Do Mutual Fund Managers Trade on Stock Intrinsic Values?

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Abstract

This paper establishes a strong link between active mutual funds' trading behavior and stock price divergence from intrinsic value. During 1981-2008, mutual funds tend to buy (sell) underpriced (overpriced) stocks as measured by a V/P ratio, where V denotes the intrinsic value estimated by a residual income valuation model. Mutual funds that significantly tilt their portfolios toward underpriced stocks can generate superior performance, outperforming the funds with the highest portfolio weights in overpriced stocks by 0.55% per month over a six-month horizon. Finally, we show that the V/P effect is more pronounced among stocks that have not been exploited heavily by mutual funds. Our evidence supports the view that the tendency of mutual funds to trade in the direction of V/P mitigates mispricing and facilitates impounding fundamental information into stock prices.

JEL classification: G10; G11; G14; G23; M41

Keywords: V/P; intrinsic value; fund performance; fundamental analysis

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1 Introduction

When information and trading costs are not trivial in reality, stock prices may diverge from their intrinsic values.[1] Mutual funds, being good candidates for informed investors given their expertise in fundamental analysis, are supposed to make advantageous valuation-based portfolio bets and thus facilitate the convergence of price to value.[2] However, their informational role in determining stock prices remains inadequately addressed in the extant literature. Shleifer and Vishny (1997) suggest that delegated portfolio managers can become most constrained when they bet against the most mispriced securities. According to their performance-based arbitrage model, fund managers' fear of temporary money outflows may significantly limit their trading effectiveness in achieving price efficiency. This study attempts to shed light on the informational advantages of actively managed mutual funds in discovering mispricing and their role in bringing prices to fundamental values.

We use a residual income model operationalized by Frankel and Lee (1998) and Lee, Myers, and Swaminathan (1999) to obtain an empirical estimate of a stock's intrinsic value (V). We empirically examine whether active fund managers trade on the mispricing indicated by a value-to-price ratio (V/P).[3] By examining the quarterly holdings of 2,537 distinct U.S. active mutual funds over the 1981 to 2008 period, we find that mutual

[1] See Shiller (1984), Summers (1986), DeBondt and Thayler (1987), Lakonishok, Shleifer, and Vishny (1994), and Shleifer and Vishny (1997) for detailed discussion of inequality of price and value. Closed-end fund literature provides more direct evidence of price-value divergence (e.g. Lee, Shleifer, and Thaler (1991) and Swaminathan (1996)).

[2] Kosowski, Timmermann, Wermers, White (2006) and Fama and French (2010) use bootstrap tests for fund performance persistence and find supporting evidence of the presence of subgroups of skilled fund managers. For other recent supportive evidence of fund skills based on fund holdings data, see Avramov and Wermers (2006) and Wermers, Yao, and Zhao (2007).

[3] Frankel and Lee (1998) and Lee, Myers, and Swaminathan (1999) find that V/P ratio has reliable cross-sectional and time-series predictive power for U.S. stock returns. They also find that residual income model is a more robust and richer valuation model than simple heuristics such as B/P and D/P that have been examined extensively in the prior finance literatures. Ali, Hwang and Trombley (2003) further show that the V/P effect is mainly concentrated around earnings announcement, consistent with the mispricing explanation for its return predictive power. Jiang and Lee (2005) find that book values and earnings in the residual income model contain more useful information than the traditional dividend discount model (DDM) for stock valuation.

funds in aggregate tend to trade in the direction of V/P, and more intensively from six months before all necessary financial information for estimating the intrinsic value is publicly released. We attribute the mutual funds' exploitation of a stock's intrinsic value to their superior expertise in forecasting and processing fundamental information (Cheng, Liu and Qian, 2006). Our findings are not subsumed by controlling for various common stock return predictors in Fama-Macbeth regressions.

To characterize the portfolio choices of mutual funds based on V/P and assess how successfully they exploit such information, we construct a fund-level V/P-timing measure, VPT, in the spirit of Grinblatt, Titman, and Wermers (1995) and similar to the accruals investing measure created by Ali, Chen, Yao, and Yu (2008). VPT is the value-weighted average V/P decile rank of all stocks held by a mutual fund. A high value of VPT indicates that the fund manager actively trades on fundamentals and tilts her portfolio toward underpriced stocks (with high V/P). We sort all active mutual funds into ten decile portfolios in ascending order (1-10) on the basis of VPT. Examining the fund characteristics across the VPT deciles, we find that small and high-turnover funds tend to trade more on V/P mispricing. Further, we show that funds with high past one year performance and low return gap (the difference between the reported fund return and the return on a portfolio that invests in the previously disclosed fund holdings) tend to significantly exploit the V/P effect.

We use fund returns before fees, net of the realized transactions costs, to evaluate the actual profitability of trading on stocks' intrinsic values. In univariate portfolio sorts, D10 funds with the highest VPT have an average return of 1.19% per month over a six-month horizon starting from portfolio formation and significantly outperform the lowest-VPT funds in D1 by 0.55% per month. We also examine how well D10 funds perform relative to D5 funds that are neutral to the V/P effect with a VPT of 5.5. The return spread of 0.26% per month between D10 and D5 is statistically significant.

Both return spreads are robust to different factor risk adjustments. More interestingly, the superior performance of D10 funds does not simply reflect that these funds take on high risks. The risk-adjusted returns on the D10 funds are 0.35%, 0.36%, and 0.27% per month based on the Capital Asset Pricing Model (CAPM), the Fama and French 3-factor model, and a 4-factor model including momentum, respectively. Hence, mutual funds that actively exploit the fundamental mispricing are able to benefit from such information and generate both statistically and economically significant profits.

Finally, we examine the impact of fund trading on V/P effect and find more pronounced effect among stocks with less intense past mutual funds' exploitation. Mutual funds with superior private information about stock values mitigate the mispricing by trading in the direction of V/P. We find that high-V/P stocks with the lowest mutual funds' ownership in each June (the time of information release) continue to generate a significant 4-factor alpha of 0.42% per month in the subsequent one year. Furthermore, we also show that high-V/P stocks that have been heavily sold by mutual funds in the recent past can generate even higher future performance. This evidence is consistent with our expectation that the tendency of mutual funds to trade in the direction of V/P facilitates impounding fundamental information into the current stock prices and thus pushes prices back toward their intrinsic values.

Our paper joins a small but growing literature that connects mutual fund investing to asset prices. Coval and Moskowitz (2001) find that fund managers have better access to local information and that their investments facilitate the transfer of information into the prices of local stocks. Cohen, Frazzini, and Malloy (2008) provide empirical evidence that information transfers through the social networks between corporate managers and fund managers into stock prices. Unlike these two studies that assume a priori links between firms and funds, we examine how actively managed mutual funds react upon the mispricing revealed by their fundamental analyses. Boehmer and Kelly (2009) show that institutional trading improves the short-horizon informational efficiency of prices, measured as deviations from a random walk. Distinct from their study, this paper is interested in the role of active mutual funds as informed traders in pushing stock prices toward their intrinsic values over a relatively longer horizon.

To the best of our knowledge, this study is among the first to empirically test the trading behavior of delegated informed traders using a stock mispricing measure based on a comprehensive valuation model.[4] Our findings that mutual funds tend to exploit mispricing opportunities are consistent with the theoretical prediction of Grossman and Miller (1988), De Long, Shleifer, Summers, Waldman (1990) and Campbell and Kyle (1993). We show that mutual funds that tilt their portfolios most aggressively toward underpriced stocks can profit from fundamental analysis, which confirms the findings of mutual funds benefiting from fundamental-relevant information in Campbell, Ramadorai, and Schwartz (2009), Baker, Litov, Wachter, and Wurgler (2010) and Jiang, Verbeek, and Wang (2010). In spite of this, our findings do not exclude the possible existence of limits of arbitrage (Shleifer and Vishny, 1997).

Our study is also related to a recent line of research in the accounting literature that attempts to address the issue of implementing the residual income model to measure intrinsic values. The valuation equation we use in this paper follows Frankel and Lee (1997, 1998), Penman and Sougiannis (1998), Dechow, Hutton, and Sloan (1999), Abarbanell and Bernard (2000), Gode and Mohanram (2003), Ali, Hwang, and Trombley (2003), Baginski and Wahlen (2003) and Jiang and Lee (2005). While these accounting studies examine the model prediction of both time-series and cross-section of stock returns, our investigation focuses on whether active fund managers exploit the fundamental information revealed by such a model. Closely related to ours is Ali, Chen, Yao, and Yu (2008), who document that on average mutual funds do not trade on the accruals anomaly.

[4] Dechow, Hutton, Meulbroek, and Sloan (2001) see short-sellers as informed investors and find that short-sellers use information in the fundamentals to market values ratios to take positions in stocks with lower expected future returns.

Compared with their study, our primary interest in this paper is in whether active funds benefit from more complete and comprehensive fundamental analyses and their role in impounding such fundamental information into stock prices. Moreover, we do find that mutual funds in aggregate trade on mispricing as indicated by the V/P ratio.

The remainder of the paper proceeds as follows. Section 2 introduces the residual income model. Section 3 describes data, sample selection and summary statistics. Section 4 and 5 explore whether mutual funds trade on and profit from V/P effect and the relation between mutual fund trading and V/P effect. Section 6 concludes our paper.

2 The Residual Income Valuation Model

To determine the extent of mispricing, it is paramount to measure the stock intrinsic value (V) with a comprehensive valuation model.[5] In this study we use a discounted residual income approach.[6] This section presents the basic residual income equation and discuss the specifics of the model implementation procedure. A stock's fundamental value is generally defined as the present value of its expected future dividends conditional on all currently available information. Specifically,

$$V_t^* = \sum_{i=1}^{\infty} \frac{E_t[D_{t+i}]}{(1+r_e)^i}, \tag{1}$$

where V_t^* is the stock's fundamental value at time t, $E_t[D_{t+i}]$ is the expected future dividends for period $t+i$ based on information available at time t, and r_e is the cost of

[5] Despite of the consensus that a stock's intrinsic value is the present value of the expected future cash flows, few academic studies have sufficiently addressed the problem of measuring it. Exceptions include a stream of studies in the accounting literature (e.g. Frankel and Lee (1997, 1998), Penman and Sougiannis (1998), Dechow, Hutton, and Sloan (1999), Abarbanell and Bernard (2000), Gode and Mohanram (2003), Ali, Hwang, and Trombley (2003), Baginski and Wahlen (2003), and Jiang and Lee (2005)).

