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Investing in the "New Economy": Mutual Fund Performance and the Nature of the Firm

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Abstract

Although stock returns of intangibles-intensive firms tend to exceed physical assets-intensive firms, risk-adjusted returns of actively managed mutual funds significantly decrease (increase) with their portfolios' exposure to intangibles-intensive (physical assets-intensive) firms. Fund managers tend to exhibit skill when they focus on difficult-to-value (e.g., small) firms, except when the firms are intangibles-intensive. In sum, the worst-performing funds are in areas of the market that seem to offer ample opportunities for professional investors due to exacerbated mispricing. The negative impact of investments in intangibles-intensive firms on fund performance appears to be driven by extrapolation bias and decreases with learning from experience.

I. Introduction

In the last two decades, the U.S. economy has been marked by the spectacular growth of intangibles-intensive firms founded on innovation and human capital. Prior to this, the economy was largely dominated by the physical assets-intensive firms that emerged following the second industrial revolution of the late 1800s (see Zingales (2000)). Several strands of research postulate on the implications of the changing nature of the firm in this "new economy." Rajan and Zingales (2000) and Rajan and Wulf (2006) underscore the changes in governance and flattening organizational structure, while others suggest that the valuation of modern firms is more opaque and less related to traditional financial variables (Core, Guay, and Van Buskirk (2003)). Some studies point to the market's misvaluation of intangibles, alluding to limitations in the valuation techniques honed

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based on the physical assets-intensive firm of the 20th century.[1] More generally, given the relatively recent emergence of industries that prioritize intangibles such as human capital and innovation, investors may value physical assets more accurately due to learning from historical experience and data.[2]

In spite of ample evidence suggesting that the nature of the firm could affect investors' ability to value firms, how it affects the actual returns earned by portfolio investors has remained unexplored. In this study, I examine the relation between the nature of the firm and the returns earned by a well-defined class of stock market investors, namely, actively managed mutual funds. There are at least two reasons why the impact of the nature of the firm on mutual fund returns is an interesting topic to study. First, intangibles-intensive firms now form a sizable segment of capital markets. Coupled with the remarkable growth of the active portfolio management industry, any impact the nature of the firm has on abnormal returns of mutual funds is economically meaningful information for investors during the selection of mutual funds, for academics interested in market efficiency, and for other stock investors during security selection. Second, return predictability and whether fund managers are skilled "arbitrageurs" who can exploit mispricing or unskilled investors who underperform passive benchmarks have remained strongly debated issues in the literature since Jensen (1968). Since return predictability and the skill required to identify mispricing could vary with the nature of the firm, it is a novel and potentially valuable lens through which to view skill in active management.

Several recent studies argue that some mutual fund managers possess skill and add value in active management (see Wermers (2000), Kacperczyk, Sialm, and Zheng (2005), (2008), Cremers and Petajisto (2009)).[3] Additionally, to the extent that intangibles-intensive firms are associated with higher information asymmetries, intangible and uncertain value-relevant information, as well as deferred resolution of uncertainty related to the long-term value of investments such as research and development (R&D), the studies on investors' behavioral biases predict that these firms are more susceptible to misvaluation than traditional firms.[4] Existing empirical evidence is consistent with this view and suggests that

[1]Studies that find misvaluation of intangibles have focused on innovative inputs such as R&D (e.g., Eberhart, Maxwell, and Siddique (2004), Cohen, Diether, and Malloy (2013)), innovative outputs such as patents (Hirshleifer, Hsu, and Li (2013)), and employee satisfaction (Edmans (2011)).

[2]See Seru, Shumway, and Stoffman (2010) and Greenwood and Nagel (2009) for evidence of learning among investors.

[3]Given the vastness of the literature on mutual fund performance, it cannot be comprehensively summarized here. Some other studies that find evidence of performance persistence and skill among mutual funds are Grinblatt and Titman (1992), Daniel, Grinblatt, Titman, and Wermers (DGTW) (1997), Bollen and Busse (2004), Cohen, Coval, and Pástor (2005), Kosowski, Timmermann, Wermers, and White (2006), and Kacperczyk and Seru (2007). Examples of representative studies with contrasting evidence include Brown and Goetzmann (1995), Carhart (1997), and Fama and French (2010), who conclude that mutual fund managers create little or no value with their skill, especially net of fees.

[4]Aboody and Lev (2000) and others argue that there are higher information asymmetries in intangibles-intensive firms. Daniel, Hirshleifer, and Subrahmanyam (DHS) (1998), (2001), and Daniel and Titman (2006) predict that investors are more prone to exhibit biases when the information is intangible and uncertain. Moreover, these effects are strongest when the outcomes are deferred (Einhorn (1980)) and information asymmetry is higher (DHS (1998), Hong and Stein (1999)).

intangibles-intensive firms are undervalued by the market and offer more opportunities for informed investors (e.g., insiders in Aboody and Lev (2000)) than do physical assets-intensive firms.[5] So, informed fund managers could tilt their portfolios toward intangibles-intensive firms to exploit mispricing and earn higher abnormal returns. Here, fund performance is likely to have a *positive* relation with the degree to which the fund's portfolio is tilted toward intangibles-intensive firms as opposed to physical assets-intensive firms.

Alternatively, fund managers, like other investors, may exhibit behavioral biases in processing complex and intangible information (e.g., Jiang (2010)). More generally, Griffin and Tversky (1992) posit that biases such as overconfidence are more likely to be exhibited by experts than nonexperts when faced with ambiguous and uncertain information. In addition, fund managers' skill in identifying mispriced firms could increase with learning and the availability of historical data, wherein they should have better valuation techniques for physical assets-intensive firms than intangibles-intensive firms. These notions suggest that fund performance is likely to have a *negative* relation with the degree to which the fund's portfolio is tilted toward intangibles-intensive firms as opposed to physical assets-intensive firms. To summarize, existing theoretical and empirical evidence presents alternative predictions on the potential link between the nature of the firm and mutual fund performance.

Innovative inputs such as R&D, which this study mainly focuses on with respect to intangibles, play a substantial role in the valuation of modern firms. To characterize the nature of the firms a fund invests in, I mainly use a measure called the "intangibles intensity ratio" (IIR). The IIR is the value-weighted R&D-to-PPE (property, plant, and equipment) expenses ratio of individual firms in a fund's portfolio, with the fund's tilt toward intangibles-intensive firms and away from physical assets-intensive firms increasing with IIR. The IIR is stable over time and contains information distinct from a fund's style (e.g., value vs. growth), self-stated objective, and other fund attributes.

Furthermore, funds tilted toward intangibles-intensive firms earn substantially lower abnormal returns on average than funds tilted toward physical assets-intensive firms. For the main analyses, funds are assigned to deciles based on IIR in the prior quarter, where the lowest decile 1 (highest decile 10) portfolio generates significantly positive (negative) alphas in the following quarter. The IIR decile 1–10 four-factor alpha is 2.85% per year. The return patterns persist for at least 3 years following portfolio formation. The results are consistent with fund managers focused on physical assets-intensive firms exhibiting more skill than those focused on intangibles-intensive firms.

To rule out an important alternative interpretation that a fund's IIR simply proxies for omitted pricing factors, the tests are sharpened by augmenting the factor models. A factor-mimicking intangibles-minus-tangibles (IMT) portfolio that is long on stocks of high R&D-to-PPE firms and short on stocks of no-R&D

[5]Eberhart et al. (2004), Hirshleifer et al. (2013), and Cohen et al. (2013) document the underpricing of innovative firms and argue that investors' cognitive limitations in assessing intangibles lead to their underpricing. Alternatively, Chambers, Jennings, and Thompson (2002) argue that omitted risk factors explain the seeming underpricing of these firms.

(i.e., zero R&D) firms is used to augment factor models. The passive IMT portfolio yields a positive monthly return of 1.63%, due to either the relative underpricing or risk of high R&D versus no-R&D firms. Adding the IMT factor strengthens the results, with the 4-factor model augmented with IMT yielding an IIR decile 1–10 alpha of 6.54% per year. Results remain robust across other tests accounting for omitted factors and across alternative risk adjustment methods.

Before-cost measures of fund manager skill, such as gross returns and characteristic selectivity (see DGTW (1997), Wermers (2000)) provide conclusions similar to net returns. Interestingly, funds with high IIR exhibit poorer stock selection ability than those with low IIR in their intangibles-intensive as well as physical assets-intensive holdings. The results survive various robustness tests that include using alternative measures of innovation-related intangible assets (e.g., patents), controlling for past intangible and total stock returns, and multivariate regression settings.

The empirical analyses also separate the effect of the nature of the firm from the effects of general information problems linked to difficult-to-value firms. Fund managers outperform (underperform) when they focus on physical assets-intensive (intangibles-intensive) difficult-to-value firms. Resonating with Jensen's (1993) premise that investors may overvalue R&D due to the uncertainty in its longer-term outcomes, and Daniel and Titman's (2006) prediction that investors misreact to intangible information, these results can be construed as fund managers overpaying for the long-term benefits of intangible innovative assets of difficult-to-value firms (e.g., small, growth firms).

Furthermore, fund managers' trend-chasing extrapolative behavior increases with their focus on intangibles-intensive firms and, consistent with extrapolation bias, this behavior is detrimental for fund performance. Also, the extrapolation bias and the negative impact of IIR on returns decreases with a fund's prior experience. In light of the much longer historical presence of firms with physical assets, and existing evidence that extrapolation bias decreases with investor experience and data, these findings are consistent with the nature of the firm being associated with behavioral biases that affect fund managers and decrease with learning.[6] This evidence fits well with the growing literature that shows that behavioral biases affect institutional investors (e.g., Frazzini (2006), Jiang (2010)), and lends fresh insights to the recent literature on the role of learning in institutional trading (see Greenwood and Nagel (2009)).

Finally, a fund's maximum payoff and volatility increases, and its mean-variance efficiency decreases, with IIR. So, the nature of the firm impacts the welfare of fund investors via multiple channels and could be linked to investor preferences in the selection of mutual funds.

To summarize, by using the easily observable nature of the firm to predict fund returns and identify the environments in which fund managers are likely to act as informed versus uninformed agents, this study contributes to the literature on informed trading and active portfolio management. The role of the nature of

[6]For studies linking forecasting errors from extrapolation bias to investor inexperience and lack of data, see Rabin (2002), Hong, Stein, and Yu (2007), Haruvy, Lahav, and Noussair (2007), and Greenwood and Nagel (2009).

the firm in predicting outperformance and underperformance presents an interesting empirical coexistence of the conflicting ideas on skill in active management, namely the view of fund managers as informed investors versus uninformed investors who fail to beat benchmarks. It is also an intriguing paradox that the delegated portfolios perform most poorly in the areas of the market that seemingly offer the most opportunities for professional investors due to exacerbated information problems and mispricing.

