Gross Profitability and Mutual Fund Performance☆

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Gross Profitability and Mutual Fund Performance

Abstract

We find that mutual funds holding a larger concentration of high gross profitability stocks generate better future performance. The outperformance of these funds is not driven by a profitability-related risk premium and is not a byproduct of fund managers' exploitation of other well-known investment strategies. We show that fund managers who trade on the gross profitability anomaly possess greater skill and create value by attracting future fund inflows and by growing fund assets under management. We contribute to both the mutual fund and market anomaly literatures by providing strong evidence that a sizable subset of mutual fund managers profit from an important market anomaly.

JEL Classification: G10, G11, G14, G23

Keywords: Gross profitability anomaly; mutual funds; active fund management

1. Introduction

Numerous financial products are designed to take advantage of market anomalies. However, a longstanding debate in the popular press and in academia concerns the extent to which professional managers are able to profit from these anomalies (Harvey and Liu, 2014; Coy, 2017).[1] We shed light on this debate 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 profit from 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). Thus, it is a practicable strategy even for investors facing 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 and robust return predictability, the gross profitability

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[1] Lewellen (2011) finds institutional investors have no significant exposure to well-known stock return anomalies. Recent studies (Edelen, Ince, and Kadlek, 2015; Akbas, Armstrong, Sorescu, and Subrahmanyam, 2015) find institutional investors and mutual funds do not exploit the predictability associated with market anomalies. Conversely, Ali, Chen, Yao, and Yu (2008) and Korajczyk and Sadka (2004) provide some evidence that mutual funds profit from anomalies. Further, although on average value stocks outperform growth stocks, after adjusting for style, Malkiel (1995) and Chan, Chen, and Lakonishok (2002) find growth-oriented funds outperform value-oriented funds.

[2] http://www.wsj.com/articles/SB10001424127887323293704578334491900368844. See also Forbes (2013) and the *CFA Institute Magazine* (2014).

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 (hereafter, we refer to this measure as GPIM) similar to the momentum investing measure of Grinblatt, Titman, and Wermers (1995). We find that on average mutual funds tilt their portfolios toward stocks with higher gross profitability. However, the degree to which the anomaly is exploited across mutual funds varies significantly. We also investigate the performance consequences of investing in the gross profitability anomaly. Using both portfolio analysis and cross-sectional regressions, we find that GPIM predicts future fund performance. Specifically, in our portfolio analysis we find that funds in the top GPIM quintile significantly outperform those in the bottom quintile by a gross monthly return of 0.22% and by a three-factor alpha of 0.28%. The difference in performance between the top and bottom GPIM quintiles also remains significant when calculating abnormal returns after including the Carhart (1997) momentum and the Pastor and Stambaugh (2003) liquidity factors. Moreover, using multivariate regressions, we document a positive relation between GPIM and future performance even after controlling for various fund characteristics and investment styles.

Having documented a positive relation between GPIM and future fund performance, we next examine potential explanations for this result. Specifically, we explore whether the positive relation is due to (1) a profitability-related risk premium, (2) an uncontrolled for correlation with investments in other well-known anomalies/strategies, or (3) managerial ability. Overall, our results support the notion that managers with superior investment ability successfully invest in the gross profitability anomaly.

First, we examine whether the outperformance of high GPIM funds can be explained by a profitability-related risk premium. Specifically, as argued by Fama and French (2015) and Hou, Xue, and Zhang (2015), conventional factor models do not capture the variation in average returns related to firm profitability. As a result, new asset pricing models have been developed to directly capture firm profitability, namely the Fama and French (2015) five-factor model, and the Hou, Xue, and Zhang (2015) q-factor model. To examine whether our finding is driven by a profitability-related risk premium, we re-estimate our results after incorporating these additional profitability factors. We continue to find that, compared with low GPIM mutual funds, high GPIM funds generate significantly higher abnormal returns. This result suggests the positive relation between GPIM and future fund performance eludes a simple explanation based on a profitability-related risk premium.

Another explanation for the positive relation between GPIM and future performance could be that GPIM captures profitable trading on other commonly used investment strategies (i.e., strategies based on size, value, and momentum). We find that funds with various investment styles (for example, Small-Cap, Core-, Growth- and Value-style funds) implement the gross profitability investment strategy. Moreover, we show that even after controlling for measures of size, book-to-market, and momentum investment strategies, the economic significance of the positive relation between GPIM and future fund performance is unchanged. This suggests our results are unlikely to be an unintentional byproduct of mutual fund managers investing in other well-known investment strategies.

Next, we examine whether our results are consistent with an investment skill-based explanation. To explore this possibility we investigate whether mutual funds with high GPIM display characteristics that are indicative of managerial skill. We find that smaller funds, funds with higher expenses, higher portfolio turnover, and superior past risk-adjusted performance are more likely to implement a gross profitability strategy. These findings suggest the exploitation of the gross profitability strategy could be a result of superior investment skill (Berk and Green, 2004; Chen, Hong, Huang, and Kubik, 2004; Pastor, Stambaugh, and Taylor, 2017). In addition, we examine the relation between GPIM and proxies of active portfolio management (i.e., Active Share measure of Cremers and Petajisto (2009) and R^2 of Amihud and Goyenko (2013)). Our results show that high GPIM funds have a significantly higher (lower) level of Active Share (R^2), which is consistent with these managers having greater ability.

Prior research argues managerial skill can also be measured using aspects of fund performance (Daniel, Grinblatt, Titman, and Wermers, 1997; Berk and van Binsbergen, 2015; Doshi, Elkamhi, and Simutin, 2015). We therefore examine whether mutual funds with high GPIM have the ability to select better-performing stocks as well as the ability to attract new capital/investors (i.e., fund flows). We find GPIM is positively associated with fund asset growth, future fund flow, and the value-added performance measure from Berk and van Binsbergen (2015). Collectively, our findings suggest that managers of mutual funds who exploit the gross profitability anomaly appear to have greater investment ability.

Given that calculating and sorting firms based on gross profitability is a trivial exercise, a natural question arising from our findings is: Why does it require skill to profit from the gross profitability anomaly? We rely on the limit-to-arbitrage literature to provide some insight into this important question. Researchers in this literature argue that arbitrage risk, proxied by idiosyncratic return volatility, presents the largest barrier to exploiting stock market anomalies (Pontiff, 1996; 2006; Shleifer and Vishny, 1997; Stambaugh, Yu, and Yuan, 2015). Consistent with the limit-to-arbitrage explanation, we find the gross profitability anomaly is concentrated in stocks with high idiosyncratic return volatility. This finding indicates that, when facing costly arbitrage, investment skill may be required to exploit this anomaly.[3]

Our findings are robust to three final considerations. First, the positive relation between GPIM and future fund performance is not due to fund managers passively expanding their existing fund positions in response to fund inflows. Second, the return predictability of the GPIM is not subsumed by alternative profitability measures (i.e., the trend in gross profitability from Akbas, Jiang, and Koch 2017 and operating profitability from Ball, Gerakos, Linnainmaa, and Nikolaev 2015). This suggests the predictive power of GPIM is not driven by mutual funds' exploitation of other profitability-related investment strategies. Third, although we previously documented that high GPIM funds tend to be actively managed (i.e., with higher "Active Share" and lower "R^2"), our findings are robust to controlling for these active management measures. This suggests GPIM is associated with investment skill that differs from the dimension captured by common active management proxies.

Our paper makes the following contributions. First, we provide strong evidence that a meaningful subset of mutual fund managers profit from an important market anomaly. Previous research finds limited evidence that mutual funds profit from market anomalies (Carhart, 1997; Korajczyk and Sadka, 2004; Ali, Chen, Yao, and Yu, 2008; 2012). We focus on the gross profitability anomaly as it provides a powerful setting to examine this issue because (1) mutual fund managers likely know of the anomaly and (2) it is practical for mutual funds to implement because it remains profitable in the presence of short-sale constraints. Second, our results suggest that fund managers' exploiting the gross profitability strategy have investment ability. Thus, our findings complement recent studies that show some fund managers possess investment ability

[3] Previous studies find that trading opportunities are more likely to arise in stocks with high arbitrage risks (Duan, Hu, and McLean, 2009; Puckett and Yan, 2011).

(Baker, Litov, Wachter, and Wurgler, 2010; Cai and Lau, 2015; Nallareddy and Ogneva, 2017; Jiang, Shen, Wermers, and Yao, 2018). Finally, a growing literature documents that profitability-related anomalies have significant predictive power for the cross section of stock returns (Novy-Marx, 2013; Ball, Gerakos, Linnainmaa, and Nikolaev, 2015; Akbas, Jiang, and Koch, 2017). Our research extends this literature and shows that trading strategies based on gross profitability also explain the cross section of mutual fund performance.

The rest of the paper is organized as follows. Section 2 describes the mutual fund data and the construction of the GPIM used in our analysis. Section 3 presents our main empirical results. Sections 4 and 5 examine alternative explanations for the relation between GPIM and future fund performance and report the results of several robustness tests. Section 6 contains our concluding remarks.

2. Sample Selection, Variable construction, and Summary Statistics

2.1. Mutual Fund Sample Selection

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

We manually match the funds in the two databases by name and ticker symbol. The matching procedure is similar to that in Wermers (2000). We focus on actively managed domestic

[4] 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. According to the *Investment Company Institute Fact Book* an estimated 92 million individual investors (44% of all U.S. households) owned mutual funds in 2014 and held 89% of total fund assets. The median amount invested in mutual funds was $100,000.

equity mutual funds for which the holdings data are most complete and reliable. Thus, we eliminate balanced, bond, money market, international, and index funds.[5] We also exclude funds managing less than $15 million in the previous month and funds in which the total market value of reported holdings are under 80% or over 120% of the total net assets. For funds with multiple share classes, we compute weighted fund-level variables using class-level total net assets as the weight. Our sample covers the period from 1984 to 2014.

2.2. Gross Profit Investing Measure (GPIM)

To quantify the degree to which funds tilt their holdings toward the gross profitability strategy, we compute the gross profitability investing measure (GPIM). GPIM is constructed using a mutual fund's holdings of common stocks traded on the NYSE, AMEX, or NASDAQ. Following Novy-Marx (2013) and Akbas, Jiang, and Koch (2017), we compute quarterly gross profitability as sales (SALEQ) minus the cost of goods sold (COGSQ) scaled by assets (ATQ). At the end of each quarter $t - 1$, we sort all stocks in the entire CRSP/Compustat universe 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 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,

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

[5] We follow the same procedure as Huang, Sialm, and Zhang (2011) when selecting active mutual funds.

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 GPIM is in line with that of the momentum investing measure (Grinblatt, Titman, and Wermers, 1995).[6] A high (low) value of GPIM indicates that a fund primarily holds high (low) gross profitability stocks.

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

We begin our empirical analysis by examining whether mutual funds trade on the gross profitability anomaly. Table 1 reports that the mean and median of GPIM are 3.39 and 3.43, respectively. This suggests that the portfolio holdings of mutual funds are on average tilted toward stocks with higher gross profitability. Also, we find substantial variation in the extent to which mutual funds use the gross profitability strategy because the standard deviation of GPIM is 0.45. Table 1 also reports summary statistics for other characteristics of the mutual funds in our sample. These 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 (Turnover); past returns cumulated over the previous year ($R_{t-12,t-1}$); past twelve-month fund flow – measured as $\left(TNA_{i,t} - TNA_{i,t-12}(1 + R_{t-12,t-1})\right)/TNA_{i,t-12}$; and fund return (flow) volatility – computed as the standard deviation of monthly fund return (flow) over the prior twelve months. In addition, we construct style measures, based on key investment styles – namely size, book-to-market, and momentum. For example, similar to the methodology described in Section 2.2., SIZEIM is the weighted average market capitalization quintile ranks of stocks held by a fund,

[6] Ali, Chen, Yao, and Yu (2008) and Jiang, Shen, Wermers, and Yao (2018), respectively, use a similar methodology to identify the extent to which mutual funds trade on accruals and information sensitive stocks.

and BMIM (MOMIM) is the weighted average book-to-market (prior twelve-month return) quintile ranks of stocks held by a fund.

[Table 1 about here]

For each variable, we report the time series average of the cross-sectional minimum, 5th percentile, mean, median, 95th percentile, maximum, and standard deviation. Our sample includes 2,889 distinct funds and 310,992 fund-month observations. The mean size and age of funds is $1,054 million and 18 years, respectively. The average family size is $42,159 million, and the average expense ratio is 1.18%. Table 1 also shows that the average turnover of mutual funds is about 81%, implying that the average holding period of a stock is 1.25 years. Past fund return (flow), on average, is 11.75% (8.09%). In addition, mutual funds, on average, tend to hold stocks with higher market capitalization (SIZEIM=3.85), lower book-to-market ratio (BMIM=2.71), and higher momentum stocks (MOMIM=3.14). The preference for mutual funds to hold large stocks, growth stocks, and stocks with higher past returns is consistent with findings in prior research (Grinblatt, Titman, and Wermers, 1995; Ali, Chen, Yao, and Yu, 2008; Kacperczyk, Sialm, and Zheng, 2008).

3. Gross Profitability Investment Strategy and Mutual Fund Performance

Our results, so far, indicate that on average mutual funds tilt their holdings toward higher gross profitability stocks. In this section we investigate the association between future fund performance and exposure to the gross profitability anomaly using portfolio and regression approaches.

