# Fund Manager Use of Public Information: New Evidence on Managerial Skills

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## ABSTRACT

We show theoretically that the responsiveness of a fund manager's portfolio allocations to changes in public information decreases in the manager's skill. We go on to estimate this sensitivity (*RPI*) as the $R^2$ of the regression of changes in a manager's portfolio holdings on changes in public information using a panel of U.S. equity funds. Consistent with *RPI* containing information related to managerial skills, we find a strong inverse relationship between *RPI* and various existing measures of performance, and between *RPI* and fund flows. We also document that both fund- and manager-specific attributes affect *RPI*.

THE CONCEPT OF SOPHISTICATED INVESTORS permeates the economic literature in several areas, including market microstructure, tests of the efficient market hypothesis, and the performance evaluation of financial institutions. Sandroni (2000, p.1303) succinctly describes these investors as those who "are consistently better in predicting prices." Whether such investors exist and whether they outperform others has been the subject of debate for at least a few decades, particularly in the literature on mutual funds. Specifically, while a vast number of performance measures have been proposed and extensively used to identify successful fund managers,[1] several studies question whether these measures actually capture managerial skills, given existing alternative explanations, such as luck, model misspecification, survivorship bias, or weak statistical

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[1] For a comprehensive summary of most of the measures, see Wermers (2004).

power of empirical tests undermining the source of high performance.[2] As a result, there is no clear consensus on whether factor-based or holding-based performance measures truly capture skills.[3] In this paper, we argue that to the extent that the value of a sophisticated investor derives from the private information he brings to the investment process, the crucial step in identifying his skill is to determine how much he relies on publicly available information. Following this argument, we provide a unique perspective on the issue of whether traditional performance measures capture skills by relating these measures to the degree to which a fund manager relies on public information.

To motivate our empirical analysis, we develop a simple model and show that the scope of a manager's private information can be measured by examining the sensitivity of his portfolio holdings to changes in information in the public domain. We build on the noisy Rational Expectations Equilibrium model of Grossman and Stiglitz (1980) and argue that the precision of relevant private information for asset investment is related to managerial skills. We show that in such a setting, the sensitivity of the investor's holdings to changes in public information decreases in his skill level. We then use this result to develop the metric *RPI* (Reliance on Public Information), which measures this sensitivity. In particular, *RPI* clarifies whether traditional performance measures indeed reflect skill, in that managers who produce high values of these measures should also have low sensitivities of their portfolio holdings to changes in public information.

We generate two empirical predictions to validate our central hypothesis that *RPI* contains information related to managerial skills. First, if *RPI* is related to managerial skills, then low *RPI* managers should outperform managers with high *RPI*.[4] Importantly, although we argue that *RPI* should be low for skilled managers, that is, those presumably with high values of traditional performance measures, *RPI* might be low for reasons not necessarily related to the use of private information. For example, if relying on information in the public domain were observable and penalized, managers with no private information would have incentives to follow investment strategies based on noise. Such investors, though unskilled, would also exhibit low *RPI*. Another possibility is that *RPI* could be low if investors followed passive strategies without considering any information. However, although managers following any of these alternatives would have low *RPI*, they would be unable to deliver abnormal performance, as measured by traditional measures. As a result, empirically, only

[2] See, Kosowski et al. (2006) for a discussion on luck; Baks, Metrick, and Wachter (2001), Pástor and Stambaugh (2002), Avramov and Wermers (2006) for clever arguments on model misspecification rooted in Bayesian inference; Brown and Goetzmann (1995) for a discussion of survivorship bias; and Kothari and Warner (2001) for a discussion on the power of empirical tests.

[3] One type of remedy, originally suggested by Dybvig and Ross (1985), is to condition returns on information sets. Several studies focus on specifying various sets of information that, in conjunction with existing performance measures, could help identify skillful managers. See, Grinblatt and Titman (1989) and Chen and Knez (1996) for earlier studies; more recent ones include Ferson and Khang (2002), Cohen, Coval, and Pástor (2005), and Kacperczyk, Sialm, and Zheng (2005).

[4] Note that this argument relies on the notion that under informationally efficient markets, reliance on any information in the public domain should not generate abnormal returns.

under our hypothesis should we find a negative relationship between traditional performance measures and *RPI*.[5] Empirical validation of this prediction would support the argument in favor of traditional performance measures capturing skills. Second, if *RPI* contains information on managerial skills, such as a manager's reliance on private information, that may not be precisely reflected in traditional performance measures, flows from outside investors would rationally chase low *RPI* funds, even after controlling for past performance. Thus, empirically, we should find a negative relationship between fund flows and *RPI*.

One of the required inputs in constructing *RPI* is information in the public domain. We rely on evidence from existing studies and use analysts' past recommendations to capture this information. In our choice of analysts' recommendations, we are mostly influenced by Elton, Gruber, and Grossman (1986, p. 699), who note that "stock recommendations are one of the few cases in evaluating information content where the forecaster is recommending a clear and unequivocal course of action rather than producing an estimate of a number, the interpretation of which is up to the user." In addition, Womack (1996), Kim, Lin, and Slovin (1997), and Jegadeesh et al. (2004) show that changes in sell-side analysts' recommendations carry useful predictive information about asset fundamentals. At the same time, Brennan, Jegadeesh, and Swaminathan (1993) show that since information contained in analysts' recommendations has a short-lasting effect on prices, following information contained in past recommendations should preclude profit opportunities.[6] Consequently, we use changes in analysts' *past* recommendations to capture changes in information in the public domain. In our empirical analysis, we calculate *RPI* of a particular fund as the $R^2$ of the regression of percentage changes in its portfolio holdings on changes in analysts' past recommendations.

Using a large panel of nearly 1,700 actively managed U.S. equity funds over the period 1993 to 2002, we document evidence consistent with our hypotheses. Consistent with our first prediction, we find that mutual funds with lower *RPI*, that is, those relying less on information in the public domain, tend to exhibit significantly higher returns adjusted for commonly used risk/style factors such as market, size, value, and momentum. Furthermore, using the holding-based performance decomposition of Daniel et al. (1997), we find that consistent with such funds having superior private information the superior performance of those funds can be largely attributed to their stock-picking abilities. Both factor- and holding-based results are robust to various fund-specific controls, such as size, age, turnover, and expenses, and are statistically and economically

[5] In expecting such a relationship between *RPI* and traditional performance measures, we are making an implicit assumption that traditional performance measures are related to skills, at least in part. If traditional measures were unrelated to skills, we would have found no relationship between these measures and *RPI*, even if our hypothesis were true.

[6] We also use analysts' *past* recommendations to avoid a possible endogeneity between changes in current portfolio holdings and changes in analysts' recommendations, that is, the case in which analysts may change recommendations in response to changes in portfolio holdings.

significant: On average, a one-standard deviation increase in *RPI* decreases the four-factor risk-adjusted return of Carhart (1997) by 0.46 % per year and the characteristic selectivity measure (*CS*) by 0.44 % per year. The results remain qualitatively unchanged if we use conditional performance measures, indicating that the superior performance of funds with low *RPI* is not due to their greater responsiveness to macroeconomic conditions or due to their superior market-timing abilities.

Consistent with our second prediction, we find that, controlling for past fund performance and other fund-specific characteristics, funds with low *RPI* are rewarded with higher money flows, suggesting that outside investors learn about managerial skills from *RPI* and allocate their wealth accordingly (Dangl, Wu, and Zechner (2006)). We conduct a variety of additional tests that, taken together, provide strong support for the robustness of our findings. In particular, our results are robust to different specifications of *RPI*, alternative public information sets, the use of fund fixed effects, the presence of information spillovers between stocks in the manager's portfolio, fund size, turnover, and style. We also find that, in addition to fund characteristics, manager-specific attributes affect *RPI* and hence may have a role to play in explaining the abnormal performance delivered by a fund. Finally, we find that funds with high *RPI* take on more risk, both systematic and idiosyncratic. This finding is consistent with the notion that managers with lower skills take on excessive risk to improve their investment record (Brown, Harlow, and Starks (1996)).

Our paper makes several contributions to the literature. First, it offers a novel approach for determining the relationship between traditional performance measures and managerial skills. Specifically, the model we develop shows that a manager's reliance on public information is related to his skills, and provides robust evidence of an economically (and statistically) significant relationship between reliance on public information and various performance measures. As a result, our findings on *RPI* strengthen the interpretation of traditional performance-based measures as reflecting skills and suggest that some fund managers may indeed be more skillful than others. Moreover, *RPI* also extends our understanding of the existing holding-based (DGTW) performance measures by relating changes in the holdings in the manager's portfolio to aggregate data at a fundamental level (changes in public information) rather than relating them to changes in observed returns, which are taken as given. In other words, while our analysis focuses on understanding what type of information causes the manager's holdings to change and then relating the sensitivity of this change to returns, the DGTW measures are concerned with understanding how changes in holdings (caused for whatever reason) are systematically related to returns. Second, besides providing a method for identifying informed managers, our measure captures information that is not captured by traditional performance measures. In particular, we find that *RPI* can be used in conjunction with the traditional performance measures to assess the value of a manager to an outside investor. Finally, we provide evidence that manager-specific attributes, apart from fund-specific characteristics, might have a role to play in explaining a mutual fund's abnormal performance.

The rest of the paper proceeds as follows. Section I outlines a simple model and delivers the main empirical predictions. Section II describes construction of the data we use to test the predictions. Section III presents the reliance on public information (*RPI*) measure and analyzes its relationship to fund-specific variables. The empirical results related to our two main predictions are discussed in Section IV. Section V presents extensions and robustness, and Section VI concludes.

## I. Simple Model and Empirical Predictions

In this section we present a simple model to detect managerial skills and we formulate the model's testable predictions. Our central premise, like in Cohen, Coval, and Pástor (2005), is that the skill level of an informed investor is captured by the precision of the private signal he receives. This premise differs from that in Grossman and Stiglitz (1980), who assume that any investor can acquire a private signal by paying a constant fee. Given our premise, our focus in the model is to establish how the portfolio holdings of informed investors move with changes in public information relative to the portfolio holdings of uninformed investors.

### *A. Base Model*

We consider a standard Grossman and Stiglitz (1980) economy with two periods, namely, today, when investors choose portfolios, and tomorrow, when assets in these portfolios pay off. An investor's opportunity set includes one risk-free asset, cash, which has a constant price normalized to one, and one risky asset ($\mathcal{A}_1$), stock, whose future value, $u$, is normally distributed with mean $\bar{u}$ and precision $\rho_0$. The per capita stock of the risky asset, $t$, is independently normally distributed with mean $\bar{t}$ and precision $\eta$. The assumption of random net supply is a standard device in rational expectation models, with one theoretical justification being that it approximates noise trading in the market. The price of the stock, $p$, is endogenously determined in the market. Traders trade at $(1, p)$ per share and receive payoffs tomorrow of $(1, \tilde{u})$ per share.

Investors in this economy receive signals today about the future value of the risky asset. For simplicity (with no loss of generality), we assume that the signals are of two kinds: $s_1$ is a private signal observed only by informed investors and $s_2$ is a public signal observed by everyone. These signals are drawn independently from a normal distribution with a common mean $\bar{u}$ and precisions of $\rho_1$ and $\rho_2$, respectively. Following the existing literature (e.g., O'Hara (2003)), let $\mu$ be the fraction of investors in the economy that receive private signals about the asset. Note that the public and private signals are independent, conditional on the value of the asset, and the form of the distributions is common knowledge. There are $N$ investors, indexed by $n = 1, \ldots, N$, each having CARA utility with a coefficient of risk aversion of $\lambda > 0$. In equilibrium, these investors hold the available supply of cash and stock. Since the investors are risk averse and the stock is risky, the risk will be priced.

Each investor chooses his demand for the risky asset that maximizes his expected utility subject to a standard budget constraint, which is given by

$$m^n + p\alpha^n = \bar{m}^n, \tag{1}$$

where $\alpha^n$ is the number of shares of the stock he buys, $m^n$ is the amount of cash he holds, and $\bar{m}^n$ is his initial wealth. His terminal wealth is given by the random variable

$$\tilde{w}^n = m^n + \tilde{u}\alpha^n. \tag{2}$$

Using (1), the wealth of the investor can be written in a standard fashion as the sum of his initial wealth plus his subsequent capital gains, that is,

$$\tilde{w}^n = \bar{m}^n + (\tilde{u} - p)\alpha^n. \tag{3}$$

Consider now the optimization problem of investor $n$. He conjectures that the payoff of the stock, conditional on his information, is normally distributed with mean $\bar{u}^n$ and precision $\rho^n$. With the assumption of CARA utility and normal distributions, investor $n$'s objective function has a standard mean-variance representation. Specifically, he chooses $\alpha^n$ that maximizes

$$E[\tilde{w}^n] - \frac{\lambda}{2}\mathrm{Var}[\tilde{w}^n]. \tag{4}$$

We find the equilibrium (details provided in Appendix A) by solving the above optimization problem for $p$ and verifying that the form of the price function is linear and of the form conjectured in (A4). As a result, we obtain the following partially revealing REE for the risky asset:

$$p = a\bar{u} + bs_1 + cs_2 - dt + e\bar{t}, \tag{5}$$

where $a = \frac{\rho_0}{\gamma}$, $b = \frac{\mu\rho_1 + (1-\mu)\rho_\theta}{\gamma}$, $c = \frac{\rho_2}{\gamma}$, $d = \frac{\lambda(1+\frac{(1-\mu)\rho_\theta}{\mu\rho_1})}{\gamma}$, $e = \frac{(1-\mu)\rho_\theta\lambda}{\mu\rho_1\gamma}$, and $\gamma = (\rho_0 + \rho_2 + (1-\mu)\rho_\theta)$.

In this REE, prices are partially revealing. As a result, informed and uninformed investors have differing expectations. Let us now analyze the properties of the demand functions of the informed and uninformed investors with respect to public information about the risky asset. Since we are interested in how much the holdings of an informed investor change relative to the holdings of an uninformed investor, we analyze the difference between the per capita holdings of informed and uninformed investors. This difference is given by:

$$\Delta \equiv x_I - x_U = \frac{s_1(\rho_1 - \rho_\theta) + p(\rho_\theta - \rho_1) + \dfrac{\rho_\theta\lambda}{\mu\rho_1}(t - \bar{t})}{\lambda}. \tag{6}$$

Note that $E[x_I - x_U] = \frac{E[\tilde{u} - p](\rho_1 - \rho_\theta)}{\lambda} > 0$, indicating that ex ante, compared to uninformed investors, informed investors hold on average more of the risky asset. This underlies the essence of our argument: Informed investors are able to use their private information to their advantage by shifting their portfolios relative to those of the uninformed.

