markets are efficient almost all the time. "Almost all" means at least 90 percent.

In other words, Black claimed that we can consider the equity market to be efficient if price is within a factor of 2 of the PV of estimated future dividends. When I first read this statement, I thought Black must be exaggerating. Surely pricing errors could not be that big! But Black's contention is important because our priors regarding the size of pricing error and how quickly it will correct will determine the weight we choose to place on the value-based measures in our investment strategies.

Closed-End Fund Research. Research on closed-end funds (some of which I participated in) changed my mind about Black's assertion.[8] A closed-end fund is a publicly traded stock whose only asset consists of a portfolio composed of other publicly traded securities. Each Friday afternoon at the close of the market in the United States, every security in the closed-end fund is marked to market. Each Monday morning, the net asset value (NAV) of a share in the closed-end fund (calculated by dividing the total asset value of the fund's portfolio by the number of shares outstanding) is reported in the *Wall Street Journal*. The stock price of a closed-end fund is rarely equal to its NAV. This problem is known as the closed-end fund puzzle.

I think of closed-end funds as the one-cell amoebas of accounting. Scientists study the single-cell amoeba because it is a simple creature. Its transparent structure allows them to see everything that is happening in the organism. Similarly, the closed-end fund facilitates market research because it is not complicated by extraneous factors, such as deferred taxes and historical cost accounting. The closed-end fund is an extreme case of mark-to-market accounting, in which all assets are reported at their fair value on a weekly basis.

Closed-end fund stocks typically trade at a discount to their NAV [Discount = (Stock price – NAV)/NAV × 100]. Occasionally, however, they also trade at a premium. For U.S. funds, the discount routinely fluctuates between an upper bound of 5 to 10 percent and a lower bound of –30 to –40 percent. This condition gives rise to two questions: What accounts for the upper and lower bounds for the discount? And if arbitrage bounds can be this wide when valuation is transparent, how wide would they be for other stocks?

The answer to the first question is related to the availability of substitutes. The lower bound is explained by the fact that it is difficult to make money on a discounted fund unless the discount is quite wide. Because it is difficult to "open-end" these funds and the discounts themselves only mean-revert slowly over time, the typical retail investor can only expect a decent return when discounts reach 20 or 30 percent. The upper bound is more constrained than the lower bound because a new fund can be economically introduced to compete with an existing fund when the existing fund's premium reaches 8–10 percent (because total underwriting costs to start a new fund are roughly 8–10 percent of total asset value).

An examination of the second question—how wide arbitrage bounds are for nontransparent stocks—illuminates the point that Fischer Black made in 1986. Gemmill and Thomas (2002) examined U.K. data for closed-end funds and found that the level of the discount is a function of arbitrage costs.[9] In other words, on average, funds that are more

[7] Fischer Black, "Noise," *Journal of Finance* (July 1986):529–543.

[8] Charles M.C. Lee, Andrei Shleifer, and Richard Thaler, "Investor Sentiment and the Closed-End Fund Puzzle," *Journal of Finance* (March 1991):75–109. (*Editor's note*: For a review of the extant literature on the closed-end fund discount, see Elroy Dimson and Carolina Minio-Paluello, *The Closed-End Fund Discount* [Charlottesville, VA: Research Foundation of AIMR, 2002]; this monograph is available online at www.aimrpubs.org/rf/issues/v2003n2/toc.html.)

difficult to arbitrage tend to have higher discounts. Gemmill and Thomas also found that changes (weekly fluctuations) in the discount are a function of noise-trader sentiment, as proxied by retail-investor inflows to open-end funds in the same sector. When net flows are positive (negative), discounts narrow (widen) for funds in the same sector. The two results in this paper are important because they help us understand the interplay between value and momentum. Because prices generally vary within a fairly wide arbitrage band, value-based signals are not useful for predicting short-horizon valuations—except when the signals indicate extreme valuations. Effectively, prices are being set in the dynamic interplay between noise traders and rational arbitrageurs, or fundamental value players.

