Why Mutual Funds "Underperform"

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Abstract

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I present a model that rationalizes the negative risk-adjusted performance of actively-managed equity mutual funds, their systematically better performance in bad states than in good states and the relatively high fees charged by bad-performing funds. The model allows for optimal fee setting and active management by a skilled fund manager and also features rational investors who competitively supply money. Since funds' active returns will be higher in bad states of the economy than in good states, mutual fund investing can be rationalized despite the measurement of negative unconditional performance. I use data on U.S. funds and find empirical evidence supporting the model.

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1 Introduction

Jensen (1968), Malkiel (1995), and Gruber (1996), among others, find that most actively managed equity mutual funds significantly underperform passive investment strategies, net of fees. So why do people invest in such funds? I show that investing in these funds can be optimal for fully rational investors, since these funds outperform passive investment strategies in bad states of the economy, as documented by Moskowitz (2000) and Kosowski (2006).

I present a partial equilibrium model of optimal fee setting and active management by a mutual fund manager. The model builds on insights from Berk and Green (2004) and features a skilled fund manager and rational investors who competitively supply money. But unlike Berk and Green's (2004) model, mine allows the fund manager to generate active returns that depend on the state of the economy. I investigate how the fund manager's ability to generate state-dependent active returns will influence the fee he will charge and the performance an econometrician will measure. The model rationalizes three well-documented empirical facts: the measured unconditional risk-adjusted performance of equity funds is negative, performance is systematically better in bad states of the economy than in good states, and bad-performing funds charge high fees compared to good-performing funds.[1]

The intuition behind my results is that a fund manager who can generate state-specific active returns at a given cost will be better off doing so in states when investors are willing to pay more for returns. Therefore, the fund manager will optimally generate active returns that covary positively with the pricing kernel and partially insure investors against bad states of the economy. Investors will be willing to pay a fee for this insurance. Given the competitive supply of money by investors, the fee charged by the fund manager in equilibrium will equal the certainty equivalent of the value added by active management. However, if a performance measure does not allow a perfect specification of the true pricing kernel, the value added by the insurance will be mismeasured. Under fairly standard conditions, a misspecified

[1] Malkiel (1995), Gruber (1996) and Carhart (1997) document the relationship between performance and fees.

performance measure will produce a negatively biased estimate of fund performance and underperformance will be observed.

It should not come as a surprise that misspecification in the performance measure will produce abnormal measured performance. What is both unique and non-trivial about the argument here is the demonstration that, under fairly standard assumptions, *any* misspecification will lead to the measurement of *negative* abnormal performance. A parameterized version of the model predicts that fund managers with better skills will provide better insurance against pricing kernel variations, charge higher fees to investors, and exhibit worse risk-adjusted performance.

I use data on 3,260 unique U.S. equity funds over the 1980-2005 period to test the empirical implications of my model. First, I find that this sample of funds exhibits the three empirical facts that my model tries to rationalize. Second, I find that fund managers are more active in bad states of the economy than in good states, based on the turnover ratio and a few measures of portfolio dispersion. Third, I find that the mutual funds that offer the worst performance also offer better insurance against bad states. To the best of my knowledge, these two latest findings are novel and provide support for my model.

The most popular measure of mutual fund performance is the intercept (alpha) from a regression of a mutual fund's excess returns, net of fees, on the excess returns of passive strategies. The linear combination of these passive excess returns represents a proxy for the empirically unobservable pricing kernel. Gruber (1996) argues that since these passive excess returns are associated with zero investment portfolios, alpha should be zero for random portfolios. When he finds a negative alpha that is smaller in absolute value than the fee charged, Gruber argues that fund managers add value, but charge investors more than the value added. According to this argument, the widely-documented negative alphas, net of fees, indicate that mutual fund investing destroys value and is irrational.

However, my model rationalizes mutual fund investing despite the negative alphas. In equilibrium, skilled fund managers will make active management decisions to maximize their expected profits while satisfying an investors' participation constraint. These optimal decisions will however result in the measurement of negative alphas. In most cases, an upper bound of zero on alpha will be attained only if the performance measure perfectly specifies the pricing kernel. A perfect specification will hold if and only if the passive returns are perfectly correlated with the pricing kernel and therefore are on the mean-variance frontier. We should not expect this to occur in empirical practice, as argued by Roll (1977) and Berk (1995).

Recently, Avramov and Wermers (2005) offer a different rationalization of mutual fund investing by treating active returns as exogenous and incorporating the possibility of predictability. My model instead endogenizes the production of active returns by a mutual fund and the fee that results. My paper is related to several papers, though none of them aims at reconciling the empirical facts rationalized by my model. Admati and Ross (1985), Dybvig and Ross (1985) and Grinblatt and Titman (1989) study the effects of active management on performance measurement without considering the delegation of portfolio management decisions. Brennan and Chordia (1993) study the fee-setting decision of a delegated portfolio manager but do not consider the effects on performance measurement. My paper studies simultaneously both elements using insights from Berk and Green (2004). The ability to generate positive active returns is a resource in scarce supply. Thus, in equilibrium the fee paid to a fund manager who possesses this ability will be set such that he collects all the rewards from his active management skills. However, unlike Berk and Green's (2004) model, mine allows fund managers to produce active returns that are state-dependent. This feature partially explains why my model, but not theirs, rationalizes mutual fund investing even when risk-adjusted performance is negative.

The paper is organized as follows. The next section presents the elements of the model. Section 3 presents the optimal mutual fund policy and derives the qualitative implications of the model in terms of measured performance. Section 4 presents the quantitative implications of a parameterized and calibrated version of the model. An empirical analysis of my model is presented in Section 5. Section 6 concludes.

2 Model

I study a one-period economy with a finite number of states $s \in S$ and excess returns r_s^e on a passive strategy. Mutual fund performance is measured by the intercept (α) from a regression of a fund's excess returns, net of fees, on the passive strategy's excess returns. The passive strategy need not be a proxy for the market portfolio as in Jensen (1968). It can be any specification of the risk-return relationship such as Carhart's (1997) four-factor model.

2.1 The Mutual Fund Manager

The model assumes optimal behavior from investors and focuses on the policies of one agent: the mutual fund manager. For each state $s \in S$, the fund manager can generate state-dependent active returns, denoted δ_s, over the passive returns, r_s^e, at a cost $C(\delta_s)$. Other agents do not possess this non-tradeable δ-generating technology. I assume that realized fund returns also contain an idiosyncratic error term υ_s which has mean zero, is independently distributed through states and through managers and which fund managers have no control over.

To manage other agents' money, the fund manager charges a fee f that is proportional to the value of the assets under management (see Chevalier and Ellison (1997), Christoffersen (2001) and Kuhnen (2004)). I investigate how the fund manager's ability to generate state-dependent active returns will influence the fee he charges and the performance an econometrician measures. The model is agnostic about the origins of active returns. The δ-generating technology is a reduced-form approach to capturing superior skills or opportunities the fund manager has, such as superior information, lower transaction costs, limited market participation, etc.

Generating active returns is costly. The cost function $C : \Re^+ \rightarrow \Re^+$ is increasing and strictly convex in the active returns δ_s. It satisfies standard regularity conditions for all $\delta \geq 0$:

$C(\delta)$ is twice-differentiable, $C'(\delta) > 0$, and $C''(\delta) > 0$, with $C(0) = 0$ and $lim_{\delta \to +\infty} C'(\delta) = +\infty$. The costs may be seen as research expenses, trading costs or as opportunity costs for the manager's effort. The cost function is assumed to be independent of the state of the economy.

The fund manager maximizes expected profits and owns no capital. Capital requirements prevent him from investing in the market independently. Investors competitively supply money to the fund manager who collects all the value he creates. This assumption is convincingly advocated by Berk and Green (2004). The ability to generate positive active returns is the resource in scarce supply; thus a fund manager who possesses this ability should set f such that he collects all the rewards from his active management skills. However, unlike Berk and Green's (2004) model, mine does not consider the dynamic features of learning and fund flows. I normalize the value of the assets under management to be one dollar. This simpler setting improves the tractability of the model and the intuition behind the results.

The timeline of the model is summarized as follows. At the beginning of the period, the fund manager offers to the investor a policy $(f, \{\delta_s\}_{s \in S})$ and commits to generate during the period an active return of δ_s if state s is being realized. If the investor accepts, he commits to pay the fund manager f at the end of the period in exchange for his active management services.

