Gross Profitability and Mutual Fund Performance☆

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Abstract

There is no consensus yet on whether and the extent to which professional money managers profit from market anomalies. Our research sheds light on this important question and examines whether actively managed equity mutual funds trade on and profit from the gross profitability anomaly (Novy-Marx, 2013). We find that mutual funds do appear to trade on the gross profitability anomaly; and that mutual funds that have a larger concentration of high gross profitability stocks generate better future performance. Moreover, the outperformance of these funds cannot be fully explained by their factor realization on firm profitability (Fama and French, 2015). Further analysis suggests that managers of mutual funds who tilt their portfolios toward the gross profitability anomaly tend to have better stock picking ability and create value by attracting future fund inflows and growing fund assets under management. Our results are robust to controlling for active fund management measures and mutual funds' potential exploitation of other profitability-related investment strategies.

Keywords: Gross profitability anomaly; Mutual funds; Active fund management

JEL Classification: G10, G11, G14, G23

I. Introduction

The question of whether professional money managers successfully exploit market anomalies has been extensively studied in prior literature. There is, however, a lack of consensus on the extent to which they are able to profit from these anomalies.[1] This question has also received public attention due to evidence that a large portion of financial products devised to exploit these anomalies do not outperform the market (Harvey and Liu, 2014; Coy, 2017). In this paper we shed light on this issue by examining whether mutual fund managers, an important subset of professional money managers, trade on and profit from the gross profitability anomaly.

Focusing on the gross profitability anomaly provides a powerful setting to examine whether mutual fund managers take advantage of market anomalies for several reasons. First, anecdotal evidence suggests professional investment managers are aware of this strategy. For example, Dimensional Fund Advisors, AQR, and Efficient Frontier Advisors have incorporated measures similar to gross profitability in their trading strategies. A recent article in *The Wall Street Journal* quotes a money manager as saying "There's something there, I don't think it [gross profitability] can be ignored."[2] Second, relative to other anomalies, a strategy based on gross profitability is profitable when trading solely on the long-leg (Stambaugh, Yu, and Yuan, 2012; Edelen, Ince, and Kadlec, 2016). It is thus a practicable strategy even for investors that face short sale restrictions (such as mutual funds). Finally, the return predictability of the gross profitability anomaly is robust. For example, it subsumes most earnings related anomalies, as well as a large number of seemingly unrelated anomalies (e.g., earnings-to-book equity and free cash flow-to-book equity; Novy-Marx, 2013). Given its practicability

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[1] See, for example, Ali, Chen, Yao, and Yu (2008), Collins, Gong, and Hribar (2003), Lev and Nissim (2006), Grinblatt, Titman, and Wermers (1995), Lewellen, (2010), and Ke and Ramalingegowda (2005) for research on anomalies driven by accruals, momentum, and the book-to-market ratio, and post-earnings announcement drift.

[2] http://www.wsj.com/articles/SB10001424127887323293704578334491900368844. For further discussions of gross profitability by practitioners, see Forbes (2013) and CFA Institute Magazine (2014)

and robust return predictability, the gross profitability anomaly could be one of the top choices for fund managers who intend to trade on and profit from market anomalies.

To examine whether mutual fund managers exploit the gross profitability anomaly, we use U.S. mutual fund data to construct a gross profitability investing measure (GPIM) in a manner similar to the momentum investing measure of Grinblatt, Titman, and Wermers (1995) and the accrual investing measure of Ali, Chen, Yao, and Yu (2008). In particular, GPIM is the weighted average of the gross profitability quintile ranks of individual stocks held by a mutual fund. A high (low) value of GPIM indicates that a fund primarily holds high (low) gross profitability stocks. We find that on average mutual funds tilt their portfolios toward stocks with higher gross profitability, however there is substantial variation in the degree to which the anomaly is exploited across mutual funds. Furthermore, we find a fund's GPIM ranking is persistent, which suggests that some fund managers deliberately concentrate their portfolios in high profitability stocks.

We next investigate the performance consequences of trading on the gross profitability anomaly. Using both portfolio analysis and cross-sectional regressions, we find that GPIM predicts future fund performance. For example, in our portfolio analysis we find that funds in the top GPIM quintile significantly outperform those in the bottom quintile by a net monthly return of 0.22%, a three-factor alpha of 0.31%, and a four-factor alpha of 0.20%. Furthermore, we show that these managers have better stock picking ability, and add value to their funds by growing assets under management and drawing in future fund flows (Daniel, Grinblatt, Titman, and Wermers, 1997; Doshi, Elkamhi, and Simutin, 2015). We also find that GPIM is positively associated with the value-added performance measure from Berk and van Binsbergen (2015). Overall, our findings provide evidence for the existence of skill among funds with concentrated holdings of high gross profitability stocks.

In order to understand more about the types of mutual funds investing in the gross profitability strategy, we examine various fund characteristics based on GPIM rankings. We find that, compared with those in the bottom or middle GPIM quintiles, funds in the top quintile have higher portfolio turnover and higher expense ratios. These findings, when considered with our findings about abnormal returns and alternative measures of fund performance, suggest mutual funds investing in the gross profitability strategy have mangers with ability as prior research has shown that skilled fund managers trade more and charge higher fees (Berk and Green, 2004; Pastor, Stambaugh, and Taylor, 2017). We also find that funds trading on the gross profitability anomaly are smaller in size, consistent with the notion that smaller funds are more likely to seize profit opportunities (Chen, Hong, Huang, and Kubik, 2004).

We also examine two non-skill related explanations for the documented GPIM-driven fund performance: 1) passive reinvestment due to high investor flow; and 2) top GPIM funds simply earn a profitability related risk premium. We first examine whether our results are driven by fund managers who simply expand their holdings due to high investor flows (i.e., passive reinvestment; Wermers, 2003; Coval and Stafford, 2007; Lou, 2012). Using a multivariate logistic regression framework, we find no evidence that a fund's GPIM ranking is associated with past fund flows, which indicates that our findings are not likely to be a result of passive reinvestment due to greater fund inflows. In contrast, we find that funds with higher risk-adjusted past performance (α_{t-1}^{4F}) are more likely to employ the gross profitability strategy. This finding supports that managerial skill helps to explain why some funds trade on the anomaly.

The second non-skill related explanation we test is whether our fund performance results are driven by the profitability-related risk premium (Fama and French, 2015). To differentiate between the skill and risk based explanations, following Fama and French (2015), we extend our benchmark four-factor model to include the profitability factor (thus a five-factor model). We find that, even after controlling for the profitability factor, the return difference between funds in the top and bottom GPIM quintiles remains economically and statistically significant (0.16% per month). This result indicates that top GPIM funds earn abnormal returns in addition to the risk premium due to their greater exposure to the profitability factor. It provides further support that some skilled fund managers exploit the gross profitability anomaly and earn abnormal returns.

While our analyses suggest that managers of high GPIM funds tend to have investment skill, we also find there are some undesirable consequences when implementing the gross profitability strategy. In particular, we find that compared with those in the bottom and middle GPIM quintiles, funds in the top quintile have significantly greater fund return volatility and higher fund flow volatility. These undesirable features could explain why trading on the gross profitability anomaly, despite being profitable, might not be attractive to all mutual fund managers. For example, given information asymmetry about their true investment ability, some managers may be reluctant to undertake a strategy that increases volatility and adds noise to performance signals about their skill (Berk and Green, 2004; Huang, Wei, and Yan, 2007). In addition, managers may be reluctant to invest in the gross profitability strategy if higher flow volatility forces more frequent liquidity related trades, which, in turn, potentially hurts future fund performance (Edelen, 1999; Rakowski, 2010). For these reasons, some managers may choose to limit their exposure to the gross profitability strategy.

Finally, our findings are robust to two important extensions. First, recent research demonstrates that active portfolio management is indicative of greater managerial skill and leads to better fund performance (Cremers and Petajisto, 2009; Petajisto, 2013; Amihud and Goyenko, 2013). In robustness tests we control for proxies of active portfolio management, and find that the predictive power of GPIM for fund performance remains significant. This suggests that managers implementing the gross profitability investment strategy possess skill beyond what is captured by leading active fund management proxies. Second, we show the predictive power of GPIM is not driven by mutual funds' potential exploitation of other profitability-related investment strategies. Following Akbas, Jiang, and Koch (2017) and Ball, Gerakos, Linnainmaa, and Nikolaev (2015), we construct measures of the trend in GPIM and operating profitability in a similar way to the construction of GPIM. We find that the return predictability associated with GPIM remains after controlling for these measures.

Our paper makes the following contributions. First, we provide evidence that mutual fund managers exploit an important market anomaly based on gross profitability. Previous research finds conflicting evidence about whether mutual fund managers take advantage of market anomalies (e.g., Carhart, 1997; Ali, Chen, Yao, and Yu, 2008; 2012; Akbas, Armstrong, Sorescu, and Subrahmanyam, 2015; Edelen, Ince, and Kadlec, 2016). Focusing on the gross profitability anomaly, which is likely known by mutual fund managers and remains profitable in the presence of short sale constraints, we find that a subset of mutual funds trade on and profit from this strategy. Importantly, we show that fund managers with greater skill are more likely to take advantage of the gross profitability anomaly. This finding complements recent studies that show that some fund managers possess investment skill (Baker, Litov, Wachter, and Wurgler, 2010; Cai and Lau, 2015; Nallareddy and Ogneva, 2017).