3.1. Portfolio Analysis

To gauge the relation between gross profitability and future fund performance, in each quarter we sort our sample into GPIM quintiles and evaluate fund performance over subsequent periods. We use 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-FF}) and Carhart (1997) four-factor model (α^{4F-FFC}). For example, the four-factor model extends the Fama and French (1993) three-factor model by including the momentum factor and is specified as follows:

$$r_{p,t} = \alpha_p^{4F-FFC} + \beta_{1,p}MKT_t + \beta_{2,p}SMB_t + \beta_{3,p}HML_t + \beta_{4,p}UMD_t + \varepsilon_p, \quad (3)$$

where $r_{p,t}$ is the monthly portfolio return in excess of the one-month T-bill rate; MKT is the excess return on a value-weighted market portfolio; and 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 (return or risk-adjusted performance), we calculate equal-weighted monthly returns before (i.e., gross return) and after subtracting expenses (i.e., net return) within each GPIM quintile portfolio.[7] Gross returns are created by adding back 1/12 of the annual expense ratio to each monthly return.

Table 2 reports the future performance of the GPIM quintile portfolios. For both gross and net fund returns, Panel A shows that subsequent one, three, and twelve-month returns are monotonically increasing with GPIM rank. Moreover, as shown in Panel B, the difference between the top and bottom GPIM quintiles is significant for each of these return windows. For example, the difference in gross returns between funds in the two extreme GPIM quintiles (i.e., top and bottom) is 0.21% per month and 2.03% per annum (*t* – statistics of 1.78 and 1.74, respectively). Panels C

[7] Examining gross returns (the returns before expenses) enables us to better evaluate the investment ability of mutual fund managers because managers with better skills may charge higher expenses to extract rents (Berk and Green, 2004).

and D report the difference between the top and bottom quintiles when measuring performance based on the Fama and French (1993) three-factor model (α^{3F-FF}) and the Carhart (1997) four-factor model (α^{4F-FFC}). As reported in Panel C, the difference in α^{3F-FF} between funds in the top and bottom GPIM quintiles is a gross return of 0.28% per month and 3.24% per annum (t – statistics of 4.19 and 3.48, respectively). Panel D shows that momentum does not entirely subsume the predictive power of GPIM for future fund performance. For example, the difference in α^{4F-FFC} between funds in the top and bottom GPIM quintiles is a gross return of 0.20% per month and 1.73% per annum (t – statistics of 2.98 and 2.59, respectively). Using net returns yields similar results.

In Panel E of Table 2 we extend the Carhart (1997) model in Equation (3) to introduce the Pastor and Stambaugh (2003) liquidity factor. We find that the difference in performance between funds in the top and bottom GPIM quintiles remains economically and statistically significant after including this additional liquidity factor ($\alpha^{5F-FFCPS}$). This finding suggests that exposure to illiquid stocks is not the sole driver of the superior performance of funds in the top GPIM quintile.

[Table 2 about here]

In Table 2 we also report the performance differences between the extreme portfolios and the middle portfolio, where the middle portfolio is created out of GPIM quintiles 2-4. This analysis helps us identify whether the performance difference is driven by funds in the top or bottom GPIM quintiles. Since mutual funds do not short sell, we expect the cross-sectional differences between the top and bottom GPIM to be driven by funds with higher exposure to the gross profitability anomaly. Consistent with this prediction, we find the difference in performance between funds in the top and bottom GPIM quintiles is driven primarily by the superior performance of funds in the top GPIM quintile. For example, for portfolios based on gross return, the difference in α^{4F-FFC} between funds in the top and middle GPIM is 0.13% per month (t – statistics = 3.08), which is nearly twice the magnitude of the difference between funds in the bottom and middle GPIM, -0.07% per month (t – statistics = -1.80). A similar pattern is observed for α^{3F-FF} and $\alpha^{5F-FFCPS}$.

Finally, we extend our analysis and replicate Table 2 using TNA-weighted portfolios. This additional analysis documents the association between future performance and GPIM for larger funds. Appendix Table A.1 reports these results. The performance difference between funds in the top and bottom GPIM quintiles remains significant, suggesting our results are not entirely driven by the small funds in our sample. Collectively the results from the equal- and TNA-weighted portfolios suggest that funds with concentrated holdings of high gross profitability stocks have better future performance.[8]

3.2. Regression analysis

In this section, we examine the performance of the gross profitability strategy using a multivariate regression framework, which allows us to control for various fund characteristics that predict future fund performance and may be correlated with GPIM. Specifically, we estimate the following regression model:

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

where i is the fund subscript and the dependent variable is $\alpha^{4F-FFC}_{t+1,t+p}$ to capture risk-adjusted fund performance. Specifically, for each fund i in month t, we obtain the loadings by running the Carhart (1997) four-factor model using fund monthly returns from the previous 36 months (we require a minimum of 30 monthly returns). Then we calculate the four-factor adjusted return (α^{4F-FFC}_{t+1}) for fund i in month $t+1$ by subtracting the sum of the products of the four-factor realizations and

[8] In an additional analysis we sort our sample into abnormal GPIM quintiles where abnormal GPIM is measured each quarter as the difference between a fund's GPIM and TNA-weighted benchmark GPIM. Consistent with our main results, we find a positive and significant relation between abnormal GPIM and future fund performance. We thank an anonymous referee for suggesting this additional analysis.

corresponding loadings. $\alpha^{4F-FFC}_{t+1,t+3}$ ($\alpha^{4F-FFC}_{t+1,t+12}$) is the cumulative four-factor adjusted returns over the following three (twelve) months.

The explanatory variable of interest in Equation (4) is 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; Pollet and Wilson, 2008; Jordan and Riley, 2015; Cici, Dahm, and Kempf, 2018), we control for a comprehensive set of fund performance determinants: the logarithm of fund TNA (Log(TNA)), the logarithm of one plus fund age (Log(Age)), the fund expense ratio (Expenses), the portfolio turnover ratio (Turnover), the logarithm of fund family size (Log(Fam. Size)), past fund return ($R_{t-1,t-12}$), the fund return volatility (Ret. Vol.), past fund flow ($Flow_{t-1,t-12}$), and the fund flow volatility (Flow. Vol.). All variables are defined in Section 2.3. To control for style fixed effects, we group funds into Small- versus Large-Cap and Value- versus Growth-style categories based on their past loadings obtained from the four-factor model (Nanda, Wang, and Zheng 2004).[9] In Table 3 the regression specified in Equation (4) is estimated following the Fama-MacBeth (1973) procedure in Panel A and multivariate panel regressions in Panels B and C. Panel A reports the time-series averages of the coefficient estimates obtained from monthly cross-sectional regressions, and the *t* – statistics (in parentheses) are computed using standard errors that are adjusted for heteroskedasticity and serial autocorrelations (Newey and West, 1987). Style fixed effects are included in Panel A. Panels B and C report the *t* – statistics (in parentheses) derived from clustered standard errors by time (month) and fund. Time and Style fixed effects are included in Panel B.[10] In Panel C, we also include fund fixed effects.

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[9] Specifically, we run the Carhart (1997) four-factor model using fund monthly returns from the previous 36 months and obtain the loadings for the four factors. Each month, we assign all funds into three groups based on the 25th and the 75th percentile of the SMB and HML loadings. Mutual funds ranked in the top 25th percentile of SMB (HML) loading are labeled as Small-Cap (Value-style) and those ranked in the bottom 25th percentile (or 75th percentile) are labeled as Large-Cap (Growth-style). Funds ranked between the 25th and 75th percentile of SMB (HML) loadings are labeled as Mid-Cap (Core-style). Similar to the Morningstar style-box categorizations, we then place funds into 3 x 3 Size/Value categories.

[10] In the remainder of the paper we present results estimated using panel regressions. However, our results are unchanged if we use Fama-MacBeth regressions. Our results are also unchanged if we use net returns rather than risk adjusted returns. These results are available upon request.

[Table 3 about here]

The results reported in Table 3 show a positive and statistically significant relation between GPIM and future fund performance for all return windows (one-, three-, and twelve-month ahead risk-adjusted performance). This finding is consistent regardless of whether we use the Fama-MacBeth (1973) procedure or multivariate panel regressions. For example, in Panel A, Column 1 (where the dependent variable is α_{t+1}^{4F-FFC}), the coefficient on GPIM is 0.001, and the *t* – statistic is 2.65. This coefficient suggests that a one standard deviation increase in GPIM leads to an additional excess return of 52.8 basis points a year. To put this 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. We find similar results in Panels B and C.

Table 3 also shows that our control variables have the expected sign. For example, smaller funds, funds with higher turnover, and those that belong to larger fund families tend to perform better. Also, the relation between fund expenses and subsequent fund performance is significantly negative. Similar to Jordan and Riley (2015), we find a negative relation between fund return volatility and future fund performance. 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.

4. Potential Explanations for the Relation between GPIM and Future Fund Performance

Overall, both the portfolio tests and multivariate regression analyses provide strong evidence that GPIM has significant predictive power for future mutual fund performance. In this section we examine explanations for the relation between GPIM and future fund performance. Specifically, we explore whether the relation is due to (1) a profitability-related risk premium, (2) an uncontrolled for correlation with investments in other well-known strategies, and/or (3) managerial ability.

4.1. Profitability-Related Risk Premium

Our first explanation for the positive relation between GPIM and future fund performance is that mutual funds with high GPIM are earning a profitability-related risk premium. As argued by Fama and French (2015), conventional factor models cannot capture the variation in average returns that is related to firm profitability. They develop an asset pricing model that explicitly includes a new factor to account for exposure to the profitability premium.[11] Their study implies that the superior performance of funds with high GPIM could be attributed to exposure to the profitability risk-factor. Similarly, Hou, Xue, and Zhang (2015) build a q-factor model that includes market, size, investment, and profitability factors. In this section we re-examine the relation between GPIM and future fund performance while controlling for the profitability and investment factors proposed by Fama and French (2015) and Hou, Xue, and Zhang (2015). Specifically, the Fama and French (2015) five-factor alpha (α^{5F-FF}) and the Hou, Xue, and Zhang (2015) q-factor alpha (α^{qF-HXZ}) models are specified as follows:

$$r_{p,t} = \alpha_p^{5F-FF} + \beta_{1,p}MKT_t + \beta_{2,p}SMB_t + \beta_{3,p}HML_t + \beta_{4,p}RMW_t + \beta_{4,p}CMA_t + \varepsilon_p, \tag{5}$$

and,

$$r_{p,t} = \alpha_p^{qF-HXZ} + \beta_{1,p}MKT_t + \beta_{2,p}SMB_t + \beta_{3,p}ROE_t^F + \beta_{4,p}I/A_t^F + \varepsilon_p, \tag{6}$$

where $r_{p,t}$ is the monthly portfolio return in excess of the 1-month T-bill rate; MKT is the excess return on a value-weighted market portfolio. SMB, HML, RMW, and CMA are the returns on the zero-investment factor mimicking portfolios for size, book-to-market, profitability, and investment, respectively, as described in Fama and French (2015).[12] ROE^F and I/A^F are the returns on the zero-investment factor mimicking portfolios for profitability and investment, respectively, as described in Hou, Xue, and Zhang (2015).

[11] There is considerable debate over the source of the gross profitability anomaly (i.e., mispricing versus risk explanations). Please see, Fama and French (2015), Wang and Yu (2013) Bouchaud, Krueger, Landier, and Thesmar (2018), Stambaugh, Yu, and Yuan (2012) and Jacobs (2015).
[12] The market, size, book-to-market, profitability, and investment factors are obtained from Ken French's website.

[Table 4 about here]

Panel A of Table 4 reports the average α^{5F-FF} for the GPIM quintile portfolios over the subsequent one, three, and twelve months. Similar to results presented in Table 2, Panel A of Table 4 shows that the five-factor alpha is monotonically increasing in GPIM rank. Because the GPIM captures the extent to which a fund's holdings are tilted toward high gross profitability stocks, it is unsurprising to find that RMW explains a large portion of the performance difference among the extreme GPIM portfolios. Nevertheless, the difference in α^{5F-FF} between the top and bottom GPIM quintile portfolios remains statistically and economically significant. Specifically, for the results based on gross fund return, the difference in α^{5F-FF} is 0.21% with a *t* – statistic of 2.90 on a monthly basis, and 2.74% with a *t* – statistic of 2.26 per annum. A similar pattern is observed in the results based on the Hou, Xue, and Zhang (2015) q-factor alpha (Table 4, Panel B). Overall, these results suggest that managers of high GPIM mutual funds generate abnormal returns beyond what is attributable to measures of systematic profitability-related risk.[13]

4.2. Correlation with Other Fund Investment Styles

We next investigate whether our results could be an unintended byproduct of mutual fund manager's investing in other anomalies. We focus our investigation on the size/value anomalies because many mutual funds are set up to exploit them. Additionally, fund rating companies, such as Morningstar, consider these anomalies important enough that they categorize mutual funds based on these dimensions. To test whether our findings are related to these anomalies, we group funds into nine style boxes based on size and value/growth dimensions as described in Section 3.2. In addition to size and value styles, previous research finds that momentum strategies are widespread among fund managers (Grinblatt and Titman, 1989, 1993; Grinblatt, Titman, and Wermers, 1995; Barroso and Santa-Clara, 2015). Thus, we further group funds into high and low momentum

[13] We also perform panel regression analysis where the risk-adjusted fund performance is estimated using the Fama and French (2015) five-factor and the Hou, Xue, and Zhang (2015) q-factor models and confirms our results are robust. These results are not reported for brevity.

subsamples based on the median level of UMD loading. We examine whether GPIM varies systematically based on these categorizations. Panel A of Table 5 reports the time series averages of the cross-sectional mean of GPIM for each style box.[14] If the gross profitability investment strategy is driven by fund managers' attempting to exploit these other anomalies, we would expect a significant difference in GPIM for funds at the extremes of these style dimensions (i.e., size, value, or momentum).