2.2 The Equilibrium Condition

A financial market equilibrium implies no arbitrage, which itself implies the existence of at least one pricing kernel that prices all tradeable assets (see, e.g., Harrison and Kreps (1979), Hansen and Richard (1987), and Campbell (2000)). In order to reach an equilibrium, the excess returns between any two assets must satisfy the following condition:

$$E\left[m_s(r_s^i - r_s^j)\right] = 0, \tag{1}$$

where r_s^i and r_s^j are returns on any two assets and $m_s(> 0)$ is the realization of a pricing kernel in state $s \in S$. Hansen and Richard (1987) show that there exists a unique portfolio yielding a payoff x_s^* in state s that can serve as m_s. If a risk-free asset exists, the return r_s^* on the unique portfolio will be perfectly correlated with that of any risky portfolio belonging to the mean-variance frontier. Hence, the return r_s^p on any risky portfolio p will be on the mean-variance frontier if and only if there exists a pair (γ_0, γ_1) such that $m_s = \gamma_0 + \gamma_1 r_s^p$ holds in all states. Otherwise, projecting m_s on returns r_s^p and a constant will yield non-zero error terms ϵ_s (see Roll (1977)).

Let r_0 denote the *gross* risk-free rate. The passive return in state s is denoted $r_0 + r_s^e$ and the mutual fund return is denoted $r_0 + r_s^e + \delta_s - f + \upsilon_s$. The difference between the fund return and the passive return is called the tracking error and simplifies to $\delta_s - f + \upsilon_s$. The tracking error is an excess return and therefore a mutual fund policy $(f, \{\delta_s\}_{s \in S})$ needs to satisfy the following condition in equilibrium:[2]

$$E\left[m_s(\delta_s - f + \upsilon_s)\right] = 0. \tag{2}$$

Suppose instead that the left-hand side of equation (2) is higher than zero. Then there will be an infinite demand for mutual fund services and the fund manager will be able to improve his profits by increasing f marginally. If instead the left-hand side of equation (2) is lower than zero, then no one will invest in the mutual fund and the fund manager will receive no revenues. Hence, equation (2) needs to hold in equilibrium.

The term υ_s has mean zero and is idiosyncratic, thus is uncorrelated to the pricing kernel m_s. From equation (2), the fee in equilibrium is $f = r_0 E\left[m_s \delta_s\right]$ and represents the certainty equivalent of the value created by active management. This differs from $f = E\left[\delta\right]$ derived by Berk and Green (2004) who do not consider the possibility of state-dependent active returns. Instead, they assume that, for a given level of assets under management, active return δ is constant over all states and the randomness of returns is purely idiosyncratic.

[2]The equilibrium condition does not preclude that active management (i.e. the non-tradeable δ-generating technology) is a positive NPV project.

As will become evident in Section 3, this difference explains why my model, but not theirs, rationalizes mutual fund investing even when risk-adjusted performance is negative.

The fund manager acts in his own interests and maximizes expected profits, subject to a demand constraint. Thus, the fund manager picks an optimal policy $(f^*, \{\delta_s^*\}_{s \in S})$ that solves

$$\max_{f, \{\delta_s\}_{s \in S}} f - E\left[C(\delta_s)\right], \tag{3}$$

subject to $f = r_0 E\left[m_s \delta_s\right]$.

A convenient property of the current framework is that it does not require a parameterization of the pricing kernel m_s. The only assumption made on m_s is that it is higher in bad states of the economy than in good states, similar to what a consumption-based model parameterization would predict. As in Hansen and Jagannathan (1991), the statistical properties of m_s are taken as given. Moreover, the model does not require m_s to be independent of the fund manager's choices. The pricing kernel may depend on characteristics of the mutual fund or of any other asset.

3 Implications of the Model

Subsection 3.1 presents the optimal mutual fund policy, while subsection 3.2 presents the qualitative implications of the model in terms of measured performance.

3.1 The Optimal Mutual Fund Policy

The following proposition derives the policy $(f^*, \{\delta_s^*\}_{s \in S})$ chosen by the fund manager in my model.

Proposition 1. *The optimal mutual fund policy has state-dependent active returns* δ_s^* *that satisfy*

$$C'(\delta_s^*) = m_s r_0 \tag{4}$$

for each state $s \in S$*. Therefore, the active return* δ_s^* *is positively related to the pricing kernel* m_s*.*

Proof. Inserting the equilibrium f into the fund manager's optimization function (3) gives the following optimization function

$$\max_{\{\delta_s\}_{s\in S}} \; r_0 E\left[m_s \delta_s\right] - E\left[C(\delta_s)\right]. \tag{5}$$

The first-order conditions with respect to δ_s are $m_s r_0 = C'(\delta_s)$, for each state $s \in S$, and are necessary and sufficient for an optimum given the assumptions made on $C(\cdot)$. It follows from the strict convexity of $C(\cdot)$ that δ_s^* is positively related to m_s. □

Equation (4), combined with the assumptions made on $C(\cdot)$, implies that the active return δ_s^* is strictly positive and positively related to m_s. The tracking error $(\delta_s^* - f^* + \upsilon_s)$ covaries positively with the pricing kernel. The fund manager knows from investors' behavior that active returns are valued more in bad states of the economy than in good states. Thus, he generates higher active returns when investors are willing to pay more for them and he provides them with a partial insurance against bad states.

From equation (2), the equilibrium fee f^* can be written as

$$f^* = E\left[\delta_s^*\right] + r_0 cov(m_s, \delta_s^*). \tag{6}$$

Since the choice of δ_s^* depends on the marginal cost function $C'(\cdot)$, cross-sectional variations in funds' cost functions will result in different fees among funds. Hence, my model provides a novel source of cross-sectional volatility in mutual fund fees (see Chordia (1996) and Christoffersen and Musto (2002)).

3.2 The Measured Performance

Using the optimal mutual fund policy $(f^*, \{\delta_s^*\}_{s \in S})$, it is possible to derive what the model implies in terms of measured fund performance. The following lemma will be useful for analyzing qualitatively these implications.

Lemma 1. *Let x_s, $s \in S$, be a random variable with $var(x_s) > 0$ and $G : \Re \rightarrow \Re$ be a strictly increasing function. Then $cov(x_s, G(x_s)) > 0$.*

Proof.

$$\begin{aligned} cov(x_s, G(x_s)) &= E[(x_s - E[x_s])(G(x_s) - E[G(x_s)])] \\ &= E[(x_s - E[x_s])(G(x_s) - G(E[x_s]))] \\ &+ E[(x_s - E[x_s])(G(E[x_s])) - E[G(x_s)])] \\ &= E[(x_s - E[x_s])(G(x_s) - G(E[x_s]))]. \end{aligned} \tag{7}$$

Since $G(\cdot)$ is strictly increasing, $cov(x_s, G(x_s)) > 0$ when $var(x_s) > 0$. □

A natural starting point to measure the performance of a mutual fund is to compare its returns with those on a passive strategy. The following proposition derives the expected tracking error of the fund.

Proposition 2. *The expected tracking error of the mutual fund is given by*

$$E\left[\delta_s^* - f^* + \upsilon_s\right] = -r_0 cov(m_s, \delta_s^*) \tag{8}$$

and is strictly negative.

Proof. By definition, $E\left[\upsilon_s\right] = E\left[m_s \upsilon_s\right] = 0$. From equation (6), $E\left[\delta_s^*\right] - f^* = -r_0 cov(m_s, \delta_s^*)$. Define the function $H(\cdot) \equiv C'^{-1}(\cdot)$ as the inverse of the marginal cost function of generating δ_s. Due to the strict convexity of $C(\cdot)$, the function $H(\cdot)$ exists and is strictly increasing over

$\Re^+$. Since $E[\delta_s^*] - f^* = -r_0 cov(m_s, H(m_s r_0))$, it follows from Lemma 1 that the expected tracking error is negative. $\square$

It is optimal for a fund manager to generate active returns that partially insure investors against variations in the pricing kernel; this allows the fund manager to request a compensation that is higher than the expected active return to be generated.

However, the expected tracking error in equation (8) is not a valid measure of abnormal performance because it does not adjust for systematic risk. A popular measure of abnormal performance is the intercept (α) from a regression of a fund's excess returns, net of fees, on a passive strategy's excess returns. These passive excess returns are priced *ex ante* by the pricing kernel m_s. The econometrician, who does not observe m_s, uses these passive excess returns to build a proxy for m_s. Unless stated otherwise, I assume that the passive strategy of the model is a financial proxy for the market portfolio as in Jensen (1968) and Gruber (1996). This assumption improves the tractability of the model and is without loss of generality. The analysis pursued in this paper will carry over to any performance measure with a potential misspecification.

Proposition 3. *The measured risk-adjusted performance of the fund is given by*

$$\alpha = -r_0 cov(\epsilon_s, \delta_s^*), \tag{9}$$

where ϵ_s denotes the error term in the projection of m_s on r_s^e and a constant, i.e. $m_s = \gamma_0 + \gamma_1 r_s^e + \epsilon_s$.