Second, we provide a plausible reason why the gross profitability anomaly remains profitable. Specifically, we show that mutual funds with portfolio holdings that are concentrated in high gross profitability stocks exhibit higher return volatility and higher fund flow volatility. These characteristics may make trading on the gross profitability anomaly unattractive to some mutual fund managers and allows the anomaly to remain profitable. Finally, a growing literature documents that gross profitability has significant predictive power for stock returns (Novy-Marx, 2013; Fama and French, 2015; 2016). We extend this line of inquiry and show that, incremental to the three- and four-factor models, GPIM possesses explanatory power for the cross section of mutual fund performance.

The rest of the paper is organized as follows. Section II describes the mutual fund data and gross profitability investing measure (GPIM) used in our analysis. Sections III, IV, and V present our main empirical results. Section VI reports the results of several robustness tests. Concluding remarks are presented in Section VII.

II. Sample Selection, Variable construction, and Summary Statistics

A. Mutual Fund Sample Selection

For our empirical analysis, we combine two mutual fund databases; the CRSP mutual fund database and Thomson-Reuters holdings database.[3] The CRSP database has information on monthly returns and fund characteristics such as total net assets, the expense ratio, and the turnover ratio for all U.S. mutual funds. The Thomson database contains quarterly or semiannual information on portfolio holdings for equity mutual funds investing in the U.S. market.[4]

We manually match the funds in the two databases by fund names and ticker symbols. The matching procedure is similar to that in Wermers (2000). We focus on actively managed domestic equity mutual funds for which the holdings data are most complete and reliable. We thus eliminate balanced, bond, money market, international, and index funds.[5] We also exclude funds that manage less than $15 million in the previous month, or of which the total market value of reported holdings is under 80% or over 120% of the total net assets. For funds with multiple share classes, we compute fund-level variables by aggregating those of different share classes. Specifically, we calculate the returns of a multi-class fund as the weighted-average returns across share classes where total net assets are

[3] Mutual fund investments represent a substantial portion of U.S. household portfolios, and account for a significant fraction of independent institutional ownership of corporate stocks. As the demand for direct investing in individual equities and bonds has declined over time, mutual funds remain an important investment vehicle for U.S. households. According to Investment Company Institute Fact Book an estimated 92 million individual investors (44% of all U.S. households) owned mutual funds and held 89% of total fund assets in 2014. The median amount invested in mutual funds was $100,000.

[4] The Thomson database is based on mandatory and voluntary fund holding disclosures. Prior to 2004, mutual funds were required to disclose their holdings semiannually; many funds voluntarily disclosed their holdings quarterly. The SEC increased the mandatory disclosure frequency from semiannual to quarterly effective May 2004.

[5] Following Huang, Sialm, and Zhang (2011), we select funds with the following Lipper objectives: CA, CG, CS, EI, FS, G, GI, H, ID, LCCE, LCGE, LCVE, MC, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, MR, NR, S, SCCE, SCGE, SCVE, SG, SP, TK, TL, UT. If a fund does not have any of the above objectives, we select funds with the following Strategic Insights objectives: AGG, ENV, FIN, GMC, GRI, GRO, HLT, ING, NTR, SCG, SEC, TEC, UTI, GLD, RLE. If a fund has neither the Lipper nor the SI objective, then we use the Wiesenberger Fund Type Code to select funds with the following objectives: G, G-I, G-S, GCI, IEQ, ENR, FIN, GRI, HLT, LTG, MCG, SCG, TCH, UTL, GPM. If none of these objectives are available and the fund has a CS policy or holds more than 80% of its value in common shares, then the fund will be included. Index funds are identified based on their names. We also manually remove from our sample the index funds that are misclassified as active domestic funds.

used as the weight. All other variables including expense ratio and turnover are calculated in a similar manner. Our sample covers the period from 1984 to 2014.

B. Gross Profit Investing Measure (GPIM)

Having assembled our sample of mutual funds, we next compute the gross profitability investing measure (GPIM) to quantify the degree to which a fund tilts to the gross profitability strategy. GPIM is constructed based on a mutual fund's holdings of common stocks traded on the NYSE, AMEX, or NASDAQ. First, we require firms to have quarterly balance sheet and income statement information from Compustat so that gross profitability can be calculated. Following Novy-Marx (2013) and Akbas, Jiang, and Koch (2017), quarterly gross profitability is computed as sales (SALEQ) minus cost of goods sold (COGSQ) scaled by assets (ATQ). Next, at the end of each quarter $t-1$, we sort all sample stocks into quintiles based on their gross profitability. Stocks are ranked from 1 to 5 with quintile 1 (5) indicating stocks with the lowest (highest) gross profitability. Finally, the GPIM of fund *i* is calculated as the weighted average of the gross profitability quintile ranks of stocks held by the fund at the end of quarter *t*:

$$\mathrm{GPIM}_{i,t} = \sum_{j=1}^{N} w_{i,j,t} \times \mathrm{GP\ Rank}_{j,t}, \tag{1}$$

where $\mathrm{GP\ Rank}_{j,t}$ is the quintile rank of stock *j*'s gross profitability, N is the number of stocks that are held by fund *i* at the end of quarter *t*, and $w_{i,j,t}$ is the value of stock *j* held by fund *i* as a percentage of its total fund value. More specifically,

$$w_{i,j,t} = \frac{n_{i,j,t} \times P_{j,t}}{\sum_{j=1}^{N} n_{i,j,t} \times P_{j,t}}, \tag{2}$$

where $n_{i,j,t}$ is the number of shares of stock *j* held by the fund, and $P_{j,t}$ is the market price of stock *j* at the end of quarter *t*. The construction of the gross profitability investing measure (GPIM) is in line with that of the momentum investing measure (Grinblatt, Titman, and Wermers, 1995) and accrual investing measure (Ali, Chen, Yao, and Yu, 2008). A high (low) value of GPIM indicates that a fund primarily holds high (low) gross profitability stocks.

III. Summary Statistics

A. The Gross Profitability Anomaly and Characteristics of Stocks Held by Mutual Funds

We begin our empirical analysis by examining the characteristics of stocks held by mutual funds. At the end of each quarter *t*, we identify stocks that are held by at least one mutual fund in our sample. These stocks are grouped into quintile portfolios using gross profitability breakpoints, which are determined using the entire CRSP/Compustat universe of firms. Table 1 reports the time series averages of monthly cross-sectional means for return and style characteristics of stocks held by our fund sample.

[Table 1 about here]

Since mutual funds do not short sell, we expect them to exploit gross profitability by mainly holdings stocks in the high quintiles of the gross profitability ranked portfolios. As reported in Panel A of Table 1, mutual funds indeed exhibit a preference for stocks with higher gross profitability. Specifically, the number of stocks held by mutual funds in the top quintile (quintile 5) of gross profitability is 585, compared to 308 in the bottom quintile (quintile 1). Mutual funds also hold a large number of stocks from quintiles 3 and 4. Moving to stock performance, as expected Table 1 shows that stocks in the top quintile outperform those in the bottom and middle quintiles when measured as either cumulative return ($R_{t+1,t+12}$) or risk-adjusted performance (α^{4F}_{t+1}). Further, Table 1 shows that stocks in the bottom gross profitability quintile have significantly higher total return volatility (Ret. Vol.) and larger idiosyncratic volatility (IVOL) than stocks in the top quintile. Specifically, Panel B shows the differences in return and idiosyncratic volatility between the two extreme gross profitability portfolios is -2.42% (*t* – statistic = -3.63) and -1.72% (*t* – statistic = -3.86), respectively. Panel C of Table 1 reports that relative to stocks in the middle gross profitability quintile (quintile 2, 3, and 4), stocks in the top quintile exhibit significantly higher stock return volatility and idiosyncratic volatility. This finding indicates the presence of arbitrage risks when investing in high gross profitability stocks, which might deter the implementation of the gross profitability strategy by some mutual funds and may be why they hold a large number of stocks from quintiles 3 and 4, in addition to holding stocks in quintile 5.[6]

Table 1 also presents information about various firm characteristics for stocks held by the mutual funds in our sample. Specifically, it reports the equal-weighted ranks of size (Size Rank), book-to-market (BM Rank), and prior twelve-month return (MOM Rank) for stocks in each portfolio. We find that stocks in the extreme gross profitability portfolios have smaller market capitalization compared with those in the middle quintiles. Moreover, Table 1 shows that firms in the top gross profitability quintile have higher market capitalization compared with those in the bottom quintile. Consistent with Novy-Marx (2013), we find gross profitability is negatively related to book-to-market ratios, suggesting that trading on gross profitability could provide a hedge for a value strategy. Finally, we find a positive relation between gross profitability and the prior twelve-month stock return (MOM Rank).

B. Do Mutual Funds Trade on the Gross Profitability Anomaly?

Moving from the individual stock-level analysis reported in the previous subsection, Table 2 reports summary statistics of the characteristics of mutual funds in our sample. Fund characteristics include fund size (TNA), fund age measured as the difference in years between current date and the date the fund was first offered, fund family size measured as the sum of the TNA under management by the fund family, fund expense ratio (Expenses), portfolio turnover, past return cumulated over

[6] These results are consistent with previous research that finds arbitrage risk concerns make investing in anomaly strategies less attractive to mutual funds. For example, Ali, Chen, Yao, and Yu (2008, 2012) find that due to the arbitrage risk associated with extreme accruals stocks and stocks with extreme earnings surprises, few funds seem to trade on these anomalies.

previous year ($R_{t-1,t-12}$), past twelve-month fund flow measured as $(TNA_{i,t} - TNA_{i,t-12}(1 + R_{t-1,t-12}))/TNA_{i,t-12}$, fund return (flow) volatility computed as the standard deviation of monthly fund return (flow) over the prior twelve months. For each variable, we report the time series average of the cross-sectional mean, median and standard deviation. Our sample includes 2,794 distinct funds and 293,287 fund-month observations. The mean size and age of funds is $1,054 million and 18 years, respectively. The average family size is $44,365 million. The average expense ratio is 1.18%. Table 2 also shows that the average turnover of mutual funds is about 85%, implying that the average holding period of a stock is 1.2 years. Past fund return (flow), on average, is 11.71% (8.08%).