[6] The residual income model is also referred to as the Edwards-Bell-Ohlson (EBO) valuation technique. Theoretical development of the model can be found in Ohlson (1990, 1995) and Feltham and Ohlson (1995).

equity.

Under the clean surplus accounting assumption, the change in a firm's book value is equal to earnings minus net dividends. Following Frankel and Lee (1998), (1) can be rewritten as the reported book value, plus the sum of an infinite series of discounted residual income:

$$V_t^* = B_t + \sum_{i=1}^{\infty} \frac{E_t[NI_{t+i} - (r_e B_{t+i-1})]}{(1+r_e)^i} = B_t + \sum_{i=1}^{\infty} \frac{E_t[(ROE_{t+i} - r_e)B_{t+i-1}]}{(1+r_e)^i}, \qquad (2)$$

where B_t is the book value at time t, NI_{t+i} is the net income for period $t+i$, and ROE_{t+i} is the after tax return on book equity for period $t+i$. Equation (2) shows that the intrinsic value of a firm can be decomposed into an accounting measure of capital invested (B_t), and a measure of the present value of future cash flows not captured in the current book value. Firms whose expected ROEs are higher (lower) than their cost of equity (r_e) will have intrinsic values greater (smaller) than their current book values.

In practice the implementation of the model requires forecasted ROEs ($FROE$s), dividend payout rates (k), current book value (B_t), cost of equity (r_e), and a terminal value, i.e. an estimate of the firm value based on the residual income earned after the explicit forecasting horizon. To calculate a stock's intrinsic value, we use a three-period expansion of the model which is the primary measure of firm value in Frankel and Lee (1998):

$$\widehat{V}_t^3 = B_t + \frac{(FROE_t - r_e)}{(1+r_e)} B_t + \frac{(FROE_{t+1} - r_e)}{(1+r_e)^2} B_{t+1} + \frac{(FROE_{t+2} - r_e)}{(1+r_e)^2 r_e} B_{t+2}, \qquad (3)$$

where

B_t: book value from the most recent financial statement.

B_{t+i}: forecasted book value for period $t+i$. $B_{t+i} = B_{t+i-1} + FY_{t+i} - FDIV_{t+i}$, where $FDIV_{t+i}$ is the forecasted dividends for year $t+i$, estimated using the dividend payout ratio k. Dividend payout ratio k is computed as the common stock dividends divided by net income before extraordinary items.[7] We assume that $FDIV_{t+i} = FY_{t+i} \times k$.

r_e: industry-specific cost of equity estimated from a three-factor risk model according to Fama and French (1997).[8]

$FROE_{t+i}$: forecasted ROE for period $t+i$. For the first two years, the variable is computed as $FY_{t+i}/[(B_{t+i-1} + B_{t+i-2})/2]$, where FY_{t+i} is the I/B/E/S consensus (mean) forecasted i-year-ahead earnings. For the third year, we use the five-year long term growth rate to compute a three-year-ahead earnings forecast: $FROE_{t+2} = FY_{t+2} * (1 + Ltg)$. When Ltg is missing in the I/B/E/S database, we use $FROE_{t+1}$ to proxy for $FROE_{t+2}$.

The model provides a framework for analyzing the relation between accounting numbers and firm value and features the importance of including forward-looking earnings information in the valuation. Frankel and Lee (1998) and Lee, Myers, and Swaminathan (1999) provide a detailed and comprehensive discussion of the insights of the model.

3 Sample Description and Summary Statistics

In this section, we describe our stock data set to analyze the V/P effect and the criteria of mutual fund sample selection, followed by the summary statistics for our sample.

3.1 *Stock Data*

The sample of stocks in this study includes all U.S. domestic non-financial companies traded on NYSE, AMEX, and NASDAQ in the Compustat/CRSP Merged database (hereafter, the CCM data) from 1981 to 2008. We require firms to have valid accounting data (for B_{t-1}, B_{t-2}, NI_{t-1}, and DIV_{t-1}) and CRSP stock prices and shares outstanding data for the fiscal-year-end $t-1$ and the end of June in year t. We also require firms to have one-year-ahead and two-year-ahead earnings forecasts from I/B/E/S. We use

[7] For firms with negative earnings, we divide dividends by 5% of total assets to derive an estimate of k. 5% is the average long run ROA in our sample period (see Table I).

[8] Frankel and Lee (1998) and Abarbanell and Bernard (2000) find that the choice of r_e has little effect on the cross-sectional analyses.

I/B/E/S forecasts announced in May and constrain our sample to firms with fiscal-year-ends between June and December, inclusively. This constraint makes sure that the forecasted earnings correspond to the correct fiscal-year-end.

To ensure that accounting variables are known to the public before portfolio formation, we form and rebalance our stock portfolios at the end of June in year t using the V/P ratios computed based on the intrinsic value estimates and market equity values at the fiscal-year-end of calendar year $t-1$. To be consistent with Fama and French (1992), we calculate the book-to-market ratio based on the book value of last fiscal-year-end and market equity in December of calendar year $t-1$. In estimating (3), we remove firms with negative book values and eliminate firms with absolute values of $FROE$s above 100% and with dividend payout ratios larger than 100%. To mitigate the concern that stock return tests might be influenced by return outliers, we eliminate stocks with prices below \$1.[9] Taken together, our filters eliminate 4,636 observations (approximately 9%), leaving a final sample of 50,246 firm-years.

3.2 *Mutual Fund Sample Selection*

We construct our mutual fund database by combining the Center for Research in Security Prices (CRSP) Survivor-Bias-Free US Mutual Fund Database (MFDB) and the CDA/Spectrum Mutual Fund Holdings Database from Thomson Financial.[10] As we wish to examine the informational advantages of mutual funds in stock markets, we only include, in our sample, active mutual funds that invest primarily in US common stocks. In particular, we eliminate balanced, bond, money market, international, index funds and sector funds, as well as funds not invested primarily in equity securities (see the Appendix for details on how we select active U.S. domestic equity funds). Our final sample covers

[9] These firms have typically unstable B/M and V/P ratios and poor market liquidity.

[10] Our merging procedure uses the MFLINKS data set maintained by Russ Wermers and the Wharton Research Data Services (WRDS).

2,537 distinct active equity funds over the period 1981 to 2008.

Data on monthly returns, prices, and market values of equity for common stocks traded on the NYSE, AMEX, and NASDAQ come from CRSP. Consistent with previous literature, we exclude closed-end funds, real estate investment trusts (REIT), American Depository Receipts (ADR), foreign companies, primes, and scores (we keep only shares with codes of 10 or 11).

3.3 *Summary Statistics*

Table I reports the summary statistics for our stock (Panel A) and mutual fund samples (Panel B). The average characteristics are calculated at the end of each June from 1981 to 2007. The average dividend payout ratio (k) for stocks in our stock sample decreases from 0.33 in 1981 to 0.11 in 2007. The average ROE and ROA also exhibit a decreasing pattern over time, though not strictly monotonically. The average ROE ranges from 0.04 to 0.16, while the average ROA stays between 0.01 and 0.07 over years. These results illustrate the stability of the key model inputs over time. Using the residual income model to estimate the intrinsic stock value, we observe that the average V/P ratio displays a general declining trend over our sample period, from 1.54 in 1981 to 0.65 in 2007. It appears that on average stocks have become more and more overvalued in recent years. Panel A of Table 1 also shows that in an average year mutual funds in aggregate hold 1,542 stocks out of 1,587 stocks that have valid data to compute V/P. Therefore, the mutual fund holdings data cover the majority of our stock sample. Furthermore, mutual funds increase their ownership in an average stock (defined as the fraction of the outstanding shares of a stock that is held by all mutual funds) almost monotonically from 2.77% in 1981 to 17.26% in 2007. The corresponding number of funds holding the stock also skyrockets from 8 to 70 over the sample period. These numbers illustrate that over the past decades mutual funds have become more important as shareholders of common equity.

Panel B of Table I presents the average mutual fund characteristics per year. We observe that the industry of active equity mutual funds has experienced a fast expansion: the number of actively managed equity funds in our sample increases from 179 in 1981 to 1,518 in 2007, with the average total assets under management growing from $million 195.51 to $million 1,743.51. On average, these funds invest 90% of their assets in common stocks, which suggests that our sample well represents the universe of U.S. active funds with an investment focus on domestic equity. Over our sample period, the expansion of mutual funds outpaced the growth of stock markets, which led them to become increasingly important shareholders of common equity. Finally, the 12b1 fees, expense ratio, and fund turnover ratio also display an increasing trend in general and a slight decrease after 2003.

4 Do Mutual Funds Trade on Intrinsic Value?

In this section, we explore whether intrinsic stock value reveal information concerning future stock returns over our sample period. More importantly, we investigate how mutual funds trade on the information content of the V/P effect and whether they can profit from discovering values.

4.1 *Confirming the* V/P *Effect*

Frankel and Lee (1998) examine an earlier stock sample from 1976 to 1993 and find that the V/P ratio is a good predictor for future cross-sectional stock returns. Specifically, they find a one-year return spread of 3.1% between the top and bottom V/P quintiles. The effect cannot be explained by a firm's market beta, size and book-to-market ratio.

To confirm the V/P effect for stocks in our CCM stock universe covering the period 1981 to 2008, we employ a univariate portfolio approach and more comprehensive risk adjustment procedures.

At the end of June in year t, we compute V/P ratios for our sample of stocks using public financial information. Then we sort stocks into 5 quintile portfolios in ascending order based on their V/P ratios for the fiscal year that ends in calendar year $t-1$. To minimize the impact of any possible analyst forecast errors on more opaque/small firms, we compute the value-weighted portfolio returns over the following 12 months from July of year t to June of year $t+1$.[11] We also consider value-weighting to be a more conservative approach to discover superior trading strategies.[12] To compute portfolio returns, we use monthly stock returns from CRSP. In case of stock delisting, we use CRSP delisting returns when they are not missing; otherwise, we follow Shumway (1997) to replace missing delisting returns with -30% if the delisting is performance related (CRSP delisting codes 500 and 520-584).

The results in Table II show that the V/P ratio strongly predicts future stock returns. A portfolio that buys stocks in Quintile 5 and sells stocks in Quintile 1 generates an average raw return of 0.72% per month on the value-weight basis. These excess returns are highly statistically significant, with a t-statistic of 3.29. To examine whether the high returns on heavily underpriced stocks (Q5) simply reflect the high systematic risks, we employ standard risk-adjustment models to examine the abnormal returns. The specific risk-adjustment models include the Capital Asset Pricing Model (CAPM), the Fama and French 3-factor model, a 4-factor model including momentum, and a 5-factor model further including the Pastor and Stambaugh (2003) liquidity factor.