The paper proceeds as follows: Section II discusses the data and sample. Section III defines the main variable used to capture the nature of the firms held in mutual funds' portfolios. Section IV presents the empirical results. Section V concludes.

II. Data and Sample Selection

The data used in this paper mainly draw from two mutual fund databases: Center for Research in Security Prices (CRSP) Survivor-Bias Free U.S. Mutual Fund Database (MFDB) and Thomson Financial holdings database. The initial sample consists of all unique funds that appear in CRSP MFDB over 1980 to 2009. The CRSP data on monthly returns, fees, and other fund characteristics are obtained.[7] The sample is then matched to the holdings database using a combination of the Mutual Fund Links (MFLINKS) interface (see Wermers (2000)) and hand-matching, and funds located in the United States are selected. While some funds report holdings semiannually as per mandatory disclosure requirements, Wermers notes that most mutual funds report holdings on a quarterly basis since 1980. I exclude funds with less than \$10 million in total net assets (TNA) as reported in Thomson Financial, and various screens are then employed to select actively managed diversified domestic equity funds.[8] Finally, since the analyses are based on holdings that can be matched to CRSP's stock files, I select funds for which the market value of the reported holdings represents at least 65% of the quarter-end TNA. To these holdings data, I merge firm-level data from the annual Compustat files, such as R&D expenses (item 46) and PPE (item 8).[9]

The final sample used in this study includes 3,165 unique actively managed U.S. equity mutual funds during the period 1980–2009. The funds map to 98,231 unique fund-quarter observations for portfolio holdings, and 285,419 monthly return observations. The mean (median) fund in the sample has a TNA of

[7]CRSP MFDB often includes multiple identifiers for the same fund if it has different share classes. I eliminate duplicate observations by first identifying the fund identifier with the longest time series of returns. If this step does not identify a fund uniquely, the identifier associated with the highest TNA in the year prior to the return observation is selected.

[8]Index, sector, bond, international, and money market funds are excluded based on stated objectives or using key words in the fund's name. Funds that have objectives defined as aggressive growth, growth, growth and income, equity income, growth with current income, income, long-term growth, maximum capital gains, small-cap core/growth/value, large-cap core/growth/value, mid-cap core/growth/value, multi-cap core/growth/value, unclassified, or missing are chosen.

[9]Unlike some other voluntary disclosures (e.g., advertising), the Statement of Financial Accounting Standards (SFAS) 2 rule requires firms to report R&D expenses separately. So, firms that are missing R&D expenses data in Compustat are noted as having zero R&D expenses.

$952 million ($170 million). The number of funds has grown substantially over time, with 216 unique funds with observed holdings in 1980, and 1,502 in 2009.

III. Measuring Mutual Funds' Portfolio Concentration in Intangibles

This section describes the main measure used to characterize the nature of the firms held by mutual funds, called the "portfolio concentration in intangibles." Time trends in portfolios are also reported.

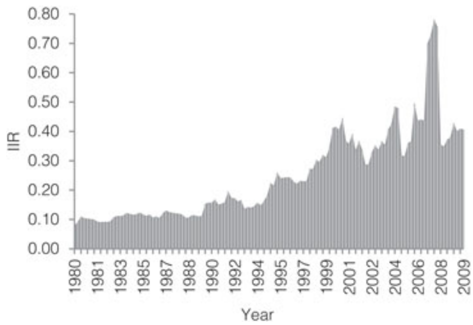
Prior studies such as Brown, Fazzari, and Peterson (2009) note that the R&D activities of publicly traded U.S. companies experienced a boom starting in the early 1990s. Based on two measures, Figure 1 graphically illustrates the time trend in mutual funds' portfolio concentration in intangibles. The measures are presented as equal-weighted means across all funds in all quarters in a calendar year. Graph A of Figure 1 plots the main measure of a fund's portfolio concentration in intangibles used in this study (the IIR). A fund's IIR in quarter t is the

FIGURE 1

Mutual Funds' Portfolio Concentration in Intangibles

Graph A of Figure 1 presents the mean intangibles intensity ratio (IIR) computed for each fund in each quarter as the value-weighted ratio of research and development (R&D) expenses to property, plant, and equipment (PPE) expenses across all the firms in the portfolio. Graph B plots the R&D-to-sales ratio computed as the value-weighted ratio of R&D expenses to sales across all the firms in the portfolio.

Graph A. IIR



Graph B. R&D/Sales

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value-weighted ratio of R&D expenses to PPE expenses of the firms held in the portfolio, computed as

$$\text{IIR}_t = \sum_{s=1}^{N} w_{s,t}(\text{R\&D}/\text{PPE})_{s,t}. \tag{1}$$

Here, $w_{s,t}$ is the portfolio weight of stock s in quarter t in the fund's portfolio of N stocks. Since R&D expenses are usually disclosed annually, $(\text{R\&D}/\text{PPE})_{s,t}$ is the ratio of R&D-to-PPE expenses of firm s in the most recent year before t. The higher (lower) the IIR of a fund, the higher is the fund's concentration in intangibles-intensive (physical assets-intensive) firms. Graph B of Figure 1 plots the value-weighted ratio of R&D expenses to sales (Compustat item 12), where R&D expenses to sales is a popular measure of R&D intensity.

Graph A of Figure 1 shows a visible upward trend in IIR. While in the early 1980s, the implicit R&D expenses were less than 10% of PPE expenses in the firms held by mutual funds, this number has typically been around 40% post-2002 and remains about four times the level in the early 1980s, even in the global recession of 2008–2009. Graph B also reinforces the growing exposure of mutual fund portfolios to firms with intangible assets.

Table 1 presents summary statistics on portfolio holdings using additional measures of mutual funds' exposure to firms with intangible assets for the full sample (Panel A) and for selected fund objectives (Panel B). Various measures are reported over 1980 to 2009, and also for 4 subperiods. In Panel A, the mean IIR for the full sample is 30.8%. The two most conspicuous trends in the portfolios are the IIR and total intangibles-to-PPE ratio, which increase from 11% to 37.4% and 15% to 208.4% between the earliest and the last period, respectively. In Panel B,

TABLE 1

Descriptive Statistics on Mutual Funds' Portfolio Concentration in Intangibles

Table 1 reports descriptive statistics on the intangible assets of firms held by mutual funds during 1980 to 2009. Panels A and B report statistics for the entire sample and for subsamples based on fund objectives, respectively. Mean values (in percentages) averaged across all funds are reported. Intangibles intensity ratio (IIR) of a fund is the value-weighted ratio of R&D-to-PPE expenses across all firms in the portfolio, weighted by the market value of holdings; % R&D stocks is the fraction of the portfolio invested in stocks of firms that spend on R&D. Several alternative measures are computed as the value-weighted ratio of R&D expenses to the following base variables: sales (R&D/Sales), book value of equity (R&D/Book equity), and total assets (R&D/Assets, R&D capital/Assets). Advertising/PPE and Total intangibles/PPE are the value-weighted ratios of advertising expenses and total intangible assets to PPE, respectively. All measures are based on annual data for the firms from the most recent year before the portfolio quarter.

	Overall	1980–1989	1990–1995	1996–2000	2001–2009
Panel A. All Objectives					
Intangibles intensity ratio (IIR)	30.8	11.0	17.2	30.8	37.4
% R&D stocks	40.0	44.3	41.9	42.4	37.8
R&D/Sales	4.3	2.7	3.2	4.6	4.7
R&D/Book equity	7.4	5.3	6.3	9.3	7.2
R&D/Assets	3.3	2.7	3.0	4.0	3.1
R&D capital/Assets	6.3	5.8	6.2	7.9	5.8
Advertising/PPE	10.4	9.6	10.6	7.4	11.6
Total intangibles/PPE	140.9	15.0	45.4	77.4	208.4

(continued on next page)

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TABLE 1 (continued)

Descriptive Statistics on Mutual Funds' Portfolio Concentration in Intangibles

	Overall	1980–1989	1990–1995	1996–2000	2001–2009
Panel B. Selected Objectives					
Aggressive Growth/Growth					
Intangibles intensity ratio (IIR)	32.9	12.0	20.2	34.0	39.9
% R&D stocks	42.1	43.7	42.7	45.0	40.6
R&D/Sales	5.0	2.8	3.8	5.4	5.5
Growth & Income					
Intangibles intensity ratio (IIR)	17.1	8.1	8.9	17.5	21.7
% R&D stocks	40.5	46.8	44.3	45.4	35.3
R&D/Sales	3.3	2.3	2.4	3.6	3.7
Small Cap					
Intangibles intensity ratio (IIR)	50.4	14.3	29.3	42.7	55.0
% R&D stocks	35.8	38.7	35.5	33.9	36.2
R&D/Sales	4.4	2.7	3.6	4.4	4.5
Large Cap					
Intangibles intensity ratio (IIR)	26.0	9.7	12.2	24.9	31.4
% R&D stocks	43.5	46.5	45.3	49.7	41.0
R&D/Sales	4.7	2.6	3.1	4.9	5.2

there is substantial dispersion in IIR across objectives, but the growth in IIR over time is noticeable within all objectives.

Table 2 presents panel regressions predicting IIR. The p-values are from Newey-West (1987) standard errors with a lag length of 3 quarters and clustered by fund. Consistent with time-related stability, PAST_IIR (i.e., the fund's average IIR in the prior 4 quarters) explains a substantial part (= 49.2%) of the variance in IIR in column 1. Objective and year fixed effects in column 2 add some incremental explanatory power (4.8%) beyond PAST_IIR. In column 3, variables that capture a fund's style (SIZE_SCORE, BM_SCORE, and MOM_SCORE) are used to explain IIR. These variables are computed for a fund as the value-weighted DGTW (1997) size, book-to-market (BM) ratio, and momentum quintile across the firms in the portfolio.[10] Column 3 shows that funds with higher IIR have portfolios tilted toward small, growth, and momentum stocks. However, along with year and objective dummy variables, the style measures only explain 36.4% of the variance in IIR. The significantly positive relation between IIR and MOM_SCORE shows that funds that focus on intangibles-intensive firms tend to follow trend-chasing (i.e., extrapolative) strategies. Since existing studies such as Haruvy et al. (2007) show that extrapolative behavior diminishes with investor experience, it is plausible that the positive relation between IIR and trend chasing diminishes with prior experience. In column 4, two variables that proxy for a fund's prior experience, log(FUND_AGE) and log(MANAGER_TENURE), are included along with their interactions with MOM_SCORE. The significantly negative coefficients on MOM_SCORE × log(FUND_AGE) and MOM_SCORE × log(MANAGER_TENURE) suggest that trend chasing in intangibles-intensive investments decreases with prior experience. Note that these tests do not directly address

[10]I am grateful to Russ Wermers for making the DGTW (1997) stock benchmark data available.