To analyze how public information affects portfolios of the informed and the uninformed, consider the impact of changes in public information, $s_2$, on the difference in holdings, $\Delta$. Taking a partial derivative with respect to $s_2$, we obtain

$$\frac{\partial \Delta}{\partial s_2} = \frac{\rho_2(\rho_\theta - \rho_1)}{\gamma\lambda} < 0. \tag{7}$$

Importantly, note that

$$\frac{\partial^2 \Delta}{\partial s_2 \partial \rho_1} = -\frac{\lambda^3 \rho_2}{\gamma(\lambda^2 + \mu^2 \rho_1 \eta)^2} < 0. \tag{8}$$

Hence, consistent with (7), the arrival of good (bad) public information lowers (boosts) the holdings of the risky asset by informed investors relative to those of the uninformed investors. This occurs in equilibrium since good (bad) public news has more of a positive (negative) effect on the uninformed investors' beliefs than it does on informed traders' beliefs simply because the uninformed investors put more weight on the public signal than the informed investors do. This implies that the holdings of the uninformed are more responsive to public information. Moreover, in line with (8), holdings of the informed investors are more responsive to public information when these investors have noisier private information. The intuition for this result is straightforward. The more precise the private signal, the less weight informed investors put on their public signal. Thus, based upon both the model and our central premise, we expect that more skilled investors receive more accurate private information ($s_1$ with higher $\rho_1$) and observe a weaker portfolio response to changes in public information. To the extent that informed investors exhibit different degrees of skill, as we define here, then in the cross section one should expect that this response, the reliance on public information (*RPI*), provides sufficient variation for us to make economic inferences.

Note that like most working models in microstructure (e.g., Foster and Viswanathan (1990)), our framework can distinguish those investors that can process public information more accurately than others (irrespective of whether they acquire $s_1$ or not). According to these models, such investors get an additional signal about $u$ on account of their accuracy, and as a result, assign a smaller weight to the public signal. Thus, processing public information more accurately and receiving private signals are in some sense synonymous.

### B. Empirical Predictions

Based on the discussion thus far, we formally state our null and alternative hypotheses as follows:

$H_N$ : *Managerial skill is related to the sensitivity of a manager's holdings to changes in information in the public domain.*

$H_A$ : *Managerial skill is not related to the sensitivity of a manager's holdings to changes in information in the public domain.*

To operationalize our hypothesis into testable predictions, we measure *RPI* based on the sensitivity of a manager's holdings to changes in information in the public domain. We then rank managers based on this measure, noting that more skilled managers should be those with lower sensitivity. Next, we develop two empirical predictions to validate that *RPI* is related to managerial skills.

Our first prediction examines whether *RPI* is related to a manager's subsequent portfolio performance.[7] If existing performance measures reflect managerial sophistication, then under the null we should find a negative relationship between current *RPI* and subsequent portfolio performance. Formally, we propose the following testable prediction:

PREDICTION 1: *A manager's reliance on information in the public domain is negatively associated with subsequent portfolio performance.*

As highlighted earlier, empirical validation of this prediction would support the argument in favor of traditional performance measures capturing skills. Rejection of this prediction would support the alternative hypothesis. This could happen, for instance, if there was little heterogeneity among managers in the sensitivity of holdings to changes in information in the public domain.

With respect to mutual funds, well-documented evidence shows that fund flows chase past performance (e.g., Gruber (1996), Chevalier and Ellison (1997)). If *RPI* contains information on managerial skills, such as the degree to which a manager relies on public information, that may not be precisely reflected in traditional performance measures, flows from outside investors would rationally chase low *RPI* funds. Consequently, under the null, we should observe a significant negative relationship between *RPI* and flows, controlling for past performance. This discussion results in our second prediction:

PREDICTION 2: *Fund flows from outside investors are negatively related to the level of a manager's RPI, conditional on his past performance.*

We would reject this prediction if either the information captured by *RPI* was fully reflected in traditional performance measures or if the outside investors believed that $H_A$ is true.

## II. Data

We form our main data set by merging four databases, namely, CRSP Survivorship Bias Free Mutual Fund Database, the CDA/Spectrum holdings database, the IBES stock analyst recommendation data, and the CRSP stock

[7] Although most of our results involve a setting with fund managers, consistent with the existing literature (e.g., Cohen et al. (2005), Wermers (2004)), in our empirical tests we will use data at fund level. In Section V.B we examine in more detail whether manager-specific attributes play an important role in determining *RPI*.

price data. The CRSP Mutual Fund Database provides information about fund returns, total net assets, different types of fees, investment objectives, and other fund characteristics. One major constraint associated with using CRSP is that it does not provide detailed information about fund holdings. We therefore follow the methodology in Wermers (2000) and Kacperczyk, Sialm, and Zheng (2005) and merge this data set with the stock holdings database published by CDA Investments Technologies. The CDA database provides the stock holdings of virtually all U.S. mutual funds, with no minimum survival requirement for a fund to be included in the database. The data are collected both from reports filed with the SEC and from voluntary reports generated by the funds. We link each reported stock holding to the CRSP stock database to find its price. The vast majority of funds have holdings of companies listed on the NYSE, NASDAQ, or AMEX stock exchanges. The funds for which we are unable to identify the price of certain holdings constitute less than 1% of all holdings.

Next, we associate each portfolio holding with the respective analysts' past recommendations of up to five quarters as published by IBES. This database provides investment recommendations for all stocks primarily tracked by sell-side analysts. The recommendations of different brokerage houses are presented in a uniform format (from 1 for "strong buy" to 5 for "strong sell"). Importantly, the recommendations are presented using an inverse scale, that is, a "lower" recommendation is better, and thus an "upgrade" is indicated by a negative change in the numerical value. In our sample, the data consist of the estimates of 8,993 analysts, covering 7,766 firms. On average, an analyst in IBES follows about 9.7 firms in a year, with a standard deviation of 7.2 firms.

Finally, we apply several filters to the data. Since *RPI* is derived using holdings of U.S. equity, we eliminate balanced, bond, and international funds. In addition, we exclude index funds since we believe that our method works best for managers whose portfolio decisions are information-sensitive. We also exclude sector funds as we only focus on funds whose performance evaluation falls under the same rubric as that of the diversified equity funds, and to avoid double-counting of funds, we include funds with multiple share classes only once. Given that the recommendations data we use run from January 1993 to December 2002, we exclude observations outside these dates. With all the exclusions, our final sample includes 1,696 actively managed diversified equity funds. To our knowledge, our data set is the most comprehensive one ever used in this context. Further details pertaining to the data construction process can be found in Appendix C.

## III. Reliance on Public Information (RPI)

In this section, we describe the construction of *RPI* and analyze its properties and its relationship to other fund-specific variables.

### *A. Construction of RPI*

We construct *RPI* based on the sensitivity of managers' portfolio holdings to information in the public domain. As we explain above, to measure information in the public domain, for any stock at a given point of time we use analysts' past recommendations for that stock. We assume that all the past recommendations are publicly observable and in the information set of all the managers at the time they make an investment decision. Such an information set has several desirable properties. First, the public information set we use is fund specific, as compared, for example, to that in Ferson and Schadt (1996) and Ferson and Khang (2002), who analyze the impact of aggregate macro information on a fund's portfolio returns. As will become clear, working with fund-specific information allows us to construct the measure without relying extensively on a time series of the data. Second, for each stock in the fund's portfolio, an analyst's recommendation is an aggregated outcome of analyst research and as such contains information that comes from many different sources. Finally, in contrast to many other potential public information events (e.g., merger announcement, CEO turnover, etc.), analyst data are vastly dispersed both along the cross section and the time series, allowing us to assemble a rich set of panel data for our tests.

We now discuss potential concerns related to our information set we have chosen. First, we are aware that this information set may form a subset of the entire set of information available in the public domain. However, we believe that taking a smaller subset of the domain biases our tests against finding a negative relationship between our measure and performance, as more investors who use public information from sources other than analysts' recommendations would likely be classified as skilled. Second, choosing analysts' recommendations does not necessarily mean that we ignore other publicly available information. In fact, it is likely that since analysts' recommendations are formed taking into account other observed data, they capture other relevant sources of information in the public domain. Finally, the design of our tests does not allow us to comment on the role of speed of managers' reactions to information in the public domain. Thus, managers with a similar sensitivity to information in the public domain would have similar *RPI*s, irrespective of the speed with which they trade.

We estimate *RPI* using a two-step procedure. In the first step, we find how much of the average percentage changes in a fund's quarterly holdings can be attributed to changes in analysts' recommendations. Specifically, for each fund $m$ and period $t$ from 1993 to 2002, we estimate the following cross-sectional regression using all stocks $i = 1$ to $n$ in the fund's portfolio:

$$\begin{aligned}\%\Delta Hold_{i,m,t} &= \beta_{0,t} + \beta_{1,t}\Delta Re_{i,t-1} + \beta_{2,t}\Delta Re_{i,t-2} + \beta_{3,t}\Delta Re_{i,t-3} \\ &\quad + \beta_{4,t}\Delta Re_{i,t-4} + \epsilon_{m,t}, \quad i = 1, \ldots, n, \end{aligned} \tag{9}$$

where $\%\Delta Hold_{i,m,t}$ denotes a percentage change in stock split-adjusted holdings of stock $i$ held by a manager of fund $m$ from time $t-1$ to $t$, $\Delta Re_{i,t-p}$ measures a change in the recommendation of the consensus forecast of stock $i$ from time $t-p-1$ to time $t-p$, and $p = 1, 2, 3, 4$ is the number of lags of the forecast. Note that with $\Delta Re = 0$, if the forecast does not change between two consecutive reports.[8] We classify an observation as missing if we do not observe a forecast for any quarter required in the specification above. Since adding a new stock position into a fund portfolio would imply an infinite increase in the holdings of the stock, in such cases we set $\%\Delta Hold_{i,m,t}$ to 100%.[9] Note also that because some of the funds disclose their information on a semiannual basis, it is possible that the time difference between the start and end dates of stock holdings may not necessarily span one quarter. To avoid the possibility of any bias, we take the recommendations of a stock over the preceding nonoverlapping time periods in reference to the horizon over which the change in the stockholding takes place. Also, in the regression above, the intercept $\beta_{0,t}$ is fund specific. Consequently, it captures other fund characteristics that may affect the change in holdings (such as size or turnover) in any given time period. Finally, since we consider *changes* in the right-hand side stock-specific variables, relatively stable stock-related variables such as stock beta are unlikely to bias our coefficients.

In the second step, we construct the measure of reliance on public information for fund $m$ at time $t$, $RPI_{m,t-1}$, as

$$RPI_{m,t-1} = 1 - \frac{\sigma^2(\epsilon_{m,t})}{\sigma^2(\%\Delta \mathrm{Hold_{m,t}})}, \tag{10}$$

where $\sigma^2(\epsilon_{m,t})$ denotes the unexplained variance of residuals from regression model in (9) and $\sigma^2(\%\Delta\mathrm{Hold_{m,t}})$ is the overall fund-level variance of a percentage change in holdings of all the stocks ($i = 1, \ldots, n$) in the fund's portfolio from time $t-1$ to $t$. Note that the time subscript for $RPI$ is $t-1$, instead of $t$. Our goal is to highlight the timing of the information investors use when changing their portfolio holdings. We maintain this timing convention throughout the entire paper. In simple terms, $RPI$ equals the unadjusted $R^2$ of regression (9). It is clear that $RPI$ does not discriminate between investors who trade in the same or in the opposite direction as information in the public domain. In accordance with our hypothesis, we are interested only in how much managers rely on information in the public domain in their portfolio decisions. Thus, only $R^2$ of equation (9) matters. Section V.F investigates in greater detail whether any

[8] For our choice of lag structure, we analyze the sensitivity of portfolio holdings for the aggregate sample of funds. We run a pooled Fama and MacBeth (1973) regression where the first stage is run at the stock level for any time $t$, and the second stage averages all coefficients over time. The results (available upon request) suggest that at an aggregate level, funds respond to up to four lags of $Re$. This is consistent with Chen and Cheng (2006), who also document a significant relationship between changes in portfolio holdings and changes in analysts' recommendations. This behavior can be rationalized within the framework with autocorrelated public information, as in Brown and Jennings (1989).

[9] We believe that setting this change to 100% is conservative. Imposing this bound reduces the actual sensitivity of changes in holdings to changes in information in the public domain. This would bias us toward classifying funds as low $RPI$ funds, thereby reducing the sorting power of $RPI$. For robustness, we also apply other bounds: 50%, 150%, and 200%. The results remain qualitatively similar.

systematic relationship between *RPI* and the direction of investors' trades is also present.[10]

Using *RPI*, we can rank managers based on their skills, where more skilled managers are those who have lower values of *RPI*. In summary, our sample exhibits significant cross-sectional variation in *RPI*. The average (median) value of *RPI* equals 29.0%(21.3%), with a standard deviation of 25.2% and a range between 0.01% and 99.9%.[11]

### B. The Anatomy of RPI

In this subsection, we examine the relationship between *RPI* and the fund-specific variables size, dollar expenses, turnover, age, and total loads. To this end, for each period we sort funds into decile portfolios according to their *RPI* level and calculate the average values of the selected variables for each such portfolio. We repeat this procedure for every subsequent time period and take a time-series average of all the cross-sectional averages. Table I reports the final values of the variables resulting from this sort.

Our results indicate that *RPI* is monotonically related to funds' total net assets. On average, smaller funds rely more on public information than do larger funds. Under the null, a simple explanation for this relationship could be that larger funds, those likely to enjoy a greater reputation and paying higher wages, employ more skilled managers, that is those that rely less on public information. Alternatively, one can argue that large funds have lower *RPI*s because they find it difficult to trade based on consensus changes in recommendations given the price impact that their trades may have (Berk and Green (2004)). We also find that funds that rely more on information in the public domain have lower dollar expenses. This result is consistent with Berk and Green (2004), who argue that more skilled managers extract higher rents for their management service.

While expenses measure operational costs of funds, they do not account for costs related, for instance, to trading. Hence, it is possible that despite lower expenses, funds with high *RPI* trade more and thus observe higher trading costs. Our results seem to support this claim. Funds with lower *RPI* have lower percentage turnover, which should lower their trading costs, ceteris paribus. Another interesting observation that can be made based on turnover is related to profit opportunities. Assuming that managers with low *RPI* are skilled, the turnover pattern suggests that their superior performance comes from exploiting longer-term (longer than one quarter) mispricing. This follows since

[10] One could argue that *RPI* might be mechanically associated with the number of stocks in a fund portfolio. For that reason, we examine whether the number of stocks in a fund portfolio is systematically related to *RPI*. We find no evidence for that in the data as the correlation between *RPI* and the number of stocks in a fund portfolio is merely −0.15%. For robustness, we include this variable in all our regressions; our main results remain unaffected.

[11] Large values of *RPI* may not be that surprising if one notes that analysts' recommendations are an aggregated outcome of analysts' research and may contain information coming from many different sources. This conjecture is supported by our analysis in Section V.A in that we obtain a similar range of values with different specifications of *RPI*.

