Origins of Mutual Fund Skill: Market versus Accounting Based Asset Pricing Anomalies [*]

Charlotte Christiansen[‡] **Ran Xing**[†] **Yue Xu**[§]

This version: December 3, 2020

[*]The authors are grateful to Yuan Li for sharing U.S. anomaly data and valuable suggestions. We thank Daniel Borup, Jonas Eriksen, Christoph Merkle, Mungo Wilson, and seminar participants at Aarhus University for helpful comments.

[‡]DFI, CREATES, Department of Economics and Business Economics, Aarhus University. Email: cchristiansen@econ.au.dk. Lund University.

[†]DFI, Department of Economics and Business Economics, Aarhus University. Email: ran.xing@econ.au.dk.

[§]CREATES, Department of Economics and Business Economics, Aarhus University. Email: yuexu@econ.au.dk.

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Abstract

We investigate the information source of active U.S. equity mutual funds' value added using 234 public asset pricing anomalies. On average, mutual funds add value through their positive exposures to anomalies based on market information (e.g., momentum and liquidity risk) and lose value through their negative exposures to anomalies based on accounting information of firm fundamentals (e.g., investment and profitability), corroborating that both the semi-strong and weak forms of the efficient market hypothesis do not hold. We also find weak evidence that mutual funds profit from their private information, supporting the rejection of the strong form efficient market hypothesis.

Keywords: Mutual funds; Anomalies; Value added; Public information; Investment decisions

JEL Classification: G11; G14; G23

This version: December 3, 2020.

I. Introduction

The strong form efficient market hypothesis (EMH) says that all information, both public and private, is priced into stock prices and that no investor can outperform the market as a whole. Yet, the recent mutual fund literature has reached the consensus that active equity mutual funds are skilled and add value over the market return before fees (e.g., Berk and van Binsbergen (2015) and Gârleanu and Pedersen (2018)), while the origins of the funds' skill (value added) remain an open question.[1] The main differences between the strong, semi-strong, and weak form EMH are the types of information that investors can profit from. Investors cannot profit from market information like prices and trading volume in the weak form, investors can also not profit from public accounting information about firm fundamentals in the semi-strong form, and investors cannot profit from private information either in the strong form. Mutual funds, as large institutional investors, can potentially distort or improve market efficiency. Therefore, knowing the information source of mutual funds' value added sheds new light on the origins of their skill, as well as the market efficiency. The large number of public stock market anomalies documented in the asset pricing literature (e.g., the 234 distinct anomalies in Hou, Xue, and Zhang (2018)) provide a natural framework for this analysis.

We categorize the anomalies into market, accounting, and accounting-to-market (AtM) based on the sources of information used to construct the anomaly variables. Anomalies in the AtM category use both market and accounting information. We find that mutual funds, on average, have significantly positive exposures to anomalies based on market information (e.g., momentum and liquidity risk) and significantly negative exposures to anomalies based on accounting information of firm fundamentals (e.g., investment and profitability). Using the return of the Vanguard S&P 500 Index fund as the benchmark, Figure I shows that U.S. equity

[1] Berk and van Binsbergen (2015) argue that the skill of a manager is measured through the fund's value added, which is the product of the gross return in excess of the benchmark and the lagged assets-under-management.

mutual funds profit 1.9 billion dollars per month from their positive exposures to market-based anomalies and lose 2.6 billion dollars from the negative exposures to accounting-based anomalies, suggesting that other investors on average profit from accounting information of firm fundamentals.[2][3] Therefore, our findings are consistent with the rejection of both the weak and semi-strong forms of the EMH. Moreover, the value added unexplained by our public asset pricing anomalies is as large as 1.3 billion dollars per month, indicating that mutual funds profit from their private strategies. This value added from private information is larger than the total value added of these mutual funds (0.9 billion dollars), though not statistically significant in our benchmark setting. Our findings are consistent with the empirical findings and the theoretical model in Kacperczyk and Seru (2007) who show that a manager's skills are negatively related to the responsiveness of her allocations to changes in public information.[4]

To investigate the origins of value added/lost in more detail, we further categorize the market anomalies into momentum, liquidity risk, and other market anomalies; and categorize the accounting anomalies into investment, profitability, and other accounting anomalies. Figure II illustrates that mutual funds have significantly positive exposures to both momentum and liquidity risk anomalies and have significantly negative exposures to investment and profitability anomalies. They profit 0.7 billion dollars per month from the positive exposure to the momentum factor and 0.5 billion dollars from the positive exposure to the liquidity risk factor, indicating that they mainly profit from market information by following the momentum strategy and by providing liquidity to (or bearing liquidity risk for) other investors. They lose 1.5 billion dollars per month from their negative exposures

[2]Since the market is neutral to any asset pricing anomaly in the aggregate, mutual funds' negative exposures to accounting-based anomalies indicate that other investors have positive exposures to these accounting-based anomalies in the aggregate.

[3]Following Berk and van Binsbergen (2015), we use the returns of Vanguard funds as the benchmark, which accounts for transaction costs and is a realistic alternative investment opportunity for mutual funds.

[4]Our work also contributes to the literature on the mutual fund skill. There are numerous studies focusing on the skills of market timing and stock picking (e.g., Kacperczyk, Nieuwerburgh, and Veldkamp (2014)), fund characteristics such as industry concentration and active share (Kacperczyk, Sialm, and Zheng (2005) and Cremers and Petajisto (2009)), fund manager characteristics such as education and SAT (Chevalier and Ellison (1999)), fund family in allocating capital and marketing (Berk, van Binsbergen, and Liu (2017) and Roussanov, Ruan, and Wei (2018)). Our results are in accordance with market and accounting information being influential sources capturing mutual fund skill.

to investment anomalies and 1.3 billion dollars from the negative exposures to profitability anomalies, suggesting that mutual funds lose money to other investors (e.g., hedge funds) who process and interpret accounting information about firms' investment and profitability better than they do. Mutual funds' exposures are negative to almost all the individual anomalies in the investment and profitability subcategories. Moreover, we find that more than 50% of the variation in gross alpha is explained by these seven anomaly subcategories, and the unexplained value added increases to two billion dollars per month and becomes significantly positive, supporting the conjecture that mutual funds profit from their private information.

Our results are robust to using three different sets of anomalies, namely all 234 anomalies and subsamples of 81 and 45 of the most important anomalies (to be defined below). Our results are also robust to using the market portfolio from the Capital Asset Pricing Model (CAPM) as a benchmark instead of the Vanguard benchmark.

Existing empirical evidence on whether mutual funds trade with or against asset pricing anomalies are mixed. For example, Lewellen (2011) shows that the aggregate portfolio of institutions closely resembles the market portfolio and that there is little evidence that mutual funds trade on anomalies. Other papers (including Lou (2012), Akbas, Armstrong, Sorescu, and Subrahmanyam (2015), Edelen, Ince, and Kadlec (2016), and McLean, Pontiff, and Reilly (2020)) document that mutual funds trade against asset pricing anomalies. Calluzzo, Moneta, and Topaloglu (2019) find that institutional investors eliminate anomalies and improve market efficiency after their publications. We contribute to this discussion by categorizing the anomalies based on the sources of their information and relating it to the three forms of EMH. Moreover, most of the previous studies use the changes in quarterly holdings of mutual funds to calculate trades for their analyses, which neglect the short-term trades within a quarter and the price impact of trades. Considering this, we use fund returns directly for our analysis. It further allows us to calculate the value added/lost by mutual funds from their exposure to each anomaly category and to decompose the total value added of mutual funds from anomaly categories, which has not been done in previous studies.

Our results on individual anomalies and anomaly subcategories are largely in accordance with existing studies of institutional trades on individual anomalies. For example, our finding that mutual funds add value through their positive exposure to the momentum factor is consistent with the large corpus of literature on the feedback trades of mutual funds (e.g., Grinblatt, Titman, and Wermers (1995), Nofsinger and Sias (1999), Wermers (1999), Wermers (2000), Badrinath and Wahal (2002), Bennett, Sias, and Starks (2003), Parrino, Sias, and Starks (2003), and Sias (2004)). The positive exposure to the liquidity risk factor echoes studies documenting that some mutual funds and hedge funds profit from liquidity provision or from bearing liquidity risks, such as Da, Gao, and Jagannathan (2011), Jame (2018), and Dong, Feng, and Sadka (2019). The negative exposures to investment anomalies corroborate the findings in Edelen, Ince, and Kadlec (2016) and Ali, Chen, Yao, and Yu (2008) that institutions trade against the investment anomaly, and few, if any, mutual funds' trades agree with the accruals anomaly. Our comprehensive set of anomalies allows us to have a more complete picture of mutual funds' exposures by categories.

This paper also contributes to the studies on the origins of asset pricing anomalies. For example, Hirshleifer, Hou, and Teoh (2012) find that misinterpretation and limited capacity for processing accounting information lead to accounting-based pricing anomalies. Other papers show that underreaction to news and inattention to accounting information lead to mispricings in the stock market, such as Frazzini (2006), Ben-Rephael, Da, and Israelsen (2017), and Cohen, Malloy, and Nguyen (2020). We find that mutual funds lose substantial value through their significantly negative exposures to accounting-based pricing anomalies (e.g., investment and profitability), indicating that these accounting-based anomalies might be caused by mutual funds' incapability to process or interpret accounting information.

The remaining part of the paper is organized as follows. Section II outlines our data and variable construction for mutual funds and anomalies. Section III offers our methodology. Section IV presents the empirical results for the aggregate anomalies, while Section V presents the empirical results for the individual anomalies. Section VI provides robustness checks, and

Section VI concludes. Various details are provided in the Appendix and the accompanying Internet Appendix.

II. Data and Definitions of Variables

We first describe our data on mutual funds and asset pricing anomalies. The time period of our analysis is from January 1984 to December 2017 at a monthly frequency based on the availability of both the mutual fund data and the anomaly data.

II.A. Mutual Fund Data and Value Added Measure

We obtain monthly mutual fund data from the Center for Research in Security Prices (CRSP) survivor-bias-free database. Since our asset pricing anomalies are based on U.S. stocks, we limit our sample to 3,178 actively managed U.S. equity mutual funds that only invest in domestic equities. Following the data cleaning process of Kacperczyk, Sialm, and Zheng (2008), we remove bond, money market, balanced, index, ETFs/ENFs, international, and sector funds. We merge funds with multiple share classes into a single fund and include mutual funds into our sample since January 1984.[5] A more detailed description of the data cleaning process is in the Appendix, and the summary statistics for our sample of mutual funds are reported in Table A1.

We use the value added measure proposed by Berk and van Binsbergen (2015) to measure fund skill. Let R_{it}^n denote fund i's net return (n denotes net) in excess of the risk-free rate (the 1-month U.S. Treasury bill rate) at month t. R_{it}^n can be decomposed as below

$$R_{it}^n = R_{it}^B + \varepsilon_{it}, \tag{1}$$

where R_{it}^B is the excess benchmark return, which is the return of the funds' next best alternative investment opportunity, and ε_{it} is the abnormal return earned by fund i.

