Mutual Fund Performance Evaluation and Best Clienteles[☆]

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Abstract

This paper develops a performance measure that considers a mutual fund's best potential clientele in incomplete market with investor disagreement. Based on the law of one price and no good-deal conditions, we obtain an upper bound on admissible performance measures that identifies the most favorable evaluation. We find that an increase in admissible investment opportunities equivalent to half the Sharpe ratio of the market index leads to generally positive performance for the best clientele. Augmenting monthly Sharpe ratio opportunities by only 0.04 is sufficient for their evaluation to achieve zero alpha. These results are robust to the use of different basis assets and conditioning information, and to adjustments for false discoveries.

JEL Classification: G12, G23

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Abstract

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1. Introduction

In today's mutual fund industry, there exist thousands of funds that cater to different investors through their management style and other attributes. In incomplete markets, as investors can disagree about the attractiveness of funds, such catering might be worthwhile in leading the funds to find their right clientele, i.e. the class of investors to whom they are the most valuable.

Some recent research examines the impact of investor disagreement and heterogeneity on mutual fund performance evaluation. Studying the issue generally, Ahn, Cao and Chrétien (2009) and Ferson and Lin (2013) find that taking into account heterogeneous preferences do not rule out large valuation disagreement. In particular, Ferson and Lin (2013) argue that such disagreement can be similar in importance to the widely documented effects of the benchmark choice problem and the statistical imprecision in estimates of alphas. Some studies instead concentrate more specifically on identifying specific clienteles. Bailey, Kumar and Ng (2011) document that behavioral bias is a factor of investor heterogeneity in the mutual fund industry. Del Guercio and Reuter (2013) find that the retail mutual fund market is formed from two broad clienteles that value funds differently: self-directed investors and investors having brokers helping them in their investment decisions. In a literature review, Ferson (2010) emphasizes that measuring performance from the point of view of different clienteles is a challenge for future research.

Despite the important contributions from this literature on establishing the importance of investor disagreement and heterogeneity, it has not focus on the valuation that can be the most important for mutual funds, the one from their potentially best clientele. A positive evaluation from such a targeted clientele could not only establish that some investors would want to buy the funds (Chen and Knez (1996) and Ferson and Lin (2013)), but could also justify the continued popularity of mutual funds, termed a "puzzle" by Gruber (1996), given the large number of studies documenting their negative value added (see Fama and French (2010) and Barras, Scaillet and Wermers (2010) for recent examples). Put differently, focusing on the best clientele could lead to a perspective on mutual funds different from the traditional look based on the implied representative investor from common asset pricing models.

The goal of this paper is to develop and implement a performance evaluation measure that considers the potentially best clientele of a mutual fund. For our purpose, this clientele is defined as the class of investors the most favorable to a fund in the sense that it values the fund at an upper performance bound in a setup where markets are incomplete. Our “best clientele performance measure” thus not only considers investor disagreement, but also focuses on the most worthy clientele that a mutual fund could target.

We develop this measure by combining the asset pricing bound literature with the stochastic discount factor (SDF) performance evaluation approach first proposed by Glosten and Jagannathan (1994) and Chen and Knez (1996). In a complete market, there is a unique SDF for asset valuation. Subsequently, there is a unique price for each asset. However, in an incomplete market, the uniqueness of the SDF is no longer guaranteed. A set of SDFs is then generally admissible, allowing for several prices for each asset. Using the insight of Hansen and Jagannathan (1991) on the correspondence between the SDF volatility and the Sharpe ratio, Cochrane and Saá-Requejo (2000) propose asset pricing bounds in incomplete market based on a maximum SDF volatility in order to rule out investment opportunities with unreasonably high Sharpe ratio, termed “good-deals”.