**Table I**

**Summary of the Data: Decile Portfolios**

This table reports the variation in *TNA* (total net assets), dollar expenses, age, turnover, and total fund load across mutual fund deciles. We form deciles every quarter based on the *RPI* measure and average the variables for the deciles across all available quarters. *RPI* measures the reliance on public information and equals the unadjusted $R^2$ of the regression of percentage changes in fund managers' portfolio holdings on changes in analysts' past recommendations of up to four lags. The sample spans the period 1993Q1 to 2002Q4. The last row reports the correlation coefficients of each of the variables with *RPI*, along with their statistical significance.

| Decile # | RPI (%) | TNA ($ Mil.) | Expenses ($ Mil.) | Age (Years.) | Turnover (%) | Load (%) |
|---|---|---|---|---|---|---|
| 1 | 1.68 | 2325.3 | 27.21 | 13.29 | 54.14 | 1.44 |
| 2 | 4.45 | 1778.2 | 21.69 | 13.81 | 59.87 | 1.62 |
| 3 | 7.46 | 1461.0 | 17.97 | 14.22 | 70.32 | 1.73 |
| 4 | 10.94 | 960.1 | 11.91 | 12.86 | 72.68 | 1.69 |
| 5 | 15.23 | 772.0 | 9.88 | 13.33 | 76.30 | 1.71 |
| 6 | 20.54 | 716.9 | 9.25 | 13.01 | 80.55 | 1.69 |
| 7 | 27.09 | 615.9 | 8.13 | 12.95 | 84.41 | 1.65 |
| 8 | 36.05 | 509.0 | 6.82 | 13.35 | 90.39 | 1.57 |
| 9 | 49.92 | 407.3 | 5.54 | 12.88 | 97.12 | 1.68 |
| 10 | 76.14 | 321.7 | 4.57 | 11.83 | 110.85 | 1.52 |
| | 1.000 | −0.1019*** | −0.0984*** | −0.0252*** | 0.1890*** | −0.0189** |

***, **, * represent 1%, 5%, 10% confidence levels, respectively.

information about short-term (within a quarter) profit opportunities would result in higher short-term trading leading to higher turnover. A more detailed discussion of this issue can be found in Pástor and Stambaugh (2002).[12] Finally, we find that age and loads are also negatively related to *RPI*, though the second association is considerably weaker. To summarize the data, the last row of Table I presents all pairwise associations of *RPI* with other fund characteristics, using standard coefficients of correlation. All statistics are highly statistically significant.

## IV. Empirical Analysis

In this section, we test our main predictions. Subsection A examines the relationship between *RPI* and fund portfolio performance, as gauged by the various factor- and holding-based measures. Subsection B investigates the relationship between *RPI* and investor fund flows.

[12] One could also argue that funds that window-dress would be classified as skilled by our measure (low *RPI*). For these funds, even if managers were skilled, abnormal performance would not be negatively related to *RPI*. Since window-dressing is difficult to quantify, our tests mitigate this explanation as a possible driving factor of our measure of skill by conditioning the relationship between *RPI* and performance on funds' turnover.

### A. RPI and Performance

As we argue above, our first prediction ties *RPI* to future fund performance: Low *RPI* managers should record higher abnormal performance. To test this prediction, we estimate the following panel regression:

$$\alpha_{m,t} = \beta_0 + \beta_1 RPI_{m,t-1} + \gamma Controls_{m,t-1} + \epsilon_{m,t}, \tag{11}$$

where $\alpha_{m,t}$ denotes the performance measure of fund $m$ at time $t$. We use two classes of measures, unconditional and conditional[13] abnormal returns using CAPM, three-factor (Fama–French), and four-factor (Carhart) risk/style adjustment, and the holding-based measures (*GT*, *CS*, *CT*, and *AS*) of Daniel et al. (1997). *GT* is the Grinblatt-Titman holding-based measure of total performance, *CS* (characteristic selectivity) measures stock selectivity skill, *CT* (characteristic timing) measures timing skill, and *AS* measures average style selection skill. Holding-based measures mitigate the possible model misspecification in the factor regressions. To obtain alpha, for each fund, we estimate the time-series regression of the excess fund returns on four zero-investment factor portfolios—excess market return, size, value, and momentum—using the preceding 36 months of data. Alpha is then measured as a sum of an intercept of the model and the residual, as in Carhart (1997). $RPI_{m,t}$ denotes the reliance on public information for fund $m$ at time $t$. The former group of performance measures accounts for any return in excess of passively traded portfolios, while the latter group records performance in excess of buy-and-hold strategies.

In our regression specification, we need to control for fund characteristics related to fund performance that might affect the *RPI*-performance relationship. For example, larger funds might perform better than smaller funds, in which case *RPI* matters only because it is correlated with size. Similarly, the relationship between *RPI* and turnover may be driven mechanically by higher turnover funds having more volatile percentage changes in the funds' holdings. A multivariate regression framework simultaneously controls for these different factors. More concretely, the vector of *Controls* includes the log size of the assets under management, the log of age, turnover, expenses, and the growth of fund flows; $\gamma$ is a vector of coefficients that correspond to these variables. All regressions are estimated with time fixed effects and the relevant standard errors are corrected for the panel using the Panel Corrected Standard Errors method. Specifically, the PCSE specification adjusts for the contemporaneous correlation and heteroskedasticity among fund returns as well as for the autocorrelation with each fund's returns (Beck and Katz (1995)). As per our first prediction, we expect a negative and significant $\beta_1$. We report the results of this regression in Table II, with the factor-based measures in Panel A and the holding-based measures in Panel B.

[13] Our specification of the conditional model, based on Ferson and Schadt (1996), directly follows Wermers (2004) and includes interaction terms between the excess market returns and the following demeaned various macroeconomic variables: The 1-month Treasury bill yield, the dividend yield of the S&P 500 Index, the Treasury yield spread (long-term minus short-term bonds), and the quality spread in the corporate bond market (low-grade minus high-grade bonds).

Columns two to four of Panel A show that *RPI* is negatively related to all three unconditional performance measures. The results are statistically significant and are robust to the inclusion of size, value, or momentum strategies that managers may follow. Our findings are also economically significant. As an example, on average, a one-standard deviation increase in *RPI* decreases the

**Table II**

## Relationship between *RPI* and Performance

This table reports the results of the regressions relating performance and *RPI*. In Panel A, we report the results of the regression $\alpha_{m,t} = \beta_0 + \beta_1 RPI_{m,t-1} + \gamma Controls_{m,t-1} + \epsilon_{m,t}$, where the dependent variable is the monthly factor-based measure $\alpha_{m,t}$. We use market-adjusted (CAPM) alpha, Fama and French's (1993) three-factor (market, size, value)-adjusted alpha, and Carhart's (1997) four-factor alpha, which adds momentum as a factor. We also include conditional measures of performance for each of the above unconditional measures using the approach of Ferson and Schadt (1996). In Panel B, we report the results of the panel regression $y_{m,t} = \beta_0 + \beta_1 RPI_{m,t-1} + \gamma Controls_{m,t-1} + \epsilon_{m,t}$, where the dependent variable $y_{m,t}$ is the monthly holding-based measure. Specifically, we include the Grinblatt–Titman measure (*GT*), the characteristic selectivity measure (*CS*), the characteristic timing measure (CT), and the average style measure (*AS*). *CS* is a measure of stock selection ability and is defined as $CS = \sum w_{j,t-1}[R_{j,t} - BR_t(j,t-1)]$, where $BR_t(j, t-1)$ is the period-$t$ return of the benchmark portfolio to which stock $j$ was allocated in period $t-1$ according to its size, value, and momentum characteristics. *CT* is a measure of style timing ability and is defined as $CT = \sum[w_{j,t-1}BR_t(j,t-1) - w_{j,t-5}BR_t(j,t-5)]$ and AS is a measure of style selection ability, and is defined as AS = $\sum[w_{j,t-5}BR_t(j,t-5)]$. *RPI* measures the reliance on public information and equals the unadjusted $R^2$ of the regression of percentage changes in fund managers' portfolio holdings on changes in analysts' past recommendations of up to four lags. Log*(TNA)* is the natural logarithm of total net assets lagged one quarter, Expenses denotes expenses lagged one year, *Log(Age)* is the natural logarithm of age lagged one quarter, Turnover is the turnover lagged one year, and *NMG* is the new money growth lagged one quarter. All regressions include quarterly time dummies. Standard errors reported in parentheses are corrected for heteroskedasticity and for the panel. Data are for the period 1993Q1 to 2002Q4.

Panel A: Factor-Based Measures (% per Month)

| | Unconditional | | | Conditional | | |
|---|---|---|---|---|---|---|
| | CAPM $\alpha$ | 3-factor $\alpha$ | 4-factor $\alpha$ | CAPM $\alpha$ | 3-factor $\alpha$ | 4-factor $\alpha$ |
| $\text{RPI}_{t-1}$ | $-0.23^{***}$ | $-0.09^{*}$ | $-0.17^{***}$ | $-0.37^{***}$ | $-0.25^{**}$ | $-0.35^{***}$ |
| (%) | (0.06) | (0.05) | (0.06) | (0.12) | (0.11) | (0.10) |
| $\text{Log(TNA)}_{t-1}$ | $-2.79^{***}$ | $1.78^{**}$ | $-2.19^{**}$ | $-12.19^{***}$ | $-7.48^{***}$ | $-5.75^{***}$ |
| | (0.87) | (0.83) | (0.86) | (1.61) | (1.50) | (1.44) |
| $\text{Log (Age)}_{t-1}$ | 0.01 | $-3.85^{*}$ | 1.06 | $24.55^{***}$ | $10.01^{***}$ | $12.33^{***}$ |
| | (2.10) | (2.03) | (2.10) | (4.05) | (3.72) | (3.53) |
| $\text{Expenses}_{t-1}$ | $-9.55^{***}$ | $-1.92$ | $-12.26^{***}$ | $-29.01^{***}$ | $-22.46^{***}$ | $-17.40^{***}$ |
| (%) | (3.45) | (3.73) | (3.83) | (7.30) | (6.82) | (6.16) |
| $\text{Turnover}_{t-1}$ | $0.08^{***}$ | $0.14^{***}$ | $-0.07^{***}$ | 0.03 | 0.01 | $-0.09^{**}$ |
| (%) | (0.02) | (0.02) | (0.02) | (0.04) | (0.04) | (0.04) |
| $\text{NMG}_{t-1}$ | $-0.01$ | $0.24^{***}$ | 0.07 | $-0.32^{**}$ | $-0.48^{***}$ | $0.44^{***}$ |
| | (0.09) | (0.08) | (0.09) | (0.16) | (0.15) | (0.14) |
| Time fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 18,096 | 18,096 | 18,096 | 18,096 | 18,096 | 18,096 |

(*continued*)

**Table II**—*Continued*

| Panel B: Holding-Based Measures (% per Month) | | | | |
|---|---|---|---|---|
| | GT | CT | CS | AS |
| $RPI_{t-1}$ | −0.16*** | −0.02 | −0.26*** | −0.10*** |
| (%) | (0.05) | (0.03) | (0.05) | (0.04) |
| $Log(TNA)_{t-1}$ | −0.29 | 0.01 | −2.88*** | −1.71*** |
| | (0.68) | (0.43) | (0.64) | (0.50) |
| $Log\ (Age)_{t-1}$ | −0.21 | −1.30 | 4.59*** | 1.16 |
| | (1.65) | (1.11) | (1.57) | (1.22) |
| $Expenses_{t-1}$ | 4.47 | 1.34 | −5.06* | −5.19** |
| (%) | (2.79) | (1.72) | (2.77) | (2.08) |
| $Turnover_{t-1}$ | 0.04** | 0.05*** | −0.03 | −0.03** |
| (in %) | (0.02) | (0.01) | (0.02) | (0.01) |
| $NMG_{t-1}$ | −0.01 | −0.07** | 0.11** | 0.03 |
| | (0.05) | (0.03) | (0.05) | (0.04) |
| Time fixed effects | Yes | Yes | Yes | Yes |
| Observations | 18,964 | 18,964 | 18,964 | 18,964 |

***, **, * represent 1%, 5%, 10% confidence levels, respectively.

risk-adjusted return of Carhart (1997) by approximately 0.46% ($23 * 0.0017$) per year. Similar conclusions obtain when we use conditional versions of the above measures, an indication that the superior performance of funds with low *RPI* is not due to their greater responsiveness to macroeconomic conditions. To further assess the economic impact of the relationship between *RPI* and abnormal performance, we also construct a zero-investment rolling portfolio. We obtain this portfolio by sorting funds on *RPI* every period and then taking a long position in funds in the first 30 percentile and a short position in funds in the last 30 percentile. We find that such a portfolio generates a statistically significant four-factor adjusted return of 2.16% per year, averaged over the sample period.[14]

Our results remain significant when we use *GT*, *CS*, and *AS* holding-based measures, as reported in Panel B. For example, on average, a one-standard deviation increase in *RPI* decreases the characteristic selectivity measure (*CS*) by 0.44% per year. In contrast, our analysis indicates no relationship between *RPI* and *CT*, a sign that the abnormal returns of managers with lower *RPI* are associated with their stock selection and style rather than with their market-timing ability. An alternative explanation of this result might be that market-timing is more likely to be detected only using high frequency data. Bollen and Busse (2001) provide evidence consistent with this claim. Overall, our findings in Panels A and B strengthen the argument in favor of traditional performance

[14] In practice, it is not possible to construct such a hedge portfolio due to constraints on shorting mutual funds. Also, we find that constructing a similar portfolio strategy based on fund alpha (CAPM, three-factor, or four-factor) does not generate a statistically significant return over the sample period.

measures indeed reflecting skill, in that managers who produce high values of these measures also record low *RPI*s—as should be the case with skillful managers.

Our predictions are robust to alternative regression specifications and variable definitions. While for brevity we do not report these results, they are available upon request. First, our results remain unchanged if we apply the cross-sectional regression tests with standard errors calculated using the method of Fama and MacBeth (1973). Moreover, we observe a fairly steady and negative coefficient on *RPI* if we examine each year of the data individually. Second, our results in Panel A remain unchanged if we define alpha as an intercept from the regression with 3 years of monthly data, a definition consistent with alpha being a stable measure of performance. Finally, our findings are qualitatively similar when we use fund fixed effects, suggesting that the relationship between *RPI* and performance exists in both the cross section and the time series of the sample. Importantly, using fund fixed effects also alleviates concerns of any family-level time invariant unobserved characteristics affecting our results.

### *B. RPI and Fund Flows*

Previous studies document that outside investors chase past fund performance when allocating their wealth (e.g., Chevalier and Ellison (1997)). Our second prediction relates *RPI* to the flow of funds from these investors. As we explain above, to the extent that *RPI* measures aspects of managerial skill, which traditional performance measures may not capture, we should expect a negative relationship between *RPI* and future fund flows.

To examine this prediction empirically, we estimate the following panel regression:

$$NetFlow_{m,t} = \beta_0 + \beta_1 RPI_{m,t-1} + \gamma Controls_{m,t-1} + \epsilon_{m,t}. \tag{12}$$

The dependent variable, $NetFlow_{m,t}$, is the proportional growth in total assets under management for fund $m$ between the beginning and the end of quarter $t$, net of internal growth (assuming reinvestment of dividends and distributions), assuming that the money is invested at the end of each quarter and the interest is compounded each month, that is,

$$NetFlow_{m,t} = \frac{TNA_{m,t} - TNA_{m,t-1}(1 + R_{m,t})}{TNA_{m,t-1}}. \tag{13}$$

The coefficient of interest in regression (12) is $\beta_1$. Consistent with our second prediction, we expect this estimate to be negative and significant. Following the existing literature, we include as our controls fund-specific characteristics such as log of size, log of age, percentage expenses, loads, and turnover. We also use a measure of a fund's total risk, which we calculate as a standard deviation of its returns over the preceding 36 months. Finally, we add time fixed effects. The standard errors in all regressions are obtained using the PCSE method.