[5] As described in Fama and French (2010), around 15% of funds only report annual returns from 1962 to 1983, which leads to a sample-selection bias in monthly return data.

Let R^g_{it} denote fund i's gross return in excess of the risk-free rate at time t. We decompose R^g_{it} into the mutual fund's net return and the expense ratio as

$$R^g_{it} = R^B_{it} + \varepsilon_{it} + f_{i,t-1} \tag{2}$$

where $f_{i,t-1}$ is the monthly expense ratio changed from month $t-1$ to t.

The benchmark return on fund i at month t is given as

$$R^B_{it} = \hat{\beta}^j_i R^j_t \tag{3}$$

where R^j_t is the excess return of benchmark j at month t, and $\hat{\beta}^j_i$ is estimated by the linear projection of the return of fund i onto the excess return of benchmark j.

We use the returns of the Vanguard S&P 500 Index Fund as the benchmark, which accounts for transaction costs and is a realistic alternative investment opportunity for mutual funds. We only use the Vanguard S&P 500 Index (VFINX) fund for the benchmark, instead of all 11 Vanguard index funds as in Berk and van Binsbergen (2015). Because we focus on U.S. equity mutual funds only, we cannot have international index funds in our benchmark; and because we investigate funds' value added from exposures to asset pricing anomalies including size and value factors, we cannot have index funds for value, growth, small-cap, and large-cap stocks in our benchmark as well. We also use the market portfolio from the Capital Asset Pricing Model (CAPM) as the benchmark for robustness check.[6]

The benchmark-adjusted gross return of mutual fund i at month t (also known as gross alpha) can be obtained by taking the difference between gross return and benchmark return.[7] We follow Fama and French (2010) and first calculate the alpha for each mutual fund and

[6]Vanguard S&P 500 Index Fund data is obtained from CRSP. The market portfolio is from Kenneth French's website.

[7]Panel A of Table A1 shows that the equally weighted CAPM alpha is 0.07% per month and the equally weighted Vanguard alpha is 0.097% per month.

then calculate the weighted average of these.[8]

$$\hat{\alpha}_{it}^{g} = R_{it}^{g} - R_{it}^{B}. \tag{4}$$

To study the relationship between the mutual fund industry and asset pricing anomalies, we calculate the value-weighted average of all the mutual funds' gross alphas for our analysis

$$\hat{\alpha}_{t}^{g} = \frac{q_{i,t-1}}{\sum_{i=1}^{I} q_{i,t-1}} \hat{\alpha}_{it}^{g} \tag{5}$$

where I is the number of mutual funds in our sample; and $q_{i,t-1}$ is fund i's AUMs at month $t-1$. AUMs are inflation-adjusted to dollars at the end of 2017. We refer to the value-weighted Vanguard S&P 500 adjusted gross return as the Vanguard alpha and the value-weighted market-adjusted gross return as the CAPM alpha.[9]

We now define the value added of each mutual fund, as proposed by Berk and van Binsbergen (2015), and the value added for U.S. active equity mutual funds in the aggregate. The value added of mutual fund i at month t is the product of the fund AUM and the fund's gross alpha is defined as

$$V_{it} = q_{i,t-1} \hat{\alpha}_{it}^{g} = q_{i,t-1}(R_{it}^{g} - R_{it}^{B}), \tag{6}$$

which measures the dollar value that funds extract from capital markets.[10]

The value added by all mutual funds at month t is calculated as

$$V_t = Q_{t-1} \hat{\alpha}_{t}^{g} \tag{7}$$

[8]The results are robust to using the value-weighted returns for all the funds to obtain alpha, cf. analysis in Section VI.B.

[9]Panel B of Table A1 shows that the average value-weighted CAPM alpha is 0.035% per month, and the value-weighted Vanguard alpha is on average 0.030% per month.

[10]Panel A of Table A1 shows the mean of surviving funds' monthly value added using different benchmarks. Mutual funds, on average, generate \$0.55 million per month in December 31, 2017 dollars using the excess return on the market portfolio as the benchmark, or generate \$0.68 million per month using Vanguard S&P 500 Index as the benchmark.

where $Q_{t-1} = q_{i,t-1} \cdot I$, which is the sum of inflation adjusted AUMs of all funds at month $t-1$. Table I shows that the U.S. actively managed equity funds extract a value of \$875 (\$706) million per month from the U.S. capital market using Vanguard S&P 500 (CAPM) as the benchmark.

II.B. Data and Variable for Asset Pricing Anomalies

Following Hou, Xue, and Zhang (2018) and Li (2020), we construct our data set of 234 anomalies using CRSP, Compustat, and IBES databases and all common stocks traded on NYSE, AMEX, and NASDAQ. Summary statistics for these 234 anomalies are in the Online Appendix. We closely follow the definitions of anomalies in Hou, Xue, and Zhang (2018) and Li (2020).[11]

For each anomaly variable, we sort all U.S. stocks traded on NYSE, AMEX, and NASDAQ into ten deciles using its NYSE breakpoints.[12] Let $A_{a,t}$ denote anomaly a's value-weighted long-short portfolio return obtained from the extreme deciles (decile 10 minus decile 1) at month t. We refer to $A_{a,t}$ as the anomaly return.

We construct all anomalies using the same procedure (decile 10 minus decile 1), so they are constructed consistently, and they all stand a fair chance of being equally important. It has the cost that not all anomalies are constructed as they are originally defined, e.g., the popular SMB and HML risk factors from Fama and French (2010).

[11] See the definitions of the anomaly variables in Appendix A of Hou, Xue, and Zhang (2018). We thank Li (2020) for sharing the data with us.

[12] We use NYSE breakpoints in portfolio sorts and form value-weighted decile portfolios to mitigate the effects of microcaps. Trades in the microcaps make it difficult to earn a desirable abnormal return to mutual funds because microcaps incur high transaction costs due to illiquidity (Novy-Marx and Velikov (2016)). Hou, Xue, and Zhang (2018) show that over half of the well-documented anomalies fail after mitigating microcaps. Mitigating the effects of microcaps also serves our research goal because we use value-weighted mutual fund returns that are also driven by returns of large funds, which are less likely to trade on microcaps due to liquidity constraints and price pressure (e.g., Berk and Green (2004), Coval and Stafford (2007)). NYSE breakpoints can avoid that over 60% of microcaps are included in the extreme deciles (Hou, Xue, and Zhang (2018)). We calculate value-weighted hedge portfolio return, not equally weighted returns because value-weighted returns can circumvent microcap-driven anomalies. Equal-weighted return is dominated by microcaps because tiny stocks only account for 3% of the market capitalization but represent about 60% of the total number of stocks (Fama and French (2008)) and rebalance based on the frequency of the anomaly variable.

III. Methods

In this section, we discuss the methods we use to (1) select important asset anomalies for our analysis; (2) aggregate anomalies within each category; and (3) calculate the value added from each anomaly category or individual anomaly.

III.A. Selecting Anomalies

Starting from the full sample of 234 anomaly variables, we select anomalies in two steps.

First, we remove statistically insignificant anomalies, that is anomalies where the average of the long-short portfolio returns are not significantly different from zero. We preserve anomalies whose long-short portfolio returns can clear the single test hurdle of $|t| \geqslant 1.645$. 81 of the 234 anomaly stay, which is consistent with the results in Jacobs and Müller (2020) and Hou, Xue, and Zhang (2018) that many anomalies fail after publication or have an economic magnitude smaller than originally reported. Even though funds may have exposures to insignificant anomalies, the value added from those exposures would be statistically insignificant. Eliminating insignificant anomalies helps to focus on the value added from robust anomalies.

Second, we exclude anomalies that mutual funds are not significantly exposed to. If funds do not have significant exposure to an anomaly, that anomaly cannot have a significant effect on the funds' value. We run a univariate regression that uses one anomaly at a time to explain the value-weighted benchmark adjusted gross returns of the mutual funds:

$$\hat{\alpha}_t^g = \gamma + \delta_a A_{a,t} + \epsilon_t \tag{8}$$

where δ_a is the mutual funds' exposure to anomaly a, γ is the gross alpha left unexplained by anomaly a, and ϵ_t is the residual. We preserve anomalies that have statistically significant exposure with a single test hurdle of $|t| \geqslant 1.645$ under both Vanguard and CAPM benchmark adjusted returns and with the same sign under these two benchmarks.[13] 45 out of 81 anomalies stay.[14]

Since eliminating insignificant anomalies increases the accuracy of our estimates and the total explanatory power, we use these 45 robust anomalies with significant mutual fund exposures (denoted as *45 anomalies*) as our benchmark analysis. We also use the sample that contains all 234 anomalies (denoted as *234 anomalies*) and the sample that contains the 81 robust anomalies (denoted as *81 anomalies*) for robustness check.[15]

III.B. Aggregating Anomalies by Category

To answer the question of whether mutual funds add value through market or accounting information, we categorize the anomalies into *market*, *accounting*, and *accounting-to-market* (*AtM*) based on the sources of information used to construct the anomaly variables. The market category includes 73 anomalies that are constructed from market information only, such as prior 11-month returns and the idiosyncratic volatility. The accounting category includes 129 anomaly variables that are constructed from accounting information only, such as firm assets and operating cash flows. The accounting-to-market category includes 32 variables that are constructed from both accounting and market information, such as ratios of accounting variables to market values.

To understand in more detail the specific types of anomalies that mutual funds are exposed to, we further classify *market* anomalies into *momentum*, *liquidity risk*, and *other market*; *accounting* anomalies into *investment*, *profitability*, and *other accounting*; and *accounting-to-market* remains the same.[16]

We calculate the equal-weighted average anomaly returns for all anomalies in one cate-

[13]Some may argue that even if the aggregate mutual fund industry has insignificant exposures to some anomalies, some funds might have positive exposures and others might have negative exposures. Since we focus on the value added of the active mutual fund industry as a whole, the fact that some funds may have positive or negative exposure does not affect our conclusion.

[14]The results of the univariate regressions are provided in the Online Appendix.

[15]A list of all anomalies in these three samples is available in the Online Appendix.

[16]Refer to Li (2020) for a more detailed rationale behind these categorizations.

gory/subcategory as

$$A_{p,t} = \frac{1}{A} \sum_{a \in \Omega_{p,t}} A_{a,t} \tag{9}$$

where p is the pth anomaly category or subcategory, a is the ath anomaly in p's category, and $\Omega_{p,t}$ is the set of all anomaly returns in category p at time t. We refer to $A_{p,t}$ as the category p's return. This approach of aggregating anomalies is also used in Dong, Feng, and Sadka (2019).[17]

III.C. Value Added by Anomalies

To calculate the value added from each anomaly (sub)category, we first run multivariate linear regressions of mutual funds' gross alpha on the aggregated returns of each anomaly (sub)category as below

$$\hat{\alpha}_t^g = \zeta + \sum_{p=1}^{P} \eta_p A_{p,t} + \kappa_t \tag{10}$$

where η_p measures the exposure of the value-weighted mutual fund gross alpha to the anomalies in the pth category, and κ_t is the residual. ζ is the constant, which represent the mutual funds' gross alpha that remains unexplained by all of the anomaly categories. ζ is caused by either the anomalies not covered by our sample or some private investment strategies used by mutual funds. Robust Newey and West (1987) standard errors are used to adjust for heteroskedasticity and serial correlation.

