On the Precision of Public Information and Mutual Fund Performance*

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Abstract

Mutual fund managers who adjust their portfolio holdings based on the variation of analyst forecasts achieve significantly lower abnormal returns. Utilizing a simple partially revealing rational expectations equilibrium setup, I show that an uninformed (hence, unskilled) investor places greater weight on the public signal relative to an informed investor given an increase in the precision of public information. Following Kacperczyk and Seru (2007), I then formulate a new measure of managerial skill based on the standard deviation of analyst recommendations. This measure, RPI^{σ}, captures the sensitivity of changes in mutual fund managers' portfolio holdings due to changes in the standard deviation of analyst forecasts. Statistical evidence shows that abnormal returns significantly decrease in RPI^{σ}. The results are robust to other conventional performance measures and alternative formulations of RPI^{σ} using analyst price targets, EPS forecasts and coefficients of variation.

Keywords: Fund Manager Skill; RPI; Mutual Fund Performance; REE

JEL Classification: G11, G12, G14

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1 Introduction

Significant theoretical, empirical and methodological progress has been made during the past two decades towards understanding the cross section of mutual fund returns and pinpointing those factors that influence it. For example, works on the persistence of performance and abnormal performance indicators based on passive benchmarks are scattered throughout the economic discourse; see Carhart (1997), Pastor and Stambaugh (2002b), Pastor and Stambaugh (2002a), Bollen and Busse (2004) and Barras et al. (2010), or for conditional based measures Ferson and Schadt (1996) and Ferson and Khang (2002). Mutual fund performance has also been addressed with respect to holdings based measures, for example in Grinblatt and Titman (1993), Daniel et al. (1997) and Wermers (2003). However, surprisingly little work has been done towards understanding the determinants of mutual fund managerial skill. Given the large array of mutual funds available to a potential investor, one may ask how skilled fund managers can be distinguished from the unskilled without looking at conventional performance indicators, which may often simply reflect luck. An answer may lie in the relationship between information acquisition and skill itself. Those who are skilled should have the ability to accumulate private information regarding which stocks to buy or sell, and those who are unskilled may be restricted to the domain of information that is already available to the majority of market participants.

In this article, I introduce a new perspective on mutual fund managerial skill. I propose that fund managers who rebalance their portfolios based on changes in the precision of public information, i.e. the variation in stock analyst recommendations, perform worse than those who trade based on other (private) information. Until now, previous literature has concentrated on portfolio sensitivities with respect to consensus means of analyst forecasts (dubbed as "RPI" in Kacperczyk and Seru (2007), henceforth RPI^{μ}) . The motivation behind this idea is straightforward. Since consensus means have informational content for the unskilled fund manager, then it is reasonable to explore if the variation in analyst recommendations contains informational content as well. Also, a measure based on the precision of public information is worthwhile to compute even though we already have one based on consensus means, because if unskilled investors are trading based on changes in both first and second moments of analyst forecasts, then the effect of increases in portfolio sensitivities to those changes may be over- or underestimated when considering only the RPI^{μ} measure proposed by Kacperczyk and Seru (2007).

The foundation of my empirical predictions stems from a simple theoretical implication based on the partially revealing rational expectations equilibrium model first proposed by Grossman and Stiglitz (1980). Kacperczyk and Seru (2007) consider a variation of the Grossman and Stiglitz setup with an information structure that reflects the economic problem that I wish to study. The model introduces a public signal observable by all, and a private signal observable only to the informed cohort, thus separating agents into informed and uninformed investors. In this context, skill is associated with being informed. Using standard tools employed in the NREE literature such as random per capita supply and CARA utility, the model is solved for prices endogenously and demand is derived for both cohorts. It is then shown that the portfolio holdings of uninformed investors are more sensitive to changes in the precision of public information than those of the informed investor. Generally, uninformed investors place more weight on the public signal when the precision of public information increases, i.e. they increase their holdings of the risky asset more so than informed investors do. These theoretical implications provide the basis for my empirical hypotheses.

Many considerations are necessary in order to approach this article from an empirical perspective. First, to test the relationship between fund performance indicators and the reliance on variation of public information, a reliable time series of portfolio sensitivities is needed. A large dataset with information on portfolio holdings, financials and other fund characteristics for active strategy equity mutual funds is also necessary in order to conduct this analysis. Using a dataset including over 1200 mutual funds from 2003 to 2009, I am able to compute portfolio sensitivities with respect to changes in the variation of public information by proposing a regression specification similiar to that of Kacperczyk and Seru

(2007) and defining RPI^{σ} as the R^2 of those regressions. Since these regressions are run using a panel according to each mutual fund's holdings at a particular point in time, the result is a unique time-series of portfolio sensitivities for each mutual fund at the quarterly time frequency. In order to make comparisons regarding performance, a benchmark is necessary, thus I use abnormal performance indicators from the unconditional and conditional CAPM and FF pricing models (Sharpe, 1964; Lintner, 1965; Fama and French, 1993; Ferson and Schadt, 1996).

The selection of the public information set also deserves some consideration. Assuming that analysts accumulate and process all information available in the public domain, I can proxy public information with summary figures communicated by those analysts. Thus, I implement analyst recommendations, price targets, and EPS forecasts as my relevant information variables and formulate separate time series of RPI^{σ} using each.

The main result of the empirical analysis is that RPI^{σ} is negatively related to passive benchmarks. Therefore, fund managers with higher levels of RPI^{σ} perform worse than those who trade based on other information, corroborating my main empirical hypothesis. The results are robust to all three formulations of RPI^{σ} based on alternative information sets. As a second empirical exercise, I also formulate portfolio sensitivities based on contemporaneous reliance on means and variation of public information, which I dub RPI^{CV}.[1] Results show that also fund managers with higher levels of RPI^{CV} perform worse than managers exhibiting a lower level of RPI^{CV}. It is important to note that the coefficients on portfolio sensitivities with respect to the precision of public information are smaller in magnitude than those based on consensus means, suggesting that previous literature was overestimating the effect of following information in the public domain, since second moments were left unconsidered.