Furthermore, the mean and median of GPIM are 3.40 and 3.45, respectively. This suggests that the portfolio holdings of mutual funds on average are tilted toward stocks with higher gross profitability. Also, we find substantial variation in the extent to which mutual funds employ the gross profitability strategy as the standard deviation of GPIM is 0.44.

[Table 2 about here]

We next examine the relation between GPIM and three key investment styles - namely size, book-to-market, and momentum (prior twelve-month fund return). This analysis allows us to better understand the style characteristics of mutual funds that exploit gross profitability. We construct style measures in a manner similar to GPIM (described in Section II.B). For example, SIZEIM is the weighted average market capitalization quintile ranks of stocks held by a fund, while BMIM (MOMIM) is the weighted average book-to-market (prior 12-month return) quintile ranks of stocks held by a fund. Table 3, Panel A summarizes the average fund style characteristics across GPIM quintile portfolios.

[Table 3 about here]

Several important patterns emerge in Panel A. First, we find substantial variation in mutual funds' exposure to the gross profitability strategy. Specifically, the average GPIM score decreases from

3.94 to 2.73 when moving from the top to bottom GPIM portfolio. Second, GPIM is positively related to several other fund style characteristics. Relative to the bottom GPIM portfolio, the top GPIM portfolio tilts towards stocks with smaller market capitalization (SIZEIM) and better past performance (MOMIM). Third, Novy-Marx (2013) argues that the gross profitability strategy provides an excellent hedge for value strategies as it improves the Sharpe ratio of a fund portfolio that focuses on value investing. Our results support this notion. Specifically, the top GPIM portfolio tends to encompass stocks with large book-to-market ratios, and BMIM monotonically decreases as we move from the top to the bottom GPIM portfolios. This finding suggests that mutual funds with a high concentration of value stocks are more likely to implement the gross profitability strategy.

To gauge the fund-level persistence of GPIM over time, we report the transition matrix for fund GPIM rank from year t and $t + 1$. Finding that mutual funds tend to stay in the same GPIM quintile is important as it would suggest they follow a deliberate strategy rather than end up in a particular portfolio by chance. As shown in Panel B of Table 3, funds in the top GPIM quintile are more likely to stay in that quintile rather than move to the middle or bottom quintiles. For example, 68.08% of funds in the top quintile remain in that quintile next year, while only 32.04% switch to quintiles 2 – 4 and only 0.45% to the bottom quintile. A similar pattern is observed for the bottom GPIM quintile funds, where 76.48% stay in the same quintile, 22.32% switch to quintiles 2 – 4, and 0.42% switch to the top quintile. Similarly, funds in the middle GPIM quintiles tend to stay in the middle quintiles rather than move to the extremes. Overall, Panel B of Table 3 shows that a large proportion of mutual funds tend to stay in the same GPIM quintile from year t to year $t+1$. This suggests that some funds might deliberately structure their holdings to maintain a tilt towards stocks with higher gross profitability.

IV. Gross Profitability Investment Strategy and Mutual Fund Performance

So far our results indicate that on average mutual funds tilt their holdings towards higher gross profitability stocks. In this section we investigate the relation between the gross profitability investment strategy and fund performance using both portfolio and regression approaches.

A. Portfolio Analysis

To gauge whether implementing the gross profitability strategy leads to better future performance, in each quarter we sort our sample into GPIM quintiles and evaluate fund performance over subsequent periods. We employ the "follow the money" approach of Elton, Gruber and Blake (1996) and Gruber (1996) to deal with merged funds. This approach mitigates survivorship bias and assumes that investors in merged funds allocate their money in the surviving fund and continue to earn returns from the fund.

Fund performance is assessed using raw returns, as well as alphas from the Fama and French (1993) three-factor model (α^{3F}) and Carhart (1997) four-factor model (α^{4F}). For example, the four-factor model extends the Fama and French (1993) three-factor model with the momentum factor and is specified as follows:

$$r_{p,t} = \alpha_p^{4F} + \beta_{1,p}MKT_t + \beta_{2,p}SMB_t + \beta_{3,p}HML_t + \beta_{4,p}UMD_t + \varepsilon_p, \tag{3}$$

where $r_{p,t}$ is the monthly portfolio return (after expenses) in excess of the 1-month T-bill rate; MKT is the excess return on a value-weighted market portfolio; SMB, HML and UMD are the returns on the zero-investment factor mimicking portfolios for size, book-to-market, and momentum, respectively. For a specific performance metric (net return or α), we calculate both equal- and total net asset (TNA)-weighted monthly returns within each GPIM quintile portfolio.

[Table 4 about here]

Table 4 reports the future performance of the GPIM quintile portfolios. Panel A shows that subsequent one, three, and twelve month net equal-weighted returns are monotonically increasing with GPIM ranks. Panel B shows that the difference between the top and bottom GPIM quintiles is significant for the one, three, and twelve month equal-weighted returns. For example, the difference in returns between funds in the two extreme GPIM equal-weighted quintiles is 0.22% with a *t* – statistic of 1.80, and 1.68% with a *t* – statistic of 3.98 on an annual basis. Panels C and D report the difference between the top and bottom quintiles when using the risk-adjusted performance measures (α^{3F} and α^{4F}). For equally-weighted portfolios, the difference in α^{3F} between funds in the top and bottom GPIM quintiles is 0.31% per month and 3.09% per year. In addition, while our findings in Table 3 suggest that the gross profitability and momentum strategies are somewhat related, Table 4, Panel D shows that momentum does not entirely subsume the predictive power of GPIM for future fund performance. Once again, for equally-weighted portfolios, the difference in α^{4F} between funds in the top and bottom GPIM quintiles is 0.20% per month and 1.59% per year. These differences are statistically significant (*t* – statistics ranging from 3.11 to 3.22). The future return patterns are similar in the TNA-weighted portfolios that place a greater emphasis on larger funds. Overall, these results suggest that managers taking advantage of the gross profitability anomaly earn abnormal future returns.

B. Regression analysis

In this subsection, we examine the performance of the gross profitability strategy in a multivariate regression framework. Multivariate analysis allows us to control for various fund characteristics that may affect fund returns and to ensure that the ability of GPIM to predict fund performance is not due to such characteristics. Specifically, for every month *t*, we estimate the following cross-sectional regression:

$$\begin{aligned} \mathrm{Ret}_{i,t+p}(\hat{\alpha}^{4F}_{t+1}) = {} & \mathrm{Intercept}_{i,t} + \beta_1 \mathrm{GPIM}_{i,t} + \beta_2 \log(\mathrm{TNA})_{i,t} + \beta_3 \log(\mathrm{TNA})^2_{i,t} \\ & + \beta_4 \mathrm{Log(Age)}_{i,t} + \beta_5 \mathrm{Expenses}_{i,t} + \beta_6 \mathrm{Ret.\,Vol.}_{i,t} + \beta_7 \mathrm{Turnover}_{i,t} \\ & + \beta_8 \log(\mathrm{Fam.\,Size})_{i,t} + \beta_9 \mathrm{Performance}_{i.t} + \beta_{10} \mathrm{Flows}_{i,t} + \beta_{11} \mathrm{Flows}^2_{i,t} \\ & + \beta_{12} \mathrm{Category\ Flows}_{i,t} + \varepsilon_{i,t}, \end{aligned} \tag{4}$$

where i is the fund subscript and the dependent variable, $\mathrm{Ret_{t+p}}$, is either the one- ($\mathrm{Ret_{t+1}}$), three- ($\mathrm{Ret_{t+3}}$), or twelve ($\mathrm{Ret_{t+12}}$) month ahead fund return. We also use risk-adjusted measures, denoted as $\widehat{\alpha}^{4F}_{t+1}$, to capture risk-adjusted fund performance calculated as the fund excess return in month $t + 1$ minus the sum of the products of the four- ($\widehat{\alpha}^{4F}_{t+1}$) factor realizations and corresponding loadings. Fund factor loadings are estimated from the four-factor model using the past 36 monthly fund returns. We require a minimum of 30 monthly returns in the estimation of the market model.