[11] Gu and Wu (2003) show that analysts tend to issue more optimistic earnings forecasts for small firms.

[12] Fama and French (2008) point out that equal-weight portfolio return may be driven by tiny stocks that are numerous in number but small in economic significance. Furthermore, in a world with mispricing, value-weight approach tends to overweight overpriced stocks and underweight underpriced stocks. This makes profiting from mispricing more difficult.

Columns 2 to 5 of Table II show the results. The high returns on stocks heavily underpriced in excess of the returns on their overpriced counterparts remain large and statistically significant after the above-mentioned risk adjustments. For example, the spread portfolio that buys stocks in Quintile 5 and shorts stocks in Quintile 1 earns abnormal returns of 0.80%, 0.81%, 0.44%, and 0.41% per month on an value-weighted basis after adjustments according to the CAPM, three-factor model, four-factor model, and five-factor model, respectively. All four versions of alphas are highly statistically significant with t-statistics ranging between 2.2 and 4.3. We note that the return-predictive power of V/P is independent of the book-to-market effect that is widely documented and applied in the prior literature. After adding the momentum factor in our risk adjustment model, the overpriced stocks in Quintile 1 do not generate significant negative abnormal return while the underpriced stocks in Quintile 5 continue to have superior and statistically significant performance. The finding suggests that overpriced stocks tend to have poor past performance. In contrast, the past good return records for underpriced stocks cannot explain all of their superior performance in the future. This is important for our subsequent analysis on mutual fund trading because mutual funds' informational advantage should be the most conspicuous among their long positions due to short-sale constraints.

Next, we examine the characteristics of stocks with low and high intrinsic values. We present univariate results based on quintile portfolios in Table III. Specifically, using the same portfolio sorts we calculate the cross-sectional averages of stock characteristics, and then report their time-series means. The results show that the average V/P ratio increases from 0.40 in Quintile 1 to 1.77 in Quintile 5, whereas the corresponding B/M ratio displays much less dispersion across the V/P quintiles. Furthermore, we find that the most underpriced stocks in Quintile 5 tend to be small-caps with an average size quintile rank value of 2.17 based on NYSE market-cap breakpoints in ascending order; they also have a slight tendency to be growth stocks and winners in the past year. Stocks in the two extreme quintiles exhibit high return volatility and high turnover, especially for underpriced stocks with an average volatility of 13.80% per year and an annual turnover of 164.94%.

Due to the high volatility of both underpriced and overpriced stocks, their average mutual funds' ownership tends to be smaller than that of the rest of the stock universe. A typical stock in Quintile 5 with the highest V/P ratio has the average mutual funds' ownership of 8.60%, which is lower than the mutual funds' ownership of 9.22% for a typical stock in Quintile 3 with medium V/P ratio. The average number of mutual funds holding a stock shows a similar pattern. However, we observe an interesting pattern when looking at the change of mutual funds' ownership in a stock from June of year $t-1$ to June of year t. We observe that both the change in mutual funds' ownership and the change in number of funds holding a stock increase in V/P ratios. Mutual funds on average tend to buy (sell) underpriced (overpriced) stocks based on stock fundamental valuation and they start trading on such information during the one year prior to the release of public financial reports. The last two columns of Table III suggest that mutual funds continue to exploit stock intrinsic values after the financial information release at the end of each June. We will explore this issue in more detail in the next subsection.

4.2 *Mutual Funds Trade on the V/P Effect*

According to De Long, Shleifer, Summers, Waldman (1990) and Campbell and Kyle (1993), mutual funds can behave as informed traders, trading on the mispricing opportunities and bringing about market efficiency. However, Shleifer and Vishny (1997) argue that delegated portfolio managers may become capital constrained when they tilt their portfolios toward severely mispriced securities. Moreover, mispricing based on V/P is associated with high return volatility as shown Table III. Hence, fund managers might have weak incentives to exploit stock intrinsic values. In this subsection, we examine the trading behavior of mutual funds in response to the information content of the V/P ratio in more detail.

We first use an event study approach to illustrate how mutual funds trade on V/P information. At the end of each June between 1981 and 2006, we form 5 quintile portfolios of stocks based on their V/P ratios calculated using the value and price information at the fiscal-year-end of year $t-1$. Quintile 1 consists of the most overpriced stocks and vice versa. We then investigate the cumulative characteristic-adjusted portfolio performance of these portfolios during the one year prior to the portfolio formation and the subsequent two-year holding period (see Daniel, Grinblatt, Titman, Wermers, 1997; Cremers, Petajisto, Zitzewitz, 2008).[13] To further examine the trading activities of mutual funds, we calculate the time-series average mutual funds' ownership for the quintile portfolios over the same ranking and holding periods. To avoid the instability of aggregate mutual funds' ownership as documented by Gompers and Metrick (2001) and Jiang (2010), we cross-sectionally demean (market-adjusted) the firm-level ownership before computing the average portfolio-level mutual funds' ownership.

Figure 1 visualizes the results. Panel A plots the cumulative characteristic-adjusted monthly portfolio returns for the two extreme quintile portfolios from 12 months before to 24 months after the portfolio formation. Month 0 is June of year t, and month -11 is July of year $t-1$. The results clearly show the strong return-predictive power of V/P ratio after the portfolio formation. The most underpriced stocks in Quintile 5 perform very well from then on till the nine months after the portfolio formation. After that, the cumulative abnormal returns start to flatten out till the end of June in year $t+2$. Similarly, the cumulative characteristic-adjusted return of the most overpriced stock in Quintile 1 start

[13] Specifically, we assign a stock to one of the 125 characteristic-sorted portfolios at the time of portfolio formation and calculate the excess return of the stock relative to its benchmark portfolio. Then we use these excess returns to compute the equally weighted quintile portfolio returns. The DGTW benchmark portfolio returns are available at http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.htm. For a more detailed description of the concern, see Wermers (2006).

to decline after the portfolio formation and the pattern substantially weakens after one quarter. At the end of the holding period, the abnormal return differential between the two extreme quintile portfolios amounts to more than 20%, consistent with the findings of Frankel and Lee (1998). Furthermore, we do not observe a significant return reversal for stocks in both extreme quintiles, which indicates investors including mutual funds do not overreact on the information content of V/P.

Panel B of Figure 1 plots the equally weighted, market-adjusted mutual funds' ownership for these portfolios. Quarter 0 denotes the period of April to June in year t, and quarter -3 denotes July to September of year $t-1$. The results suggest that mutual funds in aggregate trade on the information contained in V/P ratios in a strong manner. Mutual funds start to increase their ownership in underpriced stocks from Quarter -1 and appear to stop trading on the same information after Quarter 3. On the other hand, mutual funds tend to decrease their ownership in overpriced stocks dramatically during a shorter period (from Quarter -1 to Quarter 1). Their trading horizons correspond to the profitability of the V/P effect as we see in Panel A. Combining the results in both panels, we see that mutual funds, as an investor group, trade on the mispricing opportunities based on intrinsic value estimation. More importantly, mutual funds appear to know such valuation information half a year before it is publicly released in June and they tend to trade on stock intrinsic values in the entire calendar year t. Given the ease to obtain book value of a firm and the superior earnings forecasts provided by mutual funds' in-house fundamental analysts, it should not be surprising to observe their exploitation on the V/P effect. The results suggest that mutual funds trade in the direction of V/P and are likely to facilitate impounding fundamental information into stock prices.

To provide a more comprehensive analysis of mutual fund trading behavior in response to V/P, we use multivariate cross-sectional regressions (Fama and MacBeth, 1973) relating the changes in mutual funds' ownership to V/P, while controlling for other stock characteristics. For each calendar quarter between 1981 and 2007, we estimate the change in aggregate mutual funds' ownership in a given stock. The quintile ranks of V/P, B/M, E/P, accruals, and earnings changes are determined at last fiscal year end and assigned to each quarter in the next calendar year. Accruals are constructed following Sloan (1996) and Ali, Chen, Yao, and Yu (2008). Earnings changes are computed as the change in actual earnings for the last fiscal year scaled by price at the last fiscal year end (Bernard and Thomas, 1990). Analyst forecast revisions are calculated at the end of each June as the difference in consensus analyst earnings forecasts between June and last December scaled by the stock price at the end of last fiscal year. These revisions correpond to the fund trading for each quarter in the same calendar year. All other control variables are at the beginning of the quarter. We run quarterly cross-sectionally regressions and then report the time-series average coefficients in Table IV for each calendar quarter (Quarter -1 to Quarter +2 with Quarter 0 denoting the period of April to June). Consistent with the pattern established in the event study, mutual funds' trades are positively and significantly associated with V/P ranks in the first three calendar quarters of a year even after we control for funds' return chasing behavior by including the contemporaneous quarterly stock returns in our quarterly regressions. The quintile ranks of other fundamental-to-price ratios such as B/M and E/P are either negatively or insignificantly associated with aggregate mutual fund trading. Mutual fund managers do not trade in the direction of these simple financial ratios and rather exploit mispricing as revealed by more comprehensive valuation models. Controlling for accruals anomaly, earnings changes, and analyst forecast revisions also does not subsume our findings. When we replace the V/P ranks with dummy variables indicating quintile memberships, the results show that mutual funds mainly trade on intrinsic value in the second calendar quarter. Funds tend to sell overpriced stocks and buy underpriced stocks in Quarter 0. This positive association is robust to the inclusion of other return predictors such as firm size, the book-to-market ratio, past one-year returns, idiosyncratic volatilities, and turnover ratios. Therefore, mutual funds tend to trade more intensively in the direction of V/P during the first half of each calendar year before all necessary financial information for estimating stock values is releasesd publicly.