Measuring Investor Sentiment

Investor sentiment causes price to move away from fundamental value:

$$P_t = \sum_{k=0}^{\infty} \frac{E_t(D_{t+k}) + \phi E_t(Y_{t+k})}{(1+\rho+\phi)^{k+1}},$$

where Y_{t+k} is investor sentiment. Investor sentiment is systematic and thus has to be correlated among noise traders. As a result, investor sentiment more closely resembles mass psychology than individual animal spirits. In other words, if I get an irresistible impulse to buy IBM and you get an irresistible impulse to sell IBM, our actions will have no effect on the price of IBM; our animal spirits do not constitute an impetus that moves multiple investors in the same direction, and thus our actions do not create the mass psychology that is investor sentiment.

Sentiment Signals. What gives rise to a common sentiment? One possibility is pseudo signals, signals that contain no real information but are persuasive in their own right. Another possibility is a suboptimal use of actual signals, an underreaction to such value-relevant information as earnings surprises and quality-of-earnings indicators.

- *Pseudo signals*. Krispy Kreme Donuts (KKD), a U.S. donut maker, provides a good example of these types of signals. Through Internet chat room postings about the company, happy customers send pseudo signals to investors. For example, a visitor to a chat room remarked, "I can't understand how ANYTHING can taste that good. If this isn't the stuff classic American brand names are made of, nothing is. These things are addictive and they bring pleasure to the senses." People like these donuts, and they like the company because they like the donuts.

- *Underreaction to actual signals*. KKD also serves as a good example for the suboptimal use of actual signals. As of 30 June 2001, KKD had strong positive momentum. Price was 12 times book and 6.5 times sales. Shorts in the stock were 41 percent of the total float, and the short ratio took four days of trading to cover. Particularly disturbing was that many insiders were selling and, over the 12-month period prior to the date of this analysis, the chairman of the board, Scott A. Livengood, had sold 95,000 shares that generated proceeds of $6,434,513—a bit more than it would have cost to send his kid to college! A DCF analysis, including residual income calculations, indicates KKD stock should be valued at $14 a share. If the market is assumed to be noisy, adding a fudge factor of 2 (in accordance with Black's premise) raises the price to $21 a share, still a long way below the 1 July 2001 price of more than $40 a share.

- *Analysts' recommendations*. Another potential source of investor sentiment is the stock recommendations of sell-side analysts. I participated in a study titled "Analyzing the Analysts: When Do Stock Recommendations Add Value?," which compared the stock recommendations of analysts with the attributes that academics hold to be consistent with outperformance.[10] We found that analysts generally exhibit a strong bias in favor of growth stocks or glamour stocks with growth characteristics. Analysts get momentum right but everything else wrong. The stocks that receive the highest, most favorable analysts' recommendations tend to be the higher-P/E and higher-P/B stocks and tend to have higher trading volumes. They also tend to be stocks with higher income-inflating accruals, a characteristic that is negatively correlated with future returns.

If analysts are trying to predict positive returns, they should recommend positive momentum stocks. In fact, that is what they do; they give more favorable recommendations to positive momentum stocks. But the good news ends there. Turnover (total trading volume divided by shares outstanding) is negatively correlated with future return, so companies with higher turnover tend to underperform. Nevertheless, analysts more strongly recommend stocks with higher turnover, not lower turnover. Analysts should recommend higher-E/P stocks, but they more strongly recommend lower-E/P stocks. They should recommend higher-B/M stocks, but they more strongly

[9]Gordon Gemmill and Dylan C. Thomas, "Noise Trading, Costly Arbitrage, and Asset Prices: Evidence from Closed-End Funds," *Journal of Finance* (December 2002):2571–94.

[10]Narasimhan Jegadeesh, Joonghyuk Kim, Susan D. Krische, and Charles M.C. Lee, "Analyzing the Analysts: When Do Recommendations Add Value?" *Journal of Finance* (forthcoming 2003).

recommend lower-B/M stocks. They should recommend companies with lower long-term growth, but they recommend companies with higher long-term growth. Analysts should recommend companies with income-deflating accruals (i.e., companies with better quality of earnings); in fact, they recommend companies with income-inflating accruals.