The explanatory variable of interest in equation (4) is the gross profitability investing measure (GPIM), which directly assesses a fund's exposure to the gross profitability anomaly. In addition, following previous literature (e.g., Chen, Hong, Huang, and Kubik, 2004; Kacperczyk, Sialm, and Zheng, 2008; Cremers and Petajisto, 2009; Amihud and Goyenko, 2015; Cici, Dahm, and Kempf, 2018), we control for a comprehensive set of fund performance determinants: the logarithm of fund TNA ($\mathrm{Log(TNA)}$), the logarithm of one plus fund age ($\mathrm{Log(Age)}$), the fund expense ratio ($\mathrm{Expenses}$), the fund return volatility ($\mathrm{Ret.Vol.}$), the portfolio turnover ratio ($\mathrm{Turnover}$), the logarithm of fund family size ($\mathrm{Log(Fam.Size)}$), past fund return ($\mathrm{R_{t-1,t-12}}$) or four-factor alpha over the past 36 months ($\alpha^{4F}_{i,t-1}$). To control for persistence in flows and volatility of fund performance, we also include past fund flow ($\mathrm{Flow_{t-1,t-12}}$) and fund return volatility ($\mathrm{Ret.Vol.}$) computed as the standard deviation of monthly returns over the prior twelve months. All variables are defined in Section III.B. In addition, following Nanda, Wang, and Zheng (2004), funds are grouped into Small versus Large and Value versus Growth categories based on their past loadings obtained from the four-factor model.[7] $\mathrm{Category\ Flow_t}$ represents the growth of the fund objective category in month t. The regression specified in Equation (4) is estimated following the Fama-MacBeth (1973) procedure. The reported results are time-series averages of coefficient estimates obtained from monthly cross-sectional regressions. The t – statistics

[7] In particular, each month, we group all funds into two groups based on the median level of SMB and HML loadings. Mutual funds ranked in the top half with the higher SMB (HML) loading are classified as Small- (Value-) Style and those ranked in the bottom half are classified as Large- (Growth-) Style. We then place funds into 2 x 2 Size/Value categories.

are computed using standard errors that are adjusted for heteroskedasticity and serial autocorrelations (Newey and West, 1987).[8]

The results of equation (4), reported in Table 5, show there is a positive and statistically significant relation between GPIM and future fund performance. This relation holds when either the net fund return or risk-adjusted alpha (α^{4F}) is used. For example, using net returns measured from one- to twelve-months ahead (Columns 1 through 3), GPIM has significant predictive power for future fund performance. Similarly, the coefficient of GPIM in Column 4 (where the dependent variable is $\widehat{\alpha}^{4F}_{t+1}$) is 0.001 with a $t-$ statistic of 2.52. This suggests that a one standard deviation increase in the gross profitability measure leads to an additional excess return of 52.8 basis points a year. To put the marginal effect into perspective, Gruber (1996) shows that the average equity mutual fund underperforms a four-factor model by about 65 basis points per year. Therefore, our finding of an increase in fund performance by 52.8 basis points a year is economically meaningful.

[Table 5 about here]

The coefficients on other fund characteristics are in line with prior research. For example, smaller funds, funds with higher turnover, and those that belong to larger fund families tend to have better performance. On the other hand, the relation between fund expenses and subsequent fund performance is significantly negative. In addition, consistent with Gruber (1996), Carhart (1997), and Sapp and Tiwari (2004), we find a significantly positive association between the prior and subsequent fund performance.

Overall, both the portfolio tests and cross-sectional regressions provide strong evidence that GPIM has significant predictive power for future fund performance. That is, funds with concentrated holdings of high gross profitability stocks tend to outperform in both the near term and over longer horizons.

[8] We also confirm that our main results are robust to the use of alternative regression specifications. Specifically, we employ panel regressions with time and fund clustering. Although not reported, the results are qualitatively similar to the results presented in the paper using Fama-Macbeth (1973) cross sectional regressions.

C. Alternative Performance Measures

Besides risk-adjusted returns, fund managers' performance can be measured in other ways. In this section, we consider several additional measures to assess how gross profitability affects the all-around performance of mutual funds. These measures include 1) *Characteristic Selectivity* from Daniel, Grinblatt, Titman, and Wermers (1997), 2) the growth of assets under management, 3) future fund flows, and 4) the value added measure from Berk and van Binsbergen, (2015). The results of how each of these additional performance proxies is related to GPIM are reported in Table 6.

We first examine whether mutual fund managers investing in the gross profitability strategy are able to select stocks that outperform a portfolio of stocks with similar characteristics. To measure this we use *Characteristic Selectivity* from Daniel, Grinblatt, Titman, and Wermers (1997). To calculate this measure we construct 125 value-weighted quarterly rebalanced characteristic benchmark portfolios. We construct these portfolios from the CRSP universe of stocks by sorting on size (based on NYSE cut-offs), book-to-market, and prior 12-month stock returns. The characteristic-adjusted abnormal return for each stock is the difference between the stock's return and its benchmark portfolio return each month. As shown in Column (1) of Table 6, GPIM is positively related to *Characteristic Selectivity*, indicating that funds with concentrated holdings of high gross profitability stocks have superior stock-picking ability.

[Table 6 about here]

A fund manager's compensation is typically linked to the value of assets under management, and the value of assets under management is greatly affected by fund performance. Previous studies show that money tends to flow into (out of) funds that outperform (underperform) relative to a benchmark (Gruber, 1996; Chevalier and Ellison, 1997; Sirri and Tufano, 1998). In addition, Doshi, Elkamhi, and Simutin (2015) find that a skilled manager is more likely to generate better performance and attract higher money inflows than an unskilled manager. Consistent with their findings, Columns (2) and (3) show a significantly positive relation between GPIM and asset growth and between GPIM and future fund flows, respectively. These results suggest that funds with higher GPIM are able to not only generate better performance but also attract capital inflows.

The final additional measure of performance we examine is the value added measure from Berk and van Binsbergen, (2015). Theoretically, Berk and Green (2004) show that fund managers, even if they possess skill, do not outperform passive benchmarks due to competition among investors and decreasing returns to scale in active fund management. Similarly, Chen, Hong, Huang, and Kubik (2004) document that fund size erodes performance due to diseconomies of scale. In a recent study, Berk and van Binsbergen (2015) argue that alpha should be adjusted for the scale of a fund and propose an alternative performance measure based on the value that a fund extracts from capital markets. Following their study, we appraise skill using the value added measure, which is calculated as the product of assets under management at month t and the fund's four-factor alpha from month $t + 1$. As shown in Column (4), we find a significantly positive association between GPIM and the value extracted by a mutual fund from the stock market. This suggests that a manager who exploits the gross profitability anomaly also adds considerable dollar value to the fund. Altogether, the results presented in this section provide confirmatory evidence that fund managers who take advantage of the gross profitability exhibit investment skill.

V. Possible Explanations for GPIM-driven Fund Outperformance

Our findings suggest that fund managers who implement the gross profitability strategy are able to generate abnormal returns even after controlling for a fund's exposure to size, value, and momentum. In addition, we show that GPIM predicts fund performance along several dimensions, including characteristics selectivity, asset growth under management, fund flows, and the value added measure. In this section, we examine the characteristics of funds and managers that trade on the gross profitability anomaly. In addition, we extend our benchmark four-factor model to include the profitability factor (Fama and French, 2015) and examine the relation between the gross profitability investment strategy and fund performance. Our goal with this section is to shed further light on whether managers who exploit the gross profitability strategy have investment ability.

A. Univariate Analysis

Previous studies show that smaller funds are more likely to exploit profit opportunities due to decreasing returns to scale associated with the liquidity costs of trading (Berk and Green, 2004; Chen, Hong, Huang, and Kubik, 2004; Pastor, Stambaugh, and Taylor, 2017). Because of this, we expect high GPIM mutual funds will be smaller than low GPIM mutual funds. In addition, if trading on the gross profitability anomaly is related to investment skill, we expect managers of high GPIM funds to earn higher fees (Berk and Green, 2004). Table 7, Panel A reports descriptive statistics of various fund characteristics. Consistent with our expectations, Table 7 shows that, compared to funds in the bottom and middle GPIM quintiles, funds in the top quintile are smaller in size and belong to smaller fund families (see Panels B and C). In addition, funds in the top quintile have a higher expense ratio, further suggesting that managers of these funds have superior skill. We also find that the turnover is significantly higher for funds in the top GPIM quintile, which suggests active portfolio management and stock-picking skill (Pastor, Stambaugh, and Taylor, 2017).

Table 7 also reveals that funds in the top GPIM quintile have better past performance measured as raw returns and risk-adjusted alphas. This indicates that fund managers who exploit the gross profitability anomaly tend to persistently outperform those who do not. Specifically, as shown in Panel B, the difference in past performance between the two extreme GPIM portfolios is 1.21% per annum in raw return ($R_{t-1,t-12}$), and 0.12% per month in α^{4F} (1.44% per annum). The differences in past performance are also economically and statistically significant between the top and middle GPIM (middle and bottom GPIM) portfolios as shown in Panel C (Panel D). Overall, the superior past performance of high GPIM funds provides further evidence that managers' of high GPIM mutual funds have investment skill.

[Table 7 about here]

Furthermore, Table 7 shows that funds trading heavily on the gross profitability strategy exhibit greater fluctuations of both returns and investor flows. For example, Panel B shows that the difference in return (flow) volatility between the extreme GPIM quintiles is 0.86% with $t-$ statistic of 6.43 (0.44%; t = 2.95). Moreover, when we compare the top and middle GPIM portfolios in Panel C, the differences in return volatility and fund flow volatility remain significant, 0.59% (t = 8.27) and 0.61% (t = 5.37), respectively. As investors infer unobservable managerial ability from past fund performance, volatile fund returns provide a noisier signal of fund managers' investment skill, especially for short-term investors (Berk and Green, 2004; Huang, Wei, and Yan, 2007). In addition, higher flow volatility can impose a substantial indirect cost on fund investors due to liquidity related trades, and have a negative impact on future fund performance (Edelen, 1999; Rakowski, 2010). Taken together, these results may help explain why trading on the gross profitability anomaly might not be attractive to some mutual fund managers. Specifically, because portfolio holdings with a high exposure to gross profitability stocks exhibit more volatile returns and fund flow, some managers may have limited interest in aggressively exploiting the strategy, and thus the anomaly persists. In fact, it might be the case that only skilled managers are able to profit from this anomaly. Previous literature also documents that similar adverse consequences contribute to mutual funds' lack of interest in trading on the accruals or PEAD anomalies and could be responsible for the persistence of these anomalies (Ali, Chen, Yao, and Yu, 2008; 2012).