5 Do Mutual Funds Profit from Discovering Intrinsic Value?

In section 4, we have shown that mutual funds tend to trade on the information content of the V/P ratio, especially in the six months prior to the release of financial information to public. To ascertain that mutual fund managers have informational advantages in successfully exploiting the intrinsic value (rather than chasing the V/P effect passively) and that they are able to beat transactions costs, this section examines the profitability of mutual funds trading on V/P ratios. The stock holdings data have allowed us to test whether mutual funds actively trade on the V/P effect. Now we use fund net returns data to assess their actual profitability from implementing such fundamental-based investments

5.1 *Mutual Fund* V/P *Timing Measure*

To measure the cross-sectional dispersion in how actively mutual funds follow a V/P trading strategy, we construct a V/P timing measure in spirit of the momentum investing measure of Grinblatt, Titman, and Wermers (1995) and similar to the accruals investing measure of Ali, Chen, Yao, and Yu (2008). At the end of each June, we rank all stocks in our CCM universe into decile portfolios based on V/P and assign the ranks of 1 to 10 to each stock, with score 1 representing the 10% of the most overpriced stock and score

10 for the 10% of the most underpriced stocks.[14] The V/P timing measure for fund i at time t, $VPT_{i,t}$, is defined as the weighted average V/P rank of all stocks held by the fund:

$$VPT_{i,t} = \sum_{j=1}^{N_{i,t}} w_{i,j,t} * (V/PRank)_{j,t}, \tag{4}$$

where $(V/PRank)_{j,t}$ is the decile rank of stock j in ascending order based on V/P ratios. $N_{i,t}$ is the number of CCM stocks that are held by mutual fund i at time t, and $w_{i,j,t}$ is the stock j's weight in the fund i's portfolio at time t. A high VPT indicates that the fund tilts its portfolio toward underpriced or high V/P stocks.

5.2 *Characteristics of Funds with Extreme* VPT

This subsection examines the characteristics of mutual funds across VPT decile portfolios. We also analyze the possible determinants of VPT using Fama-Macbeth regressions.

At the end of each June, we calculate VPT and sort mutual funds into deciles based on their VPT scores in ascending order. Then we compute the cross-sectional averages of fund characteristics and report their time-series means. Table V reports the results based on the univariate sorts. D5 funds with an average VPT of 5.5 appear to be neutral to V/P ratios. In contrast, the average VPT of D1 funds is 4.13 while the average VPT for D10 funds is 7.16, which suggests that D10 funds trade on V/P effect, whereas D1 funds trade against it. The results also show that funds in the two extreme VPT deciles tend to be younger funds with higher expense ratios. Besides, high-VPT funds in Decile 10 have smaller size and higher turnover ratios. A typical fund in Decile 10 with the highest VPT has an average TNA of $million 515, which is substantially lower than the average TNA in any other decile portfolio. These high-VPT funds also have the highest average turnover ratio of 102.01% among all deciles. Finally, there exists no apparent

[14] We use decile ranks to increase the variation of VPT. In unreported results, we replace the decile ranks with quintile ranks and find that the mainly results of our analysis are not affected at all.

relation between VPT and the 12b1 fees.

We next run Fama-Macbeth regressions to better understand the determinants of the use of V/P strategy by mutual funds. We regress VPT on various fund characteristics and fund performance predictors at the end of each June and report the time-series average coefficients in Table VI. The results of Model 1 confirm our findings using the univariate portfolio approach. VPT is positively associated with fund turnover and negatively related to fund size. In Model 2 and 3, we include past fund performance and some other fund portfolio characteristics that have been shown in prior studies to have predictive power for future fund performance. Past fund performance is measured by the cumulative fund return in the past 12 months. Active share measures the extent of fund portfolio deviation from its benchmark (Cremers and Petajisto, 2009). Following Baks, Busse, and Green (2007), we use the normalized Herfindahl index to measure the fund managers' willingness to take big bets on a relatively small number of stocks. Return gap is the difference between the reported fund return and the return on a portfolio that invests in the previously disclosed fund holdings. It captures the unobserved fund intra-quarter trading activities (Kacperczyk, Sialm, and Zheng, 2008). We use the average monthly return difference over the past one year in our regressions. We find that past fund performance is positively and significantly associated with VPT. Replacing past fund performance with two dummy variables (P1 and P10) for the two extreme deciles of funds based on past performance, we find that mainly the past winning funds are inclined to exploit fundamentals. Among the three fund skills predictors, only return gap is significantly and negatively associated with VPT. Intuitively, this suggests that mutual funds that rely on frequent interim/short-term trades do not exploit investment opportunities of long-run price-value convergence. To summarize, mutual funds that engage in stock valuation and trade on such information tend to be small, active, and transparent past winners.

5.3 *Do High-VPT Funds Profit from V/P Effect?*

We have shown a wide cross-sectional dispersion in mutual funds' tendency to implement a V/P strategy. To better understand the informational role mutual funds play in financial markets, we next examine the actual fund performance taking into account the actual transactions costs that might be incurred in their V/P based trades. Since highly underpriced stocks are generally small stocks with high return volatility, mutual funds buying such stocks may face large trading friction and transactions costs. Therefore, it is of significant importance to evaluate the profitability of fund trading on V/P in reality.

We first compute the VPT scores in June of year t and then sort all active mutual funds into decile portfolios based on VPT. Since mutual fund manager may have private information about fundamentals from their in-house analysts at the beginning of the year, the June VPT best captures how actively managed mutual funds have traded on the fundamental mispricing in the first half of year t. Then we track the mutual fund performance in the subsequent one year (till June in year $t + 1$) and compute monthly TNA-weighted fund portfolio performance. For the performance evaluation, we use mutual fund performance before fees (by adding back expense ratios/12 to the net fund returns reported by CRSP) as a measure of the investment profitability because it is after the actual transactions costs and is not influenced by other fund expenses.

Table VII reports the results on fund performance. Given our finding that active funds tend to trade on V/P most intensively during the first half of each calendar year, we split the evaluation period into two half-years to better understand the fund net performance and the possible price impact of fund trading. Panel A of Table VII displays the performance results for the first six months after the portfolio formation in June. Over the six-month horizon (July-December in year t), D10 funds generate a significant return of 1.19% per month and significantly outperform their D1 counterparts by 0.55% per month. We also examine how well D10 funds perform relative to D5 funds (with a

VPT score of 5.5) that are supposed to be neutral to the V/P effect. The return spread between D10 and D5 is 0.26% per month and is statistically significant. The significant return spreads are robust to various forms of risk adjustment. More importantly, the average return for D10 funds with the highest VPT is significantly positive. In terms of 4-factor alpha, D10 funds earn 0.27% per month with a t-statistic of 2.70. On the contrary, we observe negative risk-adjusted returns for D1 funds although not significantly different from zero. Panel B presents the results for the second half-year after the portfolio formation (January-June in year $t+1$). The alpha generating abilities of the high-VPT funds seem to disappear after the first post-ranking half-year. Over this more intensive trading period (the first half of each calendar year), D10 fund managers fail to generate enough profits to offset the transactions costs associated with exploiting V/P. Besides, the stocks held by D10 funds are very likely to have been exploited the most over the ranking year. The resulting rapid convergence between price and value for these stocks over the ranking year renders their V/P anomaly much weaker during the second half-year after the portfolio formation.

Panel C of Table VII presents the performance results over the entire future one year. D10 funds with the highest VPT have an average return of 1.26% per month and outperform the lowest-VPT funds in D1 by 0.42% per month. The return spread is highly statistically significant with a t-statistic of 2.68. However, the results are not robust to controlling for momentum. In untabulated results based on the post-1999 data, we further find that over the one-year horizon D10 funds can generate a significant 4-factor alpha of 0.18% per month. Moreover, the 4-factor alpha of the return spread is 0.31% per month and statistically significant over this subperiod. This finding suggests that the funds that trade most actively on fundamentals may have benefited from the operationalization of the residual income model by Frankel and Lee since 1998.

As shown in Table III, stocks with extreme V/P ratios have small market capitalization and high idiosyncratic volatility, which makes them unattractive to mutual funds. To gain more insights on the source of profitability of high-VPT funds, we examine how funds exploit fundamental mispricing across V/P deciles. At the end of each June, we calculate for each VPT decile the aggregate portfolio weight of each V/P stock decile. Specifically, for D10 funds, the aggregate portfolio weight of a V/P decile is computed as the total value of the stocks in the V/P decile held by D1 funds divided by the total value of their equity holdings. We report the time-series averages of the portfolio weights for D1, D5, and D10 funds in Table VIII. Consistent with our expectation, D5 funds that are neutral to V/P strategy invest almost equally in all ten V/P deciles. Relative to the neutral funds, D10 funds tend to overweight stocks in the highest V/P decile (16.99%) and underweight stocks in the lowest V/P decile (3.40%). The reverse pattern can be observed for D1 funds, which overweight low-V/P stocks and underweight high-V/P stocks. The portfolio weight differences between D10 and D1 and between D10 and D5 funds in the two extreme V/P deciles are statistically significant. We shall note that D10 funds are generally small funds (with an average TNA of $million 515, see Table V). Although these high-VPT funds place large bets on underpriced stocks, their total investments in these stocks cannot be substantially large. This explains to some extent why the convergence of price and fundamental value is not immediate.

The above results suggest that mutual funds actively exploiting the fundamental mispricing are able to benefit from such information and generate both statistically and economically significant profits, net of actual transactions costs and before fund expenses, over a half-year horizon. Overall, our evidence confirms our expectation that mutual funds (at least a subgroup of funds), being good candidates for informed traders, can profit from their information-based trades.

6 Mutual Fund Trading and V/P Effect

Given the results that mutual funds tend to trade in the direction of V/P, their trading activities might mitigate mispricing by pushing stock prices back toward the fundamental values. In this section, we provide evidence consistent with this conjecture.

The idea is that the V/P effect is more pronounced among stocks with less mutual funds' exploitation. We use mutual funds' ownership in a stock as a proxy for investor sophistication for that stock. The more shares of a stock are owned by mutual funds, the more sophisticated investor base a stock should have. In particular, stocks with higher V/P ratios and lower mutual funds' ownership should have higher future returns. Besides, change in mutual funds' ownership (or the change in the number of funds holding a stock) is a signed measure of the aggregate fund trading. We expect that less fund trading (in the direction of V/P) could result in stronger V/P effect in the future.

We use a two-way independent sorting procedure. Along one dimension, we first sort stocks into five quintiles on the basis of V/P at the end of each June. Then we sort them into three tertiles based on mutual funds' ownership in June or fund trading during the past 6 months respectively. Then we hold the 15 fractile portfolios for one year and value-weighted monthly portfolio returns are computed. The portfolios are rebalanced at the end of next June. We report the Carhart 4-factor alphas for these portfolios in Table IX. The results confirm our conjectures. Panel A shows that high-V/P stocks in Quintile 5 with less sophisticated investor base continue to generate superior performance in the subsequent one year. The Fractile portfolio (1,5) has a 4-factor alpha of 0.42% per month with a t-statistic of 2.04, which is higher than the average high-V/P stock performance of 0.33% per month reported in Table II. A strategy that buys high-V/P and sells low-V/P stocks with the lowest mutual funds' ownership is able to earn a significant 4-factor alpha of 0.59% per month. When we measure fund trading using the change in the number of funds holding a stock in Panel B, we observe that stocks in Quintile 5 with the highest

V/P ratios that have been sold by mutual funds in the past 6 months can generate a significant 4-factor alpha of 0.73% per month. Panel C presents similar results as in Panel B using the changes in mutual funds' ownership as a proxy for fund trading.