Proof. To measure α, I first need to solve for β:

$$\beta = \frac{cov(r_s^e, r_s^e + \delta_s^* - f^* + \upsilon_s)}{var(r_s^e)} = 1 + \frac{cov(r_s^e, \delta_s^*)}{var(r_s^e)}. \tag{10}$$

The risk-adjusted performance α is given by

$$\begin{aligned}\alpha &= E\left[r_s^e + \delta_s^* - f^* + \upsilon_s\right] - \beta E\left[r_s^e\right] \\ &= E\left[r_s^e\right](1-\beta) - r_0 cov(m_s, \delta_s^*) \\ &= -E\left[r_s^e\right]\frac{cov(r_s^e, \delta_s^*)}{var(r_s^e)} - r_0 cov(m_s, \delta_s^*). \end{aligned} \quad (11)$$

In the projection $m_s = \gamma_0 + \gamma_1 r_s^e + \epsilon_s$, the slope coefficient γ_1 satisfies

$$\begin{aligned}E\left[r_s^e\right] &= -r_0 cov(r_s^e, m_s) = -r_0 cov(r_s^e, \gamma_0 + \gamma_1 r_s^e + \epsilon_s) \\ &= -\gamma_1 r_0 var(r_s^e), \end{aligned} \quad (12)$$

or $\gamma_1 = -\frac{E[r_s^e]}{r_0 var(r_s^e)}$. Hence, the risk-adjusted performance of the fund is given by

$$\alpha = -r_0 cov(\epsilon_s, \delta_s^*). \quad (13)$$

□

From equation (9), the risk-adjusted performance of the fund can be seen as the risk premium that would be offered in equilibrium if ϵ_s was a pricing kernel. The random component ϵ_s will equal zero in all states if and only if r_s^e is on the mean-variance frontier. Otherwise, $var(\epsilon_s)$ will be strictly positive, independently of whether markets are complete or incomplete. The unobservable statistic $var(\epsilon_s)$ represents the degree of misspecification in the pricing kernel approximation allowed by r_s^e (see Hansen and Jagannathan (1997)). Since the performance measure does not adjust for $cov(\epsilon_s, \delta_s^*)$, which is priced in equilibrium, $-r_0 cov(\epsilon_s, \delta_s^*)$ is wrongly considered as an abnormal return. The sign of α cannot be known with certainty without restricting the distribution of ϵ_s or the functional form of $C(\cdot)$. However, I show below that the conditions required to observe a negative risk-adjusted performance, net of fees, are fairly standard in the finance literature.

To get a better understanding of the conditions leading to a negative alpha, I decompose $cov(\epsilon_s, \delta_s^*)$ into

$$cov(\epsilon_s, \delta_s^*) = E[cov(\epsilon_s, \delta_s^*|r_s^e)] + cov(E[\epsilon_s|r_s^e], E[\delta_s^*|r_s^e]). \tag{14}$$

Following Lemma 1, $cov(\epsilon_s, \delta_s^*|r_s^e)$ is always positive, making the first term on the right-hand side of equation (14) positive as well. The sign of the second term is however unknown unless one restricts the conditional distribution of ϵ_s or the functional form of $C(\cdot)$. Risk-adjusted performance (α) will be positive in my model only if $cov(E[\epsilon_s|r_s^e], E[\delta_s^*|r_s^e)])$ is negative and its absolute value is higher than $E[cov(\epsilon_s, \delta_s^*|r_s^e)]$. This is possible, but unlikely: by construction ϵ_s and r_s^e are uncorrelated, hence the fact that δ_s^* moves with m_s is likely to imply that $E[\delta_s^*|r_s^e]$ moves with $E[\epsilon_s|r_s^e]$. Therefore, without more restrictive assumptions, alpha can either be positive or negative, but is arguably more likely to be negative.

As expected, a misspecification in the performance measure (i.e. $var(\epsilon_s) > 0$) is necessary to observe that $\alpha \neq 0$. In that case, two fairly standard assumptions become each sufficient to have $\alpha < 0$. On one hand, the mean independence of ϵ_s, i.e. $E[\epsilon_s|r_s^e] = 0$ for all r_s^e, is sufficient to observe that $\alpha < 0$ *regardless of the functional form of* $C(\cdot)$. In that case, the last term of equation (14) equals zero and alpha has a supremum of zero. On the other hand, a quadratic cost function $C(\cdot)$ is sufficient to observe that $\alpha < 0$ *regardless of the distribution of* ϵ_s. A quadratic cost function makes the following approximation of alpha being exact.

Proposition 4. *Using a second-order Taylor expansion for the cost function* $C(\cdot)$ *around a given value* $\overline{\delta}$*, the measured fund performance can be approximated by*

$$\alpha \approx -\frac{r_0^2}{C''(\overline{\delta})} var(\epsilon_s), \tag{15}$$

which is negative if $var(\epsilon_s) > 0$ *and equal to zero otherwise.*

Proof. Since $C(\cdot)$ is twice-differentiable, $C(\delta_s^*)$ can be approximated around a given $\overline{\delta}$ by

$$C(\delta_s^*) \approx C(\overline{\delta}) + C'(\overline{\delta})(\delta_s^* - \overline{\delta}) + \frac{1}{2}C''(\overline{\delta})(\delta_s^* - \overline{\delta})^2. \tag{16}$$

The first-order condition (4) becomes $m_s r_0 \approx C'(\overline{\delta}) + C''(\overline{\delta})(\delta_s^* - \overline{\delta})$, or equivalently $\delta_s^* \approx \overline{\delta} - \frac{C'(\overline{\delta})}{C''(\overline{\delta})} + \frac{m_s r_0}{C''(\overline{\delta})}$.

Inserting this approximation into equation (9) gives

$$\begin{aligned} \alpha &\approx -r_0 E[\epsilon_s(\overline{\delta} - \frac{C'(\overline{\delta})}{C''(\overline{\delta})} + \frac{m_s r_0}{C''(\overline{\delta})})] \\ &= -r_0(\overline{\delta} - \frac{C'(\overline{\delta})}{C''(\overline{\delta})})E[\epsilon_s] - \frac{r_0^2}{C''(\overline{\delta})}E[\epsilon_s m_s] \\ &= -\frac{r_0^2}{C''(\overline{\delta})}E[\epsilon_s(\gamma_0 + \gamma_1 r_s^e + \epsilon_s)] = -\frac{r_0^2}{C''(\overline{\delta})}var(\epsilon_s). \end{aligned} \tag{17}$$

Since $C(\cdot)$ is strictly convex and differentiable, $C''(\overline{\delta})$ is strictly positive. Hence the approximated α is strictly negative if $var(\epsilon_s) > 0$ and equal to zero otherwise. □

Although fund managers have the ability to generate positive active returns, my model with rational agents shows that the measured risk-adjusted performance of mutual funds is likely to be negative. This finding resembles the one by Berk (1995) about the size effect. In Berk (1995), a misspecification in the model of expected returns yields a negative correlation between abnormal returns and a size factor under any condition. In my model, a misspecification in the performance measure yields a negative abnormal performance under standard conditions. A perfect specification holds if and only if the passive returns r_s^e are on the mean-variance frontier. Thus following Roll (1977) and Berk (1995), negative performance should be observed in the data.

The approximation presented in Proposition 4 is exact when $C(\cdot)$ is quadratic. Quadratic cost functions are frequently used in the finance literature (see, e.g. Berk and Green (2004)) and I use such a parameterization in the remaining of the paper to get tractable closed-form solutions, without restricting the joint distribution of ϵ_s and r_s^e, or equivalently the distribution of m_s.

4 A Parameterization

This section presents the model's predictions when the cost function is parameterized and macroeconomic parameters are calibrated to the U.S. economy.

4.1 The Cost Function

I assume that the cost function for generating active returns takes the quadratic form $C(x) = \frac{\theta}{2}x^2$, for $x \geq 0$, where $\theta > 0$. Therefore $C'(x) = \theta x$ and θ is the slope of the marginal cost function. As θ increases, the cost of producing active returns increases as well. The skill level of the fund manager is symbolized by θ^{-1}. The first-order condition in equation (4) becomes $\delta_s^* = \frac{m_s r_0}{\theta}$. The following proposition derives the mutual fund policy $(f^*, \{\delta_s^*\}_{s \in S})$ chosen by the fund manager under this parameterization.