Using the exposures $\hat{\eta}_p$ estimated from Eq. (10), we calculate mutual funds' value added from the exposure to each anomaly category as

$$\bar{V}_p^M = \frac{1}{T} \sum_{t=1}^{T} Q_{t-1} \hat{\eta}_p A_{p,t} \tag{11}$$

where $\bar{V}_p^M$ is a constant, which denotes the value added from anomalies in category p,

[17] Alternatively, we could include all the individual anomalies into one multivariate regression for the calculation of exposures and value added. But this approach suffers from severe multicollinearity problems, especially when the number of anomalies is large. By categorizing anomalies based on their information sources, the multicollinearity problem is largely solved.

estimated from the multivariate regression.

Since the standard errors of the value added calculated from Eq. (11) are decided jointly by the standard errors of the exposures $\hat{\eta}_p$ and the standard errors of anomaly returns $A_{p,t}$, we use the bootstrapping method to calculate the p-values of value added. We resample the value added with 1000 replacements for this calculation.

As a robustness check of the potential multicollinearity problem in the multivariate regression, we also run a univariate regression of the value-weighted gross alpha on each anomaly (sub)category's returns as

$$\hat{\alpha}_t^g = \theta + \lambda_p A_{pt} + \chi_t \tag{12}$$

where λ_p is the regression coefficient of the gross alpha on the pth anomaly category's return, θ is the mutual funds' gross alpha that remains unexplained by this anomaly category, and χ_t is the residual.

We then calculate the value added by each anomaly category using the regression coefficients from Eq. (12)

$$\bar{V}_p^U = \frac{1}{T}\sum_{t=1}^{T} Q_{t-1}\hat{\lambda}_p A_{p,t} \tag{13}$$

where $\bar{V}_p^U$ is the constant value added from anomalies in category p, estimated from the univariate regression.

IV. Empirical Results for Anomalies by Categories

In this section, we report mutual funds' value added from their exposures to different anomaly categories and subcategories. We first show the results estimated from multivariate regressions, and subsequently, we report the results estimated from univariate regressions.

IV.A. Value Added by Anomaly Category

To obtain mutual funds' value added from market versus accounting information, we first estimate their value added from the three main categories of anomalies - market, accounting, and accounting-to-market. The second and third columns of Table I report the mutual funds' exposures to these categories using the two benchmark-adjusted returns. As the two multivariate regressions show, mutual funds have positive exposure to anomalies constructed from market information, whereas they have negative exposure to anomalies constructed from accounting information. The exposures are significantly different from zero at the 1% significance levels for both benchmarks. The average portfolio of all investors is the market portfolio, and this has zero abnormal return and no exposure to any anomaly. The fact that the aggregate portfolio of mutual funds has negative exposure to public anomalies in the aggregate (thus earn negative abnormal returns from the exposure to those anomalies) indicates that other investors have positive exposures. Therefore, the result of mutual fund alpha's negative exposure to the accounting anomalies implies that other investors profit from their positive exposures to accounting anomalies.

Mutual funds, on average, do not add value through collecting and interpreting accounting information. Mutual funds could be less sophisticated than other investors (e.g., hedge funds) at processing accounting information, and they are potentially the reason accounting-based anomalies exist in the first place. Recent studies, such as Hirshleifer, Hou, and Teoh (2012), find that misinterpretation and limited capacity for processing accounting information lead to accounting-based pricing anomalies. Consistently, other papers show that underreaction to news and inattention to accounting information lead to mispricings in the stock market, such as Frazzini (2006), Ben-Rephael, Da, and Israelsen (2017), and Cohen, Malloy, and Nguyen (2020).

Moreover, as shown in the fourth row of Table I, the exposures to the accounting-to-market anomaly category are small and not different from zero, suggesting that mutual funds are neutral to anomalies based on both accounting and market information. The last two rows of

Table I show that the three anomaly categories explain 38.8% of the variation (adjusted R^2) of the Vanguard adjusted mutual fund gross returns, but only 14.4% of the CAPM adjusted mutual fund gross returns, and the magnitude of the exposures by the Vanguard benchmark is much larger in all categories than for the CAPM benchmark. This is mainly because the Vanguard benchmark considers transaction costs while the CAPM benchmark does not.

The fourth and fifth columns of Table I report the estimated value added of active equity funds defined by Eq. (7) and the value added by categories estimated by the multivariate regressions reported in Y2017 $ millions per month adjusted by inflation. As the first row shows, our sample of actively managed U.S. equity funds adds $875 million value per month using the Vanguard index as a benchmark, which is statistically insignificant. The second and third rows show that mutual funds' value added can be credited to the positive exposures to market information, whereas value lost can be ascribed to the negative exposures to accounting information. Mutual funds add $1,918 million per month through their positive exposures to anomalies based on market information, while they lose $2,602 million per month from their negative exposures to accounting information based anomalies. The result can shed light on the efficient market theory in that our results are in accordance with the rejection of the EMH both in its weak and semi-strong form.

The fifth row of Table I shows that as much as $1,297 million per month value added is left unexplained by public information based anomalies, indicating the mutual funds add value through their private investment strategies. Although this unexplained value added is statistically insignificant, its magnitude is economically large.

All the findings above hold when the CAPM benchmark is used and are consistent with exposures to anomaly categories. The magnitude of value added estimated using Vanguard as the benchmark is greater than that using CAPM.

We also report the number of individual anomalies that mutual funds are positively exposed to, as well as the total number of anomalies in the category in the last column of Table I. Consistent with the signs of the exposure, mutual funds have positive exposures to four out of six anomalies in the market category, whereas only eight out of 36 anomalies in the accounting category have positive exposures. There are only three anomalies in the accounting-to-market category, of which two tend to have positive fund exposures.

As a robustness check, we compare the exposures using the three different sets of anomalies. Table II reports the corresponding multivariate regressions. Consistent with our previous findings, the first two rows show a consistent exposure pattern in that mutual fund alphas have significantly positive exposures to anomalies based on market information, while they have significantly negative exposures to anomalies based on accounting information. The exposures to the accounting-to-market index in the third row show mixed results but are statistically insignificant in most settings. The last row of Table II shows that the adjusted R^2 increases with the decrease of the number of anomalies in the sample, indicating that the sample of 45 anomalies explains mutual fund gross alpha the best. This finding lends support to using the 45 anomalies that are robust and have significant fund exposures as benchmark for the calculation of value added.

To sum up, we find that mutual funds add value from positive exposures to anomalies based on market information and lose value from negative exposures to anomalies based on accounting information, corroborating that the semi-strong and weak forms of the EMH do not hold. There is also weak evidence that mutual funds add value through their private investment strategies which is consistent with the rejection of the strong form EMH.

IV.B. Value Added by Anomaly Subcategory

To further understand the origins of mutual funds' value added, we conduct the same analysis for the following subcategories: momentum, liquidity risk, and other market for anomalies using market information; investment, profitability, and other accounting for anomalies using accounting information, and accounting-to-market.

In Table III, the first row reports the total value added by mutual funds. As the second row of Table III shows, funds have significant positive exposures to the momentum anomaly and add \$728 million of value per month under the Vanguard benchmark. The only robust momentum anomaly in the set of 45 anomalies is the traditional prior 2-12 returns (R11) momentum factor, as shown in Table A3. This finding is consistent with the large corpus of literature on the feedback trades of mutual funds (e.g., Grinblatt, Titman, and Wermers (1995); Nofsinger and Sias (1999); Wermers (1999),Wermers (2000); Badrinath and Wahal (2002); Bennett, Sias, and Starks (2003); Parrino, Sias, and Starks (2003); and Sias (2004)).

As shown in the third row of Table III, mutual funds also add substantial value (\$469 million per month) from their positive exposures to the liquidity risk anomaly. Similar to momentum, only one of the liquidity risk anomalies is positively related to fund alphas and statistically significant. This is one of the liquidity betas - return to illiquidity (BETALRC) that is documented by Acharya and Pedersen (2005), who argue that this liquidity risk premium is due to investors' preferences for high return securities when the market is illiquid. Our result shows that mutual funds, as a long-term investor, indeed earn a positive liquidity risk premium by providing liquidity to the markets in illiquid times. This positive exposure to the liquidity risk factor echoes those studies documenting that some mutual funds and hedge funds profit from liquidity provision or bearing liquidity risks, such as Da, Gao, and Jagannathan (2011), Jame (2018), and Dong, Feng, and Sadka (2019). The fourth row shows that mutual fund alpha is positively but insignificantly related to other market anomalies.

Furthermore, we find that mutual funds' value lost from accounting-based anomalies are mainly from their negative exposures to investment and profitability anomalies.

The fifth row of Table III shows that mutual funds lose as much as \$1,536 million per month from their negative exposures to the investment anomalies under the Vanguard benchmark. Most surprisingly, as shown in the last column, mutual funds have negative exposures to all nine individual anomalies in the investment category, which provides additional support to the finding that mutual funds lose value from investment related accounting information. The negative exposures to investment anomalies corroborate the findings in Edelen, Ince, and Kadlec (2016) and Ali, Chen, Yao, and Yu (2008) that institutions trade against investment anomaly, and few, if any, mutual funds' trades agree with the accruals anomaly. Our comprehensive set of anomalies allows us to have a more complete picture of mutual funds' exposures by categories.

The sixth row shows that mutual funds lose another $1,302 million per month from their negative exposures to the profitability anomalies under the Vanguard benchmark, and the last column reports that mutual funds only have positive exposure to one out of 14 profitability anomalies. However, the value added turns insignificant under the CAPM benchmark, which is mainly caused by the multicollinearity problem between investment and profitability anomalies, as shown in Table IV. The seventh row shows that mutual funds' exposure to other accounting anomalies is insignificantly different from zero.

The eighth row shows that mutual funds' value added from their exposure to accounting-to-market anomalies is significantly positive under the Vanguard benchmark, but the result is less reliable due to multicollinearity between it and investment, as shown in Table IV.

More importantly, the ninth row shows that the value added unexplained by asset pricing anomalies by subcategories is as large as $1,993 million per month and significant under the 5% significance level, confirming the result that mutual funds are profiting from their private investment strategies.

To understand the severity of the potential multicollinearity issue in our multivariate regressions, we report the correlations between the three anomaly categories in the Panel A of Table IV and the correlations between seven subcategories in Panel B. Panel A shows the correlations between the three categories at most 0.11, suggesting that the potential multicollinearity problem is not serious for the regression based on three categories. However, Panel B of IV shows that other accounting anomalies are highly correlated with momentum and profitability, with a correlation of 0.52 and 0.65, respectively, and profitability and investment have a correlation of 0.47. Therefore, multicollinearity remains a potential problem for subcategories. In the next section, we use univariate regressions to confirm the robustness of our findings by subcategories.