This study provides several relevant contributions to the growing discourse in mutual fund performance. First, since RPI^{μ} overstates the negative effect that increased sensitivity to public information has on abnormal performance, RPI^{σ} and RPI^{CV} are more valid measures

[1] CV stands for coefficient of variation.

of managerial skill. Moreover, RPI^{σ} should also be interesting to those who monitor the investment performance of mutual fund managers, especially given the growing pressure to regulate financial markets post 2007 subprime crisis. Most importantly, RPI^{σ} provides a relatively unique perspective on pinpointing outperforming mutual funds which has not yet been considered in this discourse. To my knowledge, this study is the first attempt to analyze the implications of second moments for portfolio decision making in empirical asset pricing.

Accordingly, this article is organized as follows. In Section 2, I will present the theoretical foundations of the economic problem that I wish to analyze. Section 3 will give a thorough overview of the dataset, including a detailed description regarding the methodology behind the formulation of RPI^{σ}. Section 4 will outline my empirical strategy and formalize my empirical predictions based on the theoretical analysis. Section 5 will present the main results of the empirical analysis. Concluding thoughts and my agenda for further research will follow in Section 6.

2 Theoretical Foundations

I will begin by presenting the theoretical foundations pertaining to public signals and mutual fund managerial skill by utilizing a noisy rational expectations equilibrium model introduced by Kacperczyk and Seru (2007), which is based on the setup first introduced by Grossman and Stiglitz (1980). The model is centered around informed and uninformed agents, and the aim will be to analyze how changes in the precision of public information influence the portfolio decision making of the unskilled agents relative to those who are skilled.

Essentially, the model setup is exactly as in Kacperczyk and Seru (2007). The timeline consists of two time periods, $t = 0$ and $t = 1$, where portfolio decisions are made in the first time period and payoffs are realized in the second. Agents trade two assets: a risk-free asset with price $p = 1$ & payoff $R_f = 1$, and a risky asset A_1 with price p & random payoff $\tilde{u} \sim \mathcal{N}(\bar{u}, \rho_0^{-1})$. The market is comprised of a finite number of agents, N, with

$n \in \{1, 2, \ldots, N\}$. Each agent is either informed or uninformed (hence, skilled or unskilled, respectively). The number of skilled agents is set equal to L where $0 < L < N$ and the fraction of skilled investors is denoted as $\mu = \frac{L}{N}$. The fraction of uninformed agents follows as $1 - \mu = \frac{N-L}{N}$. Each agent has an initial endowment, or wealth, denoted by $\bar{m}^n$. Preferences are homogeneous across agents in that all agents are CARA utility maximizers with common coefficient of risk aversion $\lambda > 0$.[2] In order to ensure a noisy rational expectations equilibrium, a random per capita supply shock t is introduced with $t \sim \mathcal{N}(\bar{t}, \eta^{-1})$.

The information structure of this economy consists of two types of signals. First, the private signal, denoted by s_1, is observable solely to skilled investors. The public signal, denoted by s_2, is observable to both skilled and unskilled investors. The private signal is modeled as $s_1 = \bar{u} + \varepsilon_1$, where $\varepsilon_1 \sim \mathcal{N}(0, \rho_1^{-1})$. Furthermore, the public signal is determined as $s_2 = \bar{u} + \varepsilon_2$, where $\varepsilon_2 \sim \mathcal{N}(0, \rho_2^{-1})$. Note that the public signal and the private signal share the same fundamental value, $\bar{u}$. Additionally, independence between ε_1, ε_2, $\bar{u}$ and t is imposed, that is $\varepsilon_1 \perp \varepsilon_2 \perp \tilde{u} \perp t$. The distribution of each signal is assumed to be common knowledge among all market participants. Given, the supply, endowments, preferences, and information structure of the economy, the market clearing price of the risky asset, denoted with p, will be endogenously determined in the model.

In order to solve the model for equilibrium prices, the terminal wealth of the investor can be expressed as

$$\tilde{w}^n = \bar{m}^n + (\tilde{u} - p)\alpha^n \tag{1}$$

where α^n denotes the stock holdings held by agent n. Thus, equation (1) represents the initial wealth, $\bar{m}^n$, plus any subsequent capital gains from trading the risky asset, $(\tilde{u} - p)\alpha^n$. Given this constraint, each investor maximizes his expected utility, where with CARA preferences the objective function follows a mean variance representation, given by $E[\tilde{w}^n] - \frac{\lambda}{2} Var[\tilde{w}^n]$.

The above utility maximization problem is solved and the price determined endogenously by imposing the market clearing condition. Uninformed investors then revise their posteriors

[2]The CARA assumption guarantees that investor demand will not depend on an agent's wealth.

based on the conjectured linear price functional where learning is induced by defining $\theta = s_1 - \frac{d}{b}(t - \bar{t})$, then individual demands are revised, and the conjectured price verified, which equates to

$$p = a\bar{u} + bs_1 + cs_2 - dt + e\bar{t} \tag{2}$$

where $\alpha = \frac{\rho_0}{\gamma}$, $b = \frac{\mu\rho_1 + (1-\mu)\rho_0}{\gamma}$, $c = \frac{\rho_2}{\gamma}$, $d = \frac{\lambda(1 + \frac{(1-\mu)\rho_\theta}{\mu\rho_1}}{\gamma}$, $e = \frac{(1-\mu)\rho_\theta\lambda}{\mu\rho_1\gamma}$, $\rho_\theta = \left[(\frac{d}{b})^2\frac{1}{\eta} + \frac{1}{\rho_1}\right]^{-1}$ and $\gamma = \rho_0 + \rho_2 + (1-\mu)\rho_\theta$.[3] In this rational expectations equilibrium, the difference between individual demands of the informed and the uninformed investors is given by

$$\Delta \equiv x_I - x_U = \frac{s_1(\rho_1 - \rho_\theta) + p(\rho_\theta - \rho_1) + \frac{\rho_\theta\lambda}{\mu\rho_1}(t - \bar{t})}{\lambda}. \tag{3}$$