Proposition 5. *Under the parameterization* $C(x) = \frac{\theta}{2}x^2$ *and the projection* $m_s = \gamma_0 + \gamma_1 r_s^e + \epsilon_s$*, the equilibrium fee charged by the fund manager is given by*

$$f^* = \theta^{-1}\left[1 + r_0^2 var(m_s)\right], \tag{18}$$

and the measured performance is given by

$$\alpha = -\frac{r_0^2}{\theta} var(\epsilon_s). \tag{19}$$

Unless $var(\epsilon_s) = 0$*,* α *is negative.*

Proof. Inserting $\delta_s^* = \frac{m_s r_0}{\theta}$ in equations (6) and (9) yields the results. □

An increase in the pricing kernel volatility leads to a higher value for the insurance generated by active management and results in a higher fee. Also, a lower θ means that the fund manager is more skilled and produces higher δ_s^*'s in equilibrium. Then, active management creates more value and the fund manager, who is assumed to possess all the bargaining power, collects larger rewards. For this reason, the equilibrium fee increases with the skill level θ^{-1} and differential ability across managers is rewarded in the model.

The model predicts that alpha will be negative unless $var(\epsilon_s) = 0$; any pricing kernel misspecification will lead to negative risk-adjusted performance. To have $var(\epsilon_s) = 0$, the volatility of the pricing kernel $\sqrt{var(m_s)}$ needs to reach its lower bound specified by Hansen and Jagannathan (1991), i.e. r_s^e has to be on the mean-variance frontier. We should not be expect this to occur in empirical practice, as argued by Roll (1977) and Berk (1995).

When $var(\epsilon_s) > 0$, risk-adjusted performance decreases as the skill level of the manager (θ^{-1}) increases. This result is counter-intuitive and completely opposite to what financial empiricists have assumed in the past. Empiricists have argued that skilled managers should provide strictly positive risk-adjusted performance. But their argument ignores the equilibrium mechanism derived in this paper, namely the optimal mutual fund policy $(f^*, \{\delta_s^*\}_{s \in S})$ that arises when investors competitively supply money.

Let SR denote the Sharpe ratio of the passive strategy ($SR = \frac{E[r_s^e]}{\sqrt{var(r_s^e)}}$). The risk-adjusted performance of the fund, *gross of fee*, is given by

$$\alpha + f^* = \theta^{-1}\left[1 + SR^2\right], \tag{20}$$

which is positive, consistent with the empirical findings of Gruber (1996), Carhart (1997), and Kacperczyk, Sialm, and Zheng (2005), among others.

The model rationalizes why bad-performing funds charge high fees compared to good-performing funds. All else being equal, fund managers with better δ-generating skills (lower θ's) offer a better insurance against pricing kernel variations. This better insurance drives

f^* up and α down in equilibrium. Hence, the better-skilled managers are those offering the worst alphas and charging the highest fees.

4.2 A Calibration

The goal here is to verify whether the model's predictions quantitatively match empirical moments of fees and performance for U.S. equity mutual funds.

The cost/skill parameter θ is the only fund-specific parameter to calibrate. It can only take strictly positive values, so I generate a cross-section of mutual funds based on the assumption that the $log(\theta)$ of each fund is drawn from the same $N(\mu + \frac{\eta^2}{2}, \eta^2)$ distribution.[3] Since α and f^* take the form $\theta^{-1} * constant$, both are log-normally distributed in the cross-section.

Before calibrating the unobservable parameters of the model, I tie down the parameters that can be inferred directly from the data. To simplify the calibration, I use the excess return on the S&P 500 index rather than a multi-factorial model of risk-adjusted returns as my passive return r_s^e.[4] I calibrate the first two moments of r_s^e and the mean risk-free rate r_0 using data for the 1980-2005 period from Kenneth French's website. Over this period, I observe a mean annual expense ratio of 1.29% with a cross-sectional standard deviation of 0.51% (see Section 5 for a description of the data). The expense ratio is the ratio of total investment that shareholders pay annually for the fund's operating expenses, which include 12b-1 fees. To account for the amortized loads not included in the reported expense ratio, I add 1/7 of the front-load fee to the expense ratio, as in Sirri and Tufano (1998) and Barber, Odean, and Zheng (2005).[5] Table 1 summarizes the calibration of the observable parameters of the model.

[3] Setting $E\left[log(\theta)\right] = \mu + \frac{\eta^2}{2}$ instead of μ simplifies the algebra because it yields $E[\theta^{-1}] = exp(-\mu)$.

[4] This simplification is not necessary for the empirical analysis presented in Section 5, in which I also use multi-factorial performance measures.

[5] Barber, Odean, and Zheng (2005) offer two reasons for not including back-load fees into the computation of total fee: back-load fees were not reported in the CRSP database prior to 1993 and back-load fees are often waived if an investor holds a fund for a specific period of time.

Table 1: Parameter Values for the Calibration

Parameter	Symbol	Value
Average Fee	$E[f^*]$	1.53%
Std. Dev. of f^*	$\sqrt{var(f^*)}$	0.51%
Net Risk-Free Rate	$r_0 - 1$	5.97%
Mean Excess Return	$E[r_s^e]$	7.99%
Std. Dev. of r_s^e	$\sqrt{var(r_s^e)}$	16.17%

Now that the observable parameters have been calibrated, I need to find values for the unobservable parameters μ, η, and $var(\epsilon_s)$ such that the model's predictions match the selected empirical estimates. I match the cross-sectional volatility of the fee by setting $\eta = 0.32$. For a given level of $var(\epsilon_s)$, μ is set to

$$\mu = log(1 + SR^2 + r_0^2 var(\epsilon_s)) - log(E[f^*]), \tag{21}$$

such that equation (18) is satisfied in expectation. The expected performance of mutual funds $E[\alpha]$, given an average fee of $E[f^*]$, is given by

$$E[\alpha] = -\frac{r_0^2 E[f^*]}{[1 + SR^2 + r_0^2 var(\epsilon_s)]} var(\epsilon_s). \tag{22}$$

Equation (22) shows that fees and risk-adjusted performance should be negatively related as observed by Malkiel (1995), Gruber (1996) and Carhart (1997). The funds that charge more are also those that produce the best performance before fees. However, the associated high fees make more skilled managers look worse than less skilled managers in terms of performance net of fees. This is the case because better skills (higher θ^{-1}) result in a higher sensitivity of δ_s^* to pricing kernel variations, including those caused by variations in ϵ_s. The inability of the performance measure to adjust for the priced covariance between δ_s^* and ϵ_s results in a bias that is amplified as this covariance increases with skills.

Figure 1 plots the relationship between $E[\alpha]$ and $var(\epsilon_s)$ using the calibration of Table 1. The figure also indicates the predicted $E[\alpha]$ for each level of $var(\epsilon_s)$ implied by the estimates of $var(m_s)$ from Hansen and Jagannathan (1991), Bekaert and Hodrick (1992), Chapman (1997), Melino and Yang (2003), Bansal and Yaron (2004), and Kan and Zhou (2006).[6][7]

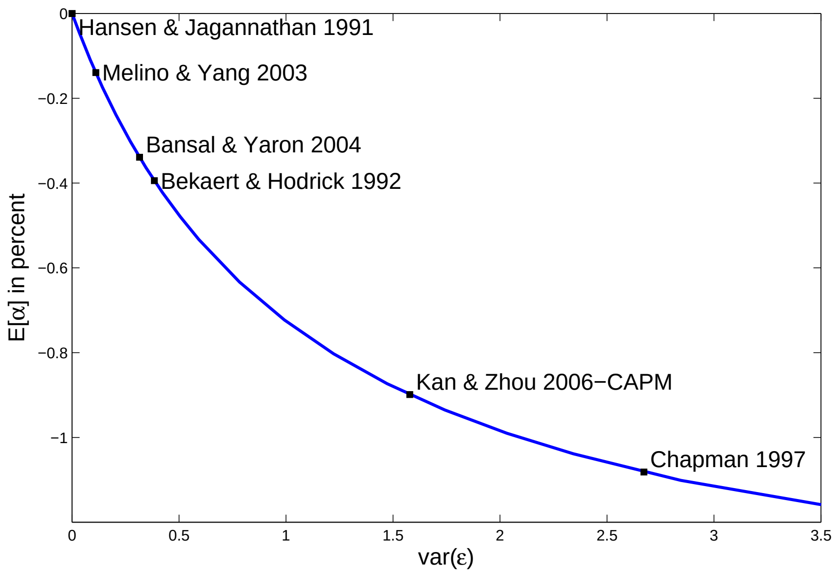

Figure 1: Misspecification and Mutual Fund Performance
This figure plots the relationship between risk-adjusted performance $E[\alpha]$ and the degree of misspecification in the performance measure $var(\epsilon_s)$ when $E[f]$ is set to 1.53%. It uses the calibration presented in Table 1. The figure indicates the predicted α for each level of $var(\epsilon_s)$ implied by the estimates of $var(m_s)$ from Hansen and Jagannathan (1991), Bekaert and Hodrick (1992), Chapman (1997), Melino and Yang (2003), Bansal and Yaron (2004), and Kan and Zhou (2006) (based on the market portfolio).