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TABLE 2

Multivariate Regressions Explaining Portfolio Concentration in Intangibles

Table 2 reports the results for regressions explaining the intangibles intensity ratio (IIR) of actively managed mutual funds computed for each fund in each quarter t during the period 1980–2009. IIR is as defined in Table 1. PAST_IIR is the fund's average IIR in the 4 prior quarters $t-4$ to $t-1$. A fund's SIZE_SCORE, BM_SCORE, and MOM_SCORE are the value-weighted DGTW (1997) size quintile, DGTW BM quintile, and DGTW momentum quintile in quarter $t-1$, across all the stocks in the fund's portfolio in the quarter, respectively. The log(FUND_AGE) and log(MANAGER_TENURE) are the natural logarithms of the age (in years) of the fund computed from the first offer date, and the number of years that the manager has managed the fund as of the end of quarter $t-1$ plus 1, respectively. EXPENSE_RATIO and TURNOVER are annual values for the expense ratio and turnover of the fund in the prior year. The log(TNA) is the natural logarithm of the fund's total net assets ($mill) as of the end of quarter $t-1$. PAST_FLOWS is the mean monthly growth in TNA due to new money over the 3 months in quarter $t-1$. INDUSTRY_CONC is the fund's Herfindahl index across 10 industry categories in the quarter $t-1$ (see Kacperczyk et al. (2005)), computed as the sum of squared weights in the 10 industries. ACTIVE_SHARE is defined as the share of a fund's portfolio holdings that differ from the fund's benchmark index (see Cremers and Petajisto (2009)) in the quarter $t-1$. The specifications in columns 2–6 include objective and year fixed effects. The p-values (in parentheses) are based on Newey-West (1987) robust standard errors with a lag length of 3 quarters, and account for clustering at the fund level. ** and * indicate significance at the 1% and 5% levels, respectively.

	Dependent Variable: IIR (t)					
	1	2	3	4	5	6
PAST_IIR	0.817**	0.740**		0.660**	0.649**	0.645**
	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)
SIZE_SCORE			−0.042**	−0.017**	−0.017**	−0.016**
			(0.00)	(0.00)	(0.00)	(0.00)
BM_SCORE			−0.191**	−0.074**	−0.077**	−0.076**
			(0.00)	(0.00)	(0.00)	(0.00)
MOM_SCORE			0.059**	0.032**	0.028**	0.027**
			(0.00)	(0.00)	(0.00)	(0.00)
MOM_SCORE × log(FUND_AGE)				−0.006**	−0.006**	−0.006**
				(0.00)	(0.00)	(0.00)
MOM_SCORE × log(MANAGER_TENURE)				−0.003*	−0.002	−0.002
				(0.05)	(0.20)	(0.28)
log(FUND_AGE)				0.022**	0.023**	0.023**
				(0.00)	(0.00)	(0.00)
log(MANAGER_TENURE)				−0.015**	−0.009	−0.010*
				(0.00)	(0.06)	(0.04)
EXPENSE_RATIO					0.202	0.145
					(0.44)	(0.55)
TURNOVER					0.043**	0.043**
					(0.00)	(0.00)
log(TNA)					0.001*	0.001
					(0.03)	(0.09)
PAST_FLOWS					−0.107**	−0.109**
					(0.01)	(0.01)
INDUSTRY_CONC						0.081**
						(0.00)
ACTIVE_SHARE						0.006
						(0.32)
Objective fixed effects	No	Yes	Yes	Yes	Yes	Yes
Year fixed effects	No	Yes	Yes	Yes	Yes	Yes
No. of obs.	96,303	96,303	93,433	70,589	70,589	70,589
R^2	0.492	0.540	0.364	0.556	0.558	0.560

whether the trend chasing by funds focused on intangibles-intensive firms is based on rational expectations or extrapolation bias. This issue is examined later in Section IV.G.

The following fund attributes also known to be related to performance are added in columns 5 and 6 of Table 2: fund size (log(TNA)), fund flows over the 3 months in the quarter (PAST_FLOWS), EXPENSE_RATIO, TURNOVER, INDUSTRY_CONC, and ACTIVE_SHARE (see Cremers and Petajisto (2009)), where the latter four measures reflect activeness.[11] INDUSTRY_CONC is computed as the sum of squared portfolio weights in the 10 industry categories in Kacperczyk et al. (2005). In general, funds with less experienced managers, higher turnover, recent outflows, and higher industry concentration tend to have higher IIR. Comparing the R^2 of the most inclusive model in column 6 with column 1, PAST_IIR has by far the most explanatory power over IIR.

IV. Empirical Results on Mutual Fund Performance

This section examines the link between IIR and the performance of actively managed funds.

A. Performance Measurement

To begin examining fund performance, I first assign each fund to a decile portfolio p at the end of quarter t based on its IIR. In each month in quarter $t+2$, decile portfolio p's excess return ($r_{p,t}$) is computed as the equal-weighted mean excess return of the funds in the portfolio.[12] The performance of each decile portfolio (re-formed quarterly) is then evaluated based on various factor adjustment models, with the most inclusive specification being the following 5-factor model:

$$(2) \quad r_{p,t} = \alpha_p + \beta_p^{\text{MKT}}(\text{RM}_t - \text{RF}_t) + \beta_p^{\text{SMB}}\text{SMB}_t + \beta_p^{\text{HML}}\text{HML}_t + \beta_p^{\text{MOM}}\text{MOM}_t + \beta_p^{\text{LIQ}}\text{LIQ}_t + \varepsilon_{p,t}.$$

Here, $(\text{RM}_t - \text{RF}_t)$ is the monthly return on a value-weighted market proxy portfolio minus T-bills; SMB_t, HML_t, MOM_t, and LIQ_t are returns on factor-mimicking portfolios for size, BM ratio, momentum, and liquidity, respectively (see Fama and French (1993), Carhart (1997), and Pastor and Stambaugh (2003)).[13] Each portfolio's factor loadings ($\widehat{\beta}_p$s) in month t are obtained from time-series regressions over a 36-month window $t-36$ to $t-1$. The abnormal return, or alpha, for decile portfolio p (α_p) is then computed as the monthly excess return minus the product of the factor loadings and factor realizations in month t. Results are generally presented for multiple factor models, which vary in the regressors.

Table 3 reports the mean IIR and factor loadings of the IIR decile portfolios. Column 1 reveals considerable dispersion in IIR between decile 1 (low) and

[11] Following prior studies, the fund flows in month t (i.e., the growth in TNA due to new investments) is calculated as

$$\text{FLOW}_t = \frac{\text{TNA}_t - \text{TNA}_{t-1}(1 + R_t)}{\text{TNA}_{t-1}},$$

where, R_t is the monthly net return of the fund during month t, and TNA_t is the fund's total net asset value at the end of month t as reported in CRSP. Outliers are eliminated by winsorizing the 2.5% tails.

[12] The returns for the decile portfolios are observed in the following quarter t+2 to allow for the portfolio holdings to become public sometime during the 3 months following quarter t (see Kacperczyk et al. (2008)). This additional implementation lag does not affect the results substantially, since the IIR measure is persistent over time.

[13] I am grateful to Kenneth French and Lubos Pastor for providing the factor data.

TABLE 3

Factor Loadings and Persistence of Mutual Funds' Portfolio Concentration in Intangibles

At the end of each quarter t, funds are sorted into decile portfolios based on their IIR as defined in Table 1. Column 1 reports the mean IIR of the funds in each decile portfolio in the ranking quarter t. Columns 2–6 report the time-series mean of the factor loadings (betas) for each decile portfolio estimated from the following 5-factor model

$$r_{p,t} \quad = \quad \alpha_p + \beta_p^{\text{MKT}}(\text{RM}_t - \text{RF}_t) + \beta_p^{\text{SMB}}\text{SMB}_t + \beta_p^{\text{HML}}\text{HML}_t + \beta_p^{\text{MOM}}\text{MOM}_t + \beta_p^{\text{LIQ}}\text{LIQ}_t + \varepsilon_{p,t}.$$

Here, $r_{p,t}$ is the excess return on the decile portfolio p in month t, computed as the equal-weighted mean monthly excess net fund return; $\text{RM}_t - \text{RF}_t$, SMB_t, and HML_t are the 3 factors from Fama and French (1993); MOM_t is the momentum factor used in Carhart (1997); and LIQ_t is the liquidity factor in Pastor and Stambaugh (2003). The factor loadings in month t are obtained by regressing $r_{p,t}$ on the factor realizations over $t-36$ to $t-1$. The "% funds in ±1 decile rank assigned at t in quarter" is the fraction of funds ranked in a decile in the ranking quarter t that remain within one rank in 5 future quarters $t+1$ through $t+5$. The p-values in parentheses are based on Newey-West (1987) standard errors (lag length 12 months). ** and * indicate statistical significance at the 1% and 5% levels, respectively.

	Portfolio-Level Factor Loadings						% Funds in ±1 Decile Rank Assigned at t in Quarter				
	Mean IIR	β_p^{MKT}	β_p^{SMB}	β_p^{HML}	β_p^{MOM}	β_p^{LIQ}	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
IIR Decile (t)	1	2	3	4	5	6	7	8	9	10	11
Decile 1 (most tangibles)	0.033	0.850	0.283	0.189	–0.016	0.018	96.8	95.1	93.9	93.2	93.2
Decile 2	0.075	0.895	0.270	0.136	–0.025	0.012	94.7	92.8	91.6	91.4	90.9
Decile 3	0.106	0.900	0.247	0.068	–0.018	0.003	91.9	88.2	86.5	86.1	86.3
Decile 4	0.136	0.912	0.235	–0.017	0.001	0.008	88.8	84.4	82.5	83.0	83.7
Decile 5	0.163	0.916	0.206	–0.086	0.008	0.004	87.7	83.5	82.0	82.3	82.8
Decile 6	0.191	0.926	0.251	–0.158	0.001	0.011	87.1	82.2	81.1	81.0	81.4
Decile 7	0.230	0.943	0.285	–0.237	0.016	–0.012	88.6	83.8	82.4	82.5	83.0
Decile 8	0.286	0.963	0.378	–0.306	0.034	–0.012	90.8	87.0	85.4	84.5	84.8
Decile 9	0.393	0.977	0.524	–0.451	0.041	–0.029	93.5	90.7	89.5	88.5	88.5
Decile 10 (most intangibles)	0.686	1.006	0.739	–0.561	0.061	–0.044	96.4	94.4	93.2	92.3	92.2
Decile 1 – 10	–0.653**	–0.156**	–0.456**	0.750**	–0.077**	0.062**					
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)					

decile 10 (high). The implicit R&D expenses are 3.3% (68.6%) of PPE on average for decile 1 (decile 10). The factor loadings in columns 2–6 show that funds with higher IIR tend to be more cyclical; comove more with small cap, growth, and momentum stocks; and have less exposure to liquidity risk than funds with lower IIR. Indicating strong persistence in the nature of the firms held by a fund, 96.8% (96.4%) of funds ranked in IIR decile 1 (decile 10) in the ranking quarter t remain within one rank of the assignment in quarter $t+1$ (column 7). The funds' movement across decile ranks remains low beyond $t+1$.

