Is Variation on Valuation Too Excessive?
A Study of Mutual Fund Holdings

Hsiu-Lang Chen*

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Abstract

I first examine whether or not the fair value of financial instruments is priced consistently across mutual funds. Mutual funds price fair value differently for illiquid stocks, value stocks, and not-IPO-yet startups. I find that U.S. equity funds with an inclination for upbeat fair value tend to underperform others particularly in months following up-markets. When an equity fund performs poorly, has positive price dispersion in its holdings, or holds more illiquid stocks, the fund tends to have positive price dispersion again in the next quarter. This behavior is more significant when the stock market is more volatile. If the fair value of securities varies due to inconsistent valuation policies across mutual funds, a comparison of the portfolio weights on their securities could be problematic. I further present the economic impact of inconsistent fair value policies by U.S. equity funds.

Keywords: Fair Value; Mutual Funds

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On December 31, 2014, Transamerica BlackRock Global Allocation VP Fund could almost double its portfolio weight on Uber Technologies Inc. if it applies the same fair value to Uber shares as John Hancock Alpha Opportunities Trust does.[1] If two mutual funds hold an identical stock but assign a different fair value to the stock, a comparison of the portfolio weights on the stock could be problematic. In this study, I mainly address the issue of whether or not the fair value pricing policy of mutual fund holdings is consistent across the board and to what degree if it is not, and whether or not there is economic distortion resulting from the inconsistency.

In the mutual fund literature, several researchers have used mutual fund holdings to identify the security selection skills of fund managers. Based on the intuition that funds with similar ability may have similar holdings, Cohen, Coval, and Pastor (2005) combine fund holdings and fund returns into a new performance measure. They show that the new measure has higher predictive ability for fund performance than traditional fund alphas. Kacperczyk, Sialm, and Zheng (2008) show that the unobserved actions of mutual funds, measured by the gap between a fund's reported return and the hypothetical buy-and-hold return based on beginning-of-period holdings, are predictive of fund performance. Cremers and Petajisto (2009) find that measures of fund activeness based on fund portfolio holdings are positively related to future fund performance. Wermers, Yao, and Zhao (2012) provide a model to efficiently aggregate stock selection information across the stock portfolios of mutual funds based on the skill levels of the managers of the funds. If two mutual funds hold the same number of shares of a stock but assign a different fair value to the stock, a comparison of the portfolio weights on the stock could be problematic. Therefore, the results based on the a plain-vanilla use of fund holdings need to be interpreted with caution if there is variation in the fair value of securities that result from incoherent valuation policies across funds.

Mutual funds in the United States must value their portfolio holdings on a daily basis, based on market values if readily available. If there is no current market quotation for a security

[1] See Case B1 in Appendix B. If Transamerica BlackRock Global Allocation VP Fund (crsp_portno=1029667) applies fair value of $33.32 to a share of Uber as John Hancock Alpha Opportunities Trust (crsp_portno=1029263) does, it approximately increases its percentage of total net asset allocated to Uber from 0.17% to 0.31%.

or the market quotation is unreliable, a fund's board of directors or trustees has a fiduciary responsibility to determine a fair value for the security.[2] Given the importance of the pricing process, mutual funds have extensive policies and procedures designed to ensure that their portfolio securities are properly valued.

Arbitrage opportunities arise when a portfolio security is not traded at the time a mutual fund calculates its net asset value (NAV).[3] These arbitrage opportunities may enable short-term traders to dilute the NAV of mutual fund long-term investors. Fair valuation of a security in a fund can result in a reduction in the arbitrage opportunities that are available to short-term traders. However, the nature of a fair value pricing policy, as determined in good faith using procedures approved by a fund's board of trustees, is still not well known. The 2015 prospectus for the Fidelity Magellan Fund states that "Fair value pricing is based on subjective judgments and it is possible that the fair value of a security may differ materially from the value that would be realized if the security were sold." The 2015 prospectus for the College Retirement Equities Fund of TIAA-CREF states that "The use of fair value pricing can involve reliance on quantitative models or individual judgment …" and "Fair value pricing is subjective in nature …" In this study, I first address the issue of whether or not the fair value pricing policy of mutual fund holdings is consistent across the board and to what degree if it is not.

On May 10, 2004, the Securities and Exchange Commission (SEC) implemented a regulation that requires mutual funds to increase their disclosure frequency from a semiannual basis to a quarterly basis. A mutual fund is required to file its complete portfolio schedules for the second and fourth fiscal quarters on Form N-CSR, and to file its complete portfolio schedules for the first and third fiscal quarters on Form N-Q, within 60 days of the end of the quarter. The certification required for Form N-Q is similar to that for Form N-CSR. The certification on both

[2] See Section 2 (a) (41) of the Investment Company Act of 1940. Given the fund is still holding the security, its fair value should be consistent with the security's fundamental value perceived by the fund manager.

[3] For example, trading in a portfolio security is halted and does not resume before a mutual fund calculates its NAV. Also, the last trade of illiquid stocks typically occurs before the market closing. SEC guidelines indicate that open-end mutual funds (other than money market funds) should limit their investments in illiquid assets to 15% of the fund's net portfolio assets, with an illiquid asset defined as one that cannot be sold at or near its carrying value within seven days. See Revisions of Guidelines to Form N-1A of SEC Release No. IC-18612 (March 20, 1992).

forms requires a certifying officer to declare that the investment schedules in the report fairly present in all material respects the investments of the registrant as of the end of the fiscal quarter for which the report is filed.[4] The schedules of investments in the reports contain shares of securities and their market value; thus, the price per share can be calculated for each security on a report date. As a result, I can examine whether the implied price of the same security on the same report date is consistent across mutual funds. Although it is important to know whether the recorded price of a security reflects its true value, without an undisputable valuation model, however, I cannot determinately answer the question. Instead, I address the issue of whether mutual funds assign the same fair value to the security at the same report date and to what degree if it is not. In this study, the issue I investigate is related to but dissimilar to the stale price issue extensively documented in the mutual fund literature.[5] The inconsistent valuation issue I examine is also different from the inflating valuation issue documented by Carhart, Kaniel, Musto, and Reed (2002). Though they present evidence that fund managers inflate quarter-end

[4] Since Form N-CSR also contains complete financial statements, the certification in Form N-CSR additionally requires a certifying officer to state that the financial statements and other financial information fairly present the financial condition, results of operations, changes in net assets, and cash flows (if the financial statements are required to include a statement of cash flows) of the registrant as of, and for, the periods presented in the report. The link http://www.sec.gov/Archives/edgar/data/61397/000088019514001202/0000880195-14-001202-index.htm provides an example of N-CSR Form while the link http://www.sec.gov/Archives/edgar/data/61397/000087846714000790/0000878467-14-000790-index.htm provides an example of the N-Q Form.

[5] The stale price issue is particularly apparent in U.S. domiciled foreign equity funds. Chalmers, Edelen, and Kadlec (2001) document that mutual fund managers typically set fund share prices that fail to account for nonsynchronous trading in the fund's underlying securities. There are often material delays between a stock's last trade and the close of the market. These delays cause the returns of portfolios computed from closing prices to be predictable. Boudoukh, Richardson, Subrahmanyam, and Whitelaw (2002), Goetzmann, Ivkovic, and Rouwenhorst (2001), and Greene and Hodges (2002) report that a substantial volume of trade in fund shares is attributable to attempts to exploit predictable fund returns. Zitzewitz (2003) documents that in addition to short-term trading fees and trading frequency restrictions for preventing arbitrage, fund management companies have proposed or adopted two types of fair value pricing. One uses fair value pricing only on days with extreme market movements while the other uses a variety of fair value pricing methodologies. Goetzmann et al. (2001) outline a methodology that estimates a top-down correction to an international equity fund's NAV based on historical relations between its NAV and market indices. Chalmers et al. (2001) propose a bottom-up methodology that estimates a fund's NAV based on the market-updated prices of securities held by the fund. Rather than contesting the good faith of a fund's board of directors in making a fair value determination, I investigate the cross-sectional inconsistency of fair value pricing methodologies used by mutual fund companies on a security-by-security basis.

portfolio prices with last-minute purchases of stocks already held, they do not investigate whether a stock's inflated price is consistent across all mutual funds holding the stock.

My paper is not the first to examine the inconsistency of security valuations across mutual funds. Cici, Gibson, and Merrick (2011) investigate the dispersion of valuations on identical corporate bonds by different fixed income funds. They document that this dispersion is related to bond-specific characteristics associated with liquidity and market volatility. In addition, they show that bond mutual funds strategically mark bonds to smooth reported returns. Marking corporate bonds is hard because the overwhelming majority of bond trading takes place in over-the-counter dealer markets. Contrastingly, it seems trivial to value equities as they are typically traded on centralized exchanges. Given that U.S. equity prices are relatively transparent and information about U.S. equities is readily available, one would not expect mutual funds to have difficulty valuing their equity holdings. The findings of this study on the cross-fund price dispersion of equity holdings by U.S. equity funds show that equity valuation is problematic. This evidence suggests a need for further clarification of the fair value policy of mutual funds.

This paper makes several contributions to the literature. The first contribution is that I systematically analyze the financial instruments held by *all* mutual funds without restricting the analyses to stocks or bonds only, and assess variation on instrument valuation across all mutual funds. Over the sample period from January 2003 to March 2015, the median variation of valuation for a $50 U.S. stock indicates that it will have a standard deviation of 30 cents in the reported prices among the 38 mutual funds holding it; the median variation of valuation for a $100 U.S. bond indicates that it will have a standard deviation of 9 cents in the reported prices among the 3 mutual funds holding it.[6] Given that most equity trading takes place in centralized exchanges, one would not expect cross-fund price dispersion to exist in equities. Second, using Fama-MacBeth (1973) regressions, I find that startup firms before IPOs and illiquid stocks both

[6] Cici, Gibson, and Merrick (2011) report that the interquartile range of the prices reported by 2,268 bond funds owning a particular corporate bond at a particular date is $0.303 ($0.559) per each $100 of par value for investment-grade (high-yield) corporate bonds. For a corporate bond to be included in their sample, three or more funds must report the price of the identical bond as of the same date. They also show that there is a gradual decline in the bond price dispersion over the sample period from January 1995 to December 2006. Note that U.S. bond category in my study includes liquid U.S. Treasury securities.

have a higher variation in fair value as determined by mutual funds in the sample. Third, I find that domestic U.S. equity funds, which mark high values to their equity holdings, tend to underperform their competitors in the following quarter. Fourth, I examine whether the pricing patterns of U.S. equity funds could be associated with the return smoothing behavior shown in the bond fund study by Cici, Gibson, and Merrick (2011). I find that when an equity fund performs poorly, has positive price dispersion in its portfolio holdings, and holds more illiquid stocks, it tends to have positive price dispersion again in the next quarter. This behavior is more significant in quarters when the stock market is more volatile. The results are more consistent with mutual fund tournament behavior than with return smoothing behavior. Fifth, the discretionary fair value determined by all fund managers on a stock can still predict the stock's opening price next day even with a control of the stock's own daily return. The call for discretionary judgement on a stock's fair value could still reflect a fund manager's skill. Finally, I show the economic impact of inconsistent fair value policies by U.S. equity funds. Given that the median reported price on a stock by all mutual funds is informative about the stock's future price, I show changes in a fund's total net assets under management if I apply the median reported price to all stock holdings in the fund portfolio and recalibrate the portfolio weights for each fund portfolio. In terms of dollar changes in TNA due to recalibrated weights, I show that the difference between the median fund adopting a conservative fair-value policy and the median fund adopting an aggressive fair-value policy is about \$0.67 million, which is significant statistically and non-trivial economically.

The rest of the paper proceeds as follows. I describe the data in Section I. I present variation in the valuation of financial instruments held by mutual funds in Section II while explore potential explanations of the variations in valuation in Section III. In Section IV, I investigate whether U.S. equity funds that previously assign high values to their equity holdings tend to underperform others. I present cross-fund predictions on the price dispersion in valuations of equity fund holdings in Section V. In Section VI, I examine whether the discretionary fair value determined by all mutual funds on a stock is informative about the stock's future price. In Section VII, I present the economic impact of inconsistent fair value policies by U.S. equity funds. Finally, I conclude in Section VIII.

I. Data

The CRSP return files and the CRSP Survivor-Bias-Free US Mutual Fund Database constitute the main data sources. The CRSP Mutual Fund Database provides open-end mutual fund data for funds of all investment objectives, principally equity funds, taxable and municipal bond funds, international funds, and money market funds. CRSP switched its primary fund data source in 2008 from Morningstar to a combination of Lipper, which provides most data points, and Thomson, which provides most holdings data. In 2010, CRSP switched the holdings source from Thomson-Reuters and Lipper to solely Lipper's Global Holdings Feed.[7] The data cover mutual fund holdings for my sample period from January 2003 to March 2015.

I investigate whether mutual funds value their holdings in a consistent manner. I only consider financial instruments held by at least two mutual funds on a given date. To identify whether an instrument held by two mutual funds is the same instrument, I use crsp_company_keys assigned by CRSP. Some mutual funds trade financial instruments that are not securities, so those funds would not have PERMNOs or/and CUSIPs in their portfolios. Furthermore, mutual funds might trade securities that are not publicly traded. For example, Fidelity Contrafund held both Uber Technologies Inc. and Dropbox Inc. in June 2014 and they did not have an assigned PERMNO or CUSIP in the fund portfolio. Crsp_company_keys are assigned to all holdings in the CRSP Mutual Fund Database. According to the CRSP, crsp_company_keys should match up one-to-one with portfolio holdings and cannot be reused. Therefore, I use crsp_company_key to systematically address the issue of whether or not the fair value of mutual fund holdings is consistent across the board and to what degree if it is not.

At the end of each month, the portfolio holdings of *all* CRSP mutual funds are classified into eight categories: U.S. Equities (with PERMNO), Non-U.S. Equities (with PERMNO), U.S.

[7] There are irregularities in the CRSP mutual fund holdings, particularly prior to 2010. Stocks with a change in CUSIPs in the CRSP stock files are commonly duplicated in errors in the fund holdings. I confirm these errors with the actual fund holdings disclosure information in the SEC's EDGAR and remove them from the study.

Equities% (without PERMNO), Non-U.S. Equities% (without PERMNO), U.S. Bonds, Non-U.S. Bonds, Swaps, and Others. See Appendix A for classification details. For each position in mutual fund holdings, CRSP reports the identifiers (crsp_company_key and others), the name, number of shares held, market value, and the report date.[8] Therefore, the price per share can be calculated for each financial instrument in a fund's portfolio on the report date. To increase accuracy of the reported price calculation, I use double-precision floating-point format in the coding algorithm. To guard against data errors, a price reported by a fund on an instrument, which is more than 15% away from the median price of the instrument held by all mutual funds, is excluded. The use of 15% as the cut-off is based on anecdotal observations.[9] In Appendix B, there are two additional anecdotal cases demonstrating that mutual funds assign different values to the same financial instrument. In the CRSP Mutual Fund database, twelve funds in Case B1 report holding Uber Technologies Inc. at the end of 2014. The recorded shares and market value of Uber held by these funds in CRSP shown in Panel A are exactly matched with those in mutual fund filings in the SEC's EDGAR shown in Panel B.[10] The varying Uber prices demonstrate the inconsistent fair value policy across funds. These inconsistencies apply not only to not-IPO-yet startups but also to illiquid stocks. In the CRSP Mutual Fund database, nine funds report holding American Independence Corp (Ticker: AMIC) at the end of 2014, shown in Panel A of Case B2. Because there is no trading on AMIC on that day shown in Panel C, a variation exists for its fair value.