Table 7 also indicates that high gross profitability funds have greater past fund inflow. For instance, Panel B shows that relative to the bottom GPIM quintile, funds in the top quintile experience higher investor flow ($\mathrm{Flow}_{t-1,t-12}$) in the prior year. The difference in fund flow between the two quintiles is 1.75% with a $t-$ statistic of 3.01. This pattern raises the possibility that investor flow might partly explain the superior future performance of high GPIM funds. In particular, previous studies show that mutual funds tend to expand (liquidate) their existing holdings in response to investor inflows (outflows) (Edelen, 1999; Wermers, 2003; Coval and Stafford, 2007; Frazzini and Lamont, 2008; Khan, Kogan, and Serafeim, 2012; Lou, 2012). Thus, in our setting it is possible that some funds inadvertently have a high concentration of stocks with greater gross profitability and simply expand their existing holdings in response to large cash inflows, which could subsequently generate better returns. This passive reinvestment argument contradicts our skill based explanation for the positive relation between GPIM and future returns. Given this possibility, in the next section we use multivariate regressions to examine how past flows and other fund characteristics affect a fund's likelihood to exploit the gross profitability anomaly.

B. Investment Skill versus Passive Reinvestment

In this section, we use multivariate regressions to provide further evidence that fund managers who implement the gross profitability strategy appear to have substantial investment ability. If managerial skill is a valid explanation for why the gross profitability strategy generates abnormal returns we expect that funds in the top GPIM quintile are smaller (Log(TNA)), have higher fees (Expenses), and have higher past performance (α^{4F}_{t-1}). However, if fund managers simply expand their existing position due to flow-induced trading (the passive reinvestment explanation), we expect the past fund flow would be a leading explanatory variable for a fund's membership of the top GPIM portfolio. We directly test these conjectures using the following cross-sectional logit regression.

$$\begin{aligned}\text{Prob}\big[\text{High GPIM}_{i,t}\ (\text{Low GPIM}_{i,t}) = 1\big] &= \Lambda(\beta_1\alpha^{4F}_{t-1} + \beta_2\ \text{Past Flow}_{i.t-1}\\ &+\beta_3\log(\text{TNA})_{i,t-1} + \beta_4\text{Log(Age)}_{i,t-1} + \beta_5\log(\text{Fam. Size})_{i,t-1} + \beta_6\text{Expenses}_{i,t-1}\\ &+\beta_7\text{Turnover}_{i,t-1} + \beta_8\text{Ret. Vol.}_{i,t-1} + \beta_9\text{Flow Vol.}_{i,t-1} + \text{Intercept}_{i,t-1}),\end{aligned} \tag{5}$$

where $\text{High GPIM}_{i,t}$ ($\text{Low GPIM}_{i,t}$) is a dummy variable that equals 1 if fund *i* is in the top (bottom) GPIM portfolio and zero if the fund falls into other (i.e., 2nd to 4th) quintile portfolios. $\Lambda(.)$ denotes the logistic link function. We use a similar set of control variables included in Equation (4). Table 8 reports the results of the cross-sectional logit regressions conducted following the Fama-MacBeth (1973) procedure. We report the time-series averages of coefficient estimates obtained from monthly cross-sectional regressions. The t – statistics are computed from standard errors that are adjusted for heteroskedasticity and serial autocorrelations following Newey and West (1987).

[Table 8 about here]

Panel A examines the likelihood that a fund belongs to the top GPIM portfolio as opposed to the middle (i.e., 2nd to 4th GPIM quintiles). As reported in column (1), the coefficients of fund characteristics are broadly consistent with our univariate analysis presented in Table 7. Specifically, funds with higher expense ratios, return volatility, flow volatility, and greater turnover are more likely to employ the gross profitability strategy and fall into the top GPIM portfolio. More importantly, Column 2 shows that, consistent with the managerial skill based explanation, funds with higher risk-adjusted past performance (α_{t-1}^{4F}) are more likely to implement the gross profitability strategy. In contrast, we find no significant relation between the net fund flows ($\mathrm{Flow}_{t-1,t-12}$) and funds' membership of the top GPIM quintile, contradictory to the passive reinvestment explanation.

Panel B compares the likelihood that a fund belongs to the bottom GPIM portfolio as opposed to the middle portfolios. As presented in Columns (3) and (4), compared to funds in the middle portfolios, funds in the bottom GPIM portfolio tend to be younger, from larger fund families, have lower turnover and return volatility. The coefficient estimate on risk-adjusted past performance (α_{t-1}^{4F}) is significantly negative. This finding further supports the notion that trading on the gross profitability strategy is related to managerial skill, which contributes to both the past and future superior fund returns. We find no strong evidence that fund flows affect the likelihood of a mutual fund's membership in the bottom GPIM quintile. In sum, the results of the cross-sectional logistic regressions provide strong support that managerial skill helps to explain why some funds trade on the anomaly.

C. Investment Skill versus Profitability-Related Risk Premium

So far, we show that a subset of fund managers profit from the gross profitability anomaly and earn significant abnormal returns. A possible explanation for the positive relation between future stock returns and firm profitability is that mutual funds with high GPIM are earning a profitability-related risk premium. This would contradict our argument that mutual funds with high GPIM are run by managers with investing skill.

As argued by Fama and French (2015), the conventional factor models cannot capture the variation in average returns that is related to firm profitability. They thus develop an asset pricing model that explicitly includes a new factor to account for exposure to the profitability premium.[9] Their study implies that the superior performance of funds with high GPIM could be attributed to their high profitability risk-factor exposure. In this section we re-examine the relation between GPIM and future fund performance while controlling for the profitability factor. Specifically, we augment the four-factor model of Carhart (1997) by adding the profitability factor (RMW_t) in Eq. (3) to directly account for the role of firm profitability in determining fund performance.[10] Then, similar to our analysis in Section IV.A., in each quarter we sort our sample into GPIM-ranked quintiles and evaluate subsequent fund performance measured by the five-factor alpha (α^{5F}).

[Table 9 about here]

Table 9 reports the average value of α^{5F} of the GPIM quintile portfolios over the subsequent one, three, and twelve months. Similar to results presented in Table 4, Panel A of Table 9 shows that the five-factor alpha is monotonically increasing with the GPIM ranks among both equal- and TNA-weighted portfolios. Panel B reports the difference in α^{5F} between the top and bottom GPIM quintiles.

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9 There is a considerable debate over the source of the gross profitability anomaly (i.e., mispricing versus risk explanations). Specifically, recent studies document that the anomaly is related to market participants' under-reaction to news about firm profitability (Wang and Yu, 2013; Bouchaud, Krueger, Landier, and Thesmar, 2017). In addition, Stambaugh, Yu, and Yuan (2012) and Jacobs (2015) find that the gross profitability anomaly is stronger following periods of high investor sentiment, consistent with the explanation of information mispricing.

10 Fama and French (2015) measure profitability as revenues minus cost of goods sold, minus selling, general, and administrative expenses, minus interest expense and then divided by book equity.

As GPIM captures to what extent a fund's holdings are tilted toward high gross profitability stocks, it is not surprising to find that RMW explains a large portion of the performance difference among extreme GPIM portfolios. Nevertheless, the difference in α^{5F} between the top and bottom GPIM quintile portfolios remains statistically and economically significant. Specifically, for equal-weighted portfolios, the difference in α^{5F} is 0.16% with a t – statistic of 2.15 on a monthly basis, and 1.49% with a t – statistic of 2.37 per annum. A similar pattern is observed, albeit weaker, in the TNA-weighted portfolios that place a greater weight on larger funds.[11] Overall, these results suggest that managers of high GPIM mutual funds may possess investment skill and generate returns beyond what is attributable to their exposure to systematic profitability-related risk.

VI. Additional Robustness Checks

We perform a number of additional analyses to examine the robustness of our main findings. First, to ensure that we are not simply documenting stock-picking skill related to active trading by fund managers, we control for multiple proxies of active portfolio management. Second, we evaluate the robustness of our baseline result in the presence of other profitability-related trading strategies.

A. Controlling for Active Fund Management

An increasing body of literature demonstrates that active fund managers with portfolio holdings that differ from the benchmark index possess superior investment ability (Cremers and Petajisto, 2009; Petajisto, 2013; Amihud and Goyenko, 2013).[12] Accordingly, an explanation of our findings could be that active fund managers implement the gross profitability strategy, and thus GPIM only reflects managerial ability captured by active management. We therefore conduct additional tests to examine whether the relation between GPIM and subsequent fund performance remains significant after

[11] Our results remain robust after further controlling for the investment factor (a six-factor model) proposed by Fama and French (2015).
[12] Recent studies by Gupta-Mukherjee (2013) and Doshi, Elkamhi, and Simutin (2015) measure active fund management as the portfolio holdings of a fund that deviates from its peer group and the absolute difference between the value weights and the actual weights held by a fund and find evidence that active fund managers have better investment abilities.

controlling for active management proxies. We augment Eq. (4) to include the active share measure (AS) measure from Cremers and Petajisto (2009) and the TR^2 measure from Amihud and Goyenko (2013).[13] The former is measured as the share of portfolio holdings that differs from the benchmark index; and the latter (TR^2) is the logistic transformation of R^2 defined as the proportion of the fund return variance explained by the four-factor model of Carhart (1997).[14] A large (small) value of Active Share (TR^2) indicates a high level of active management.

Panel A of Table 10 presents the results obtained after controlling for active fund management. We find that both AS and TR^2 are strongly related to risk-adjusted fund performance ($\widehat{\alpha}^{4F}$). This is consistent with the findings of Cremers and Petajisto (2009) and Amihud and Goyenko (2013). Importantly, after controlling for these measures of active fund management, the predictability of GPIM remains significantly positive. For example, as shown in column (2) of Panel A, the positive relation between GPIM and $\widehat{\alpha}^{4F}$ is fully retained and the predictive power of GPIM is not subsumed by AS. Similar results are shown in column (4). These results suggest that GPIM reflects managerial skill beyond what is captured by leading active fund management proxies.