B. Baseline Results

Table 4 reports fund performance using the portfolio-level approach in columns 1–4 and an alternative fund-level approach in columns 5–8. The decile 1–10 returns represent a zero-investment strategy that goes long (short) on funds tilted toward physical assets-intensive (intangibles-intensive) firms. Overall, the funds tilted toward intangibles-intensive firms significantly underperform the funds tilted toward physical assets-intensive firms. For instance, in column 1, the lowest IIR decile outperforms the highest IIR decile by a statistically significant 4.32% per year in terms of the 1-factor alpha. The 3-, 4-, and 5-factor alphas of the decile 1–10 portfolio are statistically and economically significant at 1.79%, 2.85%, and 2.67% per year, respectively. These results can be attributed to the underperformance of high-IIR funds combined with the outperformance of

TABLE 4

Mutual Fund Performance and Portfolio Concentration in Intangibles

Columns 1–4 of Table 4 report the time-series means of the portfolio-level alphas over the 3 months in quarter $t+2$, computed in month m as the excess return on the portfolio minus the product of the factor realizations in month m and the portfolio's factor loadings estimated over the 36-month rolling window $m-36$ to $m-1$. The 1-, 3-, 4-, and 5-factor alphas are obtained from the regression described in Table 3 using the first regressor (Jensen (1968)), the first three regressors (Fama and French (1993)), the first four regressors (Carhart (1997)), and all five regressors (Pastor and Stambaugh (2003)). Columns 5–8 report the time-series means of the fund-level alphas over the 3 months in quarter $t+2$ computed following the rolling-regression method based on the time series of monthly excess return for individual funds. All returns are reported in percentages on a per year basis. The p-values based on Newey-West (1987) robust standard errors with a lag length of 12 months are reported in parentheses. ** and * indicate statistical significance at the 1% and 5% levels, respectively.

	Performance Computed at the Portfolio Level				Performance Computed at the Fund Level			
	1-Factor Alpha	3-Factor Alpha	4-Factor Alpha	5-Factor Alpha	1-Factor Alpha	3-Factor Alpha	4-Factor Alpha	5-Factor Alpha
IIR Decile (t)	1	2	3	4	5	6	7	8
Decile 1 (most tangibles)	1.37*	1.15*	1.58**	1.54**	1.32	0.70	0.72	0.85
	(0.05)	(0.04)	(0.01)	(0.01)	(0.06)	(0.10)	(0.10)	(0.15)
Decile 2	–0.06	0.12	0.45	0.80	–0.14	–0.21	–0.22	0.01
	(0.95)	(0.83)	(0.40)	(0.12)	(0.85)	(0.68)	(0.53)	(0.98)
Decile 3	0.29	0.40	0.76	0.40	0.14	0.23	0.04	0.17
	(0.71)	(0.43)	(0.15)	(0.41)	(0.84)	(0.48)	(0.91)	(0.61)
Decile 4	–0.11	0.26	0.29	0.32	0.03	0.05	–0.34	–0.14
	(0.88)	(0.61)	(0.58)	(0.55)	(0.95)	(0.89)	(0.27)	(0.65)
Decile 5	–0.57	–0.20	–0.06	–0.02	–0.31	–0.04	–0.38	–0.29
	(0.39)	(0.70)	(0.92)	(0.98)	(0.61)	(0.89)	(0.25)	(0.39)
Decile 6	–0.76	–0.27	–0.10	–0.14	–0.98	–0.60	–0.97*	–0.86**
	(0.34)	(0.61)	(0.86)	(0.80)	(0.15)	(0.07)	(0.02)	(0.01)
Decile 7	–0.77	–0.03	–0.18	–0.06	–1.05	–0.38	–0.46	–0.72
	(0.43)	(0.96)	(0.78)	(0.93)	(0.23)	(0.31)	(0.24)	(0.10)
Decile 8	–0.91	–0.26	–0.09	–0.02	–1.23	–0.20	–0.69	–0.76*
	(0.10)	(0.71)	(0.90)	(0.98)	(0.25)	(0.43)	(0.14)	(0.05)
Decile 9	–1.54*	–0.33	–0.31	–0.44	–1.22	–0.64	–0.79	–0.67
	(0.05)	(0.58)	(0.72)	(0.38)	(0.20)	(0.18)	(0.17)	(0.18)
Decile 10 (most intangibles)	–2.95**	–0.64	–1.27*	–1.13	–1.81**	–0.95	–1.31*	–1.68*
	(0.01)	(0.63)	(0.04)	(0.10)	(0.01)	(0.10)	(0.05)	(0.04)
Decile 1 − 10	4.32**	1.79*	2.85**	2.67**	3.13**	1.65**	2.03**	2.53**
	(0.00)	(0.03)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
Quintile 1 − 5	2.86*	1.28*	1.78**	1.66*	1.77*	1.32	1.37*	1.56*
	(0.02)	(0.05)	(0.01)	(0.02)	(0.02)	(0.08)	(0.02)	(0.04)

low-IIR funds. The alphas appear to decline with increasing IIR deciles nearly uniformly.

In columns 5–8 of Table 4, I estimate the risk-adjusted returns at a fund level. Here, a fund's factor loadings in month t are obtained from regressing the fund's monthly excess returns on the benchmark factors over $t-36$ to $t-1$. The mean fund-level alphas across funds in each decile portfolio averaged over all the months are reported and provide similar conclusions. The results so far are consistent with mutual fund managers exhibiting more skill when they focus on traditional physical assets-based firms than when they focus on modern intangibles-intensive firms. Hereafter, the results of nonparametric analyses are reported using the portfolio approach, but they are robust to using the fund-level approach and other commonly used risk-adjustment methods.[14]

[14]In unreported robustness checks, results remained unchanged on using two additional risk adjustment methods. First, the alpha of each decile portfolio equaled the intercept of the time-series

C. Omitted Factors, Stock Returns, and IIR

An important concern in interpreting the central results is whether there are omitted systematic risk or mispricing factors common to the types of stocks held by funds that vary in their IIR. In this case, it is not straightforward to interpret the main results as fund managers of funds with low IIR exhibiting more skill in generating abnormal returns than fund managers of funds with high IIR.

To address these concerns, I first augment the common 4- and 5-factor models with a new factor that captures the cross section of expected stock returns linked to the nature of the firm. Every month, I compute the return on a factor-mimicking IMT portfolio that goes long high-R&D stocks and short no-R&D stocks.[15] The IMT factor can be viewed as an omitted risk factor (see Chambers et al. (2002)), or a mispricing factor capturing systematic misvaluation of intangibles-intensive versus physical assets-intensive firms. The interpretation of IMT is not of particular importance in this study, since it is meant simply to account for systematic factors linked inherently to IIR that also predict stock returns. The goal is to incorporate IMT as a factor into the model generating a fund's abnormal return, so that the loading and premium on IMT captures the proportion of mean return attributable to the passive strategy of going long high-R&D stocks and short no-R&D stocks. A fund's loading on IMT should increase with its IIR.

Figure 2 plots the mean equal-weighted monthly return on the IMT portfolio in each year. Consistent with existing studies, high R&D-to-PPE firms tend to earn *higher* stock returns than no-R&D firms. The IMT portfolio earns a substantial 1.63% per month on average. This is the first indication that augmenting factor models with IMT should, in fact, increase the spread in abnormal returns between funds with low IIR and funds with high IIR rather than "explain" this return spread.

Table 5 reports the abnormal returns obtained from adjustments for omitted factors linked to the nature of the firm. Column 1 reports the mean loadings on IMT (δ_p^{IMT}) for IIR decile portfolios for the augmented 5-factor model with IMT as a sixth regressor. As expected, the lower (higher) IIR deciles load negatively (positively) on IMT. Moreover, the main results hold, with the decile 1–10 alphas exceeding 6.54% per year for the augmented 4- and 5-factor models. In sum, controlling for omitted factors in the pricing of firms that vary in

regression of the monthly portfolio excess returns on common risk factors. Second, the alphas for each decile portfolio are computed following the two-step Fama and MacBeth (1973) method, where cross-sectional regressions are run in each time period for each decile on common risk factors, followed by time-series tests to determine the alphas from the intercepts. These additional methods serve to confirm the results when risk is adjusted by in-sample estimations, which could be important when R&D investments can change a firm's systematic risk (see Berk, Green, and Naik (2004)). The results are available from the author.

[15]For the IMT portfolio, at the end of each year, the R&D-to-PPE ratios for eligible stocks are computed where eligible stocks are selected following Pastor and Stambaugh (2003). The stocks are then sorted into 11 portfolios: portfolio 0 with zero R&D-to-PPE stocks ("no-R&D stocks"), and 10 equal-sized portfolios with nonzero R&D-to-PPE ranging from portfolio 1 ("low-R&D stocks") to 10 ("high-R&D stocks"). The return on the IMT portfolio is the return on the equal-weighted portfolio 10 minus portfolio 0. The subsequent results are robust to alternative specifications of the IMT portfolio, including value weighting the portfolios.

FIGURE 2

IMT Portfolio Return

Figure 2 plots the average monthly equal-weighted return for the intangibles-minus-tangibles (IMT) portfolio that goes long high-R&D stocks and short no-R&D stocks. High-R&D stocks is the equal-weighted portfolio of stocks ranked in the highest decile of R&D-to-PPE in the most recent year. No-R&D stocks is the equal-weighted portfolio of stocks with zero R&D-to-PPE in the most recent year.