In order to make inferences regarding how the demands between skilled and unskilled investors differ based on changes in the public signal and the precision of the public signal, first the partial derivative of (3) with respect to s_2 is taken and yields

$$\frac{\delta\Delta}{\delta s_2} = \frac{\rho_2(\rho_\theta - \rho_1)}{\gamma\lambda} < 0. \tag{4}$$

This result from equation (4) highlights that unskilled investors react more to changes in the public signal than skilled investors do. Thus, when s_2 increases, unskilled investors revise their portfolios with more holdings of the risky asset than skilled investors do. Likewise, when s_2 decreases, unskilled investors compensate by lowering their holdings of the risky asset more so than the skilled investor would. This result can be attributed to the unskilled investor placing more weight on changes in the public signal than a skilled investor would, since the skilled investor also trades based on his private signal.

Taking the second derivative of (3) with respect to s_2 and ρ_2 yields

$$\frac{\delta^2\Delta}{\delta s_2 \delta\rho_2} = -\frac{1}{\lambda}(\rho_1 - \rho_\theta)\frac{(\rho_0 + (1-\mu)\rho_\theta)}{(\rho_0 + \rho_2 + (1-\mu)\rho_\theta)^2} < 0. \tag{5}$$

[3]Details regarding the equilibrium analysis can be found in Kacperczyk and Seru (2007)

The result in equation (5) tells us that relative to unskilled investors, informed investors place less weight on the public signal, s_2, given an increase in the precision of public information, ρ_2. Hence, when the public signal becomes finer, unskilled investors increase their holdings of the risky asset holding constant the level of s_2 more so than a skilled investor would, and vice versa given a decrease in the precision of public information. Most importantly and to summarize, the precision of public information has more informational content for the unskilled investor than it does for the skilled investor, i.e. the unskilled investor reacts to changes in the variation of the public signal more than the skilled investor does, and uses the precision of public information when rebalancing his/her portfolio.

Given the results of the theoretical exercise, I expect any measure of portfolio sensitivity with respect to changes in variation of information in the public domain (denoted with RPI^{σ}) to proxy for managerial skill. Thus, those managers who demonstrate a high level of RPI^{σ} should perform worse than those who demonstrate low levels of RPI^{σ}. I will formalize my hypothesis in section (4.1) after presenting the data and my empirical strategy to analyze the relationship between RPI and fund performance.

3 Dataset

3.1 Mutual Fund Data

Data are accumulated and aggregated from various sources. Mutual fund details and portfolio holdings are obtained from the CRSP Survivorship Bias Free Mutual Fund Database, which contains data regarding fund size, fees, portfolio holdings, objective and performance. Portfolio holdings include both voluntary reports and mandatory SEC filings at the quarterly time frequency, and are available from March 2003 until September 2009. Stock prices are accessed from the CRSP stock files and matched to portfolio holdings.

Analyst forecasts are obtained from the I/B/E/S database at the monthly time frequency and matched with portfolio holdings. Forecasts include analyst recommendations (ranging from 1 to 5 discretely, with 1 corresponding to "strong buy" and 5 to "strong sell"), earnings per share (EPS) forecasts and price targets. Notice that a positive shock to expected future cash flows for any given stock leads to an increase in EPS forecasts and price targets for that security, whereas it has the opposite effect on the value reported under recommendations (positive shocks lead to decreases in recommendations).

For each mutual fund in the sample, unconditional and conditional 35 month alphas are computed following Carhart (1997) and Ferson and Schadt (1996). Risk factors in the unconditional model have been acquired from Kenneth French's website. Predetermined information variables[4] in the conditional model were acquired from the Federal Reserve.

Mutual funds are screened according to investment objective[5] before they are included in the final dataset. Since the focus of this study is on equity forecasts, I eliminate balanced and bond funds. I also exclude sector funds to avoid industry specific biases, and omit international funds in order to focus strictly on U.S. equity funds. Mutual funds that engage in passive investment strategies, such as index funds, have also been removed.[6] Last, I include multiple share classes only once in the sample. The final dataset includes 1220 equity mutual funds with at least 5 consecutive quarters of data from 2003-2009.

3.2 Reliance on Public Information

In order to associate fund performance with a manager's reliance on public information, it is necessary to measure the degree in which a manager uses public information variables for portfolio allocation decisions. In order to do so, it is crucial to identify a suitable proxy for the public information domain. Following Kacperczyk and Seru (2007), I use analyst recom-

[4]Information variables include lagged levels of the 1-month T-bill yield, lagged dividend yields of the CRSP value weighted NYSE and AMEX stock index (computed as the price level at $t-1$ divided by the previous 12 months of dividend payments), lagged levels of the corporate bond yield spread (Moody's BAA corporate bond yield minus Moody's AAA corporate bond yield), lagged levels of the constant maturity 10-year T-bond yield minus 3-month T-bill yields, and a dummy variable for January.

[5]Lipper objective codes are used to identify mutual fund investment strategies.

[6]Regarding mutual funds for which a passive investment strategy is not explicitly specified in the Lipper objective codes, I compute correlation coefficients between fund returns and returns on the S&P 500 stock index, and omit funds with correlations larger than 0.995.

mendations as the public information variable, but in order for recommendations to qualify as a suitable proxy, two assumptions are necessary. First, analysts must have accumulated and incorporated all publicly available information into their recommendations. Second, unskilled managers must aggregate all available analyst recommendations in their allocation decisions, thus they do not follow specific analysts and concentrate on consensus forecasts. The latter assumption is reasonable, since the knowledge to follow a specific analyst who can outperform the others could be considered as "skillful."