Therefore, we show that the trading activities of mutual funds help mitigate mispricing and bring stock prices back to fundamentals. Our results support the view that mutual fund trading tend to mitigate the mispricing as reflected in a V/P ratio. In unreported results, we postpone the portfolio formation of the V/P strategy by two months to take into account the reporting lag of fund holdings. We form portfolios at the end of August based on the V/P ratios known in June and holding the portfolios from September to the next August. Imposing this additoinal implementation lag does not affect the above results. Hence, individual investors may use the mutual fund trading information to refine the V/P strategy by identifying underpriced stocks that have not been exploited heavily by mutual funds in the recent past.

7 Conclusions

This paper explores how effectively active mutual funds trade on and profit from fundamental analyses. Over the 1981 to 2008 sample period, we find that active funds tend to trade on the V/P anomaly as documented by Frankel and Lee (1998). The V/P ratio measures the extent of stock mispricing relative to its intrinsic value based on a comprehensive valuation model, namely, residual income model. We use the residual income model and analyst earnings forecast to measure a firm's intrinsic value and show that mutual funds start to exploit such mispricing opportunities far before the financial information becomes public. Using fund returns data before fees, we show that funds that have the highest weights on underpriced stocks are able to generate a significant 4-factor alpha of 0.27% per month over a six-month horizon. Therefore, trading on V/P effect can be profitable even after the actual transactions costs for a relatively short period. Finally, we find evidence consistent with our conjecture that the V/P effect is more significant among stocks with less mutual funds' exploitation.

Our study suggests that mutual funds in aggregate trade on fundamental value and a subgroup of funds can earn significant risk-adjusted returns from it. This leaves space for the limits-of-arbitrage explanation for why other funds do not exploit the intrinsic value information as aggressively as those profitable ones. Future research could focus on examining the determinants of fundamental analyses implementation in different mutual funds. Besides, other types of institutions, such as pension funds, banks, and insurance companies, have played an increasingly important role in security markets. Given the enormous amount of resources they spend in the security analysis, those types of institutions might also be important for the incorporation of fundamental information into stock prices.

Appendix: Mutual Fund Sample Selection

We start with all U.S. equity mutual funds from the intersection between the CRSP mutual fund database and the CDA/Spectrum mutual fund holdings database. We use the MFLINKS data set available from the WRDS to link the two databases. Our sample of stock holdings spans the period from 1981 through 2008.

Because we wish to capture active mutual funds that invest primarily in U.S. equities, we follow Pastor and Stambaugh (2002) and Kacperczyk, Sialm and Zheng (2008), by eliminating balanced, bond, money market, sector, and international funds as well as funds that do not primarily invest in U.S. common equity. In particular, we use the following steps in sample selection. We select funds with the following Lipper class codes, provided by the CRSP: EIEI, G, I, LCCE, LCGE, LCVE, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, SCGE, or SCVE. If a fund does not have any of theseLipper class codes, we select funds with the following strategic Insight objectives: SCG, GRO, AGG, ING, GRI, or GMC. If both codes are missing for a fund, we pick funds with the following Wiesenberger objectives: SCG, AGG, G, G-S, S-G, GRO, LTG, I, I-S, IEQ, ING, GCI, G-I, G-I-S, G-S-I, I-G, I-G-S, I-S-G, S-G-I, S-I-G, GRI, or MCG. If none of the objective codes are available, we require that a fund have a CS policy code.

We eliminate funds with any of the following investment objectives as provided by CDA/Spectrum: International, Municipal Bonds, Bond and Preferred, and Balanced. Furthermore, we use the portfolio composition data provided by CRSP MFDB to exclude funds that invest less than 80% or more than 105%, on average, in common equity. To address the incubation bias documented by Elton, Gruber and Blake (2001) and Evans (2010), we exclude observations prior to the reported fund inception date, observations for which the names of the funds are missing in the CRSP database, and funds whose net assets fall below $5 million. To prevent outliers from driving our results, we also require that a fund have at least 10 stock holdings to be eligible for consideration in our analysis.

To ensure that we capture active mutual funds, we eliminate index funds whose names contain the following keywords: INDEX, INDE, INDX, INX, IDX, DOW JONES, ISHARE, S&P, S &P, S& P, S & P, 500, WILSHIRE, RUSSELL, RUSS, or MSCI. To lessen errors due to abbreviation and misspelling, we manually inspect fund names and filter out remaining international funds, sector funds, tax-managed funds, fixed-income funds, balanced funds, real estate funds and annuities.

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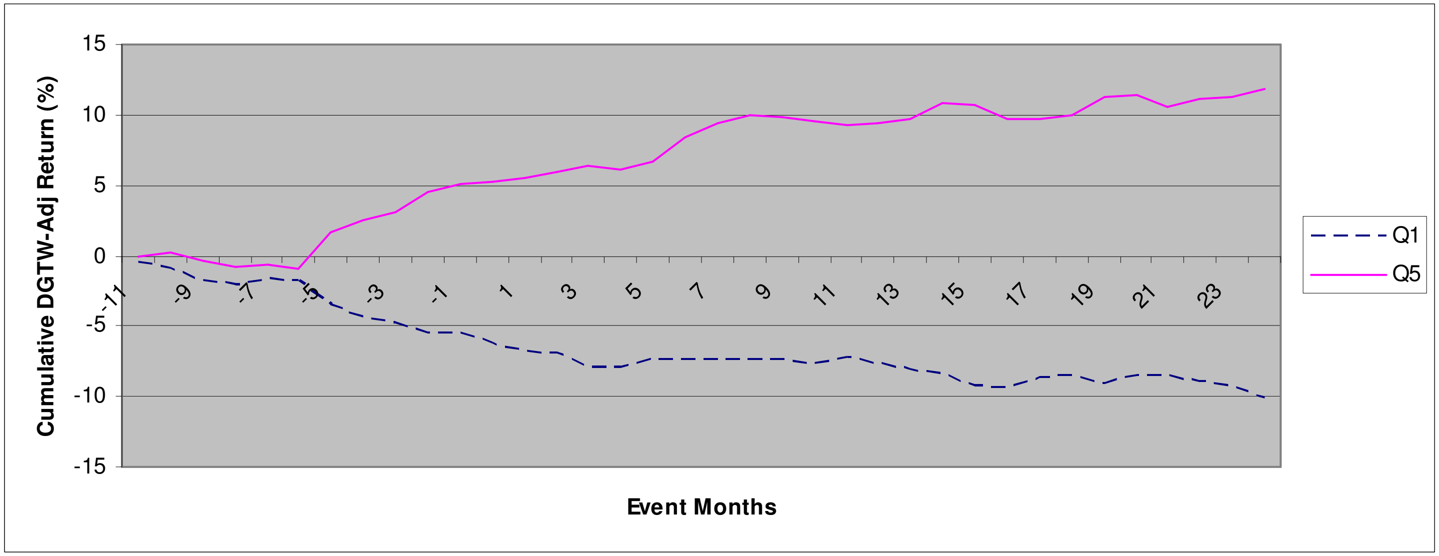
Figure 1

Characteristic-Adjusted Monthly returns and Market-Adjusted Mutual Fund Ownership for Portfolios based on *V/P*, 1981-2006

Panel A of this figure visualizes the cumulative performance of the quintile portfolios formed on the basis of value-to-price ratios, *V/P*. Specifically, at the end of each June from 1981 to 2007, we sort stocks into five quintile portfolios in ascending order based on *V/P* and compute the monthly value-weight average characteristic-adjusted returns for each portfolio from -12 months before portfolio formation to 24 months after portfolio formation. Month 0 is June of each year. Panel B corresponds to the end of each quarter. Quarter 0 is the second quarter of each calendar year. Using the same portfolio sorting procedure, we compute the equal-weight average of the cross-sectionally demeaned mutual fund ownership in stocks in each quintile portfolio from Quarter -4 to Quarter +8. Mutual fund ownership is defined as the fraction of shares held by all mutual funds. Both panels plot the time-series average returns and ownership numbers.