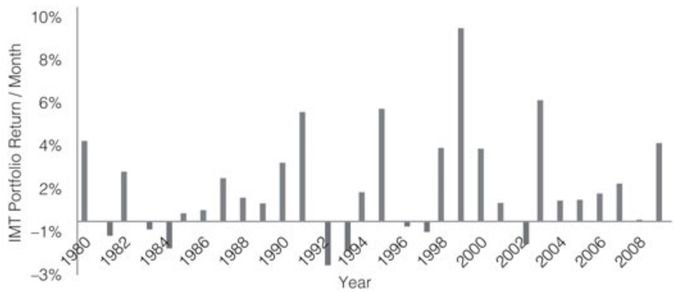

TABLE 5

Mutual Fund Performance Adjusted for Omitted Factors in Factor Adjustment Models

Table 5 reports the portfolio-level alphas for IIR portfolios formed in quarter t over the 3 months in quarter $t+2$. The alphas are obtained from the regression of the monthly net excess return on decile portfolio p in month t ($r_{p,t}$) on all or some of the 5 factors defined in Table 3, in addition to an IMT and UMO factor. IMT is the intangibles-minus-tangibles factor that is long on high-R&D stocks and short on no-R&D stocks, as defined in Figure 2. UMO is the underpricing-minus-overpricing misvaluation factor in Hirshleifer and Jiang (2010) that is long on underpriced and short on overpriced stocks. The 4- (5-) factor w/IMT alpha is obtained from the above regression using the first four (five) regressors and IMT_t. The 5-factor w/UMO (w/UMO, IMT) alpha is obtained from the above regression using the first five regressors with UMO (UMO and IMT). Here, δ_p^{IMT} is the time-series mean of the coefficient on IMT_t obtained from the 5-factor w/IMT specification. All returns are reported in percentages on a per year basis. The p-values based on Newey-West (1987) robust standard errors with a lag length of 12 months are reported in parentheses. ** and * indicate statistical significance at the 1% and 5% levels, respectively.

IIR Decile (t)	δ_{IMT} 1	4-Factor w/ IMT Alpha 2	5-Factor w/ IMT Alpha 3	5-Factor w/ UMO Alpha 4	5-Factor w/ UMO, IMT Alpha 5
Decile 1 (most tangibles)	−0.539**	2.57**	2.63**	1.82**	2.93**
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)
Decile 2	−0.491**	1.20*	1.20*	0.83	1.16*
	(0.00)	(0.03)	(0.03)	(0.12)	(0.04)
Decile 3	−0.237**	1.16*	1.27*	0.41	1.47**
	(0.00)	(0.03)	(0.02)	(0.43)	(0.01)
Decile 4	−0.235**	0.70	0.74	0.38	1.03*
	(0.00)	(0.18)	(0.17)	(0.48)	(0.05)
Decile 5	−0.105**	0.22	0.27	0.66	0.85
	(0.00)	(0.70)	(0.63)	(0.29)	(0.13)
Decile 6	−0.021	−0.13	−0.17	0.23	0.34
	(0.49)	(0.82)	(0.76)	(0.67)	(0.55)
Decile 7	0.105**	−0.35	−0.21	0.27	0.75
	(0.00)	(0.58)	(0.74)	(0.64)	(0.24)
Decile 8	0.317**	−0.50	−0.43	0.18	0.81
	(0.00)	(0.48)	(0.56)	(0.80)	(0.26)
Decile 9	0.541**	−1.43	−1.28	0.05	−0.11
	(0.00)	(0.10)	(0.20)	(0.97)	(0.87)
Decile 10 (most intangibles)	1.683**	−3.97**	−3.94**	−0.22	−1.33
	(0.00)	(0.00)	(0.00)	(0.77)	(0.08)
Decile 1 − 10	−2.222**	6.54**	6.57**	2.04**	4.26**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Quintile 1 − 5	−1.605**	4.56**	4.48**	1.53*	2.10**
	(0.00)	(0.00)	(0.00)	(0.05)	(0.00)

R&D-to-PPE *increases*, rather than explains, the underperformance of high-IIR funds relative to low-IIR funds. In columns 4 and 5 of Table 5, I also include Hirshleifer and Jiang's (2010) underpriced-minus-overpriced (UMO) factor to account for potential systematic mispricing of the style of stocks held. Consistent with earlier results, the IIR decile 1–10 alphas remain significantly positive.

D. Performance Decomposition: Fund Manager Skill, Fees, and Transaction Costs

In earlier sections, the results reported were based on net returns, which are a function of fund managers' skill as well as fees and transaction costs, and measure the returns passed on to investors. This section examines the relation between IIR and the components of fund performance, among which before-cost returns reflect the value added by managers using their selection and timing skills.

Table 6 reports the components of fund returns for the IIR decile portfolios using the performance decomposition approach of DGTW (1997) and Wermers (2000), who decompose returns into the fund manager's stock selection, style selection, timing ability, fees, and transaction costs. The following six components of returns are analyzed: gross holdings return (i.e., holdings' buy-and-hold stock return), characteristic selectivity (CS), characteristic timing (CT), average style (AS), annual expenses (EXPENSE_RATIO), and TURNOVER capturing transaction costs. The measures are further described in Wermers. By splitting each fund's portfolio into stocks with below-mean (low R&D/PPE) and above-mean (high R&D/PPE) R&D-to-PPE ratios in the quarter, Table 6 also reports the gross holdings return and CS of the subportfolios of stocks with low R&D-to-PPE and high R&D-to-PPE separately.[16] Table 6 shows that funds with high IIR charge higher fees and incur more transaction costs than funds with low IIR to at least partially explain their after-cost underperformance. However, the funds with high IIR also show significantly poorer before-cost stock selection skills relative to funds with low IIR. In columns 1 and 3, the funds in IIR decile 1 pick stocks that outperform the stocks picked by funds in IIR decile 10 by 314 (213) basis points per year based on gross returns (CS). Interestingly, the high-IIR funds underperform low-IIR funds in physical assets-intensive holdings (columns 2 and 5) as well as intangibles-intensive holdings (columns 3 and 6). The disparity in the performance of the majority holdings of funds focused on physical assets-intensive firms versus those focused on intangibles-intensive firms is notable. The low R&D/PPE portfolio of IIR decile 1 funds outperforms the high R&D/PPE portfolio of IIR decile 10 funds by a CS of 3.95%. The decile 1–10 difference in AS of 1.39% is also positive and statistically significant. Finally, the IIR decile 10 funds on average have expense ratios that are 18 basis points and turnovers that are nearly 43% higher on an annual basis than IIR decile 1 funds. The funds with high IIR exhibit the "anomaly" of inferior before-fee performers charging higher expense ratios documented by Gruber (1996) and Gil-Bazo and Ruiz-Verdu (2009), among others.

[16]The sample of funds is restricted to those that have low R&D/PPE as well as high R&D/PPE subportfolios.

TABLE 6

Return Decomposition for Mutual Funds and Portfolio Concentration in Intangibles

The following components of fund returns are reported in Table 6: value-weighted return on the stock portfolio (gross holdings return), characteristic selectivity (CS), characteristic timing (CT), average style (AS), EXPENSE_RATIO, and TURNOVER. All and low (high) R&D/PPE represent the fund's whole portfolio and subportfolio of stocks with below (above) mean values of R&D/PPE in the quarter, respectively. The components of fund returns are computed on a monthly basis and reported as percentages per year. The expense ratio and turnover are reported as annual percentage values. The components are reported for each decile portfolio as an equal-weighted average across all funds in the decile across all months. The *p*-values based on Newey-West (1987) robust standard errors with a lag length of 12 months are reported in parentheses. ** and * indicate statistical significance at the 1% and 5% levels, respectively.

	Gross Holdings Return				CS							
	All	Low R&D/PPE	High R&D/PPE	Low − High R&D/PPE	All	Low R&D/PPE	High R&D/PPE	Low − High R&D/PPE	CT	AS	EXPENSE_RATIO	TURNOVER
IIR Decile (*t*)	1	2	3	4	5	6	7	8	9	10	11	12
Decile 1 (most tangibles)	14.70	14.75	13.87	0.88	1.28	1.33	0.50	0.83	−0.01	13.43	1.16	70.28
Decile 2	13.52	13.53	13.47	0.06	1.25	1.26	1.11	0.15	0.06	12.22	1.13	71.67
Decile 3	14.14	16.32	13.87	2.45**	1.79	1.94	0.54	1.40**	−0.08	12.43	1.08	71.20
Decile 4	13.49	15.02	13.26	1.76**	1.77	1.97	0.42	1.55**	−0.16	11.88	1.09	75.49
Decile 5	12.92	14.85	12.61	2.24**	1.72	1.91	0.54	1.37*	−0.81	12.02	1.13	76.13
Decile 6	12.90	13.77	12.74	1.03*	1.02	1.11	0.57	0.54	0.21	11.67	1.11	80.20
Decile 7	12.47	12.33	13.08	−0.75	0.45	0.45	0.44	0.01	0.54	11.48	1.14	88.95
Decile 8	12.79	12.73	13.01	−0.28	0.55	0.45	0.91	−0.46	0.22	12.02	1.12	93.06
Decile 9	11.80	12.27	10.32	1.95*	0.05	0.12	−0.17	0.29	0.42	11.33	1.15	104.44
Decile 10 (most intangibles)	11.55	13.19	8.28	4.91**	−0.85	−0.01	−2.62	2.61**	0.36	12.04	1.34	113.20
Decile 1 − 10	3.15**	1.56**	5.59**		2.13**	1.34**	3.12**		−0.37	1.39*	−0.18**	−42.92**
	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)		(0.23)	(0.04)	(0.00)	(0.00)
Quintile 1 − 5	2.04**	1.43**	4.02**		1.35	1.18	1.72*		−0.09	0.99	−0.08*	−39.23**
	(0.00)	(0.01)	(0.00)		(0.06)	(0.07)	(0.02)		(0.88)	(0.13)	(0.04)	(0.00)

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E. Additional Robustness Checks

This section reports robustness tests that assess alternative explanations for the main results.

1. Does IIR Proxy for Past (Intangible or Total) Stock Returns?

Given the evidence in Daniel and Titman (2006) and Jiang (2010), if the IIR measure overweights innovative firms with high recent intangible returns, the main results may be explained by IIR proxying for stocks that are more likely to experience reversals of the intangible component of returns. This would make the interpretation based on fund managers' skill in valuing intangibles less clear.

Table 7 reports fund performance in settings that control for past stock returns. In Panel A, funds are sorted into quartiles based on the funds' value-weighted intangible stock returns over the 1-year window, and (independently) into quintiles based on IIR. The funds with high IIR continue to underperform the funds with low IIR within groups of funds with similar exposure to intangible stock returns. The results in Panel B based on a 5-year window are similar.