[8] According to CRSP, the report date is the date of holdings as reported by CRSP's sources while the effective date, another date recorded in CRSP mutual fund holdings file, is the date holdings information was received from CRSP's vendor.

[9] For example, Grind (2015) reports that four mutual funds price Uber differently. As of June 30, 2015, BlackRock Global Allocation Fund, Vanguard U.S. Growth Fund, Hartford Growth Opportunities Fund, and Fidelity Contrafund record Uber's price at $40.02, $39.64, $35.67, and $33.32 per share, respectively. The median price of these four is $37.66 and Contrafund prices Uber about 11.5% away from the median price. Since it is extremely difficult to value a high-tech startup, the 15% cut-off could be a reasonable threshold for allowing legitimate price differences. For a reference comparison, I also calculate two variables of variation on valuation based on the unfiltered data.

[10] In Case B1, the last seven funds voluntarily report portfolio holdings to Lipper, the data provider to CRSP, on 2014/12/31, and have their SEC filings in 2015. The portfolio holdings in their 2015 SEC filings are also recorded in CRSP database.

II. Excessive Variation on Valuation

To quantify the degree that funds might assign different fair value to the same instruments, I propose two measures of variation on valuation (*VV*) based on the filtered data, which exclude prices reported by funds on an identical instrument 15% away from the median reported price by all mutual funds on the instrument. The first variable (*VV1*) is the standard deviation of an instrument's price reported by all funds divided by the average reported price of the instrument ($VV1 \equiv \frac{\sigma(P)}{\bar{P}}$). This variable is known as the coefficient of variation, which measures the dispersion of data points in a data series around the mean. The second variable (*VV2*) is the average absolute difference between an instrument's reported price and its median reported price by all mutual funds divided by the median reported price ($VV2 \equiv \frac{\frac{1}{N}\sum|P-Median|}{Median}$). The variables, *VV1* and *VV2*, are used to quantify the inconsistency of the fair value pricing policy across all mutual funds in the sample on a security-by-security basis. The inconsistency is arisen because of different opinions by funds on a security or different models/parameters used by the funds to price the security.

Table 1 presents the summary statistics of fair value price discrepancy across funds. In the data, there are 4,678 U.S. equities per month with available PERMNOs held by all mutual funds and an equity is commonly held by 61 mutual funds. The average price dispersion in terms of the standard deviation per equity across funds is about 0.90% of the average price. For an average price of \$50 per share, the price dispersion implies that two funds holding the same equity might result in a price difference of \$0.45. In the second measure *VV*2, the average absolute price difference from the median price is about 0.56% of the median price. While mutual funds price non-U.S. bonds in a similar manner, there is smaller variation in their pricing of U.S. bonds. For example, the average of the two variation variables *VV*1 and *VV*2 is 0.64% and 0.42%, respectively, for U.S. bonds. The smaller variation in the pricing of U.S. bonds than the pricing for U.S. equities seems contradictory. Note that the median number of funds commonly holding an identical U.S. equity is about 38 while only about 3 funds hold an identical U.S. bond. It is uncommon to hold identical bonds because of different combinations of time-tomaturity and coupon rates even though the bond issuer could be the same. The low price variation of bonds relative to equites could be due to a mechanical reason—few bonds are identical.[11] The financial instruments of Swaps and Others exhibit higher average and standard deviation of the two variation variables. Note that not-IPO-yet startups are classified in the category of Others. Since the inputs for valuation of Swaps and Others are less observable or unobservable in the market, the determination of fair value requires more judgment, which in turn results in a higher variation.

Figures 1 and 2 present time series of variations on valuation. Figure 1A first shows the median number of mutual funds holding an identical instrument over time.[12] Although it seems that instruments other than equities are not commonly held by mutual funds, it might simply reflect that such instruments are less likely identical. Figure 1B shows the median fraction of funds reaches the 15% cut-off over time and apparently peaks in the third quarter of 2008, a high mark of the financial crisis. Table 1 also reports the ratio of number of funds reporting prices on an instrument beyond the 15% cut-off divided by the total unfiltered number of funds holding the instrument. In an untabulated result based on the unfiltered data, a U.S. stock is commonly held by 63 mutual funds on average. The average ratio of funds exceeding the 15% cut-off for U.S. stocks is 3.9%, which shows that about 2 (=0.039x63) funds reach the cut-off in a given report date. Figures 2A and 2B present time series of variation measures in a quarterly frequency. Although most financial instruments have a bigger variation in *VV*1 and *VV*2 during the recent financial crisis, the variation could exist cross-sectionally during the sample period and is examined in Section III.

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[11] According to the CRSP, a new crsp_company_key is assigned to the security whenever the name, ticker, or CUSIP changes. Arguably, the crsp_company_key might change too often, which makes identity match less practical. I re-calculate *VV*1 and *VV*2 based on a CUSIP match for defining identical instruments. The results are similar and available upon the request.

[12] The sharp drop in the number of funds holding a common instrument appears in the first quarter of 2015. This is because the first quarter disclosure of fund holdings had not been completed by May, which was when I extracted CRSP mutual fund holdings data for the analysis.

III. Further Analysis on Variation in U.S. Equity Valuation

As of the end of 2014, the total assets managed by U.S. open-end mutual funds are about $15.9 trillion. It is economically important to understand why mutual funds assign different values to their portfolio holdings. Given most equities are traded in stock exchanges and their prices are transparent, one would not expect such cross-fund price dispersion might exist in equities. In addition, Cici, Gibson, and Merrick (2011) document the cross-fund dispersion of fixed income fund valuations on a given corporate bond. In this study, I confine the further price dispersion analysis to U.S. equities with PERMNOs available. By excluding international equities, I can mitigate the influence of the stale price issue on the fair value variation of mutual fund equity holdings. Therefore, my analyses hereafter include all U.S. equities in the CRSP universe.[13]

According to a security's share code (SHRCD) in CRSP, I first classify U. S. equities into five groups, common stocks, exchange-traded funds (ETFs), closed-end funds (CEFs), real estate investment trusts (REITs), and others. I further investigate variation on valuation of these securities held by mutual funds in Table 2. In a given month, there are 3571 common stocks held by all mutual funds. As common stocks have been analyzed by many studies in the literature, a common stock is on average held by 76 mutual funds. The average price dispersion in terms of the standard deviation per common stock across funds is about 0.90% of the average price, while the average absolute price difference from the median price is about 0.55% of the median price. Among these five groups, REITs have the greatest dispersion in the reported prices by mutual funds regardless which variation measure is used.

Next, I explore causes for variation on valuation of individual stocks held by mutual funds. The explanatory variables for the variation include a stock's liquidity measure, relative volatility, firm size, book-to-market ratio, number of funds commonly holding it, and the number of months between the reporting date in the fund portfolio and its first trading date. Two variables of variation on valuation, *VV*1 and *VV*2, are constructed each month based on the

[13] Mutual funds might hold equities that are not necessary an ordinary common stock (CRSP share codes 10 and 11). For example, Chen (2016) documents that U.S. actively managed open-end equity funds hold exchange-traded equity funds in their portfolio holdings for hedging purposes. Since the focus of analyses hereafter is U.S. equities, I re-calculate *VV*1 and *VV*2 based on a PERMNO match for defining identical equities.

filtered data for stocks held by at least two mutual funds at the same report date. The stocks are sorted using *VV*1 or *VV*2 into deciles at the end of each month. A stock is assigned a rank score of one (the lowest) to ten (the highest) according to the stock's *VV*1 or *VV*2 measure. A stock with a zero variation measure is always assigned to Decile 1. As a result, the distribution of variation decile ranks is not a uniform distribution in a month when few stocks have a non-zero variation measure.[14]

I record the number of funds holding the stock (N_Funds) and the number of months (N_1stDate) between the constructed date of its *VV*1 or *VV*2 measure and its first trading date. The number of months is negative (positive) if the first trading date is after (before) the *VV*1 or *VV*2 construction date. A negative N_1stDate of a stock indicates that the stock is not IPO yet at the time mutual funds own it. For all firms in the CRSP/Compustat universe each month, I construct measures of size ($million), book-to-market (B/M), Amihud illiquidity (unit: 10^{-6}), Pastor and Stambaugh liquidity (P&S; unit: 10^{-2}), and relative volatility (RV) on the basis of individual stocks. Size is the firm's total market capitalization at the end of the month. The construction and timing of B/M follows Fama and French (1996) and is as of the previous December year-end. Stocks with a negative B/M are excluded. The illiquidity measure follows Equation (1) in Amihud (2002) and is on a monthly basis. The liquidity measure is the gamma used in Equation (1) in Pastor and Stambaugh (2003).[15] To remove market-wide shocks and better isolate the individual stock effect of volatility, I construct the monthly relative volatility measure, the standard deviation of a stock's daily returns in excess of the CRSP value-weighted market returns over a month. The list of characteristics is necessarily arbitrary, although they do possess some appeal ex ante.

Panel A of Table 3 shows the time series average and standard deviation of raw data for each variable. A large variation in liquidity measures and different units among variables might

[14] All stocks have zero variation measures in 28 months during our sample period. All occur before May 2006. An inclusion of these months will safely guard against one finding optimistic results.

[15] I follow the procedure of Pastor and Stambaugh (2003, p. 647) to estimate the gamma for all individual stocks. However, I do not exclude stocks with share prices below $5 and greater than $1,000 at the end of the previous month because their inclusion increases the complete description of mutual fund portfolios.

not provide a valuable comparison of the explanatory power of these characteristics. As a result, I construct the percentile rank scores for stocks in each characteristics variable. All stocks are sorted by the firm's measure at month-end and assigned a stock a percentile rank of zero (the lowest) to one (the highest) with one exception. For the percentile rank scores in B/M, I sort all firms by the firm's B/M at the beginning of each year and assign a firm a decile rank of zero to one. Although the percentile rank scores are constructed for all equities in the CRSP universe, in Table 3 I only report the results for the U.S. equities held by mutual funds.

I calculate the cross-sectional average for each variable for each month, as well as the Pearson correlation coefficients for each pair. I then report the time series average and standard deviation of each measure. Panel B of Table 3 shows that the number of funds holding the stock is positively correlated with the two variation variables, *VV*1 and *VV*2. A stock commonly held by many mutual funds is likely to have a higher variation on valuation. Some correlations are observed in an unexpected sign but could be due to confounding factors. At first glance, for example, the negative correlation between the variation variable and the Amihud illiquidity measure appears contradictory. However, the stocks held by mutual funds are relatively liquid and large in the entire stock universe. Thus, I do not wish to push the descriptive univariate analysis of variations on valuating stocks held by mutual funds too far. This leads to a multivariate regression analysis next.

I use Fama-MacBeth (1973) forecasting regressions to examine the variations on valuation of stocks held by mutual funds. The dependent variable is a stock's decile rank of *VV*1 or *VV*2 in month *t*. The explanatory variables in month *t*-1 include the stock's Amihud illiquidity, Pastor and Stambaugh liquidity, relative volatility, SIZE, B/M, N_1stDate, and N_Funds. All explanatory variables are in percentile rank scores. I run a cross-sectional regression every month from January 2003 to March 2015.

Panel A of Table 4 shows that illiquid stocks tend to have a higher variation on valuation. For example, a ten-percentile increase in the Amihud illiquidity measure will significantly move up the *VV*1 decile rank by 1.831 in Model 1. This result suggests that a stock becomes more illiquid, saying its Amihud illiquidity measure increases a decile rank in the CRSP stock universe, the decile rank on variation of fair values on the stock increases by 1.831 on the basis of all stocks held by at least two mutual funds. Although a higher Pastor and Stambaugh liquidity measure indicates a lower variation on valuation, the coefficient is not significant in Model 2. The lack of explanatory power indicated by the Pastor and Stambaugh liquidity measure is not inconsistent with Pastor and Stambaugh (2003). They point out that while their estimated liquidity measure seems appealing at the aggregate level, it is too noisy to be useful at the individual stock level. A not-IPO-yet startup or a newly listed equity typically in a low percentile rank in N_1stDate tends to have a higher variation on valuation. For example, a ten-percentile decrease in the N_1stDate measure significantly increases the *VV*1 decile rank by 0.324 in Model 1. A stock commonly held by many mutual funds is likely to have a higher variation on valuation. For example, a ten-percentile increase in N_Funds significantly increases *VV*1 decile rank by about 4.251 in Model 1. A value stock (higher B/M) tends to have a higher variation on valuation. For example, a ten-percentile increase in B/M significantly increases *VV*1 decile rank by 0.158 in Model 1, which may not be significant economically. Given that the correlation between the Amihud illiquidity measure and size is close to -0.926, as shown in Panel B of Table 3, I exclude size from the regressions in Models 3 and 4. The explanatory powers of Amihud illiquidity, B/M, N_1stDate, and N_Funds variables are still preserved with an exclusion of size in the models. A similar result is obtained when the dependent variable of the regressions is *VV*2.

For a robustness check, I reconstruct the distribution of variation decile ranks, the dependent variable, to a uniform distribution in a month when few stocks have a non-zero variation measure. Note stocks are sorted using *VV*1 or *VV*2 into deciles. I retain the decile ranks of all stocks with a non-zero variation measure, but randomly assign all stocks with a zero variation measure to a decile rank of one to ten so each decile can contain equal numbers of stocks. This approach makes the economic connection between explanatory variables and the variation variable less likely and will safely guard against one finding optimistic results. Furthermore, this approach can systematically address the estimation issue in a month when few stocks have a non-zero variation measure.[16] Panel B of Table 4 shows similar results.

IV. Pricing Inclination and Performance of U.S. Domestic Equity Funds

Because data for characterizing the U.S. equities in the CRSP universe is readily available and most of U.S. equity funds hold U.S. equities, in this section and hereafter I only investigate whether U.S. actively managed open-end equity funds that systematically assign high fair value to their portfolio holdings underperform those that do not.[17] Mutual funds have to invest at least 85% of total assets in liquid financial instruments, so unrealistic valuations are not sustainable in a fairly efficient market.

The reported prices on a given stock by *all mutual funds* in the CRSP universe are sorted first. A reported price on the stock held by a fund is assigned a rank score between zero (the lowest) and one (the highest), regardless whether the reported price is far away from the median

[16] Since the main research question in this section is to investigate what might explain variation in valuation, in another robustness check I exclude performing the cross-sectional regression in a month when fewer than 30 stocks have a non-zero variation measure. The result is stronger as expected. In another robustness check, I perform the cross-sectional regression quarterly using explanatory variables in quarter *t*-1 to explain the dependent variable in quarter *t*. I use the latest measure of variables in a quarter for the regressions. The explanatory power of Amihud illiquidity and N_Funds becomes stronger while the predictability of N_1stDate becomes weaker. Others are similar. The results of these two checks are available upon the request.