Panel A: Value-weight, DGTW –adjusted monthly returns



Panel B: Equal-weight, market-adjusted mutual fund ownership

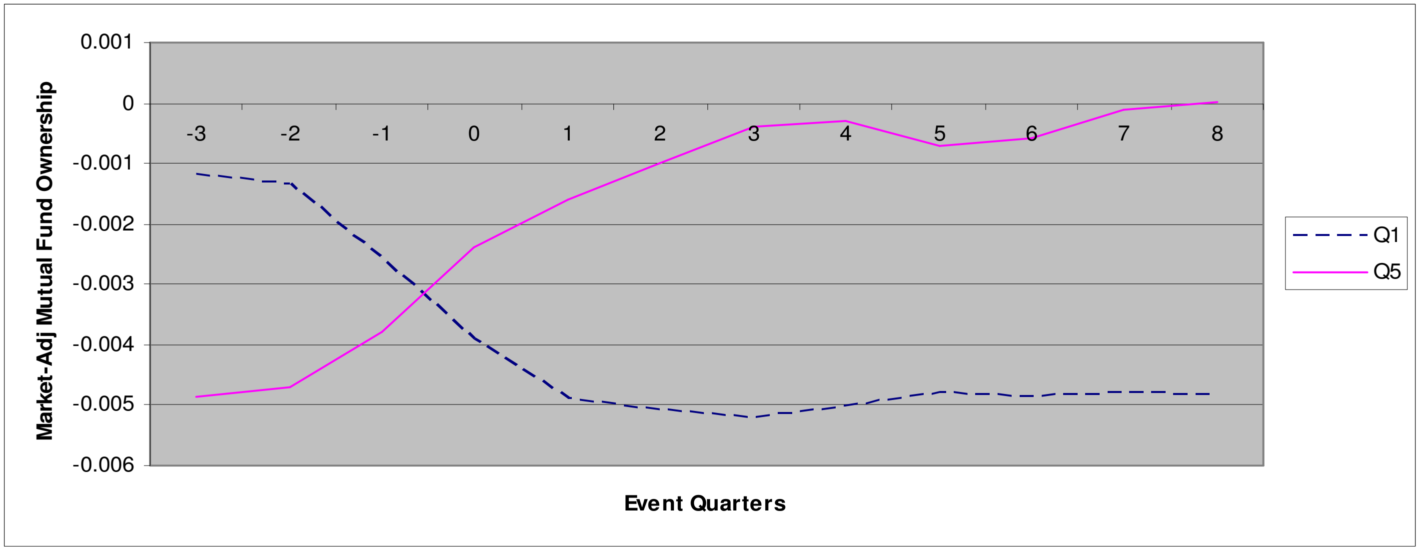


Table I
Summary Statistics: Stocks and Mutual Funds

This table presents the summary statistics for our stock (Panel A) and mutual fund (Panel B) data (see Appendix B for details on sample selection). At the end of each June from 1981 to 2007, we compute the equal-weight average characteristics. In Panel A, V is the intrinsic value of a stock and estimated based on a residual income model operationalized by Frankel and Lee (1998). Value-to price ratio (*V/P*) is computed by dividing the analyst-based intrinsic value of a firm by its market capitalization at the fiscal-year-end in the last calendar year. k is the dividend payout ratio, computed as the common stock dividends divided by earnings to common shareholders. For firms with negative earnings, k is computed as common stock dividends divided by (total assets * 0.05). ROE is the return on equity for the last fiscal year computed as net income divided by the average book equity. ROA is the return on assets for the last fiscal year. We also compute the number of distinct stocks in the Compustat/CRSP Merged (CCM) database that have valid data to compute *V/P* ratios and the number of these stocks held by mutual funds. We also present the mutual fund ownership and the number of distinct mutual funds that hold a stock over years. Mutual fund ownership in a stock is the fraction of the stock's shares outstanding held by all mutual funds. The above calculations exclude stocks with prices lower than 1 dollar at the end of each June. In Panel B, we calculate the cross-sectional average of various fund characteristics over years, including the number of distinct mutual funds, total net assets, 12b1 fees, expense ratios, turnover ratios, and the percentage of fund common stock holdings. These fund characteristics are extracted from the CRSP fund summary database. 12b1 fees data in CRSP start from 1993 and fund turnover ratios are missing in CRSP in 1992. The last row of the table presents the time-series average of the annual cross-sectional means.

	Panel A: Stock Characteristics								Panel B: Mutual Fund Characteristics					
Year	*V/P*	k	ROE	ROA	No. of Stocks (*V/P* Universe)	No. of Stocks (*V/P* & Held by Funds)	Average Mutual Fund Ownership (%)	No. of Funds Holding the Stock	No. of Mutual Funds	TNA ($millions)	12b1 Fees (%)	Expense Ratio (%)	Turnover Ratio (%)	% of Common Stock Holdings
1981	1.54	0.33	0.16	0.07	938	836	2.77	8	179	195.51		0.95	73.81	88.57
1982	1.40	0.32	0.16	0.07	1043	934	2.68	7	176	187.35		0.90	71.09	83.58
1983	1.31	0.33	0.12	0.06	1070	979	3.35	7	203	209.39		1.00	79.56	86.31
1984	1.11	0.29	0.11	0.05	1276	1181	3.81	7	211	280.93		0.89	78.92	87.30
1985	1.17	0.26	0.13	0.06	1273	1200	4.21	8	242	264.57		0.95	74.83	85.38
1986	0.99	0.25	0.10	0.05	1305	1242	4.75	9	263	333.89		0.98	80.73	85.91
1987	0.95	0.24	0.09	0.04	1305	1231	4.77	10	299	366.27		0.98	80.65	85.63
1988	1.10	0.22	0.11	0.05	1298	1225	4.70	11	311	365.61		1.03	91.77	86.03
1989	1.07	0.21	0.14	0.06	1361	1307	4.71	13	344	371.25		1.21	78.93	85.13
1990	0.96	0.22	0.13	0.06	1371	1314	5.30	14	365	446.21		1.25	77.41	86.19
1991	1.12	0.24	0.12	0.05	1368	1298	5.67	16	389	395.01		1.27	82.54	85.09
1992	0.92	0.23	0.09	0.04	1411	1324	5.76	15	431	540.76		1.06		86.97
1993	0.87	0.21	0.10	0.04	1543	1448	6.99	21	566	552.25	0.18	1.22	68.69	86.29
1994	0.84	0.19	0.09	0.04	1768	1754	8.14	26	703	602.26	0.17	1.18	71.32	87.67
1995	0.98	0.17	0.11	0.05	1909	1894	9.04	29	813	588.74	0.17	1.20	77.75	90.97
1996	0.88	0.15	0.11	0.05	2075	2063	9.82	29	894	804.72	0.16	1.23	81.77	90.94
1997	0.85	0.14	0.10	0.04	2171	2143	10.42	31	1018	950.73	0.17	1.25	84.21	92.19
1998	0.81	0.12	0.09	0.04	2294	2276	11.62	32	1138	1165.31	0.19	1.24	86.27	93.40
1999	0.86	0.12	0.08	0.03	2175	2142	11.39	34	1180	1419.84	0.20	1.25	87.12	93.71
2000	0.89	0.12	0.10	0.04	1867	1846	12.06	47	1347	1646.00	0.31	1.27	91.40	92.91
2001	0.87	0.11	0.10	0.04	1638	1633	13.30	58	1417	1514.64	0.32	1.26	100.74	92.42
2002	0.69	0.11	0.04	0.01	1619	1613	15.47	65	1485	1279.09	0.33	1.30	105.25	93.56
2003	0.76	0.11	0.05	0.02	1653	1644	15.03	66	1512	967.75	0.32	1.34	105.34	94.08
2004	0.67	0.10	0.06	0.02	1778	1771	16.19	66	1542	1278.23	0.31	1.36	92.51	95.25
2005	0.66	0.11	0.11	0.05	1785	1782	16.50	70	1556	1466.28	0.29	1.30	83.94	94.19
2006	0.70	0.11	0.11	0.05	1782	1780	17.31	69	1556	1536.13	0.27	1.27	83.71	96.43
2007	0.65	0.11	0.10	0.04	1785	1778	17.26	70	1518	1743.51	0.24	1.24	83.52	96.80
Average	0.95	0.19	0.10	0.05	1587	1542	9.00	31.05	802.15	795.27	0.24	1.16	83.61	89.74

Table II

V/P and Future Stock Returns: Quintile Portfolios

This table presents the performance of the quintile portfolios formed on the basis of value-to-price ratios, *V/P*. V is an intrinsic value measure derived based on a residual income model using the current I/B/E/S consensus earnings forecast available prior to June 30 of each year. Specifically, at the end of each June from 1981 to 2007, we sort stocks into quintiles in ascending order based on *V/P* and compute the average monthly value-weight portfolio returns in the subsequent year. We also present risk-adjusted performance of those portfolios, based on the CAPM, the Fama and French (1993) three-factor model, the Carhart (1997) four-factor model, and a five-factor model that augments the Carhart model with the Pastor and Stambaugh (2003) liquidity. Stocks with prices lower than 1 dollar at the time of portfolio formation are excluded. The t-statistics are computed using the Newey-West standard errors. *** represents statistical significance at 1% level, ** represents statistical significance at 5% level, and * represents statistical significance at 10% level.

	Value-Weight Post-Ranking Portfolio Return (%/month)				
V/P Quintile	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	5-Factor Alpha
1	0.74	-0.37	-0.36	-0.11	-0.09
	(2.47)	(-3.82)	(-3.73)	(-0.99)	(-0.82)
2	0.91	-0.09	-0.02	-0.02	0.00
	(3.68)	(-1.24)	(-0.35)	(-0.37)	(0.07)
3	1.06	0.12	0.10	0.05	0.09
	(4.83)	(1.61)	(1.52)	(0.78)	(1.27)
4	1.13	0.19	0.18	0.08	0.08
	(5.1)	(1.89)	(1.96)	(0.92)	(1.08)
5	1.46	0.44	0.46	0.33	0.32
	(6.31)	(2.73)	(3.33)	(2.69)	(2.52)
Q5-Q1	0.72***	0.80***	0.81***	0.44**	0.41**
	(3.29)	(3.65)	(4.24)	(2.39)	(2.22)

Table III

Stock Characteristics across V/P Quintiles

At the end of each June from 1981 to 2007, we compute for each stock a measure of mispricing, *V/P*, which is the value-to-price ratio based on a residual income model. We then sort stocks into quintiles in ascending order based on *V/P* and calculate the stock characteristics for each quintile portfolio. This table reports the time-series average the cross-sectional mean characteristics. Our set of characteristic variables includes the average value-to-price ratio *V/P*, the average book-to-market ratio, the average market cap, book-to-market, and past one year return (11-month cumulative return from the period *t*-11 to *t*-1) scores, the average total return volatility and stock turnover in the past year, and the levels and the changes of mutual fund ownership in a stock (or the number of funds holding s stock) in the past year and in the future one year. Market cap of a stock is computed by multiplying the stock price with the number of outstanding shares at each quarter end (in millions). V/P ratio is computed at the fiscal-year-end in the last calendar year. Book-to-market ratio is determined for each stock at the end of last calendar year using the book value of the stock at the end of last fiscal year and the market value of the stock at the end of last calendar year (see Fama and French (1992)). The stock volatility is the standard deviation of the monthly returns in the past year (we require that at least 6 monthly observations of stock return are available). Stock turnover is computed as the sum of stock volumes in the past year divided by the average stock price at the beginning and the end of the period. To facilitate comparison across deciles, we score for each year the size, book-to-market, and past returns from 1 to 5, with 5 representing the quintile with the largest market cap (based on NYSE break-points), highest book-to-market, and highest past one year return. Mutual fund ownership in a stock is the fraction of shares outstanding owned by all mutual funds. The changes in mutual fund ownership in a stock or the number of funds holding a stock is measured yearly at the end of June. Stocks with prices lower than 1 dollar at the end of each June are excluded.