IV.C. Exposures and Value Added - Univariate Regressions

Table V shows the exposures and value added estimated by univariate regressions defined by Eq. (12) to address the concern of potential multicollinearity in our multivariate regressions.

The first and second rows of Panel A of Table V show that mutual funds have positive exposure to anomalies based on market information and negative exposure to anomalies based on accounting information in univariate regressions. These results are consistent with the results in the multivariate regressions. The value added also has a similar magnitude, about $2 billion for the Vanguard benchmark. The third row shows that accounting-to-market alone produces similar insignificant and positive value added for both benchmarks.

In Panel B, the first row shows that mutual funds have significant exposure to the momentum factor in the univariate regression at the 5% significance level, confirming our findings in the multivariate regression. However, the significance level of exposure to the momentum factor in the univariate regression is lower than that in the multivariate regression. Thereby the value added by momentum becomes smaller and insignificant. The reason is that momentum is correlated with other anomaly subcategories, especially profitability and other accounting, as shown in Table IV. As discussed in Asness, Moskowitz, and Pedersen (2013), the momentum strategy works better together with other strategies such as value strategy than itself alone, which is consistent with our finding.

As the second row in Panel B of Table V shows, mutual funds add as much as $922 per month, which is significant by tilting towards liquidity risk anomaly, implying that mutual funds earn money by providing liquidity or bearing more liquidity risk. This result is consistent with our multivariate regression. In addition, the liquidity risk factor alone explains as much as 14.9% and 26.7% of the variations of CAPM alpha and Vanguard alpha, respectively.

The third row in Panel B shows that the subcategory of other market anomalies is significantly positively related to mutual funds and adds value, implying that mutual funds tilt their portfolios towards information from the stock market. The value added by mutual funds' positive exposures to the other market index accounts for at least $700 million per month using CAPM as the benchmark. The magnitude of other market anomalies is higher compared to the value added in Table III.

The next two rows in each Panel of Table III show that gross alphas of mutual funds are negatively related to the investment and profitability anomalies, and the adjusted R^2 is considerably higher than for the other subcategories, especially when we use the Vanguard benchmark. The negative relations are highly statistically significant and consistent with the result in the multivariate regression.

As the last row shows, mutual funds lose value through the negative exposures to other accounting anomalies, but only statistically significantly so for the Vanguard benchmark. This result is more reliable than that in the multivariate regression because other accounting is highly correlated with momentum and profitability, as Table IV shows. The negative relationship is consistent with two other subcategories - investment and profitability.

To summarize, the results for the value added by each anomaly using univariate regressions are consistent with the results from the multivariate regressions, suggesting that the multicollinearity problem is not severely affecting our results of the multivariate regressions.

V. Empirical Results for Individual Anomalies

In this section, we highlight which individual anomalies have significant exposures to mutual funds.[18] One might be concerned about the approach of using equally weighted anomaly returns across a given anomaly group due to information losses. Therefore, we pin down the important individual anomalies and examine the value added of these individual anomalies directly. Hereby we investigate whether the results of the individual anomalies are consistent with those using anomaly categories.

We restrict our analysis of individual anomalies to the sample of 45 anomalies. Table A3

[18]We show all the results regarding the individual anomalies in the Appendix, simply because of the size of the tables. Here we concentrate on the results based on the Vanguard benchmark, but the table also shows the CAPM benchmark results for comparison.

shows information for the 45 anomalies. Table A4 reports the value added and exposures for each of the 45 anomalies from univariate regressions. Mutual funds only have positive exposures to the traditional momentum variable R11 in the momentum category, but the value added from R11 alone is insignificant; and the adjusted R^2 is low. Studies show that value and momentum are negatively correlated with each other (e.g., Asness, Moskowitz, and Pedersen (2013)), thus momentum can add significant value when it is analyzed together with other anomalies in the multivariate regression as shown in Table III, but not individually. The liquidity risk variable (BETALRC) has significantly positive exposures, but the value added is statistically insignificant. One reason for the insignificant value added is that R11 and BETALRC long-short portfolio returns are only marginally significant. The other market anomalies also have insignificant value added when they are considered individually, which is also the case when they are considered jointly.

All the individual anomalies in the investment subcategory are negatively related to mutual funds and, thereby, funds destroy value by their negative exposures, consistent with the overall results for the investment category using the equally weighted returns approach. In particular, we find that mutual funds destroy as much as $1,903 by tilting their portfolios away from net stock issues (NSI), which is statistically significant, followed by composite equity issuance (CEI).

The results for the individual anomalies' value added in the profitability subcategory are consistent with the aggregated results in Table III and V. The negative exposures to the investment-related anomalies make mutual funds lose substantial and significant value. More anomalies are included in the profitability than in the investment subgroup. Only one of 14 anomalies in profitability add positive but insignificant value. The negative exposures to cash-based operating profitability (COP) make mutual funds destroy the most value, followed by the quarterly cash-based operating profits-to-lagged assets (CLAQ) and quarterly operating profits-to-lagged assets (OLAQ). Although anomalies in the same subcategory are correlated, we show that the results for the individual anomalies are consistent with aggregated anomalies in Table V that mutual funds lose more value to profitability than investment-related anomalies.

The results for the individual other accounting anomalies show a consistent pattern with the results for the aggregated anomalies. Around half of the anomalies in this subcategory are negatively related to mutual fund alpha and destroy value (e.g., organizational capital-to-assets (OCA)) while the other half add value. Therefore, the aggregated other accounting index is insignificant.

Finally, we consider the value added and exposures of the individual anomalies in the accounting-to-market category. For the net payout yield (NOP) anomaly, mutual funds lose value by tilting away from it, and for the R&D expense-to-market (RDM) anomaly, they add value. Given our findings that mutual funds in the aggregate rely on market information but neglect accounting information, it is reasonable that anomalies that are a combination of both information can show a mixed result.

The evidence in Table A4 suggests that our value added findings using aggregate anomaly returns for categories are consistent with using individual anomalies. This is an indication that the approach of using equally weighted anomaly returns within groups is reliable.

VI. Robustness Analysis

For robustness, we compare our findings to traditional asset pricing factors, use an alternative calculation of alpha, and consider different sample periods.

VI.A. Traditional Factors and Value Added

We examine mutual funds' exposures to traditional risk factors. Table VI reports the estimates from the multivariate regressions of mutual fund gross alpha on the Fama and French (2015) five factors plus momentum (MOM) and liquidity risk (LIQ) factors. Momentum is the long-short portfolio return (decile 10 minus decile 1) based on prior 2-12 return constructed monthly using NYSE decile breakpoints. The liquidity risk factor is constructed based on the return-to-illiquidity beta defined in Acharya and Pedersen (2005). We focus on the results based on the Vanguard benchmark but also report CAPM results for comparison.

Based on the information used to construct these factors, momentum (MOM), liquidity risk (LIQ), and the size (SMB) factor belong to the market category, the investment (CMA) and profitability (RMW) factors belong to the accounting category, and the value factor (HML) belongs to the accounting-to-market category. Consistent with our findings, mutual funds have significantly positive exposures to MOM and LIQ factors in the market category, negative exposures to CMA and RMW factors in the accounting category, and insignificant exposure to HML in the accounting-to-market category.

We expect that the results from using traditional risk factors differ from using our anomalies. All our anomaly returns are constructed as decile 10 minus decile 1. In contrast, traditional risk factors are constructed in individual ways. For instance, the SMB factor is constructed from the average return on nine small portfolios minus the average return on nine big stock portfolios.[19]

We show that mutual funds have significantly positive exposures to SMB (market information), and they do not have significant exposures to HML (AtM). Overall, the results from using our sets of anomalies are consistent with the results from using the traditional Fama and French risk factors.

VI.B. Value-Weighted Gross Alpha in the Aggregate

Our value-weighted mutual fund gross alpha is obtained by estimating each fund's gross alpha first and then calculating the value weighting gross alpha. An alternative is to estimate

[19]The reason is that over our sample period 1984 - 2017, the SMB and HML value-weighted long-short portfolio returns based on the NYSE breakpoints and decile 1 and 10 are not significantly different from zero (t=0.09 and t=1.52, respectively). A further investigation shows that traditional SMB and HML factors are significant over the full period 1927 - 2020 (t=2.00 and t=3.09 respectively), suggesting that SMB and HML are excluded due to different time periods and construction methods. Given that our mutual fund data start from 1984 and our long-short portfolio returns are constructed based on decile 10 and 1 for all anomalies, SMB and HML are not included in the 45 robust anomalies with significant mutual fund exposures for our benchmark analysis. But we document the exposures to SMB and HML here for robustness check.

the value-weighted mutual fund gross return first and estimate gross alpha subsequently

$$R_t^g = \frac{q_{i,t-1}}{\sum_{i=1}^{I} q_{i,t-1}} R_{it}^g, \tag{14}$$

and

$$\hat{\alpha}_t^g = R_t^g - R_t^j. \tag{15}$$

The difference between the two approaches is that the former adjusts each fund's gross return by the benchmark, while the latter adjusts the active mutual fund industry as a whole by the benchmark. Table A5 shows the exposures using the alternative value-weighted gross alpha. Both for the categories and subcategories, exposures are consistent with our main results that mutual funds are positively exposed to market anomalies (momentum and liquidity risk) and negatively exposed to accounting anomalies (investment and profitability).

VI.C. Subsample Analysis

Table A6 reports the results for two equally sized subperiods, 1984 - 2000 and 2001 - 2017, separately. Consistent with our main results based on the entire sample, mutual funds have positive exposures to market anomalies and negative exposures to accounting anomalies in both subperiods.

VII. Conclusion

We empirically analyze the origins of mutual fund skill (value added) using asset pricing anomalies based on public market and accounting information. We find that mutual funds add value through their positive exposures to anomalies based on market information (e.g., momentum and liquidity risk factors) and lose substantial value through their negative exposures to anomalies based on accounting information (e.g., investment and profitability factors), corroborating that both the semi-strong and weak forms of efficient market hypothesis do not hold. We also find weak evidence that mutual funds profit from their private information not covered by publicly known asset pricing anomalies. This is consistent with the rejection of the strong form of the efficient markets hypothesis.

Our study is limited to U.S. equity mutual funds. Future studies could investigate the origins of skill for other investors such as hedge funds and retail investors as well to have a complete picture of the interplay between different types of investors in the market. Since our analysis is based on public asset pricing anomalies, another interesting direction is to have a closer look at the private investment strategies used by mutual funds and their value added.

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A. Appendix

I.A. CRSP Mutual Fund Clean-up

Our raw mutual fund data is obtained from CRSP from December 1961 to December 2019. Before merging the same funds with different share classes, the Fund Summary dataset has 2,220,136 observations and 67,379 funds; the Mutual Funds Monthly Returns and Fama-French Factors dataset has 7,932,552 observations and 67,361 funds.