[Table 10 about here]

B. Other Profitability Related Anomalies

In addition to gross profitability, the role of other profitability measures in determining asset returns have gained growing attention recently. Akbas, Jiang, and Koch (2017) find that the trend of a firm's profits over the previous eight-quarters predicts cross sectional stock returns. Ball, Gerakos,

[13] Cremers and Petajisto (2009) and Petajisto (2013) show that active fund management, as measured by the share of portfolio holdings that differ from the benchmark index holdings, is positively related to future fund performance. We thank Antti Petajisto for the data on active share of mutual funds (http://www.petajisto.net/data.html). Similarly, Amihud and Goyenko (2013) document that a lower R^2, obtained from a regression of fund returns on a multifactor model, better predicts performance. They argue that this relation exists because a lower R^2 indicates mutual funds with greater stock selectivity.

[14] Amihud and Goyenko (2013) use the logistic transformation of R^2 because the distribution of R^2 is negatively skewed with its mass being in the high values that are close to its upper bound of 1. We follow their study and define $TR^2 = \log\left[(\sqrt{R^2})/(1-\sqrt{R^2})\right]$.

Linnainmaa, and Nikolaev (2015) show that operating profitability has similar return predictability as gross profitability. Arguably, the return predictability of GPIM could be partly driven by funds' exploitation of other profitability-based trading strategies.

To see whether our results are affected by other measures of profitability, we calculate firm-level measures of the trend in gross profitability and operating profitability. We then link these firm-level measures to fund holdings and create measures of the trend in profitability and operating profitability in a manner similar to the construction of GPIM (detailed in Section II. B). The fund-level weighted quintile rank of the two measures are denoted as Trend_GPIM and OPIM, respectively. Given OPIM and GPIM are highly correlated (correlation coefficient of 0.88) and to avoid a potential multicollinearity issue, we examine the potential incremental predictability of OPIM for subsequent fund performance. To do so, we regress OPIM on GPIM and obtain the residuals, denoted as $OPIM^{\perp}$. $OPIM^{\perp}$ is then included an additional control for funds' exposure to stocks with large operating profitability.

As reported in Panel B of Table 10, Columns (1) and (3) show that Trend_GPIM and OPIM are positively related to future fund performance (measured as α^{4F}). Columns 2 and 4 show that, after controlling for Trend_GPIM or $OPIM^{\perp}$, the coefficient of GPIM remains positive and statistically significant. Overall, we find that the strong predictive power of GPIM for mutual fund returns is not subsumed by the possibility that some funds may take advantage of other profitability related investment strategies.

VII. Conclusion

Previous studies find conflicting evidence about whether professional managers exploit market anomalies (e.g., Grinblatt, Titman, and Wermers, 1995; Ali, Chen, Yao, and Yu, 2008; 2012; Akbas, Armstrong, Sorescu, and Subrahmanyam, 2015; Edelen, Ince, and Kadlec, 2016). Motivated by anecdotal evidence and recent literature that shows a robust return predictability of the gross profitability anomaly, we investigate whether mutual fund managers exploit this anomaly. We find that a sizable subset of mutual funds appear to deliberately trade on the gross profitability anomaly. Our analysis shows that funds that have a larger concentration in high gross profitability stocks generate better future performance. Moreover, we show that these mutual funds create value by growing total assets under management and attracting capital inflows (Doshi, Elkamhi, and Simutin, 2015; Berk and van Binsbergen, 2015). Moreover, our finding remains robust when we gauge skill using the value extracted by a mutual fund from the stock market (Berk and van Binsbergen, 2015).

Further analysis provides strong evidence that managers who exploit the gross profitability strategy possess investment skill. We find that smaller funds are more likely to actively pursue a trading strategy tilted toward the anomaly. This is in line with the notion that their trading may cause less price impact than larger funds. In addition, funds that have a larger concentration in high gross profitability stocks exhibit higher portfolio turnover and have higher expense ratio, consistent with prior research that shows skilled fund managers trade more and charge higher fees (Berk and Green, 2004; Chen, Hong, Huang, and Kubik, 2004). Subsequent analysis corroborates that our finding is not likely to be a result of passive reinvestment due to fund flows. More importantly, we show that these funds' outperformance is not fully attributable to their exposure to the profitability factor (Fama and French, 2015) and other common risk factors (the Fama and French (1993) three factors and the Carhart (1997) momentum factor). These results suggest that fund managers who exploit the gross profitability anomaly have investment ability and earn additional returns even after accounting for their exposure to the profitability factor. Nevertheless, funds that concentrate on high gross profitability stocks have more volatile fund flow and fund return. These undesirable features help explain why trading on the gross profitability anomaly, despite being profitable, might not be attractive to all mutual fund managers.

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Table 1. Return and Stock Characteristics across Gross Profitability sorted Portfolios

Each month, we sort the stocks held by our sample of mutual funds into five quintiles based on their gross profitability in the most recent quarter. Panel A reports the mean values of returns and characteristics of stocks in each quintile. Cumulative return ($R_{t+1,t+12}$) is stock return from month $t+1$ to $t+12$. $\alpha^{4F}_{t+1}$is the Carhart (1997) four-factor alpha at month $t+1$. Return volatility (Ret. Vol.) is the standard deviation of monthly stock returns from month t - 12 to t - 1. Idiosyncratic return volatility (IVOL) is the standard deviation of estimated monthly stock residuals from the Carhart (1997) four-factor model from month t - 12 to t - 1. Size Rank (BM Rank and MOM Rank) is the equal-weighted average of market capitalization (book-to-market and prior 12-month return) quintile ranks of stocks. The middle portfolio is one equal-weighted portfolio created out of medium gross profitability portfolios 2 – 4. Panel B (Panel C, Panel D) reports the difference in returns and stock characteristics between stocks in the Top and Bottom (Top and Middle, Middle and Bottom) quintiles. Newey-West (1987) t– statistics are reported in parentheses. ***, **, * denote statistical significance at the 1%, 5%, or 10% level, respectively. The sample period is from 1984 to 2014.

	Panel A. Stock Characteristics							
	No of Stocks	$R_{t+1,t+12}$ (%)	α^{4F}_{t+1} (%)	Ret. Vol. (%)	IVOL (%)	Size Rank	BM Rank	MOM Rank
5 (Top)	585	18.34	0.49	13.20	9.06	2.47	2.85	3.32
4	705	14.96	0.24	12.44	8.42	2.52	3.06	3.12
3	655	12.73	0.01	12.23	8.28	2.65	3.03	2.97
2	518	11.67	-0.15	11.44	7.75	2.87	3.18	2.86
1 (Bottom)	308	8.08	-0.34	15.62	10.78	2.32	3.46	2.74
		Panel B. Difference: Top – Bottom						
		10.26***	0.83***	-2.42***	-1.72***	0.15***	-0.61***	0.57***
		(5.50)	(6.02)	(-3.63)	(-3.86)	(2.83)	(-9.50)	(14.77)
		Panel C. Difference: Top – Middle (2,3,4)						
		5.05***	0.44***	1.12***	0.87***	-0.20***	-0.23***	0.32***
		(4.87)	(7.42)	(5.69)	(7.38)	(-7.34)	(-3.37)	(12.14)
		Panel D. Difference: Middle (2,3,4) – Bottom						
		-2.60***	5.21***	-3.53***	-2.60***	0.35***	-0.37***	0.25***
		(-6.21)	(2.47)	(-6.06)	(-6.21)	(4.60)	(-16.17)	(7.41)

Table 2. Summary Statistics

This table reports the characteristics of mutual funds in our sample. Fund Size is the TNA at the beginning of the month, Fund Age is fund age since inception, Family Size is the fund family size at the beginning of the month; Expenses is the percentage of total investment that shareholders pay for fund's expenses; Turnover is defined as the minimum of aggregate purchases or sales of securities during the year, divided by the average TNA; Past Return is the cumulative fund return (net) over the past 12 months; Past Flow is prior twelve-month normalized net flow into a fund and defined as $\left(TNA_{i,t} - TNA_{i,t-12}(1 + R_{t-1,t-12})\right)/TNA_{i,t-12}$; Ret. Vol. (Flow Vol.) is measured as the standard deviation of monthly fund return (flow) over prior twelve-month; GPIM is the weighted average gross profit quintile ranks of stocks held by a fund. The sample period is from 1984 to 2014. The sample contains 2,794 funds and 293,287 observations.

	Mean	Median	Std. Dev.
Fund Size	1,054	291	2,315
Fund Age (in years)	18	13	14
Family Size	44,365	8,586	95,343
Expenses (%)	1.18	1.14	0.39
Turnover (%)	83.79	65.20	69.66
Past Return (12-month) (%)	11.71	11.15	8.24
Ret. Vol. (%)	4.73	4.47	1.27
Past Flow (12-month) (%)	8.08	-2.66	35.07
Flow Vol. (%)	4.97	3.22	6.56
GPIM	3.40	3.45	0.44

Table 3. Gross Profitability and Fund Style Characteristics

Panel A reports the average monthly style characteristics of portfolios of mutual funds sorted into quintiles according to the most recent quarter GPIM measures. SIZEIM (BMIM and MOMIM) is the weighted average market capitalization (book-to-market and prior 12-month return) quintile ranks of stocks held by a fund. Panel B reports the transition probabilities for one year for mutual funds sorted into quintiles according to the most recent quarter GPIM measures. All probabilities are expressed in %. Newey-West (1987) t-statistics are reported in parentheses. ***, **, * denote statistical significance at the 1%, 5%, or 10% level, respectively. The sample period is from 1984 to 2014.