The empirical methodology to measure the sensitivity of portfolio changes to changes in consensus recommendations directly follows Kacperczyk and Seru (2007), in that the following regression is estimated with OLS using stocks $i = 1, \ldots, n$ in the portfolio of each mutual fund m at each point in time t:

$$\%\Delta Hold_{i,m,t} = \beta_{0,t} + \sum_{p=1}^{4} \beta_{p,t} \Delta R^{\mu}_{i,t-p} + \varepsilon_{m,t} \quad i = 1, \ldots, n \tag{6}$$

where $\%\Delta Hold_{i,m,t}$ denotes the percentage change in holding i for mutual fund m between time $t-1$ and t, and $\Delta R^{\mu}_{i,t-p}$ represents the change in mean consensus recommendations for stock i from time $t-p-1$ to $t-p$ for $p = 1, 2, 3, 4$; hence the explanatory variable is lagged four times in equation (6). Since the dependent variable is in terms of percent change, I follow previous convention and set the increase to 100% for stocks that enter the portfolio at time t.[7] The reliance on public information using consensus means, as defined by Kacperczyk and Seru (2007), is then obtained as

$$RPI^{\mu}_{m,t-1} = 1 - \frac{\sigma^2(\varepsilon_{m,t})}{\sigma^2(\%\Delta Hold_{m,t})}. \tag{7}$$

Thus, $RPI^{\mu}_{m,t-1}$ is the unadjusted R^2 of (6). Since RPI^{μ} represents the amount of variation in changes of portfolio holdings explained by the statistical model, it also represents the

[7] Kacperczyk and Seru (2007) set the increase to 100% and find little difference using alternative benchmarks.

sensitivity of portfolio adjustments with respect to changes in consensus means. Capturing RPI^{μ} in this way allows portfolio sensitivities to be accumulated regardless of the direction of trade, however Kacperczyk and Seru (2007) reject the hypothesis that mutual funds in the lowest deciles of RPI^{μ} follow the opposite direction of changes in consensus means, and fail to reject (at the 99% confidence level) that mutual funds in the highest deciles of RPI^{μ} decrease their holdings given an increase in consensus recommendations. Hence, it is unlikely that fund managers pursue an "opposites" strategy.

In order to formulate RPI^{μ} using EPS forecasts and price targets, (6) requires a slight adjustment. Since changes in EPS forecasts and price targets are not comparable in magnitude across stocks, I take the percentage change instead of the change in levels as the independent variables in the first stage regression, that is:

$$\%\Delta Hold_{i,m,t} = \beta_{0,t} + \sum_{p=1}^{4} \beta_{p,t} \%\Delta F^{\mu}_{i,t-p} + \varepsilon_{m,t} \quad i = 1, \ldots, n \tag{8}$$

where $\%\Delta F^{\mu}_{i,t-p}$ denotes the percentage change in forecast (either EPS or price targets) from time $t-p-1$ until $t-p$. Such an adjustment is warranted, since an increase from \$1 to \$2 in earnings per share is not equivalent to an increase from \$50 to \$51, while when working with consensus recommendations the difference between a change from 1 to 2 and 4 to 5 are the same. This rationale applies for price targets as well.

Portfolio sensitivities with respect to changes in the variation of analyst forecasts are formulated in a similar fashion. The following regression is estimated using OLS as before:

$$\%\Delta Hold_{i,m,t} = \beta_{0,t} + \sum_{p=1}^{4} \beta_{p,t} \Delta R^{\sigma}_{i,t-p} + \sum_{p=1}^{3} \gamma_{p,t} \Delta A^{\mu}_{i,t-p} + \varepsilon_{m,t} \quad i = 1, \ldots, n \tag{9}$$

where $\Delta R^{\sigma}_{i,t-p}$ denotes the cross sectional change in the standard deviation of analyst forecasts from time $t-p-1$ to $t-p$ and $\Delta A^{\mu}_{i,t-p}$ represents the average number of analysts from time $t-p-1$ to $t-p$. The reliance on consensus variation, or $RPI^{\sigma}_{m,t-1}$, is defined exactly as in (7), hence it is the R^2 of (9). The underlying assumption in this empirical setup is that portfolio managers may respond to changes in both cross sectional standard deviations and also the number of analysts, i.e. unskilled managers may put less weight on variation during the portfolio decision process when the amount of analysts is small.[8] Thus, those investors that respond to variation and/or analyst following will be captured either by the β_t's or the γ_t's of (9). The formulation of $RPI^{\sigma}_{m,t-1}$ using EPS forecasts and price targets also follows as before, whereby explanatory variables of differences in standard deviations are replaced by percentage changes.

In order to capture the contemporaneous reliance on both means and standard deviations, I compute coefficients of variation with reference to consensus means and standard deviations for each stock at each point in time.[9] Then I estimate the following regression using OLS:

$$\%\Delta Hold_{i,m,t} = \beta_{0,t} + \sum_{p=1}^{4} \beta_{p,t} \Delta CV_{i,t-p} + \sum_{p=1}^{3} \gamma_{p,t} \Delta A^{\mu}_{i,t-p} + \varepsilon_{m,t} \quad i = 1, \ldots, n \tag{10}$$

where $\Delta CV_{i,t-p}$ denotes the change in coefficients of variation for consensus analyst recommendations from time $t-p-1$ to $t-p$. Equation (10) is also estimated using EPS forecasts and price targets, however $\Delta CV_{i,t-p}$ is replaced with $\%\Delta CV_{i,t-p}$ as before. The reliance on consensus means and standard deviations for each mutual fund at each point in time follows as the R^2 of (10) and is denoted as $RPI^{CV}_{m,t-1}$. For EPS forecasts and price targets, decreases in the variation of analyst forecasts and increases in consensus means are both "positives," and cause the coefficient of variation to decrease. For analyst recommendations, an increase in consensus recommendations is a "negative," since 1 corresponds to "strong buy" and 5 corresponds to "strong sell." Therefore, analyst recommendations are corrected when computing coefficients of variations by reversing the numerical values associated with each respective recommendation.[10]

[8] The variation of recommendations for a stock with a large analyst following cannot be compared with the variation of recommendations for a stock with a relatively small analyst following.