A.1. Keep Domestic Equity Funds

We follow the methodology by Kacperczyk, Sialm, and Zheng (2008). CRSP updated the database in March 2008, so ICDI Objective Codes no longer exists. Instead, CRSP Survivor-Bias-Free U.S. Mutual Fund Database now contains the new Lipper classification, asset and objective codes. Therefore, we revised the methodology by Kacperczyk, Sialm, and Zheng (2008). The only difference is that we use new Lipper classification rather than ICDI Objective Codes.

We first remove funds based on CRSP Database objective codes that are International, Municipal Bonds, Bond and Preferred, and Balanced funds. We then include a fund based on Lipper Class with the following: EIEI, G, LCCE, LCGE, LCVE, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, SCGE, SCVE. If Lipper Class is unavailable, we keep funds with the following Strategic Insight objectives: AGG, GMC, GRI, GRO, ING, or SCG. If a fund is missing both Lipper Asset Code and Strategic Insight objectives, we use the Wiesenberger Fund Type Code and select funds with the following objectives: G, G-I, AGG, GCI, GRI, GRO, LTG, MCG, and SCG. If a fund does not have any above objectives, we include the fund if it has a policy: CS. After the above screening, we still have 21,181 observations at the share class level between 1961 and 2019. Finally, we remove funds that hold less than 80% or more than 105% in stocks on average (Kacperczyk, Sialm, and Zheng (2008)).

One problem in calculating the average monthly proportion of stocks in a fund is that some missing proportions have defaulted as 0% because we observe that the proportion of common stocks varies from 0% to, i.e., 90% in the same fund. The difficulty is that we do not know whether 0% is the missing value or the true value (the fund does not invest in any common stocks). But we deduce that it is impossible that the fund holds nothing, even holds no cash. Thus, we use a method that replaces 0% with missing value if values are 0% in all asset classes, then we calculate the proportion of stock holdings monthly on average. The number of our remaining funds at this stage at the share class level is 18,064.

A.2. Remove Index Funds and Sector Funds

We define index funds if they are labeled as index funds ("B", "D", or "E"). The index fund flag only begins on June 30, 2003. Thus, we need a further cleanup. We define index funds that have fund-month observations with expense ratios below 0.1% per year because it is extremely unlikely that any actively managed funds would charge such low fees (Pástor, Stambaugh, and Taylor (2015)). We then exclude funds whose name contains the word "index" (Pástor, Stambaugh, and Taylor (2015)). Finally, we identify passive ETFs and ENFs if the CRSP variable *et_flag* equals either "F" or "N". We also identify sector funds that contain keywords "sector" but not "multi-sector" in the fund name. After dropping passive funds, there are 16,232 funds at the share class level.

A.3. Avoid Incubation Bias

We follow Kacperczyk, Nieuwerburgh, and Veldkamp (2014) to first exclude observations for which the year of the observation is prior to the reported fund starting year as well as observations for which the names of the funds are missing in the CRSP database. Mutual funds before 1984 are also excluded because there is selection bias during the period 1962 to 1983 (Fama and French (2010)).

A.4. Group Together Different Subclasses of the Same Fund

We use MFLINKS to combine different share classes of the same fund into a single fund. Following Kacperczyk, Nieuwerburgh, and Veldkamp (2014), we sum the TNAs of different share classes and get lagged TNAs monthly. We take the mutual funds' weighted average monthly returns, monthly NAVs, income yields, dividend yields, capital gains yields, actual 12b1, max 12b1, expense ratios, management fees, turnover ratios and loads with weights of lagged TNAs of each share class. For the qualitative attributes of funds (e.g., name, ticker, objectives, and year of origination), we retain the observation of the oldest fund. After merging, our final sample has 3,389 active domestic well-diversified equity mutual funds and 694,072 observations from December 1961 to December 2019.

I.B. Inflation Adjustment

We adjust for inflation to make the TNAs comparable across time. We use the *Consumer Price Index for All Urban Consumers: All Items in U.S. City Average* from FRED, Federal Reserve Economic Data provided by St. Louis Fed. This series is at the monthly frequency, and it is seasonally adjusted. The month of December 2017 is used as the baseline month to adjust TNAs in other years because our sample ends in December 2017. For example, the CPI value at the end of December 2017 is 248.8, and the CPI value at the end of December 1990 is 134.7. The adjusted monthly TNAs in 1990 are calculated as non-adjusted monthly TNAs * 248.8/134.7 so that the TNAs in 1990 can be comparable to the TNAs in 2017.

I.C. Correcting and Filling in Missing Values

At the share class level, if the value of expense ratio/management fee/turnover ratio/12b-1 is -99 or 0, we set them to missing. If the value of expense ratio/management fee is negative, we also set them to missing.

There are 76.02%, 77.92%, 76.34%, 85.75%, 89.47% expense ratio, management fee, turnover ratio, actual 12b-1, maximum 12b-1 are missing respectively. We identify that CRSP provides quarterly/annual values for the above variables, so we back-filled using the fiscal year-end information. If a fund does not have fiscal year-end value, we mainly follow Berk and van Binsbergen (2015) to assign it a fiscal year-end value. For example, to fill in the expense ratio fiscal year-end:

(1) We first check other share classes for the same fund. If the other share class reported fiscal year-end, we fill in the expense ratio using the value reported by the same fund but a different share class. We assume that all investors have the same investment horizons, and they are indifferent towards expenses of different share classes.

(2) If a fund never reported a fiscal year but reported at least five consecutive quarters of expense ratios and the month when the expense ratio change is consistent. Then we assign this month as the fiscal year-end month for this fund. We check these eligible months. Surprisingly, 100% of the eligible months in our sample are December.

(3) If there are no reported five consecutive quarters of expense ratios, we assume that the value is the same as the previous fiscal year-end because the expense ratio is highly persistent over time. We assign it as the month of the same fund with a different share class.

(4) If there is no previous fiscal year-end at the share class level, we fill in it using the value by the same fund but a different share class in the previous fiscal year-end.

(5) If fiscal year-end is still missing, finally, we assume that the value is the same as the next fiscal year-end by the same fund with a different share class.

After implementing the above steps, there is still 2.63% fiscal year-end and expenses ratios missing at the fund level. We decide to exclude these funds. Finally, we have 3,178 funds.

Figure I: Value Added - Three Categories

This figure shows the value added defined by Eq. (11) using the Vanguard S&P500 index fund as a benchmark with 95% confidence intervals. The sample of 45 anomalies is categorized into market, accounting, and accounting-to-market (AtM). We aggregate returns by taking an equally weighted average of anomaly returns in the category defined by Eq. (9). The sample period is from January 1984 to December 2017.

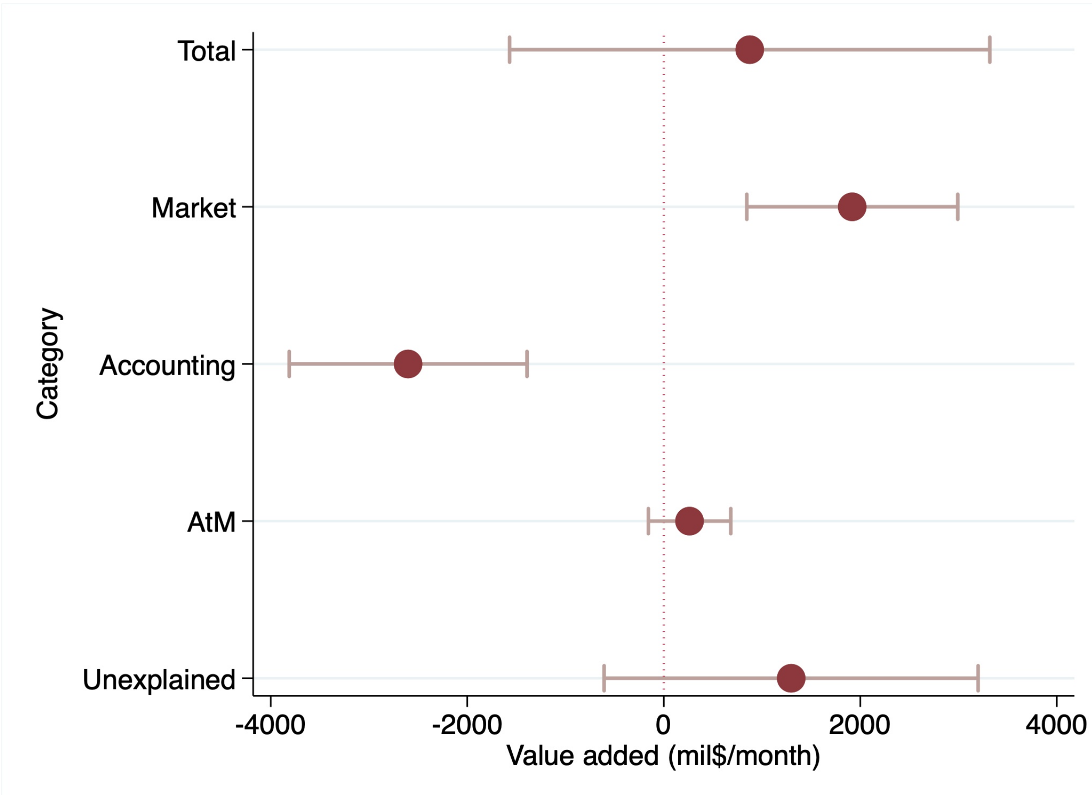

Figure II: Value Added - Subcategories

This figure shows the value added defined by Eq. (11) using the Vanguard S&P500 index fund as a benchmark with 95% confidence intervals. The sample of 45 anomalies is categorized into momentum, liquidity Risk, other Market, investment, profitability, other accounting, and accounting-to-market. We aggregate returns by taking an equally weighted average of anomaly returns in the category defined by Eq. (9). The sample period is from January 1984 to December 2017.