As made obvious by equation (19) and Figure 1, the magnitude of underperformance depends highly on the fit of the projection of m_s on r_s^e and a constant. Active returns δ_s^* vary with m_s and this form of insurance corresponds to the value created by active management. In the current parameterization, a performance measure using r_s^e provides a negatively biased estimate of the value of active management because it does not account for the positive covariance between active returns δ_s^* and the misspecification term ϵ_s. As the degree of misspecification $var(\epsilon_s)$ increases, the measured underperformance increases as well.

[6] I use $var(m_s) = \gamma_1^2 var(r_s^e) + var(\epsilon_s) = \frac{SR^2}{r_0^2} + var(\epsilon_s)$ where SR denotes the Sharpe ratio of the passive strategy.

[7] Hansen and Jagannathan (1991) find a lower bound for the volatility of m_s based on the maximal Sharpe ratio available. Here I suppose that the Sharpe ratio on the S&P 500 is the maximal Sharpe ratio and look at the predicted $E[\alpha]$.

Bekaert and Hodrick (1992) hint that $var(\epsilon_s)$ should be positive when performance is measured with Jensen's (1968) one-factor alpha. They compute the maximal Sharpe ratio (SR) attainable with conditional trading strategies in international markets and find that international investing sharpens the Hansen and Jagannathan (1991) lower bound on $\sqrt{var(m_s)}$. Hence, $\sqrt{var(m_s)}$ should be higher than the lower bound predicted by domestic investing only, which is represented by $\frac{SR}{r_0}$ in the model. When investors have access to financial instruments that allow better diversification than what is provided by the proxy used for the market portfolio (the S&P 500 in this case), then $var(\epsilon_s)$ is strictly positive.

In the sample of U.S. mutual funds that I use, I observe an annual one-factor alpha of -0.48% (see Table 2 in Section 5). This is significantly better than the -1.10% that Jensen (1968) finds, but is still economically significant. In order to generate $E[\alpha] = -0.48\%$, I set $\mu = 4.77$ and $var(\epsilon_s) = 0.50$. Then the model produces a cross-section of mutual funds with $E[f^*] = 1.53\%$, $\sqrt{var(f^*)} = 0.51\%$ and $E[\alpha] = -0.48\%$, as I observe empirically. For the median fund, a two standard deviation shock in m_s implies a change of 1.52% in δ_s^*.

In the calibration of Table 1, the standard deviation of m_s required to produce $E[\alpha] = -0.48\%$ is 0.85. This level is close to the empirical estimates of Bekaert and Hodrick (1992) and Bansal and Yaron (2004) presented in Figure 1. Moreover, the higher estimates of $\sqrt{var(m_s)}$ by Chapman (1997) and Kan and Zhou (2006) make the alpha measured by Jensen (1968) (-1.10%) quantitatively consistent with my model. On the other hand, even the lower volatility estimate by Melino and Yang (2003) generates a level of underperformance that is economically significant. In light of the analysis presented in this section, one should not be puzzled to observe significantly negative alphas for actively managed mutual funds.

5 Empirical Tests

The main goal of this paper is to rationalize three previously documented facts: the unconditional risk-adjusted performance of equity funds is negative, performance is systematically better in bad states of the economy than in good states, and bad-performing funds charge high fees compared to good-performing funds. The model also provides additional predictions that have not yet been tested empirically. In this section, I first describe the sample of equity funds used for the empirical tests. Then I confirm that the previously documented facts hold in this sample. Finally, I test two previously undocumented implications of the model: fund managers are more active in bad states of the economy than in good states and the funds that provide the worst alphas also offer better insurance against bad states.

5.1 Data

For the empirical analysis, I use the CRSP Survivorship-Bias-Free Mutual Fund database. The sample covers the time period between 1980 and 2005. The CRSP mutual fund database includes information on fund returns, fees, investment objectives, and other fund characteristics such as assets under management and turnover.

I focus the analysis on actively managed open-end domestic diversified equity mutual funds and eliminate balanced, bond, money market, international, sector, and index funds. I exclude funds that hold less than 10 stocks, and those that invest less than 80% of their assets in equity. For funds with multiple share classes, I eliminate the duplicate funds and compute the fund-level variables by aggregating across the different share classes.

Elton, Gruber, and Blake (2001) and Evans (2004) document a bias in the CRSP mutual fund database. Fund families occasionally incubate several private funds. However, only the track records of the surviving incubated funds are made public, while the records for the funds that were terminated are kept private. To address this bias, I try to exclude all observations of funds during their incubation period. I exclude observations for which the observation year precedes the reported fund starting year and observations with missing fund name. Since incubated funds tend to be small, I also exclude funds that had less than $5 million in assets under management at the beginning of the quarter.

Table 2 reports summary statistics for the main fund attributes. The current sample includes 3,260 distinct funds and 82,081 fund-quarter observations. The number of funds in each quarter ranges from 158 (1980, Q2) to 1,636 (2001, Q4). I report summary statistics on assets under management, age, turnover, expenses, load fees, raw returns, and risk-adjusted performance.

Table 2: **Summary Statistics**

This table presents summary statistics for the sample of 3,260 equity mutual funds over the 1980-2005 period from the CRSP Survivorship-Bias-Free Mutual Fund database.

	Mean	**S.D.**	**Median**	**p25**	**p75**
Asset Size ($M)	939.94	3697.02	159.08	46.98	558.73
Age (years)	13.02	14.23	8.00	4.00	16.00
Turnover (%, per year)	91.90	122.02	67.00	35.20	114.51
Expense Ratio (%, per year)	1.29	0.51	1.23	0.97	1.54
Front-Load Fee (%)	1.70	2.38	0.00	0.00	3.44
Back-Load Fee (%)	0.52	0.96	0.00	0.00	0.80
Raw Return (%, per quarter)	2.62	10.47	3.13	-2.26	8.68
One-Factor Alpha (%, per quarter)	-0.12	5.33	-0.18	-2.40	2.09
Three-Factor Alpha (%, per quarter)	-0.29	4.36	-0.31	-2.15	1.51
Four-Factor Alpha (%, per quarter)	-0.36	4.28	-0.32	-2.15	1.47

Consistent with Moskowitz (2000) and Kosowski (2006), I use NBER recessions to proxy for bad states of the economy. I also use consumption growth to derive an alternative proxy of bad states. According to consumption-based asset pricing, consumption growth will be negatively related to the pricing kernel. Hence, I use quarterly data on real per-capita consumption of nondurables and services from the Bureau of Economic Analysis and consider as a bad state any period in which per-capita consumption exhibited a negative growth. The indicator function $I(BadState)_t$ is used in the next tables to identify interchangeably both proxies of bad states.

5.2 Previously Documented Implications

The first empirical fact that my model rationalizes is the negative risk-adjusted performance, net of fees, of actively managed equity mutual funds. Table 3 presents results from panel regressions measuring the unconditional performance of U.S. equity mutual funds. Quarterly data are used. To account for the possible correlation between the residuals of a particular fund, standard errors are clustered by funds (see Petersen (2007) for an analysis of panel data econometrics in finance). I measure the risk-adjusted performance of funds using the one-factor model of Jensen (1968), the three-factor model of Fama and French (1993), and the four-factor model of Carhart (1997).

Table 3: Unconditional Mutual Fund Performance

This table presents results from panel regressions measuring the unconditional performance of U.S. equity mutual funds over the 1980-2005 period. Quarterly data are used. Returns are in % terms. I measure the risk-adjusted performance of funds using the one-factor model of Jensen (1968), the three-factor model of Fama and French (1993), and the four-factor model of Carhart (1997). All regressions include fund fixed effects. Standard errors reported between brackets are corrected for heteroskedasticity and within-fund correlation. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

Dependent Variable: Fund Excess Return$_t$ (%, per quarter)			
	(1)	(2)	(3)
MKT_t	1.026	0.985	0.996
	[0.006]***	[0.003]***	[0.004]***
SMB_t		0.203	0.212
		[0.008]***	[0.009]***
HML_t		0.032	0.043
		[0.010]***	[0.009]***
MOM_t			0.026
			[0.004]***
Intercept	-0.101	-0.229	-0.334
	[0.010]***	[0.016]***	[0.019]***
Observations	82081	82081	82081
Number of Funds	3260	3260	3260
R^2	0.73	0.74	0.74
Fund Fixed Effects	Yes	Yes	Yes

In the current sample, mutual fund performance as measured by the intercept of the regression is significantly negative, both statistically and economically. This is consistent with the findings of Jensen (1968), Malkiel (1995), Gruber (1996), and Carhart (1997), among others.