[Table 5 about here]

As shown in Panel A, we find some evidence that the gross profitability investment strategy is related to other well-known anomalies. For example, the difference in GPIM between growth- and value-style funds is significant among large-cap funds. Similarly, managers' choice of investing in small- versus large-cap firms explains the difference in GPIM among value-oriented funds. We also find that compared to low momentum funds, high momentum funds have relatively higher GPIM. However, the difference in preferences of fund managers for value versus growth firms does not account for the differences in GPIM among funds investing in small- and mid-cap firms.

Because the results in Table 5, Panel A, suggest a possible relation between the gross profitability strategy and the size and value/growth strategies, we augment Equation (4) to include controls for size (SIZEIM), value (BMIM), and momentum (MOMIM). The construction of these variables is described in Section 2.3. The results of this test are reported in Panel B of Table 5. For specifications (1) thorough (6) we include time fixed effects. For specifications (7) thorough (9), we include time and style fixed effects. As shown in Columns (1), (2), and (3), the coefficients of SIZEIM, BMIM, and MOMIM are consistent with prior studies (i.e., Carhart 1997; Kacperczyk, Sialm, and Zheng, 2008; Jiang, Shen, Wermers, and Yao, 2018). More important for our analysis,

[14] Prior research shows a fund's self-reported investment style does not necessarily correlate with its actual style as measured using the fund's actual portfolio holdings (Brown and Goetzmann, 1997; Cooper, Gulen, and Rau, 2005; Sensoy, 2009). We provide an overview in Appendix Table A.2 of the top and bottom 10 funds based on GPIM quintile rankings.

in Columns (4) to (9) the positive and significant relation between GPIM and future fund performance is unaffected by the inclusion of SIZEIM, BMIM, and MOMIM. This suggests our results are unlikely to be an unintentional byproduct of mutual fund managers investing in other well-known strategies.

To better understand the relation between the gross profitability investment strategy and mutual fund styles, we further examine the fund-level persistence of GPIM over time. To the extent a specific investment style drives the gross profitability investment strategy, we would expect GPIM to remain persistently high only in funds with this style. For example, if high GPIM is driven by size (growth), the investment strategy should be primarily implemented by small-cap (growth) funds but not large-cap (value) funds. Figure 1 depicts the transition probabilities for funds in the top and bottom GPIM ranks from year t to year $t + 1$. As shown in Panel A1 (B1) of Figure 1, funds in the top (bottom) GPIM quintile are more likely to stay in that quintile rather than move to the middle or bottom (top) quintiles. Similar patterns emerge across different style categorizations based on the size/value dimensions, suggesting fund managers with different investment styles consistently implement the gross profitability investment strategy.

[Figure 1 about here]

4.3. Investment Skill

So far, our analyses show (i) the outperformance (underperformance) of funds with high (low) past GPIM is not attributable to the risk premium associated with firm profitability, and (ii) fund managers who implement the gross profitability strategy are able to generate superior abnormal returns even after controlling for a fund's exposure to the size, value, and momentum strategies. In this section, we investigate whether successfully implementing the gross profitability strategy is related to managerial skill.

Previous studies show that smaller funds are more likely to exploit profit opportunities because of 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 in 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 6, Panel A, reports descriptive statistics for the various fund characteristics described in Section 3.2. Consistent with our expectations, Table 6 shows that, compared with funds in the bottom and middle GPIM quintiles, funds in the top quintile are younger, smaller in size, and have a higher expense ratio, suggesting managers of these funds could have investment skill (see Panels B and C). We also find that funds in the top GPIM quintile exhibit significantly higher portfolio turnover. These characteristics fit the profile of more active funds (Pastor, Stambaugh, and Taylor, 2017).[15]

[Table 6 about here]

Table 6 also reveals that funds in the top GPIM quintile have better past performance. Specifically, as shown in Panel B, the difference in past performance between the two extreme GPIM portfolios is 1.21% per annum based on raw returns ($R_{t-1,t-12}$), and 0.12% per month in α_{t-1}^{4F-FFC} (or 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). This indicates that fund managers who exploit the gross profitability anomaly tend to consistently outperform those who do not. In addition, Table 6 also shows that high

[15] Another interesting result, revealed in Table 6, is that relative to funds in the middle GPIM quintiles, funds in the bottom quintile have a higher average expense ratio. Given the finding that funds in the bottom GPIM quintile significantly underperform, one possible explanation is that these funds could be targeting naïve investors who are not responsive to expenses (Gil-Bazo and Ruiz-Verdo, 2009).

gross profitability funds have greater past fund inflow. Finally, funds in the top GPIM quintile exhibit greater fluctuations of both returns ($Ret.Vol.$) and investor flows ($Flow\ Vol.$).

We also examine the association between GPIM and two recently developed measures of mutual fund manager ability. These measures, Active Share (Cremers and Petajisto, 2009; Petajisto, 2013) and R^2 (Amihud and Goyenko, 2013), capture how the holdings of active fund managers differ from a benchmark index.[16] As reported in Panel B and Panel C of Table 6, relative to funds in the bottom and middle GPIM quintiles, funds in the top quintile deviate significantly from common benchmarks. For example, when we compare the top and middle GPIM portfolios in Panel C, the difference in Active (R^2) is significantly positive (negative), 0.04 with a *t* – statistic of 5.00 (-0.07 with a *t* – statistic of -9.28). These results further support the notion that fund managers implementing the gross profitability investment strategy appear to have ability.

We next examine how GPIM is related to fund characteristics using the following multivariate logit regression:

$$\begin{aligned}
&\mathrm{Prob}\big[\mathrm{High\ GPIM}_{i,t}\ \big(\mathrm{Low\ GPIM}_{i,t}\big) = 1\big] = \Lambda(\beta_1 \log(\mathrm{TNA})_{i,t-1} + \beta_2 \mathrm{Log(Age)}_{i,t-1} \\
&\quad +\beta_3 \mathrm{Expenses}_{i,t-1} + \beta_4 \mathrm{Turnover}_{i,t-1} + \beta_5 \log(\mathrm{Fam.\,Size})_{i,t-1} \\
&\quad +\beta_6 \mathrm{Ret.\,Vol.}_{i,t-1} + \beta_7 \mathrm{Flow\ Vol.}_{i,t-1} + \beta_8 \alpha^{4F}_{t-1} + \beta_9\ \mathrm{Flow}_{i.t-1:t-12} \\
&\quad +\beta_{10} \mathrm{Active\ Share}_{t-1} + \beta_{11} R^2_{t-1} + \beta_1 \mathrm{GPIM}_{t-1} + \mathrm{Intercept}_{i,t-1}),
\end{aligned} \tag{7}$$

where $\mathrm{High\ GPIM}_{i,t}$ ($\mathrm{Low\ GPIM}_{i,t}$) 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 quintile portfolios (i.e., 2nd to 4th). $\Lambda(.)$ denotes

[16] Active Share is measured as the share of portfolio holdings that differ from the fund's benchmark index; and R^2 is defined as the proportion of the variance of the fund return explained by the Carhart (1997) four-factor model. We thank Antti Petajisto for the data on active fund management (http://www.petajisto.net/data.html) that covers the years 1984 to 2009.

the logistic link function. We use a similar set of control variables to those included in Equation (4). All fund characteristics are lagged one month except for Active Share, which is lagged one quarter.

[Table 7 about here]

Table 7, Panel A, reports which characteristics explain the likelihood that a fund belongs to the top GPIM portfolio as opposed to the bottom. Panel B (Panel C) reports which characteristics explain the likelihood that a fund belongs to the top (bottom) GPIM portfolio as opposed to the middle. If managerial skill explains why a subset of fund managers exploit the gross profitability anomaly, we expect high GPIM funds will be smaller (Log(TNA)), have higher fees (Expenses), higher portfolio turnover, higher past performance (α_{t-1}^{4F-FFC}), and greater managerial skill as proxied by the Active Share measure of Cremers and Petajisto (2009) and the R^2 measure of Amihud and Goyenko (2013).

The results reported in Table 7 are consistent with these expectations. Specifically, relative to funds in the bottom and the middle GPIM quintiles, funds in the top GPIM quintile are more likely to have higher expense ratios and higher turnover. Further, funds with higher risk-adjusted past performance (α_{t-1}^{4F}), higher Active Share, and lower R^2 are more likely to implement a gross profitability strategy. These findings support the notion that skilled managers are more likely to implement the gross profitability investment strategy. Finally, the coefficients of Return Volatility and Fund Flow Volatility are consistent with our univariate analysis presented in Table 6. That is, relative to funds in the middle GPIM quintile portfolios, those in the top GPIM quintile are more likely to have higher return volatility and flow volatility.

4.4. Investment Skill: Further Evidence Based on Alternative Performance Measures

Prior research argues that managerial skill can also be measured by examining whether managers are able to select better-performing stocks and attract new capital/investors (i.e., flows).

If implementing the gross profitability strategy is related to managerial skill, as the evidence in the last section seems to suggest, then we would expect a positive relation between GPIM and alternative fund performance measures. In this section, we consider several additional measures including (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).

We first examine whether mutual fund managers investing in the gross profitability strategy select stocks that outperform a portfolio of stocks with similar characteristics. To measure this we use the *Characteristic Selectivity* measure 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 twelve-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, cumulated over the subsequent three months. As shown in Column (1) of Table 8, GPIM is positively related to Characteristic Selectivity ($\mathrm{CS}_{t+1,t+3}$), indicating that funds with high GPIM have superior stock-picking ability.

[Table 8 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 skilled managers are more likely to generate better performance and attract higher money inflows than unskilled managers. Columns (2) and (3) of Table 8 show that GPIM is positively related to asset growth ($\mathrm{AG}_{t+1,t+3}$) and future fund flows

($Flow_{t+1,t+3}$) over the subsequent quarter. These results suggest that funds with higher GPIM are able not only to generate better performance but also to 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 those who are skillful, do not outperform passive benchmarks because of the competition among investors and the decreasing returns to scale in active fund management. Similarly, Chen, Hong, Huang, and Kubik (2004) and Pollet and Wilson (2008) 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 ($VA_{t+1,t+3}$) measure, which is calculated as the product of assets under management at month t and the fund's four-factor alpha (based on gross return) from month $t + 1$ to $t + 3$. As shown in Column (4) of Table 8, we find a significantly positive association between GPIM and the value a mutual fund extracts 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 strengthen the evidence that fund managers who take advantage of the gross profitability anomaly exhibit investment skill.

4.5. Further Analysis: Why Does It Require Skill to Exploit the Gross Profitability Anomaly?

Our results suggest that a subset of skilled fund managers profitably trade on the gross profitability anomaly. This raises a natural question: Why are high gross profitability stocks hard to exploit? We argue that limits to engaging in arbitrage may provide an answer. The limit-to-arbitrage literature contends that, because risk-averse traders avoid or are otherwise impeded from trading on stocks with high limits to arbitrage, mispricing opportunities are often not fully exploited (Pontiff, 1996, 2006; Shleifer and Vishny, 1997). The risk that accompanies arbitraging stocks is especially acute for fund managers because mutual funds are exposed to withdrawal risk that is greatly intensified by poor performance in the short run (Stein, 2005).[17] As a result, it is possible that only managers with considerable investment ability are able to invest in the gross profitability strategy. Consistent with this possibility, previous studies show that the investment ability of fund managers is more evident in stocks with high idiosyncratic volatility (or arbitrage risk) (Duan, Hu, and McLean, 2009; Puckett and Yan, 2011; Jiang and Verardo, 2018).

To provide insight into this issue, at the end of each quarter we sort all stocks in the CRSP/Compustat universe into five portfolios based on their most recent gross profitability (similar to the procedure in Section 2.2). Using quintile rankings based on the entire CRSP/Compustat universe, we provide descriptive statistics for the stocks that are actually held by mutual funds in Table 9. Because mutual funds do not hold all stocks in the CRSP/Compustat universe, the number of stocks in each quintile portfolio differs. Although Table 9 reports information about various stock characteristics, the most relevant characteristics for this analysis are two proxies for arbitrage risk: stock return volatility and idiosyncratic return volatility. Following prior studies (Ali, Hwang, and Trombley, 2003; Mashruwala, Rajgopal, and Shevlin, 2006), we measure stock return volatility (SRetVol) as the standard deviation of monthly stock returns from months $t + 1$ to $t + 12$, and idiosyncratic volatility (SIVOL) as the standard deviation of estimated monthly stock residuals from the Carhart (1997) four-factor model from months $t + 1$ to $t + 12$.

As reported in Panels C and D, among stocks held by mutual funds, SRetVol and SIVOL are higher for stocks in the top and bottom gross profitability quintiles when compared with stocks in the middle quintiles. Because mutual fund managers cannot engage in short selling, we focus

[17] Previous studies show that arbitrage risk, proxied by idiosyncratic return volatility, is the largest barrier arbitrageurs' face when trying to fully exploit stock market anomalies (Pontiff, 1996, 2006; Shleifer and Vishny, 1997; Ali, Hwang, and Trombley, 2003; Mendenhall, 2004; Mashruwala, Rajgopal, and Shevlin, 2006; Arena, Haggard, and Yan, 2008; Wang and Yu, 2013; Stambaugh, Yu, and Yuan, 2015; DeLisle, Yuksel, and Zaynutdinova, 2019).

our discussion on the differences between stocks in the top and middle quintiles. Specifically, Panel C shows that, relative to stocks in the middle quintiles, stocks with the highest gross profitability tend to have higher arbitrage risks. The difference in SIVOL (SRetVol) between stocks in the top and middle quintiles is 0.84% with a t – statistic of 8.05 (1.06% with a t – statistic of 6.18). These higher arbitrage risks could create a barrier for unskilled managers and limit their ability to take advantage of the gross profitability anomaly.