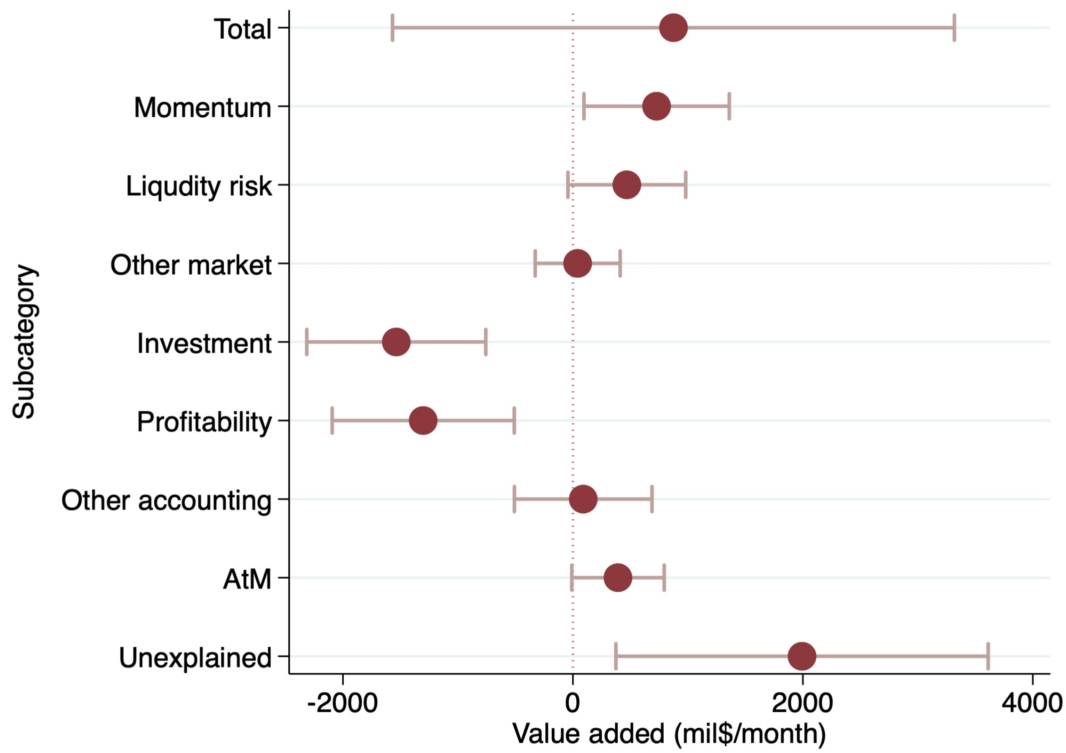

Table I: Exposures and Value Added - Three Categories

This table shows the coefficient estimates from multivariate regressions of mutual fund gross alpha on the anomaly category returns defined by Eq. (10) and the corresponding value added defined by Eq. (11). The sample of 45 anomalies is categorized into market, accounting, and accounting-to-market (AtM). We aggregate returns by taking an equally weighted average of anomaly returns in the category defined by Eq. (9). #positive/total refers to the number of anomalies that mutual funds are positively exposed to over the total number of anomalies in the category. Vanguard alpha/CAPM alpha is the monthly value-weighted benchmark adjusted gross return estimated by Eq. (5) using the Vanguard S&P500 index fund/market portfolio as a benchmark. The sample period is from January 1984 to December 2017. p-values are reported below the regression coefficients. Bootstrapped p-values are reported below the value added. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Exposure		Value added		#positive/total
	Vanguard	CAPM	Vanguard	CAPM	
Value added (total)			875	706	
			0.483	0.256	
Market	0.187***	0.090***	1,918***	921***	4/6
	0.000	0.000	0.000	0.000	
Accounting	-0.239***	-0.060***	-2,602***	-656***	8/36
	0.000	0.002	0.000	0.008	
AtM	0.025	0.014	262	142	2/3
	0.149	0.255	0.220	0.313	
Constant/Unexplained	0.001	0.000	1,297	299	
	0.232	0.617	0.182	0.598	
Observations	408	408			
Adj R^2	0.388	0.144			

Table II: Exposures - Three Samples

This table shows the coefficient estimates from multivariate regressions of mutual fund gross alpha on the anomaly category returns defined by Eq. (10) using three anomaly samples. The sample of 45 anomalies is categorized into market, accounting, and accounting-to-market (AtM). We aggregate returns by taking an equally weighted average of anomaly returns in the category defined by Eq. (9). 234 anomalies include all anomalies in Hou, Xue, and Zhang (2020); 81 anomalies include anomalies that have significant value-weighted abnormal hedge portfolio returns using NYSE breakpoint with the single test hurdle of $|t| \geqslant 1.645$; 45 anomalies include anomalies that have significant mutual funds' exposures with the single test hurdle of $|t| \geqslant 1.645$. Vanguard alpha/CAPM alpha is the monthly value-weighted benchmark adjusted gross return estimated by Eq. (5) using the Vanguard S&P500 index fund/market portfolio as a benchmark. The sample period is from January 1984 to December 2017. p-values are reported below the regression coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	234 Anomalies		81 Anomalies		45 Anomalies	
	Vanguard	CAPM	Vanguard	CAPM	Vanguard	CAPM
Market	0.293***	0.129***	0.174***	0.097***	0.187***	0.090***
	0.000	0.003	0.000	0.000	0.000	0.000
Accounting	-0.622***	-0.175***	-0.337***	-0.097***	-0.239***	-0.060***
	0.000	0.000	0.000	0.001	0.000	0.002
AtM	-0.055**	-0.013	0.001	0.020*	0.025	0.014
	0.012	0.311	0.959	0.082	0.149	0.002
Constant	0.001***	0.001**	0.001**	0.000	0.001	0.000
	0.002	0.046	0.018	0.511	0.232	0.617
Observations	408	408	408	408	408	408
Adj R^2	0.280	0.068	0.306	0.105	0.388	0.144

Table III: Exposures and Value Added - Subcategories

This table shows the coefficient estimates from multivariate regressions of mutual fund gross alpha on the anomaly subcategory returns defined by Eq. (10) and the corresponding value added defined by Eq. (11). The sample of 45 anomalies is categorized into momentum, liquidity risk, other market, investment, profitability, other accounting, and accounting-to-market. We aggregate returns by taking an equally weighted average of anomaly returns in the category defined by Eq. (9). #positive/total refers to the number of anomalies that mutual funds are positively exposed to over the total number of anomalies in the category. Vanguard alpha/CAPM alpha is the monthly value-weighted benchmark adjusted gross return estimated by Eq. (5) using the Vanguard S&P500 index fund/market portfolio as a benchmark. The sample period is from January 1984 to December 2017. p-values are reported below the regression coefficients. Bootstrapped p-values are reported below the value added. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Exposure		Value added		#positive/total
	Vanguard	CAPM	Vanguard	CAPM	
Value added (total)			875	706	
			0.483	0.256	
Market:					
Momentum	0.040***	0.014***	728**	262*	1/1
	0.000	0.002	0.024	0.069	
Liqudity risk	0.052***	0.032***	469*	285*	1/1
	0.000	0.000	0.073	0.080	
Other market	0.005	0.019	41	166	2/4
	0.828	0.224	0.827	0.241	
Accounting:					
Investment	-0.186***	-0.091***	-1,536***	-755***	0/9
	0.000	0.000	0.000	0.001	
Profitability	-0.093***	0.012	-1,302***	165	1/14
	0.000	0.487	0.001	0.528	
Other accounting	0.010	-0.031	90	-296	7/13
	0.756	0.168	0.769	0.205	
Accounting-to-market:					
AtM	0.038**	0.022*	392*	226	
	0.015	0.068	0.056	0.125	2/3
Constant/Unexplained	0.001**	0.000	1,993**	653	
	0.011	0.201	0.016	0.205	
Observations	408	408			
Adj R^2	0.563	0.247			

Table IV: Correlations of Anomaly Returns by Category

This table shows the pairwise correlation coefficients of the anomaly returns. Panel A shows the correlations between average returns of three anomaly categories. Panel B shows the correlations between average returns of seven anomaly subcategories. The sample of 45 anomalies is categorized into market, accounting and accounting-to-market and are further categorized into momentum, liquidity risk, other market, investment, profitability, other accounting, and accounting-to-market. We aggregate returns by taking an equally weighted average of anomaly returns in the category defined by Eq. (9). The sample period is from January 1984 to December 2017. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Three Categories

	Market	Accounting	AtM
Market	1.000		
Accounting	-0.022	1.000	
AtM	0.100**	0.111**	1.000

Panel B: Subcategories

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Momentum	1.000						
(2) Liqudity risk	-0.060	1.000					
(3) Other market	-0.163***	-0.011	1.000				
(4) Investment	0.148***	-0.297***	-0.162***	1.000			
(5) Profitability	0.370***	-0.387***	-0.160***	0.471***	1.000		
(6) Other accounting	0.523***	-0.130***	-0.159***	0.123**	0.647***	1.000	
(7) AtM	0.134***	0.217***	-0.121**	0.341***	0.047	-0.015	1.000

Table V: Exposures and Value Added - Univariate Regressions

This table shows the coefficient estimates from univariate regressions of mutual fund gross alpha on the anomaly category returns defined by Eq. (12) and the corresponding value added defined by Eq. (13). Panel A uses three categories, and Panel B uses subcategories. We aggregate returns by taking an equally weighted average of anomaly returns in the category defined by Eq. (9). Vanguard alpha/CAPM alpha is the monthly value-weighted benchmark adjusted gross return estimated by Eq. (5) using the Vanguard S&P500 index fund/market portfolio as a benchmark. The sample period is from January 1984 to December 2017. *p*-values are reported below the regression coefficients. Bootstrapped *p*-values are reported below the value added. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Vanguard			CAPM		
	Value added	Exposure	Adj R^2	Value added	Exposure	Adj R^2
Panel A: Three Categories						
Market	2,022***	0.197***	0.128	958***	0.093***	0.093
	0.004	0.000		0.000	0.000	
Accounting	-2,601***	-0.239***	0.264	-653**	-0.060***	0.052
	0.000	0.000		0.015	0.006	
AtM	175	0.017	-0.000	150	0.014	0.003
	0.543	0.519		0.290	0.231	
Panel B: Subcategories						
Momentum	281	0.015**	0.010	140	0.008**	0.008
	0.373	0.022		0.363	0.040	
Liqudity risk	922*	0.102***	0.265	382*	0.042***	0.147
	0.068	0.000		0.074	0.000	
Other market	267	0.031	0.002	197	0.023	0.005
	0.496	0.475		0.273	0.255	
Investment	-2,149***	-0.260***	0.311	-770***	-0.093***	0.128
	0.000	0.000		0.002	0.000	
Profitability	-1,940***	-0.139***	0.257	-420**	-0.030**	0.037
	0.001	0.000		0.041	0.016	
Other accounting	-752**	-0.080***	0.017	-126	-0.013	-0.001
	0.030	0.009		0.500	0.472	
AtM	175	0.017	-0.000	150	0.014	0.003
	0.543	0.519		0.290	0.231	

Table VI: Exposures to Factor Models

This table shows the coefficient estimates from multivariate regressions of mutual fund gross alpha on the and Fama-French five factors plus Momentum and Liquidity Risk. The variable definition MOM (momentum) is the long-short portfolio return (decile 10 minus decile 1) based on prior 2-12 return constructed monthly using NYSE decile breakpoints. The variable definition LIQ (return-to-illiquidity) follows the original paper of Acharya and Pedersen (2005). The definitions of the variables SMB, HML, RMW, CMA follow the original paper of Fama and French (2015). The sample period is from January 1984 to December 2017. *p*-values are reported below the regression coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Vanguard	CAPM
Market:		
MOM	0.023***	0.009**
	0.000	0.014
LIQ	0.041***	0.032***
	0.000	0.000
SMB	0.201***	0.046***
	0.000	0.000
Accounting:		
CMA	-0.063***	-0.033*
	0.008	0.097
RMW	-0.050***	0.011
	0.002	0.549
Accounting-to-market:		
HML	-0.028	-0.006
	0.129	0.663
Constant	0.000	0.000
	0.534	0.586
Observations	408	408
Adj R^2	0.668	0.214

Table A1: Summary Statistics - Mutual Funds

This table shows summary statistics for our sample of actively managed U.S. equity mutual funds from January 1984 to December 2017. Returns, expense ratios and alphas are reported in percentages per month. Size and value added are reported on December 31, 2017 as millions dollars per month adjusted by inflation. The unit of observation in Panel A is the fund-month. Fund size is the fund's total assets under management (AUM) aggregated across different share classes and is adjusted by inflation using CPI from FRED by expressing all numbers in December 31, 2017 dollars. Net return is the return received by investors. Gross return equals net return plus expense ratio. We fill in the expense ratios when a fund's expense ratio for a year is missing. Details of filling in missing values are in the Appendix. Vanguard alpha/CAPM alpha is the monthly value-weighted benchmark adjusted gross return estimated by Eq. (5) using the Vanguard S&P500 index fund/market portfolio as a benchmark. Following Berk and van Binsbergen (2015), Vanguard S&P500/CAPM value added is the product of the fund's lagged size and Vanguard alpha/CAPM alpha defined by Eq. (6). Vanguard value added/CAPM value added in Panel A is reported as the equal-weighted average of all funds' value added in the same month. The unit of observation in Panel B is the time-series averages across 408 months. Fund size is the sum of inflation-adjusted AUMs of all funds in our sample in the same month. Vanguard alpha/CAPM alpha in Panel B is the value-weighted average of all funds' alphas in the same month defined by Eq. (5). Vanguard value added/CAPM value added in Panel B is the sum of value added of all funds in our sample in the same month defined by Eq. (7).