[9] The coefficient of variation is defined as $\sigma_{i,t}/\mu_{i,t}$, where $\sigma_{i,t}$ denotes the standard deviation of analyst forecasts and $\mu_{i,t}$ denotes the consensus mean of analyst forecasts for each stock i at time t.

[10] I adjust recommendations by subtracting the consensus mean from 6, thus "strong sell" consequently corresponds to 1 and "strong buy" to 5.

The final dataset consists of a time series of RPI^{μ}, RPI^{σ} and RPI^{CV} formulated using analyst recommendations, price targets and EPS forecasts for each mutual fund in the sample. Summary statistics are provided in Table 1, where mutual fund data are separated into deciles according to each fund's average level of RPI^{σ} formulated with analyst recommendations.

4 Empirical Strategy

In order to show that RPI^{μ}, RPI^{σ} and RPI^{CV} are measures of mutual fund managerial skill, the relationship between RPI and traditional empirical benchmarks must be evaluated. In specific, I estimate the following regression as in Kacperczyk and Seru (2007):

$$\alpha_{m,t} = \beta_0 + \beta_1 RPI_{i,t-1} + \gamma' Controls_{i,t-1} + \varepsilon_{m,t} \tag{11}$$

where $\alpha_{m,t}$ denotes the fund-specific performance measurement at time t, $Controls_{i,t-1}$ a column vector consisting of fund characteristic control variables and γ' a row vector of coefficients. Notice that the specification in (11) is forward looking. RPI has implications regarding future performance, in the sense that today's portfolio decisions affect tomorrow's returns,[11] and this convention is maintained throughout the empirical analysis. Four specifications for the performance measure $\alpha_{m,t}$ are considered. I follow Carhart (1997) and derive alpha as the intercept of the unconditional CAPM and Fama-French pricing equations using a 35 month rolling window of mutual fund returns, plus the error term at time t (Sharpe, 1964; Lintner, 1965; Fama and French, 1993). Conditional alphas are also computed as in Ferson and Schadt (1996) and Wermers (2003), whereby a vector of predetermined information variables are interacted with the market risk premium and supplemented to the

[11] Although RPI is highly persistent with $AR(1)$ coefficients between 0.3 and 0.6 depending on the specification, the forward looking model highlights the timing implications of RPI. Nevertheless, the results remain consistent albeit somewhat weaker when contemporaneous variables are inserted.

Table 1: Summary Statistics

Data are from March 2003 until September 2009. Each mutual fund is assigned to a decile portfolio based on their time series average of RPI_{σ}, where RPI^{μ} and RPI^{σ} represent portfolio sensitivities measured with respect to consensus means and standard deviations of analyst recommendations and are the R^2s of regression specifications (6) and (9), respectively. TNA represents the total net assets of the mutual fund for month t. *Age* is the age of the fund, in years. *TurnoverRatio* is the turnover ratio of each mutual fund, lagged by one year. *ExpenseRatio* represents the ratio of total investment paid by investors for the mutual fund's operating expenses in the most recently completed fiscal year, and *Returns* is the monthly return of each mutual fund for month t.

Decile of $RPI\sigma$	Mean						
	$RPI\sigma$	$RPI\mu$	TNA (monthly)	Age (yrs)	Turnover Ratio (%)	Expense Ratio (%)	Returns (monthly)
1	3.0	2.6	493.2	1.1	48.4	0.9	1.9
2	7.4	4.9	49.2	1.4	64.9	1.1	1.5
3	10.8	7.4	197.2	1.4	68.4	1.1	1.3
4	14.3	9.6	137.3	1.9	68.3	1.3	1.8
5	17.3	10.5	1,034.9	1.8	80.3	1.3	1.7
6	20.7	13.2	95.9	1.8	67.1	1.2	1.5
7	24.7	14.4	286.2	1.9	79.1	1.3	1.3
8	30.2	17.3	323.1	2.0	87.0	1.3	1.4
9	38.5	21.6	121,262.3	3.7	91.0	1.4	1.6
10	61.3	33.9	54,432.8	2.9	124.6	1.4	1.6
Total	22.8	13.5	17,814.8	2.0	77.8	1.2	1.6

unconditional CAPM and Fama-French specifications.[12] The vector of controls includes total net assets (TNA), age, expense ratio, turnover ratio and new money growth.

Regression (11) must be corrected for autocorrelation and heteroskedasticity in the panels. Thus, the panel corrected standard errors estimator with panel specific $AR(1)$ structures is used to estimate equation (11) with robust standard errors (Beck and Katz, 1995). Note that a correction for contemporaneous correlation is omitted, which is warranted when the panel dataset is highly unbalanced and contains a small time dimension and a relatively large cross sectional dimension (Pesaran, 2004).

4.1 Empirical Predictions

In Section 2, it was shown that unskilled investors place more weight on the public signal given an increase in the precision of information in the public domain, as opposed to skilled investors whose demand for the risky asset is less sensitive to changes in precision. Given that RPI^{σ} provides a ranking of mutual funds from 0 (portfolios which are least sensitive to precision) to 1 (portfolios which are most sensitive to precision), I expect any formulation of RPI^{σ} to have a negative relationship with fund performance indicators.

> HYPOTHESIS 1: *RPI^{σ} is negatively related to fund performance indicators. Hence, a relationship between mutual fund managerial skill and a fund manager's reliance on the precision of public information exists, and those fund managers who rely more heavily on the precision of public information perform worse than those who trade based on other (superior) information.*

Hypothesis 1 can be considered the null hypothesis in this research exercise. The alternative hypothesis would state that no relationship exists between RPI^{σ} and traditional fund

[12]The vector of predetermined information variables is de-meaned and includes the lagged level of the 30 day annualized T-bill yield, the lagged dividend yield of the CRSP value-weighted NYSE/AMEX stock index, the lagged level of the constant maturity 10-year T-bond yield minus the 3 month T-bill yield, the lagged level of Moody's BAA corporate bond yield minus Moody's AAA corporate bond yield, and a dummy variable for January.

performance indicators. That would imply that managers following changes in the precision of public information neither perform worse nor better than those who trade based on other information.