We do not know why analysts' recommendations exhibit these biases. Perhaps, analysts are not really focusing on these variables. Perhaps, they are focusing instead on the incentives in their economic structure. Investment bankers like companies that exhibit high growth because they are the ones most likely to need their services, the ones most likely to need to come to the market for new cash. And the sales people and traders like companies with high volume and the greatest liquidity. Regardless of the incentives behind the recommendations, if the recommendations are taken at face value by investors, they will contribute to noise trading. Undoubtedly, analysts' recommendations contribute to prevailing investor sentiment.

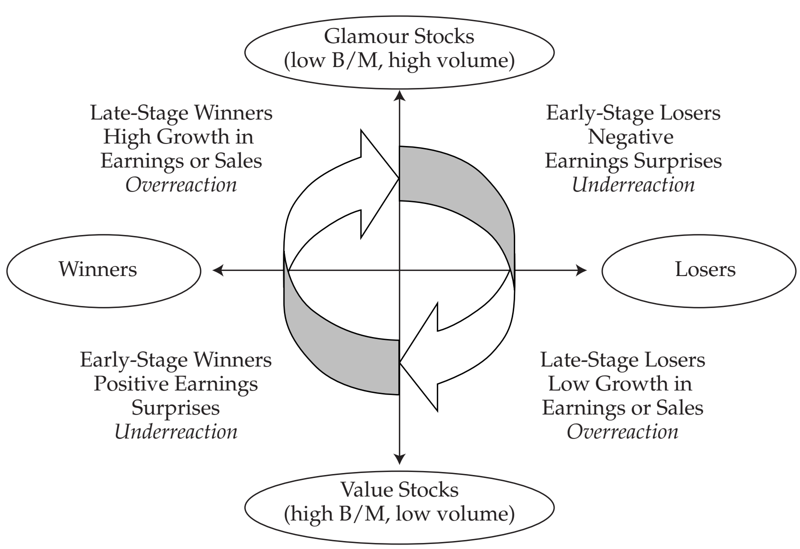
Price Momentum and Trading Volume. Price momentum and trading volume are two variables that also help predict investor sentiment over short horizons. Swaminathan and I (2000) found that recent trading volume (shares traded scaled by shares outstanding) is a good indicator of investor sentiment about a stock .[11] High (low) volume stocks exhibit glamour (value) characteristics and earn lower (higher) subsequent returns. Integrating volume into the forecasting analysis greatly enhances the predictive power of the overall model.

The momentum life cycle hypothesis, illustrated in **Figure 2**, summarizes our findings about the impact of price momentum and trading volume on investor sentiment. We can think of companies as moving into and out of the glamour spotlight. There are times when they are out of favor with the market and times when they are in favor. The momentum literature calls the companies on the right of Figure 2 "losers" and the ones on the left "winners." Valuation provides a sense of whether a winner or loser is in the early stage or late stage of its momentum cycle. The typical momentum strategy supports buying all the winners and shorting all the losers.

Many market participants find momentum trading to be counterintuitive, or even anti-intellectual. A typical momentum investor buys the stocks that other investors bought over the past six months, and the higher the price moves, the more he or she likes the stock. Such an investment strategy does not seem to make sense. It is like a Ponzi scheme that is bound to collapse over time. Even though momentum strategies might seem profitable in backtests, investors shy away from them primarily because it is difficult to know when to exit such a strategy.

[11] Charles M.C. Lee and Bhaskaran Swaminathan, "Price Momentum and Trading Volume," *Journal of Finance* (October 2000):2017–70.

Figure 2. The Momentum Life Cycle Hypothesis



According to the momentum life cycle hypothesis, the game is to buy early-stage winners and sell early-stage losers. Notice that the strategy is asymmetric in terms of volume. The early-stage momentum strategy buys winners on low volume and shorts losers on high volume. The late-stage momentum strategy (which is far less profitable) buys high-volume winners and shorts low-volume losers.