While the no good-deal bounds approach was developed for pricing derivative assets, this paper is the first to adapt it to the performance evaluation of mutual funds. Even though other restrictions exist, we argue that the no good-deal restriction is particularly well suited for performance evaluation. The Sharpe ratio has a long history in performance evaluation and is widely used in practice. The literature, including Ross (1976), MacKinlay (1995) and Cochrane and Saá-Requejo (2000), has also established some useful guidance on reasonable choice for the maximum Sharpe ratio that specifies the restriction.

In addition to the no good-deal restriction, we impose another restriction that is particularly meaningful in the mutual fund performance context: the law of one price (LOP) condition (Hansen and Jagannathan (1991)). The LOP condition implies that mutual fund investors give zero value to passive portfolios. As argued by Chen and Knez (1996) and Ahn, Cao and Chrétien (2009), imposing this condition can resolve the widely documented benchmark choice or "bad model" problem (see Roll (1978), Dybvig and Ross (1985a, b), Green (1986), Lehmann and Modest (1987), among others). In particular, Chen and Knez (1996) show that this condition is the most important in the minimum set of requirements for the admissibility of a performance measure.

Taken together, the LOP condition and the no good-deal condition lead to our best clientele performance evaluation approach. Specifically, the best clientele performance value or alpha is defined as the upper performance bound obtained when the set of SDFs for mutual fund investors is assumed to respect both conditions. Cochrane and Saá-Requejo (2000) show not only that economically meaningful bounds can be obtained in such a setup, but also that a closed-form solution is available for the bounds, which facilitates and accelerates its implementation when evaluating a large number of mutual funds.

Using the generalized method of moment of Hansen (1982), we estimate the best clientele SDF alphas with monthly returns of 2786 actively managed U.S. open-end equity mutual funds from January 1984 to December 2012. Our main empirical results rely on a set of passive portfolios based on ten industry portfolios. They assume that the maximum Sharpe ratio (specifying the no good-deal restriction) considers investment opportunities in addition to the ones from the passive portfolios equivalent to either half the Sharpe ratio of the market index or its full value.

Empirically, we find that considering investor disagreement and focusing on the potentially best clientele leads to generally positive performance for mutual funds. For example, when adding opportunities equivalent to half the market Sharpe ratio, the mean monthly best clientele performance alpha is equal to 0.23%. Comparatively, the mean alpha when disagreement is ruled out is -0.18%, a value similar to the findings from traditional measures that consider the point of view of a representative investor. Accordingly, the proportions of positive and significantly positive alphas increase when allowing for more disagreement, going from 20% to 78% for positive alphas and from 1% to 24% for significantly positive alphas. Increasing further the maximum Sharpe ratio improves even more the performance for the mutual funds.

These results are robust to the use of different sets of passive portfolios and various choices of maximum Sharpe ratio. In particular, we show that augmenting monthly Sharpe ratio opportunities by only 0.04 (about a third on the market index Sharpe ratio) is sufficient for the best clientele to give a nonnegative performance to mutual funds on average. A conditional version of the best clientele performance approach and adjustments for false discoveries also lead to the same conclusion.

Overall, our best clientele alpha results suggest that there is a clientele that would want to buy a majority of the mutual funds, consistent with the real-life continued investments of investors in mutual funds. As Ferson and Lin (2013), they support an economically important divergence in performance evaluation between clienteles.

The remainder of this paper is organized as follows. Section 2 develops the best clientele performance measure. Section 3 presents our methodology for estimating the performance values and summarizing the results. Section 4 describes the mutual fund data and the passive portfolio returns. Section 5 presents and interprets our empirical results. Finally, section 6 concludes.