Given the findings of Kacperczyk and Seru (2007) and the implications derived in Section 2 regarding the relationship between the reliance on consensus means and mutual fund managerial skill, I would also expect similar results regarding the contemporaneous reliance on both consensus means and the precision of public information, since unskilled managers rely on both in the theoretical framework. Thus, a fund manager who makes portfolio decisions based on simultaneous changes in consensus means and variation in the consensus (hence, the coefficient of variation) should perform worse than those who do not. In this case, the relevant indicator RPI^{CV} should have a negative relationship with fund performance measures, and the effect on those measures should be similar in magnitude as RPI^{σ}.[13]

> HYPOTHESIS 2: *RPI^{CV} is negatively related to fund performance indicators. Thus, a relationship between mutual fund managerial skill and a fund manager's reliance on the coefficient of variation of consensus forecasts exists, and those who rely on the coefficient of variation of consensus forecasts perform worse than those who do not.*

The latter hypothesis postulates that both the mean and standard deviation of consensus forecasts simultaneously have informational content for the unskilled trader. The alternative hypothesis would assert that no relationship exists between fund performance and RPI^{CV}.

An interesting exercise will be to compare the magnitude in which fund performance decreases relative to RPI^{μ}, RPI^{σ} and RPI^{CV}.

[13] RPI^{σ} and RPI^{CV} should have a similar effect in magnitude because unskilled mutual fund managers require the consensus mean in order to ascertain the directionality of their trades, and more precise signals simply determine the weight of the public signal on portfolio decision making for unskilled managers. Since RPI^{σ} is simply a measure of sensitivity between the variation of public information and portfolio allocations, directionality is embedded in it. RPI^{CV} is also embedded with directionality, however more formally with the inclusion of consensus means in its formulation.

5 Empirical Analysis and Results

Here I will show the main empirical results pertaining to the relationship between variation in information from the public domain and mutual fund performance. Subsection 5.1 presents evidence linking RPI^{σ} to managerial skill using various information sets, while subsection 5.2 will show that managers who rely on coefficients of variation of consensus analyst forecasts to make portfolio decisions perform worse than those who trade based on other information.

5.1 Mutual Fund Performance and RPI^{σ}

Table 2 presents the results from panel corrected standard error passive factor-based regressions of equation (11) using analyst recommendations (denoted with REC) to formulate RPI^{μ} and RPI^{σ}. Quarterly time dummies are included in each regression specification to control for time fixed effects. Each regression model was also estimated using fund specific fixed effects, the output of which is omitted for brevity since the results remain quantitatively similar to the ones presented here, but are available to the reader upon request. Models (1) and (2) verify previous literature using unconditional CAPM and Fama-French alphas as dependent variables, and models (5) and (6) verify it using conditional alphas. The coefficient on RPI^{μ}_{t-1} is negative and statistically significant with similar magnitude as in Kacperczyk and Seru (2007) in all four specifications. Models (3), (4), (7) and (8) include RPI^{σ}_{t-1}, the coefficient of which is also negative and statistically significant with respect to conditional and unconditional CAPM and Fama-French alphas. The coefficient on RPI^{μ}_{t-1} varies between -.37% and -.19%, while the coefficient on RPI^{σ}_{t-1}, however, is much more stable between -.12% and -.15%. RPI^{σ}_{t-1} seems to be a more robust indicator of managerial skill with respect to passive benchmarks than RPI^{μ}_{t-1}. Generally, the results corroborate my hypothesis that RPI^{σ} is associated with mutual fund managerial skill when considering passive factor-based portfolios as benchmarks.

For robustness, the analysis was also repeated with alternative formulations of RPI^{σ}

Table 2: Factor Based Regressions on RPI Formulated using Analyst Recommendations as the Information Set
This table presents the results of regressions based on equation (11) corrected for autocorrelation and heteroskedasticity using panel corrected standard errors (Beck and Katz, 1995). Data are from March 2003 until September 2009. The dependent variable in each regression specification is fund specific alpha, $\alpha_{m,t}$. Unconditional and conditional CAPM and Fama-French alphas are considered as performance benchmarks for the analysis (Sharpe, 1964; Fama and French, 1993; Ferson and Schadt, 1996). RPI^{μ}(REC) and RPI^{σ}(REC) represent portfolio sensitivities measured with respect to consensus means and standard deviations of analyst recommendations and are the R^2s of regression specifications (6) and (9), respectively. $lnTNA$ represents the natural logarithm of each mutual fund's total net assets, lagged one quarter. $lnAge$ is the natural logarithm of mutual fund age, lagged one quarter. *Expenses* represents the ratio of total investment paid by investors for the mutual fund's operating expenses in the most recently completed fiscal year. $Turnover$ is the turnover ratio of each mutual fund, lagged by one year. NMG is new money growth lagged by one quarter, and is given by $NMG = \frac{TNA_{m,t} - TNA_{m,t-1}(1+R_{m,t})}{TNA_{m,t-1}}$ where $R_{m,t}$ represents fund specific return at time t.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	α_{CAPM}	α_{FF}	α_{CAPM}	α_{FF}	$\alpha_{CAPM,Cond}$	$\alpha_{FF,Cond}$	$\alpha_{CAPM,Cond}$	$\alpha_{FF,Cond}$
RPI^{μ}_{t-1}(REC)	-0.364***	-0.172*			-0.261***	-0.190**		
	(0.104)	(0.0884)			(0.0959)	(0.0851)		
RPI^{σ}_{t-1}(REC)			-0.129*	-0.131**			-0.134**	-0.155***
			(0.0738)	(0.0619)			(0.0683)	(0.0600)
$lnTNA_{t-1}$	-0.505	0.357	-0.441	0.348	-0.368	0.558	-0.336	0.551
	(1.038)	(0.842)	(1.043)	(0.842)	(0.973)	(0.805)	(0.975)	(0.806)
$lnAge_{t-1}$	-3.048	-0.876	-3.307	-0.896	-4.146**	-1.245	-4.274**	-1.235
	(2.168)	(1.670)	(2.169)	(1.669)	(2.076)	(1.656)	(2.079)	(1.654)
$Expenses_{t-1}$(%)	13.27	7.103	13.06	7.378	7.765	6.482	7.832	6.863
	(10.89)	(9.346)	(10.92)	(9.363)	(10.32)	(9.625)	(10.34)	(9.641)
$Turnover_{t-1}$(%)	0.181***	0.157***	0.178***	0.160***	0.101***	0.117***	0.101***	0.120***
	(0.0262)	(0.0206)	(0.0263)	(0.0207)	(0.0233)	(0.0201)	(0.0234)	(0.0201)
NMG_{t-1}	-0.0340**	-0.0204	-0.0337**	-0.0205	-0.0258*	-0.0140	-0.0257*	-0.0141
	(0.0170)	(0.0207)	(0.0170)	(0.0208)	(0.0153)	(0.0205)	(0.0154)	(0.0207)
N	11624	11624	11624	11624	11624	11624	11624	11624
N_g	1219	1219	1219	1219	1219	1219	1219	1219