The second empirical fact that my model rationalizes is that actively managed funds exhibit a better performance in bad states than in good states. Table 4 presents results from panel regressions measuring the performance of U.S. equity mutual funds, allowing for the regression coefficients to take values that differ between bad states and good states.

Table 4: Mutual Fund Performance Conditional on Indicators of Bad States

This table presents results from panel regressions measuring the performance of U.S. equity mutual funds over the 1980-2005 period, allowing for the regression coefficients to take values that differ between bad states (denoted by the indicator function $I(BadState)_t$) and good states. Regressions in Panel A use NBER recessions to proxy for bad states while regressions in Panel B use periods of negative (per-capita) consumption growth. Quarterly data are used. Returns are in % terms. I measure the risk-adjusted performance of funds using the one-factor model of Jensen (1968), the three-factor model of Fama and French (1993), and the four-factor model of Carhart (1997). All regressions include fund fixed effects. Standard errors reported between brackets are corrected for heteroskedasticity and within-fund correlation. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

	Dependent Variable: Fund Excess Return$_t$ (%, per quarter)					
	Panel A. NBER Recession			Panel B. Consumption Growth < 0		
	(1)	(2)	(3)	(4)	(5)	(6)
$I(BadState)_t$	0.289	0.121	0.414	0.268	0.323	0.513
	[0.055]***	[0.072]*	[0.078]***	[0.085]***	[0.088]***	[0.127]***
MKT_t	1.005	0.982	0.994	1.022	0.975	0.985
	[0.006]***	[0.003]***	[0.004]***	[0.007]***	[0.003]***	[0.004]***
$MKT_t * I(BadState)_t$	0.106	0.037	0.028	0.034	0.042	0.032
	[0.007]***	[0.021]*	[0.020]	[0.006]***	[0.007]***	[0.006]***
SMB_t		0.204	0.207		0.228	0.233
		[0.009]***	[0.009]***		[0.009]***	[0.009]***
$SMB_t * I(BadState)_t$		-0.073	-0.114		-0.119	-0.144
		[0.016]***	[0.017]***		[0.018]***	[0.023]***
HML_t		0.033	0.050		0.049	0.058
		[0.010]***	[0.009]***		[0.010]***	[0.010]***
$HML_t * I(BadState)_t$		-0.053	-0.034		-0.103	-0.114
		[0.031]*	[0.032]		[0.013]***	[0.013]***
MOM_t			0.037			0.022
			[0.005]***			[0.005]***
$MOM_t * I(BadState)_t$			-0.076			-0.038
			[0.016]***			[0.012]***
Intercept	-0.097	-0.218	-0.367	-0.101	-0.220	-0.309
	[0.012]***	[0.019]***	[0.019]***	[0.013]***	[0.019]***	[0.023]***
Observations	82081	82081	82081	82081	82081	82081
Number of Funds	3260	3260	3260	3260	3260	3260
R^2	0.73	0.74	0.74	0.73	0.74	0.74
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Consistent with the findings of Moskowitz (2000) and Kosowski (2006), fund performance is significantly better in bad states than in good states. For the one-factor model (columns (1) and (4)), performance becomes positive in bad states regardless of the proxy of bad state that I use. For the three-factor model (columns (2) and (5)), performance becomes positive in periods of negative consumption growth but not in NBER recessions. For the four-factor model (columns (3) and (6)), performance is positive in bad states regardless of the proxy of bad state that I use. For example, the average performance goes from -0.309% in quarters of positive consumption growth to 0.204% in quarters of negative consumption growth, an annualized difference of over 2%. According to the model, this pattern in performance might rationalize mutual fund investing despite the negative unconditional performance.

Also, I find that the market exposure of equity funds is higher in bad states than in good states. This is consistent with Ferson and Warther's (1996) finding that fund inflows decrease in bad states, resulting in lower cash balances and higher market exposure.

The third empirical fact that my model rationalizes is that bad-performing funds charge high fees compared to good-performing funds. To test if this is true in the current sample, I measure the unconditional monthly alpha of each fund over its entire life span. I also compute each fund's average expense ratio and average total fee, i.e. expense ratio + (1/7)*front-load fee. Then I divide all the funds into ten decile portfolios based on their unconditional alphas. Table 5 presents the mean alpha, expense ratio and total fee of each decile portfolio.

Whether I adjust for front-load fees or not, the difference between the fees of the first decile portfolio and the tenth decile portfolio is always economically and statistically significant: bad-performing funds charge high fees compared to other funds. For example, the average expense ratio for the decile of worst-performing funds (in terms of the four-factor model) is 1.68% while it is 1.47% for the decile of best-performing funds. However, as documented by Carhart (1997), the empirical relationship between fees and alphas is not strictly decreasing as my model would predict. Cross-decile differences in fees are concentrated in deciles 1 and 10. Still, my model provides a possible explanation for the high fees charged by bad-performing funds.

Table 5: Unconditional Performance and Fees

This table presents the mean unconditional alpha, expense ratio and total fee of ten decile portfolios sorted on unconditional alpha. Results in Panels A, B and C are respectively based on the one-factor model of Jensen (1968), the three-factor model of Fama and French (1993), and the four-factor model of Carhart (1997). Total fee is measured as expense ratio + (1/7)*front-load fee. Monthly data for over 2,000 U.S. equity mutual funds during the 1980-2005 period are used to compute alpha over the entire life span of each fund. Numbers are in % terms. The differences between the averages of decile 1 and 10 are reported with their standard errors. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

Decile (Alpha)	Alpha (%, per month)	Expenses (%)	Total Fee (%)
	Panel A. One-Factor Model		
1	-1.35	1.67	1.89
2	-0.51	1.52	1.77
3	-0.31	1.38	1.63
4	-0.19	1.35	1.60
5	-0.09	1.27	1.51
6	-0.01	1.23	1.44
7	0.09	1.23	1.46
8	0.22	1.34	1.58
9	0.42	1.35	1.50
10	1.21	1.45	1.65
1-10	-2.56	0.21	0.24
	[0.09]***	[0.04]***	[0.04]***
	Panel B. Three-Factor Model		
1	-1.84	1.70	1.93
2	-0.47	1.45	1.67
3	-0.29	1.37	1.61
4	-0.19	1.30	1.54
5	-0.12	1.29	1.51
6	-0.05	1.27	1.49
7	0.02	1.25	1.47
8	0.11	1.26	1.48
9	0.27	1.41	1.63
10	1.82	1.48	1.69
1-10	-3.65	0.22	0.23
	[0.98]***	[0.04]***	[0.05]***
	Panel C. Four-Factor Model		
1	-1.47	1.68	1.89
2	-0.46	1.46	1.70
3	-0.29	1.42	1.67
4	-0.19	1.37	1.60
5	-0.12	1.29	1.51
6	-0.06	1.20	1.41
7	0.01	1.27	1.49
8	0.11	1.26	1.49
9	0.25	1.37	1.60
10	1.36	1.47	1.68
1-10	-2.83	0.21	0.21
	[0.25]***	[0.04]***	[0.05]***

In summary, I observe in the sample of 3,260 equity mutual funds over the 1980-2005 period the three stylized facts that my model tries to rationalize. Next, I test whether the model's previously undocumented predictions hold empirically.

5.3 Previously Undocumented Implications

The fundamental prediction of my model is presented in Proposition 1: a fund manager will generate active returns that are higher in bad states of the economy than in good states. To do so, he will have to pay a larger cost in bad states, for example by trading more or exerting a higher effort. Several authors, including Wermers (2000), Kacperczyk, Sialm, and Zheng (2005), and Kacperczyk and Seru (2007), respectively use turnover, industry concentration, and insensitivity to public announcements to find that more "active" fund managers outperform, net-of-fees, less "active" managers. This evidence suggests that a fund manager who wants to generate active returns that are higher in bad states than in good states should be able to do so by being more active and increasing his effort in bad states. I test this prediction using different measures of managerial activity.

I use the level of portfolio turnover, which is available through the CRSP database, as a first measure of managerial activity. Table 6 presents results from panel regressions of the turnover ratio (%) on lagged fund characteristics and an indicator function $I(BadState)_t$ of bad state. Since the variable $turnover_t$ is updated annually in most of the CRSP database, I use annualized data for the regressions of Table 6. To account for the possible correlation between the residuals of a particular fund, standard errors are clustered by funds. Columns (1) and (3) show the results from a regression of turnover on lagged fund characteristics only. To ensure that changes in turnover are not explained entirely by contemporaneous fund flows or market returns, I control for the effects of these variables and present the results in columns (2) and (4).

