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Mutual Fund Stock-Picking Skill: New Evidence from Valuation- versus Liquidity-Motivated Trading

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We propose a novel Trade Motivation Matrix that allows differentiating funds' valuation-motivated (VM) and liquidity-motivated (LM) trades on single trade level. It thus enables analyses of stock-picking skill on three levels: trade, stock, and fund. On trade level, we find significant outperformance of VM buys and significant underperformance of VM sells, indicating manager stock-picking skills, especially during illiquid market periods. VM trades outperform LM trades, confirming negative performance effects due to flow risk, especially when market liquidity is low. On stock level, collective VM buying explains high future stock returns while collective VM selling is related to future losses, indicating wisdom of the crowd. On fund level, higher trading discretion, measured by a higher degree of VM trading, is observed for smaller, older funds holding higher cash buffers. Finally, higher trading discretion is related to higher future fund alpha, especially during illiquid times.

When assessing the stock-picking skill of professional investors such as mutual funds, it is vital to distinguish valuation-motivated (VM) trades from liquidity-motivated (LM) trades. Only trades based on valuations allow judging managers' stock-picking skill, while forced trades based on fund holders' liquidity demands may be thought of as noise trading and do not represent skill (Edelen, 1999). Based on portfolio holdings, we propose a novel Trade Motivation Matrix (TMM), which is the first to differentiate between single holdings-based VM and LM trades. With the TMM, it is therefore possible to run analyses on three different levels—individual trades, individual stocks, and individual funds—whereas previous research remains on an aggregated trade level (Alexander, Cici, and Gibson, 2007). Thus, our model enables more precise measurement of stock-picking skill and of the costs of liquidity provision to fund investors due to flow risk (Rakowski, 2010), a very relevant matter to which the Securities Exchange Commission (SEC)

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recently turned their attention.[1] Moreover, it allows investigating which stocks are traded based on VM and LM and whether funds' VM trading is related to future stock and fund performance.

Applying the TMM to a sample of more than 4.7 million trades results in several contributions. First, on trade level, we contribute to the literature on stock-picking skill by finding that VM buys have on average higher returns and VM sells have significantly lower returns than their respective benchmarks, consistent with stock-picking skill. Additionally, by being the first to conduct such an analysis during different market liquidity regimes, we show that VM trading decisions are more successful during times of low market liquidity. Such times are usually associated with higher pricing uncertainty (Chordia, Roll, and Subrahmanyam, 2008, 2011) during which fundamental or private signals may have higher informational value, consistent with reduced information efficiency of the market. This creates more opportunities for VM trading (Sadka and Scherbina, 2007; Dong, Feng, and Sadka, 2017; Pástor, Stambaugh, and Taylor, 2017), which is also reflected in an overproportionally high number of VM trades during illiquid times. It is also consistent with the finding that manager skill is time varying and depends on the overall economic conditions (Kacperczyk, van Nieuwerburgh, and Veldkamp, 2014).

Second, we are the first to consider different benchmark universes to measure trade performance. Specifically, we use all Center for Research in Security Prices (CRSP) stocks to measure trade performance relative to stocks with similar characteristics (Daniel et al., 1997, henceforth DGTW). However, for sells, this assumes unrestricted short selling, which is not allowed by the SEC and therefore seldom done (Chen, Desai, and Krishnamurthy, 2013). Therefore, we alternatively use the respective fund's holdings at the time of the trades to measure if trades improve portfolio quality. With this distinction, we are the first to show specifically that funds' VM trades overall improve portfolio quality, while LM trades do not.

Third, we contribute to the literature on flow risk as the TMM facilitates a more detailed analysis of funds' LM trading compared to previous research. Contrasting VM and LM trades clearly shows that funds are forced to make disadvantageous trading decisions if investors' and managers' investment strategies are not aligned. This represents strong empirical evidence that mutual fund performance suffers significantly from investor-induced flow risk. It also indicates that previous trade-based approaches to measuring skill are biased by LM trading. We show that this adverse effect of investor flows also worsens during illiquid times.

Fourth, on stock level, we contribute to the general understanding of fund manager's trading preferences. Specifically, the TMM allows detailed analyses of the characteristics of stocks traded by mutual fund managers based on VM and LM. We show that with their VM buys, fund managers prefer smaller over bigger companies and value over growth stocks—that is, fund managers chase size and value premiums (Fama and French, 1993). Moreover, if funds have a clear valuation, they are prepared to accept higher market risk exposure as well as higher illiquidity risk, even during times of low market liquidity. If managers are forced to trade without clear valuations (LM buys and sells), they prefer to engage in momentum trading (Jegadeesh and Titman, 1993; Carhart, 1997), sell very liquid stocks, and reduce risk with their LM sells.

Fifth, we find that the collective VM trading decisions of mutual funds in single stocks—that is, the ratio of VM buys (sells) to all buys (sells) in a specific stock during a certain quarter—represents wisdom of the fund manager crowd (Chalmers, Kaul, and Phillips, 2013; Jiang, Verbeek, and Wang, 2014; Sias, Turtle, and Zykaj, 2016). Specifically, we show that stock-specific VM buying ratios are significantly related to positive future stock performance over horizons at least up to 12 months, while VM selling ratios are significantly related to negative future stock performance.

[1] https://www.sec.gov/news/pressrelease/2015-201.html.

Sixth, on fund level, we contribute to the literature on differences between mutual funds by analyzing the fund characteristics associated with a higher degree of VM trading—that is, the ratio of VM trades to all trades by a fund during a certain quarter. We show that inflows and higher cash increase buying discretion, while outflows and low cash decrease buying discretion (Simutin, 2014). Moreover, younger and smaller funds have higher buying discretion, consistent with the prior literature on diseconomies of scale (Berk and Green, 2004; Chen et al., 2004; Pollet and Wilson, 2008; Pástor, Stambaugh, and Taylor, 2015). Fee structures such as expense ratios and load fees have no effect on the degree of VM trading. Turnover as a measure of overall trading is positively related to VM trading, consistent with Pástor, Stambaugh, and Taylor (2017).

Seventh, we show that a higher degree of VM trading is significantly related to funds' future Carhart (1997) alpha and thus translates directly into benefits for investors, especially during illiquid market periods. It also confirms our previous finding that stock-picking skill is valuable primarily in periods with low market efficiency and high valuation uncertainty.

Our work is thus related to various popular streams of mutual fund research. The flow-performance relation and the potentially adverse effect of investor flows on the discretion of open-end mutual fund managers—that is, flow risk—was first empirically investigated by Edelen (1999). He finds that the general underperformance of actively managed funds compared to passive alternatives can partly be explained by LM trading. Dubofsky (2010) as well as Fulkerson and Riley (2017) confirm the strong relation between investor gross flows and aggregated mutual fund trading during later periods.[2] Therefore, the SEC recently turned their attention to flow risk and mutual fund liquidity, considering new regulation to protect buy-and-hold investors from negative effects of LM trading caused by purchasing and redeeming investors (Hanouna et al., 2015). Within this literature, the TMM builds particularly on the study by Pollet and Wilson (2008) who investigate mutual fund behavior in reaction to growth. They argue that mutual funds may react to investor flows by means of two alternative strategies: scaling and diversification. On the one hand, a manager without new investment ideas or valuations uses investor flows to scale her existing holdings, thereby maintaining her old portfolio allocation. On the other hand, a manager possessing new investment ideas and valuations may utilize investor flows to alter her allocation and to invest in new stocks.

The TMM is also related to the fund trading literature, which attempts to assess manager performance directly from the success of buying and selling decisions. The first study to use such an approach is Grinblatt and Titman (1993) which documents a significantly positive covariance between mutual fund holdings-weight-changes and subsequent stock returns based on quarterly holdings.[3] Chen, Jegadeesh, and Wermers (2000) use quarterly holdings and DGTW benchmark-adjusted stock returns and find that stocks bought by mutual funds significantly outperform stocks sold.[4] Using the same approach, Dyakov, Jiang, and Verbeek (2017) report that the informational advantage leading to this pattern turned negative after 2001. However, none of these studies consider trade motivation and thereby potentially underestimate skill. Moreover, these studies do

[2] Further empirical studies confirming the existence of flow risk are, for example, Coval and Stafford (2007), Frino, Leopone, and Wong (2009), Cherkes, Sagi, and Stanton (2009), Rakowski (2010), and Rohleder, Schulte, and Wilkens (2017).

[3] There are studies using actual mutual fund trades from the Abel Noser Corp. ANCERNO database (Puckett and Yan, 2011; Eisele, Nefedova, and Parise 2017; Busse et al., 2017). However, this database includes only 8% of total trading volume in US stocks and 10% of total trading volume by US domestic equity funds. Thus, these data are very valuable for specific types of studies such as those studying the transaction costs of mutual funds (Busse et al., 2017) but inadequate for large-scale studies on the mutual fund universe.

[4] Further studies using holdings-based mutual fund trades include Pinnuck (2003), Baker et al. (2010), Cullen, Gasbarro, and Monroe (2010), Brown, Wei, and Wermers (2014), and Wei, Wermers, and Yao (2014).

Figure 1. The Trade Motivation Matrix (TMM)

	Weight Change in the Direction of the Trade	*No Weight Change in the Direction of the Trade*
Buy	VM buy	LM buy
Sell	VM sell	LM sell

not consider different benchmark universes for trades and thus cannot assess the trades' effects on portfolio quality.

Alexander, Cici, and Gibson (2007) are the first to infer trade motivation from the direction and size of trades and flows. Aggregating single trades to portfolios, they show that a higher probability of VM trading results in higher trade performance. However, our methodology is distinctively different to theirs and enables a wider range of analyses. We therefore explicitly discuss the differences between the methods as well as advantages of the TMM in Section I.C.[5]

We proceed as follows: Section I introduces the TMM in detail and explains how we measure trade performance against different benchmark universes. Additionally, it distinguishes our model from previous approaches. Section II describes the data. Section III presents our empirical analysis on trade level, Section IV on stock level, and Section V on fund level. Section VI presents robustness checks and further tests. Section VII concludes the article.

I. Methodology

A. The Trade Motivation Matrix (TMM)

To assign each single mutual fund trade to one of the four categories of the TMM, we combine two intuitive measures: trade direction and weight change. As shown in Figure 1, we first categorize trades into buys and sells.[6] Following the related literature (Chen, Jegadeesh, and Wermers, 2000; Pinnuck, 2003; Alexander, Cici, and Gibson, 2007; Dyakov, Jiang, and Verbeek, 2017), fund i's trade in stock $j = 1, \ldots N$ between quarterly holdings reports in $q-1$ and q is given by Equation (1):

$$trade_{i,j,q} = shares_{i,j,q} - shares_{i,j,q-1}, \tag{1}$$

where $shares_{i,j,q}$ is the split and corporate action-adjusted number of shares that fund i holds in stock j at time q. A positive trade represents a buy, whereas a negative trade represents a sell.

Then, we consider the weight change of stock j in fund i caused by a trade (Grinblatt and Titman, 1993). Specifically, we define weight change as the difference between the actual portfolio weight

[5] Another approach to considering trade motivation is provided by Da, Gao, and Jagannathan (2011) who derive fund-level motivation from the traded stocks' probability of informed trading (PIN; Easley et al., 1996).

[6] In addition to VM and LM, funds may also trade due to tax motives (Bergstresser and Poterba, 2002) or for window dressing (Agarwal, Gay, and Ling, 2014). We address those in Section VI.C.

of stock j at time q and the hypothetical benchmark weight of stock j that would have occurred if the fund had not traded between times $q-1$ and q except for direct reinvestment of dividends.[7] The assumption underlying the hypothetical benchmark portfolio is that each holdings report represents the fund manager's efficient portfolio allocation and is based on her current valuations. If these do not change, the allocation should not change. Thus, the TMM should only consider weight changes if the manager's valuations are updated. Further, we include cash as a separate asset $N+1$ to control for funds managing investor flows using cash as a buffer (Simutin 2010, 2014). Weight change is thus calculated as shown in Equation (2) where $P_{j,q}$ is the price of stock j at time q and $r_{j,q}^{total}$ is the total return of stock j from $q-1$ to q including dividends.[8]

$$weight\,change_{i,j,q} = \frac{shares_{i,j,q} P_{j,q}}{\sum_{j=1}^{N+1} shares_{i,j,q} P_{j,q}} - \frac{shares_{i,j,q-1} P_{j,q-1}\left(1 + r_{j,q}^{total}\right)}{\sum_{j=1}^{N+1} shares_{i,j,q-1} P_{j,q-1}\left(1 + r_{j,q}^{total}\right)}, \tag{2}$$

If a fund manager possesses a positive (negative) valuation regarding a stock, she will increase (decrease) its weight in her portfolio. Hence, VM buys are trades where a buy in stock j leads to an increase of its portfolio weight. Similarly, VM sells are trades where a sell transaction in stock j leads to a decrease in its portfolio weight. Both VM trade categories can occur during times of inflow and outflow.

$$\text{VM buy}_{i,j,q} = 1 \quad \text{if} \quad trade_{i,j,q} > 0 \quad \& \quad weight\,change_{i,j,q} > 0, \tag{3a}$$

$$\text{VM sell}_{i,j,q} = 1 \quad \text{if} \quad trade_{i,j,q} < 0 \quad \& \quad weight\,change_{i,j,q} < 0. \tag{3b}$$

Conversely, if the fund manager has no valuation, Pollet and Wilson (2008) argue that inflowing money is allocated by simply upscaling existing portfolio holdings. Because these trades lack a clear investment idea, we consider them to be LM buys. The same holds for disproportionately small buys in times of inflow, resulting in a decrease of stock j's portfolio weight.[9]

$$\text{LM buy}_{i,j,q} = 1 \quad \text{if} \quad trade_{i,j,q} > 0 \quad \& \quad weight\,change_{i,j,q} \leq 0. \tag{3c}$$

Similarly, we argue that sell transactions that simply downscale existing portfolio holdings in times of outflows without considerably changing portfolio weights lack clear valuation-motivation

[7] The majority of dividends and other distributions obtained by mutual funds are usually directly reinvested into the fund. If the manager invests the dividends directly into the same stocks, this does not present a new investment idea and is thus identified by the TMM as an LM buy. If the manager invests the dividend into a different stock, the TMM identifies this as a VM buy. In unreported robustness tests, we abstract from the assumption, obtaining economically similar results.