[Table 9 about here]

Table 9 also shows that stocks in the top gross profitability portfolio, relative to stocks in the middle portfolios, likely have larger information asymmetry, which may allow skilled managers to profitably use their privately generated information (Wermers, 1999; Sias, 2004). Specifically, as reported in Panel C, high gross profitability stocks have less analyst coverage (#Analysts) and lower market capitalization (SizeRank).[18] Further, prior research argues that if fund managers have superior investment skill, their abilities should be more apparent for firms with more growth opportunities because these firms face more uncertainty and their value is difficult to assess (Yan and Zhang, 2009). Consistent with these arguments, in Table 9 we find that, relative to stocks in the middle quintiles, those in the top gross profitability quintile have a lower book-to-market score (BM Score) and a lower earnings-to-price ratio (E/P). Collectively, these results support the notion that fund managers investing in high gross profitability stocks possess better investment abilities. Table 9 also shows that the dividend yield (DY) of high gross profitability stocks is lower than that for stocks in the middle quintiles. This is unsurprising

[18] Prior research shows that analyst coverage is related to stock visibility and information asymmetry (Hong, Lim, and Stein, 2000; Pomorski, 2009; Hameed, Morck, Shen, and Yeung, 2015).

because high gross profitability stocks tend to be smaller, growth firms. Finally, Panel C shows no significant difference in price between stocks in the top and middle portfolios.[19]

5. Robustness Checks

In this section we perform additional analyses to ensure the robustness of our main findings. First, we examine whether past fund flows drive the positive relation between GPIM and fund performance. Second, we control for alternative measures of firm profitability (i.e., trend in GPIM and operating profitability). Third, we control for active portfolio management measures.

In Table 6 we reported that relative to funds in the middle and bottom GPIM quintiles, those in the top GPIM quintile experience higher past investor flows. 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 hold a large number of high gross profitability stocks 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. Therefore, we reexamine our portfolio results conditioned on past fund flow. Specifically, similar to our analysis in Section 2.2., each quarter, we sort our sample into five quintiles based on GPIM. Within each GPIM quintile, we then divide funds into a high and low-flow sample based on the median of the previous three-month flow and evaluate fund performance over the subsequent three-month horizon.

[Table 10 about here]

[19] Although not reported for brevity, we compare the characteristics of stocks in the entire CRSP/Compustat universe to those held by mutual funds. The results of this analysis shows that SIVOL (#Analysts) of stocks held by mutual funds is smaller (larger) than those in the entire CRSP/Compustat universe. Moreover, stocks held by mutual funds have larger market capitalization, have higher E/P, dividend yield (DY), and stock prices than those in the entire CRSP/Compustat universe. Although not the focus of our paper, the limited interest of fund managers in high gross profitability stocks with these characteristics might provide one explanation for why the gross profitability anomaly persists.

Table 10 documents the results of this analysis. As reported in Panel A, for both gross and net returns, and each GPIM-quintile, we find no significant difference in return between the high- and low-flow subsamples. In addition, as shown in Panels B and C, the difference between the top and bottom GPIM quintiles is significant for both high- and low-flow subsamples regardless of whether performance is measured using net fund return or the four-factor alpha. More importantly, inconsistent with flow-induced trading explanation, Panels B and C show no significant difference in return spread between funds in the top and bottom GPIM quintiles across high- and low-flow subsamples of funds.

Second, 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, Linnainmaa, and Nikolaev (2015) show that operating profitability has a similar return predictability to gross profitability. To see whether our results are robust to the use of other measures of profitability, we calculate stock-level measures of the trend in gross profitability and operating profitability. We then create measures of the trend in profitability and operating profitability in a manner similar to the construction of GPIM (detailed in Section 2.2). The fund-level weighted quintile rank of the two measures are denoted as Trend_GPIM and OPIM, respectively.

[Table 11 about here]

As reported in Table 11, Trend_GPIM and OPIM are positively related to future fund performance, measured as α^{4F-FFC} (See Columns (1), (3), (5), (7), (9) and (11)). Moreover, after controlling for Trend_GPIM or OPIM, the coefficient of GPIM remains positive and statistically significant (See Columns (2), (4), (6), (8), (10) and (12)). This result indicates 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.

Finally, as documented in Section 4.3., we find that active fund managers who deviate from benchmark indexes are more likely to implement the gross profitability strategy. Accordingly, GPIM may only reflect managerial ability captured by active management. Therefore, we conduct additional tests to examine whether the relation between GPIM and subsequent fund performance remains significant after controlling for active management proxies. We augment Equation (4) to include the active share measure (R^2) measure from Cremers and Petajisto (2009) (Amihud and Goyenko (2013)).

[Table 12 about here]

Table 12 presents the results obtained after controlling for active fund management. We find that both Active Share and R^2 are strongly related to risk-adjusted fund performance (α^{4F-FFC}). Consistent with the findings of Cremers and Petajisto (2009) and Amihud and Goyenko (2013), we find a significantly positive (negative) relation between Active Share (R^2) and future fund performance over one-, three-, and twelve-month horizons. Importantly, after controlling for these measures of active fund management, the predictability of GPIM remains significantly positive. These results suggest that GPIM reflects managerial skill beyond what is captured by leading active fund management proxies.

6. Conclusion

Despite the popularity of financial products designed to exploit market anomalies, there is little empirical evidence supporting the profitability of these products. In this paper, we examine whether mutual fund managers trade on and profit from the gross profitability anomaly. We focus on this anomaly because anecdotal evidence suggests mutual fund managers are aware of it and because recent research shows it has robust return predictability at the stock level. Using both portfolio and multivariate regression analyses, we find that mutual funds with substantial investments in high gross profitability stocks (high GPIM) significantly outperform other mutual funds.

We explore potential explanations for the positive relation between GPIM and mutual fund performance and fail to find evidence that it is driven by a profitability-related risk premium or that it is a byproduct of fund managers following a particular investment style or investing in other well-known investment strategies. Instead, we show skilled fund managers are more likely to trade profitably on the gross profitability anomaly. Moreover, relative to low-GPIM funds, managers of high-GPIM funds exhibit better stock-picking ability and create value by attracting future fund inflows and growing fund assets under management. Finally, we show that the gross profitability anomaly is concentrated in stocks with high arbitrage risk and lower analyst coverage, suggesting it may require skill to take advantage of this anomaly.

Appendix

Table A.1. GPIM and Mutual Fund Performance: Portfolio Analysis (TNA-weighted)

This table reports the TNA-weighted future returns of mutual funds sorted according to the most recent quarter's GPIM. R_{t+1} ($R_{t+1,t+3}$, $R_{t+1,t+12}$) is the one-month (three- and twelve-month cumulative) return. GPIM is measured as the portfolio weighted average gross profit quintile rank of stocks held by a fund as described in Section 2.2. Funds ranked in the top (bottom) quintile of the GPIM portfolio are classified as High (Low) GPIM funds. Gross returns are created by adding back 1/12 of the annual expense ratio to each monthly net return. The methodology for calculating alphas is the same as described in Table 3. 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. Future Returns of Mutual Funds Sorted on GPIM					
	Gross Returns			Net Returns		
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)	1.12	3.40	13.50	1.02	3.12	12.28
4	1.02	3.13	12.85	0.94	2.87	11.71
3	0.98	3.07	12.54	0.90	2.80	11.41
2	0.97	3.00	12.23	0.89	2.74	11.12
1 (Bottom)	0.89	2.80	11.73	0.80	2.53	10.59
	Panel B. Difference in Return					
Top-Bottom	0.23*	0.61*	1.77**	0.22*	0.59*	1.68**
	(1.71)	(1.81)	(2.13)	(1.69)	(1.75)	(2.05)
Top-Middle (2,3,4)	0.11	0.29	0.72	0.11	0.30	0.76
	(1.56)	(1.41)	(0.93)	(1.62)	(1.47)	(0.99)
Bottom-Middle (2,3,4)	-0.12*	-0.32*	-1.05*	-0.11	-0.29	-0.92
	(-1.68)	(-1.69)	(-1.78)	(-1.55)	(-1.54)	(-1.58)
	Panel C. Difference in α^{3F-FF}					
Top-Bottom	0.32***	0.93***	3.36***	0.31***	0.91***	3.27***
	(4.29)	(4.50)	(3.30)	(4.23)	(4.43)	(3.26)
Top-Middle (2,3,4)	0.18***	0.52***	1.78***	0.18***	0.53***	1.82***
	(3.60)	(4.19)	(2.66)	(3.69)	(4.30)	(2.77)
Bottom-Middle (2,3,4)	-0.14***	-0.41***	-1.58***	-0.13***	-0.38***	-1.45***
	(-3.47)	(-3.45)	(-3.80)	(-3.23)	(-3.22)	(-3.55)
	Panel D. Difference in α^{4F-FFC}					
Top-Bottom	0.23***	0.60***	1.72**	0.22***	0.58***	1.66**
	(3.11)	(3.21)	(2.36)	(3.04)	(3.13)	(2.31)
Top-Middle (2,3,4)	0.13**	0.34***	0.88*	0.13***	0.35***	0.93*
	(2.56)	(2.96)	(1.79)	(2.64)	(3.08)	(1.92)
Bottom-Middle (2,3,4)	-0.10**	-0.26**	-0.85***	-0.09**	-0.23**	-0.73**
	(-2.45)	(-2.34)	(-2.70)	(-2.22)	(-2.09)	(-2.35)
	Panel E. Difference in $\alpha^{5F-FFCPS}$					
Top-Bottom	0.26***	0.68***	1.74***	0.25***	0.67***	1.68**
	(3.56)	(3.54)	(2.64)	(3.49)	(3.47)	(2.57)
Top-Middle (2,3,4)	0.14***	0.38***	0.91**	0.14***	0.39***	0.96**
	(2.81)	(3.21)	(2.07)	(2.90)	(3.33)	(2.20)
Bottom-Middle (2,3,4)	-0.12***	-0.31***	-0.84***	-0.11***	-0.28**	-0.72**
	(-3.02)	(-2.76)	(-2.81)	(-2.79)	(-2.51)	(-2.44)

Table A.2. The Funds in Top and Bottom GPIM Quintiles in 2014

At the end of 2014, we sort mutual funds into five quintiles according to the most recent quarter GPIM. This table provides an overview of the top (bottom) 10 funds that engage most (least) in the gross profitability investment strategy.

Panel A. Funds in the Top GPIM Quintile in 2014	Panel B. Funds in the Bottom GPIM Quintile in 2014
MORGAN STANLEY MULTI CAP FUND	ARTISAN MID CAP VALUE FUND
BIONDO GROWTH FUND	RIDGEWORTH MID CAP VALUE FUND
BAIRD MID CAP FUND	COMMERCE VALUE FUND
BROWN CAPITAL MGMT SMALL CAP FUND	SUNAMERICA FOCUSED VALUE FUND
CONESTOGA SMALL CAP FUND	RYDEX SGI MID CAP VALUE FUND
DREYFUS THE BOSTON SMALL CAP FUND	RIDGEWORTH LARGE CAP VALUE FUND
STEPHENS MID CAP GROWTH FUND	DODGE & COX STOCK FUND
PRINCIPAL MID CAP GROWTH FUND	PENN SERIES LARGE CORE VALUE FUND
FEDERATED MDT SMALL CAP GROWTH FUND	ASTON/M.D. ENHANCED EQUITY FUND
YACKTMAN FOCUSED FUND	JOHN HANCOCK MID CAP VALUE FUND

References

Akbas, F., Jiang, C., Koch, P.D., 2017. The trend in firm profitability and cross section of stock returns. The Accounting Review 92, 1-32.

Akbas, F., Armstrong W.J., Sorescu, S., Subrahmanyam, A., 2015. Smart money, dumb money, and capital market anomalies. Journal of Financial Economics 118, 355-382.

Ali, A., Chen, X., Yao, T., Yu, T., 2008. Do mutual funds profit from the accrual anomaly? Journal of Accounting Research 46, 1-26.

Ali, A., Chen, X., Yao, T., Yu, T., 2012. Mutual fund competition and profiting from the post earnings announcement drift. Working Paper.

Ali, A., Hwang, L., Trombley, M.A., 2003. Arbitrage risk and the book-to-market anomaly. Journal of Financial Economics 69, 355-373.

Amihud, Y., Goyenko, R., 2013. Mutual Fund's R^2 as predictor of performance. Review of Financial Studies 26, 667-694.

Arena, M.P., Haggard, K.S., Yan, X., 2008. Price momentum and idiosyncratic volatility. Financial Review 43, 159-190.

Ball, R., Gerakos, J., Linnainmaa, J.T., Nikolaev, V.V., 2015. Deflating profitability. Journal of Financial Economics 117, 225-248.

Baker, M., Litov, L., Wachter, J.A., Wurgler, J., 2010. Can mutual fund managers pick stocks? Evidence from their trades prior to earnings announcements. Journal of Financial and Quantitative Analysis 45, 1111-1131.

Barroso, P., Santa-Clara P., 2015. Momentum has its moments. Journal of Financial Economics 116, 111-120.

Berk, J.B., Green, R.C., 2004. Mutual fund flows and performance in rational markets. Journal of Political Economy 112, 1269-1295.

Berk, J.B., van Binsbergen J.H., 2016. Assessing asset pricing models using revealed preference. Journal of Financial Economics 119, 1-23.

Bouchaud, J., Krueger, P., Landier, A., Thesmar, D., 2018. Sticky Expectations and the Profitability Anomaly. Journal of Finance, forthcoming.

Brown, S.J., Goetzmann, W.N., 1997. Mutual fund styles. Journal of Financial Economics 43, 373-399.

Cai, Y., Lau, S.T., 2015. Informed trading around earnings and mutual fund alphas. Journal of Banking & Finance 60, 168-180.