[17] Domestic equity funds have "E" and "D" in the first two characters of the CRSP Style Code (variable: *crsp_obj_cd*), which CRSP maps the objective codes of Strategic Insights, Wiesenberger, and Lipper into a continuous series. The third character "S" in the variable—*crsp_obj_cd*—indicates a sector fund. Some mutual funds switch from sector funds to non-sector funds or vice versa. I exclude sector funds and identify portfolios of non-sector funds based on their style codes at the beginning of each calendar quarter. I use the CRSP variable *index_fund_flag* to separate actively managed funds from passively managed funds. Prior to 2008, no such flag variable existed for an indicator of index funds. I follow Shive and Yun (2013) to classify funds as index funds based on the word "index" in the mutual fund names, in conjunction with a hand check. Mutual fund families introduced different share classes in the 1990s. Because different share classes have the same holdings composition, I aggregate all the observations pertaining to different share classes into one observation. For the qualitative attributes of funds (e.g., objectives and year of origination), I retain the observation of the oldest fund. For the total net assets (TNAs) under management, I sum the TNAs of the different share classes. Finally, for the other quantitative attributes of funds (e.g., returns and expenses), I take the weighted average of the attributes of the individual share classes, where the weights are the lagged TNAs of the individual share classes. To address the incubation bias documented by Elton, Gruber, and Blake (2001) and Evans (2010), following the procedure proposed by Kacperczyk, Sialm, and Zheng (2008), I exclude the observations in which the year of observation is prior to the reported fund-starting year and the observations in which the names of the funds are missing from the CRSP database. In addition, I include newly established funds in the calculation only after they first reach at least $5 million in assets under management. Once they reach the first threshold of $5 million, they remain in the sample until the end.

price or not.[18] I then subtract 0.5 from the price rank score in order to assign a score of 0 to the median observation. An assignment of a zero score to the median price ensures that a short position by an equity fund on a stock with a negative rank score can contribute a positive rank score to the fund's portfolio. To completely quantify the consistency of a fund's fair value pricing policy, I include the reported price of all stocks commonly held by at least two mutual funds without filtering the data. The conversion of price to a rank score mitigates the outlier problem in the reported prices. Since all of these complications add noise to the price rank score measure, they should make it more difficult for the measure to predict fund returns. In addition, to quantify the magnitude of overall value deviation on an equity fund's portfolio, on the basis of individual stock holdings I first calculate $\%PD \equiv \frac{P-Median}{Median}$, the percentage a stock's reported price deviates from the median. Note that the median reported price is identified for the given stock held by *all mutual funds*.

For each U.S. domestic equity fund portfolio, I then calculate both the value-weighted price rank score (VW_PR) and the value-weighted percentage of price deviation (VW_%PD) using a stock's percentage of the total net assets in the portfolio as a weight.[19] If a fund has multiple disclosures of portfolio holdings in a quarter, both VW_PRs and VW_%PDs are averaged first. While VW_PR quantifies an equity fund's pricing inclination in its fair value policy relative to other mutual funds, VW_%PD measures the overall percentage of price dispersion in the fund's holdings. Unlike VW_PR, the VW_%PD for an equity fund portfolio could be dominated by an extreme deviation of a stock in the portfolio. Thus, in calculating the VW_%PD for a fund's portfolio, stock holdings with the absolute value of %PD greater the 15% are excluded first as a safeguard against potential data errors. At the end of each calendar quarter from 2003 to 2014, equity funds are sorted into quintiles based on the VW_PR in the quarter.

[18] Since a cluster of reported prices is commonly observed, I rank unique reported prices on a given stock and assign each unique price a percentile rank score between zero (the lowest reported price) and one (the highest reported price) with an exception. The exception is the case when all funds price the stock identically and all will have a rank score of 0.5 on the stock. All funds that report the same price on a stock receive the same rank score.

[19] For the non-equity financial instruments held by equity funds, I assume that their price rank scores and price deviations are zero.

Funds in Quintile 1 (5), which have the lowest (highest) value-weighted price rank scores, are the ones that assign a low (high) fair value in their holdings. Each quintile portfolio is value-weighted, using as a weight the total net asset (TNA) value of a fund at the beginning of each month, and held for one month to three months following portfolio formation. I further classify a portfolio formation quarter as an up-market or down-market depending on whether the market's return that exceeds the risk-free rate is positive or negative over the quarter. For each holding period, the quintile portfolio's monthly net-of-expense excess returns are regressed against the five-factor (Fama-French's three factors, a momentum factor, and Pastor and Stambaugh's (2003) liquidity factor) portfolios. I perform a five-factor regression for the up-market and the down-market separately.

The results in Panel A of Table 5 show that funds in Quintiles 4 and 5 adopt a more aggressive fair-value policy and result in a negative and significant alpha consistently for one to three-month holding periods following the up-markets. On the other hand, funds in Quintile 1 employ a more conservative policy on fair value and result in a positive and significant alpha consistently for one to three-month holding periods following the up-markets. Interestingly, although the funds in Quintile 5 assign an average value that is 27.0 bps (VW_%PD) higher than the corresponding median in the portfolio formation quarter, they experience an almost complete reversal of 29.0 bps drop in the five-factor alpha in the following month. However, the market seems to reward funds in Quintile 1—they assign an average value that is 27.4 bps lower than the corresponding median in their portfolio holdings but generate 37.2 bps in the 5-factor alpha one month ahead. The hedge portfolio (Q1 – Q5) delivers positive and significant alphas of 66.2 bps to 41.1 bps for the holding period of one to three months. Panels B shows that funds in the extreme quintiles and the hedge portfolio deliver insignificant alphas in all three holding periods following the down-markets. It seems that variation in fair-value policy across equity funds is much larger in the down-markets as indicated by a large spread in VW_%PD between the extreme quintiles (52.9 bps versus -41.5 bps). Such a large variation in conjunction with few down-market quarters might contribute insignificant alphas. Table 6 reports the factor loadings of the five-factor model for the one-month holding period for each quintile. The hedge portfolio loads positively on the liquidity factor in the period following the up-market while it loads positively on the momentum factor in the period following the down-market. To other factors, the hedge portfolio has neutral exposures.

Given that equity funds historically assigning high fair value to their stock holdings tend to underperform others, it is important for investors to know what ex-ante investment styles of equity funds might have such a tendency. For each quarter, I classify domestic equity funds into 14 groups according to Lipper classification codes (CRSP variable: *lipper_class*): LCCE (Large-Cap Core Funds), LCGE (Large-Cap Growth Funds), LCVE (Large-Cap Value Funds), MCCE (Mid-Cap Core Funds), MCGE (Mid-Cap Growth Funds), MCVE (Mid-Cap Value Funds), SCCE (Small-Cap Core Funds), SCGE (Small-Cap Growth Funds), SCVE (Small-Cap Value Funds), MLCE (Multi-Cap Core Funds), MLGE (Multi-Cap Growth Funds), MLVE (Multi-Cap Value Funds), MAT+MT (Mixed-Asset Target-Date and Target-Allocation Funds), and others. I calculate the percentage of fund observations and fund net asset under management in each style each quarter for each quintile. The results in Panels A and B in Table 7 confirm that small-cap growth funds tend to take an optimistic approach while multi-cap value funds and others tend to take conservative approach when valuing their portfolio holdings. For example, the total assets managed by small-cap growth equity funds account for 4.74% of fund assets in Quintile 5 while it is for 3.29% Quintile 1, as shown in Panel B. The difference is statistically significant.

In a robustness check, I examine mutual fund performance adjusted for Lipper investment styles. Chan, Chen, and Lakonishok (2002) document that an approach using portfolio characteristics is more predictive of fund returns even though a fund's factor loadings and its portfolio characteristics generally yield similar conclusions about its style. I conduct the Lipper style-adjusted performance in an out-of-sample test. Equity funds are sorted into quintiles based on the value-weighted price rank score (VW_PR). According to a fund's Lipper classification at the time of the quintile portfolio formation, I calculate its Lipper's style-adjusted return, the fund's net-of-expense return minus the value-weighted return on the Lipper style to which the fund is assigned, for the following three months.[20] The result based on Lipper style-adjusted performance, which is untabulated, almost echoes what I find in the analysis of the five-factor alphas.

Given that U.S. equity market is fairly efficient and equity funds assigning high fair value to their stock holdings tend to underperform others, why do equity funds still adopt aggressive fair-value policy? Next, I examine whether an adoption of aggressive fair-value policy by fund managers can be an effective mechanism to mitigate fund outflow. I first calculate monthly net fund flows for each individual fund according to Sirri and Tufano (1998). The value-weighted net fund flows are then calculated for each quintile portfolio, using as a weight the total net asset (TNA) value of a fund at the beginning of each month. The quintiles are held for one month to three months following the portfolio formation. Panel A of Table 8 shows that funds in Quintile 5 employing aggressive fair-value policy are able to attract fund inflow one-month ahead, and experience insignificant fund outflow two-month ahead. Note that funds in Quintile 5 underperform others in all three months following the portfolio formation quarter in which the market is up. The hedge portfolio (Q1 – Q5) experience significant and positive net fund flow for the holding periods of two- and three-month. Though fund managers adopting aggressive fair-value policy can temporarily mitigate the adverse impact of poor performance on the fund flow, the evidence is weak. After knowing the consequence of adopting an aggressive fair-value policy by a fund manager, it is even more important to understand what might trigger the fund manager to price the fund's portfolio holdings higher than the median of reported prices by all mutual funds. I examine this issue next.

[20] Monthly returns for fourteen Lipper styles are constructed as follows: At the beginning each quarter, all U.S. equity funds are classified into fourteen groups according to a fund's Lipper classification code (CRSP variable: *lipper_class*): LCCE (Large-Cap Core Funds), LCGE (Large-Cap Growth Funds), LCVE (Large-Cap Value Funds), MCCE (Mid-Cap Core Funds), MCGE (Mid-Cap Growth Funds), MCVE (Mid-Cap Value Funds), SCCE (Small-Cap Core Funds), SCGE (Small-Cap Growth Funds), SCVE (Small-Cap Value Funds), MLCE (Multi-Cap Core Funds), MLGE (Multi-Cap Growth Funds), MLVE (Multi-Cap Value Funds), MAT+MT (Mixed-Asset Target-Date and Target-Allocation Funds), and others. The detailed description of Lipper classification codes can be found in http://www.crsp.com/products/documentation/lipper-objective-and-classification-codes. In the quarter following the portfolio formation, monthly value-weighted net-of-expense returns are calculated for each of Lipper style, using as a weight the total net asset (TNA) value of a fund at the beginning of each month.

V. Cross-Fund Prediction on Price Dispersion in Portfolio Holdings

In this section, I investigate whether the price dispersion of portfolio holdings is related to equity funds engaging in return smoothing behavior. Return smoothing involves marking positions such that a fund's net asset value is set above or below the true value of a fund's shares, resulting in wealth transfers across existing, new, and redeeming fund investors. According to the return smoothing hypothesis, high values ought to be observed for portfolio holdings positions when the fund reports returns that underperform the index. Conversely, low values ought to be observed for portfolio holdings positions when the fund reports returns that outperform the index. Cici, Gibson, and Merrick (2011) investigate whether bond mutual funds strategically mark bonds to smooth reported returns. They analyze individual bond marks on the basis of treating each holding by each fund on each date as a separate observation, and find results consistent with return smoothing.

To mitigate the issue of a few large fund portfolios in the sample that contain more than 1,000 securities and might dominate the results, I conduct a forecasting logistic regression at the portfolio level with each fund in a given quarter representing a distinct unit of observation. More importantly, I focus on understanding how individual equity funds determine their fair value policy. I relate the tendency for equity funds to fair value their underlying assets above the associated median reported price to the prior-quarter fund characteristics and market conditions. The dependent variable is a dummy variable that equals one for each fund portfolio in quarter t+1 that its value-weighted percentage of price deviation (VW_%PD) is positive. The main set of independent variables in quarter t include negative return (D_NEG), a dummy variable that equals one if the fund's past 12-month Lipper style-adjusted net-of-expense return is in the lowest negative return tercile; positive return (D_POS), a dummy variable that equals one if the fund's past 12-month Lipper style-adjusted return is in the highest positive return tercile; Amihud illiquidity measure; a natural log of total net asset value (TNA in $million); a fund's age in years; the market's quarterly excess returns; and the standard deviation of the market's three-month excess returns. In the estimation of logistic regression coefficients, all standard errors are adjusted for error correlations clustered by fund and quarter according to Petersen (2009).

The dummy variables, D_NEG and D_POS, are constructed similar to those of Cici, Gibson, and Merrick (2011). According to a fund's Lipper classification at the beginning of each measurement period, I first measure a fund's performance by its Lipper's style-adjusted return, which is the fund's net-of-expense return minus the value-weighted net-of-expense return on the Lipper style to which the fund is assigned. For each quarter, I group all the negative and positive Lipper style-adjusted returns separately and rank them within each group into terciles. D_NEG equals to one if a fund's Lipper past 12-month style-adjusted return as of the end of that quarter is in the bottom tercile of all negative returns. Similarly, D_POS equals to one if a fund's Lipper past 12-month style-adjusted return as of the end of that quarter is in the top tercile of all positive returns.

It is important to control the illiquidity of a fund's portfolio in order to test its return smoothing behavior. Getmansky, Lo, and Makarov (2004) find significant serial correlation in hedge fund returns and suggest that their findings could be driven either by problems in valuing illiquid assets or by discretionary returns management. To empirically distinguish between the illiquidity and discretionary returns management explanations, I include a fund's portfolio illiquidity measure in the regression. To construct it, I first sort all stocks in the CRSP universe according to the stock's Amihud illiquidity at month-end and assign a firm a percentile rank of zero (the lowest) to one (the highest). For each U.S. equity fund portfolio, I then calculate the value-weighted illiquidity rank score (VW_Illiquidity) using a stock's absolute percentage of total net assets in the portfolio divided the aggregate absolute percentages of all traded stocks and cash in the portfolio as a weight.[21] A fund's TNA is measured at the end of each quarter

[21] Broadly speaking, illiquidity is the difficulty with which a financial asset can be traded. To quantify illiquidity about a security, Amihud (2002) proposes a measure of price impact that is intuitive and simple to implement. However, it is less clear how to determine a mutual fund portfolio's liquidity constraints because the fund's portfolio is not traded. I propose *VW_Illiquidity*, $\frac{\sum_{i=1}^{N}|\omega_i|S_i}{\sum_{i=1}^{N}|\omega_i|}$, where *N* is the number of stocks and cash held by an equity fund portfolio, and S_i is a percentile score of Amihud (2002) illiquidity assigned to a security *i*. Cash is assigned a zero illiquidity score. A fund's portfolio holdings other than cash and stocks are implicitly assumed to have the same illiquidity score as the rest of the portfolio. Note that the absolute percentage is taken in the portfolio illiquidity measure to avoid the cross-elimination of illiquidity scores due to long and short positions in securities.

while a fund's age is the year difference between the calculation year and the fund's year of origination.