**Table III**

## Relationship between *RPI* and Fund Flows

This table reports the results of the regression $NetFlow_{m,t} = \beta_0 + \beta_1 RPI_{m,t-1} + \gamma Controls_{m,t-1} + \epsilon_{m,t}$. *NetFlow* measures the percentage flow of funds into mutual fund $m$ between time $t-1$ and $t$. *RPI* measures the reliance on public information and equals the unadjusted-$R^2$ of the regression of percentage changes in fund managers' portfolio holdings on changes in analysts' past recommendations of up to four lags. $R$ is the return on the fund portfolio lagged one quarter, Log*(TNA)* is the natural logarithm of total net assets lagged one quarter, Expenses denotes expenses lagged one year, Log(*Age*) is the natural logarithm of age lagged one quarter, Turnover is the turnover lagged one year, and other controls include the load of the fund lagged one quarter, raw returns of the fund in the last period, and the standard deviation of the fund returns based on the past 36 monthly returns. All regressions include quarterly time dummies. Standard errors reported in parentheses are corrected for heteroskedasticity and for the panel. Data are for the period 1993Q1 to 2002Q4.

| | | $NMG_t$ | |
|---|---|---|---|
| $RPI_{t-1}$ | | | $-3.71^{***}$ |
| (%) | | | (0.51) |
| $\alpha^{4f}_{t-1}$ | $0.73^{***}$ | 0.084 | 0.086 |
| | (0.06) | (0.08) | (0.07) |
| $R_{t-1}$ | | $1.29^{***}$ | $1.28^{***}$ |
| (%) | | (0.08) | (0.08) |
| $\text{Log(TNA)}_{t-1}$ | −6.02 | −8.55 | −16.50 |
| | (9.60) | (9.90) | (9.88) |
| $\text{Log(Age)}_{t-1}$ | $-231.65^{***}$ | $-231.27^{***}$ | $-220.43^{***}$ |
| | (14.53) | (14.60) | (14.70) |
| $\text{Expenses}_{t-1}$ | 23.23 | 7.50 | 15.23 |
| (%) | (29.67) | (29.70) | (29.60) |
| $\text{Turnover}_{t-1}$ | $0.61^{**}$ | $0.49^{*}$ | $0.68^{**}$ |
| (%) | (0.30) | (0.30) | (0.31) |
| $\text{Load}_{t-1}$ | $0.15^{***}$ | $0.17^{***}$ | $0.16^{***}$ |
| (%) | (0.06) | (0.05) | (0.05) |
| $\text{St. deviation}_{t-1}$ | $-25.63^{***}$ | −9.10 | −5.80 |
| | (7.46) | (7.10) | (7.50) |
| Time fixed effects | Yes | Yes | Yes |
| Observations | 17,851 | 17,851 | 17,851 |

$^{***}$, $^{**}$, $^{*}$ represent 1%, 5%, 10% confidence levels, respectively.

The estimates of the coefficients in the basic flow regression are presented in Table III. Specifically, in columns two and three we reproduce results documented in the literature: (1) Fund flows from outside investors chase past performance, and (2) the effect in (1) is driven primarily by past raw returns. In column four, we report results pertaining to our second prediction. The coefficient $\beta_1$ is negative and significant, both statistically and economically: A one-standard deviation increase in *RPI* increases the subsequent fund flows by 3.71% $(4 * 3.71\% * 0.25)$ per year. Note that our results hold *conditional* on past performance of the fund since both past raw and abnormal returns are included in the regression in column four. This suggests that *RPI* measures some characteristics of managerial skill that are not measured by past returns. Our findings in this section are also robust to alternative specifications, including conditioning on other factor-based performance measures and fund fixed effects.

## V. Extensions and Robustness

In this section, we stress-test the robustness of our main findings as well as extend our analysis along various dimensions. Specifically, in Subsection A we analyze whether our results hold up to alternative specifications of *RPI* and public information sets. In Subsection B, we examine how much of the variation in *RPI* can be attributed to manager-specific characteristics. Subsection C explores the importance of information spillovers among stocks in a fund's portfolio. Subsection D investigates whether the *RPI*-performance relationship is affected when we condition in various ways on fund turnover. Subsection E explores the relationship between *RPI* and risk in the portfolio strategies of the fund, while Subsection F examines whether trading direction and *RPI* are systematically related. Finally, Subsection G summarizes additional miscellaneous tests. For brevity, several of the results we discuss in this section are merely noted without providing exact numbers. Further details can be obtained upon request from the authors.

### A. Alternative Measures of RPI

An immediate concern regarding our empirical setting relates to the degree to which the proposed *RPI* measure can be generalized. In particular, two questions may be of interest. First, are our results robust to alternative specifications of *RPI*, instead of $R^2$ from equation (10)? Second, are our results robust to other public information events? In this subsection, we address both these questions.

#### A.1. Alternative Specifications

To address the first question, we propose an alternative measure, $RPI^{\beta}$, where in the first step we estimate equation (9) as before, but in the second step, we derive a measure of reliance on public information for fund $m$ at time $t$, $RPI^{\beta}_{m,t-1}$, as

$$RPI^{\beta}_{m,t-1} = \sum_{p=1}^{4} \left| \frac{\beta_{p,m,t}}{se_{p,m,t}} \right|, \tag{14}$$

where $\beta_{p,m,t}$ and $se_{p,m,t}$ denote, respectively, the coefficients and standard errors of the coefficients on $\Delta Re_{i,t-p}$ from regression (9), and $p = 1, 2, 3, 4$ is the number of lags of the forecast. In contrast to *RPI*, this specification does not directly depend on the variation in analysts' recommendations and as such allows us to examine how sensitive our results are to variation in analysts' recommendations. In this specification, taking the absolute value is important since fund holdings may be sensitive to public information both positively and negatively, and our objective is to measure reliance on this information without regard to an investor's trading direction. Scaling by standard errors adjusts for the noise in the estimated coefficients for different funds. According to this measure, a high $RPI^{\beta}$ manager relies more on information available in the public domain as compared to a low $RPI^{\beta}$ manager. Subsequently, we use this measure to test our predictions.

We estimate the *RPI* performance equation (11) to examine whether our first prediction holds with this alternative construct of *RPI*. The results, reported in Table IV, suggest that consistent with our first prediction, low-$RPI^{\beta}$ managers record higher abnormal performance. As the table shows, our findings are robust to various unconditional and conditional abnormal return

**Table IV**

**Relationship between $RPI^{\beta}$ and Performance**

This table reports the results of the regressions relating performance and modified *RPI* ($RPI^{\beta}$). In Panel A, we report the results of the regression $\alpha_{m,t} = \beta_0 + \beta_1 RPI^{\beta}_{m,t-1} + \gamma Controls_{m,t-1} + \epsilon_{m,t}$, where the dependent variable is the factor-based measure, $\alpha_{m,t}$. The risk-adjusted measures include the monthly unconditional (columns two-four) and conditional (columns five-seven) CAPM, three-factor, and four-factor alpha. The conditional measures are derived using the modified procedure of Ferson and Schadt (1996), proposed by Wermers (2000). In Panel B, we report the results of the panel regression $y_{m,t} = a + \beta_1 RPI^{\beta}_{m,t-1} + \gamma Controls_{m,t-1} + \epsilon_{m,t}$, where the dependent variable $y_{m,t}$ is the monthly holding-based measure. We use respectively the Grinblatt and Titman measure (*GT*), the characteristic selectivity measure (*CS*), the characteristic timing measure (*CT*), and the average style measure (*AS*) of Daniel et al. (1997). *CS* is a measure of stock selection ability and is defined as $CS = \sum w_{j,t-1}[R_{j,t} - BR_t(j, t-1)]$ where $BR_t(j, t-1)$ is the period-$t$ return of the benchmark portfolio to which stock $j$ was allocated in period $t-1$ according to its size, value, and momentum characteristics. *CT* is a measure of the style-timing ability and is defined as $CT = \sum[w_{j,t-1}BR_t(j, t-1) - w_{j,t-5}BR_t(j, t-5)]$ and *AS* is a measure of the style-selection ability and is defined as $AS = \sum[w_{j,t-5}BR_t(j, t-5)]$. $RPI^{\beta}$ is an alternative specification to measure the reliance on public information and is calculated as per equation (14). Log*(TNA)* is the natural logarithm of total net assets lagged one quarter, Expenses denotes expenses lagged 1 year, Log*(Age)* is the natural logarithm of age lagged one quarter, Turnover is the turnover lagged 1 year, and *NMG* is the new money growth lagged one quarter. All regressions include quarterly time dummies. Standard errors reported in parentheses are corrected for heteroskedasticity and for the panel. Data are for the period 1993Q1 to 2002Q4.

Panel A: Factor-Based Measures (% per Month)

| | Unconditional | | | Conditional | | |
|---|---|---|---|---|---|---|
| | CAPM $\alpha$ | 3-factor $\alpha$ | 4-factor $\alpha$ | CAPM $\alpha$ | 3-factor $\alpha$ | 4-factor $\alpha$ |
| $RPI^{\beta}_{t-1}$ | −0.25** | −0.12** | −0.19** | −0.42*** | −0.29** | −0.38** |
| (in %) | (0.12) | (0.05) | (0.07) | (0.16) | (0.14) | (0.17) |
| $\text{Log(TNA)}_{t-1}$ | −2.71*** | 1.88*** | −2.01*** | −12.00*** | −7.40*** | −6.01*** |
| | (0.66) | (0.63) | (0.72) | (1.41) | (1.53) | (1.31) |
| $\text{Log (Age)}_{t-1}$ | 0.03 | −3.99* | 1.01 | 25.40** | 10.06*** | 12.89*** |
| | (2.21) | (2.00) | (2.34) | (4.20) | (3.03) | (3.05) |
| $\text{Expenses}_{t-1}$ | −9.51*** | −1.90 | −12.21*** | −29.10*** | −22.64*** | −17.45*** |
| (in %) | (3.50) | (3.32) | (3.80) | (7.23) | (6.23) | (6.45) |
| $\text{Turnover}_{t-1}$ | 0.08*** | 0.14*** | −0.07*** | 0.03 | 0.01 | −0.11*** |
| (in %) | (0.01) | (0.02) | (0.02) | (0.05) | (0.05) | (0.03) |
| $\text{NMG}_{t-1}$ | −0.04 | 0.24*** | 0.07 | −0.32*** | −0.48*** | 0.44*** |
| | (0.09) | (0.08) | (0.10) | (0.10) | (0.13) | (0.16) |
| Time fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 18,096 | 18,096 | 18,096 | 18,096 | 18,096 | 18,096 |

(*continued*)

**Table IV**—*Continued*

| Panel B: Holding-Based Measures (% per Month) | | | | |
|---|---|---|---|---|
| | GT | CT | CS | AS |
| $\mathrm{RPI}^{\beta}_{t-1}$ | −0.19*** | −0.04 | −0.31** | −0.13*** |
| (%) | (0.06) | (0.03) | (0.15) | (0.04) |
| $\mathrm{Log(TNA)}_{t-1}$ | −0.20 | 0.07 | −2.97*** | −1.88*** |
| | (0.99) | (0.48) | (0.51) | (0.53) |
| $\mathrm{Log\ (Age)}_{t-1}$ | −0.12 | −1.41 | 5.04*** | 1.11 |
| | (1.80) | (2.01) | (1.60) | (1.45) |
| $\mathrm{Expenses}_{t-1}$ | 4.71 | 1.45 | −5.66* | −5.97** |
| (%) | (3.01) | (1.88) | (2.93) | (1.99) |
| $\mathrm{Turnover}_{t-1}$ | 0.04*** | 0.04** | −0.06* | −0.02** |
| (%) | (0.01) | (0.02) | (0.04) | (0.01) |
| $\mathrm{NMG}_{t-1}$ | −0.07 | −0.08** | 0.13** | 0.02 |
| | (0.06) | (0.04) | (0.05) | (0.04) |
| Time fixed effects | Yes | Yes | Yes | Yes |
| Observations | 18,964 | 18,964 | 18,964 | 18,964 |

***, **, * represent 1%, 5%, 10% confidence levels respectively.

specifications as well as to holding-based measures. The coefficients on $RPI^{\beta}$ are both statistically and economically significant. As an example, on average, a one-standard deviation increase in $RPI^{\beta}$ decreases the Carhart risk-adjusted return by approximately 0.45% $(20 * 0.0019)$ per year. These results also indicate that this relationship is robust to the size, value, or momentum strategies that managers may follow. Similarly, we find the same negative relationship when we use conditional versions of the above measures, which indicates that the superior performance of funds with low *RPI* is not due to their greater responsiveness to macroeconomic conditions. As before, the results remain significant when we use *GT*, *CS*, and *AS* holding-based measures, as reported in Panel B, indicating that the abnormal returns of managers with lower $RPI^{\beta}$ are driven by their stock selection and style rather than by their market-timing ability. In unreported tests, we also find that our results remain unchanged when we estimate equation (12) related to our second prediction. In particular, we find that the coefficient $\beta_1$ in the regression is negative (−3.88) and significant at the 1% level. Hence, we conclude that our results are not due merely to variation in analysts' recommendations.

We also consider another modified metric to measure reliance on public information, *RPIT*. In contrast to *RPI*, this measure takes the *absolute* changes in the holdings in the *RPI* regression (9), instead of the *percentage* changes. When we use *RPIT* to test our main performance and flows predictions, we find that our estimates remain qualitatively unchanged, both in terms of their economic magnitude and statistical significance (unreported for brevity).

### *A.2. Alternative Information Sets*

*RPI* is derived using analysts' past recommendations as a proxy for information in the public domain. In this subsection, we use an alternative information set, namely, analysts' past earnings forecasts, and examine whether our findings are generalizable to this public information set. Similar to analysts' recommendations, this alternative information set also exhibits desirable properties (discussed in Section III.A). However, earnings forecasts do have a limitation in that the forecaster of information does not give a clear and unequivocal course of action and as a result changes in the consensus of earnings forecasts over subsequent quarters may not be interpreted similarly by all managers.

We estimate reliance on public information based on earnings forecasts ($RPI^{earn}$) using the same two-step procedure that we describe earlier with the only change being that now we use changes in earnings forecasts rather than changes in analysts' recommendations. Specifically, in the first step, we estimate (9) for each fund $m$ and period $t$ from 1993 to 2002 using all stocks in the fund's portfolio. In the second step, we construct $RPI^{earn}$ for fund $m$ at time $t$ as the $R^2$ of (9). Our sample indicates significant cross-sectional variation in $RPI^{earn}$, with an average (median) value of 33.4% (27.1%), a standard deviation of 20.3%, and a range between 0.90% and 76.3%. These characteristics are fairly similar to those we obtain for *RPI*.

Next, we use $RPI^{earn}$ to test our predictions. In particular, we estimate equation (11) to examine whether our first prediction holds with this measure. The estimates, reported in Table V, suggest that consistent with our first prediction, low $RPI^{earn}$ managers record higher abnormal performance, as measured by various factor- and holding-based measures. Similarly, untabulated results indicate that the qualitative aspects of the second prediction remain unchanged. In particular, $\beta_1$ in regression (12) is negative (−2.72) and significant at the 1% level.