The returns for the early- and late-stage price momentum strategies are quite different over a five-year horizon. **Table 3** (which is based on data spanning from 1965 to 1995) reports the raw returns for three price momentum strategies. The simple strategy is a Jegadeesh–Titman (1993) strategy in which the top decile of winners (R10) over the previous six months are bought and the bottom decile of losers (R1) over the previous six months are shorted.[12] This strategy produces an abnormal return of 12.49 percent in Year 1. But thereafter, in each year over the five-year horizon, the returns for the strategy dissipate.

The result for the late-stage strategy shows that reversing the direction of the trading volume when designing a momentum strategy can be costly. The return in Year 1 for the late-stage strategy—buying high-volume winners (R10V3) and shorting low-volume losers (R1V1)—is 6.8 percent, but nearly all of that return is lost in Year 2, followed by losses in Years 3, 4, and 5.

Conversely, an early-stage strategy—buying high-volume winners (R10V1) and shorting low-volume losers (R1V3)—generates a much more persistent return. The return to this strategy in Year 1 is 16.7 percent, followed by returns of 6.19 percent and 5.85 percent in Years 2 and 3. Remember that all three of these strategies involve buying winners and shorting losers. In this sense, they are all momentum strategies. But when the momentum strategy is conditioned on valuation and/or trading volume, the expected return can be quite different.

Figure 3 shows the Table 3 buy-and-hold returns adjusted for size. The difference in returns for each of the strategies is even stronger when the returns are industry adjusted. The "simple" line is the cumulative return for the simple long winner/short loser strategy. The "late" line is the cumulative return for the late-stage momentum strategy, and the "early" line is the cumulative return for the early-stage momentum strategy.

Panel A of **Figure 4** shows the returns for the winners (divided into two groups—high-volume winners and low-volume winners) for the sort year (Year 0), the four years prior to the sort year, and the five years following the sort year. Both high-volume

Figure 3. Size-Adjusted Buy-and-Hold Returns for Early- and Late-Stage Momentum Strategies, 1965–1995

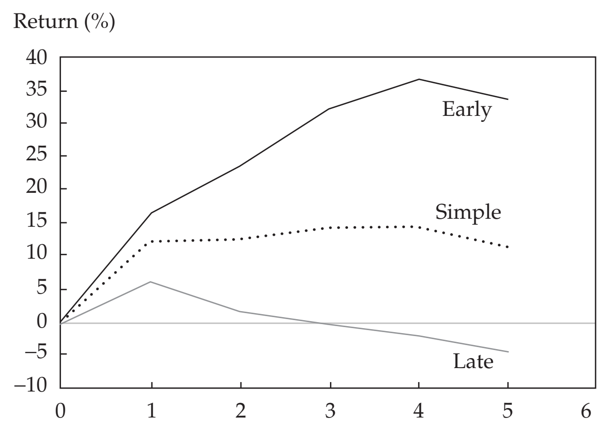
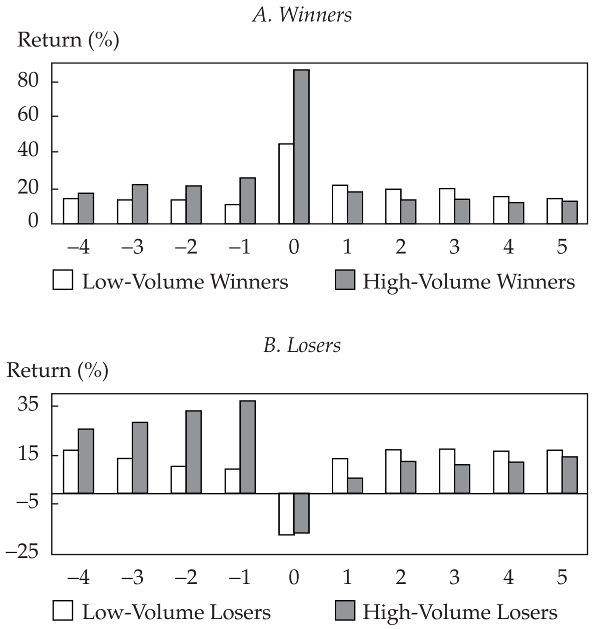