Cao, J., Han B., Wang, Q., 2017. Institutional investment constraints and stock prices. Journal of Financial and Quantitative Analysis 52, 465-489.

Carhart, M., 1997. On the persistence in mutual fund performance. Journal of Finance 52, 57-82.

CFA Institute Magazine, 2014. Quality control: Can new research help investors define a "quality" stock? S. Trammel, March/April, pp. 29–33.

Chan, L.K.C., Chen, H., Lakonishok, J., 2002. On mutual fund investment styles. Review of Financial Studies 15, 1407-1437.

Chen, J., Hong H.G., Huang M., Kubik, J., 2004. Does fund size erode performance? Liquidity, organizational diseconomies, and active money management. American Economic Review 94, 1276-1302.

Chevalier, J., Ellison, G., 1997. Risk taking by mutual funds as a response to incentives. Journal of Political Economy 6, 1167-1200.

Cici, G., Dahm, L.K., Kempf, A., 2018. Trading efficiency of fund families: Impact on fund performance and investment behavior. Journal of Banking and Finance 88, 1-14.

Cooper, M.J., Gulen, H., Rau, P.R., 2005. Changing names with style: Mutual fund name changes and their effects on fund flows. Journal of Finance 60, 2825-2858.

Coval, J., Stafford, E., 2007. Asset fire sales (and purchases) in equity markets. Journal of Financial Economics 86, 479-512.

Coy, P., 2017. Investors Always Think They're Getting Ripped Off. Here's Why They're Right, Bloomberg Businessweek April 6 https://www.bloomberg.com/news/articles/2017-04-06/lies-damn-lies-and-financial-statistics.

Cremers K.J.M., Petajisto A., 2009. How active is your fund manager? A new measure that predicts performance. Review of Financial Studies 22, 3329-3365.

Daniel, K., Grinblatt, M., Titman, S., Wermers, R., 1997. Measuring mutual fund performance with characteristic-based benchmarks. Journal of Finance 52, 1035-1058.

DeLisle, R.J., Yuksel, H.Z., Zaynutdinova, G., 2019. What's in a name? A cautionary tale of profitability anomalies. Working Paper.

Doshi, H., Elkamhi, R., Simutin, M., 2015. Managerial activeness and mutual fund performance. Review of Asset Pricing Studies 5, 156-184.

Duan, Y., Hu, G., McLean, R.D., 2009. When is stock picking likely to be successful? Evidence from mutual funds. Financial Analysts Journal 65, 55-66.

Edelen, R., 1999. Investor flows and the assessed performance of open-end mutual funds. Journal of Financial Economics 53, 439–466.

Edelen R., Ince, O.S., Kadlec, G.B., 2016. Institutional investors and stock return anomalies. Journal of Financial Economics 119, 472–488.

Elton, E.J., Gruber, M.J., Blake, C.R., 1996. Survivorship bias and mutual fund performance. Journal of Business 9, 1097-1120.

Fama, E.F., French, K., 1993. Common risk factors in the return on stocks and bonds. Journal of Financial Economics 33, 3-53.

Fama, E.F., French, K., 2015. A five-factor asset pricing model. Journal of Financial Economics 116, 1–22.

Fama, E.F., MacBeth, J.D., 1973. Risk, return, and equilibrium: Empirical tests. Journal of Political Economy 81, 607–636.

Forbes, 2013. The mysterious factor 'P': Charlie Munger, Robert Novy-Marx and the profitability factor. P. DeMuth, June.

Frazzini, A., Lamont, O.A., 2008. Dumb money: Mutual fund flows and the cross-section of stock returns. Journal of Financial Economics 88, 299-322.

Gil-Bazo, J., Ruiz-Verdu, P., 2009. The relation between price and performance in the mutual fund industry. Journal of Finance 64, 2153-2183.

Grinblatt, M., Titman, S., 1989. Mutual fund Performance: An analysis of quarterly portfolio holdings. Journal of Business 62, 393-416.

Grinblatt, M., Titman, S., 1993. Performance measure without benchmarks: An examination of mutual fund returns. Journal of Business 66, 47-68.

Grinblatt, M., Titman, S., Wermers, R., 1995. Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior. American Economic Review 85, 1088-1105.

Gruber, M.J., 1996. Another puzzle: The growth in actively managed mutual funds. Journal of Finance 51, 783-810.

Hameed, A., Morck, R., Shen, J., Yeung, B., 2015. Information, analysts, and stock return comovement. Review of Financial Studies 28, 3153-3187.

Harvey, C.R., Liu, Y., 2014. Evaluating trading strategies. Journal of Portfolio Management 40, 108-118.

Hong, H., Lim, T., Stein, J.C., 2000. Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies. Journal of Finance 55, 265-295.

Hou, K., Xue, C., Zhang, L., 2015. Digesting anomalies: An investment approach. Review of Financial Studies 28, 650-675.

Huang, J., Sialm, C., Zhang, H., 2011. Risk shifting and mutual fund performance. Review of Financial Studies 24, 2575-2616.

Jacobs, H., 2015. What explains the dynamics of 100 anomalies? Journal of Banking and Finance 57, 65-85.

Jiang, G.J., Shen, K., Wermers, R., Yao, T., 2018. Costly information production, information intensity, and mutual fund performance. Working Paper.

Jiang, H., Verardo, M., 2018. Does herding behavior reveal skill? An analysis of mutual fund performance. Journal of Finance 73, 2229-2269.

Jordan, B.D., Riley, T.B., 2015. Volatility and mutual fund manager skill. Journal of Financial Economics 118, 289-298.

Kacperczyk, M., Sialm, C., Zheng, L., 2008. Unobserved actions of mutual funds. Review of Financial Studies 21, 2379-2416.

Khan, M., Kogan, L., Serafeim, G., 2012. Mutual fund trading pressure: Firm-level stock price impact and timing of SEOs. Journal of Finance 67, 1371-1395.

Korajczyk, R.A., Sadka, R., 2005. Are momentum profits robust to trading costs? Journal of Finance 59, 1039-1082.

Lewellen, J., 2010. Accounting anomalies and fundamental analysis: An alternative view. Journal of Accounting and Economics 50, 455-466.

Lou, D., 2012. A flow-based explanation for return predictability. Review of Financial Studies 25, 3457-3489.

Nallareddy, S., Ogneva, M., 2017. Accrual quality, skill, and the cross-section of mutual fund returns. Review of Accounting Studies 22, 503-542.

Nanda, V., Wang, Z.J., Zheng, L., 2004. Family values and the star phenomenon: Strategies of mutual fund families. Review of Financial Studies 17, 667-698.

Newey, W.K., West, K.D., 1987. A simple, positive semi-definite, heteroscedasticity and autocorrelation consistent covariance matrix. Econometrica 55, 703-708.

Novy-Marx, R., 2013. The other side of value: The gross profitability premium. Journal of Financial Economics 108, 1-28.

Malkiel, B.G., 1995. Returns from investing in equity mutual funds 1971 to 1991. Journal of Finance 50, 549-572.

Mashruwala, C., Rajgopal, S., Shevlin, T., 2006. Why is the accruals anomaly not arbitraged away? The role of idiosyncratic risk and transactions costs. Journal of Accounting 42, 3-33.

Mendenhall, R.R., 2004. Arbitrage risk and post-earnings-announcement drift. Journal of Business 77, 875-894.

Pastor, L., Stambaugh, R.F., 2003. Liquidity risk and expected stock returns. Journal of Political Economy 111, 642-685.

Pastor, L., Stambaugh, R.F., Taylor, L.A., 2017. Do funds make more when they trade more? Journal of Finance 72, 1483-1528.

Petajisto, A., 2013. Active share and mutual fund performance. Financial Analysts Journal 60, 73-93.

Pollet, J.M., Wilson, M., 2008. How does size affect mutual fund behavior? Journal of Finance 63, 2941-2969.

Pomorski, L., 2009. Follow the leader: Peer effects in mutual fund portfolio decisions. Working Paper.

Pontiff, J., 1996. Costly arbitrage: Evidence from closed-end funds. Quarterly Journal of Economics 111, 1135-11152.

Pontiff, J., 2006. Costly arbitrage and the myth of idiosyncratic risk. Journal of Accounting & Economics 42, 35-52.

Puckett, A., Yan, X., 2011. The interim trading skills of institutional investors. Journal of Finance 56, 601-633.

Sapp, T., Tiwari, A., 2004. Does stock market momentum explain the ‘smart money’ effect? Journal of Finance 59, 2605-2622.

Sensoy, B.A., 2009. Performance evaluation and self-designated benchmark indexes in the mutual fund industry. Journal of Financial Economics 92, 25-39.

Shleifer, A., Vishny, R.W., 1997. The limits of arbitrage. Journal of Finance 52, 35-55.

Sias, R., 2004. Institutional Herding. Review of Financial Studies 17, 165-206.

Sirri, E.R., Tufano, P., 1998. Costly search and mutual fund flows. Journal of Finance 53, 1589-1622.

Stambaugh, R.F., Yu, J., Yuan, Y., 2012. The short of it: Investor sentiment and anomalies. Journal of Financial Economics 104, 288-302.

Stambaugh, R.F., Yu, J., Yuan, Y., 2015. Arbitrage asymmetry and the idiosyncratic volatility puzzle. Journal of Finance 70, 1903-1948.

Stein, J.C., 2005. Why are most funds open-end? Competition and the limits of arbitrage. Quarterly Journal of Economics 120, 247-272.

Wang, H., Yu, J., 2013. Dissecting the Profitability Premium. Working Paper.

Wermers, R., 1999. Mutual fund trading and impact on stock prices. Journal of Finance, 54, 581-622.

Wermers, R., 2000. Mutual fund performance: An empirical decomposition into stock-picking talent, style, transactions costs, and expenses. Journal of Finance 55, 1655-1695.

Wermers, R., 2003. Is money really 'smart'? New evidence on the relation between mutual fund flows, manager behavior, and performance persistence. Working Paper.

Yan, X., Zhang, Z., 2009. Institutional investors and equity returns: Are short-term institutions better informed? Review of Financial Studies 22, 893-924.

Table 1. Summary Statistics

This table reports the characteristics of mutual funds in our sample. GPIM is the portfolio weighted average gross profit quintile rank of stocks held by a fund as described in Section 2.2. Fund Size ($million) is the total net assets under fund management (TNA) at the beginning of the month; Fund Age is fund age in years 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 a 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 the prior twelve-month normalized net flow into a fund and defined as $\left(\mathrm{TNA}_{i,t} - \mathrm{TNA}_{i,t-12}(1 + \mathrm{R}_{t-1,t-12})\right)/\mathrm{TNA}_{i,t-12}$; Ret. Vol. (Flow Vol.) is measured as the standard deviation of monthly fund return (flow) over the prior twelve months; SIZEIM, BMIM, and MOMIM are the portfolio weighted average market capitalization, book-to-market, and prior twelve-month return (momentum) quintile ranks of stocks held by a fund as described in Section 2.2. The sample period is from 1984 to 2014. The sample contains 2,889 unique funds and 310,992 observations.

	Min	5^{th} pctl.	Mean	Median	95^{th} pctl.	Max	Std. Dev
GPIM	1.51	2.61	3.39	3.43	4.02	4.57	0.45
Fund Size ($million)	16	29	1,054	291	4,745	15,524	2,315
Fund Age (in years)	3	4	18	13	50	76	15
Family Size ($million)	106	281	42,159	8,586	125,134	318,493	86,093
Expenses (%)	0.64	0.75	1.18	1.14	1.71	1.90	0.35
Turnover (%)	11.09	17.84	80.55	65.20	172.70	220.99	58.33
Past Return (12-month) (%)	-2.49	0.78	11.75	11.35	23.48	27.86	8.24
Ret. Vol. (%)	2.40	3.02	4.70	4.46	7.17	8.93	1.27
Past Flow (12-month) (%)	-30.62	-23.37	8.09	-2.66	57.47	111.11	35.08
Flow Vol. (%)	0.20	1.07	4.97	3.22	14.06	56.98	6.56
SIZEIM	1.02	2.32	3.85	4.07	4.77	4.98	0.79
BMIM	0.87	2.01	2.71	2.72	3.36	4.58	0.45
MOMIM	1.21	2.35	3.14	3.15	3.93	4.64	0.48

Table 2. GPIM and Mutual Fund Performance: Portfolio Analysis

Panel A reports the equal-weighted future returns of mutual funds sorted according to the most recent quarter's GPIM. R_{t+1} ($R_{t+1,t+3}$, $R_{t+1,t+12}$) is the one-month (three- and twelve-month cumulative) return. GPIM is measured as the portfolio weighted average gross profit quintile rank of stocks held by a fund as described in Section 2.2. Funds ranked in the top (bottom) quintile of the GPIM portfolio are classified as High (Low) GPIM funds. Gross returns are created by adding back 1/12 of the annual expense ratio to each monthly net return. The three-factor alpha (α^{3F-FF}) reported in Panel C is the intercept of three-factor model (Fama and French, 1993): $r_{p,t} = \alpha_p^{3F-FF} + \beta_{1,p}MKTRF_t + \beta_{2,p}SMB_t + \beta_{3,p}HML_t + \varepsilon_{pt}$. The four-factor alpha (α^{4F-FFC}) reported in Panel D is based on the three-factor model but also includes the momentum factor (Carhart, 1997). The five-factor alpha, ($\alpha^{5F-FFCPS}$) reported in Panel E is based on the four-factor model but also includes the Pastor and Stambaugh (2003) liquidity factor. Panel B (Panel C, D, and E) reports differences in fund returns (α^{3F-FF}, α^{4F-FFC}, $\alpha^{5F-FFCPS}$) between various quintiles. The Middle quintile portfolio is calculated as one equal-weighted portfolio based on GPIM quintiles 2-4. 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 1984 to 2014.