Finally, all our results in this subsection are robust to the inclusion of fund fixed effects, which control for any time-invariant fund characteristics. This suggests that the relationship between $RPI^{\beta}$, *RPIT*, $RPI^{earn}$, and performance exists in both the cross section and the time series of the sample.[15] In addition, our results are not affected by the fact that some holdings might be stale from period to period. To test this possibility, we examine if the number of "buy-and-holds" in a fund portfolio in any quarter is systematically related to *RPI* (*RPIT*). We find no evidence for this in our sample: The correlation between *RPI* (*RPIT*) and the number of buy and holds in a fund portfolio is a mere −9% (−5%). In sum, on average an increase in the fund $RPI^{\beta}$ (*RPIT*, $RPI^{earn}$) is associated with a decrease in the fund's risk-adjusted return.[16]

[15] All the measures of reliance on public information are highly positively correlated. In particular, the correlation between *RPI* and $RPI^{earn}$ is 53.2% and the correlation between $RPI^{\beta}$ and *RPI* equals 59.9%.

[16] Since our model does not have any trading costs associated with the manager, any contrarian behavior by the manager based on an informational advantage is not predicated by the model. However, with liquidity concerns, the manager may have motivation to trade against his information in order to save on transaction costs. To account for such a possibility, in the process of constructing *RPI* we also control for liquidity of the fund manager portfolio (based on value-weighted turnover of stocks in the manager's portfolio) and find that this alternative construction of *RPI* does not alter our results.

## *B. RPI and Managerial Turnover*

Given that *RPI* can be attributed to either a fund or its manager, a potentially interesting issue is whether *RPI* is primarily associated with the fund manager or with the fund. Since *RPI* provides insight into skills, examining this issue would enhance our understanding of whether observed abnormal performance is largely a fund or a manager attribute.

**Table V**

**Relationship between $RPI^{earn}$ and Performance**

This table reports the results of the regressions relating performance and modified *RPI* ($RPI^{earn}$). In Panel A, we report the results of the regression $\alpha_{m,t} = \beta_0 + \beta_1 RPI^{earn}{}_{m,t-1} + \gamma Controls_{m,t-1} + \epsilon_{m,t}$, where the dependent variable is the factor-based measure, $\alpha_{m,t}$. The risk-adjusted measures include the monthly unconditional (columns two-four) and conditional (columns five-seven) CAPM, three-factor, and four-factor alpha. The conditional measures are derived using the modified procedure of Ferson and Schadt (1996), proposed by Wermers (2000). In Panel B, we report the results of the panel regression $y_{m,t} = a + \beta_1 RPI^{earn}{}_{m,t-1} + \gamma Controls_{m,t-1} + \epsilon_{m,t}$, where the dependent variable $y_{m,t}$ is the monthly holding-based measure. We use respectively the Grinblatt and Titman measure (*GT*), the characteristic selectivity measure (*CS*), the characteristic timing measure (*CT*), and the average style measure (*AS*) of Daniel et al. (1997). *CS* is a measure of stock selection ability and is defined as $CS = \sum w_{j,t-1}[R_{j,t} - BR_t(j, t-1)]$ where $BR_t(j, t-1)$ is the period-$t$ return of the benchmark portfolio to which stock $j$ was allocated in period $t-1$ according to its size, value, and momentum characteristics. *CT* is a measure of the style-timing ability and is defined as $CT = \sum[w_{j,t-1}BR_t(j, t-1) - w_{j,t-5}BR_t(j, t-5)]$ and *AS* is a measure of the style-selection ability and is defined as $AS = \sum[w_{j,t-5}BR_t(j, t-5)]$. $RPI^{earn}$ is an alternative measure of reliance on public information and equals the unadjusted $R^2$ of the regression of changes in fund managers' portfolio holdings on changes in analysts' past earning forecasts of up to four lags. Log*(TNA)* is the natural logarithm of total net assets lagged one quarter, Expenses denotes expenses lagged 1 year, Log*(Age)* is the natural logarithm of age lagged one quarter, Turnover is the turnover lagged 1 year, and *NMG* is the new money growth lagged one quarter. All regressions include quarterly time dummies. Standard errors reported in parentheses are corrected for heteroskedasticity and for the panel. Data are for the period 1993Q1 to 2002Q4.

| Panel A: Factor-Based Measures (% per Month) | | | | | | |
|---|---|---|---|---|---|---|
| | Unconditional | | | Conditional | | |
| | CAPM $\alpha$ | 3-factor $\alpha$ | 4-factor $\alpha$ | CAPM $\alpha$ | 3-factor $\alpha$ | 4-factor $\alpha$ |
| $\mathrm{RPI}^{earn}_{t-1}$ | −0.30* | −0.17* | −0.26** | −0.44** | −0.36* | −0.39** |
| (%) | (0.17) | (0.09) | (0.12) | (0.22) | (0.21) | (0.20) |
| $\mathrm{Log(TNA)}_{t-1}$ | −2.89*** | 1.89** | −2.91** | −11.12*** | −8.99*** | −5.52*** |
| | (0.80) | (0.69) | (0.90) | (2.03) | (3.22) | (2.03) |
| $\mathrm{Log\ (Age)}_{t-1}$ | 0.02 | −5.38** | 2.61 | 20.15*** | 12.11*** | 12.07*** |
| | (2.19) | (2.20) | (2.89) | (5.11) | (3.04) | (3.05) |
| $\mathrm{Expenses}_{t-1}$ | −10.01*** | −1.97 | −12.60*** | −31.92*** | −24.62*** | −14.70*** |
| (%) | (3.51) | (3.77) | (3.38) | (8.83) | (8.42) | (3.61) |
| $\mathrm{Turnover}_{t-1}$ | 0.09*** | 0.12*** | −0.09*** | 0.02 | 0.02 | −0.07** |
| (%) | (0.03) | (0.03) | (0.03) | (0.05) | (0.05) | (0.03) |
| $\mathrm{NMG}_{t-1}$ | −0.10 | 0.12*** | 0.71 | −0.12** | −0.18*** | 0.14*** |
| | (0.09) | (0.03) | (0.59) | (0.06) | (0.05) | (0.05) |
| Time fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 18,096 | 18,096 | 18,096 | 18,096 | 18,096 | 18,096 |

(*continued*)

**Table V**—*Continued*

| Panel B: Holding-Based Measures (% per Month) | | | | |
|---|---|---|---|---|
| | GT | CT | CS | AS |
| $\mathrm{RPI}_{t-1}^{earn}$ | −0.29* | −0.15 | −0.48** | −0.21** |
| (%) | (0.16) | (0.10) | (0.20) | (0.11) |
| $\mathrm{Log(TNA)}_{t-1}$ | −0.19 | 0.11 | −2.20*** | −1.91*** |
| | (0.80) | (0.31) | (0.49) | (0.56) |
| $\mathrm{Log\ (Age)}_{t-1}$ | −0.71 | −0.90 | 4.01*** | 1.68 |
| | (1.55) | (0.99) | (0.60) | (1.18) |
| $\mathrm{Expenses}_{t-1}$ | 3.71 | 1.43 | −5.62* | −5.91** |
| (%) | (3.91) | (2.27) | (2.89) | (2.01) |
| $\mathrm{Turnover}_{t-1}$ | 0.03** | 0.04*** | −0.07 | −0.04** |
| (%) | (0.01) | (0.01) | (0.06) | (0.02) |
| $\mathrm{NMG}_{t-1}$ | −0.22 | −0.13** | 0.16** | 0.13 |
| | (0.15) | (0.05) | (0.07) | (0.14) |
| Time fixed effects | Yes | Yes | Yes | Yes |
| Observations | 18,964 | 18,964 | 18,964 | 18,964 |

***, **, * represent 1%, 5%, 10% confidence levels, respectively.

There are two views in the literature that offer insights into this issue. According to the first view, managers are considered homogeneous and thus are regarded as perfect substitutes for one another. While managers might differ in their preferences, risk aversion, or skill levels, none of these translate into actual corporate policies. Under this view, we would not expect individual managers to matter for *RPI*. In other words, two funds sharing similar technology, factor, and product market conditions will make similar choices, whether or not they share the same management team.[17] The alternative view posits that fund decisions may be affected by manager heterogeneity. Specific to our context, there are at least two distinct interpretations as to how these managerial differences might translate into *RPI*. The first is an extension of the standard agency models, in which a manager can impose his own idiosyncratic style on a company if a fund's management control is not limited. Alternatively, if some management styles are more performance-enhancing than others, better governed funds may be more likely to select managers with low *RPI*. Note that this view does not preclude fund characteristics besides manager attributes from influencing corporate policies.

To examine which of the views might be applicable for *RPI*, we track changes in *RPI* around managerial turnover. If *RPI* is related to manager-specific attributes, then we should expect managerial turnover to affect *RPI*. On the other hand, if the fund largely dictates the manager's portfolio choice, we should expect *RPI* to be unaffected by managerial changes in the fund. This test requires extensive information on managerial changes during our sample period. Unfortunately, the CRSP mutual fund data are arranged by fund. Therefore, to construct the manager database, we need to reorient the data by manager and

[17] This view finds some support in the context of mutual funds in the recent research by Baks (2003), who concludes that most of the production function of the fund is fund-specific rather than manager-specific.

create a profile of the managerial changes in each fund. To ensure that manager entities remain identical over time, we only consider managers or manager teams that are specified by a single person(s). At times, the names are abbreviated differently (short surnames or first names), have spelling errors, and are part of different manager combinations. Therefore, to clean these data we require more elaborate filtering techniques.

To analyze the manager changes in a fund, we code all the managers manually, carefully correcting for any format change and spelling errors. In case of manager combinations (teams), we keep each manager as being the one in charge of managing the fund. We augment this procedure by a number of random checks to ensure that the coding of managers is consistent in the sample. Overall, our sample includes 2,193 managers that manage a total of 1,696 funds. For our purpose, we define managerial change as an event in which the manager moves from the current fund that he is managing and either disappears from the CRSP database or re-appears in a different fund. We have 952 such manager changes during our sample period. The CRSP database also reports annual information on the date and month in which the manager commenced at a fund. The starting date is an error-prone field (Baks (2003)); hence, if there is any inconsistency in this field over time, we remove the fund from the career profile of the manager. Based on the starting date, we construct a *Tenure* variable for each manager in our sample. Note that this is the *only* manager-specific time-varying variable that is available in the CRSP tapes. The average tenure of a manager in our sample is 3.36 years.

Since we are interested in tracking changes in *RPI* along with managerial turnover, the nature of our identification strategy closely follows that of Bertrand and Schoar (2003), who examine whether corporate policies are affected by managerial styles. Specifically, we first take a benchmark specification, from which we derive the residual *RPI*. This benchmark specification is estimated at the fund-year level after controlling for any average differences across funds and years, as well as for any fund-year-specific shocks, such as flows, that might affect the *RPI* of a fund. We then ask how much of the variance in the residual *RPI* can be attributed to manager-specific effects. More precisely, the method we propose is equivalent to estimating the regression

$$RPI_{it} = \alpha_t + \gamma_i + \beta X_{it} + \lambda_{mgr}, \tag{15}$$

where $\alpha_t$ are year fixed effects, $\gamma_i$ are fund fixed effects, $X_{it}$ represents a vector of time-varying fund-level controls (log of size, percentage expenses, log of age, turnover, and new money growth), and $\lambda_{mgr}$ represents manager fixed effects. It is evident from this equation that the estimation of the manager fixed effects is not possible for managers that never leave a given fund during our sample period. We also include managerial tenure in the fund (*Tenure*) as an additional control variable.[18]

[18] To obtain some basic insight into changes in *RPI* around manager turnover, we calculate an average *RPI* over the tenure of each manager in a fund. We then take the difference in the average values around the turnover period and average this value across funds. The resulting quantity is negative and a $t$-test indicates that it is significantly different from zero at the 1% level. This suggests that, on average, *RPI* falls when a manager change occurs.

**Table VI**

**Relationship between *RPI* ($RPI^{earn}$) and Managerial Turnover**

This table reports the results of the regressions relating manager turnover and *RPI* ($RPI^{earn}$). The nature of our identification strategy closely follows that of Bertrand and Schoar (2003), who examine whether corporate policies are affected by managerial styles. Specifically, we first take a benchmark specification, from which we derive the residual *RPI*. This benchmark specification is estimated at the fund-year level after controlling for any average differences across funds and years, as well as for any fund-year specific shocks, such as flows, that might affect the *RPI* of a fund. We then ask how much of the variance in the residual *RPI* can be attributed to manager-specific effects. In Panel A, we estimate the following regression: $RPI_{it} = \alpha_t + \gamma_i + \beta X_{it} + \lambda_{mgr}$, where $\alpha_t$ are year fixed effects, $\gamma_i$ are fund fixed effects, $X_{it}$ represents a vector of time-varying fund level controls. $\lambda_{mgr}$ in equation (15) denotes manager fixed effects. In Panel B, we replace *RPI* by $RPI^{earn}$. In each row in both panels, we report the $F$-test statistics and adjusted $R^2$ from the estimation of equations with relevant fund and manager controls. More concretely, in the first row of the table we report the fit of a benchmark specification that includes only fund fixed effects and year fixed effects. In the second row we also include time-varying fund controls, while in the third row we add manager fixed effects. The second and the third rows, respectively, also report the adjusted $R^2$ after adding time-varying fund controls and manager fixed effects. The third row also reports $F$-statistics from tests of the joint significance of the manager fixed effects. Finally, the fourth row also includes the interaction of manager fixed effects with Bad, a dummy variable that takes a value of one in time period $t$ if the market-adjusted abnormal return of the fund in the past three consecutive quarters is negative and zero otherwise. $RPI^{earn}$ is an alternative measure of reliance on public information and equals the unadjusted $R^2$ of the regression of changes in managers' portfolio holdings on changes in analysts' past earning forecasts of up to four lags. *RPI* measures the reliance on public information and equals the unadjusted $R^2$ of the regression of percentage changes in managers' portfolio holdings on changes in analysts' past recommendations of up to four lags. Fund controls include Log*(TNA)*, the natural logarithm of total net assets lagged one quarter; Expenses, expenses lagged 1 year; Log*(Age)*, the natural logarithm of age lagged one quarter; Turnover, the turnover lagged 1 year; and *NMG*, the new money growth lagged one quarter. Data are for the period 1993Q1 to 2002Q4.

| | Fund Controls | Fund and Time Fixed Effects | Manager Fixed Effects | Manager Fixed Effects × Bad | $N$ (Observations) | Adjusted $R^2$ |
|---|---|---|---|---|---|---|
| | | | Panel A: $F$-tests on Manager Fixed Effects Using *RPI* | | | |
| *RPI* | No | Yes | | | 18,096 | 0.25 |
| *RPI* | Yes | Yes | | | 18,096 | 0.27 |
| *RPI* | Yes | Yes | 18.77 (<0.0001, 943) | | 18,096 | 0.35 |
| *RPI* | Yes | Yes | 1.21 (0.5327, 943) | 5.93 (<0.0001, 688) | 18,096 | 0.36 |
| | | | Panel B: $F$-Tests on Manager Fixed Effects Using $RPI^{earn}$ | | | |
| *RPI* | No | Yes | | | 18,096 | 0.19 |
| *RPI* | Yes | Yes | | | 18,096 | 0.22 |
| *RPI* | Yes | Yes | 15.44 (<0.0001, 943) | | 18,096 | 0.27 |
| *RPI* | Yes | Yes | 0.92 (0.3789, 943) | 6.59 (<0.0001, 688) | 18,096 | 0.30 |

In Panel A of Table VI, we present the $F$-test statistics and adjusted $R^2$ from the estimation of equation (15) for *RPI*. In the first row of the table, we report the fit of a benchmark specification that includes only fund fixed effects and year fixed effects. In the second row, we add time-varying fund controls, while in the third row we add manager fixed effects. The second and the third rows also report the adjusted $R^2$ after adding time-varying fund controls and manager fixed effects, respectively. The third row additionally reports $F$-statistics from the test of the joint significance of the manager fixed effects. Overall, the findings in Panel A suggest that manager-specific effects matter both economically and statistically for the fund's *RPI*. In particular, including manager fixed effects significantly increases the adjusted $R^2$ of the estimated model from 0.27 to 0.35. Similarly, we find that the $F$-test statistics are large and allow us to reject the null hypothesis that all the manager fixed effects are zero. Intuitively, the results suggest that changes in *RPI* can be associated with managerial turnover. Moreover, the average sign of the joint coefficient (unreported) is negative and significant, suggesting that, on average, *RPI* falls whenever management changes occur.