Panel A: Style Characteristics

	GPIM	SIZEIM	BMIM	MOMIM
5 (Top)	3.94	3.78	2.81	3.14
4	3.64	3.78	2.75	3.03
3	3.43	3.85	2.70	2.91
2	3.21	3.91	2.67	2.80
1 (Bottom)	2.73	3.94	2.61	2.65
Difference: 5-1	1.21***	-0.16***	0.20**	0.49***
	(46.32)	(-4.38)	(2.17)	(10.62)

Panel B: Transition Matrix

	Year $t + 1$				
	5 (Top)	4	3	2	1 (Bottom)
5 (Top)	68.06	24.40	5.46	1.66	0.42
4	23.97	45.77	23.35	5.92	1.00
3	6.30	23.06	44.90	22.77	2.97
2	1.77	6.32	23.12	50.44	18.35
1 (Bottom)	0.45	1.11	3.26	18.70	76.48

Table 4. GPIM and Mutual Fund Performance: Portfolio Analysis

This table reports the equal- and TNA-weighted future returns of mutual funds sorted according to the most recent quarter GPIM in Panel A. R_{t+1} ($R_{t+1,t+3}$, $R_{t+1,t+12}$) is one-month (three- and twelve-month cumulative) net return of GPIM sorted portfolio. Funds ranked in the top (bottom) quintile of the *GPIM* portfolio are classified as High (Low) GPIM funds. The three-factor alpha (α^{3F}) is the intercept of three-factor model (Fama and French, 1993): $r_{p,t} = \alpha_p^{4F} + \beta_{1,p}MKTRF_t + \beta_{2,p}SMB_t + \beta_{3,p}HML_t + \varepsilon_{pt}$ (Fama and French, 1993). The four-factor alpha, α^{4F} is based on the three-factor model but also includes the momentum factor (Carhart, 1997). Panel B (Panel C, Panel D) reports difference in net return (α^{3F}, α^{4F}) between funds in the Top and Bottom quintiles. Newey-West (1987) *t*-statistics are reported in parentheses. All returns are expressed in %. ***, **, * denote statistical significance at the 1%, 5%, or 10% level, respectively. The sample period is from 1984 to 2014.

	Panel A. Gross Profit Investing Measure (GPIM)					
	Equal-Weighted			TNA-Weighted		
GPIM Ranks	R_{t+1}	$R_{t+1,t+3}$	$R_{t+1,t+12}$	R_{t+1}	$R_{t+1,t+3}$	$R_{t+1,t+12}$
5 (Top)	1.04	3.16	12.72	1.03	3.12	12.28
4	0.95	2.90	11.84	0.94	2.87	11.71
3	0.91	2.82	11.44	0.90	2.80	11.41
2	0.89	2.75	11.24	0.89	2.74	11.12
1 (Bottom)	0.81	2.53	10.59	0.83	2.59	10.76
	Panel B. Difference in Top – Bottom: Net Return (R)					
	0.22*	0.59**	1.68***	0.20*	0.53**	1.52***
	(1.80)	(2.56)	(3.98)	(1.71)	(2.47)	(3.07)
	Panel C. Difference in Top – Bottom: 3-Factor Alpha (α^{3F})					
	0.31***	0.90***	3.09***	0.27***	0.76***	2.97***
	(4.32)	(4.42)	(4.86)	(4.24)	(4.21)	(4.23)
	Panel D. Difference in Top – Bottom: 4-Factor Alpha (α^{4F})					
	0.20***	0.57***	1.59***	0.19***	0.50***	1.57***
	(3.16)	(3.11)	(3.22)	(2.98)	(2.84)	(3.18)

Table 5. GPIM and Mutual Fund Performance: Regression Analysis

Each month, we perform cross-sectional regressions of fund performance on the most recent quarter GPIM and other fund characteristics. GPIM is measured as the weighted average gross profit quintile ranks of stocks held by a fund. Other fund characteristics are defined in Table 2. R_{t+1} ($R_{t+1,t+3}$ and $R_{t+1,t+12}$) is fund return over the next one (three and twelve) month(s). $\widehat{\alpha}^{4F}$ is the four-factor alpha and is obtained from the fund excess return less the sum of the products of each of the four factor realizations; market, size, value, and momentum and corresponding estimates of factor loadings based on the preceding 36 monthly fund returns. $\text{Category Flow}_{t-1}$ represents the growth of the fund objective category at month *t* – 1. The table reports time-series averages of the coefficient estimates of the monthly cross-sectional regressions as well as their Newey-West (1987) *t*-statistics (in parentheses). ***, **, * denote statistical significance at the 1%, 5%, or 10% level, respectively. The sample period is from 1984 to 2014.

	R_{t+1} (1)	$R_{t+1,t+3}$ (2)	$R_{t+1,t+12}$ (3)	$\widehat{\alpha}^{4F}$ (4)
GPIM	0.001**	0.003**	0.012**	0.001**
	(2.53)	(2.20)	(2.14)	(2.52)
Log(TNA)	-0.001**	-0.001**	-0.006***	-0.001***
	(-2.28)	(-2.29)	(-2.73)	(-3.24)
Log(TNA)^2	0.000*	0.000	0.000*	0.000***
	(1.65)	(1.50)	(1.85)	(2.62)
Log(Age)	0.000*	0.000*	0.001	0.000
	(1.68)	(1.76)	(0.81)	(0.83)
Expenses	-0.065***	-0.208***	-0.846***	-0.045**
	(-3.00)	(-2.95)	(-2.97)	(-2.20)
Ret. Vol.	0.034	0.141*	0.466	-0.034*
	(1.20)	(1.71)	(1.45)	(-1.74)
Turnover	0.001***	0.002***	0.006***	0.000
	(3.32)	(3.01)	(2.83)	(0.47)
Log(Fam. Size)	0.000***	0.000***	0.002***	0.000***
	(2.69)	(3.27)	(4.97)	(2.80)
$R_{t-1,t-12}$	0.017***	0.042***	0.106***	
	(4.96)	(4.58)	(3.83)	
α^{4F}_{t-1}				0.199***
				(3.61)
$\text{Flow}_{t-1,t-12}$	-0.000	-0.001	-0.008**	-0.000
	(-1.33)	(-1.11)	(-2.48)	(-0.62)
$\text{Flow}^2_{t-1,t-12}$	-0.013	0.010	-0.045	0.008
	(-1.39)	(0.42)	(-0.56)	(0.53)
$\text{Category Flow}_{t-1}$	0.001	-0.000	-0.001	0.000
	(1.19)	(-0.43)	(-0.25)	(0.52)
Intercept	0.002	0.007	0.041	0.000
	(0.48)	(0.64)	(1.04)	(0.23)
Average N	777	777	777	777
Adjusted R^2	0.337	0.359	0.303	0.142

Table 6. GPIM and Alternative Measures of Fund Performance

Each month, we perform cross-sectional regressions of fund performance on GPIM and other fund characteristics. Fund performance is evaluated using 1) Characteristic Selectivity from Daniel, Grinblatt, Titman, and Wermers (1997), 2) Asset Growth measured as the growth in fund's total assets between two consecutive months, 3) Fund Flows in month $t + 1$, and 4) Value Added measured as the product of assets under management of month t and the fund's four-factor alpha (before cost) in month $t + 1$. GPIM is the weighted average gross profit quintile ranks of stocks held by a fund. Other fund characteristics are defined in Table 2. The table reports time-series averages of the coefficient estimates of the monthly cross-sectional regressions as well as their Newey-West (1987) t-statistics (in parentheses). ***, **, * denote statistical significance at the 1%, 5%, or 10% level, respectively. The sample period is from 1984 to 2014.

	Characteristic Selectivity	Asset Growth	Fund Flows	Value Added
	(1)	(2)	(3)	(4)
GPIM	0.003**	0.002**	0.014**	1.208***
	(2.16)	(2.09)	(2.39)	(2.90)
Log(TNA)	-0.001**	0.001	-0.006***	4.923
	(-2.21)	(0.84)	(-6.48)	(1.59)
Log(TNA)^2	0.000**	-0.000**	0.000***	-0.487*
	(2.17)	(-2.15)	(5.40)	(-1.70)
Log(Age)	0.001**	0.002***	0.001**	-0.054
	(2.27)	(4.06)	(2.48)	(-0.38)
Expenses	0.043	0.058	0.039	-0.67**
	(0.79)	(0.82)	(0.53)	(-2.00)
Ret. Vol.	-0.004	0.038	-0.073*	-25.281
	(-0.07)	(0.53)	(-1.78)	(-1.24)
Turnover	0.001**	0.000	0.001	-0.214
	(2.38)	(0.59)	(1.57)	(-1.08)
Log(Fam. Size)	0.000	0.000	0.001***	0.148***
	(0.59)	(1.45)	(5.59)	(3.23)
α^{4F}_{t-1}	0.164**	0.422***	0.926***	1.38*
	(2.23)	(3.67)	(5.61)	(1.89)
$\text{Flow}_{t-1,t-12}$	-0.002*	0.074***	0.045***	-0.155
	(-1.87)	(27.65)	-6.63	(-0.25)
$\text{Flow}^2_{t-1,t-12}$	0.004**	-0.021***	-0.007*	-0.345
	(2.18)	(-4.97)	(-1.68)	(-0.44)
$\text{Category Flow}_{t-1}$	0.005	-0.032	-0.012	-0.347
	(0.34)	(-1.39)	(-0.75)	(-0.02)
Intercept	-0.009	-0.014**	0.043***	-13.087
	(-1.07)	(-2.29)	(2.68)	(-1.62)
Average N	777	777	777	777
Adjusted R^2	0.203	0.263	0.188	0.101

Table 7. GPIM and Fund Characteristics

This table summarizes the average portfolio characteristics of mutual funds sorted according to the most recent GPIM (Panel A). GPIM is measured as the weighted average gross profit quintile ranks of stocks held by a fund. All other variables are defined in Table 2. Panel B (Panel C, Panel D) reports the differences in fund characteristics between Top and Bottom (Top and Middle, Middle and Bottom) quintiles. Newey-West (1987) $t-$ statistics are reported in parentheses. ***, **, * denote statistical significance at the 1%, 5%, or 10% level, respectively. The sample period is from 1984 to 2014.