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

using price targets and EPS forecasts instead of analyst recommendations to proxy for information in the public domain. Table 3 presents the results of panel corrected standard error estimations of equation (11) using unconditional and conditional Fama-French alphas as dependent variables and lagged levels of RPI^{σ} based on price targets and EPS forecasts as independent variables (denoted with PTG and EPS, respectively). The coefficient on RPI^{σ}_{t-1} remains negative in all four model specifications and statistically significant at the 10% level in the unconditional Fama-French specifications and at the 5% level in the conditional Fama-French specifications.

5.2 Mutual Fund Performance and Managerial Reliance on Coefficients of Variation

In order to test Hypothesis 2 empirically, equation (11) is estimated using RPI formulated with consensus means and standard deviations (hence the coefficient of variation), denoted with RPI^{CV}. Table 4 presents the results from passive factor-based regressions of equation (11) using the PCSE estimator as before and RPI^{CV}_{t-1} as the RPI measure. Unconditional Fama-French alphas are used as the dependent variable in model specifications (1), (2) and (3), while conditional Fama-French alphas are used in models (4), (5) and (6). Alternative information sets are also considered in the formulation of RPI^{CV}_{t-1}, with columns (1) & (4) pertaining to RPI^{CV}_{t-1} formulated with analyst recommendations (REC), columns (2) & (5) to EPS forecasts (EPS), and (3) & (6) to price targets (PTG). Results show that the coefficient on RPI^{CV}_{t-1} is negative for all six specifications. When considering unconditional Fama French alphas as the performance benchmark, the coefficient on RPI^{CV}_{t-1} formulated with analyst recommendations and price targets are statistically significant at the 10% level. Furthermore, the performance of RPI^{CV}_{t-1} as a predictor of fund performance improves when considering conditional Fama French alphas as the dependent variable, with all three formulations improving in statistical significance, where the coefficient on RPI^{CV}_{t-1} (PTG) is also significant at the 1% level. Moreover, when comparing the results of Table 4 with those of

Table 3: Factor Based Regressions with Alternative Formulations of RPI^{σ} using Price Targets and EPS Forecasts
This table presents the results of regressions based on equation (11) corrected for autocorrelation and heteroskedasticity using panel corrected standard errors (Beck and Katz, 1995). Data are from March 2003 until September 2009. The dependent variable in each regression specification is fund specific alpha, $\alpha_{m,t}$. Unconditional and conditional Fama-French alphas are considered as performance benchmarks for the analysis (Fama and French, 1993; Ferson and Schadt, 1996). RPI^{σ}(PTG) and RPI^{σ}(EPS) represent portfolio sensitivities measured with respect to standard deviations of analyst price targets and EPS forecasts and are the R^2s of regression specification (9) with the explanatory variables of differences in standard deviations replaced by percentage changes. $lnTNA$ represents the natural logarithm of each mutual fund's total net assets, lagged one quarter. $lnAge$ is the natural logarithm of mutual fund age, lagged one quarter. $Expenses$ represents the ratio of total investment paid by investors for the mutual fund's operating expenses in the most recently completed fiscal year. $Turnover$ is the turnover ratio of each mutual fund, lagged by one year. NMG is new money growth lagged by one quarter, and is given by $NMG = \frac{TNA_{m,t} - TNA_{m,t-1}(1+R_{m,t})}{TNA_{m,t-1}}$ where $R_{m,t}$ represents fund specific return at time t.

	(1)	(2)	(3)	(4)
	α_{FF}	α_{FF}	$\alpha_{FF,Cond}$	$\alpha_{FF,Cond}$
RPI^{σ}_{t-1}(PTG)	-0.103*		-0.149**	
	(0.0605)		(0.0580)	
RPI^{σ}_{t-1}(EPS)		-0.108*		-0.125**
		(0.0594)		(0.0578)
$lnTNA_{t-1}$	0.307	0.392	0.437	0.561
	(0.843)	(0.843)	(0.809)	(0.808)
$lnAge_{t-1}$	-0.984	-0.986	-1.073	-1.277
	(1.667)	(1.674)	(1.645)	(1.662)
$Expenses_{t-1}$(%)	6.820	7.458	6.505	6.779
	(9.510)	(9.408)	(9.599)	(9.687)
$Turnover_{t-1}$(%)	0.162***	0.160***	0.126***	0.119***
	(0.0209)	(0.0207)	(0.0203)	(0.0201)
NMG_{t-1}	-0.0205	-0.0204	-0.0142	-0.0140
	(0.0207)	(0.0207)	(0.0205)	(0.0205)
N	11618	11616	11618	11616
N_g	1218	1220	1218	1220

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Tables 2 and 3, the magnitude of changes in RPI_{t-1}^{CV} on performance benchmarks is very similar to those of RPI_{t-1}^{σ}. Overall, the results from Table 4 support my hypothesis that RPI^{CV} is a sufficient proxy for mutual fund managerial skill. The results are also robust to RPI^{CV} formulated with alternative information sets and passive benchmarks.