V/P Quintile	*V/P*	B/M	ME Score (1~5)	BM Score (1~5)	Pr1Yr Score (1~5)	Volatility (%)	Turnover (%)	MFO_t (%)	No. of Funds (NoF_t)	ΔMFO_t (%)	ΔNoF_t	ΔMFO_{t+1} (%)	ΔNoF_{t+1}
1	0.40	0.62	2.40	2.70	2.44	13.30	155.29	8.57	26.56	0.08	-0.16	-0.24	0.29
2	0.67	0.58	2.80	2.59	2.86	10.78	124.98	9.40	35.46	0.26	1.03	-0.11	1.02
3	0.84	0.63	2.79	2.86	3.02	10.12	116.13	9.22	33.86	0.31	1.59	-0.14	1.10
4	1.05	0.66	2.66	2.92	3.14	10.75	126.70	9.22	33.04	0.43	2.14	-0.03	1.09
5	1.77	0.73	2.17	2.82	3.46	13.80	164.94	8.60	26.34	0.65	2.91	0.13	1.58
Q5-Q1	1.37	0.10	-0.23	0.12	1.02	0.50	9.65	0.03	-0.22	0.57	3.07	0.37	1.29

Table IV

V/P and Mutual Fund Trading: Fama and Macbeth (1973) Cross-Sectional Regressions

This table presents the relation between stock value-to-price ratio, *V/P*, at the end of each June and mutual fund trading over the prior two quarters and the subsequent two quarters, controlling for other stock characteristics at the beginning of each quarter, following the Fama and MacBeth (1973) procedure. The dependent variable is the quarterly change of mutual fund ownership in a given stock. *MFO* is the fraction of shares held by mutual funds. We rank stocks at the end of June into five quintiles based on *V/P* and use the ranks from 1-5 as the regression inputs fro Model 1, 3, 5, and 7. Besides, we construct two dummy variables, Q1 (Q5) equals one when a stock in the Quintile 1 (5) and zero otherwise. We also construct quintile ranks for accruals, earnings changes, B/M ratios, and E/P ratios at the end of last fiscal-year-end in a similar way to V/P. Analyst earnings forecast revisions are computed at the end of June as the difference in consensus forecast between June and last December. Market cap, the book-to-market ratio, past one year return, and stock turnover ratio are defined as previously. E/P ratio is calculated by dividing the earnings by the market cap at the last fiscal-year-end. Stock turnovers are now calculated on a quarterly basis. We also regress the daily stock returns against daily Fama French factors in a given quarter and use the standard deviation of the residuals as the residual volatility of the stock for that quarter (we require that at least 40 daily observations of stock returns are available).. We also include the contemporaneous quarterly stock return to control for funds' return-chasing behavior. Stocks with prices lower than 1 dollar at the beginning of each quarter are excluded. The time-series average coefficients are reported in the table. The t-statistics are computed using the Newey-West standard errors. *** represents statistical significance at 1% level, ** represents statistical significance at 5% level, and * represents statistical significance at 10% level.

	Dependent Variable: ΔMFO_t (%)							
	Quarter (-1)		Quarter (0)		Quarter (+1)		Quarter (+2)	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
V/P Rank	0.0280**		0.0561***		0.0297**		-0.0047	
	(2.28)		(5.27)		(2.28)		(-0.36)	
Q1		-0.0759*		-0.1010***		-0.0594		0.0289
		(-1.92)		(-3.53)		(-1.46)		(0.63)
Q5		0.0227		0.1340***		0.0530*		0.0054
		(0.53)		(3.04)		(1.81)		(0.20)
B/M Rank	-0.0568***	-0.0551***	-0.0139	-0.0115	-0.0210	-0.0206	-0.0203	-0.0205
	(-3.58)	(-3.44)	(-1.21)	(-1.01)	(-1.65)	(-1.61)	(-1.53)	(-1.54)
E/P Rank	-0.0030	-0.0011	-0.0409***	-0.0376***	-0.0051	-0.0032	0.0058	0.0068
	(-0.18)	(-0.06)	(-3.15)	(-3.05)	(-0.44)	(-0.27)	(0.38)	(0.44)
Accrual Rank	-0.0184*	-0.0187*	-0.0141	-0.0143	-0.0170**	-0.0177**	0.0158	0.0155
	(-1.84)	(-1.87)	(-1.44)	(-1.47)	(-2.16)	(-2.23)	(1.54)	(1.50)
Earnings Changes Rank	0.0141	0.0161	-0.0196	-0.0197	-0.0249***	-0.0247***	-0.0136	-0.0144
	(1.20)	(1.39)	(-1.68)	(-1.67)	(-3.34)	(-3.31)	(-1.23)	(-1.29)
Analyst Rev	0.0194	0.0201	-0.0267	-0.0217	-0.0722	-0.0718	-0.0341	-0.0329
	(0.49)	(0.51)	(-0.80)	(-0.69)	(-1.21)	(-1.19)	(-1.52)	(-1.52)
$Log(ME)_{t-1}$	-0.0268**	-0.0273**	-0.0347**	-0.0359**	-0.0253	-0.0265*	-0.0386**	-0.0385**
	(-2.31)	(-2.31)	(-2.07)	(-2.18)	(-1.69)	(-1.83)	(-2.69)	(-2.70)
$Pr1Yr_{t-1}$	0.0322	0.0325	0.4196***	0.4200***	0.2772***	0.2816***	0.3792***	0.3795***
	(1.18)	(1.21)	(6.58)	(6.63)	(4.94)	(4.97)	(5.32)	(5.39)
Idio Vol_{t-1}	-7.5841***	-7.2726***	-14.203***	-14.247***	-9.5613***	-9.4989***	-12.118***	-12.245***
	(-3.85)	(-3.69)	(-4.21)	(-4.24)	(-4.60)	(-4.51)	(-6.67)	(-6.61)
$Turnover_{t-1}$	0.2212**	0.2235**	0.1693	0.1657	0.0296	0.0300	-0.0242	-0.0215
	(2.09)	(2.09)	(1.66)	(1.61)	(0.32)	(0.32)	(-0.25)	(-0.22)
MFO_{t-1}(%)	-6.4185***	-6.4344***	-6.0269***	-6.0229***	-6.0739***	-6.0841***	-6.5123***	-6.5113***
	(-9.85)	(-9.89)	(-11.74)	(-11.72)	(-12.38)	(-12.42)	(-9.13)	(-9.10)
R_t	0.8707***	0.8779***	0.8056***	0.8042***	0.8386***	0.8409***	0.5202***	0.5239***
	(7.29)	(7.40)	(4.69)	(4.64)	(7.00)	(7.05)	(3.89)	(3.93)
Intercept	0.9982***	1.0731***	1.2248***	1.3771***	1.0094***	1.1007***	1.0758***	1.0576***
	(6.73)	(7.24)	(5.88)	(6.62)	(5.57)	(6.20)	(7.91)	(7.73)
Adj-R^2	6.25%	6.29%	5.73%	5.74%	5.47%	5.44%	5.81%	5.80%

Table V

Fund Characteristics across VPT – Sorted Decile Portfolios

At the end of each June from 1981 to 2007, we compute for each fund a measure of *V/P* timing, *VPT*, which is defined as the weighted average of *V/P* decile ranks of individual stocks held by the mutual fund. We then sort mutual funds into deciles in ascending order based on *VPT* and calculate the equal-weight average fund characteristics for each decile portfolio. The D1 decile has funds with the lowest *VPT*s and D10 decile has funds with the highest *VPT*s. This table reports the time-series average the cross-sectional mean fund characteristics. Our set of characteristic variables includes the average *V/P* timing measure *VPT*, the average fund age (in years), the average fund size, 12b1 fees expense ratios, and fund turnover ratios. All fund characteristics are extracted from CRSP MFDB fund summary database. Stocks with prices lower than 1 dollar at the end of each June are excluded.

Decile	*VPT*	Age (years)	TNA ($Millions)	12b1 Fees (%)	Expense Ratio (%)	Turnover Ratio (%)
1	4.13	13.96	852	0.25	1.20	75.10
2	4.76	16.04	907	0.25	1.18	74.37
3	5.05	16.76	879	0.24	1.14	75.04
4	5.29	17.11	871	0.24	1.13	77.52
5	5.49	17.64	912	0.23	1.12	79.05
6	5.69	17.53	721	0.25	1.13	86.07
7	5.91	17.43	808	0.25	1.14	82.35
8	6.16	17.97	840	0.24	1.13	88.45
9	6.49	15.62	649	0.23	1.19	97.02
10	7.16	13.36	515	0.22	1.27	102.01
D10 - D1	3.03	-0.61	-337	-0.03	0.07	26.91

Table VI
Determinants of *VPT*: Cross-Sectional Regressions

This table presents the relation between fund *V/P* timing measure, *VPT*, at the end of each June and mutual fund characteristics, controlling for other stock characteristics at the end of June from 1981 to 2007, following the Fama and MacBeth (1973) procedure. The dependent variable is the *VPT*, which is defined as the weighted average of *V/P* decile ranks of individual stocks held by the mutual fund. Fund age, fund size (TNA), fund expense ratios and fund turnover ratios are included in Model 1 as control variables. In Model 2, we fruther add as control variables past fund performance measured as the cumulative fund return in the past 12 months, the average Active Share in the past one year, the portfolio concentration, and average return gap in the past one year. Active Share is a measure of the extent of fund portfolio deviation from their benchmarks developed by Cremers and Petajisto (2009). We follow Baks, Busse, and Green (2007) to measure portfolio concentration using a normalized Herfindahl inex. Return gap is the difference between the return on a hypothetical holdings-based portfolio and the realized fund return (see Kacperczyk, Sialm, and Zheng, 2008). For these regressions, we restrict our sample period to 1990-2006 since the Active Share data are available from 1990Q1 to 2006Q4 from the website of Antti Petajisto. In Model 3, we rank funds at the end of June into ten deciles based on their past one-year performance and construct two dummy variables, P1(P10) equals one when a fund in the Decile 1 (10) and zero otherwise. Stocks with prices lower than 1 dollar are excluded when calculating the I measures. The time-series average coefficients are reported in the table. The t-statistics are computed using the Newey-West standard errors. *** represents statistical significance at 1% level, ** represents statistical significance at 5% level, and * represents statistical significance at 10% level.

	Dependent Var: VPT		
	Model 1	Model 2	Model 3
Log(1+Fund Age)	-0.0067	-0.0076	-0.0095
	(-0.54)	(-0.48)	(-0.65)
Log(TNA)	-0.0358**	-0.0178*	-0.0212**
	(-2.58)	(-2.04)	(-2.34)
Expense Ratio	0.0048	-0.0081	-0.0385
	(0.13)	(-0.24)	(-1.04)
Turnover Ratio	0.0011***	0.0013***	0.0011***
	(4.02)	(5.62)	(4.58)
Past Fund Performance		0.0146**	
		(2.31)	
P1			-0.1849
			(-1.35)
P10			0.2836**
			(2.22)
Active Share		0.2097	0.3439
		(0.72)	(1.17)
Portfolio Concentration		-0.0222	-0.0374
		(-0.96)	(-1.51)
Return Gap		-0.1915**	-0.1361**
		(-2.70)	(-2.30)
Intercept	5.5532***	5.2213***	5.2826***
	(46.49)	(21.83)	(17.95)
Adj-R^2	3.21%	17.86%	13.96%

Table VII

VPT and Fund Performance: Decile Portfolios

This table presents the performance of the decile portfolios formed on the basis of *V/P* timing measures, *VPT*, which is the weighted average of *V/P* decile ranks of individual stocks held by the mutual fund. The D1 decile contains funds with the lowest *VPT*s and D10 decile for funds with the highest *VPT*s. For each June from 1981 to 2007, we sort funds into deciles in ascending order based on *VPT* and compute the average monthly fund size-weight portfolio returns for the next 12 months (from June in year t to June in year t+1). Panel A and B present the results for the next two half-years, and Panels C shows the results for the next one year respectively. We also present risk-adjusted performance of those portfolios, based on the CAPM, the Fama and French (1993) three-factor model and the Carhart (1997) four-factor model. *** represents statistical significance at 1% level, ** represents statistical significance at 5% level, and * represents statistical significance at 10% level.