	#Obs	Mean	SD	Min	Max	Percentile				
						1st	25th	50th	75th	99th
Panel A: Fund-month										
Fund size	528,055	1,476	5,932	0	238,751	1	56	225	912	22,234
Net return	522,255	0.0075	0.0529	-0.9190	3.4300	-0.1510	-0.0191	0.0113	0.0375	0.1310
Expense ratio	525,523	0.0011	0.0004	0.0000	0.0104	0.0002	0.0008	0.0010	0.0013	0.0023
Gross return	522,250	0.0085	0.0529	-0.9186	3.4309	-0.1498	-0.0181	0.0123	0.0386	0.1318
Vanguard excess return	560,355	0.0055	0.0428	-0.2233	0.1285	-0.1101	-0.0186	0.0099	0.0337	0.0928
Market excess return	560,355	0.0057	0.0440	-0.2324	0.1247	-0.1072	-0.0196	0.0116	0.0340	0.0954
Vanguard alpha	522,250	0.0010	0.0293	-0.9360	3.3310	-0.0741	-0.0108	0.0006	0.0120	0.0812
CAPM alpha	522,250	0.0007	0.0266	-0.9340	3.3230	-0.0680	-0.0104	0.0003	0.0110	0.0741
Vanguard value added	522,250	0.683	150	-11,377	68,867	-183	-2.127	0.019	2.539	191
CAPM value added	522,250	0.551	143	-10,213	69,037	-172	-2.078	0.007	2.277	178
Panel B: Across 408 months										
Fund size	408	1,909,686	1,255,465	14,430	3,742,297	15,846	501,366	2,364,636	3,015,390	3,686,866
Vanguard alpha	408	0.0003	0.0101	-0.0518	0.0733	-0.0220	-0.0051	0.0004	0.0063	0.0236
CAPM alpha	408	0.0004	0.0056	-0.0193	0.0244	-0.0153	-0.0030	0.0006	0.0038	0.0130
Vanguard value added	408	875	25,083	-177,955	238,603	-55,899	-6,751	103	9,091	63,988
CAPM value added	408	706	12,670	-56,321	79,347	-36,671	-3,347	126	5,014	33,327

Table A2: Summary Statistics - Categorized Anomaly Returns

This table shows summary statistics for three samples of anomaly returns. Panel A shows the average returns of three anomaly categories. Panel B shows the average returns of seven anomaly subcategories. The sample of 45 anomalies is categorized into market, accounting, and accounting-to-market and are further categorized into momentum, liquidity risk, other market, investment, profitability, other accounting, and accounting-to-market. We aggregate returns by taking an equally weighted average of anomaly returns in the category defined by Eq. (9). 234 anomalies include all anomalies in Hou, Xue, and Zhang (2020); 81 anomalies include anomalies that have significant value-weighted abnormal hedge portfolio returns using NYSE breakpoint with the single test hurdle of $|t| \geqslant 1.645$; 45 anomalies include anomalies that have significant mutual funds' exposures with the single test hurdle of $|t| \geqslant 1.645$. The sample period is from January 1984 to December 2017. t-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	234 anomalies	81 anomalies	45 anomalies
Panel A: Category			
Market	0.002***	0.006***	0.005***
	(4.98)	(6.19)	(5.92)
Accounting	0.003***	0.005***	0.006***
	(5.38)	(6.04)	(5.33)
AtM	0.003**	0.006***	0.005***
	(2.00)	(3.89)	(4.00)
Panel B: Subcategory			
Momentum	0.005***	0.006***	0.010***
	(3.04)	(3.85)	(2.62)
Liquidity Risk	0.001	0.005*	0.005*
	(0.81)	(1.88)	(1.88)
Other market	0.002***	0.005***	0.005***
	(3.01)	(6.45)	(4.47)
Investment	0.002**	0.004***	0.004***
	(2.48)	(4.50)	(4.06)
Profitability	0.006***	0.007***	0.007***
	(3.94)	(4.29)	(4.02)
Other accounting	0.002***	0.005***	0.005***
	(5.31)	(6.84)	(5.77)
AtM	0.003**	0.006***	0.005***
	(2.00)	(3.89)	(4.00)

Table A3: Information for Anomalies with Significant Fund Exposures

This table shows the information for 45 anomalies that mutual funds have significant exposures to. Sign of Exposure is the sign of coefficient δ_a in Eq. (8) when regressing the fund's gross alpha on the value-weighted hedge portfolio return of the anomaly. Subcategory is the group that an anomaly belongs to. Return is the anomaly's value-weighted hedge portfolio return obtained from long-short positions in the extreme deciles (decile 10 minus decile 1) each month using NYSE breakpoints from January 1984 to December 2017.

Anomaly	Description	Literature	Sign of Exposure	Subcategory	Return
R11	Prior 11-month returns	Jegadeesh and Titman (1993)	Positive	Momentum	0.956%
BETALRC	Liquidity betas (return-illiquidity)	Acharya and Pedersen (2005)	Positive	Liquidity risk	0.475%
RA16TO20	Seasonality	Heston and Sadka (2008)	Negative	Other market	0.356%
RA6TO10	Seasonality	Heston and Sadka (2008)	Negative	Other market	0.692%
RN16TO20	Seasonality	Heston and Sadka (2008)	Positive	Other market	0.395%
RN11TO15	Seasonality	Heston and Sadka (2008)	Positive	Other market	0.365%
CEI	Composite equity issuance	Daniel and Titman (2006)	Negative	Investment	0.570%
DLNO	Changes in long-term net operating assets	Fairfield, Whisenant, and Yohn (2003)	Negative	Investment	0.330%
DNCO	Changes in net non-current operating assets	Richardson et al. (2005)	Negative	Investment	0.450%
DPIA	Changes in PPE and inventory-to-assets	Lyandres, Sun, and Zhang (2008)	Negative	Investment	0.360%
DWC	Changes in net non-cash working capital	Richardson et al. (2005)	Negative	Investment	0.391%
IG	Investment growth	Xie (2001)	Negative	Investment	0.291%
INVC	Inventory changes	Thomas and Zhang (2002)	Negative	Investment	0.432%
NSI	Net stock issues	Pontiff and Woodgate (2008)	Negative	Investment	0.608%
NXF	Net external financing	Bradshaw, Richardson, and Sloan (2006)	Negative	Investment	0.485%
CLA	Cash-based operating profits-to-lagged assets	Ball et al. (2016)	Negative	Profitability	0.784%
CLAQ	Quarterly cash-based operating profits-to-lagged assets	Ball et al. (2016)	Negative	Profitability	1.030%
COP	Cash-based operating profitability	Ball et al. (2016)	Negative	Profitability	0.883%
DROA	4-quarter change in return on assets	Balakrishnan, Bartov, and Faurel (2010)	Positive	Profitability	0.458%
OLA	Operating profits-to-lagged assets	Ball et al. (2016)	Negative	Profitability	0.675%

Anomaly	Description	Literature	Sign of Exposure	Subcategory	Return
OLAQ	Quarterly operating profits-to-lagged assets	Ball et al. (2016)	Negative	Profitability	1.100%
OLEQ	Quarterly operating profits-to-lagged equity	Fama and French (2015)	Negative	Profitability	0.864%
OPA	Operating profits-to-asset	Ball et al. (2016)	Negative	Profitability	0.782%
OPE	Operating profits to equity	Fama and French (2015)	Negative	Profitability	0.507%
PMQ	Quarterly profit margin	Soliman (2008)	Negative	Profitability	0.633%
RNA	Return on net operating assets	Soliman (2008)	Negative	Profitability	0.404%
RNAQ	Quarterly return on net operating assets	Soliman (2008)	Negative	Profitability	0.776%
ROA	Return on assets	Balakrishnan, Bartov, and Faurel (2010)	Negative	Profitability	0.646%
ROE	Return on equity	Haugen and Baker (1996)	Negative	Profitability	0.747%
FPQ	Failure probability, annual and monthly sorts	Campbell, Hilscher, and Szilagyi (2008)	Negative	Other accounting	0.645%
OQ	Quarterly O-score	Dichev (1998)	Negative	Other accounting	0.533%
ALMQ	Quarterly asset liquidity scaled by 1-quarter-lagged market value of assets	Ortiz-Molina and Phillips (2014)	Positive	Other accounting	0.439%
KZQ	Quarterly Kaplan-Zingales index	Lamont, Polk, and Saa-Requejo (2001)	Negative	Other accounting	0.341%
SDD	Secured debt-to-total debt	Valta (2016)	Positive	Other accounting	0.449%
DUR	Equity duration	Dechow, Sloan, and Soliman (2004)	Negative	Other accounting	0.505%
DAC	Discretionary accruals	Xie (2001)	Negative	Other accounting	0.326%
PDA	Percent discretionary accruals	Hafzalla, Lundholm, and Van Winkle (2011)	Positive	Other accounting	0.233%
ATO	Assets turnover	Soliman (2008)	Positive	Other accounting	0.450%
ATOQ	Quarterly assets turnover	Soliman (2008)	Positive	Other accounting	0.789%
SGQ	Quarterly sales growth	Fama and French (1992)	Positive	Other accounting	0.356%
EPRD	Earnings predictability	Francis et al. (2004)	Positive	Other accounting	0.688%
OCA	Organizational capital-to-assets	Eisfeldt and Papanikolaou (2013)	Negative	Other accounting	0.689%
NOP	Net payout yield	Boudoukh et al. (2007)	Negative	AtM	0.475%
VFP	Analysts' forecasts-based intrinsic value-to-market	Frankel and Lee (1998)	Positive	AtM	0.425%
RDM	R&D expense-to-market	Chan, Lakonishok, and Sougiannis (2001)	Positive	AtM	0.728%