TABLE 7

Past Stock Returns and Portfolio Concentration in Intangibles

Panels A and B of Table 7 report the portfolio-level 4-factor alphas from monthly net excess returns in quarter $t+2$ for portfolios formed in quarter t by independently sorting funds into quintile portfolios based on IIR, and quartile portfolios based on the intangible returns on the stocks they hold. In Panel A (Panel B), the intangible returns on the stocks held by a fund are computed as the value-weighted intangible stock returns, where a stock's intangible return is computed in the most recent calendar year as the intangible component of the 1-year (5-year) stock return. Panel C reports the portfolio-level 4-factor alphas from monthly net excess returns for quintile portfolios sorted based on IIR in quarter t, where the portfolio weights used to compute IIR are based on stock prices lagged by m months from the last month of quarter t, where m is 3, 6, 9, or 12 months. The p-values based on Newey-West (1987) robust standard errors with a lag length of 12 months are reported in parentheses. ** and * indicate statistical significance at the 1% and 5% levels, respectively.

IIR Quintile (t)	Quartile 1	Quartile 2	Quartile 3	Quartile 4
Panel A. Sorting on Past Intangible Stock Returns (1 year)				
Quintile 1 (most tangibles)	0.80	0.89	0.61	1.79*
Quintile 2	0.39	0.23	0.46	0.96
Quintile 3	0.02	−0.60	−0.45	−0.88
Quintile 4	−0.01	−0.59	−0.48	−0.74
Quintile 5 (most intangibles)	−0.19	−0.63	−1.08	−1.58*
Quintile 1 − 5	0.99	1.52*	1.69**	3.37**
	(0.19)	(0.03)	(0.01)	(0.00)
Panel B. Sorting on Past Intangible Stock Returns (5 year)				
Quintile 1 (most tangibles)	0.39	0.87*	0.70	1.24*
Quintile 2	0.40	−0.21	0.17	0.75
Quintile 3	−0.05	−0.40	−0.84	−0.56
Quintile 4	−0.19	−0.21	−0.68	−0.91
Quintile 5 (most intangibles)	0.09	−0.70	−1.33	−1.45*
Quintile 1 − 5	0.30	1.57*	2.03**	2.69**
	(0.60)	(0.05)	(0.00)	(0.00)
IIR Quintile (t)	$m = 3$	$m = 6$	$m = 9$	$m = 12$
Panel C. Portfolio Weights from Stock Prices Lagged by m Months				
Quintile 1 (most tangibles)	1.81**	1.79**	1.60*	1.30*
Quintile 2	0.35	0.45	0.32	0.28
Quintile 3	−0.24	−0.26	−0.29	−0.40
Quintile 4	−0.80	−0.80	−0.75	−0.72
Quintile 5 (most intangibles)	−1.21*	−1.17	−1.12	−1.20*
Quintile 1 − 5	3.02**	2.96**	2.72**	2.50**
	(0.00)	(0.00)	(0.00)	(0.01)

The setting in Panel C of Table 7 controls for past total (instead of intangible) stock returns. To separate out the impact of recent price run-ups that may proxy for mispricing, I compute IIR at the end of quarter t from portfolio weights that use lagged stock prices instead of end-of-quarter prices. I report returns in quarter $t+2$ for funds sorted into IIR quintiles, where the IIR uses stock prices lagged by 1–4 quarters. The results remain very robust, thereby ruling out patterns in recent stock returns as an explanation for the negative relation between IIR and future fund returns.

2. Long-Term Fund Performance

Another possibility that has not been considered so far is that funds with higher IIR benefit from market corrections of underpriced stocks over longer horizons. Table 8 addresses this issue by using decile ranks based on longer lags in IIR. Table 8 reports 4-factor alphas for the IIR decile portfolios with IIR measured from holdings lagged by up to 12 quarters, reported in 2-quarter increments. The decile 1–10 return spread remains statistically and economically meaningful until 10 quarters following the measurement of IIR. Thus, IIR predicts long-term fund performance.

TABLE 8

Long-Term Performance and Portfolio Concentration in Intangibles

Table 8 reports the portfolio-level 4-factor alphas from monthly net excess returns for decile portfolios in quarters $t+4$, $t+6$, $t+8$, $t+10$, and $t+12$ based on the rolling-regression method described in Table 4. The 4 benchmark factors used to compute alphas are ($RM_t - RF_t$), SMB_t, HML_t, and MOM_t and are as defined in Table 3. The *p*-values based on Newey-West (1987) robust standard errors with a lag length of 12 months are reported in parentheses. ** and * indicate statistical significance at the 1% and 5% levels, respectively.

	4-Factor Alpha in Quarter				
	$t+4$	$t+6$	$t+8$	$t+10$	$t+12$
IIR Decile (t)	1	2	3	4	5
Decile 1 (most tangibles)	1.42**	1.21*	1.12*	1.08*	0.77
	(0.01)	(0.04)	(0.03)	(0.04)	(0.15)
Decile 2	0.63	0.63	0.67	0.73	1.00
	(0.25)	(0.21)	(0.21)	(0.17)	(0.08)
Decile 3	0.61	0.52	0.77	0.21	0.76
	(0.23)	(0.34)	(0.15)	(0.71)	(0.16)
Decile 4	0.27	0.71	0.85	0.60	0.02
	(0.61)	(0.20)	(0.13)	(0.30)	(0.98)
Decile 5	−0.19	0.32	0.43	0.28	0.24
	(0.73)	(0.55)	(0.42)	(0.61)	(0.68)
Decile 6	−0.02	0.26	0.07	0.03	−0.07
	(0.98)	(0.65)	(0.90)	(0.96)	(0.90)
Decile 7	0.20	0.05	0.08	0.21	0.21
	(0.73)	(0.93)	(0.90)	(0.74)	(0.76)
Decile 8	0.04	0.02	0.16	0.10	0.50
	(0.95)	(0.98)	(0.82)	(0.89)	(0.49)
Decile 9	−0.73	0.06	−0.10	−0.13	−0.22
	(0.14)	(0.94)	(0.91)	(0.88)	(0.76)
Decile 10 (most intangibles)	−1.11	−0.41	−0.33	−0.28	−0.35
	(0.10)	(0.73)	(0.23)	(0.49)	(0.77)
Decile 1 − 10	2.53**	1.62**	1.45*	1.36	1.12
	(0.00)	(0.01)	(0.05)	(0.07)	(0.17)
Quintile 1 − 5	1.70*	1.13	0.98	0.77	0.59
	(0.05)	(0.09)	(0.10)	(0.21)	(0.26)

3. Fund Attributes

The existing literature suggests that certain fund attributes affect fund performance, and perhaps the relation between IIR and fund returns (e.g., fund size in Berk and Green (2004)). I perform robustness checks to see whether the main results hold across funds that vary in their attributes by double-sorting based on IIR and various fund attributes. The main results hold across the subsamples of funds that vary in their attributes (e.g., size and activeness). Due to space considerations, these results are reported in Table A1 in the Online Appendix (www.jfqa.org).

4. Alternative Measures of Intangibles

Apart from innovative assets, a firm's value may also be driven by intangibles captured by advertising expenses or other noninnovative intangibles (e.g., copyrights). Furthermore, the investors' ability to value intangibles may depend on the category of intangibles. Table 9 reports 4-factor alphas for decile portfolios

TABLE 9

Portfolios of Mutual Funds Sorted on
Alternative Measures of Portfolio Concentration in Intangibles

Table 9 reports the portfolio-level 4-factor alphas from monthly net excess returns in quarter $t+2$ of the funds in decile portfolios based on various measures of mutual funds' exposure to intangibles-intensive firms in quarter t. Columns 1–6 sort funds based on R&D as the measure of intangible assets. In column 7, funds are sorted based on the value-weighted number of patents granted to a firm in the prior year. In columns 8–10, funds are sorted based on the value-weighted ratio of PPE expenses to total assets, advertising expenses to PPE, and total intangibles as reported in accounting statements to PPE. The p-values based on Newey-West (1987) robust standard errors with a lag length of 12 months are reported in parentheses. ** and * indicate statistical significance at the 1% and 5% levels, respectively.

	Firms' Intangibles Based on									
	% R&D Stocks	R&D/ Sales	R&D/ Book Equity	R&D/ Market Equity	R&D Capital/ Assets	R&D Increase/ Sales	No. of Patents	PPE/ Assets	Adver-tising/ PPE	Total Intan-gibles/ PPE
	1	2	3	4	5	6	7	8	9	10
Decile 1 (most tangibles)	1.25*	1.76**	1.95**	0.67	1.62**	1.21	0.62	–1.81**	0.50	–0.39
	(0.04)	(0.01)	(0.00)	(0.31)	(0.00)	(0.07)	(0.32)	(0.01)	(0.46)	(0.53)
Decile 2	0.77	0.73	0.70	0.99*	0.74	0.28	0.58	–0.06	0.39	–0.03
	(0.24)	(0.23)	(0.29)	(0.05)	(0.24)	(0.60)	(0.51)	(0.95)	(0.54)	(0.95)
Decile 3	0.06	0.71	0.56	0.40	0.65	0.23	0.36	0.47	–0.23	–0.28
	(0.93)	(0.26)	(0.37)	(0.41)	(0.32)	(0.64)	(0.67)	(0.52)	(0.70)	(0.57)
Decile 4	–0.05	0.62	–0.18	0.23	0.34	0.66	0.81	0.16	0.37	0.11
	(0.94)	(0.28)	(0.78)	(0.88)	(0.57)	(0.20)	(0.30)	(0.80)	(0.53)	(0.83)
Decile 5	–0.40	–0.09	–0.07	0.03	–0.47	–0.04	0.20	0.38	–0.58	0.63
	(0.55)	(0.88)	(0.91)	(0.98)	(0.43)	(0.94)	(0.74)	(0.54)	(0.34)	(0.28)
Decile 6	–0.18	0.08	–0.23	0.02	–0.32	0.34	–0.72	0.14	–0.08	0.53
	(0.78)	(0.89)	(0.70)	(0.96)	(0.62)	(0.52)	(0.20)	(0.80)	(0.90)	(0.40)
Decile 7	0.15	–0.42	–0.18	–0.11	–0.26	–0.12	–0.20	0.13	0.40	0.99
	(0.79)	(0.47)	(0.77)	(0.80)	(0.65)	(0.85)	(0.71)	(0.79)	(0.39)	(0.15)
Decile 8	0.26	–0.50	0.03	–0.20	–0.38	–0.02	–0.42	0.01	–0.15	0.27
	(0.64)	(0.46)	(0.96)	(0.59)	(0.59)	(0.98)	(0.33)	(0.98)	(0.82)	(0.71)
Decile 9	–0.18	–0.77	–0.61	–0.45	–0.01	–0.99	–0.56	0.20	–0.22	–0.18
	(0.78)	(0.34)	(0.40)	(0.50)	(0.97)	(0.11)	(0.20)	(0.72)	(0.61)	(0.84)
Decile 10 (most intangibles)	–0.76	–1.05	–0.98	–0.81	–0.98	–0.72	–0.90*	0.19	–0.48	–0.51
	(0.21)	(0.16)	(0.18)	(0.10)	(0.10)	(0.23)	(0.05)	(0.83)	(0.34)	(0.57)
Decile 1 — 10	2.01**	2.81**	2.93**	1.48*	2.60**	1.93*	1.52*	–2.00**	0.98	0.12
	(0.01)	(0.00)	(0.00)	(0.05)	(0.00)	(0.04)	(0.04)	(0.01)	(0.22)	(0.81)
Quintile 1 — 5	1.55*	2.02**	2.10**	0.98	1.95**	1.12	1.04	–1.49*	0.16	0.08
	(0.02)	(0.01)	(0.00)	(0.09)	(0.01)	(0.06)	(0.10)	(0.05)	(0.75)	(0.91)