Additional independent variables include a dummy for the fund's VW_%PD being positive in quarter *t* and a dummy representing the fourth quarter each year. The dummy of the fund's lag VW_%PD is designed to control the fund's existing fair value policy in place. With inclusion of the lag VW_%PD, the model is able to detect other explanatory variables, which equity funds might take into consideration to influence their fair value policy next quarter away from the existing one. The dummy for the fourth quarter, D (4^{th} Quarter), is designed to capture a possible "window dressing" effect. Lakonishok, Shleifer, Thaler, and Vishny (1991) provide evidence that pension plans dump stocks deemed to be "mistakes" at the end of each quarter, although the practice is most pronounced in December and for small funds. Carhart, Kaniel, Musto, and Reed (2002) find that mutual fund managers mark up their holdings particularly at the fourth quarter end. A window dressed fund is more likely to report misleading holdings and thus, might contribute more in price dispersion in the portfolio holdings.

After checking with SEC filings, Schwarz and Potter (2016) document that the portfolio positions of the mutual funds in CRSP are inaccurate prior to 2008. As a result, I only run the forecasting logistic regression analysis for the sub-period, January 2009 to March 2015. Table 9 shows a positive and significant loading on D_NEG for all of the logit model specifications. These results imply that the probability of observing a fund's reported price above the median of prices reported by all mutual funds is higher when the fund performed poorly last quarter. When funds underperform their peers, the fund managers could be more desperate to discretionarily set fair value upward in order to stay in the mutual fund tournament. The results on the loadings on D_POS are almost insignificant across models. Unlike the findings of Cici, Gibson, and Merrick (2011) that corporate bond funds engage in return smoothing, my findings do not provide evidence that U.S. equity funds exhibit return smoothing behavior. Rather, they are more in line with the implications of tournament behavior—underperforming fund managers improve their positions by marking fair value favorably while outperforming managers preserve their lead positions by maintaining existing fair value policy.[22]

I find that the U.S. equity funds that assign a high fair value to their holdings do so across the sample period examined. In Model 4, the odds of observing a fund experiencing positive VW_%PD next quarter for the fund reporting positive VW_%PD this quarter over the odds of observing the fund experiencing positive VW_%PD next quarter for the fund reporting negative VW_%PD this quarter is 11.68. The results suggest that a mutual fund will adopt a fair value policy that will be consistent over time. Assigning higher fair values to holdings is consistently higher following volatile markets. The results for Model 4 show that when stock market volatility is 1% higher, the odds of observing a fund experiencing a positive VW_%PD next quarter is increasing about 18%. U.S. equity funds with more illiquid assets are more likely to assign a higher fair value to holdings. Model 4 also shows that a one-unit increase in the illiquidity percentile rank score results about 123% increase in the odds of observing a fund experiencing a positive VW_%PD next quarter. Other explanatory variables are not significant.

In a tournament, all mutual fund managers have an incentive to outperform their peers. However, the means and opportunity for mutual fund managers to engage in discretionary judgement for the determination of fair value could be significantly limited because of the SEC oversight regarding the valuation policies of mutual funds, particularly on their adherence to the policies. The majority of funds describe their valuation of investments in their prospectuses. They generally state "Portfolio investments are valued at fair value utilizing various valuation methods approved by the Board" without specifying the specific methods. Managers of funds concentrating on U.S. liquid stocks have little scope to shade their marks. However, my conjecture is that mutual fund managers likely have discretion to adjust the prices of their illiquid and thinly traded securities, particularly when the stock market is volatile. The findings show that the predictability of VW_Illiquidity and the market volatility are robust in all model

[22] Brown, Harlow, and Starks (1996) argue that in a mutual fund tournament, portfolio managers compete for better performance, greater fund inflows, and, ultimately, higher compensation. Specifically, they document that first-half underperforming managers increase their risk levels in an attempt to improve their positions against other managers, while first-half outperforming managers reduce risk levels to preserve their positions. Chen and Pennacchi (2009) show that declining performance does not necessarily lead a fund manager to raise the volatility of the fund's return but to increase the standard deviation of tracking errors.

specifications and support my conjecture. Cici, Gibson, and Merrick (2011) also document that price dispersion for individual bonds increases during periods when bond market return volatility is high.

VI. Is Fair Value Informative?

I have documented that equity fund managers are more likely engaging in discretionary judgement for the determination of fair value when in the prior quarter they performed poorly, had positive price dispersion in its portfolio holdings, or held more illiquid stocks. The result leads one to suspect that the discretionary determinant of fair value is likely reflecting a fund manager's price management. However, the call for discretionary judgement on a stock's fair value could still be reflecting a fund manager's skill if the determined fair value is informative about the stock's future price. I test this important issue next.

On a given reported date, stocks held by at least two mutual funds are included in the analysis. The median reported price is identified for a stock held by *all mutual funds* based on the filtered data, which exclude prices reported by funds on the stock 15% away from the median reported price by all mutual funds on the stock. I retrieve the stock's last closing price on the reported date and its opening price next day from the CRSP daily stock file, and test if the median reported price can predict the opening price next day in an OLS panel regression. The dependent variable is a stock's price percentage change from the last closing price to the next opening price while the independent variable is the stock's price percentage change from the last closing price to the median reported price on the stock held by all mutual funds. A stock's return on the reported day is included as a control. A stock on a given reported date is excluded from the regression analysis if the stock's last closing price falls below $1. The sample period is from January 2009 to March 2015. In total, there are 376,677 firm-day observations and about 70% of them have the median price reported by all mutual funds on a stock same as the stock's last closing price. The high percentage of 70 also indicates that the median reported price is the appropriate benchmark for evaluating fund fair value pricing. In the estimation, all standard errors are adjusted for error correlations clustered by both firm and year according to Petersen (2009).

Table 10 clearly shows that the median reported price on a stock held by all mutual funds significantly predicts the stock's opening price next day.[23] In Model 2 and 4 when a stock's daily return is included as a control, though the stock's day return predicts more on its overnight return, the discretionary fair value determined by all fund managers can still predict the stock's opening price next day. Therefore, the determined fair value at the aggregate level of all mutual funds is at least still informative about the stock's future price.

VII. The Economic Impact of Inconsistent Fair Value Policies

An advocate of fair value pricing might argue that variation in individual stock valuations by mutual funds is fairly innocuous. Variation on valuation at a portfolio level is all that is relevant to funds when setting NAV. Therefore, it is an important but uneasy task to quantify the economic impact of inconsistent fair value policy on a mutual fund's portfolio. Given that the median reported price on a stock by all mutual funds is informative about the stock's future price, I make an attempt to document the impact of inconsistent fair value policies by showing changes in a fund's total net assets under management if I apply the median reported price to all stock holdings in a given fund portfolio.

I recalibrate the portfolio weights for each fund portfolio. Suppose Stock *i*'s original weight in a fund portfolio is $\omega_i^O \equiv \frac{V_i^O}{TNA^O}$ where TNA^O is the fund's total net assets under management and V_i^O is the fund's investment on Stock *i*. Define $\Delta_i \equiv \frac{P_i^{Median} - P_i^{Fund}}{P_i^{Fund}}$, where P_i^{Fund} is the reported price by the fund on Stock *i* and P_i^{Median} is the median reported price by all

[23] Since the actual filing date of a fund's portfolio disclosure is later than its documented reported date, one may conjecture that the fund may assign a stock's fair value ex post according to the next opening price. Given the fact that the fund officer has to certify the fair value and only 4.8% of observations in the panel data have the median price reported by all mutual funds on a stock same as the stock's opening price next day, the conjecture is short of evidence. Note that among the 4.8% of observations mentioned, about 92% of them have the stock's last closing price same as its opening price next day.

funds on Stock i. Then Stock i's recalibrated weight in the fund portfolio is $\omega_i^{Recalibrated} = \frac{V_i^O(1+\Delta_i)}{TNA^O+\sum_{i=1}^{N}\Delta_i \times V_i^O} = \frac{\omega_i^O \times TNA^O \times (1+\Delta_i)}{TNA^O+\sum_{i=1}^{N}\Delta_i \times \omega_i^O \times TNA^O} = \frac{\omega_i^O \times (1+\Delta_i)}{1+\sum_{i=1}^{N}\Delta_i \times \omega_i^O}$, where N is the number of stocks held by the fund. To guard against data errors, I still apply the same filtering rule by excluding a stock held by the fund from portfolio weight recalibration if its price reported by the fund is more than 15% away from the median reported price by all mutual funds on the stock. An exclusion of extreme reported prices ensures a conservative measure in recalibration. Portfolio weights are recalibrated for the latest disclosure if the fund has multiple portfolio disclosures in a quarter. At the end of each quarter from January 2009 to March 2015, U.S. actively-managed open-end equity funds are sorted into quintiles based on the fund's value-weighted price rank score (VW_PR) as in Tables 5 to 8. Table 11 shows the quartile distribution as well as the average (AVG) and the standard deviation (SD) for three interest variables, TNA, Changes in Recalibrated Weights ($\sum_{i=1}^{N}\Delta_i \times \omega_i^O$), and Changes in TNA based on the Recalibrated Weights ($\sum_{i=1}^{N}\Delta_i \times \omega_i^O \times TNA^O$) in each quintile. The unit for the 2nd variable is a percentage while it is $million for the other two.

Panel A of Table 11 clearly indicates that extreme quintiles have similar total net assets under management in the inter-quartile range of distribution. Panel B shows that the median fund adopting conservative fair-value policy (Quintile 1) could increase overall portfolio weights by 0.404% while the median fund adopting aggressive fair-value policy (Quintile 5) would have to decrease overall portfolio weights by 0.296% if all funds adopt the same fair value policy of using the median reported price. The difference of the median changes in recalibrated weights between two extreme quintiles is 0.7%, which is statistically significant at 2%. An increase (decrease) in the recalibrated weights for a fund portfolio can be thought as a reduction (mark-up) of the fund's expense ratio because changes in the recalibrated weights lead to changes in the TNA. According to 2015 Fact Book published by Investment Company Institute, the median expense of all equity mutual funds is about 1.25% as of 2014. Therefore, the difference of 0.7% is economically significant. A difference of 0.7% could change a fund's leading position in the mutual fund performance tournament. In terms of dollar changes in TNA due to recalibrated weights, Panel C shows that the median fund adopting conservative fair-value policy (Quintile 1) could increase total net assets by $0.397 million while the median fund adopting aggressive fair-value policy (Quintile 5) would have to decrease $0.273 million. The difference is about $0.67 million, which is significant statistically and non-trivial economically. Again, the U.S. stock market is fairly efficient. Mutual fund managers need opportunities to engage in discretionary fair value on quite a few their stock holdings in order to have a measurable impact. Therefore, if one could zoom in on individual equity fund's quarterly changes in TNA due to recalibrated weights, one could observe that most of the changes concentrate in Year 2009 and the first quarter of 2010. This observation is consistent with Figures 2A and 2B showing that a big variation in security valuation reported by mutual funds occurs around Year 2008.

VIII. Conclusion

In this study, I address the issue of whether or not the fair value policy of mutual funds is consistent across the board and to what degree if it is not. I analyze the financial instruments held by all mutual funds without restricting the analyses to common stocks only, and examine variation on instrument valuation across all mutual funds. I further examine U.S. equities in detail. The results of forecasting regressions show that mutual funds value illiquid stocks, value stocks, and not-IPO-yet startups differently. To help understanding how a mutual fund's performance interacts with its fair value policy, I further investigate U.S. domestic equity funds. Equity funds that previously assign high value to their stock holdings tend to underperform others particularly in the month following an up-market.

Furthermore, the findings show that the fair value policy of underperforming funds is more consistent with mutual fund tournament behavior than with return smoothing behavior. When an equity fund performed poorly, had positive price dispersion in its portfolio holdings, or held more illiquid stocks, it tended to have positive price dispersion again in the next quarter. This behavior is more significant in the quarters when the stock market is more volatile. Furthermore, the discretionary fair value determined by all fund managers on a stock can still predict the stock's opening price next day even with a control of the stock's own daily return.

The call for discretionary judgement on a stock's fair value could still reflect a fund manager's skill. Finally, I present the economic impact of inconsistent fair value policies by mutual funds. I show changes in a fund's total net asset under management if I apply the median reported price to all stock holdings in the fund portfolio and recalibrate the portfolio weights for each fund portfolio. The difference between the median fund adopting a conservative fair-value policy and the median fund adopting an aggressive fair-value policy is about \$0.67 million, which is significant statistically and non-trivial economically.

If the fair value of securities varies due to inconsistent valuation policies across mutual funds, a comparison of the portfolio weights on their securities could be problematic. Therefore, the results based on a plain-vanilla use of fund portfolio holdings should be interpreted with caution. Alternatively, a regulatory requirement on the consistency in the fair value policies across mutual funds could be more effective.

Appendix A: Classifications of Mutual Fund Portfolio Holdings

At the end of each month, portfolio holdings of all CRSP mutual funds are classified into eight categories: U.S. Equities (with PERMNO), Non-U.S. Equities (with PERMNO), U.S. Equities% (without PERMNO), Non-U.S. Equities% (without PERMNO), U.S. Bonds, Non-U.S. Bonds, Swaps, and Others. I use the 8-character CUSIP numbers assigned by the CUSIP Service Bureau to issues of financial instruments, as well as permanent numbers (PERMNOs) assigned by CRSP to each equity security to classify fund holdings.

According to CUSIP, CUSIPs are not re-used. Issues with numeric values in both the seventh and eighth positions of CUSIPs are equity-type issues. Issues with a letter in either the seventh and/or eighth position of CUSIPs are debt-type issues.[24] Issues with a letter in the first position of CUSIPs are non-U.S. issues.[25] Therefore, the classification of the first six categories is described as follows:

1. U.S. Equities (with PERMNO): Fund holdings are U.S. equity-type issues according to CUSIPs and have PERMNOs.
2. Non-U.S. Equities (with PERMNO): Fund holdings are non-U.S. equity-type issues according to CUSIPs and have PERMNOs.
3. U.S. Equities% (without PERMNO): Fund holdings are U.S. equity-type issues according to CUSIPs and do not have PERMNOs.
4. Non-U.S. Equities% (without PERMNO): Fund holdings are non-U.S. equity-type issues according to CUSIPs and do not have PERMNOs.
5. U.S. Bonds: Fund holdings are U.S. debt-type issues according to CUSIPs.

[24] According to CUSIP, equity issues include American/Global Depositary Receipts, Common Shares, Exchange Traded Funds, Indices, Limited Partnerships, Mutual Funds, Preferred Shares, Real Estate Investment Trusts, Rights, Unit Investment Trusts, and Warrants. Debt issues include Asset Backed Securities, Certificates of Deposit–Retail, Certificates of Deposit-Institutional, Collateralized Debt Obligations, Collateralized Mortgage Obligations, Corporate Bonds, Medium Term Notes, Mortgage Backed Securities, Municipal Bonds, Secondarily-Insured Securities, Structured Products, U.S. Federal Government Agencies, and U.S. Treasuries (Bonds, Bills, and Notes). According to Data Descriptions Guide for CRSP U.S. Stock & U.S. Index Databases, the following items are included in the stock databases: Common Stocks, Certificates ADRs, Shares of Beneficial Interest Units (Depository Units, Units of Beneficial Interest, Units of Limited Partnership Interest, Depository Receipts, etc.), ETFs, Closed-End Mutual Funds, Foreigns on NYSE, NYSE MKT, NASDAQ, and NYSE Arca, Americus Trust Components (Primes and Scores), HOLDRs Trusts, REITs (Real Estate Investment Trusts). CRSP stock databases exclude: Rights and Warrants, Preferreds, Units Representing Common Stocks Bundled with Rights or Warrants, Over the Counter Bulletin Board Issues, When Issued Trading.