[8] The intuitive way to consider direct reinvestment of dividends in the hypothetical benchmark portfolio is to adjust the number of shares held by a fund in the following way: $\frac{shares_{i,j,q-1}(1+D_{j,t}/P_{j,t}^{exD})P_{j,q}}{\sum_{j=1}^{N} shares_{i,j,q-1}(1+D_{j,t}/P_{j,t}^{exD})P_{j,q}}$. Here, $D_{j,t}$ is the dollar amount of dividends paid per stock j at time t. This amount is instantaneously reinvested into shares of stock j at its price ex dividends $P_{j,t}^{exD}$. However, instead of considering the exact timing of t, we employ the total return conveniently provided by CRSP.

[9] To test against misclassifications due to imperfect scaling that can arise because only integer numbers of stocks can be sold or bought, we provide some robustness tests in Section VI.B.

and are thus defined as LM sells. The same holds for sells in times of outflow that are so small in comparison to other sells that they result in an increase of the portfolio weight of stock j.

$$\text{LM sell}_{i,j,q} = 1 \quad \text{if} \quad \mathit{trade}_{i,j,q} < 0 \quad \& \quad \mathit{weight\,change}_{i,j,q} \geq 0. \tag{3d}$$

B. Measuring Trade Performance against Different Benchmark Universes

To measure the stock-picking performance of mutual fund trades, we use an approach similar to Chen, Jegadeesh, and Wermers (2000) and calculate the stocks' cumulative monthly characteristics-based benchmark-adjusted return in the spirit of the DGTW characteristics selectivity (CS) measure. Specifically, we measure the cumulative DGTW-adjusted return of the trade, assuming that the respective stocks are held over the subsequent 1, 3, 6, and 12 months.

Further, we consider different benchmark universes for different trade categories. As in the classic DGTW approach, we use all CRSP stocks assuming that funds may freely choose from this benchmark universe. A positive buy trade performance thus indicates that managers buy stocks that subsequently outperform other stocks with similar stock characteristics with regard to firm size, book-to-market ratio, and momentum. Similarly, a negative sell trade indicates that managers sell stocks that subsequently underperform other stocks with similar characteristics. Both are consistent with superior stock-picking skill. However, for sells, such an approach assumes unrestricted short selling. Taking into account that short selling is strictly regulated by the Investment Company Act of 1940 and thus seldom used by mutual funds (Chen, Desai, and Krishnamurthy, 2013), we use as an alternative universe only the stocks held by the fund at the time of the trade. Specifically, we measure performance of single trades against the equal-weighted DGTW benchmark-adjusted returns of all stocks held by the respective fund at time $q-1$. A positive buy performance thus indicates that the stock outperforms the average stock held by the fund and thus improves portfolio quality. A negative sell performance similarly indicates that a manager sells a stock that subsequently underperforms the average stock she keeps in the portfolio, also consistent with improved portfolio quality. In addition, we present results where we measure all trades against their respective relevant universes—that is, buys against all CRSP stocks and sells against the funds' holdings.

C. Advantages of the TMM over Previous Approaches

The approach that is closest to ours is developed by Alexander, Cici, and Gibson (2007, hereafter ACG). They derive probabilities of VM and LM trading from the direction and size of trades and flows. Aggregating single trades to portfolios, they show that a higher probability of VM trading results in higher trade performance. Specifically, in each period, they aggregate the trade volume of all buys (sells) of a fund and the fund's experienced flow to build a "buy-flow" (BF) portfolio ("sell-flow" [SF]). Then, motivation is assigned to BFs (SFs) by sorting them into quintiles within the fund over time. In a secondary sorting within the quintiles, higher VM is assigned to larger trades. While this approach is also very intuitive, it has some differences and disadvantages compared to the TMM.[10]

The first difference is that ACG requires a fund to have a very long reporting history to provide reliable results. To be able to have all BF and SF quintiles occupied, a minimum of six consecutive

[10] For comparison, we also apply the ACG method on our data. The results to this additional test are consistent with theirs and with our main results, but only if we consider the weight change instead of the trade volume as the second sorting dimension. In addition, our expectation that the results are pronounced during illiquid times holds in the ACG framework. The tables are available upon request.

holdings reports per fund are required (5 + 1 starting report). Having all quintiles balanced to reduce noise even requires integer multiples of this number. In contrast, the TMM can be applied for every two consecutive fund reports. As a result, the lower data requirement of the TMM reduces incubation and survivorship bias, allows more timely analysis, and is the only alternative to assess funds that are either new or from countries with low reporting availability.

The second important difference is that sorting BFs and SFs into quintiles following ACG assumes that each fund makes as many VM trades (BF1 and SF1) as it makes LM trades (BF5 and SF5). However, this is very unlikely the case due to differential skill in the cross section of mutual funds (Fama and French, 2010) and because funds face differential levels of flow risk (Rakowski, 2010; Rohleder, Schulte, and Wilkens, 2017). For example, consider a fund with a skilled manager who is excellent at flow risk management or faces overall low flow risk. It is safe to assume that this fund performs more VM trades than LM trades. The TMM adequately considers this difference. According to ACG, this fund performs 20% VM trades and 20% LM trades.[11] Consider another fund that is unskilled or faces high flow risk. According to the TMM, this fund may have many LM trades and only a few VM trades. According to ACG, it performs 20% VM trades and 20% LM trades. Thus, by construction, the ACG may mechanically lead to false classifications. While we concede that the TMM may make some false classifications, too, we argue that they are not mechanical. In Sections VI.A and VI.B, we run robustness tests controlling for potential misclassifications by the TMM.

Moreover, once assigned to, for example, the BF1 quintile, all of the fund's buys during that period are considered VM, while the TMM allows for VM and LM buys of the fund within the same period, which may also be the more realistic case. Furthermore, the TMM allows for VM buys and VM sells during the same period. Conversely, with ACG, which conditions on the flow direction, a simultaneous occurrence of VM buys and VM sells is very unlikely by definition. However, especially during phases of high overall pricing heterogeneity, we consider it very realistic that funds have over- and undervaluations of different stocks at the same time.

In addition, due to the sorting approach, the ACG method may lead to unstable classifications of BFs and SFs into the quintiles when the sample period is extended—for instance, by incorporating new holdings reports—or shortened—for instance, for subperiod analyses. Conversely, the TMM results in a stable classification of trades independent of the sample period.

Furthermore, the direct assignment of motivation to single trades by the TMM guarantees that 100% of the trades made by the sample funds over the sample period are considered. Conversely, ACG base their interpretations on only the extreme portfolios and thus ignore >90% of the trades. While one may argue that looking at only the extremes reduces noise in motivation assignment, it does not allow for any conclusions regarding the average skill of mutual fund managers or regarding the profit and loss resulting from average mutual fund trading with different motivations. With the TMM, this is possible.

As a consequence of the direct assignment of motivation to single trades, the TMM facilitates further analyses on fund level as in Section V by utilizing, for example, in each period the ratio of VM trades to overall trades. Here, a higher ratio may proxy for more investment ideas, higher skill, or lower exposure to flow risk. Moreover, the variation of the ratio over time may be used to link fund behavior to macroinfluences such as market illiquidity and other economic or market crises. With the ACG method, similar analyses are not possible because for each fund in the cross section, the ratio of VM trades to overall trades is 20% by definition (respectively, 4%

[11] Four percent each if we take into account that ACG additionally sorts by trade size within the BFs (SFs) and base all interpretations on the corner portfolios of the resulting 5 x 5 matrices.

when combined with trade size). Over time within the fund, the ratio may be only 1 or 0, and the assignment is dependent on the sample period also aggravating such analyses.

Finally, the ACG puts a focus on a trade's absolute trade volume, while TMM attaches more attention to the trade's weight change. This can result in different categorizations. Consider a fund manager who experiences high outflows and scales down the existing holdings to maintain her old allocation. Unless the fund holds an equal-weighted portfolio, some trades have a larger dollar volume than others. According to the TMM, all trades are clearly categorized as LM sells. According to ACG, larger trades will be assigned a higher probability of VM than smaller trades, despite both having no impact on portfolio composition. Overall, we therefore think that the TMM fixes some of the limitations of the ACG approach and offers a wide range of further applications.

II. Data

Fund characteristics and information on mutual fund holdings are from the CRSP Survivorship-Bias-Free Mutual Fund Database. As fund data from CRSP are mostly at the share class level, we aggregate them to fund level by value weighting with the respective total net assets (TNAs) of each share class. Only TNA is exempt from this procedure, as it is defined as the sum of individual share class TNA. We only include funds that are listed as domestic equity style or cap-based funds (EDY or EDC). We follow Amihud and Goyenko (2013) and exclude index funds by eliminating those with names containing words such as *index*, *S&P*, *Dow*, *WILSHIRE*, and *RUSSELL*. We further exclude funds before they first surpass the threshold of five million in TNA as in Fama and French (2010). In line with Kacperczyk, Sialm, and Zheng (2008), we delete fund periods with less than 10 reported holdings, as this is an indication of bad reporting quality.

Information on stock returns and characteristics are obtained from the CRSP Stock Database and from Compustat. We include only equity holdings with share codes 10 and 11 and delete all stocks with a price less than $1. Following ACG, we account for stock splits when computing quarterly holdings-based fund trades by using the cumulative adjustment factors from the CRSP stock return file. The final sample consists of 79,814 quarterly fund observations for 3,802 active US domestic equity funds in the period 2003–2012.[12]

To measure the performance of stocks bought and sold by mutual funds, we use the returns of the DGTW characteristics-based benchmark portfolios developed by Daniel et al. (1997) and kindly provided by Russ Wermers.[13] Further, we use the market liquidity factor from Pástor and Stambaugh (2003), which is kindly provided on Ľuboš Pástor's home page.[14] To measure fund performance, we use the Fama/French/Carhart factors from Kenneth R. French's data library.[15]

Table I displays descriptive statistics of the fund characteristics in our sample of 3,802 funds. Overall, the statistics are in line with previous mutual fund research. Especially important for our analysis are the cash positions of funds, as these may serve as a potential liquidity buffer.

[12] During our sample period, mutual funds are obliged to report portfolio holdings to the SEC on a quarterly basis. Empirically, however, actual reporting frequencies deviate from strictly quarterly reports, even within individual funds, and may be as high as monthly or as low as semiannually in a few cases. As the average time between reporting frequency is close to three months, we simplify by referring to reporting periods as quarterly.

[13] We thank Russ Wermers for providing the data. For details on benchmark construction, please refer to Daniel et al. (1997) and Wermers (2003). http://www.smith.umd.edu/faculty/rwermers/ftpsite/Dgtw/coverpage.html.

[14] We thank Ľuboš Pástor for providing the data. For details on factor construction, please refer to Pástor and Stambaugh (2003). http://faculty.chicagobooth.edu/lubos.pastor/research/.

[15] We thank Kenneth R. French for providing the data. For details on benchmark construction, please refer to Fama and French (1993) and http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Table I. Mutual Fund Characteristics

This table reports pooled summary statistics of fund characteristics for 3,802 actively managed US domestic equity funds in the period 2003–2012.