6 Conclusion

In this paper, I have argued that fund managers who make portfolio decisions based on the precision of public information perform worse than those who trade based on superior (or private) information, hence those who trade based on the consensus mean and variation of information in the public domain are unskilled. In order to support my claim, I first presented a noisy rational expectations equilibrium model which featured multiple types of signals, and included agents who were either informed or uninformed. The main results of the model showed that portfolio holdings of uninformed investors were more sensitive to changes in the precision of public information than portfolio holdings of the informed investors. This measure of portfolio sensitivity to precision, which I have denoted as RPI^{σ}, should then be a suitable proxy for mutual fund managerial skill. Managers who feature a high level of RPI^{σ} should perform worse than those who feature relatively low levels.

Consequently, by using a detailed database on U.S. mutual fund holdings, financials and fund characteristics, I was able to construct a measure of RPI^{σ} for each mutual fund on a quarterly basis and found that a negative and statistically significant relationship exists between RPI^{σ} and traditional passive factor-based performance indicators.[14] These results were also robust to alternative information sets produced by analysts. Thus, empirical evidence supports the hypothesis that RPI^{σ} is a measure of mutual fund managerial skill.

This article contributes to the growing literature on the cross section of mutual fund returns. First, RPI^{σ} and RPI^{CV} should complement RPI^{μ} as a proxy for managerial

[14]The analysis should be repeated with holdings based measures as performance indicators (Wermers, 2004), and is on my agenda for future research.

Table 4: Factor Based Regressions using RPI^{σ} Formulated with Coefficients of Variation
This table presents the results of regressions based on equation (11) corrected for autocorrelation and heteroskedasticity using panel corrected standard errors (Beck and Katz, 1995). Data are from March 2003 until September 2009. The dependent variable in each regression specification is fund specific alpha, $\alpha_{m,t}$. Unconditional and conditional Fama-French alphas are considered as performance benchmarks for the analysis (Fama and French, 1993; Ferson and Schadt, 1996). RPI^{CV}(REC), RPI^{CV}(PTG) and RPI^{CV}(EPS) represent portfolio sensitivities measured with respect to the coefficients of variation using analyst recommendations, analyst price targets and EPS forecasts, respectively, and are the R^2s of regression specification (10). $lnTNA$ represents the natural logarithm of each mutual fund's total net assets, lagged one quarter. $lnAge$ is the natural logarithm of mutual fund age, lagged one quarter. $Expenses$ represents the ratio of total investment paid by investors for the mutual fund's operating expenses in the most recently completed fiscal year. $Turnover$ is the turnover ratio of each mutual fund, lagged by one year. NMG is new money growth lagged by one quarter, and is given by $NMG = \frac{TNA_{m,t}-TNA_{m,t-1}(1+R_{m,t})}{TNA_{m,t-1}}$ where $R_{m,t}$ represents fund specific return at time t.

	(1)	(2)	(3)	(4)	(5)	(6)
	α_{FF}	α_{FF}	α_{FF}	$\alpha_{FF,Cond}$	$\alpha_{FF,Cond}$	$\alpha_{FF,Cond}$
RPI^{CV}_{t-1}(REC)	-0.112*			-0.132**		
	(0.0593)			(0.0572)		
RPI^{CV}_{t-1}(EPS)		-0.0754			-0.101*	
		(0.0582)			(0.0564)	
RPI^{CV}_{t-1}(PTG)			-0.108*			-0.147***
			(0.0592)			(0.0567)
$lnTNA_{t-1}$	0.365	0.404	0.377	0.571	0.570	0.540
	(0.845)	(0.846)	(0.841)	(0.808)	(0.810)	(0.808)
$lnAge_{t-1}$	-0.928	-1.051	-1.029	-1.277	-1.323	-1.177
	(1.668)	(1.675)	(1.667)	(1.653)	(1.662)	(1.645)
$Expenses_{t-1}$(%)	7.278	7.267	7.030	6.723	6.624	6.700
	(9.349)	(9.392)	(9.482)	(9.624)	(9.675)	(9.577)
$Turnover_{t-1}$(%)	0.159***	0.158***	0.162***	0.120***	0.118***	0.125***
	(0.0209)	(0.0208)	(0.0209)	(0.0203)	(0.0202)	(0.0203)
NMG_{t-1}	-0.0204	-0.0204	-0.0206	-0.0140	-0.0139	-0.0142
	(0.0208)	(0.0208)	(0.0207)	(0.0206)	(0.0206)	(0.0205)
N	11624	11616	11618	11624	11616	11618
N_g	1219	1220	1218	1219	1220	1218

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

skill. Besides the obvious interest to those who choose to invest in mutual funds, RPI^{σ} and RPI^{CV} would also be interesting to those who monitor the investment performance of mutual fund managers, especially with the growing pressure to regulate financial markets after the subprime crisis. RPI^{σ} also provides a relatively unique perspective on mutual fund performance which has not yet been considered in this discourse, in that second moments can also have informational content to some portfolio managers.

Interesting questions arise as I consider my agenda for further research. First, can anything be said regarding the dominance of the variation of mutual fund performance over consensus means? Results from Table 4 suggest that those who rely on both aspects of public information perform better than those who trade simply based on consensus means. Furthermore, can something else be said regarding the timing implications of portfolio rebalancing? Skilled portfolio managers should be able to "beat the analysts" and predict the future performance of stocks before analysts do. A similar measure to RPI could be made using regressions with changes in recommendations as the dependent variable and lagged changes in portfolio holdings as the independent variable, and extracting the R^2 as a reverse measure of managerial skill. Such a measure would be interesting to compare with RPI^{σ}.

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