[25] For securities actively traded on an international basis that are either underwritten (debt issues) or domiciled (equities) outside the U.S. and Canada, the security will be identified by a CINS (CUSIP International Numbering System) identifier. CINS numbers employ the same Issuer (6 character)/Issue (2 character & check digit) concept espoused by the CUSIP Numbering System. Note that the first position of a CINS code is always represented by an letter, signifying the issuer's country code (domicile) or geographic region. See CUSIP_db Master File User Documentation, page 41.

6. Non-U.S. Bonds: Fund holdings are non-U.S. debt-type issues according to CUSIPs.

The remaining un-classified fund holdings have neither CUSIPs nor PERMNOs. Using the names of fund holdings as the main input, I use an algorithm in Practical Extraction and Report Language (PERL) that further identifies the remaining positions that contain an independent text string of ‘‘SWAP’’ or ‘‘TRS’’ (total return swap) in the names, and flag these instances as swap holdings in the seventh category: Swaps. All others are classified into in the eighth category: Others.

Appendix B: Anecdotal Cases of Variation on Valuation

Case B1: Uber Technologies Inc. (crsp_company_key: 4305445)

Panel A: CRSP Survivor-Bias-Free Mutual Fund Database

crsp_portno	report_dt	nbr_shares	market_val	*P*	(P-Median)/Median
1029667	20141231	129064	2341857	18.14	-0.395
1029263	20141231	142224	4738548	33.32	0.111
1025437	20141231	584504	19474212	33.32	0.111
1023383	20141231	759876	22785505	29.99	0.000
1023410	20141231	815160	24443241	29.99	0.000
1022061	20141231	2311920	69324817	29.99	0.000
1024477	20141231	2000820	59996228	29.99	0.000
1030227	20141231	4556	136615.4	29.99	0.000
1027368	20141231	168432	5050572	29.99	0.000
1024818	20141231	133140	4435902	33.32	0.111
1029265	20141231	277136	9233479	33.32	0.111
1027590	20141231	1059388	35296160	33.32	0.111

Panel B: Mutual Fund Filings at the SEC's EDGAR Website

crsp_portno	Form	report_dt	nbr_shares	market_val	Link
1029667	N-CSR	20141231	129064	2341857	https://www.sec.gov/Archives/edgar/data/778207/000119312515082708/d850143dncsr.htm
1029263	N-CSR	20141231	142224	4738548	https://www.sec.gov/Archives/edgar/data/756913/000114544315000330/d32131.htm
1025437	N-CSR	20141231	584504	19474212	https://www.sec.gov/Archives/edgar/data/756913/000114544315000330/d32131.htm
1023383	N-CSR	20141231	760000	22785000	https://www.sec.gov/Archives/edgar/data/790558/000114420415012531/v401890_ncsr.htm
1023410	N-CSR	20141231	815000	24443000	https://www.sec.gov/Archives/edgar/data/1053425/000114420415012529/v401889_ncsr.htm
1022061	N-Q	20150131	2312000	69325000	https://www.sec.gov/Archives/edgar/data/49905/000114420415019205/v404603_nq.htm
1024477	N-Q	20150131	2001000	59996000	https://www.sec.gov/Archives/edgar/data/1006415/000114420415019207/v404602_nq.htm
1030227	N-Q	20150131	5000	136000	https://www.sec.gov/Archives/edgar/data/1006415/000114420415019207/v404602_nq.htm
1027368	N-Q	20150131	168000	5050000	https://www.sec.gov/Archives/edgar/data/1006415/000114420415019207/v404602_nq.htm
1024818	N-CSR	20150131	133140	4436000	https://www.sec.gov/Archives/edgar/data/908695/000090869515000075/ncsrsstech013115.txt
1029265	N-CSR	20150228	277136	9233479	https://www.sec.gov/Archives/edgar/data/1331971/000114544315000613/d32275.htm
1027590	N-CSR	20150228	1059388	35296160	https://www.sec.gov/Archives/edgar/data/1331971/000114544315000613/d32275.htm

Note: The last seven funds voluntarily report portfolio holdings to Lipper on 2014/12/31 and their 2015 filings can be found in CRSP database.

Case B2: American Independence Corp (Ticker: AMIC; crsp_company_key: 3000791; PERMNO: 43617; crsp_shrcd: 11)

Panel A: CRSP Survivor-Bias-Free Mutual Fund Database

crsp_portno	report_dt	nbr_shares	market_val	*P*	(*P*-Median)/Median
1022819	20141231	14970	147604.2	9.86	0.000
1024865	20141231	7500	73950	9.86	0.000
1026804	20141231	1482	14612.52	9.86	0.000
1027484	20141231	765	8048	10.52	0.067
1030602	20141231	16900	166634	9.86	0.000
1031372	20141231	1800	17748	9.86	0.000
1033984	20141231	146	1439.56	9.86	0.000
1026884	20141231	848	8361.28	9.86	0.000
1027293	20141231	1020	10057.2	9.86	0.000

Panel B: Mutual Fund Filings at the SEC's EDGAR Website

crsp_portno	Form	report_dt	nbr_shares	market_val	Link
1022819	N-Q	20141231	14970	147604	http://www.sec.gov/Archives/edgar/data/1272950/000119312515069063/d875324dnq.htm
1024865	N-CSR	20141231	7500	73950	http://www.sec.gov/Archives/edgar/data/916006/000119312515078466/d846369dncsrs.htm
1026804	N-CSR	20141231	1482	14613	http://www.sec.gov/Archives/edgar/data/756913/000114544315000330/d32131.htm
1027484	N-Q	20141231	765	8048	http://www.sec.gov/Archives/edgar/data/1100663/000119312515065725/d875299dnq.htm
1030602	N-CSR	20141231	16900	166634	http://www.sec.gov/Archives/edgar/data/916006/000119312515078466/d846369dncsrs.htm
1031372	N-CSR	20141231	1800	17748	http://www.sec.gov/Archives/edgar/data/916006/000119312515078466/d846369dncsrs.htm
1033984	N-CSR	20141231	146	1440	http://www.sec.gov/Archives/edgar/data/1027263/000119312515073201/d833791dncsr.htm
1026884	N-Q	20150228	848	9074	http://www.sec.gov/Archives/edgar/data/205323/000032035115000121/Comm_main.htm
1027293	N-Q	20150131	1020	11000	http://www.sec.gov/Archives/edgar/data/898745/000089874515000289/finalonefifteennq.htm

Note: The last two funds voluntarily report portfolio holdings to Lipper on 2014/12/31 and their 2015 filings can be found in CRSP database.

Panel C: Daily Stock File in CRSP

Date	PRC	VOL	BID	ASK	SHROUT	OPENPRC	NUMTRD
20141229	10.55	1460	10.20	10.90	8079	10.55	18
20141230	10.26	3141	10.20	10.90	8079	10.55	35
20141231	-10.81	0	10.11	11.50	8079		0
20150102	10.45	122	10.20	10.90	8079	10.45	6
20150105	-10.55	155	10.20	10.90	8079		7

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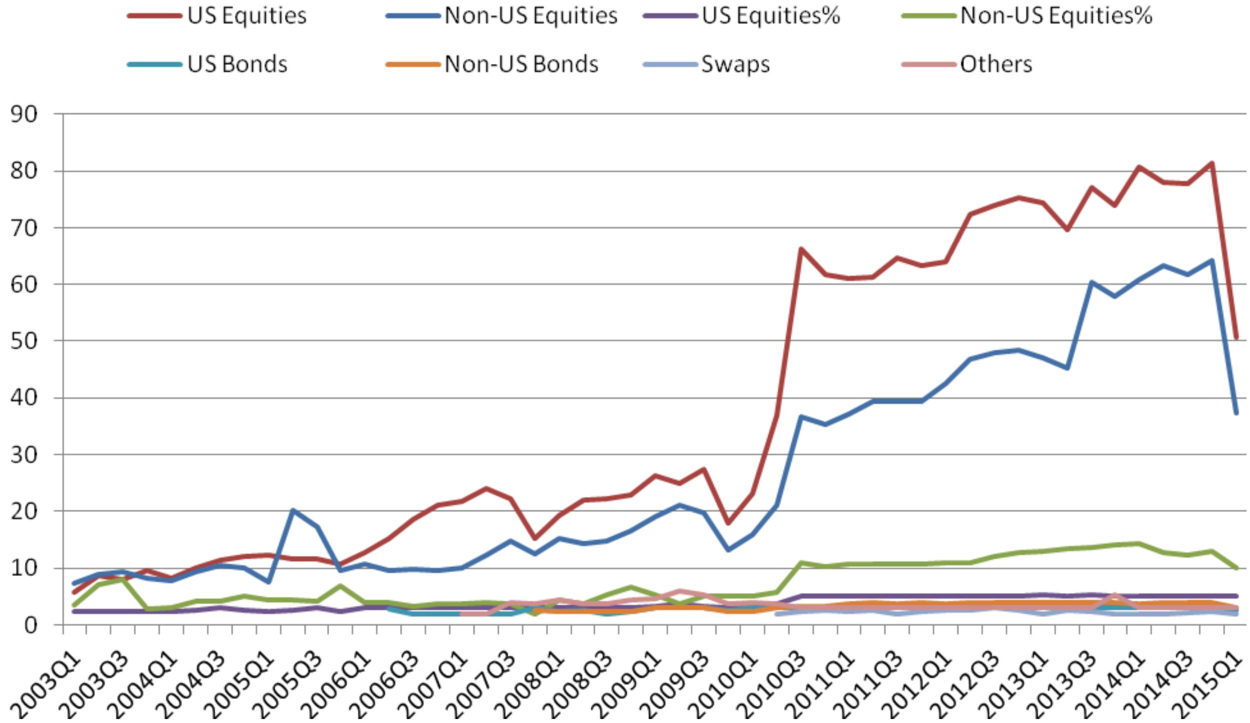

Figure 1A Time Series of Number of Funds Commonly Holding an Identical Instrument
For each financial instrument, the figure counts the number of funds commonly holding the instrument. The figure presents the median number across instruments in each category.

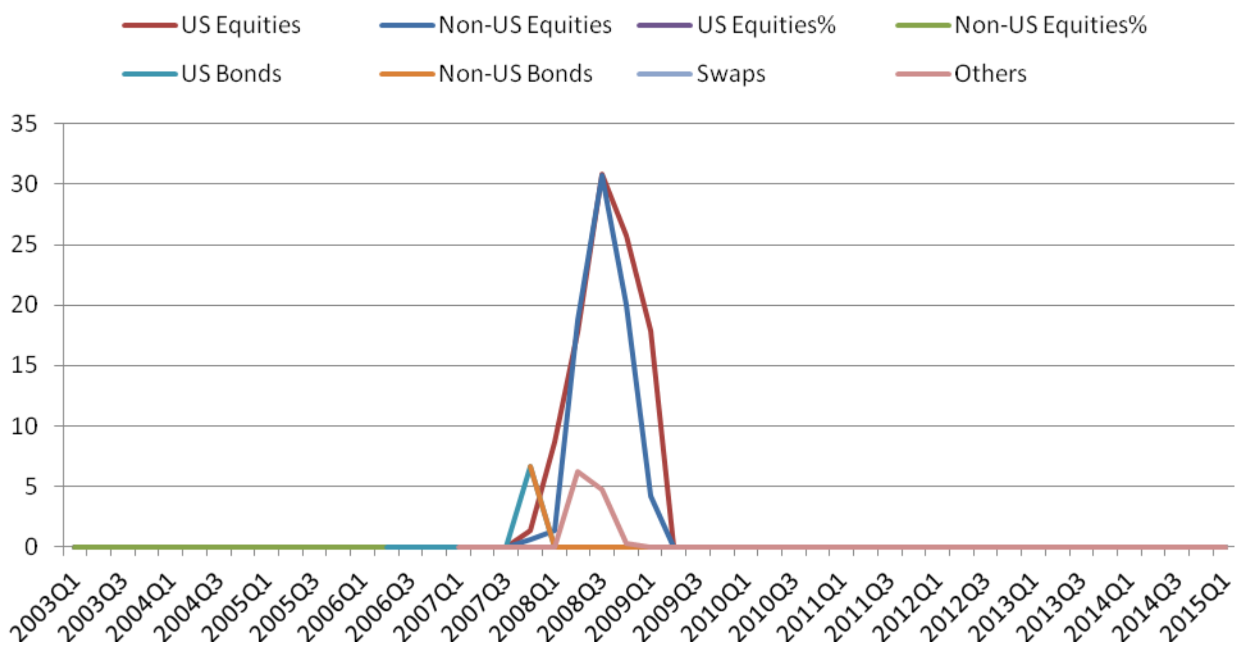

Figure 1B Time Series of Fraction of All Funds Pricing a Common Instrument 15% Away from the Median Price
For each financial instrument, the ratio (%) of number of funds reporting price on the instrument beyond the 15% cut-off divided by the total unfiltered number of funds holding the instrument is calculated. The figure presents the median fraction across instruments in each category.