of funds formed based on the portfolio concentration in intangibles, measured as the fraction of a fund's portfolio invested in stocks of firms that spend on R&D in column 1, and the value-weighted ratio of R&D expenses to various base variables in columns 2–4.[17] In column 5, R&D capital is scaled by total assets;[18] in column 6, annual R&D expense increase is scaled by lagged sales. Column 7 employs a widely used measure of innovative output (i.e., patents granted). Column 8 sorts funds on the value-weighted PPE intensity. Finally, columns 9 and 10 present results based on other categories of intangibles (scaled by PPE) that include noninnovative assets, namely, advertising and total intangible assets (Compustat items 45 and 33). The results based on innovative assets (columns 1–7) are qualitatively very similar to those reported earlier. The decile 1–10 alpha in column 8 is also consistent with other findings, since funds focused on firms with low PPE intensity underperform those focused on firms with high PPE intensity. Interestingly, returns do not vary significantly between funds that vary in their exposure to intangibles-intensive firms based on advertising expenses and total (accounting-based) intangible assets. These findings suggest that fund managers perform poorly when they focus on firms valued on innovative assets, while noninnovative intangibles do not appear to have a significant effect on abnormal returns. Perhaps the long-term value of innovative assets is particularly hard to assess due to their uniqueness to the firm (Aboody and Lev (2000)), while other intangible inputs (e.g., advertising) may share more commonalities across firms.

5. Other Robustness Checks

Additional tests summarized in Table A2 in the Online Appendix show that the results are not driven by the dot-com bubble and bust period (1997–2002), since they hold in the 1980–1996, 1997–2002, and 2003–2009 periods. The results are also robust to skewness in returns, TNA weighting the alphas, exclusion of technology stocks in computing IIR, and excluding funds with extreme TNA and risk factor loadings, and do not simply mirror compositional effects related to fund objectives.

F. Valuation Difficulty versus the Nature of the Firm

Can the cross-sectional differences in fund performance across funds that vary in their IIR be attributed to the nature of the firm? In addition to the misvaluation of intangibles, studies in behavioral finance suggest alternative channels via which forecasting errors could enter fund managers' valuation of firms. For instance, when the information is sparse, and valuation uncertainty and information asymmetry is high, behavioral biases lead to magnified forecasting errors (DHS (1998), (2001)).

This section presents parsimonious tests that separate the effect of general information problems from the effect of the nature of the firm. Controlling for

[17] Market value of equity is computed following Chan, Lakonishok, and Sougiannis (2001).

[18] Following Chan et al. (2001), the R&D_CAPITAL for firm s at the end of year t in which annual R&D expenses are denoted by $\mathrm{RD}_{s,t}$ is computed as

$$(\mathrm{R\&D\_CAPITAL})_{s,t} = \mathrm{RD}_{s,t} + 0.8\,\mathrm{RD}_{s,t-1} + 0.6\,\mathrm{RD}_{s,t-2} + 0.4\,\mathrm{RD}_{s,t-3} + 0.2\,\mathrm{RD}_{s,t-4}.$$

information problems such as valuation uncertainty, if the performance of funds with high IIR is similar to those with low IIR, the results reported in earlier sections are most likely driven by forecasting errors linked to general valuation difficulties rather than the nature of the firm. For these tests, based on previous studies, I first select the following asset characteristics that proxy for a firm's information environment: firm size, firm age, BM ratio, and volume turnover.[19] While each of these stock or firm attributes may reflect other noninformational factors (e.g., liquidity), they share the theme of proxying for the difficulty in firm valuation. Based on aggregating these asset characteristics on a value-weighted basis, I develop fund-level measures of what I call the "proxies for valuation difficulty" (VD).

Table 10 reports 4-factor alphas for portfolios formed by double-sorting funds on VD and IIR. Three portfolios of funds (low 25%, medium 50%, and high 25%) are formed in each quarter, including funds that have a VD ranked in the lowest 25%, middle 50%, and highest 25%. Within each group, funds are then sorted into quintiles on IIR. The disparity in the risk-adjusted return of small-cap funds (i.e., low 25% or high VD group based on SIZE_SCORE) across IIR quintiles is striking. Small-cap funds in IIR quintile 1 (quintile 5) produce an alpha of 3.01% (−2.42%). The IIR quintile 1–5 alpha for these funds is a large 5.43% per year. Taken with the evidence in Schultz (2010) that funds focused on difficult-to-value small firms outperform, it appears that fund managers display significant skill when they focus on stocks with low information availability and high information asymmetry, except when they invest in intangibles-intensive innovative segments.[20] This is in spite of the fact that, controlling for firm size, firms having intangible assets are actually linked to *more* analyst following and effort than traditional firms (Barth, Kasznik, and McNichols (2001)). For the medium 50% and high 25% SIZE_SCORE groups, the IIR quintile 1–5 alphas remain positive and significant. The results based on firm age, BM ratio, and trading volume are similar. In general, the significantly positive (negative) alphas of larger magnitude are generated by funds focused on difficult-to-value firms in the lower (higher) IIR quintiles.

Overall, the results are consistent with the fund managers' forecasting errors in valuation being associated with the nature of the firm, and not by firms' information problems per se.[21] In fact, fund managers exhibit significant skill when they focus on difficult-to-value firms in physical assets-intensive segments.

[19]Small-cap stocks have more information uncertainty and lower information availability due to less analyst following (Zhang (2006), Hong, Lim, and Stein (2000)). Young firms with shorter histories have more information uncertainty and less publicly available information compared to older firms. Glamour (i.e., low BM) stocks are valued based mainly on intangible information regarding future growth prospects, where investors find intangible information difficult to process (DHS (2001), Lakonishok, Shleifer, and Vishny (1994)). Volume turnover measured for a stock as the ratio of the monthly trading volume to the shares outstanding proxies for the ambiguity in the stock's true value (Kumar (2009)).

[20]Consistent with Schultz (2010), who uses gross returns, the 4-factor alphas from net returns reveal the outperformance of small-cap funds on average. The low 25% SIZE_SCORE funds have an overall mean alpha of 2.73% per year.

[21]Note that the analyses do not test for specific types of forecasting errors (e.g., errors due to overconfidence vs. limited attention), since the main goal is to examine general forecasting errors, irrespective of mechanism.

TABLE 10

Portfolios of Mutual Funds Sorted on Proxies for Valuation Difficulty and Portfolio Concentration in Intangibles

Funds are sorted into three groups representing the funds with the lowest 25%, middle 50%, and highest 25% in quarter *t* based on valuation difficulty (VD) of portfolios: SIZE_SCORE, AGE_SCORE, BM_SCORE, or TRADING_VOLUME_SCORE. SIZE_SCORE, AGE_SCORE, BM_SCORE, and TRADING_VOLUME_SCORE are the value-weighted DGTW (1997) size quintile, firm age, DGTW BM quintile, and mean monthly trading volume in the most recent quarter across all the fund's holdings in the quarter, respectively. Within each group, funds are then sorted into quintiles based on IIR. Table 10 reports the portfolio-level 4-factor alphas from monthly net excess returns in quarter $t+2$ of the quintile portfolios within each low-/medium-/high-VD group. The *p*-values (in parentheses) are based on Newey-West (1987) robust standard errors (lag length of 12 months). ** and * indicate statistical significance at the 1% and 5% levels, respectively.

	SIZE_SCORE			AGE_SCORE		
IIR Quintile (*t*)	Low 25% (high VD)	Medium 50%	High 25% (low VD)	Low 25% (high VD)	Medium 50%	High 25% (low VD)
Quintile 1 (most tangibles)	3.01**	0.59	−0.45	2.27**	0.95	−0.55
	(0.00)	(0.40)	(0.26)	(0.01)	(0.07)	(0.23)
Quintile 2	1.83**	−0.06	−0.72	0.79	0.96	−0.62
	(0.01)	(0.91)	(0.18)	(0.39)	(0.10)	(0.12)
Quintile 3	1.66*	−0.39	−0.58	−0.24	−0.34	−0.19
	(0.03)	(0.40)	(0.17)	(0.81)	(0.45)	(0.59)
Quintile 4	0.33	−0.07	−0.77	−1.11	−0.21	−0.63
	(0.74)	(0.91)	(0.10)	(0.20)	(0.69)	(0.15)
Quintile 5 (most intangibles)	−2.42*	−1.58*	−1.89**	−2.44**	−0.55	−1.64
	(0.02)	(0.04)	(0.00)	(0.00)	(0.54)	(0.06)
Quintile 1 − 5	5.43**	2.17**	1.44*	4.71**	1.50**	1.09
	(0.00)	(0.01)	(0.05)	(0.00)	(0.01)	(0.08)
	BM_SCORE			TRADING_VOLUME_SCORE		
IIR Quintile (*t*)	Low 25% (high VD)	Medium 50%	High 25% (low VD)	High 25% (high VD)	Medium 50%	Low 25% (low VD)
Quintile 1 (most tangibles)	−0.05	0.37	1.21*	1.01*	1.08	1.02
	(0.93)	(0.46)	(0.03)	(0.05)	(0.12)	(0.06)
Quintile 2	−0.32	−0.08	0.29	−0.57	0.28	0.09
	(0.66)	(0.88)	(0.55)	(0.56)	(0.65)	(0.84)
Quintile 3	−0.69	−0.41	0.29	−1.13	0.00	0.62
	(0.42)	(0.31)	(0.50)	(0.17)	(1.00)	(0.19)
Quintile 4	−1.82*	−0.37	0.25	−0.99	−0.43	−0.11
	(0.02)	(0.45)	(0.61)	(0.17)	(0.48)	(0.82)
Quintile 5 (most intangibles)	−3.51**	−1.01	0.20	−2.91**	−0.80	−0.25
	(0.00)	(0.09)	(0.73)	(0.01)	(0.07)	(0.55)
Quintile 1 − 5	3.46**	1.38*	1.01	3.92**	1.88*	1.27*
	(0.00)	(0.05)	(0.15)	(0.00)	(0.02)	(0.04)