	Mean	Median	*SD*
Net excess return (% p.a.)	9.36	16.44	16.66
Net Carhart alpha (% p.a.)	−1.69	−1.21	4.79
TNA ($mil)	1,159.91	200.32	4,853.91
Expense ratio (% TNA, p.a.)	1.20	1.17	0.45
Max. front load (%)	2.96	3.77	2.43
Max. rear load (%)	1.10	1.00	1.11
Turnover ratio (% TNA, p.a.)	90.73	67.00	110.49
Cash (% TNA)	3.19	1.79	6.16
Age (years)	12.91	10.32	10.83
Net flow (% TNA)	0.66	−0.74	9.89
Abs. net flow (% TNA)	5.42	2.56	8.31

Table II. Fund Stock Holdings

This table reports year-end summary statistics on stock holdings of 3,802 actively managed US domestic equity funds in the period 2003–2011. It contains statistics on all stocks with available returns over the following 12 months.

			Mean Number of Stocks per Fund and Quarter		
Year	Funds	Stocks Held by All Funds	Held	Bought	Sold
2003	1,747	3,935	82	58	26
2004	1,658	3,806	108	96	54
2005	1,711	3,657	114	91	50
2006	1,731	3,631	83	105	54
2007	2,020	3,474	86	123	61
2008	2,326	3,129	125	110	78
2009	2,232	3,274	180	108	72
2010	2,876	3,152	199	90	69
2011	2,876	3,122	221	96	76
Average	2,131	3,464	133	98	60
Total	3,802	5,246	3,368,497	2,458,616	2,277,088

On average, funds hold 3.19% of their TNA in cash; however, there is substantial variation in the cross section indicated by the standard deviation of 6.16%. This is consistent with statistics in Simutin (2014) and Hanouna et al. (2015). Even more importantly, the funds in our sample experience substantial investor flows with absolute monthly net percentage flows of about 5.42% of TNA on average. Over the period 2003–2012, the funds experience monthly net inflows of 0.66% of TNA on average, while the median represents an outflow of −0.74% of TNA, indicating that a few funds experienced extreme inflows.

Table II provides year-end summary statistics on the funds' stock holdings. Overall, funds report holdings in 5,246 distinct stocks over our sample period, which makes up a substantial portion of all stocks available in the CRSP stock database.

Table III. TMM Sorting

This table reports numbers (*N*) and fractions (%) of trades sorted into valuation-motivated buys (VM buys), liquidity-motivated buys (LM buys), valuation-motivated sells (VM sells), and liquidity-motivated sells (LM sells) according to the Trade Motivation Matrix (TMM).

	N	%
All Trades	4,735,704	100.00
Buys	2,458,616	51.92
VM buys	1,710,743	36.12
LM buys	747,873	15.79
Sells	2,277,088	48.08
VM sells	2,111,743	44.59
LM Sells	165,345	3.49

Table III illustrates the number of trades assigned to the different categories according to the TMM. Our sample includes more than 4.7 million trades. Fifty-two percent of these trades are buys and 48% are sells. Thirty-six percent of all trades are VM buys, 16% are LM buys, 45% are VM sells, and only 3.5% of all trades are LM sells.[16] As a rough comparison, Edelen (1999, table III) reports that 29% of the buying volume and 27% of the selling volume were liquidity motivated during the late 1980s, documenting high flow risk. This effect seems to decrease over time as Dubofsky (2010, table III) reports that 13.2% of the buying volume and 7.5% of the selling volume were liquidity motivated in the late 1990s and early 2000s. Thus, our fractions of 16% LM buys and 3.5% LM sells for 2003–2012 are in line with the related literature. Involuntary noise trading is thus more prevalent in buys than in sells, as the number of LM buys is nearly five times the number of LM sells.

III. Trade-Level Analysis

A. Mutual Fund Stock-Picking Skill and the Costs of Liquidity Provision

In this section, we analyze the performance of single trades regarding the existence of stock-picking skill and flow risk. Whether mutual fund managers are skilled should show most prominently in their VM trading activities. Hence, we argue that if managers exhibit significant stock-picking skills, their VM buys should subsequently outperform and their VM sells should underperform. If, on the other hand, mutual fund managers possess no stock-picking skill, there should be no significant outperformance of VM buys and no significant underperformance of VM sells.

Panel A of Table IV presents pooled single-trade performance for the overall period against the CRSP universe, which is the standard approach in the literature (Daniel et al. 1997; Chen, Jegadeesh, and Titman, 2000). On the one hand, the cumulative performance of VM buys is positive and statistically significant over all tested investment horizons (e.g., 0.240% over the first three months), indicating that the stocks bought based on VM subsequently outperform other stocks with similar stock characteristics, consistent with stock-picking skill. On the other hand, the performance of VM sells is also positive and statistically significant against the CRSP

[16] The number of LM sells is very small and may stem from imperfect downscaling by mutual funds in an attempt to reduce transaction costs. We consider such gray cases in robustness Section VI.B.

Table IV. Pooled Single-Trade Performance—Overall Period

This table reports cumulative DGTW benchmark-adjusted performance over the next 1-, 3-, 6-, and 12-month periods resulting from trades sorted according to the Trade Motivation Matrix (TMM) of 3,802 actively managed US domestic equity funds in the period 2003–2012.

		Cumulative DGTW-Adjusted Performance (in %) over the Next			
	N	**1 Month**	**3 Months**	**6 Months**	**12 Months**
Panel A. Benchmarked against the CRSP Stock Universe—Unlimited Short Selling					
VM buys	1,710,743	0.177***	0.240***	0.352***	0.362***
VM sells	2,111,743	0.029***	0.088***	0.148***	0.194***
VM buys – VM sells		0.148***	0.152***	0.204***	0.168***
LM buys	747,873	0.045***	0.094***	0.226***	0.392***
LM sells	165,345	0.228***	0.358***	0.599***	0.621***
VM buys – LM buys		0.132***	0.146***	0.126***	−0.030
VM sells – LM sells		−0.199***	−0.270***	−0.451***	−0.427***
Panel B. Benchmarked against the Holdings—No Short Selling					
VM buys	1,710,743	0.055***	0.013	−0.026	−0.153***
VM sells	2,111,743	−0.077***	−0.105***	−0.144***	−0.178***
VM buys – VM sells		0.131***	0.118***	0.118***	0.025
LM buys	747,873	−0.023**	−0.038**	−0.011	0.014
LM sells	165,345	0.001	0.034	−0.053	−0.143*
VM buys – LM buys		0.078***	0.051**	−0.014	−0.167***
VM sells – LM sells		−0.077***	−0.139***	−0.091	−0.035
Panel C. Benchmarked against the Relevant Universe (Buys: CRSP, Sells: Holdings)					
VM buys	1,710,743	0.177***	0.240***	0.352***	0.362***
VM sells	2,111,743	−0.077***	−0.105***	−0.144***	−0.178***
VM buys – VM sells		0.254***	0.344***	0.496***	0.540***
LM buys	747,873	0.045***	0.094***	0.226***	0.392***
LM sells	165,345	0.001	0.034	−0.053	−0.143*
VM buys – LM buys		0.132***	0.146***	0.126***	−0.030
VM sells – LM sells		−0.077***	−0.139***	−0.091	−0.035

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

universe indicating that funds sell stocks that subsequently outperform other stocks with similar stock characteristics, counterintuitive to stock-picking skill.

However, the CRSP universe is not relevant for sells due to short selling restrictions (Chen, Desai, and Krishnamurthy, 2013). Therefore, Panel B shows trade performance against the respective fund's holdings. Here, VM buys are positive and significant only over the first month, indicating that VM buys slightly increase portfolio quality in the short run. More interestingly, the cumulative performance of VM sells is negative and statistically significant over all tested horizons (e.g., −0.105% over the first three months), indicating that the stocks sold based on VM subsequently underperform the stocks held. Hence, funds sell the right stocks on average, revealing that selling skill is a valuable contributor to fund performance, which has widely been ignored in the literature so far.

Panel C considers all CRSP stocks for buys and the holdings for sells. The difference between VM buys and VM sells, the "value added" compared to the relevant benchmark universe, is thus positive and statistically significant over all tested horizons (e.g., 0.344% over the first three months). Overall, all our findings regarding VM trades are consistent with the existence of stock-picking skill in active mutual fund management.

Next, we analyze the existence of flow risk based on single trades. In this context, Edelen (1999) argues that a fund manager holding a—from her perspective—optimal portfolio is moved away from this allocation by investor flows. To regain an optimal portfolio, the fund is forced to trade. In a standard expectations model, this investor flow is interpreted as exogenous supply noise trading, which faces expected losses in comparison to informed trading. In the TMM model, this should show in significant outperformance of VM buys over LM buys and in significantly higher avoided losses through VM sells compared to LM sells.

In Panel A of Table IV, the cumulative performance of LM buys is positive and statistically significant over all tested horizons (e.g., 0.094% over the first three months), indicating that even with less discretion, managers may make good decisions, on average, compared to the overall market. However, VM buys still significantly outperform LM buys, leading to a positive and statistically significant difference at least over the first six months (e.g., 0.146% over the first three months) and indicating that the restricted trading discretion caused by investor flows is costly. After 12 months, we see no significant difference between VM buys and LM buys. In Panel B, measured against the respective fund's holdings, the performance of LM buys is negative over all tested horizons and statistically significant over the first three months, indicating that LM buys—despite showing positive performance in Panel A—cannot improve portfolio quality on average and thus hurt performance.

LM sells in Panel A are positive, high, and statistically significant over all tested horizons (e.g., 0.358% over the first three months). We interpret this so that funds selling without a clear valuation consider the relative liquidity of the stocks, thereby generating "losses" to informed traders. Moreover, it is consistent with our previous assumption that mutual funds hold a positive selection of the CRSP universe on average. However, the difference between VM sells and LM sells is very large and significant (e.g., −0.270% over the next three months), indicating high illiquidity costs caused by flow risk.

Contrasting VM sells and LM sells using the more relevant holdings benchmark universe in Panel B, the cumulative performance of LM sells is insignificant over the first six months before turning slightly negative after 12 months, indicating that LM sells cannot improve portfolio quality. The difference between VM sells and LM sells is negative and statistically significant over the first three months and then becomes insignificant, indicating that higher discretion leads to better selling decisions and that flow-induced LM selling is costly. The results in Panel C using the respective relevant benchmarks confirm the previous panels and show that both LM buys and LM sells are detrimental to performance at least in the short run, consistent with the existence of flow risk.

Further, to investigate why the difference of VM buys over LM buys—that is, flow risk—reverses after 12 months, we additionally analyze the average "motivation duration" of different trade categories—that is, the time period until the same stocks are traded by a fund with a different motivation. Panel A of Table V shows that for all trade categories, the average motivation duration is well below the hypothetical 12-month holding period in Table IV. This indicates that the result in Table IV that LM buys outperform VM buys over the 12-month horizon is of minor relevance compared to three-month and six-month holding periods, for which we find strong evidence of flow risk. Moreover, the motivation duration of VM trades is clearly longer than that of LM sells, which is also economically intuitive.

Table V. Motivation Duration of TMM Trade Categories

This table reports the average and median motivation duration in months of trades categorized by the TMM of US domestic equity mutual funds during the period 2003–2012. We define the motivation duration of a trade as the time period until the same stock is traded by the fund in another direction or in the same direction with a different motivation.

	Panel A. Overall Period			*Panel B. Illiquid Market Periods*		
	N	**Average**	**Median**	***N***	**Average**	**Median**
VM buys	1,659,887	5.85	3.00	373,105	6.62	4.00
LM buys	737,687	4.94	3.00	160,613	5.94	3.00
VM sells	2,020,433	6.43	4.00	449,869	7.06	5.00
LM sells	160,843	3.02	2.00	30,267	3.76	3.00

B. Skill in Illiquid Market Periods, Liquidity Costs, and Market Efficiency

In this section, we perform additional analyses that focus on the interplay between stock-picking skill, flow risk, and market illiquidity. Regarding stock-picking skill in illiquid times, prior research (Sadka and Scherbina, 2007; Chordia et al., 2008, 2011; Dong, Feng, and Sadka, 2017; Pástor, Stambaugh, and Taylor, 2017) indicates that market efficiency is lower and pricing uncertainty is higher during periods of low market liquidity. Thus, these periods frequently present more opportunities for VM trades, and the potential gains from such trades should be higher. In the TMM, this should show in higher returns to VM buys, in higher avoided losses through VM sells, and ultimately in a wider performance spread between VM buys and VM sells compared to nonilliquid times. Moreover, during illiquid times, the mispricing may be more fundamental and thus provide long-term opportunities to informed traders, while mispricing during nonilliquid times may present only short-term opportunities. In the TMM, this should show in clearer patterns over longer holding periods during illiquid market periods.