	Panel A. Future Returns of Mutual Funds Sorted on GPIM					
	Gross Returns			Net Returns		
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)	1.14	3.47	14.07	1.04	3.16	12.72
4	1.05	3.19	13.12	0.95	2.90	11.84
3	1.01	3.12	12.70	0.91	2.82	11.44
2	0.99	3.05	12.49	0.89	2.75	11.24
1 (Bottom)	0.93	2.89	12.05	0.83	2.59	10.76
	Panel B. Difference in Return					
Top-Bottom	0.21*	0.57*	2.03*	0.21*	0.56*	1.96*
	(1.78)	(1.71)	(1.74)	(1.75)	(1.68)	(1.70)
Top-Middle (2,3,4)	0.13**	0.35**	1.30**	0.12**	0.33**	1.21*
	(2.17)	(2.10)	(1.97)	(2.08)	(2.00)	(1.86)
Bottom-Middle (2,3,4)	-0.08	-0.23	-0.73	-0.09	-0.23	-0.75
	(-1.23)	(-1.17)	(-1.26)	(-1.26)	(-1.20)	(-1.31)
	Panel C. Difference in α^{3F-FF}					
Top-Bottom	0.28***	0.80***	3.24***	0.28***	0.78***	3.17***
	(4.19)	(4.27)	(3.48)	(4.13)	(4.21)	(3.43)
Top-Middle (2,3,4)	0.17***	0.48***	1.97***	0.16***	0.46***	1.89***
	(4.03)	(4.26)	(2.89)	(3.90)	(4.12)	(2.80)
Bottom-Middle (2,3,4)	-0.11***	-0.32***	-1.27***	-0.11***	-0.33***	-1.28***
	(-2.94)	(-2.93)	(-3.91)	(-2.99)	(-2.98)	(-3.97)
	Panel D. Difference in α^{4F-FFC}					
Top-Bottom	0.20***	0.52***	1.73**	0.19***	0.51***	1.67**
	(2.98)	(2.91)	(2.59)	(2.92)	(2.84)	(2.52)
Top-Middle (2,3,4)	0.13***	0.36***	1.12**	0.12***	0.34***	1.05**
	(3.08)	(3.33)	(2.22)	(2.94)	(3.17)	(2.10)
Bottom-Middle (2,3,4)	-0.07*	-0.17	-0.61**	-0.07*	-0.17	-0.62**
	(-1.80)	(-1.56)	(-2.33)	(-1.85)	(-1.60)	(-2.38)

	Panel E. Difference in $\alpha^{5F-FFCPS}$					
Top-Bottom	0.22***	0.60***	1.68***	0.22***	0.58***	1.62***
	(3.29)	(3.17)	(2.70)	(3.23)	(3.10)	(2.61)
Top-Middle (2,3,4)	0.14***	0.39***	1.07**	0.13***	0.37***	1.00**
	(3.26)	(3.53)	(2.41)	(3.13)	(3.37)	(2.26)
Bottom-Middle (2,3,4)	-0.08**	-0.20*	-0.61**	-0.08**	-0.21*	-0.62**
	(-2.18)	(-1.86)	(-2.37)	(-2.23)	(-1.91)	(-2.42)

Table 3. GPIM and Mutual Fund Performance: Regression Analysis

This table reports results from cross-sectional (in Panel A) and panel regressions (in Panel B) of fund performance on the most recent quarter's GPIM. GPIM is measured as the portfolio weighted average gross profit quintile rank of stocks held by a fund as described in Section 2.2. Other fund characteristics are defined in Table 1. α_{t+1}^{4F-FFC} is the fund's one-month Carhart (1997) four-factor alpha and is obtained from the fund's excess return less the sum of the products of each of the four-factor realizations: market, size, value, and momentum. These factors are estimated using the preceding 36 monthly fund returns. $\alpha_{t+1,t+3}^{4F-FFC}$ ($\alpha_{t+1,t+12}^{4F-FFC}$) is the fund's four-factor alpha cumulated over the next three (twelve) months. Panel A 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). Panels B and C report the panel regression results with *t* – statistics (in parentheses) derived from double-clustered standard errors by fund and time (month). Time and Style fixed effects are also included. Panel C also includes fund fixed effects. Mutual funds are classified into size/value categories based on a fund's four-factor loadings described in Section 3.2. *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively. The sample period is 1984 to 2014.

	Panel A. Fama-MacBeth Regressions			Panel B. Panel Regressions			Panel C. Panel Regressions with Fund Fixed Effects		
	α^{4F-FFC}_{t+1} (1)	$\alpha^{4F-FFC}_{t+1,t+3}$ (2)	$\alpha^{4F-FFC}_{t+1,t+12}$ (3)	α^{4F-FFC}_{t+1} (4)	$\alpha^{4F-FFC}_{t+1,t+3}$ (5)	$\alpha^{4F-FFC}_{t+1,t+12}$ (6)	α^{4F-FFC}_{t+1} (7)	$\alpha^{4F-FFC}_{t+1,t+3}$ (8)	$\alpha^{4F-FFC}_{t+1,t+12}$ (9)
GPIM	0.001***	0.003***	0.010***	0.001**	0.002***	0.009***	0.001***	0.003***	0.012***
	(2.65)	(2.79)	(3.58)	(2.30)	(2.89)	(4.03)	(3.40)	(4.92)	(5.11)
Log(TNA)	-0.000***	-0.001***	-0.002***	-0.000***	-0.001***	-0.002***	-0.002***	-0.005***	-0.017***
	(-3.81)	(-4.29)	(-5.88)	(-3.49)	(-4.80)	(-5.21)	(-20.11)	(-21.37)	(-22.30)
Log(Age)	0.000	0.000	-0.001	0.000	0.000	-0.000	0.000	-0.000	-0.001
	(0.89)	(0.13)	(-1.07)	(0.68)	(0.20)	(-0.52)	(0.20)	(-0.40)	(-0.39)
Expenses	-0.047**	-0.151***	-0.736***	-0.057***	-0.169***	-0.627***	-0.039	-0.180**	-0.558*
	(-2.56)	(-3.09)	(-5.28)	(-2.94)	(-3.71)	(-4.18)	(-1.34)	(-2.14)	(-1.83)
Turnover	0.000	0.000	-0.000	-0.000	-0.001*	-0.003***	0.000***	0.001**	0.001*
	(0.31)	(0.21)	(-0.36)	(-0.89)	(-1.93)	(-3.17)	(2.58)	(2.09)	(1.89)
Log(Fam. Size)	0.000***	0.000***	0.002***	0.000***	0.000***	0.002***	-0.000	-0.000	-0.001
	(2.97)	(3.55)	(6.14)	(2.88)	(4.63)	(6.22)	(-0.96)	(-1.49)	(-1.22)
$R_{t-1,t-12}$	0.010***	0.028***	0.090***	0.008*	0.016**	0.023*	0.006***	0.008***	-0.008
	(3.32)	(3.71)	(5.21)	(1.78)	(2.08)	(1.77)	(7.43)	(4.02)	(-1.43)
Ret. Vol.	-0.055**	-0.092	-0.248	-0.029	-0.072	-0.247**	-0.010*	-0.012	-0.068
	(-2.47)	(-1.54)	(-1.62)	(-0.80)	(-1.30)	(-2.22)	(-1.67)	(-0.74)	(-1.09)
$Flow_{t-1,t-12}$	0.000	0.001	-0.001	0.000	0.000	-0.003**	0.000	-0.000	-0.004***
	(1.18)	(1.03)	(-0.68)	(0.37)	(0.18)	(-2.04)	(0.15)	(-0.43)	(-3.28)
Flow Vol.	0.000	-0.003	-0.000	0.000	0.002	0.017**	0.000	0.003	0.019***
	(0.15)	(-0.86)	(-0.04)	(0.19)	(0.89)	(2.26)	(0.33)	(1.23)	(2.67)
Intercept	-0.004**	-0.011**	-0.024*	-0.006***	-0.013***	-0.037***	-0.002	0.001	0.021
	(-2.09)	(-2.13)	(-1.96)	(-2.95)	(-3.62)	(-4.07)	(-1.04)	(0.12)	(1.30)
Style FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time FE	N	N	N	Y	Y	Y	Y	Y	Y
Fund FE	N	N	N	N	N	N	Y	Y	Y
Cluster: Fund and Time	N	N	N	Y	Y	Y	Y	Y	Y
Avg. N/ N	806	806	806	299,792	299,792	299,792	299,792	299,792	299,792
Adj. R^2/ R^2	0.163	0.163	0.168	0.085	0.089	0.085	0.087	0.097	0.116

Table 4. GPIM and Profitability-Related Risk Premium: Portfolio Analysis

Panel A reports the equal-weighted future performance of mutual funds sorted according to the most recent quarter's GPIM. GPIM is measured as the portfolio weighted average gross profit quintile rank of stocks held by a fund as described in Section 2.2. Funds ranked in the top (bottom) quintile of the GPIM portfolio are classified as High (Low) GPIM funds. In Panel A, α_{t+1}^{5F-FF} ($\alpha_{t+1,t+3}^{5F-FF}$, $\alpha_{t+1,t+12}^{5F-FF}$) is the gross or net one-month (three- and twelve-month cumulative) Fama-French (2015) five-factor alpha measured as the intercept of the five-factor model: $r_{p,t} = \alpha_p^{5F-FF} + \beta_{1,p}MKTRF_t + \beta_{2,p}SMB_t + \beta_{3,p}HML_t + \beta_{4,p}RMW_t + \beta_{5,p}CMA_t + \varepsilon_{pt}$ where RMW (CMA) is the profitability (investment) factor proposed by Fama and French (2015). In Panel B, α_{t+1}^{qF-HXZ} ($\alpha_{t+1,t+3}^{qF-HXZ}$, $\alpha_{t+1,t+12}^{qF-HXZ}$) is the gross or net one-month (three- and twelve-month cumulative) Hou, Xue, and Zhang (2015) q-factor alpha measured as the intercept of the factor model: $r_{p,t} = \alpha_p^{qF-HXZ} + \beta_{1,p}MKT_t + \beta_{2,p}SMB_t + \beta_{3,p}ROE_t^F + \beta_{4,p}I/A_t^F + \varepsilon_p$, where ROE^F (I/A^F) is the profitability (investment) factor proposed by Hou, Xue, and Zhang (2015). Newey-West (1987) *t* – statistics are reported in parentheses. This table also reports the differences in α^{5F-FF} (or α^{qF-HXZ}) between various quintiles. The Middle quintile portfolio is calculated as one equal-weighted portfolio based on GPIM quintiles 2-4. 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 1984 to 2014.

	Panel A. Five-Factor Alphas (Fama and French, 2015)					
	Gross Alphas			Net Alphas		
GPIM Ranks	α_{t+1}^{5F-FF}	$\alpha_{t+1,t+3}^{5F-FF}$	$\alpha_{t+1,t+12}^{5F-FF}$	α_{t+1}^{5F-FF}	$\alpha_{t+1,t+3}^{5F-FF}$	$\alpha_{t+1,t+12}^{5F-FF}$
5 (Top)	0.15**	0.46***	2.63***	0.04	0.16	1.37
4	0.05	0.17	1.22*	-0.05	-0.12	0.03
3	0.05	0.20**	0.95*	-0.05	-0.08	-0.23
2	-0.00	0.01	0.40	-0.10**	-0.28***	-0.77
1 (Bottom)	-0.07	-0.16	-0.00	-0.16***	-0.45***	-1.17**
	Difference in α^{5F-FF}					
Top-Bottom	0.21***	0.62***	2.63**	0.21***	0.61***	2.54**
	(2.90)	(2.78)	(2.27)	(2.85)	(2.71)	(2.21)
Top-Middle (2,3,4)	0.11***	0.33**	1.77**	0.11**	0.32**	1.69**
	(2.65)	(2.55)	(2.18)	(2.52)	(2.42)	(2.11)
Bottom-Middle (2,3,4)	-0.10**	-0.29**	-0.86*	-0.10**	-0.29**	-0.86*
	(-2.29)	(-2.25)	(-1.89)	(-2.33)	(-2.27)	(-1.89)
	Panel B. Q-Factor Alphas (Hou, Xue, and Zhang, 2015)					
GPIM Ranks	α_{t+1}^{qF-HXZ}	$\alpha_{t+1,t+3}^{qF-HXZ}$	$\alpha_{t+1,t+12}^{qF-HXZ}$	α_{t+1}^{qF-HXZ}	$\alpha_{t+1,t+3}^{qF-HXZ}$	$\alpha_{t+1,t+12}^{qF-HXZ}$
5 (Top)	0.24***	0.72***	2.77***	0.14**	0.41***	1.50*
4	0.12**	0.37***	1.66***	0.03	0.08	0.44
3	0.08	0.29**	1.09**	-0.02	0.00	-0.10
2	0.02	0.18*	0.93**	-0.07	-0.11	-0.25
1 (Bottom)	-0.05	-0.06	0.36	-0.15***	-0.36**	-0.82*
	Difference in α^{qF-HXZ}					
Top-Bottom	0.30***	0.78***	2.41***	0.29***	0.77***	2.32***
	(4.34)	(4.48)	(3.08)	(4.28)	(4.40)	(3.00)
Top-Middle (2,3,4)	0.17***	0.44***	1.54***	0.16***	0.42***	1.46***
	(4.17)	(4.12)	(2.80)	(4.04)	(3.98)	(2.69)
Bottom-Middle (2,3,4)	-0.13***	-0.35***	-0.87**	-0.13***	-0.35***	-0.85**
	(-3.08)	(-3.16)	(-2.51)	(-3.12)	(-3.19)	(-2.49)

Table 5. GPIM and Fund Style Categories

Panel A reports the average GPIM for fund style categories based on size/value/momentum dimensions as well as the differences in GPIM between Growth- versus Value- and Small- vs. Large-Cap styles. Mutual funds are classified into size/value as well as momentum categories based on a fund's four-factor loadings as described in Section 3.2. Panel B reports the results from panel regressions of fund performance on the most recent quarter's GPIM, SIZEIM, BMIM, MOMIM and other fund characteristics. α_{t+1}^{4F-FFC} is the fund's one-month Carhart (1997) four-factor alpha and is obtained from the fund's excess return less the sum of the products of each of the four-factor realizations: market, size, value, and momentum. $\alpha_{t+1,t+3}^{4F-FFC}$ ($\alpha_{t+1,t+12}^{4F-FFC}$) is the fund's four-factor alpha cumulated over the next three (twelve) months. GPIM (SIZEIM, BMIM, and MOMIM) is measured as the weighted average gross profit (market capitalization, book-to-market-value, and prior twelve-month stock return) quintile ranks of stocks held by a fund. All other control variables are defined in Table 1. Panel B reports *t* – statistics (in parentheses) derived from double-clustered standard errors by fund and time (month). Time and Style fixed effects are also included. *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively. The sample period is 1984 to 2014.