So far, we have documented that manager-specific effects explain a fraction of the variation in *RPI*. We would also like to assess how large the observed differences between managers are. Therefore, we look at the distributions of the fixed effects estimated above. Specifically, we examine how much, in terms of *RPI*, a manager in the upper tail of the *RPI* fixed effects distribution contributes relative to a manager who is in the lower tail of that distribution. To compute these statistics, we weigh each fixed effect by the inverse of its standard error to account for estimation error. We find that the difference between a manager at the 25$^{\text{th}}$ percentile of the distribution of *RPI* and one at the 75$^{\text{th}}$ percentile is 0.17. This number is large if we note that the mean *RPI* in our sample is about 0.29, suggesting that the difference in *RPI* that can be attributed to the managers is large and significant. Overall, the findings support the second view and suggest that, in addition to fund characteristics, manager-specific attributes have a significant role in explaining *RPI*.

We conclude this subsection by examining why *RPI* falls after managerial turnover. One plausible reason could be that on average a high *RPI* manager, associated with a string of bad alphas, is replaced by a manager who relies more on his informative private signal. To examine if this is indeed the case, we interact manager fixed effects in (15) with *Bad*—a dummy variable that takes a value of one in time period $t$ if the market-adjusted abnormal return of the fund in the past three consecutive quarters is negative, and zero otherwise.[19] This interaction term measures how changes in *RPI* vary with managerial turnover after a string of bad alphas by the manager. We expect the joint $F$-test statistic on the interaction term to be negative and significant and to primarily account for the significance of manager fixed effects that we found earlier. Our results, presented in the fourth row in the table, support this conjecture. This evidence suggests that *RPI* changes associated with managerial turnover of a fund are driven primarily by changes of managers after having recorded a string of bad performance. For robustness, we repeat all the tests in this section by taking

[19] For robustness, we also use an alternative definition where we code *Bad* to be one if the fund experiences negative abnormal returns over four consecutive quarters. Our results remain unchanged with this alternative definition.

the alternative measure of reliance on public information ($RPI^{earn}$) and find qualitatively similar results (reported in Panel B).

### C. RPI and Spillover Effects

The notion underlying our tests is that portfolio holdings of informed investors are less sensitive to changes in information in the public domain. We derive this implication using a single risky asset. We use this setting because we believe that information about the asset itself drives the managerial decision regarding portfolio position in the asset. Nevertheless, it is reasonable to hypothesize that additional effects may result from information spillovers related to other similar assets. We therefore extend our model to include another risky asset and examine whether information spillovers between the risky assets in the portfolio have additional implications for our findings.[20]

To account for the potential spillover effects, we augment our economy with risky asset $\mathcal{A}_2$ whose future value, $v$, is normally distributed with mean $\bar{v}$ and precision $\rho_v$. The fundamental values of both risky assets are correlated and their correlation is captured by the variance $\sigma_{12}$ (precision $\rho$). The per capita stock of the second risky asset, $t_v$, is independently normally distributed with mean $\bar{t}_v$ and precision $\eta_v$. The price of the stock, $p_v$, is endogenously determined in the market. As before, the informed investor receives a private signal ($s_1 \sim N(\bar{u}, \rho_1)$) in addition to the public signal ($s_2 \sim N(\bar{u}, \rho_2)$) about asset $\mathcal{A}_1$ and his demand choice for this asset is the same as that outlined in Section I. In contrast, the investors do not receive any private or public signal directly about the second risky asset. We choose this signal structure since our objective is to understand how information about the first asset affects the demand of the second asset. Since the asset values are correlated, the informed investor's demand for the second asset will be affected by the private and public signal he receives about the first asset. Also, since uninformed investors condition their decisions on the public signal and price, in equilibrium the demand for asset $\mathcal{A}_2$ by uninformed investors will be affected by the information spillover from asset $\mathcal{A}_1$.

More formally, it is easy to see that an investor's demand for the risky asset depends on his posterior about $\mathcal{A}_2$'s risk and return, and is given by

$$x_v^n \equiv \alpha_v^n = \frac{\bar{v}^n - p_v}{\lambda\left(\rho_v^n\right)^{-1}}. \tag{16}$$

From (16) and the derivations in Appendix B, the informed investors' demand for the second risky asset becomes

[20] We note that the current framework is not particularly restrictive and can be readily extended to incorporate more than two risky assets. While the qualitative results of the model do not change, the computational part becomes more involved.

$$x_{Iv}^{n*} = \frac{1}{\lambda}\left\{\begin{array}{l}\frac{\rho_v\rho^2(\rho_0+\rho_1+\rho_2)}{A}(\bar{v}-p_v)+\frac{\rho_v\rho\rho_0\rho_1}{A}s_1\\ \quad+\frac{\rho_v\rho\rho_0\rho_2}{A}s_2-\frac{\rho_v\rho\rho_0(\rho_1+\rho_2)}{A}\bar{u}\end{array}\right\}, \tag{17}$$

where $A = \rho^2(\rho_0+\rho_1+\rho_2) - \rho_v\rho_0(\rho_1+\rho_2)$. To learn from the price, uninformed investors conjecture the following linear price function:

$$p_v = a_v\bar{v} + b_v s_1 + c_v s_2 - d_v t + e_v\bar{t}_v + f_v\bar{u}. \tag{18}$$

In a rational expectations equilibrium, this conjecture is correct and the coefficients $a_v, b_v, c_v, d_v, e_v$, and $f_v$ are determined, assuming that the conjectured price function is the same as the one that clears the market. Based on the analysis in Appendix B, it is clear that the uninformed investors' demand for the second risky asset can be written as

$$x_{Uv}^{n*} = \frac{1}{\lambda}\left\{\begin{array}{l}\frac{\rho_v\rho^2\left(\rho_0+\rho_\theta^v+\rho_2\right)}{B}(\bar{v}-p_v)+\frac{\rho_v\rho\rho_0\rho_\theta^v}{B}\theta_v\\ \quad+\frac{\rho_v\rho\rho_0\rho_2}{B}s_2-\frac{\rho_v\rho\rho_0\left(\rho_\theta^v+\rho_2\right)}{B}\bar{u}\end{array}\right\}, \tag{19}$$

where $B = \rho^2(\rho_0+\rho_\theta^v+\rho_2) - \rho_v\rho_0(\rho_\theta^v+\rho_2)$, $\theta_v = s_1 - \frac{d_v}{b_v}(t_v - \bar{t}_v)$. To analyze how information in the public domain affects portfolios of the informed relative to the uninformed investors, consider the impact of changes in public information, $s_2$, on the difference in holdings, $\Delta_v \equiv x_{Iv}^{n*} - x_{Uv}^{n*}$. Taking a partial derivative with respect to $s_2$, after tedious algebraic manipulations we obtain

$$\frac{\partial\Delta_v}{\partial s_2} = \frac{2\rho_2\rho_v\rho\rho_0\mu(1-\mu)\left(\rho_\theta^v-\rho_1\right)}{\lambda\begin{pmatrix}\mu(\rho_0+\rho_1+\rho_2)B\\ +(1-\mu)\left(\rho_0+\rho_\theta^v+\rho_2\right)A\end{pmatrix}}. \tag{20}$$

Importantly, note that

$$\text{sign}\left\{\frac{\partial\Delta_v}{\partial s_2}\right\} = \text{sign}\{\rho\}\times\text{sign}\left\{\left(\rho_\theta^v-\rho_1\right)\right\}. \tag{21}$$

Since $\rho_\theta^v < \rho_1$, this expression is positive or negative depending on the sign of $\rho$, that is,

$$\text{sign}\left\{\frac{\partial\Delta_v}{\partial s_2}\right\} = \begin{cases}<0, & \text{if } \rho>0\\ >0, & \text{if } \rho<0\end{cases}. \tag{22}$$

Moreover, after cumbersome calculations one can also show that

$$\text{sign}\left\{\frac{\partial^2\Delta_v}{\partial s_2\partial\rho_1}\right\} = \begin{cases}<0, & \text{if } \rho>0\\ >0, & \text{if } \rho<0\end{cases}. \tag{23}$$

As is the case with our base model, the sensitivity of the holdings of informed investors with respect to the holdings of the uninformed investors is lower for the risky asset ($\mathcal{A}_2$), which is affected by the information spillover. The economic intuition behind this result is as follows. The public signal $s_2$ is solely about $\mathcal{A}_1$ and therefore gives information about $\mathcal{A}_2$ only because the two assets are correlated. This correlation only affects the direction in which the trade in $\mathcal{A}_2$ is carried out by both the informed and uninformed investors after receiving the signal about $\mathcal{A}_1$ (e.g., given a positive correlation, buy $\mathcal{A}_2$ when $s_2$ is positive, whereas given a negative correlation, sell $\mathcal{A}_2$ when $s_2$ is positive). However, the informed traders' beliefs will still be less responsive to public information since they put lower weight on the public signal than uninformed investors do. This induces holdings of the informed investors to be less responsive to public information. Moreover, in this scenario, an increase in the precision of a private signal about $\mathcal{A}_1$ will lead to more precise information about the value of asset $\mathcal{A}_2$. Hence, more informed investors will downplay the role of the public signal to a greater extent.

To recap, we show that in an extended model with informational spillovers, the main inference about the impact on relative changes in informed versus uninformed investors' holdings in $\mathcal{A}_1$ to changes in its public information remains unchanged. However, changes in public information of one asset (say $\mathcal{A}_1$) can impact the relative changes in the holdings of informed versus uninformed investors in the other asset (say $\mathcal{A}_2$). Our analysis therefore suggests that while constructing *RPI* empirically, it is important to control for the possibility of spillovers among related stocks. What makes this exercise difficult is the fact that it is hard to establish which assets in the manager's portfolio might be correlated. Our empirical strategy tries to side-step the issue of identifying which particular stock(s) might be affected by information spillovers. Instead, it involves including in the construction of *RPI* additional variables that would account for any potential information that might be spilled to a stock (i.e., $\mathcal{A}_2$ in the model) in the fund's portfolio from other stocks related to it (i.e., $\mathcal{A}_1$ in the model).

Specifically, we modify the construction of *RPI* by including aggregate recommendation information about additional stocks operating in *S*'s industry. In the first step, we estimate the following cross-sectional regression for each fund $m$ and period $t$ from 1993 to 2002 using all stocks in the fund's portfolio:

$$\begin{aligned}\%\Delta Hold_{i,m,t} = {} & \beta_{0,t} + \beta_{1,t}\Delta Re_{i,t-1} + \beta_{2,t}\Delta Re_{i,t-2} + \beta_{3,t}\Delta Re_{i,t-3} \\ & + \beta_{4,t}\Delta Re_{i,t-4} + \gamma_{1,t}\Delta IRe_{-i,t-1} + \gamma_{2,t}\Delta IRe_{-i,t-2} \\ & + \gamma_{3,t}\Delta IRe_{-i,t-3} + \gamma_{4,t}\Delta IRe_{-i,t-4} + \epsilon_{m,t}, \end{aligned} \tag{24}$$

where $\Delta IRe_{-i,t-p}$ measures a change in the recommendation of the consensus forecast for all the stocks in the three-digit SIC of stock $i$ from time $t-p-1$ to time $t-p$, except for stock $i$, and $p = 1, 2, 3, 4$ is the number of lags of the forecast. In the second step, we construct the measure $RPI^s$ for fund $m$ at time $t$ as the $R^2$ of regression (24). Empirical tests in this section use a slightly smaller sample of funds as compared to that we use earlier, since more degrees of freedom are needed to estimate $RPI^s$. Our sample indicates significant cross-sectional variation in $RPI^s$ with an average (median) value of 30.1% (29.3%), a standard deviation of 22.0%, and a range between 1.01% and 88.7%. These characteristics of $RPI^s$ closely relate in magnitude to $RPI$.

Finally, we use $RPI^s$ to test our predictions. We estimate equation (11) to examine whether our first prediction holds with $RPI^s$. The results, reported in Table VII, suggest that consistent with our first prediction, low $RPI^s$ managers record higher abnormal performance, as measured by various factor- and

**Table VII**

## $RPI^s$ and Performance

This table reports the results of the regressions relating performance and modified *RPI* ($RPI^s$). In Panel A, we report the results of the regression $\alpha_{m,t} = \beta_0 + \beta_1 RPI^s{}_{m,t-1} + \gamma Controls_{m,t-1} + \epsilon_{m,t}$, where the dependent variable is the factor-based measure, $\alpha_{m,t}$. The risk-adjusted measures include the monthly unconditional (columns two-four) and conditional (columns five-seven) CAPM, three-factor, and four-factor alpha. The conditional measures are derived using the modified procedure of Ferson and Schadt (1996), proposed by Wermers (2000). In Panel B, we report the results of the panel regression $y_{m,t} = a + \beta_1 RPI^s{}_{m,t-1} + \gamma Controls_{m,t-1} + \epsilon_{m,t}$, where the dependent variable $y_{m,t}$ is the monthly holding-based measure. We use respectively the Grinblatt and Titman measure (*GT*), the characteristic selectivity measure (*CS*), the characteristic timing measure (*CT*), and the average style measure (*AS*) of Daniel et al. (1997). *CS* is a measure of stock selection ability and is defined as $CS = \sum w_{j,t-1}[R_{j,t} - BR_t(j,t-1)]$ where $BR_t(j,t-1)$ is the period-$t$ return of the benchmark portfolio to which stock $j$ was allocated in period $t-1$ according to its size, value, and momentum characteristics. *CT* is a measure of the style-timing ability and is defined as $CT = \sum[w_{j,t-1}BR_t(j,t-1) - w_{j,t-5}BR_t(j,t-5)]$ and *AS* is a measure of the style-selection ability and is defined as $AS = \sum[w_{j,t-5}BR_t(j,t-5)]$. $RPI^s$ measures the reliance on public information and equals the unadjusted $R^2$ of the regression of changes in managers' portfolio holdings on explanatory variables given in equation (24). Log*(TNA)* is the natural logarithm of total net assets lagged one quarter, Expenses denotes expenses lagged 1 year, Log*(Age)* is the natural logarithm of age lagged one quarter, Turnover is the turnover lagged 1 year, and *NMG* is the new money growth lagged one quarter. All regressions include quarterly time dummies. Standard errors reported in parentheses are corrected for heteroskedasticity and for the panel. Data are for the period 1993Q1 to 2002Q4.

| Panel A: Factor-Based Measures (% per Month) | | | | | | |
|---|---|---|---|---|---|---|
| | Unconditional | | | Conditional | | |
| | CAPM $\alpha$ | 3-factor $\alpha$ | 4-factor $\alpha$ | CAPM $\alpha$ | 3-factor $\alpha$ | 4-factor $\alpha$ |
| $RPI^s_{t-1}$ | −0.20*** | −0.14** | −0.18** | −0.38*** | −0.26** | −0.32** |
| (%) | (0.12) | (0.07) | (0.08) | (0.14) | (0.17) | (0.18) |
| Time fixed effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 17,944 | 17,944 | 17,944 | 17,944 | 17,944 | 17,944 |

| Panel B: Holding-Based Measures (% per Month) | | | | |
|---|---|---|---|---|
| | GT | CT | CS | AS |
| $RPI^s_{t-1}$ | −0.16*** | −0.03 | −0.35** | −0.14*** |
| (%) | (0.04) | (0.04) | (0.19) | (0.04) |
| Time fixed effects | Yes | Yes | Yes | Yes |
| Observations | 18,820 | 18,820 | 18,820 | 18,820 |

***, **, * represent 1%, 5%, 10% confidence levels, respectively. We do not report estimates on fund controls in each column for brevity.

holding-based measures. In unreported tests, we also find that our results are unchanged when we estimate equation (12) to test our second prediction. Our findings using this measure of reliance on public information indicate that the coefficient $\beta_1$ in regression (12) is negative ($-2.93$) and significant at the 1% level. The effects remain qualitatively unchanged if we instead use the Fama and French (1997) 48-industry classification. In sum, our analysis is robust to accounting for information spillovers among stocks in a fund's portfolio.