Table VI presents pooled single-trade performance separately for illiquid and nonilliquid periods.[17] Panel A presents results for illiquid times, defined as the bottom 10% of the Pástor and Stambaugh (2003) aggregated market liquidity factor, against the holdings benchmark.[18] With slightly more than one million trades, about 22.5% of all trades occur during the 10% illiquid times, indicating higher trading activity during such phases consistent with, for example, Pástor, Stambaugh, and Taylor (2017). The performance of VM buys is positive over all tested periods and significant in three out of four cases (e.g., 0.373% over the first 12 months). This indicates that VM buys improve portfolio quality. The performance of VM sells is negative and statistically significant for all tested periods (e.g., −0.735% over the first 12 months), so that the difference between VM buys and VM sells is statistically significant and economically relevant with, for instance, 1.107% over the first 12 months. It also confirms that VM sells improve portfolio quality more strongly than VM buys.

[17] In Table VI, we drop the panel using all CRSP stocks as a benchmark for sells as it is economically irrelevant due to short selling restrictions.

[18] For robustness, we also test a 20% Pástor and Stambaugh (2003) cutoff to identify illiquid periods, for economic contractions following the definition of the National Bureau of Economic Research, and stock market crises following Ben-David, Franzoni, and Moussawi (2012). The results are economically similar and available upon request.

Table VI. Pooled Single-Trade Performance—Illiquid versus Nonilliquid Market Periods

This table reports cumulative DGTW benchmark-adjusted performance over the next 1-, 3-, 6-, and 12-month periods resulting from trades sorted according to the Trade Motivation Matrix (TMM) of 3,802 actively managed US domestic equity funds in the period 2003–2012. Nonilliquid (Illiquid) market periods are defined as periods with Pástor and Stambaugh's (2003) aggregated market liquidity factor above (below) the 10th percentile.

		Cumulative DGTW-Adjusted Performance (in %) over the Next			
	N	**1 Month**	**3 Months**	**6 Months**	**12 Months**
Panel A. Illiquid Market Periods (Bottom 10%), Benchmarked against Holdings					
VM buys	387,368	0.091***	0.049	0.188***	0.373***
VM sells	479,154	−0.149***	−0.202***	−0.453***	−0.735***
VM buys – VM sells		0.240***	0.251***	0.641***	1.107***
LM buys	165,761	−0.039	−0.032	−0.030	−0.198**
LM sells	31,991	−0.001	0.041	−0.252	−0.322
VM buys – LM buys		0.130***	0.081	0.218***	0.571***
VM sells – LM sells		−0.148*	−0.243**	−0.201	−0.413*
Panel B. Illiquid Market Periods (Bottom 10%), Benchmarked against Relevant Universe					
VM buys	387,368	0.476***	0.739***	1.462***	2.007***
VM sells	479,154	−0.149***	−0.202***	−0.453***	−0.735***
VM buys – VM sells		0.625***	0.941***	1.915***	2.742***
LM buys	165,761	0.217***	0.495***	0.906***	0.725***
LM sells	31,991	−0.001	0.041	−0.252	−0.322
VM buys – LM buys		0.259***	0.244***	0.556***	1.282***
VM sells – LM sells		−0.148*	−0.243**	−0.201	−0.413*
Panel C. Nonilliquid Market Periods (Top 90%), Benchmarked against Holdings					
VM buys	1,323,375	0.044***	0.003	−0.088***	−0.307***
VM sells	1,632,589	−0.056***	−0.076***	−0.053***	−0.014
VM buys – VM sells		0.100**	0.079***	−0.035	−0.293***
LM buys	582,112	−0.019*	−0.039**	−0.006	0.075***
LM sells	133,354	0.001	0.032	−0.005	−0.100
VM buys – LM buys		0.063***	0.042*	−0.083**	−0.382***
VM sells – LM sells		−0.057**	−0.109***	−0.048	0.085
Panel D. Nonilliquid Market Periods (Top 90%), Benchmarked against Relevant Universe					
VM buys	1,323,375	0.089***	0.094***	0.027	−0.119***
VM sells	1,632,589	−0.056***	−0.076***	−0.053***	−0.014
VM buys – VM sells		0.145***	0.170***	0.080***	−0.105***
LM buys	582,112	−0.004	−0.020	0.032	0.297***
LM sells	133,354	0.001	0.032	−0.005	−0.100
VM buys – LM buys		0.094***	0.114***	−0.005	−0.417***
VM sells – LM sells		−0.057**	−0.109***	−0.048	0.085

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

Panel B shows results against the respective relevant benchmarks for buys and sells. The results are even stronger with a performance of VM buys of 2.007% over the first 12 months and the difference to VM sells, the value added, increasing to 2.742%. Overall, these findings confirm our expectation that stock-picking skill is more valuable during times of low market efficiency. Moreover, the results support our assumption that this informational advantage allows outperformance over longer periods as all figures are statistically and economically significant over all tested horizons. In addition, Panel B of Table V shows that motivation durations are longer during illiquid times, in accordance with economic intuition.

Comparing the results for illiquid times with those for nonilliquid times in Panels C (holdings universe) and D (relevant universe) shows that VM buys have positive but rather low returns only over the first six months and then turn negative after 12 months. Similarly, VM sells are only slightly negative compared to illiquid times. The value added from VM trading during nonilliquid times is thus comparably low (e.g., Panel D, 0.170% over the first three months) and turns negative after 12 months. Therefore, the results for the overall period presented in Table IV are driven by the strong positive VM trading performance during illiquid times. This is also consistent with the efficient markets hypothesis (Fama, 1970) that during nonilliquid times, there exists no informational advantage even for skilled managers, at least not over long horizons.

Regarding the interplay between flow risk and market illiquidity, it should be more costly to provide liquidity to investors while facing illiquidity on the stock market. In the TMM model, this should show in inferior performance of LM trades during illiquid times compared to non-illiquid times. To test this, we first look at LM buys in illiquid times. In Panel A, LM buys show insignificant but slightly negative performance that turns significantly negative after 12 months (−0.198%) and thus cannot improve portfolio quality. Compared to VM buys, LM buys underperform with 0.571% over the first 12 months, which represents economically significant liquidity "costs" and confirms increased flow risk. In Panel B, LM buys show positive performance over all tested periods (e.g., 0.725% over the following 12 months) but still clear, significant, and economically relevant underperformance compared to VM buys with statistically significant differences of, for example, 1.282% over the following 12 months.

Similar interpretations apply to LM sells, which are negative but statistically insignificant for most tested periods (e.g., −0.252% over the following six months). However, they are significantly less negative compared to VM sells with differences of, for instance, −0.413% over the first three months. This supports our assumption that the "costs" of providing liquidity to investors are higher during illiquid times. Interestingly, the liquidity costs from capital inflows (VM buys minus LM buys) are higher and show higher statistical significance than the costs from capital outflows (VM sells minus LM sells). One explanation of this result could be that during illiquid times, those funds that provide liquidity to other market participants (LM sellers) gain a liquidity premium, while funds demanding liquidity (LM buyers) pay the premium. This may at least partly offset the disadvantages of LM selling compared to VM selling while increasing the disadvantages of LM buying compared to VM buying.

Finally, looking at the costs of liquidity provision during nonilliquid times (Panels C and D), we see that VM buys outperform LM buys by only a small margin and for only the first six months before turning negative. This is also consistent with an efficient market where the disadvantage of low trading discretion is not too harmful after all.

IV. Stock-Level Analysis

A. Manager Preferences and Characteristics of Stocks

After showing that mutual funds' VM trades generally outperform their LM trades in the previous section, we now analyze whether the stocks that funds trade due to VM are significantly different from the stocks they trade based on LM. Table VII therefore shows average stock characteristics for the TMM categories during illiquid (Panel A) and nonilliquid times (Panel B). Overall, the table shows clearer patterns during illiquid times, which is consistent with our previous finding that there exist clearer valuations in illiquid markets. Therefore, we concentrate on the respective results in Panel A and comment on the results of nonilliquid times in Panel B only if they follow a different pattern.

As measures for stock liquidity, we use monthly trading volume and the Amihud (2002) illiquidity ratio. With their VM trading, funds tend to buy illiquid stocks and sell nonilliquid stocks (Cao, Simin, and Wang, 2013; Dong, Feng, and Sadka, 2017). This difference is most striking in the Amihud illiquidity ratio, which is 0.124 for VM buys and 0.052 for VM sells on average. Moreover, VM buys have a distinctly higher illiquidity ratio than LM buys. This is consistent with funds capturing illiquidity premiums during times of low market liquidity if they have a clear valuation regarding the stock. With their LM trading, funds tend to sell highly liquid stocks. Overall, their LM sells have the highest level of liquidity, even in times of low market liquidity, which is consistent with funds reacting to investor outflows by selling off the assets with the lowest liquidity-related transaction costs (Clarke, Cullen, and Gasbarro, 2007).

Next, we consider the stock characteristics accounted for by the DGTW benchmarks (Daniel et al., 1997). Regarding market capitalization, funds tend to buy smaller stocks and sell larger ones with their VM trades, consistent with a small-cap premium strategy (Fama and French, 1993). Conversely, with their LM trades, funds buy larger stocks and sell smaller ones. During nonilliquid times (Panel B), we see a similar pattern for VM trades but a reversed one for LM trades, as funds sell larger and buy smaller stocks, as is also consistent with a small-cap premium strategy.

Regarding the book-to-market ratio, we observe that funds capture the value premium with their VM trades, as they generally buy stocks with high book-to-market ratios and sell stocks with low ratios. LM trades do not differ in their average book-to-market ratios. Regarding momentum, we compute the stocks' prior year's DGTW-adjusted return based on daily returns. With their VM buys, funds buy stocks with moderately negative prior returns, which might be an indication of current undervaluation. Similarly, VM sells show moderately positive prior returns, potentially indicating current overvaluation. The clearer pattern, however, can be observed in funds' LM trades, as they buy stocks with prior positive returns and sell stocks with very high negative returns, consistent with a classic momentum strategy (Jegadeesh and Titman, 1993; Carhart, 1997). Thus, if they have no clear fundamental valuation, funds strongly rely on technical analysis when forced to trade by investors' liquidity needs.

Concerning measures of risk, the market beta is significantly higher for VM buys than for LM buys, suggesting that mutual funds are prepared to take more systematic risk if they have a positive fundamental valuation of a stock. Comparing VM sells with LM sells shows the opposite pattern, suggesting that if funds have no clear valuation, they tend to sell stocks with higher systematic risk exposure. This pattern is also observable but less pronounced for the standard deviation of daily returns to reduce risk. As further risk characteristics, the skewness and kurtosis of returns show no clear patterns between VM and LM trading.

Table VII. Average Stock Characteristics for TMM Trade Categories

This table reports pooled average characteristics of the stocks traded by 3,802 actively managed US domestic equity funds in the period 2003–2012 sorted according to the Trade Motivation Matrix (TMM). Panel A presents results for illiquid market periods defined as the bottom 10% of the Pástor and Stambaugh (2003) market liquidity measure at the time of the trade. Panel B reports the results for all trades in the remaining periods (top 90%).

	N (tsd)	VM Buy	VM Sell	VM Buy – VM Sell	LM Buy	LM Sell	LM Buy – LM Sell	VM Buy – LM Buy	VM Sell – LM Sell
Panel A. Illiquid Market Periods—Bottom 10%									
Trading volume ($mil p.m.)	1,064	134.500***	139.900***	−5.318***	112.800***	139.800***	−26.940***	21.709***	0.086
Amihud illiquidity ratio	1,064	0.124***	0.052***	0.073***	0.065***	0.031***	0.034***	0.060***	0.020***
Market capitalization ($bil)	1,064	19.409***	22.797***	−3.387***	21.241***	20.470***	0.770***	−1.831***	2.327***
Book-to-market ratio+	810	0.956***	0.844***	0.112***	0.864***	0.872***	−0.008	0.092***	−0.028
Prior 1y DGTW-adj. ret (% p.a.)	997	−2.919***	1.825***	−4.743***	2.850***	−11.619***	14.469***	−5.768***	13.444***
CAPM beta	1,064	1.179***	1.121***	0.057***	1.139***	1.159***	−0.021***	0.040***	−0.038***
Return *SD* (% p.a.)	1,064	3.402***	3.258***	0.144***	3.062***	3.657***	−0.596***	0.341***	−0.399***
Return skewness	1,064	0.114***	0.115***	−0.001	0.117***	0.129***	−0.012***	−0.003	−0.015***
Return kurtosis	1,064	3.379***	3.343***	0.036***	3.343***	3.304***	0.039***	0.037***	0.039***
Short interest (mil)+	620	9.845***	10.098***	−0.253***	9.202***	10.105***	−0.904***	0.644***	−0.007
Price-to-earnings ratio+	491	16.721***	17.656***	−0.934***	17.622***	15.782***	1.840***	−0.901***	1.874***
Price-to-cash flow ratio+	446	12.137***	12.712***	−0.574***	12.629***	11.082***	1.547***	−0.492***	1.630***
Return on equity (% p.a.)+	610	9.898***	11.495***	−1.597***	10.761***	9.668***	1.092***	−0.863***	1.826***
Return on investment (% p.a.)+	611	7.348***	8.479***	−1.131***	7.931***	7.162***	0.769***	−0.583***	1.317***
S&P short-term credit rating+	107	102.575***	102.552***	0.023***	102.562***	102.577***	−0.015	0.013**	−0.025**
S&P long-term credit rating+	281	10.566***	10.458***	0.107***	10.461***	10.348***	0.113***	0.104***	0.111***
Total assets to total equity ratio+	512	3.380***	3.260***	0.120***	3.424***	3.586***	−0.162***	−0.044***	−0.326***
Retained earnings ($bil)+	392	2.266***	2.402***	−0.136***	2.218***	2.414***	−0.196***	0.047*	−0.012