Panel A. GPIM and Fund Style Categories: Size/Value/Momentum Dimensions

	High Momentum				Low Momentum			
	Small-Cap	Mid-Cap	Large-Cap	Difference in GPIM: Small-Cap – Large-Cap	Small-Cap	Mid-Cap	Large-Cap	Difference in GPIM: Small-Cap – Large-Cap
Growth	3.63	3.48	3.46	0.17	3.36	3.28	3.30	0.06
				(1.63)				(0.75)
Core	3.62	3.52	3.41	0.20*	3.40	3.30	3.30	0.10
				(1.81)				(1.03)
Value	3.56	3.36	3.08	0.49***	3.29	3.16	3.01	0.28**
				(3.22)				(2.13)
	Difference in GPIM: Growth-Value				Difference in GPIM: Growth-Value			
	0.08	0.12	0.38**		0.07	0.12	0.28*	
	(1.00)	(0.90)	(2.22)		(1.30)	(1.01)	(1.88)	

Panel B. Regression Analysis Controlling for Investment Strategies Based on Size, Book-to-Market, and Momentum

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	α_{t+1}^{4F-FFC}	$\alpha_{t+1,t+3}^{4F-FFC}$	$\alpha_{t+1,t+12}^{4F-FFC}$	α_{t+1}^{4F-FFC}	$\alpha_{t+1,t+3}^{4F-FFC}$	$\alpha_{t+1,t+12}^{4F-FFC}$	α_{t+1}^{4F-FFC}	$\alpha_{t+1,t+3}^{4F-FFC}$	$\alpha_{t+1,t+12}^{4F-FFC}$
GPIM				0.001**	0.003***	0.011***	0.001**	0.003***	0.011***
				(2.45)	(3.51)	(5.19)	(2.56)	(3.75)	(5.54)
SIZEIM	-0.000	-0.001**	-0.005***	-0.000	-0.001*	-0.004***	-0.000	-0.000	-0.001
	(-1.27)	(-1.97)	(-3.62)	(-1.04)	(-1.72)	(-3.22)	(-0.26)	(-0.11)	(-0.85)
BMIM	0.000	0.000	0.000	-0.000	-0.001	-0.002	-0.000	-0.001	-0.003
	(0.14)	(0.18)	(0.17)	(-0.37)	(-0.52)	(-0.86)	(-0.42)	(-0.52)	(-0.92)
MOMIM	-0.002***	-0.003***	-0.009***	-0.002***	-0.004***	-0.012***	-0.002***	-0.004***	-0.012***
	(-3.18)	(-3.50)	(-4.07)	(-3.59)	(-4.21)	(-5.16)	(-3.59)	(-4.20)	(-5.18)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Style FE	N	N	N	N	N	N	Y	Y	Y
Time FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cluster: Fund and Time	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	299,792	299,792	299,792	299,792	299,792	299,792	299,792	299,792	299,792
R^2	0.087	0.091	0.089	0.087	0.091	0.089	0.087	0.091	0.090

Table 6. GPIM and Fund Characteristics

This table reports the portfolio characteristics of mutual funds sorted according to the most recent quarter's GPIM (Panel A). GPIM is measured as the portfolio weighted average gross profit quintile ranks of stocks held by a fund described Section 2.2. Funds ranked in the top (bottom) quintile of the GPIM portfolio are classified as High (Low) GPIM funds. Active share 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 the four-factor model of Carhart (1997) over the previous 36 months (from month *t* – 1 to *t* – 36). All other variables are defined in Table 1. Panel B (Panel C, Panel D) reports the differences in fund characteristics between the various quintiles. The middle quintile portfolio is calculated as one equal-weighted portfolio based on GPIM quintiles 2-4. Newey-West (1987) *t* – statistics are reported 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 1984 to 2014.

GPIM Ranks	Log(TNA)	Log(Age)	Log(Fam. Size)	Expenses (%)	Turnover (%)	Ret. Vol. (%)	Flow Vol (%)	$R_{t-1,t-12}$ (%)	α_{t-1}^{4F-FFC} (%)	Active Share	R^2	$Flow_{t-1,t-12}$ (%)
Panel A. Fund Characteristics												
5 (Top)	5.41	5.00	8.35	1.24	87.37	5.21	4.86	12.44	0.04	0.85	0.84	9.06
4	5.61	5.07	8.39	1.18	84.35	4.88	4.31	11.71	-0.03	0.83	0.89	8.91
3	5.72	5.09	8.45	1.16	81.12	4.61	4.11	11.55	-0.02	0.82	0.91	7.00
2	5.87	5.10	8.60	1.15	75.46	4.46	4.04	11.82	-0.02	0.83	0.91	7.54
1 (Bottom)	5.85	4.98	8.93	1.18	74.22	4.35	4.41	11.22	-0.07	0.81	0.92	7.87
Panel B. Difference: Top-Bottom												
	-0.44***	0.02	-0.58***	0.06***	13.14***	0.86***	0.45**	1.21**	0.12***	0.04***	-0.07***	1.19**
	(-6.68)	(0.87)	(-11.98)	(6.11)	(4.29)	(4.56)	(2.14)	(2.37)	(4.19)	(5.00)	(-9.28)	(2.27)
Panel C. Difference: Top-Middle (2,3,4)												
	-0.32***	-0.09***	-0.13**	0.07***	7.05***	0.56***	0.70***	0.74***	0.07***	0.03***	-0.06***	1.24***
	(-6.00)	(-4.13)	(-2.28)	(8.44)	(4.31)	(5.15)	(4.25)	(2.91)	(4.55)	(3.19)	(-7.24)	(3.20)
Panel D. Difference: Bottom-Middle (2,3,4)												
	0.11***	-0.10***	0.45***	0.02*	-6.09***	-0.30***	0.26***	-0.47	-0.05***	-0.02***	0.01***	0.05
	(4.51)	(-3.59)	(8.88)	(1.71)	(-3.09)	(-2.90)	(4.08)	(-1.57)	(-3.05)	(-4.57)	(3.23)	(0.24)

Table 7. Determinants of GPIM

This table reports results from logistic regressions that compare the characteristics of mutual funds in the top and bottom GPIM quintiles to mutual funds in the middle GPIM quintiles. GPIM is measured as the portfolio weighted average gross profit quintile ranks of stocks held by a fund described Section 2.2. 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 the top or bottom GPIM quintile (middle). All other variables are defined in Tables 1 and 6. The *t* – statistics (in parentheses) are derived from clustered standard errors by fund. Time and Style fixed effects are also included. Mutual funds are classified into size/value categories based on a fund's four-factor loadings as described in Section 3.2. ***, **, * 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 1984 to 2014.

	Panel A. Top vs. Bottom			Panel B. Top vs. Middle (2,3,4)			Panel C. Bottom vs. Middle (2,3,4)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log(TNA)	-0.12***	-0.15***	-0.24***	-0.09***	-0.08**	-0.09**	0.06*	0.06*	0.12**
	(-2.64)	(-3.08)	(-3.72)	(-2.81)	(-2.47)	(-2.18)	(1.81)	(1.71)	(2.35)
Log(Age)	0.05	0.04	0.10	-0.30***	-0.32***	-0.41***	-0.15**	-0.23***	-0.23**
	(0.99)	(0.76)	(1.50)	(-3.15)	(-3.39)	(-3.13)	(-2.12)	(-3.34)	(-2.23)
Expenses	0.43***	0.52**	0.31**	0.23*	0.21*	0.20*	0.13	0.17	0.02
	(3.10)	(2.54)	(2.04)	(1.97)	(1.95)	(1.70)	(1.02)	(1.41)	(0.12)
Turnover	0.46***	0.47***	0.43***	0.11**	0.10**	0.11**	-0.32***	-0.36***	-0.24***
	(5.19)	(5.21)	(3.54)	(2.36)	(2.35)	(2.14)	(-4.80)	(-5.51)	(-2.75)
Log(Fam. Size)	-0.13***	-0.10***	-0.10**	-0.02	-0.03	-0.08***	0.09***	0.05**	-0.01
	(-4.05)	(-3.15)	(-2.50)	(-1.04)	(-1.48)	(-2.99)	(3.86)	(2.42)	(-0.40)
Std. Ret.	0.25***	0.24***	0.40***	0.15***	0.17***	0.13***	-0.06**	-0.06**	-0.19***
	(6.97)	(6.50)	(5.82)	(8.07)	(9.15)	(5.19)	(-2.26)	(-2.55)	(-3.87)
Std. Flow	0.01	0.00	0.02	0.03***	0.02***	0.02***	0.03***	0.01*	0.01
	(0.89)	(0.31)	(1.27)	(4.11)	(3.10)	(2.65)	(4.36)	(1.95)	(0.54)
α^{4F-FFC}	0.56***	0.67***	0.43***	0.26***	0.14**	0.12*	-0.24***	-0.48***	-0.29**
	(5.89)	(6.96)	(2.68)	(3.83)	(2.09)	(1.83)	(-2.99)	(-6.25)	(-2.13)
$Flow_{t-1,t-12}$	0.23***	0.28***	0.22*	0.17***	0.14***	0.11**	-0.06	-0.10	-0.12
	(2.70)	(3.34)	(1.80)	(3.15)	(2.64)	(1.99)	(-0.87)	(-1.17)	(-1.47)
R^2		-6.26***			-3.59***			2.82***	
		(-15.35)			(-6.61)			(7.13)	
Active Share			2.90**			1.60***			-1.00***
			(2.11)			(3.42)			(-2.60)
Intercept	-2.30***	-5.85***	-1.96*	-2.48***	0.22	-3.02***	-0.78	5.68***	-1.19
	(-3.40)	(-6.80)	(-1.88)	(-5.80)	(0.40)	(-4.54)	(-1.58)	(8.46)	(-1.49)
FE: Style-Month	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cluster: Fund	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	112,330	112,330	51,722	224,661	224,661	103,444	224,659	224,659	103,441
Pseudo-R^2	0.236	0.253	0.276	0.055	0.063	0.059	0.072	0.123	0.091

Table 8. GPIM and Alternative Measures of Fund Performance

This table reports the results from panel regressions of fund performance on the most recent quarter's GPIM and other fund characteristics that are defined in Table 1. GPIM is measured as the portfolio weighted average gross profit quintile rank of stocks held by a fund as described in Section 2.2. Fund performance is evaluated using (1) Characteristic Selectivity ($CS_{t+1,t+3}$) over the following three months from Daniel, Grinblatt, Titman, and Wermers (1997), (2) Asset Growth measured as the growth in a fund's total assets over the following three months ($AG_{t+1,t+3}$), (3) Fund Flows over the following three months ($Flow_{t+1,t+3}$), and (4) Value Added ($VA_{t+1,t+3}$) measured as the product of assets under management of month *t* and the four-factor alpha (before expenses) over the following three months. The *t* – statistics (in parentheses) are derived from double-clustered standard errors by time (month) and fund. Time and Style fixed effects are also included. Mutual funds are classified into size/value categories based on fund's four-factor loadings described in Section 3.2. *, **, and *** represent significance levels of 10%, 5%, and 1%, respectively. The sample period is 1984 to 2014.