In an NBER recession year, the average fund manager increases his turnover ratio by at least 4%. This increase is economically significant compared to the unconditional average

Table 6: Mutual Fund Portfolio Turnover

This table presents results from panel regressions of the turnover ratio (%) on lagged fund characteristics and an indicator function $I(BadState)_t$ of bad state. Regressions in Panel A use NBER recessions to proxy for bad states while regressions in Panel B use periods of negative (per-capita) consumption growth. Annualized data for U.S. equity mutual funds over the 1980-2005 period are used. Expenses, returns and flows are in % terms. All regressions include fund fixed effects. Standard errors reported between brackets are corrected for heteroskedasticity and within-fund correlation. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

	Dependent Variable: $Turnover_t$ (%, per year)			
	Panel A. NBER Recession		Panel B. Consumption Growth < 0	
	(1)	(2)	(3)	(4)
$I(BadState)_t$	7.621	4.718	-10.615	-10.605
	[1.461]***	[1.291]***	[2.877]***	[2.949]***
$Log(Assets_{t-1})$	-7.883	-8.233	-7.883	-8.403
	[1.514]***	[1.495]***	[1.535]***	[1.505]***
Age_{t-1}	0.922	0.948	0.809	0.861
	[0.199]***	[0.200]***	[0.199]***	[0.199]***
$Expenses_{t-1}$	8.687	8.770	8.544	8.790
	[3.630]**	[3.626]**	[3.645]**	[3.641]**
$Flow_t$		-0.106		-0.110
		[0.039]***		[0.041]***
MKT_t		-0.240		-0.277
		[0.042]***		[0.044]***
$Intercept$	106.266	108.505	109.150	111.597
	[8.511]***	[8.382]***	[8.598]***	[8.446]***
Observations	16168	16164	16168	16164
Number of Funds	3260	3260	3260	3260
R^2	0.73	0.73	0.73	0.73
Fund Fixed Effects	Yes	Yes	Yes	Yes

turnover ratio of 91.9% presented in Table 2. This evidence suggests that fund managers update their portfolios significantly more in bad states than in good states. However, results when bad states of the economy are proxied by periods of negative consumption growth are opposite to those based on NBER recessions. The only finding of interest in Table 6 robust to both proxies of bad states is that fund managers trade significantly more in years of bad market returns. This is consistent with the model's predictions.

How active a fund manager is can also be measured by looking at the risk of his portfolio, as in Chevalier and Ellison (1997). A fund manager who is more active during a certain period is expected to update more frequently the risk of his portfolio. I also expect him to choose a portfolio that is farther away from the average fund portfolio. His portfolio can diverge from the average fund portfolio either in terms of market risk, unexplained returns or both. Hence, in bad states I expect to observe larger adjustments in the level of market risk and more cross-sectional dispersion in both market risk and unexplained returns.

I measure market risk using β_{it}, the exposure to the market factor in a Carhart's (1997) four-factor model. I estimate β_{it} using a rolling regression with monthly returns over the past 36 months. Then I use the fund-specific quarterly adjustments in systematic risk (i.e. $|\beta_{it} - \beta_{it-1}|$) and the absolute deviation of β_{it} from its cross-sectional mean (i.e. $|\beta_{it} - \overline{\beta_{it}}|$) as measures of how active fund manager i is in period t.

I also identify the part of a fund's realized return that cannot be explained by systematic risk. To do so, I use $(\alpha_{it} + e_{it})$ where α_{it} is the intercept and e_{it} is the residual from a 3-year rolling regression of Carhart's (1997) four-factor model. Together, these two terms represent fund i's realized excess return over the required rate of return suggested by the four-factor model in period t. The absolute deviation of the unexplained return from its cross-sectional mean (i.e. $|(\alpha_{it} + e_{it}) - \overline{(\alpha_{it} + e_{it})}|$) is the last measure that I use to estimate managerial activity. Summary statistics for these measures are reported in Table 7.

Table 7: **Summary Statistics for Mutual Fund Risk Regressions**

This table presents summary statistics for the measures of managerial activity for the sample of 3,260 equity mutual funds over the 1980-2005 period from the CRSP Survivorship-Bias-Free Mutual Fund database.

	Mean	**S.D.**	**Median**	**p25**	**p75**
β_{it}	0.993	0.183	0.983	0.896	1.080
$\|\beta_{it} - \overline{\beta_{it}}\|$	0.128	0.125	0.093	0.042	0.174
$\|\beta_{it} - \beta_{it-1}\|$ (per quarter)	0.031	0.035	0.020	0.009	0.040
$(\alpha_{it} + e_{it})$ (%, per quarter)	-0.300	3.586	-0.285	-1.979	1.391
$\|(\alpha_{it} + e_{it}) - \overline{(\alpha_{it} + e_{it})}\|$ (%, per quarter)	2.363	2.525	1.648	0.738	3.136

Table 8 presents results from panel regressions of the quarterly adjustment in market risk, the cross-sectional dispersion in market risk and the cross-sectional dispersion in unexplained returns on lagged fund characteristics, an indicator function $I(BadState)_t$ of bad state, contemporaneous fund flows, market returns and three indicator functions identifying quarters.

Quarterly data are used. To account for the possible correlation between the residuals of a particular fund, standard errors are clustered by funds. For each measure of managerial activity, I run panel regressions with fund fixed effects using NBER recessions and periods of negative (per-capita) consumption growth to proxy for bad states of the economy.

Table 8: Mutual Fund Risks

This table presents results from panel regressions of the quarterly adjustment in market risk $|\beta_{it} - \beta_{it-1}|$, the cross-sectional dispersion in market risk $|\beta_{it} - \overline{\beta_{it}}|$ and the cross-sectional dispersion in unexplained returns $|(\alpha_{it} + e_{it}) - \overline{(\alpha_{it} + e_{it})}|$ on lagged fund characteristics, an indicator function $I(BadState)_t$ of bad state, contemporaneous fund flows, market returns and three indicator functions identifying quarters. Regressions with odd numbers use NBER recessions to proxy for bad states while regressions with even numbers use periods of negative (per-capita) consumption growth. Quarterly data for U.S. equity mutual funds over the 1980-2005 period are used. Expenses, returns (including $\alpha_{it} + e_{it}$) and flows are in % terms. All regressions include fund fixed effects. Standard errors reported between brackets are corrected for heteroskedasticity and within-fund correlation. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

	Dependent Variable					
	$\lvert\beta_{it} - \beta_{it-1}\rvert$		$\lvert\beta_{it} - \overline{\beta_{it}}\rvert$		$\lvert(\alpha_{it} + e_{it}) - \overline{(\alpha_{it} + e_{it})}\rvert$	
	NBER	$\Delta c_t < 0$	NBER	$\Delta c_t < 0$	NBER	$\Delta c_t < 0$
	(1)	(2)	(3)	(4)	(5)	(6)
$I(BadState)_t$	0.014	0.006	0.015	0.020	0.414	0.551
	[0.001]***	[0.001]***	[0.002]***	[0.002]***	[0.039]***	[0.042]***
$Log(Assets_{t-1})$	-0.001	-0.001	-0.006	-0.006	0.069	0.076
	[0.000]***	[0.000]***	[0.002]***	[0.002]***	[0.024]***	[0.024]***
Age_{t-1}	0.000	0.000	0.002	0.002	-0.015	-0.014
	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.004]***	[0.004]***
$Expenses_{t-1}$	0.001	0.000	-0.005	-0.006	-0.078	-0.088
	[0.001]	[0.001]	[0.007]	[0.007]	[0.082]	[0.083]
$Flow_t$	0.000	0.000	0.000	0.000	0.002	0.002
	[0.000]	[0.000]	[0.000]**	[0.000]***	[0.001]**	[0.001]**
MKT_t	0.000	0.000	0.000	0.000	-0.029	-0.025
	[0.000]***	[0.000]***	[0.000]***	[0.000]***	[0.001]***	[0.001]***
$I(Quarter2)_t$	-0.005	-0.003	-0.001	0.003	-0.117	-0.018
	[0.000]***	[0.000]***	[0.000]**	[0.000]***	[0.022]***	[0.022]
$I(Quarter3)_t$	-0.004	-0.003	-0.005	-0.002	-0.037	0.032
	[0.000]***	[0.000]***	[0.001]***	[0.000]***	[0.022]*	[0.022]
$I(Quarter4)_t$	0.003	0.005	0.000	0.002	0.276	0.344
	[0.000]***	[0.000]***	[0.000]	[0.000]***	[0.027]***	[0.027]***
$Intercept$	0.027	0.028	0.143	0.140	2.278	2.176
	[0.002]***	[0.002]***	[0.012]***	[0.012]***	[0.150]***	[0.153]***
Observations	62010	62010	63561	63561	63561	63561
Number of Funds	2620	2688	2688	2620	2688	2688
R^2	0.21	0.53	0.23	0.20	0.53	0.23
Fund Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Using both proxies of bad states, estimated coefficients for $I(BadState)_t$ are positive and significant, both economically and statistically. Results in columns (1) and (2) suggest that fund managers update the market risk of their portfolios significantly more in bad states than in good states. Quarterly adjustments in market risk go up by 0.014 in NBER recession quarters and by 0.006 in quarters of negative consumption growth, which are economically large changes relative to the unconditional average of 0.031. Columns (3) to (6) show that the cross-sectional dispersion in market risk and unexplained returns increase in bad states of the economy as well. The average dispersion in market risk increases by 0.015 in NBER recession quarters and by 0.020 in quarters of negative consumption growth while the average dispersion in unexplained returns increases by 0.414 in NBER recession quarters and by 0.551 in quarters of negative consumption growth. These increases are economically large compared to their unconditional average levels of 0.128 and 2.363% respectively. In bad states of the economy, fund managers pick portfolios that diverge more from the portfolio of the average fund manager. Altogether, these results suggest that fund managers are more active in bad states of the economy than in good states.