(Continued)

Table VII. Average Stock Characteristics for TMM Trade Categories (*Continued*)

	N (tsd)	VM Buy	VM Sell	VM Buy – VM Sell	LM Buy	LM Sell	LM Buy – LM Sell	VM Buy – LM Buy	VM Sell – LM Sell
Panel B. Nonilliquid Market Periods—Top 90%									
Trading volume ($mil p.m.)	3,671	119.400***	123.000***	−3.576***	95.939***	132.500***	−36.525***	23.465***	−9.484***
Amihud illiquidity ratio	3,671	0.045***	0.020***	0.025***	0.039***	0.024***	0.015***	0.006	−0.004
Market capitalization ($bil)	3,671	20.831***	23.052***	−2.221***	20.261***	23.562***	−3.301***	0.570***	−0.509***
Book-to-market ratio+	2,939	0.697***	0.631***	0.066***	0.687***	0.659***	0.028**	0.009	−0.028**
Prior 1y DGTW-adj. ret. (% p.a.)	3,596	22.312***	26.273***	−3.961***	22.022***	20.318***	1.704***	0.289***	5.955***
CAPM beta	3,671	1.190***	1.173***	0.016***	1.154***	1.163***	−0.010***	0.036***	0.010***
Return *SD* (% p.a.)	3,671	2.211***	2.158***	0.052***	2.050***	2.231***	−0.181***	0.161***	−0.073***
Return skewness	3,671	0.106***	0.118***	−0.011***	0.107***	0.102***	0.004*	0.000	0.015***
Return kurtosis	3,671	3.469***	3.458***	0.011***	3.466***	3.369***	0.097***	0.004***	0.089***
Short interest (mil)+	2,192	9.137***	9.312***	−0.174***	8.173***	9.883***	−1.710***	0.965***	−0.571***
Price-to-earnings ratio+	1,826	18.334***	18.972***	−0.639***	18.743***	17.697***	1.046***	−0.410***	1.275***
Price-to-cash flow ratio+	1,705	13.135***	13.527***	−0.392***	13.345***	12.521***	0.823***	−0.210***	1.005***
Return on equity (% p.a.)+	2,178	12.067***	13.236***	−1.169***	12.285***	13.127***	−0.842***	−0.218***	0.108**
Return on investment (% p.a.)+	2,186	8.827***	9.652***	−0.825***	8.981***	9.420***	−0.439***	−0.155***	0.232***
S&P short-term credit rating+	407	102.594***	102.577***	0.017***	102.592***	102.614***	−0.021***	0.002	−0.037***
S&P long-term credit rating+	1,055	10.685***	10.610***	0.075***	10.661***	10.456***	0.205***	0.024***	0.154***
Total assets to total equity ratio+	1,884	3.331***	3.249***	0.081***	3.406***	3.402***	0.004	−0.075***	−0.153***
Retained earnings ($bil)+	1,711	3.083***	3.231***	−0.148***	2.854***	3.929***	−1.074***	0.229***	−0.698***

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.
+Compustat firm characteristics are filtered at the 1st and 99th percentiles to control for extreme outliers.

The short interest of the stocks, represented by the number of shares sold short by investors and not yet covered, is generally higher for sells than for buys, consistent with the interpretation as a measure of the market's sentiment regarding the stock (Lamont and Stein, 2004). For LM trades, this pattern is stronger than for VM sells, especially during nonilliquid times. Thus, if funds have no clear valuations and especially during times with low overall investment opportunities, funds tend to follow market sentiment in their LM selling decisions.

Regarding commonly used multiples, the price-to-earnings ratio and the price-to-cash flow ratio show different patterns between VM and LM trades. Specifically, with their VM trades, funds buy stocks with lower ratios on average. Such stocks may be considered undervalued and offer each unit of earnings or cash flow at a cheaper price. With their LM buys, on the other hand, funds tend to buy stocks with higher ratios, which may be interpreted as the market having higher growth expectations and positive sentiment regarding these stocks.

Regarding measures of firms' operating profitability, funds tend to buy stocks with lower return on equity (ROE) and with lower return on investment (ROI) and sell stocks with higher measures. This is against the intuition used by Fama and French (2015) in creating the profitability factor RMW (robust minus weak), which is long in firms with robust profitability and short in firms with weak profitability. The only exception is the pattern of LM trading during illiquid times, when funds buy stocks with higher profitability as they sell, which is consistent with the Fama and French (2015) intuition.

Regarding the credit worthiness of the firms, we see no relevant differences between the Standard & Poor's (S&P) short-term or long-term credit ratings. Moreover, we see no relevant differences in the firm's ratio of total assets to total equity, which we interpret as the leverage of the firms playing no important role for the trading decisions of mutual funds.

Finally, we look at the retained earnings of the firms as indicators of past profitability but also of the stocks' tendency to withhold earnings from the investors instead of paying profits out as dividends. While during illiquid times, there seem to be no clear tendencies, we observe that during nonilliquid times, LM buys are in stocks with low retained earnings and LM sells are in stocks with high retained earnings. This may be explained by the lack of investment ideas and growth expectations so that funds rely on the tendency of firms to at least pay a dividend (Harris, Hartzmark, and Solomon, 2015).

Overall, we find that funds tend to display rather different trading patterns with their VM and LM trades. These can be rationalized in many cases with the funds capturing risk premiums and following fundamental valuations with their VM trades versus relying on common multiples, sentiment, and technical valuations such as momentum with their LM trades.

B. Explaining Stock Performance with Collective Mutual Fund Trading—Wisdom of Crowds

Considering the findings in the previous sections, we deem it reasonable to assume that the collective valuations of all mutual funds may have explanatory power over the future performance of single stocks. In this context, several recent articles analyzing the "wisdom of crowds" in financial markets indicate that the collective trading decisions of mutual fund managers (Chalmers, Kaul, and Phillips, 2013) and hedge fund managers (Sias, Turtle, and Zykaj, 2016) predict future raw and risk-adjusted stock returns. However, these studies do not consider trading motivation.

Therefore, we define two new stock-specific variables based on the TMM: VM buying ratio ($VMB\ ratio_{j,q}$) is defined as the number of funds buying stock j due to VM during quarterly reporting period q divided by the total number of funds buying stock j during q. Similarly, VM selling ratio ($VMS\ ratio_{j,q}$) is defined as the number of funds selling the stock due to VM divided by the total number of funds selling the stock. A higher VMB ratio thus indicates a stronger positive consensus valuation of a stock, and a higher VMS ratio indicates a stronger negative consensus valuation of a stock. Thus, our VM ratios reverse the approach by Da, Gao, and Jagannathan (2011), who use the stocks' probability of informed trading (PIN) based on stock characteristics to derive fund-level motivation from the funds' trades.

To test our expectation that the VM ratios represent wisdom of the (fund manager) crowd, we run panel regressions for the overall period with stock- and time-fixed effects to explain future stock performance, measured by the DGTW-adjusted returns over up to 12 months going forward, with the stocks' VM ratios controlling for the stock characteristics presented in Table VII following Equation (4).[19] To ease interpretation, all variables are standardized to mean zero and unit standard deviation. Standard errors are two-dimensionally clustered by stock and reporting period following Petersen (2009) to control for heteroskedasticity and cross-sectional as well as time-series correlation.

$$performance_{i,q+x} = \varphi_0 + \varphi_1 VM\ ratio_{j,q} + \sum_{c=2}^{C} \varphi_c\ stock\ characteristics_{j,c,q} + \eta_{j,q}. \tag{4}$$

The results are presented in Table VIII. Panel A reports results for mutual fund VM buying. Univariate (specification (1)) as well as multivariate regression results specification (2)) indicate that a higher degree of VM buying is significantly related to positive future DGTW-adjusted stock returns over all tested time horizons. Thus, the collective VM buying decisions of mutual fund managers represent wisdom of the crowd. Moreover, as the pattern can be observed over long horizons, this shows that our finding is not driven by a potential price impact by funds' collective trading.

Similarly, Panel B reports results for mutual fund VM selling. As expected, the coefficients of the VMS ratio are negative and in most cases statistically significant for all tested horizons. Thus, also, the collective VM selling decisions of mutual fund managers represent wisdom of the crowd.[20] Further, the coefficients on the stock characteristics indicate that trading volume has an overall negative effect and market beta has a positive effect on DGTW-adjusted stock returns. The fund characteristics explicitly controlled for by the DGTW benchmarks—size, book-to-market ratio, and momentum—still have significant effects on DGTW-adjusted returns, similar to findings on fund level by Busse, Jiang, and Tang (2017).

V. Fund-Level Analysis

A. Determinants of Mutual Funds' Extent of VM Trading

This section analyzes which fund characteristics are associated with discretionary trading. Hence, similar to our stock-level analysis, we define three fund-specific variables based on the TMM: $VM\ ratio_{i,q}$ is defined as the number of VM trades of fund i during quarterly reporting period q divided by the number of fund i's total trades during q. Similarly, $VMB\ ratio_{i,q}$ ($VMS\ ratio_{i,q}$) is defined as the number of VM buys (sells) divided by the total number of

[19] We use only those fund characteristics as control variables that have a high number of observations available to retain a high number of observations in our regression analysis.

[20] Unreported additional panel regressions using future cumulative raw returns as independent variables lead to qualitatively similar results, which are available upon request.

Table VIII. Prediction of Future Stock Performance with the Stocks' Degree of Valuation-Motivated Trading

This table reports panel regressions with stock- and time-fixed effects (within) of future cumulative DGTW-adjusted stock performance with the amount of collective valuation-motivated mutual fund trading in 5,246 common US stocks in the period 2003–2012. VMB ratio (VMS ratio) is the number of VM buying (selling) funds divided by the number of total buying (selling) funds. All independent variables are measured over quarterly reporting period q except "Prior 1y DGTW-adjusted return" that is measured over year y−1. P-values are given in parentheses. All variables are standardized to mean zero and unit standard deviation. Standard errors are two-dimensionally clustered by stock and reporting period following Petersen (2009) to control for heteroskedasticity and cross-sectional as well as time-series correlation.

	Cumulative DGTW-Adjusted Performance over the Next							
	1 Month		**3 Months**		**6 Months**		**12 Months**	
	(1)	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**	**(1)**	**(2)**
	Panel A. Collective VM Mutual Fund Buying							
VMB ratio	0.007**	0.007*	0.012***	0.011***	0.010***	0.009**	0.016***	0.015***
	(0.036)	(0.051)	(0.001)	(0.001)	(0.009)	(0.013)	(0.000)	(0.000)
Trading volume		−0.005*		−0.005		−0.008		−0.014***
		(0.088)		(0.238)		(0.125)		(0.007)
Amihud illiquidity ratio		0.004		−0.001		0.007		0.006
		(0.209)		(0.903)		(0.165)		(0.316)
Market capitalization		−0.024***		−0.041***		−0.055***		−0.074***
		(0.000)		(0.000)		(0.000)		(0.000)
Book-to-market ratio		−0.012**		−0.015**		−0.014*		−0.010
		(0.041)		(0.040)		(0.083)		(0.189)
Prior 1y DGTW adj. ret.		−0.046***		−0.080***		−0.112***		−0.142***
		(0.000)		(0.000)		(0.000)		(0.000)
Market beta		0.027*		0.021		0.020		0.022*
		(0.085)		(0.116)		(0.125)		(0.072)
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.000	0.004	0.000	0.009	0.000	0.017	0.000	0.028
N	154,565	154,565	154,565	154,565	154,565	154,565	154,565	154,565
	Panel B. Collective VM Mutual Fund Buying							
VMB ratio	−0.007*	−0.005	−0.009**	−0.006*	−0.011**	−0.007**	−0.010***	−0.005
	(0.075)	(0.155)	(0.023)	(0.092)	(0.001)	(0.031)	(0.007)	(0.132)
Trading volume		−0.004*		−0.004		−0.007		−0.013***
		(0.093)		(0.325)		(0.164)		(0.009)
Amihud illiquidity ratio		0.007		0.009*		0.019**		0.018*
		(0.285)		(0.081)		(0.050)		(0.099)
Market capitalization		−0.023***		−0.039***		−0.053***		−0.071***
		(0.000)		(0.000)		(0.000)		(0.000)
Book-to-market ratio		−0.007		−0.014**		−0.013*		−0.009
		(0.143)		(0.020)		(0.075)		(0.248)
Prior 1y DGTW adj. ret.		−0.050***		−0.085***		−0.117***		−0.149***
		(0.000)		(0.000)		(0.000)		(0.000)
Market beta		0.033**		0.029*		0.029**		0.030**
		(0.048)		(0.046)		(0.047)		(0.022)

(*Continued*)

Table VIII. Prediction of Future Stock Performance with the Stocks' Degree of Valuation-Motivated Trading (*Continued*)

	Cumulative DGTW-Adjusted Performance over the Next							
	1 Month		3 Months		6 Months		12 Months	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
	Panel B. Collective VM Mutual Fund Buying							
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.000	0.004	0.000	0.010	0.000	0.018	0.000	0.030
N	143,143	143,143	143,143	143,143	143,143	143,143	143,143	143,143

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

buys (sells).[21] To determine which fund characteristics are associated with a higher degree of VM trading, Table IX shows the results of panel regression (Equation (5)) with fund- and time-fixed effects (within) of the VM ratios on the fund characteristics reported in Table I. To ease interpretation, all variables are standardized to mean zero and unit standard deviation. Standard errors are two-dimensionally clustered by fund and reporting period following Petersen (2009) to control for heteroskedasticity and cross-sectional as well as time-series correlation.

$$VM\ ratio_{i,q} = \varphi_0 + \sum_{c=1}^{C} \varphi_c\, fund\ characteristics_{i,c,q} + \eta_{i,q}. \tag{5}$$

As our previous findings on the value of funds' VM trading are more pronounced during illiquid market periods, Panels A and B report results separately for the different liquidity regimes. The first overall impression is that fund characteristics explain VM trading quite well with R^2 of 18% overall and of 32% for VM buying. However, the R^2 for VM selling is only 2%, possibly due to the low overall number of LM sells compared to LM buys documented in Table III.