2. Performance Measure for the Best Potential Clientele

2.1. Basic Performance Setup

Our approach starts by measuring the performance, or alpha, with the stochastic discount factor (SDF) approach such that:

$$\alpha_{MF,t} = E_t\left[m_{t+1}R_{MF,t+1}\right] - 1,$$

where m_{t+1} is the SDF of an investor interested in valuing the mutual fund with gross return $R_{MF,t+1}$, and the expectation operator $E_t[\quad]$ is understood to be conditional on the investor's or public information set. Taking the unconditional expectation on both sides, and dropping time subscripts except when needed to avoid ambiguity, the expected alpha is given by:

$$\alpha_{MF} = E[m\, R_{MF}] - 1.$$

Glosten and Jagannathan (1994) and Chen and Knez (1996) are the first to propose SDF alphas for performance evaluation. As explained by Cochrane (2001), the SDF approach does not require any assumptions about complete markets, utility functions and aggregation. The existence of the SDF requires only that the law of one price is not violated, so that two assets with the same payoffs have the same price. In the context of performance evaluation, Ferson (2010) argues that the SDF approach is general enough to properly account for heterogeneous investors and differentially-informed managers. In contrast, for traditional regression-based alpha, a positive (negative) value does not necessarily imply buying (selling) the fund, and manager with superior information does not necessarily generate a positive value. Ferson (2010, p. 227) thus concludes that "the SDF alpha seems to be on the most solid theoretical footing, and should probably get more attention than it has in the literature".

In this setup, the SDF is a scalar random variable used by the investor to risk adjusted the mutual fund payoffs per dollar invested by "discounting" them. It thus captures the effects of both time value of money and risk. Under general conditions in intertemporal asset pricing, the SDF can also be interpreted as the investor's intertemporal marginal rate of substitution, the relevant asset pricing representation of the investor's marginal preferences. In this sense, given the investor's "marginal preferences", his expected alpha for the fund can be found.

Unfortunately, the investor's SDF is not observable. Hence the literature typically uses the marginal preferences from a representative investor obtained through economic assumptions and equilibrium conditions. For example, the CAPM supposes that the SDF is a linear function of the market return. The main advantage of such a choice is that it provides a unique performance evaluation that can be relevant for all investors. However, it rules out investor disagreement that occurs when one client views the performance of a fund differently from another client (see Ferson and Lin (2013)). Furthermore, it exposes the results to the benchmark problem choice, as the selected performance model does not necessarily price correctly passive portfolios (see Chen and Knez (1996), Fama (1998) and Ahn, Cao and Chrétien (2009)).

Instead, in this paper, we impose an economically relevant structure on the set of SDFs of all investors in order to obtain a restricted set useful to identify the most favorable performance. Let M represents this restricted set. Under the assumption that this set is constrained enough to be close and convex, Chen and Knez (1996) and Ahn, Chrétien and Cao (2009) demonstrate that it is possible to find an upper bound on the performance of a fund:

$$\bar{\alpha}_{MF} = sup_{m \in M} \, E[m \, R_{MF}] - 1,$$

where $\bar{\alpha}_{MF}$ represents the upper bound on the expected alpha, the highest average performance value that can be found from the heterogeneous investors considered in M.

By considering a set of SDFs, as opposed to selecting a unique SDF, our setup results in a finite range of performance values (see Chen and Knez (1996) and Ahn, Chrétien and Cao (2009)). Hence, it allows for the investor disagreement that can occur in incomplete market. As argued by Chen and Knez (1996, p. 529), "given that mutual funds are set up to satisfy different clienteles, such an evaluation outcome may not be unrealistic". Empirically, the results of Ferson and Lin (2013) suggest that in fact investor disagreement is economically important.

While, for example, a lower performance bound could be found, we focus on the upper bound as it can be interpreted as the performance from the class of investors the most favorable to the mutual fund (in a valuation sense). It is thus possible to evaluate whether mutual funds add value from the perspective of their potentially best clientele. In particular, Chen and Knez (1996) and Ferson and Lin (2013) show that if this value is positive, there exists some investor that would want to buy the fund, with an optimal investment proportional to the alpha.

2.2. Restricting the Stochastic Discount Factors

One key to our approach is restricting the set M of SDFs in an economically meaningful way. We impose two conditions that the SDF of mutual fund investors should meet: the law of one price and the no good-deal condition.