Table 3. Returns to Early- and Late-Stage Price Momentum Strategies, 1965–1995
(*t*-statistics in parentheses)

Strategy	Year 1	Year 2	Year 3	Year 4	Year 5
R10–R1 (simple)	12.49	–1.10	–0.32	–2.77	–2.96
	(5.04)	(–0.66)	(–0.15)	(–1.68)	(–2.46)
R10V3–R1V1 (late)	6.84	–5.35	–3.91	–6.33	–4.78
	(2.53)	(–2.17)	(–1.53)	(–3.54)	(–2.64)
R10V1–R1V3 (early)	16.70	6.19	5.85	1.53	–0.11
	(5.85)	(3.16)	(2.56)	(0.64)	(–0.06)
(R10V3–R1V1)–(R10–R1)	–5.65	–4.25	–3.59	–3.56	–1.81
	(–5.21)	(–3.00)	(–2.93)	(–3.14)	(–1.37)
(R10V1–R1V3)–(R10–R1)	4.21	7.29	6.17	4.29	2.85

[12]Narasimhan Jegadeesh and Sheridan Titman, "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency," *Journal of Finance* (March 1993):65–91.

Figure 4. Annual Return for Low- and High-Volume Winners and Losers, 1965–1995



and low-volume winners have positive returns in Year 0. High-volume winners outperformed low-volume winners. The returns for high-volume winners were higher in the years before the sort year and lower in the years after the sort year. In other words, the high-volume winners can be thought of as late-stage winners that will not do as well in the future as they have in the past, and low-volume winners are essentially early-stage winners. Panel B of Figure 4 shows the same analysis for losers. Again, volume plays a role in the return prospects of the loser stocks. High-volume losers are early-stage momentum plays.

Referring back to Figure 2, the stocks in the top two quadrants (late-stage winners and early-stage losers) are glamour stocks and tend to attract the greatest number of analysts. The average number of analysts following the high-volume stocks is about 9. The average number of analysts following the low-volume stocks is about 3. Recall these numbers are conditioned on the fact that a stock is covered by at least one analyst. Otherwise, the stock would not be in this sample. As a company moves through its cycle, it loses analysts on the way down (as earnings and volume fall) and gains analysts on the way up (as earnings and volume rise). In short, analysts like momentum, or trend chasing.

■ *Momentum, volume, and valuation implications*. In summary, fusion investing takes the view that both mid-horizon-momentum and long-horizon-value effects are elements of a single process by which information is incorporated in price. Sentiment indicators, such as trading volume, help us to understand the transitional dynamics between long-term reversal and short-term momentum. In other words, sentiment indicators help us understand how a glamour stock essentially becomes a neglected stock.

When selecting stocks, it is necessary to think in terms of both value and momentum. For example, KKD has extremely positive momentum, extremely high volume, and extremely high valuation; it looks very expensive. In the fusion-investing framework, KKD is a late-stage winner. But how long can it remain a winner? No one knows. It depends on how the time-series behavior of noise-trader demand changes over time. Unless we can predict with some confidence when that positive momentum will turn, it is better to leave this stock alone, despite its lofty valuation multiples.

Summary

I have tried to argue that both value and momentum indicators are variables that can be used to measure investor sentiment. Momentum investors should pay attention to value because it can indicate when to sell, and an exit strategy is essential for momentum investors. Value investors should pay attention to momentum because it can indicate when to buy, and a crucial factor for value investors is knowing when to get into the market.

These are exciting times. A lot of the traditional paradigms, particularly the capital asset pricing model and the efficient market hypothesis, are being modified by behavioral theory. We are not discarding traditional models but working to create more robust models. A new brand of fusion research is emerging that integrates accounting and finance, fundamental and behavioral indicators, and noise traders and rational arbitrageurs.