As expected, investor flows are negatively related to the degree of VM trading at all times. Specifically, higher net inflows are associated with a significantly lower degree of discretionary buying. Conversely, higher net inflows are positively associated with significantly higher discretionary selling. This is consistent with previous studies showing that mutual funds face flow risk (Edelen, 1999; Rakowski, 2010; Rohleder, Schulte, and Wilkens, 2017). The same applies to higher cash holdings, which are negatively related to VM buying and positively related to VM selling at all times. This is in accordance with the related literature (Simutin, 2014) and indicates that holding cash can be an efficient buffer against flow risk.[22]

[21] In unreported tests, we use similar VM ratios based on trading (buying/selling) volume. The results are economically similar and available upon request.

[22] In unreported tests, we confirm the findings in this paragraph by conducting trade-level analyses analog to Table IV where we distinguish trades occurring when funds have (i) high versus low absolute flows and (ii) high versus low cash holdings. The results are available upon request.

Table IX. Determinants of Extent of Valuation-Motivated Mutual Fund Trading

This table reports panel regressions with fund- and time-fixed effects (within) of the extent of VM mutual fund trading for 3,802 actively managed US domestic equity funds in the period 2003–2012. VM ratio is the number of VM trades divided by the number of total trades per fund in quarterly reporting period q, and VMB ratio (VMS ratio) is the number of VM buys (sells) divided by the number of total buys (sells). Alpha is the intercept from the Carhart (1997) four-factor model calculated using daily net returns. All dependent and independent variables are measured over quarterly reporting period q except Alpha$_{q-1}$ and VM ratio$_{q-1}$ that are lagged one reporting period. P-values are given in parentheses. All variables are standardized to mean zero and unit standard deviation. Standard errors are two-dimensionally clustered by fund and reporting period following Petersen (2009) to control for heteroskedasticity and cross-sectional as well as time-series correlation.

	VM Ratio			VMB Ratio			VMS Ratio		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Panel A. Illiquid Market Periods—Bottom 10%									
Net flow	−0.414***	−0.414***	−0.418***	−0.556***	−0.553***	−0.567***	0.137***	0.135***	0.140***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cash	−0.032**	−0.031**	−0.029**	−0.050***	−0.047***	−0.048***	0.043***	0.040***	0.044***
	(0.022)	(0.033)	(0.045)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.003)
Log-Size	−0.011	−0.008	−0.010	−0.024**	−0.022*	−0.023*	0.001	0.004	0.011
	(0.457)	(0.582)	(0.533)	(0.041)	(0.079)	(0.059)	(0.965)	(0.834)	(0.545)
Age	−0.011	−0.013	−0.014	0.027***	0.027**	0.021*	−0.057***	−0.059***	−0.062***
	(0.334)	(0.336)	(0.259)	(0.006)	(0.015)	(0.071)	(0.000)	(0.000)	(0.000)
Expense ratio	−0.009	−0.008	−0.009	−0.011	−0.010	−0.011	−0.004	−0.004	−0.006
	(0.449)	(0.514)	(0.509)	(0.378)	(0.441)	(0.432)	(0.741)	(0.775)	(0.618)
Front load	0.000	0.004	−0.003	0.011	0.015	0.008	−0.007	−0.008	−0.011
	(0.980)	(0.840)	(0.882)	(0.579)	(0.447)	(0.695)	(0.557)	(0.486)	(0.372)
Rear load	−0.018	−0.022	−0.019	−0.011	−0.016	−0.013	−0.006	−0.005	−0.009
	(0.298)	(0.198)	(0.294)	(0.545)	(0.394)	(0.449)	(0.645)	(0.683)	(0.501)
Turnover ratio	0.010	0.011	0.005	0.018**	0.017**	0.015	−0.001	0.000	−0.002
	(0.429)	(0.354)	(0.743)	(0.029)	(0.050)	(0.123)	(0.882)	(0.961)	(0.837)
Alpha$_{q-1}$		0.001			0.007			−0.010	
		(0.951)			(0.556)			(0.424)	

(*Continued*)

Table IX. Determinants of Extent of Valuation-Motivated Mutual Fund Trading (*Continued*)

	VM Ratio			VMB Ratio			VMS Ratio		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Panel A. Illiquid Market Periods—Bottom 10%									
VM ratio$_{q-1}$			−0.017			0.006			−0.054
			(0.531)			(0.810)			(0.295)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within R^2	0.176	0.178	0.176	0.324	0.327	0.324	0.025	0.024	0.028
N	5,785	5,467	5,486	5,583	5,277	5,170	5,646	5,334	5,248
Panel B. Nonilliquid Market Periods—Top 90%									
Net flow	−0.452***	−0.454***	−0.422***	−0.551***	−0.552***	−0.513***	0.141***	0.141***	0.144***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cash	−0.020***	−0.020***	−0.015**	−0.031***	−0.032***	−0.021***	0.029***	0.028***	0.027***
	(0.003)	(0.002)	(0.017)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Log-Size	−0.023**	−0.025***	−0.013	−0.041***	−0.043***	−0.026***	0.039***	0.039***	0.038***
	(0.014)	(0.010)	(0.136)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Age	0.022***	0.022***	0.016***	0.028***	0.027***	0.019***	−0.012**	−0.011**	−0.011**
	(0.001)	(0.001)	(0.006)	(0.000)	(0.000)	(0.001)	(0.034)	(0.037)	(0.029)
Expense ratio	−0.001	−0.001	0.001	−0.015**	−0.016**	−0.011*	0.015**	0.016**	0.014*
	(0.872)	(0.860)	(0.917)	(0.048)	(0.043)	(0.068)	(0.039)	(0.025)	(0.061)
Front load	0.010	0.009	0.012*	0.016**	0.015**	0.019***	−0.009*	−0.009*	−0.009*
	(0.173)	(0.212)	(0.056)	(0.020)	(0.033)	(0.002)	(0.089)	(0.069)	(0.072)
Rear load	0.004	0.004	0.005	−0.005	−0.005	−0.006	0.006	0.007	0.007
	(0.580)	(0.590)	(0.513)	(0.520)	(0.540)	(0.462)	(0.357)	(0.344)	(0.307)

(*Continued*)

Table IX. Determinants of Extent of Valuation-Motivated Mutual Fund Trading (*Continued*)

	VM Ratio			VMB Ratio			VMS Ratio		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Panel B. Nonilliquid Market Periods—Top 90%									
Turnover ratio	0.012*	0.013*	0.009	0.000	0.001	0.000	0.021***	0.021**	0.022***
	(0.071)	(0.062)	(0.137)	(0.954)	(0.823)	(0.980)	(0.010)	(0.012)	(0.003)
Alpha_{q-1}		−0.002			−0.006			0.002	
		(0.780)			(0.373)			(0.721)	
VM ratio_{q-1}			0.147***			0.171***			0.038***
			(0.000)			(0.000)			(0.009)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within R^2	0.208	0.208	0.2225	0.313	0.314	0.341	0.023	0.023	0.025
N	35,072	34,623	33,661	33,565	33,143	31,421	33,703	33,275	31,511

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

Fund size, measured by the natural logarithm of TNA, is negatively related to the degree of VM trading, especially to VM buying for which the coefficients are significant. Comparing different liquidity regimes, the relation is especially prevalent during nonilliquid times. This is consistent with diseconomies of scale in general (Chen et al., 2004; Pástor, Stambaugh, and Taylor, 2015) and especially with the findings in Pollet and Wilson (2008) that larger funds hold more different assets than smaller funds and thus may have greater difficulties generating new investment ideas. This leads to a tendency of larger funds toward scaling instead of diversification. In illiquid times, however, these difficulties are less severe due to lower market efficiency and more opportunities of VM trading. Moreover, when explaining VM selling, size shows positive coefficients during nonilliquid times, which may also be consistent with larger funds holding more different assets and thus having a larger selling universe to choose from—once again, assuming that short sales are scarcely used by mutual funds (Chen, Desai, and Krishnamurthy, 2013).

Fund age is positively related to VM buying and negatively related to VM selling. The former result may be explained by older funds having more mature and sophisticated structures and overall experience. Moreover, more successful managers may get promoted to older and thus more prestigious funds (Kempf and Rünzi, 2008; Evans, 2009). The negative relation with selling discretion, however, may indicate that selling skill is not equally recognized as buying skill when it comes to promoting fund managers.

Concerning mutual fund fee structures, the coefficients of expense ratio, front load, and rear load are unrelated to VM trading during both liquidity regimes. A possible explanation is that many mutual funds recently stopped charging front loads to become more attractive to increasingly well-informed and fee-sensitive investors (Barber, Odean, and Zheng, 2005).

In terms of the overall trading behavior of funds, the turnover ratio is positively related to VM buying in illiquid times and with VM selling in nonilliquid times. This is in accordance with findings by Pástor, Stambaugh, and Taylor (2017), who argue that abnormal turnover may proxy for a higher degree of valuations and new investment ideas, especially during times with high valuation uncertainty.

Finally, we also include past performance in specification (2) of the panel regressions to control for endogeneity. However, the coefficients are insignificant during illiquid and nonilliquid times so that there is no endogeneity in our results. Moreover, we include lagged VM ratio in specification (3) of the panel regressions to control for persistence in discretionary trading. While there is no significant effect during illiquid times, the results for nonilliquid times show significantly positive coefficients, so that the trading discretion of funds is persistent in such periods.

B. Explaining Fund Performance with the Extent of VM Trading

The findings in previous sections indicate that managers generally possess stock-picking skill and that collective VM trading represents wisdom of the (fund manager) crowd. These findings may be in contrast to the majority of mutual fund studies beginning with Jensen (1968) that consistently show that funds deliver negative risk-adjusted performance to investors. Thus, it remains questionable whether the skill we find on trade and stock level actually translates into investor benefits via higher fund performance. However, following Pástor, Stambaugh, and Taylor (2017), we argue that VM trading may have a direct effect on performance rather than a cross-sectional one.

Therefore, Table X shows the results of panel regressions (Equation (6)) with fund- and time-fixed effects of future investor performance $alpha_{i,q+1}$, measured by applying the Carhart (1997) four-factor model on daily fund net returns during quarter $q+1$, on the VM ratios defined in Subsection V.A and controlling for the fund characteristics reported in Table I. To ease

Table X. Predicting Future Fund Performance by Extent of Valuation-Motivated Mutual Funds Trading

This table reports panel regressions with fund- and time-fixed effects (within) of future risk-adjusted performance Alpha_{q+1} by the extent of VM mutual fund trading for 3,802 actively managed US domestic equity funds in the period 2003–2012. VM ratio is the number of VM trades divided by the number of total trades per fund during reporting period q, and VMB ratio (VMS ratio) is the number of VM buys (sells) divided by the number of total buys (sells). Alpha is the intercept from the Carhart (1997) four-factor model calculated using daily net returns. All independent variables are measured over quarterly reporting period q. P-values are given in parentheses. All variables are standardized to mean zero and unit standard deviation. Standard errors are clustered by fund and reporting period following Petersen (2009) to control for heteroskedasticity and cross-sectional as well as time-series correlation.