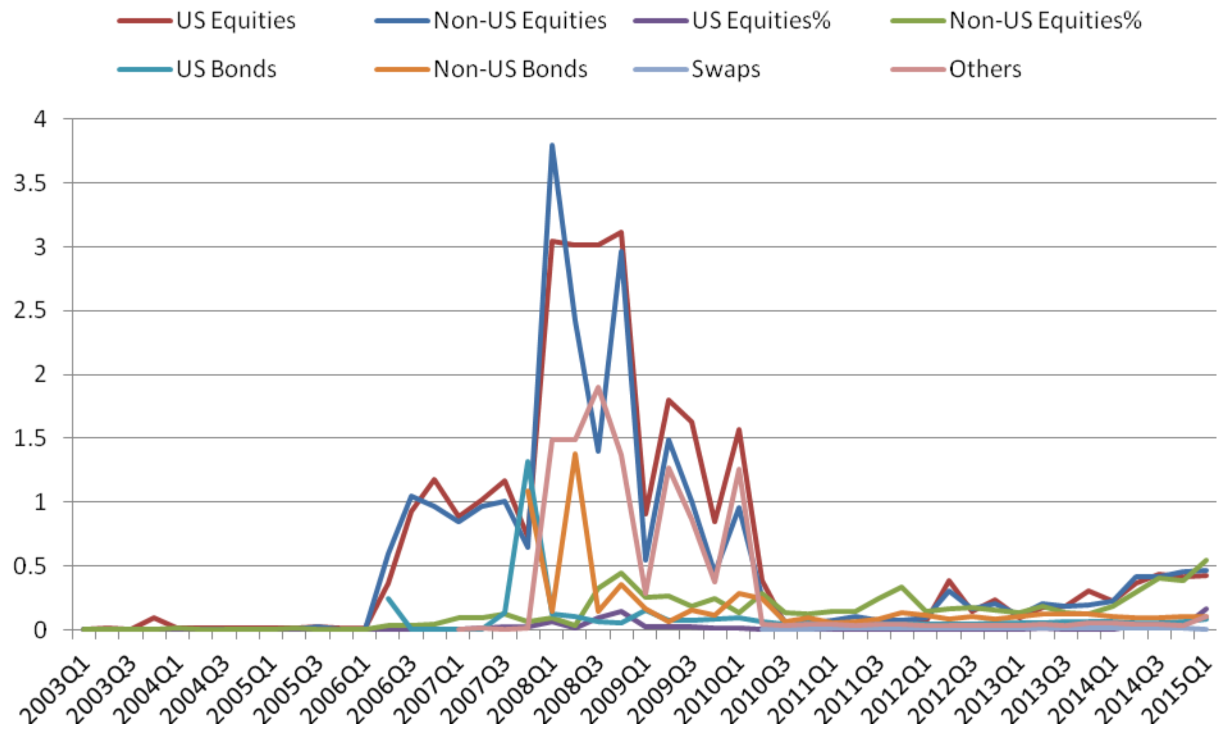

Figure 2A Time Series of Variation Variable *VV*1

For each financial instrument, *VV*1 is calculated in a percentage format. The figure presents the median *VV*1 across instruments in each category.

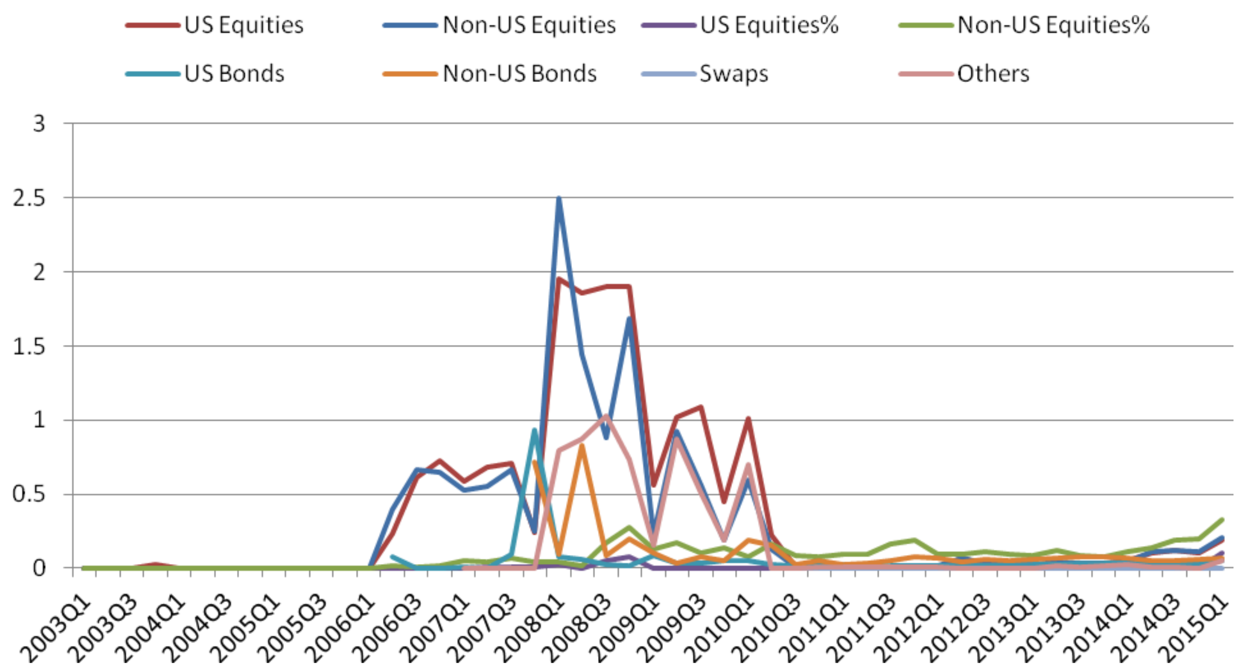

Figure 2B Time Series of Variation Variable *VV*2

For each financial instrument, *VV*2 is calculated in a percentage format. The figure presents the median *VV*2 across instruments in each category.

Table 1 Summary Statistics of Price Discrepancy

At the end of each month, the holdings of all CRSP mutual funds are classified into eight categories: U.S. Equities (with PERMNO), Non-U.S. Equities (with PERMNO), U.S. Equities% (without PERMNO), Non-U.S. Equities% (without PERMNO), U.S. Bonds, Non-U.S. Bonds, Swaps, and Others. For an instrument held by at least two mutual funds at the same report date (CRSP variable: *report_dt*), I examine the price discrepancy across funds. An instrument with a zero price in the fund holdings data is excluded. To further safely guard data errors, a price reported by a fund, which is more than 15% away from the median price of the instrument held by all mutual funds, is excluded first. Based on the filtered data, the table constructs the quartile distribution of three variables every month at the individual holding level, as well as the average and standard deviation across all fund holdings. The three variables are the number of funds holding a common instrument (*N*), the standard deviation of an instrument's price reported by all funds divided by the average reported price of the instrument ($VV1 \equiv \frac{\sigma(P)}{\bar{P}}$), and the average of the absolute difference between an instrument's reported price and the median reported price of the instrument held by all mutual funds divided by the median reported price ($VV2 \equiv \frac{\frac{1}{N}\sum|P-Median|}{Median}$). The latter two are the variables of variation on valuation (*VV*) in a percentage format. The variable NOBS denotes the number of securities for the quartile distribution. The table also reports the ratio of number of funds reporting price on an instrument beyond the 15% cut-off divided by the total unfiltered number of funds holding the instrument (%Cut-off) in a percentage format. Multiple instrument-day observations for an instrument are averaged across days in a month first. The table reports average statistics across months from January 2003 to March 2015.

	Quartile Distribution				
	25%	Median	75%	AVG	STD
Panel A: U.S. Equities (with PERMNO) (NOBS: 4678)					
N	7.49	37.59	84.52	61.00	74.29
$\frac{\sigma(P)}{\bar{P}}$	0.09	0.60	1.35	0.90	1.11
$\frac{\frac{1}{N}\sum\lvert P-Median\rvert}{Median}$	0.05	0.34	0.82	0.56	0.77
%Cut-Off	0.35	2.09	5.61	3.90	5.63
Panel B: Non-U.S. Equities (with PERMNO) (NOBS: 171)					
N	6.42	26.49	74.86	52.09	63.89
$\frac{\sigma(P)}{\bar{P}}$	0.07	0.51	1.22	0.83	1.06
$\frac{\frac{1}{N}\sum\lvert P-Median\rvert}{Median}$	0.04	0.28	0.75	0.53	0.74
%Cut-Off	0.13	1.54	4.61	3.07	4.59
Panel C: U.S. Equities% (without PERMNO) (NOBS: 1645)					
N	2.39	3.71	7.22	7.46	12.82
$\frac{\sigma(P)}{\bar{P}}$	0.00	0.01	0.45	0.54	1.35
$\frac{\frac{1}{N}\sum\lvert P-Median\rvert}{Median}$	0.00	0.01	0.26	0.35	0.93
%Cut-Off	0.00	0.00	0.81	1.34	4.50

Table 1—*Continued*

	Quartile Distribution				
	25%	Median	75%	AVG	STD
Panel D: Non-U.S. Equities% (without PERMNO) (NOBS: 4827)					
N	3.24	7.46	18.44	16.13	21.92
$\frac{\sigma(P)}{\bar{P}}$	0.05	0.15	0.31	0.29	0.59
$\frac{\frac{1}{N}\sum\lvert P - Median\rvert}{Median}$	0.03	0.08	0.18	0.17	0.38
%Cut-Off	0.00	0.00	0.32	0.39	2.32
Panel E: U.S. Bonds (NOBS: 38568)					
N	2.02	2.80	5.69	6.11	8.74
$\frac{\sigma(P)}{\bar{P}}$	0.03	0.09	0.64	0.64	1.30
$\frac{\frac{1}{N}\sum\lvert P - Median\rvert}{Median}$	0.02	0.06	0.41	0.42	0.89
%Cut-Off	0.00	0.20	0.44	1.00	3.42
Panel F: Non-U.S. Bonds (NOBS: 2134)					
N	2.11	3.35	7.11	5.52	5.33
$\frac{\sigma(P)}{\bar{P}}$	0.10	0.29	0.85	0.85	1.65
$\frac{\frac{1}{N}\sum\lvert P - Median\rvert}{Median}$	0.06	0.18	0.54	0.56	1.15
%Cut-Off	0.22	0.22	0.44	2.23	6.66
Panel G: Swaps (NOBS: 316)					
N	2.00	2.36	3.71	3.21	2.28
$\frac{\sigma(P)}{\bar{P}}$	0.00	0.00	1.04	1.49	3.37
$\frac{\frac{1}{N}\sum\lvert P - Median\rvert}{Median}$	0.00	0.00	0.67	1.02	2.35
%Cut-Off	0.00	0.00	30.31	17.57	26.93
Panel H: Others (NOBS: 4803)					
N	2.26	3.50	7.25	7.93	21.79
$\frac{\sigma(P)}{\bar{P}}$	0.00	0.33	1.25	1.04	2.06
$\frac{\frac{1}{N}\sum\lvert P - Median\rvert}{Median}$	0.00	0.19	0.80	0.69	1.45
%Cut-Off	0.00	0.35	3.91	4.48	11.54

Table 2 Variation on Valuation of US Equities Held by Mutual Funds

According to a security's share code (SHRCD in CRSP), this table further investigates variation on valuation of U.S. equities analyzed for Panel A of Table 1, and classifies the equities into five groups. Following the methodology of Table 1, this table reports the quartile distribution as well as the average and standard deviation of the same four variables, N, VV1 ($\frac{\sigma(P)}{\bar{P}}$), VV2 ($\frac{\frac{1}{N}\sum|P-Median|}{Median}$), and %Cut-off. The last three variables are in a percentage format. The variable NOBS denotes the number of securities in each group. The table reports average statistics across months from January 2003 to March 2015.

	Quartile Distribution				
	25%	Median	75%	AVG	STD
Panel A: Common Stocks (SHRCD: 10 & 11) (NOBS: 3571)					
N	20.70	54.48	101.62	76.27	79.64
$\frac{\sigma(P)}{\bar{P}}$	0.13	0.60	1.37	0.90	1.04
$\frac{\frac{1}{N}\sum\lvert P-Median\rvert}{Median}$	0.06	0.34	0.83	0.55	0.71
%Cut-Off	0.55	2.44	6.00	4.18	5.58
Panel B: : Exchange-Traded Funds (SHRCD: 73) (NOBS: 175)					
N	2.37	3.85	7.82	6.99	8.31
$\frac{\sigma(P)}{\bar{P}}$	0.01	0.30	1.03	0.75	1.17
$\frac{\frac{1}{N}\sum\lvert P-Median\rvert}{Median}$	0.01	0.17	0.64	0.48	0.78
%Cut-Off	0.00	0.10	1.55	1.21	2.80
Panel C: Closed-End Funds (SHRCD: 14, 44, & 74) (NOBS: 97)					
N	2.18	3.05	5.24	7.51	12.13
$\frac{\sigma(P)}{\bar{P}}$	0.05	0.40	1.06	0.80	1.16
$\frac{\frac{1}{N}\sum\lvert P-Median\rvert}{Median}$	0.03	0.23	0.70	0.53	0.78
%Cut-Off	0.03	0.14	1.57	1.41	3.25
Panel D: Real Estate Investment Trusts (SHRCD: 48) (NOBS: 36)					
N	50.01	80.94	112.23	86.72	51.84
$\frac{\sigma(P)}{\bar{P}}$	0.30	0.81	1.52	1.04	0.93
$\frac{\frac{1}{N}\sum\lvert P-Median\rvert}{Median}$	0.16	0.45	0.89	0.61	0.60
%Cut-Off	1.42	2.15	5.00	3.82	4.43
Panel E: Others (NOBS: 726)					
N	4.26	12.17	39.28	31.31	45.46
$\frac{\sigma(P)}{\bar{P}}$	0.04	0.49	1.32	0.92	1.35
$\frac{\frac{1}{N}\sum\lvert P-Median\rvert}{Median}$	0.02	0.27	0.80	0.58	0.93
%Cut-Off	0.14	1.53	4.25	3.23	5.81

Table 3 Statistics of Variables in Examining Variation on Valuation

Stocks are sorted by *VV*1 or *VV*2 into deciles at the end of each month. A stock is assigned a rank score of one (the lowest) to ten (the highest) according to the stock's *VV*1 or *VV*2. A stock with a zero variation measure is always assigned to Decile 1. The table reports the number of funds holding the stock (N_Funds) and the number of months (N_1stDate) between the constructed date of its *VV*1 or *VV*2 and its first trading date. The number of months is negative (positive) if the first trading date is after (before) the *VV*1 or *VV*2 construction date. For all firms in the universe of CRSP/Compustat each month, the table reports results for size ($million), book-to-market (B/M), Amihud illiquidity (unit: 10^{-6}), Pastor and Stambaugh liquidity (P&S; unit: 10^{-2}), and relative volatility (RV) on the basis of individual stocks. Size is the firm's total market capitalization at the month-end. The construction and timing of B/M follows Fama and French (1996) and is as of the previous December year-end. Stocks with a negative B/M are excluded. The illiquidity measure follows Equation (1) in Amihud (2002) on a monthly basis. The liquidity measure is the gamma in Equation (1) in Pastor and Stambaugh (2003). The monthly relative volatility measure in a percentage format is the standard deviation of a stock's daily returns in excess of the CRSP value-weighted market returns over a month. To create the percentile rank score for universe stocks in each characteristics variable, all firms are sorted by the firm's measure at the month-end and assigned a percentile rank of zero (the lowest) to one (the highest) with one exception. For the percentile rank scores in B/M, all firms are sorted by the firm's B/M at the beginning of each year and assigned a firm a decile rank of zero to one. This table only presents results for U.S. equities held by mutual funds. Each variable is first averaged cross-sectionally each month. Panel A reports the time series average and standard deviation of monthly measures. In Panel B, the Pearson correlation coefficients are calculated based on the percentile rank scores each month first and the time series average of the correlation coefficients is reported. Note that *VV*1 and *VV*2 are still in a decile rank. The average number of stocks available each month is reported in the row NOBS. The sample period is January 2003 to March 2015.