### *D. Fund Turnover and RPI*

It is possible that under semi-strong efficient markets trading on public information will erode performance due to explicit transaction costs and the price impact of trading. Thus, it is possible that the relationship between *RPI* and alpha may occur "mechanically," especially if *RPI* is positively related to fund turnover. A brief inspection of Table I cannot exclude such possibility. Indeed, *RPI* and turnover show a strong monotonic relationship. In this subsection, we examine whether this association affects the relationship between *RPI* and future performance.

If a strong cross correlation between *RPI* and fund turnover is prevalent in our sample this could potentially invalidate the regression specification in (11) due to multicollinearity. To assess the robustness of this specification, we use a series of simple tests for multicollinearity and inspect individual cross-sectional correlations between *RPI* and fund turnover. We find little evidence that *RPI* and turnover are strongly correlated. Specifically, the correlations are mostly low and the standard variance inflation factor (VIF) test for multicollinearity does not raise the red flag (i.e., all values are significantly below the critical value of four). Nevertheless, as an additional test we estimate our regressions using the following two-stage procedure. In the first stage, we obtain residuals from the panel (cross-sectional) regression of *RPI* on lagged fund characteristics. These residuals represent the part of *RPI* that is not related to fund characteristics, including fund turnover. In the second stage, we use these residuals as an independent variable in the panel (cross-sectional) regressions with various factor-based performance measures as dependent variables. The coefficient estimate on the residual in the second stage is then the quantity of interest.

The results of this two-stage estimation procedure, presented in Table VIII, illustrate that controlling for other fund-specific variability, *RPI* remains a significant predictor of future performance, both in the panel and in the cross-sectional setting. Thus, it is unlikely that our findings are an artifact of a spurious correlation between *RPI* and other observed fund characteristics, including turnover.

### *E. Risk Taking and RPI*

In this subsection, we explore how *RPI* is associated with levels of systematic or idiosyncratic risk that managers take in their portfolio strategies. Our first

**Table VIII**

**Relationship between *RPI* and Performance: Two-Stage Analysis**

This table reports the results of the panel and cross-sectional regression relating performance and residuals from the panel and cross-sectional regression of *RPI* on other fund characteristics (first stage). The results of the first stage are unreported for brevity. In columns two-four, we report the results of the panel regression (second stage; first stage estimated in panel): $\alpha_{m,t} = \beta_0 + \beta_1 Residual_{m,t-1} + \epsilon_{m,t}$, where the dependent variable is the monthly factor-based measure $\alpha_{m,t}$. We use market-adjusted (CAPM) alpha, three-factor (market, size, value) adjusted alpha of Fama and French (1993), and four-factor alpha of Carhart (1997), which additionally includes momentum as a factor. In columns five–seven, we report the results of the cross sectional regression (alternative specification for second stage; first stage estimated as cross-section) with standard errors calculated as in Fama and MacBeth (1973). *RPI* measures the reliance on public information and equals the unadjusted $R^2$ of the regression of percentage changes in managers' portfolio holdings on changes in analysts' past recommendations of up to four lags. Fund characteristics include Log*(TNA)* is the natural logarithm of total net assets lagged one quarter, Expenses denotes expenses lagged 1 year, Log*(Age)* is the natural logarithm of age lagged one quarter, Turnover is the turnover lagged 1 year, and *NMG* is the new money growth lagged one quarter. Data are for the period 1993Q1 to 2002Q4.

| | Factor-Based Measures (% per Month) | | | | | |
|---|---|---|---|---|---|---|
| | Panel Regression | | | Cross-Sectional Regression | | |
| | CAPM $\alpha$ | 3-factor $\alpha$ | 4-factor $\alpha$ | CAPM $\alpha$ | 3-factor $\alpha$ | 4-factor $\alpha$ |
| Residual | $-0.29^{***}$ | $-0.12^{**}$ | $-0.22^{***}$ | $-0.19^{*}$ | $-0.11^{*}$ | $-0.16^{***}$ |
| (%) | (0.06) | (0.06) | (0.06) | (0.10) | (0.06) | (0.07) |
| Time fixed effects | Yes | Yes | Yes | | | |
| Observations | 18,096 | 18,096 | 18,096 | 33 | 33 | 33 |

***, **, * represent 1%, 5%, 10% confidence levels, respectively.

test investigates whether managers with distinct *RPI*s differ in terms of the total risk they take on in their portfolios. One possible reason for risk to be associated with *RPI* follows from the incentive contracts for fund managers (Chevalier and Ellison (1997)). Since the incentives are likely to be increasing in the value of assets under management, the positive relationship between fund flows relative to performance creates an implicit incentive for the managers to increase the likelihood of future fund inflows, thus distorting their asset allocation choice. The same notion has been used in the literature that relies on the theory of tournaments. For example, Brown, Harlow, and Starks (1996) show that managers who perform poorly in the first half of the year tend to shift into more risky portfolios in the second half of the year.

To test this relationship formally, we estimate a panel regression with total risk as a dependent variable and *RPI* as an independent variable. To account for possible dependence related to other fund characteristics, we include the following fund-specific controls: fund returns, log size of total assets under management, log of age, turnover, and expenses. Returns and size are lagged one quarter, while age, turnover, and expenses are lagged one year. We also include time fixed effects.

$$TotRisk_{m,t} = \beta_0 + \beta_1 RPI_{m,t-1} + \gamma Controls_{m,t-1} + \epsilon_{m,t}. \tag{25}$$

**Table IX**

## Relationship between *RPI* and Risk-Taking

This table reports results related to managerial risk taking and *RPI*. Specifically, we report the results of the regression of total and unsystematic risk of a fund on its *RPI*, lagged returns, *TNA*, Age, Expenses, and Turnover. *TotRisk* measures the total fund risk and is calculated as a standard deviation of a fund's past 36 monthly returns. *UnsysRisk* measures the level of fund unsystematic risk and is calculated as a residual of the regression of fund returns on four risk/style factors of Carhart (1997). *RPI* measures the reliance on public information and equals the unadjusted $R^2$ of the regression of percentage changes in managers' portfolio holdings on changes in analysts' past recommendations of up to four lags. *R* is the return on the fund portfolio lagged one quarter, Log*(TNA)* is the natural logarithm of total net assets lagged one quarter, Expenses denotes expenses lagged 1 year, Log*(Age)* is the natural logarithm of age lagged one quarter, Turnover is the turnover lagged 1 year. All regressions include quarterly time dummies. Standard errors reported in parentheses are corrected for heteroskedasticity and for the panel. Data are for the period 1993Q1 to 2002Q4.

| | $\text{TotRisk}_t$ | $\text{UnsysRisk}_t$ |
|---|---|---|
| $RPI_{t-1}$ | 0.54*** | 0.41*** |
| (%) | (0.06) | (0.03) |
| $\text{R}_{t-1}$ | −13.14*** | −1.37** |
| (%) | (1.12) | (0.65) |
| $\text{Log(TNA)}_{t-1}$ | 10.31*** | 0.79* |
| | (0.83) | (0.47) |
| $\text{Log(Age)}_{t-1}$ | −22.67*** | −5.58*** |
| | (2.00) | (1.13) |
| $\text{Expenses}_{t-1}$ | 65.27*** | 44.30*** |
| (%) | (4.74) | (3.29) |
| $\text{Turnover}_{t-1}$ | 0.70*** | 0.31*** |
| (in %) | (0.04) | (0.02) |
| Time fixed effects | Yes | Yes |
| Observations | 18,131 | 18,131 |

***, **, * represent 1%, 5%, 10% confidence levels, respectively.

In the regression, *TotRisk* measures total fund risk and is calculated as a standard deviation of the preceding 36 monthly fund returns. Table IX (column two) presents the coefficients from the estimation. The coefficient of our primary interest is $\beta_1$. The results indicate that funds with higher *RPI* do take on more total risk. The relationship is highly significant, both statistically and economically. To examine which part of the total risk is more sensitive to *RPI*, we consider the level of idiosyncratic risk as our next dependent variable. We then estimate a panel regression of the form

$$UnsysRisk_{m,t} = \beta_0 + \beta_1 RPI_{m,t-1} + \gamma Controls_{m,t-1} + \epsilon_{m,t}, \tag{26}$$

where *UnsysRisk* is a measure of idiosyncratic risk, calculated as a residual from the regression of fund excess returns on the four factors of Carhart (1997). The relevant coefficients are presented in column three. We find that funds with higher *RPI* take on significantly more idiosyncratic risk. Overall, our findings suggest a positive relationship between manager *RPI* and their portfolio risk, both idiosyncratic and total. This behavior is consistent with that of managers who do not produce enough private information (high *RPI* managers) and take on an excessive amount of risk hoping for higher relative performance, that is, they "gamble for resurrection."

### *F. Trade Direction and RPI*

As discussed briefly in Section III.A, *RPI* does not discriminate between investors who trade in the same or opposite direction as the information in the public domain. In this subsection, we investigate whether there is any systematic relationship between fund *RPI* and the direction in which it trades with respect to changes in information in the public domain.

To examine this formally, we follow a two-step procedure. In the first step, for each time period we estimate the regression in (9) for the funds in our sample. In the second step, we take the time-series average of the resulting estimates within each decile portfolio sorted in each period with respect to *RPI*. We calculate standard errors as in Fama and MacBeth (1973), with the correction for autocorrelation as in Newey and West (1987). The results, reported in Table X, indicate that, on average, while the behavior of managers in the low *RPI* decile does not show any systematic pattern, managers in the high *RPI* decile take a contrarian view with respect to changes in information in the public domain.[21]

Overall, we note that while the above results do not affect the economic inferences made in the paper, they do help us understand the trading behavior of managers who rely more on information in the public domain.

### *G. Other Robustness Tests*

To further check the robustness of our findings, we conduct several additional tests related to our main predictions. First, since the construction of our sample depends on the availability of analysts' recommendations in IBES, it is quite possible that certain stocks held by mutual funds would have missing analysts' data and, as a result, such funds would drop out from our sample. If we assume that the reason for fund managers to hold stocks with no analyst coverage is due to their having private information about the stocks, such funds would have zero *RPI*. Thus, if the sample with no analyst coverage had lower performance, dropping these funds could lead to a possible sample selection bias. To address this issue, we evaluate the performance of funds sorted with respect to the percentage of their stocks covered by analysts. Specifically, for each period we group all funds from CRSP that we are able to match to the CDA database into

[21] Barber et al. (2001) note that investors who trade with analysts' recommendation changes generate positive market-adjusted returns, whereas investors who trade against analysts' recommendation changes generate negative market-adjusted returns. On the other hand, Irvine (2004) finds the opposite behavior by portfolio managers based on trading costs. Our results in Table X suggest that while for high *RPI* funds the relationship between changes in holdings and changes in recommendations is negative and statistically significant, for low *RPI* funds this relationship is positive and statistically insignificant.

**Table X**

## Relationship between *RPI* and Trade Direction

This table reports the average values of the coefficients' estimates of the regression $\%\Delta Hold_{i,t} = \alpha + \beta_1 \Delta R_{i,t-1} + \beta_2 \Delta R_{i,t-2} + \beta_3 \Delta R_{i,t-3} + \beta_4 \Delta R_{i,t-4} + \epsilon$, where the dependent variable $\%\Delta Hold_{i,t}$ is the percentage change in the stock split-adjusted holdings of stock $i$ from time $t-1$ to $t$. $R_{i,t-p}$ is the change in recommendation of the consensus forecast of stock $i$ from time $t-p-1$ to time $t-p$, where $p = 1, 2, 3, 4$ is the number of the $p^{\text{th}}$ forecast, with $R = 0$ if the forecast did not change during the two consecutive forecasts. The loadings are obtained using a two-stage procedure. In the first stage, for each time period we run the holding regression. In the second stage, we take the time-series average of the resulting estimates within each decile portfolio sorted with respect to *RPI* in each time period. Standard errors, calculated as in Fama and MacBeth (1973), are controlled for heteroskedasticity using the Newey and West (1987) procedure. The data span the period 1993Q1 to 2002Q4.

| *RPI* Decile | *RPI* (%) | $\beta_1$ | $\beta_2$ | $\beta_3$ | $\beta_4$ |
|---|---|---|---|---|---|
| 1 | 1.34*** | 0.76 | −6.86 | 3.68 | 4.85 |
| | (0.04) | (7.80) | (7.05) | (9.32) | (6.06) |
| 2 | 4.38*** | 3.60 | 6.02 | −11.18 | −1.12 |
| | (0.14) | (5.22) | (6.44) | (7.98) | (5.74) |
| 3 | 7.91*** | 3.20 | −3.20 | 6.57 | 1.02 |
| | (0.27) | (0.04) | (9.14) | (9.02) | (4.56) |
| 4 | 12.30*** | −10.81* | −19.92*** | 16.08 | 4.52 |
| | (0.43) | (6.59) | (8.20) | (9.99) | (5.52) |
| 5 | 17.54*** | −11.44* | −12.17** | −10.22 | −6.32 |
| | (0.64) | (6.75) | (6.13) | (7.01) | (4.93) |
| 6 | 23.88*** | −17.08** | −26.90*** | −10.77 | −4.68 |
| | (0.85) | (7.40) | (7.81) | (8.62) | (4.05) |
| 7 | 32.10*** | −38.97*** | −31.44*** | −8.50 | 0.78 |
| | (1.11) | (6.82) | (9.25) | (7.20) | (5.81) |
| 8 | 42.54*** | −37.93*** | −45.42*** | −10.70 | −3.88 |
| | (1.30) | (12.10) | (10.09) | (10.57) | (7.40) |
| 9 | 56.92*** | −62.42*** | −27.17* | 3.59 | −6.63 |
| | (1.43) | (14.49) | (16.04) | (11.73) | (6.70) |
| 10 | 81.19*** | −73.17*** | −10.40 | 3.80 | −9.41 |
| | (1.17) | (17.90) | (26.55) | (27.35) | (8.79) |

***, **, * represent 1%, 5%, 10% confidence levels, respectively.

deciles based on their analyst coverage and calculate the average performance of each decile. We then take the time-series average over the entire sample period for each decile portfolio. Our results indicate a negative relationship between percentage coverage and various measures of performance, suggesting that our sample is not biased by missing analysts' data.