	Alpha_{q+1} Explained by VM Ratio			Alpha_{q+1} Explained by VMB Ratio			Alpha_{q+1} Explained by VMS Ratio		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Panel A. Illiquid Market Periods—Bottom 10%									
VM ratio	0.041***	0.039***	0.033**	0.026*	0.026*	0.012	0.030**	0.029***	0.034***
	(0.002)	(0.002)	(0.012)	(0.071)	(0.072)	(0.394)	(0.014)	(0.005)	(0.001)
Net flow			−0.003			−0.010			−0.024
			(0.846)			(0.594)			(0.128)
Cash			0.001			0.002			0.001
			(0.931)			(0.886)			(0.957)
Log-Size			−0.114***			−0.111***			−0.113***
			(0.000)			(0.000)			(0.000)
Age			0.005			0.005			0.004
			(0.771)			(0.795)			(0.807)
Expense ratio			−0.007			−0.005			−0.008
			(0.644)			(0.751)			(0.620)
Front load			−0.027			−0.026			−0.023
			(0.200)			(0.203)			(0.304)
Rear load			0.023			0.024			0.021
			(0.125)			(0.111)			(0.203)
Turnover ratio			0.047**			0.052***			0.048**
			(0.015)			(0.005)			(0.015)
Alpha		−0.093**	−0.097**		−0.095**	−0.098***		−0.086**	−0.090**
		(0.022)	(0.011)		(0.013)	(0.006)		(0.035)	(0.019)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within R^2	0.002	0.010	0.027	0.001	0.010	0.027	0.001	0.008	0.026
N	5,434	5,239	5,239	5,246	5,059	5,059	5,306	5,118	5,118
Panel B. Liquid Market Periods—Top 90%									
VM ratio	0.007	0.006	−0.006	0.013**	0.013*	−0.001	−0.018***	−0.017***	−0.013**
	(0.254)	(0.286)	(0.386)	(0.038)	(0.050)	(0.915)	(0.005)	(0.008)	(0.027)
Net flow			−0.027***			−0.024***			−0.023***
			(0.000)			(0.001)			(0.001)
Cash			0.007			0.004			0.010
			(0.371)			(0.605)			(0.243)
Log-Size			−0.066***			−0.065***			−0.068***
			(0.000)			(0.000)			(0.000)

(*Continued*)

Table X. Predicting Future Fund Performance by Extent of Valuation-Motivated Mutual Funds Trading (*Continued*)

	Alpha$_{q+1}$ Explained by VM Ratio			Alpha$_{q+1}$ Explained by VMB Ratio			Alpha$_{q+1}$ Explained by VMS Ratio		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Panel B. Liquid Market Periods—Top 90%									
Age			−0.022***			−0.022***			−0.024***
			(0.001)			(0.001)			(0.000)
Expense ratio			0.005			0.006			0.003
			(0.506)			(0.471)			(0.688)
Front load			−0.013**			−0.012*			−0.013**
			(0.037)			(0.054)			(0.033)
Rear load			−0.004			−0.003			−0.002
			(0.594)			(0.633)			(0.735)
Turnover ratio			0.005			0.005			0.004
			(0.461)			(0.522)			(0.539)
Alpha		0.015	0.012		0.014	0.011		0.015	0.012
		(0.365)	(0.481)		(0.398)	(0.519)		(0.362)	(0.482)
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within R^2	0.000	0.000	0.006	0.000	0.000	0.006	0.000	0.001	0.007
N	33,238	32,760	32,760	31,838	31,387	31,387	31,956	31,505	31,505

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

interpretation, all variables are standardized to mean zero and unit standard deviation. Standard errors are two-dimensionally clustered according to fund and reporting period, following Petersen (2009) to control for heteroskedasticity and cross-sectional as well as time-series correlation.[23]

$$alpha_{i,q+1} = \varphi_0 + \varphi_1 VM\ ratio_{i,q} + \sum_{c=2}^{C} \varphi_c\, fund\ characteristics_{i,c,q} + \eta_{i,q}. \tag{6}$$

The results for the univariate specification (1) of the panel regressions in Panel A for illiquid times show significantly positive coefficients for all three VM ratios. Thus, a higher degree of trading discretion during illiquid market periods is significantly related to higher investor performance in the following quarter. This is in line with the observation that under crisis conditions, the overall pricing heterogeneity creates an environment in which managers more easily identify over- and underpriced stocks and discipline themselves more strongly in both their buying and selling decision (Jin and Taffler, 2016). This relation also holds for the inclusion of alpha in specification (2) of the panel regressions as a control variable for short-term persistence (Bollen and Busse, 2004). However, we find significant evidence for short-term reversal during illiquid times, which may be a result of performance chasing (Gruber, 1996). When we include the other fund characteristics as controls in specification (3) of the panel regressions, the coefficients for overall VM trading and VMS trading remain significantly positive, while the positive effect of

[23] In unreported tests, we use similar VM ratios based on trading (buying/selling) volume. The results are economically the same, but statistical significance is a bit lower.

Figure 2. The Extended Trade Motivation Matrix (eTMM)

	Weight Change in the Direction of the Trade	*No Weight Change in the Direction of the Trade*
Buy	Heavy VM buy / Light VM buy	LM buy
Sell	Heavy VM sell / Light VM sell	LM sell

VM buying on future performance seems to be subsumed by the other fund characteristics. With regard to the fund characteristics, size is negatively related to future performance, consistent with diseconomies of scale (Chen et al., 2004; Pástor, Stambaugh, and Taylor, 2015) and turnover is positively related to future performance, consistent with the findings in Pástor, Stambaugh, and Taylor (2017).

The results in Panel B for nonilliquid market periods are less pronounced compared to the results for illiquid times. This could be expected from the previous sections, as under noncrisis conditions, there is low pricing heterogeneity, which aggravates the identification of over- and underpriced stocks. Consequentially, the coefficients of the overall VM trading ratio on alpha are insignificant. However, VM buying still positively predicts future alpha, which is in line with the higher overall buying discipline found by Jin and Taffler (2016).

As for the control variables, higher net flows during nonilliquid times result in significantly lower future performance, consistent with flow risk. Log size and age are negatively related to future performance as in Panel A. Turnover loses its predictive power over performance in nonilliquid times. Finally, there is no significant relation between current and future alpha, indicating no performance persistence, which is consistent with an efficient market (Fama, 1970).

VI. Further Tests and Robustness Checks

A. Considering Heavy and Light Valuation Motivation

One of the advantages of the TMM is its limited set of assumptions and hence its intuitiveness and clarity. However, the assignment of single trades to TMM categories may be further enhanced by additionally considering that within all VM trades, there might exist different degrees of valuation. Therefore, we consider an extended TMM (eTMM), which further distinguishes VM buys and VM sells into "heavy" and "light" ones as indicated in Figure 2.

The first intuitive approach to further differentiate the degree of valuation is based on the magnitude of the weight increase. This makes sense, as one would assume that, for example, VM buys with high weight increases contain clearer valuation than VM buys with only small weight increases. For this reason, the first test with the eTMM separates VM trades at the median weight change—that is, their influence on portfolio allocation. The results are presented in Table XI. They are as expected in that more influential VM buys clearly outperform less influential VM buys for up to six months (overall), respectively, 12 months (illiquid). Similarly, the mitigated losses from heavy VM sells are higher than those from light VM sells in most cases.

Table XI. Pooled Single-Trade Performance—Valuation Separated by Weight Change

This table reports cumulative DGTW benchmark-adjusted performance over the next 1-, 3-, 6-, and 12-month periods resulting from trades sorted according to the Trade Motivation Matrix (TMM) of 3,802 actively managed US domestic equity funds in the period 2003–2012. VM trades are further categorized as heavy (weight increase above 50th percentile within all VM trades) and light (weight increase below 50th percentile within all VM trades).

		Cum. DGTW-Adjusted Performance (in %) over the Next			
	N	**1 Month**	**3 Months**	**6 Months**	**12 Months**
Panel A. Overall Period—Benchmark: Relevant Universe (Buys: CRSP, Sells: Holdings)					
VM buys	1,710,743	0.177***	0.240***	0.352***	0.362***
VM buys (heavy)	855,371	0.203***	0.269***	0.377***	0.311***
VM buys (light)	855,372	0.151***	0.210***	0.326***	0.409***
VM buys (h) – VM buys (l)		0.052***	0.059**	0.051	−0.099*
VM sells	2,111,743	−0.077***	−0.105***	−0.144***	−0.178***
VM sells (heavy)	1,055,871	−0.078***	−0.098***	−0.159***	−0.276***
VM sells (light)	1,055,872	−0.077***	−0.114***	−0.132***	−0.084***
VM sells (h) – VM sells (l)		−0.001	0.016	−0.028	−0.192***
LM buys	747,873	0.045***	0.094***	0.226***	0.392***
LM sells	165,345	0.001	0.034	−0.053	−0.143*
Panel B. Illiquid Periods—Benchmark: Relevant Universe (Buys: CRSP, Sells: Holdings)					
VM buys	387,368	0.476***	0.739***	1.462***	2.007***
VM buys (heavy)	193,672	0.518***	0.898***	1.832***	2.488***
VM buys (light)	193,673	0.434***	0.577***	1.088***	1.511***
VM buys (h) – VM buys (l)		0.083**	0.321***	0.745***	0.977***
VM sells	479,154	−0.149***	−0.202***	−0.453***	−0.735***
VM sells (heavy)	239,550	−0.120***	−0.203***	−0.491***	−0.793***
VM sells (light)	239,551	−0.179***	−0.207***	−0.422***	−0.690***
VM sells (h) – VM sells (l)		0.059*	0.004	−0.069	−0.103
LM buys	165,761	0.217***	0.495***	0.906***	0.725***
LM sells	31,991	0.684***	0.986***	1.856***	2.561***

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

The second test with the eTMM takes into account that in some scenarios, a clear assignment of trade motivation is not always possible. Imagine a fund that experiences outflow and does not sell every holding in proportion but sells only some of its holdings to reduce transaction costs. Such trades would be identified as VM sells, whereas on the other hand, one could argue that these are gray cases because the transactions are triggered by flow. For this reason, we use the direction of the flow to separate heavy (clear valuation) and light (vague valuation) VM trades. Specifically, heavy VM sells occur during periods with net inflow and light (vague) VM sells, as in the example, occur during periods with net outflow. A similar logic applies to VM buys. This approach of distinguishing valuation clearness is also closest to the BF and SF definitions of ACG. The results are presented in Table XII. Overall, the results are as expected in that heavy

Table XII. Pooled Single-Trade Performance—Valuation Separated by Valuation Clearness

This table reports cumulative DGTW benchmark-adjusted performance over the next 1-, 3-, 6-, and 12-month periods resulting from trades sorted according to the Trade Motivation Matrix (TMM) of 3,802 actively managed US domestic equity funds in the period 2003–2012. VM trades are further categorized as heavy (if buy despite of outflow and sell despite of inflow) and light (upscaling buy in case of inflow and downscaling sell in case of outflow).

		Cum. DGTW-Adjusted Performance (in %) over the Next			
	N	**1 Month**	**3 Months**	**6 Months**	**12 Months**
Panel A. Overall Period—Benchmark: Relevant Universe (Buys: CRSP, Sells: Holdings)					
VM buys	1,710,743	0.177***	0.240***	0.352***	0.362***
VM buys (heavy)	954,939	0.201***	0.250***	0.355***	0.366***
VM buys (light)	755,804	0.146***	0.227***	0.349***	0.357***
VM buys (h) – VM buys (l)		0.055***	0.023	0.006	0.008
VM sells	2,111,743	−0.077***	−0.105***	−0.144***	−0.178***
VM sells (heavy)	543,736	−0.095***	−0.129***	−0.229***	−0.302***
VM sells (light)	1,568,007	−0.070***	−0.096***	−0.114***	−0.135***
VM sells (h) – VM sells (l)		−0.025*	−0.033	−0.115***	−0.168***
LM buys	747,873	0.045***	0.094***	0.226***	0.392***
LM sells	165,345	0.001	0.034	−0.053	−0.143*
Panel B. Illiquid Period—Benchmark: Relevant Universe (Buys: CRSP, Sells: Holdings)					
VM buys	387,368	0.476***	0.739***	1.462***	2.007***
VM buys (heavy)	228,868	0.557***	0.782***	1.616***	2.363***
VM buys (light)	158,500	0.359***	0.677***	1.240***	1.493***
VM buys (h) – VM buys (l)		0.198***	0.105	0.377***	0.870***
VM sells	479,154	−0.149***	−0.202***	−0.453***	−0.735***
VM sells (heavy)	126,737	−0.126***	−0.154***	−0.528***	−0.812***
VM sells (light)	352,417	−0.157***	−0.219***	−0.426***	−0.707***
VM sells (h) – VM sells (l)		0.030	0.065	−0.102	−0.105
LM buys	165,761	0.217***	0.495***	0.906***	0.725***
LM sells	31,991	0.684***	0.986***	1.856***	2.561***

***Significant at the 0.01 level.
*Significant at the 0.10 level.

trades outperform light trades, however, less clear than in the test using the median weight change (see Table XI).