Panel A. Statistics of Variables

	*VV*1	*VV*2	Amihud	P&S	RV	Ln(Size)	Ln(B/M)	N_1stDate	N_Funds
A1. Raw Data									
AVG	4.44	4.38	1.56	-3.98	2.46	6.47	-0.22	200.93	63.22
STD	(2.52)	(2.57)	(25.86)	(269.06)	(1.92)	(1.82)	(1.26)	(187.33)	(75.18)
A2. Percentile Rank Scores									
AVG			0.41	0.50	0.52	0.60	0.49	0.65	0.50
STD			(0.27)	(0.29)	(0.27)	(0.25)	(0.28)	(0.23)	(0.29)
NOBS	4566	4566	4450	2418	4449	4442	3898	4566	4566

Panel B. Pearson Correlation Coefficients based on Percentile Rank Scores

	*VV*2	Amihud	P&S	RV	Size	B/M	N_1stDate	N_Funds
*VV*1	0.796	-0.211	0.002	-0.073	0.242	-0.059	0.097	0.362
*VV*2		-0.188	0.001	-0.075	0.219	-0.043	0.082	0.318
Amihud			-0.004	0.480	-0.926	0.140	-0.150	-0.725
P&S				-0.003	0.006	-0.003	0.019	0.007
RV					-0.495	-0.029	-0.185	-0.281
Size						-0.131	0.179	0.744
B/M							-0.006	-0.186
N_1stDate								0.302

Table 4 Fama-MacBeth Cross-Sectional Regressions of Variation on Valuation

This table reports Fama-MacBeth (1973) forecasting regression results of variations on valuation of U.S. equities held by mutual funds. The dependent variable is a stock's decile rank of *VV*1 or *VV*2 in month *t*. A stock is assigned a rank score of one (the lowest) to ten (the highest) according to the stock's *VV*1 or *VV*2. A stock with a zero variation measure is always assigned to Decile 1. As a result, the distribution of variation decile ranks is not a uniform distribution in a month when few stocks have a non-zero variation measure. The explanatory variables include the stock's Amihud illiquidity, Pastor and Stambaugh liquidity, relative volatility, SIZE, B/M, N_1stDate, and N_Funds in month *t*-1. All explanatory variables are in the percentile rank scores. The construction of variables is described in Table 3. A cross-sectional regression is run every month from January 2003 to March 2015. At least 30 observations are required for each regression. The table reports time series averages of the regression coefficients with Newey-West adjustment with three-month lags for potential heteroscedastic and serially correlated errors. The asterisk of ***, **, and * indicates statistical significance at the 1%, 5%, and 10% levels, respectively. The number of times that the coefficient is significant at 10% in the monthly runs is in brackets. Panel B reports the results for reconstructing the distribution of variation decile ranks to a uniform distribution in a month when few stocks have a non-zero variation measure. See the context for the details. There are 147 months in the sample period from January 2003 to March 2015. During the sample period, there are 28 months in which all stocks have zero variation measures.

Panel A: Coefficient Estimates in Monthly Regressions

Independent Variables	Dependent Variable							
	*VV*1				*VV*2			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Amihud	1.831***		1.091***		2.050***		0.944***	
	[124]		[134]		[125]		[129]	
Pastor & Stambaugh		-0.004		-0.005		-0.006		-0.007
		[25]		[26]		[27]		[28]
Relative Volatility	-0.263**	-0.324***	-0.350***	-0.204*	-0.376***	-0.471***	-0.506***	-0.415***
	[114]	[111]	[114]	[115]	[115]	[114]	[118]	[116]
SIZE	0.981***	-0.618***			1.475***	-0.336		
	[94]	[121]			[98]	[117]		
B/M	0.158***	0.170***	0.152***	0.154***	0.189***	0.206***	0.176***	0.184***
	[88]	[85]	[90]	[86]	[90]	[86]	[89]	[83]
N_1stDate	-0.324***	-0.292***	-0.336***	-0.296***	-0.329***	-0.296***	-0.344***	-0.320***
	[112]	[97]	[114]	[95]	[113]	[97]	[114]	[99]
N_Funds	4.251***	3.979***	4.367***	3.545***	3.604***	3.303***	3.782***	3.098***
	[142]	[144]	[142]	[146]	[135]	[135]	[140]	[142]
Adj. R^2 (%)	17.20	17.55	16.97	16.67	14.28	14.57	13.88	13.55
NOBS	3872	2167	3872	2167	3872	2167	3872	2167

Table 4—*Continued*

Panel B: Coefficient Estimates in Monthly Regressions with Reconstruction of Variation Distribution

Independent Variables	Dependent Variable							
	*VV*1				*VV*2			
	Model 1	Model 2	Model 3	Model 4	Model 1	Model 2	Model 3	Model 4
Amihud	1.649***		0.914***		1.814***		0.815***	
	[100]		[115]		[100]		[112]	
Pastor & Stambaugh		-0.016		-0.017		-0.019		-0.020
		[19]		[19]		[18]		[18]
Relative Volatility	-0.219*	-0.317***	-0.307**	-0.223**	-0.284**	-0.405***	-0.404***	-0.357***
	[98]	[95]	[100]	[108]	[97]	[99]	[103]	[105]
SIZE	0.980***	-0.484**			1.337***	-0.284		
	[79]	[123]			[85]	[119]		
B/M	0.134***	0.185***	0.129***	0.169***	0.160***	0.212***	0.149***	0.192***
	[73]	[66]	[76]	[69]	[73]	[71]	[73]	[67]
N_1stDate	-3.934***	-3.840***	-3.945***	-3.841***	-3.952***	-3.861***	-3.965***	-3.877***
	[129]	[111]	[130]	[110]	[130]	[107]	[129]	[111]
N_Funds	3.824***	3.789***	3.941***	3.438***	3.192***	3.130***	3.354***	2.942***
	[128]	[127]	[124]	[133]	[123]	[119]	[124]	[130]
Adj. R^2 (%)	32.12	31.25	31.89	30.36	29.26	28.28	28.89	27.27
NOBS	3872	2167	3872	2167	3872	2167	3872	2167

Table 5 Five-Factor Alphas of Fund Quintiles Sorted by Valuation on Stock Holdings

On a given reported date (CRSP variable: *report_dt*), stocks held by at least two mutual funds are included in the analysis. The reported prices on a given stock by all mutual funds are sorted first and a reported price of the stock is assigned a rank score between 0 (the lowest) and 1 (the highest). The table then subtracts 0.5 from the price rank score in order to assign a score of 0 to the median observation. In addition, the median reported price is identified for a given stock held by *all* mutual funds. The table calculates the percentage a reported price by a fund deviated from the median, $\%PD \equiv \frac{P-Median}{Median}$. For each U.S. equity fund portfolio, the table then calculates the value-weighted price rank score (VW_PR) and value-weighted percentage of price deviation (VW_%PD), using a stock's percentage of the total net assets in the portfolio as a weight. In calculation of VW_%PD for a fund portfolio, stock holdings with the absolute value of %PD greater the 15% are excluded from the calculation as a safe guard against data errors. If a fund has multiple disclosures of portfolio holdings in a quarter, both VW_PRs and VW_%PDs are averaged first. Equity funds are sorted into quintiles based on the fund's VW_PR in each quarter for the period from 2003 to 2014. A portfolio formation quarter is classified into an up-market or a down-market according to the market return in excess of the risk-free rate positive or negative in the quarter. The market returns are the value-weighted returns of all CRSP firms. Over the sample period, 34 quarters are classified as up-markets while 14 quarters are classified as down-markets. Funds in Quintile 1 (5) have the lowest (highest) value-weighted price ranks. VW_PR and VW_%PD are reported for each quintile portfolio using as a weight the total net asset (TNA) value of a fund at the beginning of the portfolio formation quarter. Each quintile portfolio is held for one month to three months following the portfolio formation, and value-weighted monthly returns are calculated for each quintile, using as a weight the total net asset (TNA) value of a fund at the beginning of each month. For each holding period, the quintile portfolio's monthly net-of-expense excess returns are regressed against the five-factor (Fama-French three factors, a momentum factor, and Pastor and Stambaugh (2003) liquidity factor) portfolios. The intercept and its associated *p*-value in parentheses are reported. The performance of the long/short hedge portfolio (Quintile 1 – Quintile 5) is also reported. All alphas and VW_%PD are in a percentage format.

Panel A. Performance Following the Up-Markets

	Portfolio Formation Quarter			Holding Period		
	# Funds	VW_PR	VW_%PD	1-Month	2-Month	3-Month
Quintile 1	389	-0.080	-0.274	0.372	0.194	0.173
				(0.011)	(0.035)	(0.030)
Quintile 2	388	-0.030	-0.022	0.182	0.046	0.100
				(0.160)	(0.570)	(0.139)
Quintile 3	388	0.003	0.040	0.030	0.024	0.028
				(0.653)	(0.625)	(0.533)
Quintile 4	388	0.034	0.098	-0.175	-0.145	-0.095
				(0.095)	(0.038)	(0.085)
Quintile 5	389	0.078	0.270	-0.290	-0.284	-0.238
				(0.066)	(0.002)	(0.001)
Q1- Q5				0.662	0.478	0.411
				(0.009)	(0.001)	(0.001)

Table 5—*Continued*

Panel B. Performance Following the Down-Markets

	Portfolio Formation Quarter			Holding Period		
	# Funds	VW_PR	VW_%PD	1-Month	2-Month	3-Month
Quintile 1	389	-0.133	-0.415	-0.263	-0.122	-0.213
				(0.421)	(0.556)	(0.145)
Quintile 2	389	-0.073	-0.179	-0.613	-0.279	-0.285
				(0.040)	(0.106)	(0.020)
Quintile 3	389	-0.034	0.037	-0.332	-0.105	-0.159
				(0.041)	(0.465)	(0.144)
Quintile 4	389	0.002	0.235	-0.706	-0.280	-0.264
				(0.033)	(0.167)	(0.069)
Quintile 5	390	0.072	0.529	-0.472	-0.229	-0.126
				(0.220)	(0.332)	(0.452)
Q1- Q5				0.209	0.107	-0.087
				(0.714)	(0.765)	(0.724)

Table 6 Risk Exposures of Fund Quintiles Sorted by Valuation on Stock Holdings

For brevity, this table reports the factor loadings of quintiles for the one-month holding period shown in Table 5. The table reports the coefficient estimates and the associated *p*-values in parentheses for the quintiles, as well as the long/short portfolio (Quintile 1 – Quintile 5). One exception is that the *p*-value for a quintile's β_{RMRF} is to test the null hypothesis if β_{RMRF} equals to one.

	β_{RMRF}	β_{SMB}	β_{HML}	β_{MOM}	β_{LIQ}	Adjusted R^2(%)
Panel A. The Period Following the Up-Markets (Number of observations: 34 months)						
Quintile 1	0.895	0.085	0.055	0.002	0.072	95.04
	(0.035)	(0.143)	(0.329)	(0.957)	(0.090)	
Quintile 2	0.902	0.043	-0.007	0.033	0.053	95.43
	(0.034)	(0.422)	(0.892)	(0.422)	(0.178)	
Quintile 3	0.964	-0.005	-0.039	0.033	0.006	98.84
	(0.125)	(0.844)	(0.154)	(0.120)	(0.777)	
Quintile 4	0.977	0.054	-0.08	0.013	-0.02	97.44
	(0.516)	(0.209)	(0.064)	(0.700)	(0.521)	
Quintile 5	1	0.13	-0.069	0.062	-0.05	94.99
	(0.994)	(0.051)	(0.271)	(0.210)	(0.287)	
Q1- Q5	-0.104	-0.044	0.124	-0.06	0.122	5.87
	(0.215)	(0.658)	(0.207)	(0.435)	(0.099)	
Panel B. The Period Following the Down-Markets (Number of observations: 14 months)						
Quintile 1	1.065	0.026	-0.210	0.046	-0.028	98.52
	(0.282)	(0.858)	(0.188)	(0.280)	(0.655)	
Quintile 2	1.044	-0.077	-0.194	-0.027	-0.010	99.03
	(0.361)	(0.519)	(0.140)	(0.427)	(0.839)	
Quintile 3	0.997	-0.115	-0.068	-0.072	0.030	99.71
	(0.901)	(0.100)	(0.321)	(0.003)	(0.289)	
Quintile 4	1.029	-0.216	-0.060	-0.098	0.040	98.92
	(0.580)	(0.119)	(0.656)	(0.024)	(0.470)	
Quintile 5	0.977	-0.063	-0.242	-0.193	-0.006	98.23
	(0.726)	(0.705)	(0.186)	(0.003)	(0.930)	
Q1- Q5	0.088	0.089	0.032	0.239	-0.022	47.29
	(0.403)	(0.730)	(0.906)	(0.010)	(0.844)	

Table 7 Lipper Investment Styles of Fund Quintiles Sorted by Valuation on Stock Holdings

U.S. actively managed open-end equity funds are sorted into quintiles based on the fund's VW_PR defined in Table 5. For each quarter of the January 2003 to March 2015 sample period, equity funds are classified into 14 groups according to a fund's Lipper classification code (CRSP variable: *lipper_class*): LCCE (Large-Cap Core Funds), LCGE (Large-Cap Growth Funds), LCVE (Large-Cap Value Funds), MCCE (Mid-Cap Core Funds), MCGE (Mid-Cap Growth Funds), MCVE (Mid-Cap Value Funds), SCCE (Small-Cap Core Funds), SCGE (Small-Cap Growth Funds), SCVE (Small-Cap Value Funds), MLCE (Multi-Cap Core Funds), MLGE (Multi-Cap Growth Funds), MLVE (Multi-Cap Value Funds), MAT+MT (Mixed-Asset Target-Date and Target-Allocation Funds), and others. The percentage of fund observations in each style group is calculated to the total number of all funds each quarter for each quintile. Total fund net asset value is also calculated across all funds assigned to each style group and expresses relative to the total net assets of all funds each quarter for each quintile. The table reports the average of percentages across quarters in each style group for each quintile, as well as the long/short hedge portfolio (Quintile 1 – Quintile 5). The *p*-values are reported in parentheses for the null hypothesis that the average of differences is zero.