Panel A. Fund Characteristics

GPIM Ranks	Log(TNA)	Log(Fund Age)	Log(Fam Size)	Expenses (%)	Turnover (%)	$R_{t-1,t-12}$ (%)	α^{4F}_{t-1} (%)	Ret. Vol. (%)	Flow Vol. (%)	$Flow_{t-1,t-12}$ (%)
5 (Top)	5.41	5.00	8.29	1.25	91.45	12.47	0.04	5.21	4.85	9.07
4	5.61	5.07	8.35	1.19	87.77	11.70	-0.03	4.88	4.32	7.50
3	5.72	5.08	8.39	1.16	84.15	11.56	-0.02	4.61	4.11	7.48
2	5.87	5.10	8.53	1.15	78.29	11.84	-0.02	4.47	4.02	7.76
1 (Bottom)	5.84	4.98	8.88	1.18	77.49	11.24	-0.07	4.35	4.41	7.31
Panel B. Difference: Top – Bottom										
	-0.43***	0.02	-0.59***	0.07***	13.96***	1.23***	0.12***	0.86***	0.44***	1.75***
	(-9.80)	(1.02)	(-13.57)	(7.87)	(4.02)	(3.18)	(4.16)	(6.43)	(2.95)	(3.01)
Panel C. Difference: Top – Middle (2,3,4)										
	-0.31***	-0.08***	-0.10*	0.08***	7.31***	0.89***	0.07***	0.59***	0.61***	0.38**
	(-8.29)	(-3.60)	(-1.89)	(12.17)	(3.70)	(2.60)	(4.08)	(8.27)	(5.37)	(2.39)
Panel D. Difference: Bottom – Middle (2,3,4)										
	0.12***	-0.10***	0.49***	0.02***	-6.65***	-0.32	-0.05***	-0.27***	0.17**	-0.02
	(5.49)	(-3.53)	(11.61)	(2.75)	(-2.62)	(-0.74)	(-2.95)	(-3.33)	(2.13)	(-0.17)

Table 8. Determinants of GPIM: Managerial Skill versus Passive Reinvestment

This table presents results from monthly cross-sectional logistic regressions which compare the characteristics of mutual funds in the top and bottom GPIM quintiles to mutual funds in the middle GPIM quintiles. The dependent variable is Top (Bottom), which is an indicator variable that equals 1, if fund *i* is in the top (bottom) GPIM quintile in month *t* and zero if fund *i* does not belong to either top or bottom GPIM quintile (middle). All other variables are defined in Table 2. The table reports time-series averages of the coefficient estimates of the monthly cross-sectional logistic regressions as well as their Newey-West (1987) $t-$statistics (in parentheses). ***, **, * denote statistical significance at the 1%, 5%, or 10% level, respectively. The sample period is from 1984 to 2014.

	Panel A. Top vs. Middle		Panel B. Bottom vs. Middle	
	(1)	(2)	(3)	(4)
α^{4F}_{t-1}		0.289***		-0.215***
		(4.75)		(-3.37)
$\mathrm{Flow}_{t-1,t-12}$		0.071		-0.008
		(1.04)		(-0.18)
Log(TNA)	-0.092***	-0.094***	0.008	0.018
	(-3.28)	(-3.32)	(0.29)	(0.58)
Log(Age)	-0.106**	-0.106**	-0.074	-0.082
	(-2.14)	(-2.08)	(-1.31)	(-1.44)
Log(Fam. Size)	-0.009	-0.009	0.087***	0.086***
	(-0.49)	(-0.53)	(4.15)	(4.11)
Expenses	0.268***	0.278***	0.173*	0.169*
	(3.01)	(3.14)	(1.69)	(1.65)
Turnover	0.001*	0.001**	-0.002***	-0.002***
	(1.72)	(2.03)	(-3.96)	(-4.08)
Ret. Vol.	0.140***	0.132***	-0.119***	-0.117***
	(8.49)	(8.00)	(-5.52)	(-5.32)
Flow Vol.	0.035***	0.041***	0.011*	0.016*
	(3.55)	(3.81)	(1.79)	(1.81)
Intercept	-2.348***	-2.352***	-1.423***	-1.444***
	(-5.97)	(-5.96)	(-3.40)	(-3.46)
Style FE	Y	Y	Y	Y
Avg. N	626	626	622	622
Avg. Pseudo-R^2	0.019	0.019	0.016	0.016

Table 9. Investment Skill versus Profitability-related Risk Premium

This table reports the equal- and TNA-weighted future abnormal returns of mutual funds sorted according to the most recent quarter GPIM (Panel A). Funds ranked in the top (bottom) quintile of the GPIM portfolio are classified as High (Low) GPIM funds. α^{5F}_{t+1} ($\alpha^{5F}_{t+1,t+3}$, $\alpha^{5F}_{t+1,t+12}$) is one-month (three- and twelve-month cumulative) five-factor alpha. The five-factor alpha (α^{5F}) is the intercept of the five-factor model: $r_{p,t} = \alpha^{5F}_p + \beta_{1,p}MKTRF_t + \beta_{2,p}SMB_t + \beta_{3,p}HML_t + \beta_{4,p}UMD_t + \beta_{5,p}RMW_t + \varepsilon_{pt}$, where RMW is the profitability factor proposed by Fama and French (2015) and the other variables are defined in Table 4. Newey-West (1987) *t*-statistics are reported in parentheses. Panel B reports the difference in α^{5F} between funds in the Top and Bottom GPIM quintiles. All returns are expressed in %. ***, **, * denote statistical significance at the 1%, 5%, or 10% level, respectively. The sample period is from 1984 to 2014.

Panel A. Gross Profit Investing Measure (GPIM)

	Equal-Weighted			TNA-Weighted		
GPIM Ranks	α^{5F}_{t+1}	$\alpha^{5F}_{t+1,t+3}$	$\alpha^{5F}_{t+1,t+12}$	α^{5F}_{t+1}	$\alpha^{5F}_{t+1,t+3}$	$\alpha^{5F}_{t+1,t+12}$
5 (Top)	0.03	0.13	0.79*	0.00	0.06	0.69*
4	-0.06	-0.10	-0.18	-0.07	-0.16	-0.48
3	-0.06	-0.04	-0.09	-0.06*	-0.08	-0.32
2	-0.07*	-0.13	-0.34	-0.08**	-0.16*	-0.48*
1 (Bottom)	-0.13**	-0.27*	-0.70**	-0.12**	-0.24	-0.67**

Panel B. Difference: Top – Bottom

	0.16**	0.40**	1.49*	0.12*	0.29*	1.36*
	(2.14)	(2.22)	(1.94)	(1.95)	(1.68)	(1.96)

Table 10. Robustness Checks: Active Management and Other Profitability-Related Investment Measures

Each month, we perform cross-sectional regressions of fund performance on the most recent quarter GPIM. GPIM is measured as the weighted average gross profit quintile ranks of stocks held by a fund. Panel A reports results when controlling for measures of active fund management. Panel B reports results when controlling for other profitability related anomalies. Active fund management measures include: Active share (AS) that represents the share of portfolio holdings that differ from the benchmark index at the month $t-1$ (Cremers and Petajisto, 2009); R^2 is the proportion of the fund return variance that is explained by the variation in four-factor model of Carhart (1997) over the previous 36 months (from month $t-1$ to $t-36$). TR^2 is measured as the logistic transformation of R^2 (Amihud and Goyenko, 2013). Other profitability related anomalies include: the trend in gross profitability (Akbas, Jiang, and Koch, 2017) and operating profitability (Ball, Gerakos, Linnainmaa, and Nikolaev, 2015). Trend_GPIM (OPIM) is measured as the weighted average Trend in Gross Profitability (Operating Profitability) quintile ranks of stocks held by a fund. All other control variables (not reported for brevity) are defined in Table 2. The table reports time-series averages of the coefficient estimates of the monthly cross-sectional regressions as well as their Newey-West (1987) $t-$ statistics (in parentheses). ***, **, * denote statistical significance at the 1%, 5%, or 10% level, respectively. Data for Active Share measure is obtained from Antti Petajisto and spans from 1984 to 2009. The sample period is from 1984 to 2014.

	$\widehat{\alpha}^{4F}$			
	(1)	(2)	(3)	(4)
Panel A. Active Fund Management				
GPIM		0.001**		0.001**
		(2.05)		(2.07)
AS	0.002**	0.002**		
	(2.02)	(1.99)		
TR^2			-0.001**	-0.001**
			(-1.99)	(-2.26)
Controls	Y	Y	Y	Y
Average N	420	420	777	777
Adjusted R^2	0.125	0.145	0.121	0.143
Panel B. Other Profitability Related Anomalies				
GPIM		0.001**		0.001***
		(2.42)		(2.62)
Trend_GPIM	0.000**	0.000		
	(1.98)	(1.41)		
OPIM			0.015**	
			(2.06)	
$OPIM^{\perp}$				0.000
				(0.22)
Controls	Y	Y	Y	Y
Average N	777	777	777	777
Adjusted R^2	0.132	0.156	0.189	0.161