	Panel A: Size-Weight Fund Portfolio Returns from July in Year t to December in Year t (%/month)				Panel B: Size-Weight Fund Portfolio Returns from January in Year t+1 to June in Year t+1 (%/month)				Panel C: Size-Weight Fund Portfolio Returns from July in Year t to June in Year t+1 (%/month)			
Decile	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha	Average Return	CAPM Alpha	FF Alpha	Carhart Alpha
1	0.64	-0.26	-0.07	-0.05	1.05	-0.17	0.02	0.07	0.85	-0.22	-0.08	-0.04
	(1.48)	(-2.28)	(-0.76)	(-0.57)	(3.1)	(-1.67)	(0.25)	(0.7)	(2.96)	(-2.52)	(-1.27)	(-0.55)
2	0.74	-0.14	-0.03	-0.03	1.06	-0.10	0.02	0.05	0.90	-0.12	-0.06	-0.02
	(1.83)	(-1.82)	(-0.43)	(-0.38)	(3.43)	(-1.27)	(0.21)	(0.63)	(3.41)	(-2.15)	(-1.08)	(-0.44)
3	0.84	-0.02	0.06	0.07	1.02	-0.12	-0.04	-0.05	0.93	-0.07	-0.01	-0.01
	(2.22)	(-0.28)	(1.06)	(1.12)	(3.45)	(-1.89)	(-0.59)	(-0.71)	(3.81)	(-1.48)	(-0.26)	(-0.26)
4	0.82	-0.04	-0.02	-0.05	1.09	-0.04	-0.00	-0.01	0.95	-0.04	-0.03	-0.05
	(2.14)	(-0.77)	(-0.35)	(-0.85)	(3.76)	(-0.71)	(-0.01)	(-0.12)	(3.87)	(-1.11)	(-0.8)	(-1.07)
5	0.93	0.08	0.12	0.05	1.15	0.04	0.06	0.02	1.04	0.05	0.08	0.02
	(2.46)	(1.38)	(2.34)	(0.9)	(4.06)	(0.68)	(0.92)	(0.36)	(4.33)	(1.27)	(1.93)	(0.62)
6	0.93	0.08	0.09	0.03	1.20	0.10	0.07	0.06	1.06	0.09	0.07	0.04
	(2.53)	(1.56)	(1.73)	(0.65)	(4.32)	(1.9)	(1.3)	(1.11)	(4.64)	(2.04)	(1.9)	(1.03)
7	0.89	0.04	0.02	-0.03	1.19	0.10	0.01	-0.01	1.04	0.07	0.00	-0.04
	(2.4)	(0.66)	(0.37)	(-0.49)	(4.32)	(1.48)	(0.08)	(-0.18)	(4.42)	(0.99)	(0.02)	(-0.68)
8	0.93	0.10	0.05	0.06	1.23	0.15	0.01	-0.02	1.08	0.12	0.03	0.01
	(2.57)	(1.19)	(0.63)	(0.74)	(4.47)	(2.06)	(0.17)	(-0.24)	(4.69)	(1.55)	(0.51)	(0.17)
9	0.99	0.15	0.16	0.12	1.30	0.20	0.01	-0.03	1.15	0.17	0.10	0.05
	(2.65)	(1.6)	(1.77)	(1.27)	(4.52)	(2.11)	(0.18)	(-0.31)	(4.8)	(1.97)	(1.54)	(0.72)
10	1.19	0.35	0.36	0.27	1.34	0.26	-0.01	-0.04	1.26	0.29	0.19	0.13
	(3.15)	(3.15)	(3.66)	(2.7)	(4.61)	(2.11)	(-0.05)	(-0.39)	(5.21)	(2.8)	(2.39)	(1.53)
D10-D1	0.55***	0.61***	0.43***	0.33**	0.28	0.43**	-0.03	-0.11	0.42***	0.51***	0.28**	0.16
	(3.04)	(3.52)	(2.76)	(2.03)	(1.56)	(2.44)	(-0.18)	(-0.67)	(2.68)	(3.15)	(2.24)	(1.31)
D10-D5	0.26**	0.27**	0.24**	0.23**	0.18*	0.21*	-0.06	-0.06	0.22**	0.24**	0.11	0.10
	(2.3)	(2.42)	(2.29)	(2.08)	(1.69)	(1.93)	(-0.61)	(-0.6)	(2.19)	(2.26)	(1.25)	(1.16)

Table VIII
Portfolio Weights of D1, D5, and D10 Mutual Funds across *V/P* Stock Deciles

At the end of each June from 1981 to 2007, we compute for each fund a measure of *V/P* timing, *VPT*, which is defined as the weighted average of *V/P* decile ranks of individual stocks held by the mutual fund. We then sort mutual funds into deciles in ascending order based on *VPT* and calculate the equal-weight average fund characteristics for each decile portfolio. The D1 decile has funds with the lowest *VPT*s and D10 decile has funds with the highest *VPT*s. This table reports the portfolio weights in each stock *V/P* decile for different groups of mutual funds, D1, D5 and D10 funds respectively. The portfolio weight of a stock *V/P* decile is the total value of the funds' equity holdings. We report the time-series means of the portfolio weights. The t-statistics in parentheses are computed using Newey-West standard errors.

V/P Decile	D1 Funds Portfolio Weights (%)	D5 Funds Portfolio Weights (%)	D10 Funds Portfolio Weights (%)	D10-D1	D10-D5
1	21.19	10.38	3.40	-17.79	-6.99
				(-11.26)	(-6.71)
2	16.70	10.37	2.93	-13.78	-7.44
				(-9.04)	(-6.91)
3	12.88	11.74	3.23	-9.65	-8.51
				(-7.12)	(-7.94)
4	9.78	11.93	4.87	-4.91	-7.06
				(-4.37)	(-5.94)
5	8.21	11.87	5.74	-2.46	-6.13
				(-2.13)	(-4.45)
6	6.34	11.56	7.43	1.09	-4.14
				(1.02)	(-2.90)
7	5.26	11.69	8.74	3.47	-2.96
				(2.86)	(-2.16)
8	4.51	10.78	10.04	5.52	-0.75
				(4.60)	(-0.51)
9	3.82	9.73	13.78	9.96	4.04
				(7.99)	(2.76)
10	3.97	9.67	16.99	13.01	7.32
				(7.93)	(3.86)

Table IX

Mutual Fund Trading and the Return-Predictive Power of *V/P*

This table presents the performance of the quintile portfolios formed on the basis of value-to-price ratios, *V/P* conditional on mutual fund trading in the past 6 months. *V/P*, MFO, and number of funds holding a stock are defined as previously. We use independent two-way sorts. Specifically, at the end of each June from 1981 to 2007, we sort stocks into five quintile portfolios in ascending order based on *V/P* and independently sort these stocks again into three tertiles in ascending order based on mutual fund aggregate holding and trading information in the past 6 months (We use mutual fund ownership to measure fund holdings (Panel A) and use the changes of ownership or the changes of number of funds holding a stock to measure mutual fund trading (Panel B and C)). Then we compute the average monthly value-weight portfolio returns in the subsequent one year. This table presents the risk-adjusted performance of those portfolios based on the Carhart (1997) four-factor model. Stocks with prices lower than 1 dollar at the time of portfolio formation are excluded. The t-statistics are computed using the Newey-West standard errors. *** represents statistical significance at 1% level, ** represents statistical significance at 5% level, and * represents statistical significance at 10% level.

	Value-Weight Post-Ranking Portfolio Return (Carhart Alpha %/month)					
Ranking Var	V/P					
Panel A: MFO	1	2	3	4	5	Q5-Q1
1	-0.17	0.03	0.11	0.28	0.42**	0.59**
	(-0.92)	(0.27)	(0.7)	(1.89)	(2.04)	(2.1)
2	-0.13	-0.02	0.05	0.16	0.37**	0.50**
	(-1.02)	(-0.3)	(0.55)	(1.29)	(2.11)	(2.26)
3	-0.07	-0.15	-0.03	-0.06	0.36	0.43
	(-0.47)	(-1.43)	(-0.24)	(-0.39)	(1.45)	(1.51)
T3-T1	0.09	-0.19	-0.14	-0.34	-0.06	
	(0.46)	(-1.16)	(-0.67)	(-1.56)	(-0.19)	
Panel B: ΔNoF	1	2	3	4	5	Q5-Q1
1	0.00	-0.12	0.08	0.05	0.73***	0.73***
	(0.04)	(-0.96)	(0.61)	(0.35)	(3.38)	(3.02)
2	-0.12	-0.06	0.03	0.04	0.17	0.29
	(-0.84)	(-0.44)	(0.17)	(0.28)	(0.91)	(1.14)
3	-0.04	0.02	0.06	0.14	0.25	0.29
	(-0.27)	(0.24)	(0.8)	(1.31)	(1.6)	(1.25)
T3-T1	-0.04	0.14	-0.01	0.09	-0.48*	
	(-0.27)	(0.86)	(-0.08)	(0.56)	(-1.89)	
Panel C: ΔMFO	1	2	3	4	5	Q5-Q1
1	-0.05	-0.02	0.01	0.04	0.52***	0.57**
	(-0.32)	(-0.15)	(0.05)	(0.29)	(3.17)	(2.3)
2	-0.01	-0.07	-0.00	0.11	0.10	0.11
	(-0.04)	(-0.64)	(-0.01)	(0.82)	(0.57)	(0.4)
3	-0.17	-0.01	0.05	0.00	0.37	0.54
	(-1.05)	(-0.11)	(0.42)	(0.03)	(1.42)	(1.57)
T3-T1	-0.12	0.01	0.04	-0.04	-0.15	
	(-0.53)	(0.06)	(0.28)	(-0.18)	(-0.5)	