Open-End Equity funds	Lipper Classification Codes													
	LCGE	LCCE	LCVE	MCGE	MCCE	MCVE	SCGE	SCCE	SCVE	MLGE	MLCE	MLVE	MAT+MT	Other
Panel A. The style distribution by percentages of fund observations														
Quintile 1	9.72	11.21	6.74	5.89	4.26	3.39	6.29	9.38	4.36	5.80	9.76	6.77	3.62	8.19
Quintile 2	10.06	12.25	5.88	7.98	5.09	3.96	6.96	7.97	3.65	6.72	9.86	5.60	2.18	7.23
Quintile 3	9.30	11.39	5.99	7.44	5.26	3.49	8.16	9.14	4.49	6.69	10.76	5.25	1.41	6.63
Quintile 4	9.49	12.20	5.68	7.31	4.55	3.29	9.44	9.68	4.33	6.55	9.93	4.80	1.51	6.65
Quintile 5	10.06	10.90	5.31	7.69	4.64	3.08	9.24	10.42	4.67	6.15	9.51	5.31	1.55	6.87
Q1 - Q5	-0.34	0.31	1.44	-1.80	-0.38	0.31	-2.95	-1.03	-0.31	-0.35	0.26	1.46	2.07	1.32
p-value	(0.34)	(0.31)	(0.05)	(0.02)	(0.17)	(0.18)	(0.00)	(0.15)	(0.22)	(0.19)	(0.25)	(0.05)	(0.04)	(0.05)
Panel B. The style distribution by percentages of fund net assets														
Quintile 1	13.38	14.41	10.39	5.30	4.22	3.61	3.29	6.80	2.51	6.03	8.74	8.29	1.19	7.23
Quintile 2	11.93	15.58	10.60	6.31	3.80	3.16	3.27	4.34	1.27	10.63	8.51	8.73	0.79	6.47
Quintile 3	11.13	14.70	13.50	5.50	3.23	2.37	2.79	5.12	1.90	13.67	8.24	5.42	0.84	6.97
Quintile 4	12.35	16.06	12.17	4.38	3.65	2.69	3.72	5.31	1.78	10.38	9.75	4.89	0.73	7.52
Quintile 5	12.31	14.44	10.28	6.04	3.85	2.75	4.74	6.81	2.23	10.26	9.07	6.23	1.01	5.37
Q1 - Q5	1.07	-0.04	0.11	-0.73	0.37	0.85	-1.44	-0.01	0.28	-4.23	-0.33	2.06	0.18	1.87
p-value	(0.20)	(1.00)	(1.00)	(0.16)	(0.20)	(0.07)	(0.03)	(1.00)	(0.21)	(0.01)	(0.30)	(0.07)	(0.31)	(0.03)

Table 8 Net Fund Flow of Fund Quintiles Sorted by Valuation on Stock Holdings

At the end of each calendar quarter from 2003 to 2014, U.S. actively-managed open-end equity funds are sorted into quintiles based on the fund's value-weighted price rank score (VW_PR). Funds in Quintile 1 (5) have the lowest (highest) VW_PRs. VW_PR and VW_%PD are defined in Table 5 and reported for each quintile portfolio. According to the definition of net fund flows by Sirri and Tufano (1998), the table first calculates monthly net fund flows for each individual fund. The value-weighted net fund flows are then calculated for each quintile portfolio, using as a weight the total net asset (TNA) value of a fund at the beginning of each month. The quintiles are held for one month to three months following the portfolio formation. The *p*-value reported in the parenthesis is associated with a null hypothesis that the average of net fund flows over a holding period is zero. A portfolio formation quarter is classified into an up-market or a down-market according to the market return in excess of the risk-free rate positive or negative in the quarter. The market returns are the value-weighted returns of all CRSP firms. All net fund flows and VW_%PD are in a percentage format. The net fund flows of the long/short hedge portfolio (Quintile 1 – Quintile 5) is also reported.

	Portfolio Formation Quarter			Holding Period		
	# Funds	VW_PR	VW_%PD	1-Month	2-Month	3-Month
Panel A. Net Fund Flow Following the Up-Markets						
Quintile 1	389	-0.080	-0.274	0.178	0.120	0.121
				(0.114)	(0.123)	(0.077)
Quintile 2	388	-0.030	-0.022	0.113	0.081	0.025
				(0.254)	(0.247)	(0.676)
Quintile 3	388	0.003	0.040	0.147	0.056	0.011
				(0.094)	(0.401)	(0.835)
Quintile 4	388	0.034	0.098	0.093	0.044	-0.034
				(0.323)	(0.493)	(0.525)
Quintile 5	389	0.078	0.270	0.048	-0.102	-0.189
				(0.565)	(0.292)	(0.011)
Q1- Q5				0.130	0.223	0.309
				(0.350)	(0.074)	(0.002)
Panel B. Net Fund Flow Following the Down-Markets						
Quintile 1	389	-0.133	-0.415	-0.293	-0.303	-0.340
				(0.092)	(0.005)	(0.000)
Quintile 2	389	-0.073	-0.179	-0.328	-0.294	-0.281
				(0.032)	(0.004)	(0.001)
Quintile 3	389	-0.034	0.037	-0.321	-0.216	-0.231
				(0.122)	(0.110)	(0.044)
Quintile 4	389	0.002	0.235	-0.330	-0.290	-0.262
				(0.047)	(0.012)	(0.017)
Quintile 5	390	0.072	0.529	-0.325	-0.232	-0.218
				(0.174)	(0.104)	(0.061)
Q1- Q5				0.032	-0.070	-0.122
				(0.909)	(0.680)	(0.378)

Table 9 Return Smoothing or Tournament Behavior

This table reports a forecasting logistic regression that relates the tendency for equity funds to mark above the median reported price to the prior-quarter fund characteristics and market conditions. The analysis is done at a fund portfolio level with each fund in a given quarter representing a distinct unit of observation. The dependent variable is a dummy variable that equals one for each fund portfolio in quarter $t+1$ that its value-weighted percentage of price deviation (VW_%PD) is positive. The VW_%PD is defined in Table 5. The main set of independent variables in quarter t include Negative Return (D_NEG), a dummy variable that equals one if the fund's past 12-month Lipper style-adjusted return is in the lowest negative return tercile; Positive Return (D_POS), a dummy variable that equals one if the fund's past 12-month Lipper style-adjusted return is in the highest positive return tercile; Amihud illiquidity measure; a natural log of total net asset value (TNA in $million); a fund's age in years; the market's quarterly excess returns; and the standard deviation of the market's 3-month excess returns. The dummy variables, D_NEG and D_POS, are constructed as follows. According to a fund's Lipper classification at the beginning of each measurement period the table first measures the fund performance by its Lipper's style-adjusted return, the fund's net-of-expense return minus the value-weighted net-of-expense return on the Lipper style to which the fund is assigned. Lipper fourteen style classifications, defined in Table 7, are used. Each quarter the table groups all the negative and positive Lipper style-adjusted returns separately and ranks them within each group into terciles. D_NEG equals to one if the fund's Lipper past 12-month style-adjusted return as of the end of that particular quarter is in the bottom tercile of all negative returns. Similarly, D_POS equals to one if the fund's Lipper past 12-month style-adjusted return as of the end of that particular quarter is in the top tercile of all positive returns. To construct a fund's portfolio illiquidity measure, the table first sorts all stocks in the CRSP universe according to the stock's Amihud illiquidity at the month-end and assigns a firm a percentile rank of zero (the lowest) to one (the highest). For each of U.S. equity fund portfolio, the table then calculates the value-weighted illiquidity rank score (VW_Illiquidity), using a stock's absolute percentage of the total net assets in the portfolio divided the aggregate absolute percentages of all traded stocks and cash in the portfolio as a weight. Additional independent variables include a dummy of the fund's VW_%PD being positive in quarter t and a dummy of the fourth quarter each year. The table reports the regression coefficients (Coef) with their p-value in parentheses, their associated odds ratios (Odds), the number of fund-quarters, and the model deviance statistics G^2. In the estimation, all standard errors are adjusted for error correlations clustered by both fund and quarter. The sample period is from January 2009 to March 2015.

Table 9—*Continued*

Independent Variables in Quarter *t*	Dependent Variable: D (VW_%PD>0) in Quarter *t+1*							
	Model 1		Model 2		Model 3		Model 4	
	Coef	Odds	Coef	Odds	Coef	Odds	Coef	Odds
Constant	-3.521	0.03	-3.664	0.03	-3.539	0.03	-3.765	0.02
	(0.000)		(0.000)		(0.000)		(0.000)	
D_NEG	0.141	1.15	0.133	1.14	0.133	1.14	0.139	1.15
	(0.033)		(0.027)		(0.080)		(0.081)	
D_POS	-0.075	0.93	-0.080	0.92	-0.059	0.94	-0.060	0.94
	(0.125)		(0.087)		(0.235)		(0.324)	
D(VW_%PD>0)			2.431	11.37			2.458	11.68
			(0.000)				(0.000)	
D(4^{th} Quarter)					0.076	1.08	0.328	1.39
					(0.936)		(0.598)	
D(4^{th} Quarter) x D_NEG					0.029	1.03	-0.029	0.97
					(0.758)		(0.789)	
D(4^{th} Quarter) x D_POS					-0.065	0.94	-0.082	0.92
					(0.480)		(0.348)	
VW_Illiquidity	1.249	3.49	0.796	2.22	1.256	3.51	0.804	2.23
	(0.000)		(0.004)		(0.000)		(0.004)	
LN(TNA)	-0.044	0.96	-0.034	0.97	-0.044	0.96	-0.033	0.97
	(0.072)		(0.215)		(0.082)		(0.244)	
Age	0.006	1.01	0.004	1.00	0.006	1.01	0.004	1.00
	(0.024)		(0.066)		(0.025)		(0.070)	
Market Excess Returns	0.038	1.04	0.038	1.04	0.037	1.04	0.036	1.04
	(0.342)		(0.081)		(0.407)		(0.144)	
SD (Market Excess Returns)	0.277	1.32	0.158	1.17	0.278	1.32	0.162	1.18
	(0.022)		(0.027)		(0.022)		(0.034)	
Standard Errors Clustered by both Fund and Quarter	Yes		Yes		Yes		Yes	
Fund-Quarters	54,154		54,113		54,154		54,113	
G^2	33005.8		27846.5		33001.3		27778.9	

Table 10 Prediction of the Median Fair-Value Assigned by Mutual Funds

On a given reported date (CRSP variable: *report_dt*), stocks held by at least two mutual funds are included in the analysis. The median reported price is identified for a stock held by *all mutual funds*. The table retrieves the stock's last closing price on the reported date and its opening price next day. The table tests if the median reported price can predict the opening price next day in an OLS panel regression. The dependent variable is the percentage change from the last closing price to the next opening price ($\frac{Opening\ Price_{i,t+1} - Closing\ price_{i,t}}{Closing\ Price_{i,t}}$) while the independent variable is the percentage change from the last closing price to the median reported price ($\frac{Median\ Price_{i,t} - Closing\ Price_{i,t}}{Closing\ Price_{i,t}}$). A stock's return on the reported day is included as a control. All variables are in a percentage format. A stock on a given reported date is excluded from the regression analysis if the stock's closing price falls below $1. The sample period is from January 2009 to March 2015. The table reports the regression coefficients with their *p*-value in parentheses. In the estimation, all standard errors are adjusted for error correlations clustered by both firm and year.

Independent Variables	Dependent Variable: $\frac{Opening\ Price_{i,t+1} - Closing\ price_{i,t}}{Closing\ Price_{i,t}}$			
	Model 1	Model 2	Model 3	Model 4
Constant	0.101	0.172		
	(0.528)	(0.140)		
$\frac{Median\ Price_{i,t} - Closing\ Price_{i,t}}{Closing\ Price_{i,t}}$	0.179	0.190	0.155	0.164
	(0.026)	(0.031)	(0.078)	(0.084)
$Return_{i,t}$		1.169		1.099
		(0.000)		(0.000)
Firm Fixed Effect	No	No	Yes	Yes
Year Fixed Effect	No	No	Yes	Yes
Standard Errors Clustered by both Firm and Year	Yes	Yes	Yes	Yes
Adjusted R^2	4.70	38.65	22.47	47.43
Observations (Firm-Days)	376,677	376,636	376,677	376,636

Table 11 Changes in Total Net Asset Value due to Changes in Reported Prices

At the end of each quarter from January 2009 to March 2015, U.S. actively-managed open-end equity funds are sorted into quintiles based on the fund's value-weighted price rank score (VW_PR) defined in Table 5. Funds in Quintile 1 (5) have the lowest (highest) VW_PRs. This table recalibrates the portfolio weights for each fund portfolio according to the median reported price by all mutual funds on each stock held by the fund portfolio. Suppose Stock *i*'s original weight in a fund portfolio is $\omega_i^O \equiv \frac{V_i^O}{TNA^O}$where TNA^O is the fund's total net assets under management and$V_i^O$is the fund's investment on Stock *i*. Define $\Delta_i \equiv \frac{P_i^{Median} - P_i^{Fund}}{P_i^{Fund}}$, where $P_i^{Fund}$is the reported price by the fund on Stock *i* and P_i^{Median} is the median reported price by all funds on Stock *i*. Then Stock *i*'s recalibrated weight in the fund portfolio is $\omega_i^{Recalibrated} = \frac{V_i^O(1+\Delta_i)}{TNA^O + \sum_{i=1}^N \Delta_i \times V_i^O} = \frac{\omega_i^O \times TNA^O \times (1+\Delta_i)}{TNA^O + \sum_{i=1}^N \Delta_i \times \omega_i^O \times TNA^O} = \frac{\omega_i^O \times (1+\Delta_i)}{1+\sum_{i=1}^N \Delta_i \times \omega_i^O}$, where N is number of stocks held by the fund. Three interest variables are constructed for individual fund portfolio each quarter. TNA is at the beginning of each quarter while changes in recalibrated weights are calculated for the latest portfolio disclosure in a quarter. The table generates the quartile distribution as well as the average (AVG) and the standard deviation (SD) for each quintile in each quarter, and report the time-series average of statistics. The difference in each statistics variable for the hedge portfolio (Q1 – Q5) is reported. The *p*-value reported in the parenthesis is associated with a null hypothesis that the average of the differences is zero with one exception. The *p*-value reported in SD is associated with a null hypothesis that the ratio of variances equals one.

	# Funds	Quartile Distribution			AVG	SD
		25%	Median	75%		
Panel A. TNA ($million)						
Quintile 1	526	44.099	171.354	667.583	1174.403	4358.402
Quintile 2	526	62.778	245.952	873.059	1397.221	5209.525
Quintile 3	526	68.313	245.166	855.719	1306.643	4757.479
Quintile 4	526	65.646	247.906	853.119	1257.363	4508.896
Quintile 5	527	47.242	178.054	660.592	949.914	3056.871
Q1 – Q5 (Q1/Q5 in SD^2)		-3.143	-6.700	6.991	224.489	2.033
		(0.44)	(0.66)	(0.90)	(0.07)	(0.00)
Panel B. Changes in Recalibrated Weights (%) ($\sum_{i=1}^N \Delta_i \times \omega_i^O$) at a Fund Portfolio Level						
Quintile 1	526	0.231	0.404	0.608	0.429	0.387
Quintile 2	526	-0.076	0.022	0.125	0.037	0.267
Quintile 3	526	-0.176	-0.063	0.047	-0.078	0.278
Quintile 4	526	-0.356	-0.155	0.000	-0.190	0.282
Quintile 5	527	-0.512	-0.296	-0.164	-0.361	0.355
Q1 – Q5 (Q1/Q5 in SD^2)		0.743	0.700	0.773	0.790	1.187
		(0.01)	(0.02)	(0.02)	(0.00)	(0.05)
Panel C. Changes in TNA ($million) based on the Recalibrated Weights ($\sum_{i=1}^N \Delta_i \times \omega_i^O \times TNA^O$)						
Quintile 1	526	0.090	0.397	1.491	2.828	13.147
Quintile 2	526	-0.125	0.007	0.175	0.267	5.241
Quintile 3	526	-0.583	-0.062	0.066	-1.144	6.479
Quintile 4	526	-0.866	-0.162	0.056	-1.515	9.816
Quintile 5	527	-1.270	-0.273	-0.065	-2.270	9.327
Q1 – Q5 (Q1/Q5 in SD^2)		1.360	0.670	1.556	5.098	1.987
		(0.05)	(0.03)	(0.07)	(0.01)	(0.00)