Table A4: Exposures and Value added - Individual Anomalies

This table shows the coefficient estimates from univariate regressions of mutual fund gross alpha on the individual anomaly return defined by Eq. (8) and the corresponding value added defined by Eq. (13). The sample of 45 anomalies is categorized into momentum, liquidity risk, other market, investment, profitability, other accounting, and accounting-to-market. Each Panel shows the individual anomalies included in each subcategory. We aggregate returns by taking an equally weighted average of anomaly returns in the category defined by Eq. (9). Vanguard alpha/CAPM alpha is the monthly value-weighted benchmark adjusted gross return estimated by Eq. (5) using the Vanguard S&P500 index fund/market portfolio as a benchmark. Value added is ranked in ascending order in each category based on the Vanguard value added. The sample period is from January 1984 to December 2017. *p*-values are reported below the regression coefficients. Bootstrapped *p*-values are reported below the value added. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Vanguard			CAPM		
	Value added	Exposure	Adj R^2	Value added	Exposure	Adj R^2
Panel A: Momentum						
R11	281	0.015**	0.010	140	0.008**	0.008
	0.373	0.022		0.363	0.040	
Panel B: Liquidity risk						
BETALRC	926	0.102***	0.265	384	0.042***	0.147
	0.160	0.000		0.168	0.000	
Panel C: Other market						
RA16TO20	-224	-0.033**	0.012	-99	-0.015*	0.007
	0.195	0.015		0.255	0.052	
RA6TO10	-351	-0.027**	0.008	-169	-0.013*	0.006
	0.183	0.035		0.222	0.068	
RN11TO15	332	0.048*	0.033	170	0.024**	0.027
	0.344	0.064		0.272	0.019	
RN16TO20	577	0.058**	0.034	361*	0.036***	0.044
	0.154	0.021		0.071	0.000	

	Vanguard			CAPM		
	Value added	Exposure	Adj R^2	Value added	Exposure	Adj R^2
Panel D: Investment						
NSI	-1,903**	-0.150***	0.313	-596**	-0.047***	0.098
	0.014	0.000		0.024	0.000	
CEI	-1,423**	-0.130***	0.275	-481**	-0.044***	0.100
	0.027	0.000		0.043	0.000	
NXF	-1,235	-0.162***	0.448	-403	-0.053***	0.153
	0.140	0.000		0.132	0.000	
DNCO	-707***	-0.083***	0.052	-164	-0.019**	0.007
	0.009	0.000		0.212	0.049	
DPIA	-624*	-0.093***	0.079	-301	-0.045***	0.059
	0.082	0.000		0.102	0.000	
DWC	-489	-0.097***	0.090	-175	-0.035***	0.036
	0.224	0.001		0.238	0.003	
DLNO	-407	-0.074***	0.049	-153	-0.028**	0.021
	0.191	0.000		0.271	0.044	
INVC	-337*	-0.035**	0.008	-248*	-0.025***	0.016
	0.098	0.045		0.051	0.005	
IG	-260	-0.039**	0.011	-147	-0.022**	0.012
	0.223	0.036		0.183	0.046	
Panel E: Profitability						
COP	-2,053***	-0.116***	0.227	-460**	-0.026**	0.035
	0.001	0.000		0.032	0.010	
CLAQ	-1,948***	-0.098***	0.141	-503**	-0.025**	0.029
	0.001	0.000		0.043	0.017	
OLAQ	-1,702***	-0.081***	0.125	-300	-0.014**	0.010
	0.001	0.000		0.158	0.022	
CLA	-1,621***	-0.109***	0.176	-333*	-0.022**	0.022
	0.005	0.000		0.066	0.025	
OLEQ	-1,449**	-0.088***	0.179	-275	-0.017*	0.019
	0.016	0.000		0.117	0.076	
OPA	-1,432***	-0.097***	0.173	-331*	-0.023***	0.028
	0.009	0.000		0.062	0.010	
RNAQ	-1,338**	-0.098***	0.223	-310*	-0.023***	0.037
	0.041	0.000		0.087	0.006	
PMQ	-1,102	-0.101***	0.272	-281	-0.026***	0.055
	0.108	0.000		0.127	0.001	
ROE	-1,071*	-0.089***	0.216	-202	-0.017*	0.023
	0.097	0.000		0.203	0.097	
OLA	-1,023***	-0.080***	0.105	-156	-0.012*	0.006
	0.009	0.000		0.259	0.069	
OPE	-1,000	-0.116***	0.316	-246	-0.029***	0.060
	0.170	0.000		0.170	0.003	
ROA	-896	-0.089***	0.191	-164	-0.016*	0.019
	0.147	0.000		0.263	0.075	
RNA	-847	-0.120***	0.265	-256	-0.036***	0.077
	0.198	0.000		0.176	0.000	
DROA	232	0.027*	0.004	184	0.021**	0.011
	0.213	0.099		0.113	0.018	

	Vanguard			CAPM		
	Value added	Exposure	Adj R^2	Value added	Exposure	Adj R^2
Panel F: Other accounting						
OCA	-1,177**	-0.096***	0.120	-317*	-0.026**	0.026
	0.014	0.000		0.076	0.024	
DAC	-1,144	-0.131***	0.319	-296	-0.034***	0.067
	0.107	0.000		0.125	0.000	
KZQ	-844**	-0.069***	0.072	-414**	-0.034***	0.056
	0.039	0.000		0.050	0.000	
SDD	-585*	-0.044***	0.036	-239	-0.018*	0.019
	0.058	0.000		0.186	0.067	
SGQ	-408	-0.137***	0.270	-167	-0.056***	0.146
	0.506	0.000		0.515	0.000	
DUR	-391	-0.043***	0.074	-120	-0.013***	0.021
	0.281	0.000		0.337	0.008	
FPQ	172	0.045**	0.017	86	0.022**	0.013
	0.467	0.038		0.434	0.047	
PDA	222	0.050**	0.011	106	0.024**	0.007
	0.233	0.019		0.159	0.045	
ATO	416	0.049***	0.039	109	0.013*	0.007
	0.108	0.000		0.271	0.052	
ALMQ	492	0.077***	0.104	199	0.031***	0.054
	0.240	0.000		0.256	0.000	
EPRD	748**	0.079***	0.091	388**	0.041***	0.079
	0.026	0.000		0.031	0.000	
ATOQ	876**	0.087***	0.121	381**	0.038***	0.073
	0.033	0.000		0.047	0.000	
OQ	1,085**	0.061***	0.049	462**	0.026***	0.028
	0.040	0.008		0.046	0.010	
Panel G: Accounting-to-Market						
NOP	-1,231*	-0.133***	0.321	-386*	-0.042***	0.101
	0.099	0.000		0.090	0.000	
VFP	363	0.035**	0.028	177	0.017***	0.023
	0.235	0.010		0.265	0.008	
RDM	1,110*	0.076***	0.153	390*	0.027***	0.060
	0.060	0.000		0.066	0.000	

Table A5: Exposures - Alternative Value-Weighted Gross Alpha

This table shows the coefficient estimates from multivariate regressions of mutual fund gross alpha on the anomaly category returns defined by Eq. (10). The sample of 45 anomalies is categorized into market, accounting, and accounting-to-market (AtM) in Panel A; and is categorized into momentum, liquidity risk, other market, investment, profitability, other accounting, and accounting-to-market in Panel B. We aggregate returns by taking an equally weighted average of anomaly returns in the category defined by Eq. (9). Vanguard alpha/CAPM alpha is the difference between mutual funds' monthly value-weighted gross return and monthly benchmark return defined by Eq. (14) (15), using the Vanguard S&P500 index fund/market portfolio as a benchmark. The sample period is from January 1984 to December 2017. p-values are reported below the regression coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Vanguard	CAPM
Panel A: Three categories		
Market	0.184***	0.090***
	0.000	0.000
Accounting	-0.247***	-0.067***
	0.000	0.000
AtM	0.022	0.011
	0.187	0.329
Constant/Unexplained	0.000	-0.000
	0.345	0.808
Observations	408	408
Adj R^2	0.403	0.165
Panel B: Subcategories		
Market:		
Momentum	0.042***	0.019***
	0.000	0.000
Liqudity risk	0.045***	0.023***
	0.000	0.002
Other market	0.009	0.025
	0.692	0.105
Accounting:		
Investment	-0.186***	-0.090***
	0.000	0.000
Profitability	-0.098***	0.007
	0.000	0.668
Other accounting	-0.005	-0.051**
	0.879	0.021
AtM:		
AtM	0.037**	0.020*
	0.012	0.063
Constant/Unexplained	0.001**	0.000
	0.024	0.476
Observations	408	408
Adj R^2	0.560	0.241

Table A6: Exposures and Value Added - Three Categories - Subsamples

This table shows the regression coefficient estimates from multivariate regressions of mutual fund gross alpha onto the anomaly category returns defined by Eq. (10) and corresponding value added defined by Eq. (11). Panel A shows the sample period from January 1984 to December 2000. Panel B shows the sample period from January 2001 to December 2017. The sample of 45 anomalies is categorized into market, accounting, and accounting-to-market (AtM). We aggregate returns by taking an equally weighted average of anomaly returns in the category defined by Eq. (9). #positive/total refers to the number of anomalies that mutual funds are positively exposed to over the total number of anomalies in the category. Vanguard alpha/CAPM alpha is the monthly value-weighted benchmark adjusted gross return estimated by Eq. (5) using the Vanguard S&P500 index fund/market portfolio as a benchmark. p-values are reported below the regression coefficients. Bootstrapped p-values are reported below the value added. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Exposure		Value added	
	Vanguard	CAPM	Vanguard	CAPM
Panel A: 1984-2000				
Value added (total)			203	979
			0.915	0.208
Market	0.220***	0.090***	1,557***	636**
	0.000	0.002	0.005	0.012
Accounting	-0.289***	-0.019	-2,101***	-139
	0.000	0.560	0.000	0.559
AtM	0.007	0.015	49	108
	0.778	0.392	0.797	0.448
Constant/Unexplained	0.000	-0.000	698	374
	0.555	0.773	0.650	0.548
Observations	204	204		
Adj R^2	0.435	0.089		
Panel B: 2001-2017				
Value added (total)			1,546	433
			0.312	0.654
Market	0.140***	0.103***	1,316**	966**
	0.000	0.000	0.016	0.011
Accounting	-0.188***	-0.096***	-2,016*	-1,027*
	0.000	0.000	0.050	0.071
AtM	0.040*	0.015	383	147
	0.092	0.308	0.261	0.441
Constant/Unexplained	0.001	0.000	1,863	347
	0.111	0.600	0.179	0.706
Observations	204	204		
Adj R^2	0.333	0.267		