	Characteristic Selectivity ($CS_{t+1,t+3}$)	Asset Growth ($AG_{t+1,t+3}$)	Fund Flows ($Flow_{t+1,t+3}$)	Value Added ($VA_{t+1,t+3}$)
	(1)	(2)	(3)	(4)
GPIM	0.002***	0.001**	0.001**	3.298**
	(2.59)	(2.41)	(2.24)	(2.34)
Log(TNA)	-0.000***	-0.008***	-0.003***	-4.666***
	(-2.73)	(-10.65)	(-4.57)	(-3.84)
Log(Age)	0.000**	-0.001	-0.002***	-0.735
	(2.47)	(-1.06)	(-3.03)	(-1.37)
Expenses	0.117***	-0.148	-0.131*	-3.587***
	(2.80)	(-0.70)	(-1.71)	(-2.93)
Turnover	0.000	0.006**	-0.004***	-0.963*
	(1.19)	(2.52)	(-4.85)	(-1.94)
Log(Fam. Size)	0.000***	0.003***	0.002***	0.389**
	(2.74)	(6.14)	(4.86)	(2.57)
$R_{t-1,t-12}$	0.060***	0.301***	0.171***	11.440
	(6.32)	(6.01)	(7.21)	(0.73)
Ret. Vol.	-0.277***	-0.652***	-0.315***	-0.144*
	(-3.08)	(-2.63)	(-3.92)	(-1.75)
$Flow_{t-1,t-12}$	-0.002***	0.115***	0.086***	1.166
	(-3.64)	(22.63)	(20.34)	(1.12)
Flow Vol.	0.001	0.025	-0.022	-3.155
	(1.41)	(1.31)	(-1.33)	(-0.73)
Intercept	0.001	-0.038**	0.018**	17.511*
	(0.12)	(-2.22)	(2.12)	(1.75)
FE: Style and Month	Y	Y	Y	Y
Cluster: Fund and Time	Y	Y	Y	Y
N	307,699	308,213	308,213	299,792
R^2	0.122	0.120	0.269	0.020

Table 9. Stock-Level Analysis: Return and Stock Characteristics Across Gross Profitability Sorted Portfolios

At the end of each quarter, we sort all stocks in the entire CRSP/Compustat universe into five quintiles based on their most recent gross profitability. Using quintile ranking based on the entire CRSP/Compustat universe, Panel A the average (equal-weighted) characteristics of stocks held by mutual funds in each quintile. Stock characteristics include: Cumulative return ($R_{t+1,t+12}$) measured as stock return from month t + 1 to t + 12; α_{t+1}^{4F} , which is the Carhart (1997) four-factor alpha at month t + 1; Return volatility (SRetVol) measured as the standard deviation of monthly stock returns from month t - 12 to t - 1. Idiosyncratic return volatility (SIVOL) is the standard deviation of estimated monthly stock residuals from the Carhart (1997) four-factor model from month t - 12 to t - 1. #Analysts is the number of analysts following a stock obtained from the Institutional Brokers' Estimate System (I/B/E/S). Size Rank (BM Rank) is the average of market capitalization (book-to-market) quintile ranks of stocks. E/P (×100) is the earnings-to-price ratio computed as the income before extraordinary items divided by the market value of firm. DY (%) is the dividend yield measured as dividends divided by the market value of firm. Price is the previous month's stock price. The middle portfolio is one equal-weighted portfolio created out of medium gross profitability portfolios 2 – 4. Panels B, C, and D report the difference in the average stock characteristics between stocks in various 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 1984 to 2014.

				Panel A. Stocks Held by Mutual Funds							
Rank: GP	No of Stock	$R_{t+1,t+12}$ (%)	α_{t+1}^{4F} (%)	SRetVol (%)	SIVOL (%)	#Analysts	Size Rank	BM Rank	E/P	DY	Price
5 (Top)	549	18.83	0.52	13.28	9.12	3.34	3.45	2.33	2.12	0.96	23.30
4	592	15.73	0.32	12.53	8.51	4.02	3.51	2.72	2.73	1.08	23.52
3	582	13.46	0.07	12.31	8.33	3.45	3.57	3.04	2.56	1.26	23.02
2	580	12.34	-0.10	11.84	8.03	3.26	3.73	3.40	2.53	2.00	23.58
1 (Bottom)	481	9.73	-0.27	14.10	9.68	3.07	3.51	3.25	-1.64	1.89	20.65
					Panel B. Difference: Top-Bottom						
		9.10***	0.78***	-0.82**	-0.56**	0.27***	-0.06***	-0.92***	3.76***	-0.93***	2.64***
		(6.51)	(6.90)	(-2.25)	(-2.32)	(3.49)	(-3.44)	(-14.18)	(5.41)	(-5.27)	(2.40)
					Panel C. Difference: Top-Middle (2,3,4)						
		5.00***	0.42***	1.06***	0.84***	-0.24***	-0.16***	-0.72***	-0.49*	-0.49***	-0.08
		(4.56)	(6.52)	(6.18)	(8.05)	(-3.32)	(-4.44)	(-24.45)	(-1.73)	(-3.42)	(-0.17)
					Panel D. Difference: Bottom-Middle (2,3,4)						
		-4.10***	-0.36***	1.88***	1.40***	-0.51***	-0.09**	0.20***	-4.25***	0.43***	-2.72***
		(-2.69)	(-3.44)	(6.75)	(7.21)	(-7.93)	(-2.40)	(4.00)	(-5.27)	(7.47)	(-2.64)

Table 10. Robustness Checks: GPIM and the Effect of Fund Flows on Fund Performance

Each month, mutual funds are sorted into five quintiles according to the most recent quarter's GPIM. GPIM is measured as the portfolio weighted average gross profit quintile rank of stocks held by a fund as described in Section 2.2. Funds ranked in the top (bottom) quintile of the GPIM portfolio are classified as High (Low) GPIM funds. $R_{t+1,t+3}$ is the three-month cumulative gross or net return. Gross returns are created by adding back 1/12 of the annual expense ratio to each monthly net return. Funds in each GPIM-quintile are further divided into two groups based on whether their fund flows over the past three-months are above (High Flow) or below (Low Flow) the median flow. Table 10 reports the difference in the performance between funds in the High Flow and Low Flow subsamples. Panels B (Panel C) reports differences in fund returns (α^{4F-FFC}), as described in Section 3.1, between various 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 1984 to 2014.

	Panel A. Future Return of GPIM-sorted Mutual Fund Portfolios Conditional on Past Flow					
	Gross Return			Net Return		
	High Flow	Low Flow	Diff:	High Flow	Low Flow	Diff:
GPIM Ranks	$R_{t+1,t+3}$	$R_{t+1,t+3}$	H-L	$R_{t+1,t+3}$	$R_{t+1,t+3}$	H-L
5 (Top)	3.55	3.41	0.13	3.24	3.09	0.14
			(0.98)			(1.08)
4	3.20	3.25	-0.05	2.90	2.94	-0.04
			(-0.41)			(-0.38)
3	3.19	3.02	0.17	2.89	2.72	0.18
			(1.29)			(1.32)
2	3.08	3.03	0.05	2.79	2.73	0.06
			(0.33)			(0.44)
1 (Bottom)	2.92	2.88	0.05	2.63	2.56	0.07
			(0.36)			(0.50)
	Panel B. Difference in Return					
Top-Bottom	0.62**	0.54*	0.08	0.61*	0.53*	0.08
	(2.05)	(1.81)	(0.57)	(1.81)	(1.69)	(0.53)
Top-Middle (2,3,4)	0.38**	0.32**	0.06	0.37**	0.31*	0.07
	(2.19)	(1.98)	(0.61)	(2.13)	(1.88)	(0.67)
Bottom-Middle (2,3,4)	-0.24	-0.22	-0.02	-0.24	-0.23	-0.01
	(-1.11)	(-1.08)	(-0.20)	(-1.11)	(-1.13)	(-0.11)
	Panel C. Difference in α^{4F-FFC}					
Top-Bottom	0.61***	0.43**	0.18	0.60***	0.42**	0.18
	(2.87)	(2.48)	(1.26)	(2.82)	(2.42)	(1.25)
Top-Middle (2,3,4)	0.36***	0.33***	0.03	0.35***	0.32***	0.04
	(2.81)	(3.39)	(0.31)	(2.73)	(3.21)	(0.38)
Bottom-Middle (2,3,4)	-0.25*	-0.10	-0.15	-0.25*	-0.11	-0.14
	(-1.83)	(-0.83)	(-1.28)	(-1.83)	(-0.91)	(-1.21)

Table 11. Robustness Checks: Other Profitability-Related Investment Measures

This table reports results from panel regressions of fund performance on the most recent quarter's GPIM, other investment strategies based on alternative profitability measures, and fund characteristics. α_{t+1}^{4F-FFC} is the fund's one-month Carhart (1997) four-factor alpha and is obtained from the fund's excess return less the sum of the products of each of the four-factor realizations: market, size, value, and momentum. These factors are estimated using the preceding 36 monthly fund returns. $\alpha_{t+1,t+3}^{4F-FFC}$ ($\alpha_{t+1,t+12}^{4F-FFC}$) is the fund's four-factor alpha cumulated over the next three (twelve) months. GPIM is measured as the portfolio weighted average gross profit quintile ranks of stocks held by a fund as described in Section 2.2. 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 portfolio weighted average Trend in Gross Profitability (Operating Profitability) quintile ranks of stocks held by a fund. All other control variables are defined in Table 1. The *t* – statistics (in parentheses) are derived from clustered standard errors by fund and time (month). Time and Style fixed effects are also included. Mutual funds are classified into size/value categories based on a fund's four-factor loadings described in Section 3.2. ***, **, * denote statistical significance at the 1%, 5%, or 10% level, respectively. The sample period is 1984 to 2014.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	α_{t+1}^{4F-FFC}	α_{t+1}^{4F-FFC}	$\alpha_{t+1,t+3}^{4F-FFC}$	$\alpha_{t+1,t+3}^{4F-FFC}$	$\alpha_{t+1,t+12}^{4F-FFC}$	$\alpha_{t+1,t+12}^{4F-FFC}$	α_{t+1}^{4F-FFC}	α_{t+1}^{4F-FFC}	$\alpha_{t+1,t+3}^{4F-FFC}$	$\alpha_{t+1,t+3}^{4F-FFC}$	$\alpha_{t+1,t+12}^{4F-FFC}$	$\alpha_{t+1,t+12}^{4F-FFC}$
GPIM		0.001**		0.002**		0.008***		0.001**		0.002***		0.008**
		(2.09)		(2.19)		(4.05)		(2.23)		(3.46)		(2.32)
Trend_GPIM	0.001*	0.000	0.001*	0.001	0.002**	0.001						
	(1.71)	(0.66)	(1.87)	(-0.47)	(2.11)	(0.63)						
OPIM							0.001**	0.000	0.002**	0.000	0.006**	0.003
							(2.16)	(1.23)	(2.43)	(0.38)	(1.97)	(0.59)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
FE: Style and Time	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cluster: Fund and Time	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	279,792	279,792	279,792	279,792	279,792	279,792	299,792	299,792	299,792	299,792	299,792	299,792
R^2	0.085	0.085	0.088	0.089	0.083	0.085	0.085	0.085	0.089	0.089	0.084	0.085

Table 12. Robustness Checks: Controlling for Active Management Measures

This table reports results from panel regressions of fund performance on the most recent quarter's GPIM, active fund management proxies, and fund characteristics. α_{t+1}^{4F-FFC} is a fund's one-month Carhart (1997) four-factor alpha and is obtained from the fund's excess return less the sum of the products of each of the four-factor realizations; market, size, value, and momentum. These factors are estimated using the preceding 36 monthly fund returns. $\alpha_{t+1,t+3}^{4F-FFC}$ ($\alpha_{t+1,t+12}^{4F-FFC}$) is the fund's four-factor alpha cumulated over the next three (twelve) months. GPIM is measured as the portfolio weighted average gross profit quintile ranks of stocks held by a fund as described in Section 2.2. Active fund management measures include: Active Share represents the share of portfolio holdings that differ from the benchmark index (Cremers and Petajisto, 2009); R^2 is the proportion of the fund return variance explained by the variation in the four-factor model of Carhart (1997) over the previous 36 months. All other control variables (not reported for brevity) are defined in Table 1. The *t* – statistics (in parentheses) are derived from clustered standard errors by fund and time (month). Time and Style fixed effects are also included. Mutual funds are classified into size/value categories based on a fund's four-factor loadings as described in Section 3.2. ***, **, * denote statistical significance at the 1%, 5%, or 10% level, respectively. Data for the Active Share measure is obtained from Antti Petajisto and spans from 1984 to 2009. The sample period is 1984 to 2014.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	α_{t+1}^{4F-FFC}	α_{t+1}^{4F-FFC}	$\alpha_{t+1,t+3}^{4F-FFC}$	$\alpha_{t+1,t+3}^{4F-FFC}$	$\alpha_{t+1,t+12}^{4F-FFC}$	$\alpha_{t+1,t+12}^{4F-FFC}$	α_{t+1}^{4F-FFC}	α_{t+1}^{4F-FFC}	$\alpha_{t+1,t+3}^{4F-FFC}$	$\alpha_{t+1,t+3}^{4F-FFC}$	$\alpha_{t+1,t+12}^{4F-FFC}$	$\alpha_{t+1,t+12}^{4F-FFC}$
GPIM		0.001***		0.003***		0.008***		0.001**		0.002**		0.011***
		(3.90)		(3.89)		(3.51)		(2.38)		(2.54)		(5.19)
Active Share	0.003*	0.003*	0.009***	0.009***	0.041***	0.041***						
	(1.77)	(1.79)	(3.26)	(3.30)	(6.04)	(6.08)						
R^2							-0.002**	-0.002**	-0.005**	-0.006***	-0.024***	-0.028***
							(-2.44)	(-2.52)	(-2.41)	(-2.88)	(-5.11)	(-6.02)
Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
FE: Style and Time	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cluster: Fund and Time	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
N	149,305	149,305	149,305	149,305	149,305	149,305	299,792	299,792	299,792	299,792	299,792	299,792
R^2	0.110	0.110	0.118	0.118	0.110	0.110	0.085	0.085	0.089	0.090	0.086	0.089

Figure 1. Persistence of the GPIM: Transition Probabilities

Each quarter, mutual funds are sorted according to the most recent quarter's GPIM (i.e., portfolio formation). Panel A (Panel B) shows the transition probabilities of mutual funds in the top (bottom) quintiles four quarters after the portfolio formation. Panel A1 (B1) illustrates transition probabilities for all funds; Panel A2 and A3 (B2 and B3) for Large- and Small-Cap funds; Panel A4 and A5 (B4 and B5) for Growth- and Value-style funds in the top (bottom) GPIM-quintile. Mutual funds are classified into size/value categories based on a fund's four-factor loadings as described in Section 3.2. The sample period is 1984 to 2014.

Panel A. Funds in the Top GPIM Quintile

Panel B. Funds in the Bottom GPIM Quintile