It is plausible that learning from past experience and data equip fund managers' valuation techniques to handle information difficulties in traditional firms, hence turning mispricing into attractive opportunities, while the techniques for intangibles-intensive firms remain flawed.[22]

G. Multivariate Regressions Explaining Fund Performance

The results reported earlier in nonparametric settings show that fund managers outperform (underperform) when their portfolios are concentrated in physical assets-intensive (intangibles-intensive) firms. Moreover, Table 2 shows

[22]This notion is consistent with the data, since the value-weighted firm age of the firms in which funds with low IIR invest is twice that of the firms in which funds with high IIR invest.

a positive relation between a fund's trend-chasing tendency and investments in intangibles-intensive firms, alluding to forecasting errors arising from extrapolation bias in valuing intangibles as a potential source of the underperformance of funds with high IIR. If this trend-chasing tendency does indeed represent extrapolation bias for funds with high IIR, it should be detrimental for fund performance. Also, since prior studies suggest that forecasting errors and behavioral biases such as extrapolation bias decrease with learning, prior experience of fund managers could serve to reduce any such biases that affect their valuation of intangibles. With these possibilities in mind, this section analyzes fund performance in a multivariate setting with a twofold purpose: to examine the robustness of the link between IIR and fund returns in a parametric setting, and to explore whether extrapolation bias and learning are among the channels via which the nature of the firm affects fund performance.

In addition to the mean returns, I examine two other attributes of fund returns that could be pertinent to mutual fund investors during the selection of funds (i.e., volatility and maximum payoffs). Portfolio theory proposes that traditional investors maximize expected returns and minimize the volatility of returns. Given the higher volatility of R&D stocks (see Chan et al. (2001)), the volatility of fund returns likely increases with IIR, thereby proposing another channel via which IIR may affect the welfare of fund investors. Also, given the skewness of innovative assets' returns, investors may care about the potentially higher skewness of funds with higher IIR.[23]

Table 11 presents the results of regressions explaining fund-level excess returns, 4-factor alphas, volatility of excess returns (volatility), and maximum excess returns (maximum return). A fund's volatility and maximum return are measured in month t as the standard deviation of the fund's monthly excess returns and maximum monthly excess returns over the next 12 months $t+1$ to $t+12$. All specifications include year fixed effects. The significant negative relation between IIR and fund performance (i.e., excess return and 4-factor alpha) in specifications that control for fund fixed effects lends further support to the preferred explanation of the main results in this study, that is, that fund managers exhibit more skill when they focus on physical assets-intensive firms than when they focus on intangibles-intensive firms, since the fixed effects largely subsume any fund-, manager-, and family-level heterogeneities in skill and performance.

Several interesting results emerge when variables representing trend-chasing behavior and prior experience are incorporated in columns 2 and 5. First, the significantly negative coefficient on MOM_SCORE $\times$ IIR shows that the return of funds that exhibit trend-chasing behavior significantly decreases with their IIR. These findings point to the trend-chasing behavior representing extrapolation bias (vs. rational momentum strategies) for funds with higher IIR. Second, consistent with fund managers learning about valuing intangibles with experience,

[23]Recent papers show that some stock market investors prefer assets with positive skewness in returns, in spite of their potentially negative expected returns (e.g., Barberis and Huang (2008), Bali, Cakici, and Whitelaw (2011)). For studies documenting the skewness of innovative asset returns, see Scherer and Harhoff (2000), Hall, Jaffe, and Trajtenberg (2005), and Silverberg and Verspagen (2007). Anecdotal evidence also points to high skewness in the returns on innovative assets such as patents. For example, Pfizer's Lipitor patent generated sales of more than $12.2 billion in 2005.

TABLE 11

Multivariate Regressions Explaining Attributes of Fund Returns

The dependent variables are annualized monthly excess returns (columns 1–3), monthly 4-factor alpha (columns 4–6), volatility (columns 7–9), and maximum return (columns 10–12) over the 3 months in each quarter $t + 2$, respectively. Volatility and maximum return in a month are the standard deviation of monthly excess returns and the maximum monthly excess return over the next 12 months, respectively. LAGGED_IMT_RETURN is the mean IMT portfolio return (defined in Table 5) over the 6 months $t - 5$ to t. Fund controls (suppressed) are SIZE_SCORE, BM_SCORE, EXPENSE_RATIO, TURNOVER, log(TNA), INDUSTRY_CONC, ACTIVE_SHARE, and PAST_FLOWS. All specifications include year fixed effects, and fund or objective fixed effects. The *p*-values (in parentheses) are based on Newey-West (1987) standard errors with a lag length of 12 months, and account for clustering at the fund level. ** and * indicate significance at the 1% and 5% levels, respectively.

	Excess Return			4-Factor Alpha			Volatility			Maximum Return		
	1	2	3	4	5	6	7	8	9	10	11	12
IIR	–0.148**	–0.028*	–0.031**	–0.027**	–0.019**	–0.016**	0.017**	0.010**	0.017**	0.052**	0.201**	0.379**
	(0.00)	(0.02)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)
IIR × LAGGED_IMT_RETURN		–0.366*	–0.562**		–0.131*	–0.157**		0.115**	0.115**		1.814**	1.796**
		(0.03)	(0.00)		(0.04)	(0.00)		(0.00)	(0.00)		(0.00)	(0.00)
IIR × MOM_SCORE		–0.042**	–0.035**		–0.028**	–0.026**		0.001	0.000		0.026	0.011*
		(0.01)	(0.00)		(0.00)	(0.00)		(0.23)	(0.27)		(0.23)	(0.05)
LAGGED_IMT_RETURN		0.811**	0.860**		0.196**	0.190**		–0.034**	–0.038**		–1.701**	–1.791**
		(0.00)	(0.00)		(0.00)	(0.00)		(0.00)	(0.00)		(0.00)	(0.00)
MOM_SCORE		–0.008*	–0.002		0.001	–0.003*		0.002**	0.004**		0.015**	0.061**
		(0.03)	(0.36)		(0.56)	(0.03)		(0.00)	(0.00)		(0.01)	(0.00)
IIR × log(FUND_AGE)		0.026**	0.019**		0.008*	0.009**		–0.003**	–0.003**		–0.078**	–0.102**
		(0.00)	(0.00)		(0.03)	(0.00)		(0.00)	(0.00)		(0.00)	(0.00)
IIR × log(MANAGER_TENURE)		0.013*	0.007		0.005	0.004		–0.002**	–0.001*		–0.077**	–0.024**
		(0.04)	(0.10)		(0.14)	(0.26)		(0.00)	(0.04)		(0.00)	(0.00)
log(FUND_AGE)		–0.017**	–0.002		–0.012**	–0.004**		0.001**	0.001**		0.014**	0.024**
		(0.00)	(0.41)		(0.00)	(0.00)		(0.01)	(0.00)		(0.01)	(0.00)
log(MANAGER_TENURE)		–0.010**	0.000		–0.000	0.003**		0.001**	–0.000		0.020**	–0.002
		(0.00)	(0.98)		(0.85)	(0.00)		(0.00)	(0.22)		(0.00)	(0.47)
Fund fixed effects	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No
Fund controls	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Objective fixed effects	No	No	Yes	No	No	Yes	No	No	Yes	No	No	Yes
Year fixed effects	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
No. of obs.	285,970	279,452	166,449	265,773	259,255	146,252	274,827	267,711	154,708	274,827	267,711	154,708
R^2	0.013	0.100	0.106	0.021	0.030	0.019	0.265	0.751	0.676	0.255	0.597	0.489

the negative impact of IIR on returns significantly reduces with past experience. The results are similar where fund fixed effects are replaced with objective fixed effects and various untabulated fund-level control variables.

Additionally, columns 7–12 of Table 11 show that volatility and maximum returns significantly increase with IIR. Taken together with earlier results on fund returns, it is evident that the mean-variance efficiency of a fund's portfolio decreases, and the maximum payoff increases, with the fund's IIR. Furthermore, the results in columns 7–12 suggest that trend-chasing behavior increases the volatility and maximum payoff of funds to a larger extent for funds with higher IIR, and past experience reduces the positive impact of IIR on volatility and maximum payoff.

V. Summary and Conclusions

Using the portfolio holdings of actively managed U.S. mutual funds, this paper uncovers a significant link between the value created by fund managers' skill and the nature of the firms they invest in. First, fund managers exhibit significantly inferior (superior) skill in generating risk-adjusted returns when their portfolios are tilted toward stocks of intangibles-intensive (physical assets-intensive) firms. The results are stronger when the factor models are adjusted for potential omitted systematic factors associated with the nature of the firm. Funds tilted toward intangibles-intensive firms underperform those tilted toward physical assets-intensive firms in the intangibles-intensive as well as physical assets-intensive components of their portfolios. Second, mutual fund managers tend to exhibit skill when they focus on difficult-to-value firms, except when the difficult-to-value firms are valued based on intangibles. Third, there is evidence that funds' extrapolation bias increases with their focus on intangibles-intensive firms, and this bias is detrimental to performance. In line with the presence of learning, the extrapolation bias and the negative impact of investments in intangibles-intensive firms on returns decrease with funds' prior experience. Finally, the nature of the firm affects the welfare of fund investors via multiple channels, since the maximum payoff and volatility increases, and the mean-variance efficiency decreases, with the funds' exposure to intangibles-intensive firms.

The findings in this study raise several issues that may be promising avenues for future research. Although this paper clearly suggests that mutual funds tilted toward intangibles-intensive firms have inferior mean-variance properties but higher maximum payoffs than those tilted toward physical assets-intensive firms, it does not test whether fund investors account for how the properties of fund returns satisfy their preferences. Such clientele effects could be a critical factor in the survival of poor performers. Also, this study calls attention to the possibility that active management may not justify its costs in some market segments that seem to offer ample opportunities for exploiting market inefficiencies (e.g., innovative firms). Further research along these lines could lend fresh perspectives to comparisons between passive and active portfolio management.

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