The other new prediction of the model is derived from Proposition 5: unconditional performance will be associated with a positive covariance between active returns and the pricing kernel. The model rationalizes the existence of mutual funds offering negative alphas when these funds are also offering insurance against pricing kernel variations. To proxy for the level of insurance offered by a fund, I use the difference in a fund's risk-adjusted performance between bad states and good states. For each fund, I run a regression similar to the panel regressions presented in Table 4: I regress the fund's returns on the NBER recession indicator, the risk factors and the cross-products of the NBER recession indicator and the factors. A fund's OLS coefficient for $I(BadState)_t$ becomes my proxy for the insurance against pricing kernel variations that this fund offers.

In Table 9, I construct ten decile portfolios based on unconditional alpha as I constructed in Table 5, but I only consider the funds that went through at least one NBER recession (over 2,000 funds). The average unconditional alpha, expense ratio, total fee, and insurance offered are presented for each decile portfolio. Panels A, B and C respectively use the one-factor model of Jensen (1968), the three-factor model of Fama and French (1993), and the four-factor model of Carhart (1997).

Results for the three different performance measures show a difference between the average insurance offered by funds in decile 1 and in decile 10. These differences (at least 0.18%) are economically significant considering that those are monthly estimates. The difference resulting from the use of Fama and French's (1993) three-factor model is statistically significant at the 1% level. However, as in Table 5, the empirical relationship studied is not strictly monotone as my model would predict. The cross-decile difference in insurance is concentrated in decile 1. Still, these empirical results support the prediction that the funds with the worst risk-adjusted performance also provide better insurance against bad states of the economy. Therefore, investing in those funds can be rationalized by my model. In unreported tests, I find that these patterns do not hold when I use an indicator of negative consumption growth (a quarterly series) and quarterly data instead of monthly data (as in Table 5). Quarterly estimates are more volatile than monthly estimates, which is not surprising given the fact that the median fund has only 32 quarterly return observations and my performance measures require the estimation of up to 10 coefficients. For this reason, empirical tests based on NBER recessions are assumed to be more accurate.

Overall, I draw the following conclusions from the work reported in this section. First, I find support in the current sample for the three empirical facts that my model tries to rationalize: the negative unconditional risk-adjusted performance of equity mutual funds, their systematically better performance in bad states than in good states and the relatively high fees charged by bad-performing funds. Second, reported results suggest that fund managers are more active in bad states than in good states because they update their portfolios more and pick portfolios that diverge more from the average mutual fund portfolio. Third, the mutual funds that offer the worst performance in terms of unconditional risk-adjusted performance also offer better insurance against NBER recessions, which might explain their existence. To the best of my knowledge, these two latest findings are novel and provide

Table 9: Unconditional Performance and Insurance Against NBER Recessions This table presents the mean unconditional alpha and insurance against NBER recessions offered by ten decile portfolios sorted on unconditional alpha. Results in Panels A, B and C use respectively the one-factor model of Jensen (1968), the three-factor model of Fama and French (1993), and the four-factor model of Carhart (1997). Total fee is measured as expense ratio + (1/7)*front-load fee. Monthly data for over 2,000 U.S. equity mutual funds that went through at least one recession over the 1980-2005 period are used to compute alpha and the level of insurance offered over the entire life span of each fund. Numbers are in % terms. The differences between the averages of decile 1 and 10 are reported with their standard errors. ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.

Decile (Alpha)	Alpha (%, per month)	Expenses (%)	Total Fee (%)	Insurance (%, per month)
		Panel A. One-Factor Model		
1	-0.89	1.73	1.99	0.12
2	-0.37	1.40	1.70	-0.10
3	-0.23	1.38	1.65	0.10
4	-0.13	1.31	1.58	-0.23
5	-0.05	1.20	1.43	0.12
6	0.03	1.19	1.45	-0.06
7	0.12	1.26	1.52	-0.09
8	0.26	1.29	1.51	-0.08
9	0.45	1.35	1.52	-0.01
10	1.16	1.46	1.64	-0.06
1-10	-2.04	0.28	0.35	0.18
	[0.08]***	[0.05]***	[0.06]***	[0.23]
		Panel B. Three-Factor Model		
1	-0.87	1.70	1.96	0.15
2	-0.36	1.43	1.69	0.18
3	-0.24	1.30	1.53	0.13
4	-0.17	1.34	1.58	-0.05
5	-0.10	1.25	1.48	-0.02
6	-0.04	1.26	1.51	0.00
7	0.03	1.23	1.48	-0.18
8	0.11	1.25	1.51	-0.65
9	0.25	1.33	1.57	-0.36
10	0.85	1.47	1.68	-0.64
1-10	-1.72	0.23	0.28	0.80
	[0.09]***	[0.05]***	[0.06]***	[0.30]***
		Panel C. Four-Factor Model		
1	-0.94	1.69	1.93	0.57
2	-0.37	1.48	1.75	-0.10
3	-0.24	1.34	1.59	0.10
4	-0.16	1.34	1.59	-0.23
5	-0.10	1.32	1.56	0.12
6	-0.05	1.18	1.40	-0.06
7	0.01	1.28	1.52	-0.09
8	0.10	1.20	1.44	-0.08
9	0.22	1.28	1.53	-0.01
10	0.81	1.47	1.69	-0.06
1-10	-1.75	0.23	0.24	0.63
	[0.11]***	[0.05]***	[0.06]***	[0.35]

support for my model. Finally, all these results suggest that business cycle variables matter to mutual fund managers and investors. Hence, future attempts to measure mutual fund performance should account for the macroeconomic risks captured by the NBER recession indicator and by consumption growth but that are not captured by returns on the standard long-short portfolios of Fama and French (1993) and Carhart (1997).[8]

6 Conclusion

In this paper, I rationalize and link three empirical facts that might seem surprising at first: the observed unconditional risk-adjusted performance of equity funds is negative, performance is systematically better in bad states of the economy than in good states and bad-performing funds charge high fees compared to good-performing funds.

I present a model of optimal fee setting and active management by a mutual fund manager in which the production of state-dependent active returns is costly and investors competitively supply money. I investigate how the fund manager's ability to generate state-dependent active returns will influence the fee he will charge and the performance an econometrician will measure. I show that a fund manager will optimally generate active returns that are higher in bad states than in good states. By doing so, the fund manager will provide investors with a partial insurance against pricing kernel variations. Under fairly standard assumptions, a performance measure that does not allow a perfect specification of the true pricing kernel will provide a negatively biased estimate of fund performance. The fee charged by the fund will equal the certainty equivalent of the value added through active management and be higher than the estimated value added. Since a perfect specification holds if and only if the passive returns used by the measure are on the mean-variance frontier, negative mutual fund performance will be observed in empirical practice, even when fund managers have active management skills. A parameterized version of the model predicts that a fund

[8]For example, in an early paper Grinblatt and Titman (1989) suggest briefly to weight alpha by the marginal utility of wealth.

manager with better skills will provide a better insurance against pricing kernel variations, charge higher fees to investors and exhibit worse risk-adjusted performance.

I calibrate the model and find that standard empirical estimates of pricing kernel volatility generate levels of mutual fund underperformance consistent with the data. Finally, I use data on more than 3,000 unique U.S. equity funds over the 1980-2005 period to test the empirical implications of my model. I find evidence supporting the model. Fund managers seem to be more active in bad states than in good states and the mutual funds that offer the worst unconditional risk-adjusted performance also offer better insurance against bad states of the economy.

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