In summary, we consider the results from the eTMM as valuable additional insights into the effects of heavy and light VM trading. However, by considering only heavy VM trades, the eTMM ignores a significant proportion of trades and thus makes inferences on average manager skill impossible. As the overall difference to our main analysis is not substantial, we conclude that the simple classification method is robust.

B. Imperfect Scaling

Another possible source of imprecise categorization by the TMM can arise from imperfect scaling. This occurs if a manager wants to scale—that is, trade LM without new investment

Table XIII. Pooled Single-Trade Performance Adjusted for Marginal Weight Changes—Overall Period

This table reports cumulative DGTW benchmark-adjusted performance over the next 1-, 3-, 6-, and 12-month periods resulting from trades sorted according to the Trade Motivation Matrix (TMM) of 3,802 actively managed US domestic equity funds in the period 2003–2012. The benchmark universe for buys consists of all CRSP stocks. The benchmark universe for sells consists of all stocks currently held by the respective fund, assuming no short selling. In Panel A, the performance is weighted by the underlying weight changes. Weights below the 1st percentile and above the 99th percentile were excluded from this analysis to account for outliers. In Panel B (C), trades with absolute weight changes below 5% (10%) of the previous weight are reclassified as LM trades.

		Cumulative DGTW-Adjusted Performance (in %) over the Next			
	N	**1 Month**	**3 Months**	**6 Months**	**12 Months**
Panel A. Weight Change-Weighted Trades					
VM buys	1,613,953	0.190***	0.258***	0.383***	0.385***
VM sells	2,019,455	−0.091***	−0.129***	−0.169***	−0.189***
VM buys – VM sells		0.281***	0.387***	0.552***	0.575***
LM buys	747,368	0.044***	0.094***	0.229***	0.401***
LM sells	165,304	0.002	0.037***	−0.050***	−0.138***
VM buys – LM buys		0.146***	0.165***	0.154***	−0.016***
VM sells – LM sells		−0.093***	−0.165***	−0.119***	−0.052***
Panel B. Reclassification of Trades with Absolute Weight Changes below 5% as LM Trades					
VM buys	1,435,856	0.191***	0.245***	0.346***	0.341***
VM sells	1,659,298	−0.091***	−0.113***	−0.171***	−0.247***
VM buys – VM sells		0.282***	0.358***	0.517***	0.587***
LM buys	1,022,760	0.060***	0.126***	0.268***	0.415***
LM sells	617,790	−0.019*	−0.045**	−0.047	0.017
VM buys – LM buys		0.131***	0.120***	0.079***	−0.074*
VM sells – LM sells		−0.071***	−0.068***	−0.124***	−0.264***
Panel C. Reclassification of Trades with Absolute Weight Changes below 10% as LM Trades					
VM buys	1,345,131	0.191***	0.246***	0.350***	0.345***
VM sells	1,419,339	−0.088***	−0.105***	−0.166***	−0.257***
VM buys – VM sells		0.279***	0.351***	0.516***	0.602***
LM buys	1,113,485	0.071***	0.135***	0.269***	0.403***
LM sells	857,749	−0.043***	−0.077***	−0.090***	−0.040
VM buys – LM buys		0.120***	0.111***	0.082***	−0.058
VM sells – LM sells		−0.046***	−0.029	−0.076**	−0.217***

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

idea—but fails to keep the weight change of the stock perfectly at zero—for example, due to trading integer numbers of stocks. The TMM may thus falsely classify such trades as VM. To mitigate the influence of such possible imprecise classifications, we control for "marginal" weight changes from imperfect scaling by weighting trade performance with the respective weight changes in Panel A in Table XIII (overall) and Table XIV (illiquid). As a result, the performance of VM buys increases, while the performance of VM sells decreases as expected,

Table XIV. Pooled Single-Trade Performance Adjusted for Marginal Weight Changes—Illiquid Periods

This table reports cumulative DGTW benchmark-adjusted performance over the next 1-, 3-, 6-, and 12-month periods resulting from trades sorted according to the Trade Motivation Matrix (TMM) of 3,802 actively managed US domestic equity funds in the period 2003–2012. The benchmark universe for buys consists of all CRSP stocks. The benchmark universe for sells consists of all stocks currently held by the respective fund, assuming no short selling. In Panel A, the performance is weighted by the underlying weight changes. Weights below the 1st percentile and above the 99th percentile were excluded from this analysis to account for outliers. In Panel B (C), trades with absolute weight changes below 5% (10%) of the previous weight are reclassified as LM trades.

		Cumulative DGTW-Adjusted Performance (in %) over the Next			
	N	**1 Month**	**3 Months**	**6 Months**	**12 Months**
Panel A. Weight Change-Weighted Trades					
VM buys	357,641	0.511***	0.794***	1.590***	2.156***
VM sells	448,490	−0.183***	−0.239***	−0.507***	−0.840***
VM buys – VM sells		0.693***	1.033***	2.096***	2.996***
LM buys	165,368	0.222***	0.505***	0.945***	0.763***
LM sells	31,982	0.002	0.048	−0.243***	−0.315***
VM buys – LM buys		0.289***	0.289***	0.645***	1.394***
VM sells – LM sells		−0.185***	−0.286***	−0.263***	−0.524***
Panel B. Reclassification of Trades with Absolute Weight Changes below 5% as LM Trades					
VM buys	346,443	0.492***	0.741***	1.498***	2.092***
VM sells	417,617	−0.166***	−0.222***	−0.507***	−0.802***
VM buys – VM sells		0.658***	0.963***	2.005***	2.894***
LM buys	206,686	0.241***	0.540***	0.957***	0.837***
LM sells	93,528	−0.020	−0.031	−0.144	−0.291**
VM buys – LM buys		0.251***	0.201***	0.541***	1.255***
VM sells – LM sells		−0.145***	−0.190**	−0.363***	−0.511***
Panel C. Reclassification of Trades with Absolute Weight Changes below 10% as LM Trades					
VM buys	327,801	0.497***	0.762***	1.534***	2.156***
VM sells	370,214	−0.165***	−0.227***	−0.521***	−0.821***
VM buys – VM sells		0.662***	0.989***	2.055***	2.977***
LM buys	225,328	0.254***	0.527***	0.949***	0.848***
LM sells	140,931	−0.073**	−0.082	−0.228***	−0.415***
VM buys – LM buys		0.243***	0.235***	0.585***	1.308***
VM sells – LM sells		−0.092**	−0.145**	−0.293***	−0.405***

***Significant at the 0.01 level.
**Significant at the 0.05 level.

resulting in a higher difference between VM buys and VM sells, which is significant for all tested horizons.

In addition, in Panel B (C), we reclassify VM trades as LM trades if the respective absolute weight change is below 5% (below 10%) of the previous portfolio weight. This clearly increases the numbers of LM trades. In particular, the frequency of LM sells goes up from 3.5% to 13.0% (18.1%). The results are very similar to those presented in Panel A in that the outperformance

Table XV. Pooled Single-Trade Performance—Window Dressing and Tax-Motivated Trades

This table reports cumulative DGTW benchmark-adjusted performance over the next 1-, 3-, 6-, and 12-month periods resulting from trades sorted according to the Trade Motivation Matrix (TMM) of 3,802 actively managed US domestic equity funds in the period 2003–2012. The benchmark universe for buys are all CRSP stocks. The benchmark universe for sells are all stocks currently held by the respective fund, assuming no short selling. To control for window dressing and tax-motivated trading, we drop all trades in the last quarter of each year. Due to the large number of observations, all figures are statistically significant at conventional levels. For readability, we do not report test statistics in the table.

		Cumulative DGTW-Adjusted Performance (in %) over the Next			
	N	**1 Month**	**3 Months**	**6 Months**	**12 Months**
Panel A. Overall Single-Trade Analysis					
VM buys	1,246,547	0.160***	0.153***	0.254***	0.255***
VM sells	1,533,962	−0.071***	−0.100***	−0.161***	−0.159***
VM buys – VM sells		0.232***	0.253***	0.415***	0.414***
LM buys	557,122	0.049***	0.125***	0.182***	0.384***
LM sells	117,834	−0.024	−0.044	−0.084	−0.157
VM buys – LM buys		0.112***	0.028	0.072*	−0.130**
VM sells – LM sells		−0.048*	−0.056	−0.077	−0.002
Panel B. Illiquid Market Periods—Bottom 10%					
VM buys	288,272	0.663***	0.881***	1.117***	1.635***
VM sells	352,310	−0.191***	−0.251***	−0.414***	−0.619***
VM buys – VM sells		0.854***	1.132***	1.531***	2.254***
LM buys	122,492	0.293***	0.606***	0.718***	0.721***
LM sells	23,535	−0.055	−0.046	−0.365*	−0.441
VM buys – LM buys		0.370***	0.275***	0.399***	0.915***
VM sells – LM sells		−0.136	−0.205	−0.049	−0.178
Panel C. Liquid Market Periods—Top 90%					
VM buys	958,275	0.009	−0.066***	−0.006	−0.161***
VM sells	1,181,652	−0.036***	−0.055***	−0.086***	−0.023
VM buys – VM sells		0.045***	−0.011	0.080***	−0.138***
LM buys	434,630	−0.020	−0.011	0.031	0.289***
LM sells	94,299	−0.016	−0.043	−0.014	−0.086
VM buys – LM buys		0.029*	−0.055**	−0.036	−0.450***
VM sells – LM sells		−0.020	−0.012	−0.071	0.064

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

of VM trades over LM trades increases for all holding periods. We therefore conclude that our findings in the previous sections are not driven by these possible misclassifications.

C. Window Dressing, Portfolio Pumping, and Tax-Motivated Trading

Apart from pure VM and LM, mutual fund trades may also be driven by other motives such as window dressing, portfolio pumping, and tax optimization (Alexander, Cici, and Gibson, 2007). Specifically, regarding window dressing (Agarwal, Gay, and Ling, 2014), mutual funds might alter their portfolio composition prior to reporting to disguise their true holdings and prevent copycat funds from hurting their performance (Phillips, Pukhtuanthong, and Rau, 2014), as well as to make their portfolio look more attractive to investors. Similarly, mutual funds might artificially try to inflate performance by placing large bets on existing holdings (Patel and Sarkissian, 2017). The reason for tax-motivated trading is to realize capital losses in order to lower the tax base of investors (Sialm and Starks, 2012; Bergstresser and Pontiff, 2013). Thus, efficient tax management by mutual funds is another service provided to investors and often credited as performance (Sialm and Zheng, 2016). Moreover, mutual fund flows might be affected by after-tax returns (Bergstresser and Poterba, 2002).

To rule out the possibility that such trades drive our findings, we utilize the fact that most of these trades occur in the fourth calendar quarter and replicate our pooled single-trade performance analysis using only trades from the first three quarters (Alexander, Cici, and Gibson, 2007). Table XV reports the results analog to Tables IV and VI with the fund's holdings as the relevant benchmark universe for sells assuming no short selling. Panel A shows results for the overall period, while Panels B and C show results for illiquid and liquid market periods, respectively. They are economically similar to the findings in our main analysis. Therefore, we conclude that our findings are not driven by alternative trade motives.

VII. Conclusion

We propose a novel approach to distinguishing VM trades from LM trades of mutual funds. The TMM is the first to allow the direct classification of single trades, whereas previous approaches remain on the aggregated portfolio level. This allows more accurate measurement of stock-picking skill than previous approaches not considering motivation and thus underestimating skill as well as previous approaches considering motivation only for aggregated trades. Moreover, we are the first to consider different benchmark universes for trades thereby distinguishing the success of VM and LM trading compared to all stocks with similar characteristics from their actual effects on portfolio quality. Based on funds' VM trading according to the TMM, we thus find clear evidence for the existence of stock-picking skill, which is significantly related to future stock and fund performance. This is especially the case during illiquid market periods with low market efficiency. Based on funds' LM trading, we find clear evidence for the existence of flow risk—that is, negative performance effects due to investors' liquidity demand. This is also especially pronounced during illiquid market periods and overall driven more strongly by inflows than outflows, probably due to liquidity premiums earned by LM sellers and paid by LM buyers when overall liquidity is low.

Overall, due to these clear and novel findings, we deem it very important to consider trading motivation in future analyses of stock-picking skill and flow risk. Therefore, the TMM provides an intuitive, easy-to-apply way to accurately distinguishing between single VM and LM trades. Future research should also concentrate on the differential effects of buys and sells relative to their relevant benchmark universes when measuring the performance of active mutual fund management.

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