Second, we investigate whether variation in analyst coverage in the portfolio of stocks by the manager can explain the relationship between funds' *RPI* and performance. It is well known that stocks differ with respect to the number of analyst reports they receive. As a result, the precision with which we can obtain consensus recommendations will also differ. For example, Cheng, Liu, and Qian (2006) argue that more analysts produce less biased and more accurate information about a stock. Given that mutual funds exhibit different preferences for stocks, it is possible that the variation in analyst coverage can explain the relationship between a fund's *RPI* and performance. To examine this possibility, we calculate the average number of analysts tracking a stock held at each period in the portfolio of the fund (*Number*) and include this variable and an interaction term between *RPI* and *Number* in the performance regression (11). Our results remain qualitatively similar.

Third, we examine how our results might be affected by differences in the size of assets under fund management. As Berk and Green (2004) argue, fund size may proxy for managerial skill, and therefore, after controlling for differences in size, the power of *RPI* to predict future performance might disappear. Another reason for fund size to affect our results might be decreasing returns to scale in the money management sector, as highlighted by Berk and Green (2004) and Chen et al. (2004). This fact makes it difficult for very large funds to outperform passive benchmarks, even if fund managers are skilled. To identify possible size dependence, we first sort funds in our sample into size quintiles based on their total net assets at the end of the preceding quarter. Subsequently, we sort the funds within each size quintile into two equal-size groups according to their *RPI*. We observe a positive performance difference between funds with low and high *RPI* in four of the size quintiles using the unconditional four-factor alpha. The results are even stronger if we use the *CS* measure, for which the effect is present in all quintiles. Moreover, the magnitude of the effect does not vary significantly across the different size quintiles. Hence, we conclude that our results are not driven by one particular group of funds with a specific size, nor is fund size able to explain away the relationship between *RPI* and performance. Similar results hold for the relationship between *RPI* and new money growth in size quintiles.

Fourth, we relate *RPI* to investing styles of the fund manager. The choice of a particular style may be directly related to managerial skill since managers often tend to invest in specific classes of assets constrained by their management companies. For our analysis, our initial selection of styles includes typical zero-investment portfolios—market (MKT), size (SMB), value (HML), and momentum (MOM).[22] To obtain the average loading values on the above style factors, for each quarter we sort all funds into quintiles with respect to their *RPI* and calculate equal-weighted excess gross returns for each such portfolio. Subsequently, using time series of the returns, for each quintile portfolio we obtain style loadings from the regression of quintile excess returns on the four distinct factors. The results indicate that all groups of funds load positively on market, size, and value factors. In contrast, the sign of the loadings on the momentum factor is mixed. The difference in loadings between funds with low and high *RPI* is insignificant for size and significant for market, value, and momentum factors. This finding suggests that *RPI* is not related in any systematic fashion to the typical classification of style. For robustness, we enrich

[22] We define MKT as the excess return of the market portfolio over the risk-free rate; SMB is the return difference between small and large capitalization stocks; HML is the return difference between high and low book-to-market stocks; MOM is the return difference between stocks with high and low past returns.

our analysis by additionally classifying each fund based on its investment objective, as disclosed in the CRSP data. In particular, we group funds into two categories, growth and value. The former group includes all funds under the heading of aggressive growth, growth, and small company growth; the latter includes growth & income and income funds. For the two groups, we estimate the regression in (11) using the unconditional four-factor alpha and the characteristic selectivity measure, *CS*. The results indicate that the relationship we find for all funds is not limited to any particular investment objective.

Fifth, since Dische (2002) argues that the dispersion in analysts' recommendations contains useful information for predicting stock returns, we include average dispersion in analysts' recommendations in the fund portfolio. We find that including this variable also does not affect our results. Finally, we use the first difference transformation instead of the fund fixed effects transformation to test our predictions. This addresses the concern that the fixed effects estimator might be biased due to a serial correlation of fund characteristics. Our findings are robust to using the first difference transformation.

## VI. Concluding Remarks

Professional investors constitute an important group that is generally deemed to possess superior information. We argue that the precision of relevant private information is related to managerial skills. Based on this notion, we build a simple model that relates the skills of the manager to his reliance on public information (*RPI*). The main implication of the model is that portfolio holdings of skilled managers are less sensitive to changes in information in the public domain. As a consequence, fund *RPI* provides us a unique insight that enhances our understanding of traditional performance measures: Skilled managers, those with high performance measures, should also have low *RPI*s. Using a large sample of U.S. equity mutual funds, we find that managers with lower *RPI* perform better, irrespective of the performance measures or information sets we condition on. These results strengthen the interpretation of traditional performance-based measures as indeed reflecting skills and suggest that some fund managers may be more skillful than others. In addition, we find that *RPI* contains information on managerial skills that may not be precisely reflected in traditional performance measures since flows from outside investors chase low *RPI* funds, controlling for past fund performance.

The findings in this paper offer several broad implications for issues related to delegated portfolio management. First, we offer a policy implication for the financial sector of mutual funds. If the degree of reliance on information in the public domain is less transparent to outside investors, one may call for more disclosure of information of this type.[23] Second, we show that *RPI* may be useful in setting managerial contracts. The problem in rewarding portfolio managers

[23] While there might be benefits to disclosing some information, funds might not want to disclose all types of information since it may adversely impact their performance. Examining what type of information funds should disclose remains an issue that we leave for future research.

based on abnormal performance alone is that it could be luck that causes the abnormal performance. Our analysis suggests that it would be desirable for management to also investigate how much their managers rely on information in the public domain and to set incentive mechanisms accordingly. In fact, there is some indication that a few players in the fund industry might have realized the importance of reliance on private information as an evaluation metric. For example, in his recent open letter to investors, Robert Litterman (Litterman (2003)), Managing Director and Head of Quantitative Resources at Goldman Sachs, defines reliance on "the data not already fully digested by the market" as one of the important factors to consider in judging the investment skills of fund managers.

Our study is subject to limitations. First, while our methodology allows us to detect any information a manager may have about future asset returns, it does not tell us what this information is about. Second, the implementation of our methodology is data-intensive in that it requires data on trading records in addition to profits and losses. Finally, due to the paucity of data, we are able to measure *RPI* only at discrete periods in time.

## Appendix A: Noisy Rational Expectation Equilibrium

It is easy to see that an investor's demand for the risky asset depends on his posterior about the asset's risk and return, and thus is given by

$$x^n \equiv \alpha^n = \frac{\bar{u}^n - p}{\lambda(\rho^n)^{-1}}. \tag{A1}$$

Using Bayes's rule, the predicted distribution of the asset value perceived by an informed investor $n$ is normal, with conditional mean and precision given by

$$\bar{u}^n = \frac{\rho_0\bar{u} + \rho_1 s_1 + \rho_2 s_2}{\rho_0 + \rho_1 + \rho_2}, \quad \rho^n = \rho_0 + \rho_1 + \rho_2. \tag{A2}$$

From (A2), the informed investors' demand for the risky asset becomes

$$x_I^{n*} = \frac{\rho_0\bar{u} + \rho_1 s_1 + \rho_2 s_2 - p(\rho_0 + \rho_1 + \rho_2)}{\lambda}. \tag{A3}$$

Following GS, we assume that uninformed investors know that the informed investor's demand affects the equilibrium price, so they make rational inferences about the informed investor's information from the price. To learn from the price, uninformed investors conjecture the following linear price function:

$$p = a\bar{u} + bs_1 + cs_2 - dt + e\bar{t}. \tag{A4}$$

In a rational expectations equilibrium (REE), this conjecture is correct and the coefficients $a, b, c, d$, and $e$ are determined assuming that the conjectured price function is the same as the one that clears the market. To estimate the demand function for the uninformed investors, let us define random variable $\theta$ as

$$\theta = \frac{p - a\bar{u} - cs_2 + \bar{t}(d - e)}{b} = s_1 - \frac{d}{b}(t - \bar{t}). \tag{A5}$$

It follows then that the uniformed investors' demand for the risky asset can be written as

$$x_U^{n*} = \frac{\rho_0\bar{u} + \rho_2 s_2 + \rho_\theta\theta - p(\rho_0 + \rho_2 + \rho_\theta)}{\lambda}, \tag{A6}$$

where $\theta$ is a random variable defined earlier with mean $u$ and precision $\rho_\theta$ given by

$$\rho_\theta = \left[\left(\frac{d}{b}\right)^2 \frac{1}{\eta} + \frac{1}{\rho_1}\right]^{-1}. \tag{A7}$$

Note that $\rho_\theta < \rho_1$. In equilibrium, for the risky asset, per capita supply must equal per capita demand, that is,

$$\mu x_I^{n*} + (1 - \mu)x_U^{n*} = t. \tag{A8}$$

In the main text we analyze the effect of changes in public information on $\Delta$. We can also analyze the effect of changes in private information, which we capture by looking at the impact of changes to signal $s_1$ on the difference in holdings $\Delta$. Here, we assume that $\rho_1 = \rho_2 = \rho$ (O'Hara (2003)). The following holds:

$$\frac{\partial\Delta}{\partial s_1} = \frac{(\rho_1 - \rho_\theta)(\rho_0 + \rho_2 - \mu\rho_1)}{\gamma\lambda} > 0. \tag{A9}$$

Thus, arrival of good (bad) private news raises (decreases) informed investors' holdings of the risky asset relative to the uninformed investors. Not surprisingly, since the uninformed see a noisy estimate of the private information $\theta$, their holdings are less responsive to the private information.

## Appendix B: Incorporating Spillovers

Using Bayes's rule, the predicted distribution of the second asset value perceived by an informed investor $n$ is normal, with conditional mean and precision given by

$$\begin{aligned} \bar{v}^n &= \bar{v} + \frac{\rho_0\rho_1}{\rho(\rho_0 + \rho_1 + \rho_2)}s_1 + \frac{\rho_0\rho_2}{\rho(\rho_0 + \rho_1 + \rho_2)}s_2 - \frac{\rho_0(\rho_1 + \rho_2)}{\rho(\rho_0 + \rho_1 + \rho_2)}\bar{u} \\ \rho_v^n &= \left\{\frac{1}{\rho_v} - \frac{\rho_0(\rho_1 + \rho_2)}{\rho^2(\rho_0 + \rho_1 + \rho_2)}\right\}^{-1}. \end{aligned} \tag{B1}$$

The uninformed investors make rational inferences about the informed investors' information from the price. To conduct our analysis we define a random variable $\theta_v$:

$$\theta_v = \frac{p_v - a_v\bar{u} - c_v s_2 + \bar{t}(d_v - e_v) - f_v\bar{u}}{b_v} = s_1 - \frac{d_v}{b_v}(t_v - \bar{t}_v). \tag{B2}$$

This random variable has mean $\bar{u}$ and precision $\rho_\theta^v$, given by

$$\rho_\theta^v = \left[\left(\frac{d_v}{b_v}\right)^2 \frac{1}{\eta_v} + \frac{1}{\rho_1}\right]^{-1}. \tag{B3}$$

To solve for the price, we note that in equilibrium, for the risky asset, per capita supply must equal per capita demand, that is,

$$\mu x_{Iv}^{n*} + (1-\mu)x_{Uv}^{n*} = t_v. \tag{B4}$$

The equilibrium price can be solved as before and is given by

$$\begin{aligned}
p_v = {} & \frac{1}{\mu\left(\frac{\rho_v\rho^2(\rho_0+\rho_1+\rho_2)}{A}\right) + (1-\mu)\left(\frac{\rho_v\rho^2\left(\rho_0+\rho_\theta^v+\rho_2\right)}{B}\right)} \\
& \times \left\{\begin{aligned}
& \left[\mu\left(\frac{\rho_v\rho^2(\rho_0+\rho_1+\rho_2)}{A}\right) + (1-\mu)\left(\frac{\rho_v\rho^2\left(\rho_0+\rho_\theta^v+\rho_2\right)}{B}\right)\right]\bar{v} \\
& + \left[\mu\left(\frac{\rho_v\rho\rho_1\rho_0}{A}\right) + (1-\mu)\left(\frac{\rho_v\rho\rho_\theta^v\rho_0}{B}\right)\right]s_1 + \left[\mu\left(\frac{\rho_v\rho\rho_2\rho_0}{A}\right) + (1-\mu)\left(\frac{\rho_v\rho\rho_2\rho_0}{B}\right)\right]s_2 \\
& - \left[\mu\left(\frac{\rho_v\rho\rho_0(\rho_1+\rho_2)}{A}\right) + (1-\mu)\left(\frac{\rho_v\rho\rho_0\left(\rho_\theta^v+\rho_2\right)}{B}\right)\right]\bar{u} \\
& - \left[1 + \frac{(1-\mu)\rho_\theta^v A}{\mu\rho_1 B}\right]t - \left[\frac{(1-\mu)\rho_\theta^v A}{\mu\rho_1 B}\right]\bar{t}.
\end{aligned}\right\}.
\end{aligned} \tag{B5}$$

## Appendix C: Matching of the CRSP and the CDA Data Sets

To analyze the relationship between mutual funds' performance and their style characteristics, one of our main tasks includes matching the CDA mutual fund holdings database against the CRSP mutual fund database. Specifically, given that the data sets have different identifying numbers, we need to use different characteristics to perform the merge. A natural common characteristic to employ as a merging variable is the fund name. The matching procedure is performed manually and often to avoid any spurious matches, it is supplemented by additional information from the web sites of particular funds. In cases in which matching by name is not conclusive, we support our matching with additional information about the total net assets and the investment objective of the fund. At the outset, our matched data set includes 4,253 different funds identified both in the CRSP and the CDA databases that existed at any time between January 1993 and December 2002. For funds with multiple share classes, we include the dominant class of shares in CRSP. For this sample, we apply another filter in which we exclude all bond, balanced, money market, index, international, and sector funds. This results in a sample of 2,998 funds. Next, we match every stockholding in the fund portfolio with the respective analyst recommendation available from IBES. Our final sample includes 1,696 distinct equity funds with complete characteristics of returns, total net assets, age, expenses, loads, turnover, portfolio holdings, style objective, and full name in at least one quarter between 1993 and 2002.

Although both the CRSP and the CDA data sets are generally free from survivorship bias, in matching the two we are unable to perform a perfect match. This problem is a consequence of the delayed updating of the CDA database and is discussed in detail in Wermers (2000). To address the difficulties in matching CRSP and CDA, we examine the performance of funds that can be identified in CRSP, but that we are unable to match to the CDA database. Since we are unable to conclusively determine whether funds outside of the match file have higher or lower *RPI*s, finding a difference in any direction in performance for both groups of funds could indicate a potential sample selection problem. To test this possibility formally, we split the universe of the U.S. diversified equity funds into those for which we are able to find the match in the CDA database and those for which we are unable to obtain such a match. For both samples, we calculate the average performance using previously used metrics, and construct $t$-tests of the respective differences in means. The results, available upon request, indicate that the average performance difference between both samples is not statistically significant. This suggests that our matching process is unlikely to introduce any bias in performance.

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