The first condition is the law of one price condition, as discussed extensively by Hansen and Jagannathan (1991): the SDFs used for our performance measurement should price correctly passive portfolios or basis assets:

$$E[m\,\mathbf{R_K}] - \mathbf{1} = 0,$$

where $\mathbf{R_K}$ is a vector of returns on K passive portfolios and $\mathbf{1}$ is a $K \times 1$ unit vector. It is plausible to assume that mutual fund investors would agree that passively-managed portfolios should have zero average alphas.

The main benefit of imposing the law of one price condition is to alleviate the previously mentioned benchmark choice problem. Chen and Knez (1996) argue that this condition is the most important in the minimum set of requirements for the admissibility of a performance measure. Yet the literature has established that commonly-used performance measures often do not price correctly passive portfolios and thus suffer from the Fama (1998) "bad model" problem (see also Roll (1978), Green (1986), Chen and Knez (1996) and Ahn, Cao and Chrétien (2009)).

To see how the law of one price condition restricts the set M of SDFs for the mutual fund investors, we can refer to the literature on SDF bounds. Hansen and Jagannathan (1991) provide the best-known bound by showing that the law of one price condition translates into a minimum standard deviation for SDFs that is related to the highest Sharpe ratio attainable in the passive portfolios. Other restrictions on SDFs that can be developed from the law of one price condition include the bounds of Snow (1991) on selected higher SDF moments, the bound of Bansal and Lehmann (1997) on the expectation of the log SDF, the bound of Chrétien (2012) on the SDF autocorrelation, as well as numerous tighter SDF volatility bounds that consider conditioning information (Gallant, Hansen and Tauchen (1990), Bekaert and Liu (2004) and Ferson and Siegel (2003)), the implications of economic factors (Balduzzi and Kallal (1997)) and the role of state variables (Kan and Zhou (2006).

While the law of one price provides important restrictions on the set of SDFs, it is not sufficient to make it close and convex, and thus would allow for an infinite range of performance values, as discussed in Chen and Knez (1996). The second condition we impose is the no good-deal condition of Cochrane and Saá-Requejo (2000): the SDFs used for performance measurement should not permit investment opportunities with Sharpe ratios that are too high:

$$\frac{E\left[R_j - R_F\right]}{\sigma\left[R_j - R_F\right]} < \bar{h},$$

where R_j is the return on any asset j, $\bar{h}$ is the maximum Sharpe ratio allowable and R_F is the risk-free rate. We thus stipulate that mutual fund investors would find it implausible that allowable investment opportunities could provide Sharpe ratios that are too high, making them too-good deals.

Reasons why too-high Sharpe ratios should be ruled out are discussed by Ross (1976), MacKinlay (1995), Cochrane and Saá-Requejo (2000) and Ross (2005), among others. Ross (1976) argues that Sharpe ratios that are too high (more than twice the market Sharpe ratio) are unreasonable from the perspective of the CAPM, and thus rules them out in studying deviations from the arbitrage pricing theory. In the same spirit, in developing a specification test for multifactor models, Mackinlay (1995) uses a bound on the maximum Sharpe ratio, arguing that high ratios are unlikely from the perspective of risk-based models. Cochrane and Saá-Requejo (2000), referring to the initial justification of the Sharpe ratio, argue that implausibly high Sharpe ratio opportunities should be rapidly exploited by investors. Unless there are limits to exploiting them, their presence would imply implausibly high investor risk aversion. But risk aversion should not exceed a certain limit, because the market risk premium would then tend to infinity. A similar argument is formalized in Ross (2005), who concludes that the highest expected Sharpe ratio should not exceed five times the Sharpe ratio of the market.

By extension of the analysis of Hansen and Jagannathan (1991), Cochrane and Saá-Requejo (2000) demonstrate that the no good-deal condition restricts the set M of SDFs for the mutual fund investors by limiting its second moment:

$$E[m^2] \leq \frac{\left(1+\bar{h}^2\right)}{{R_F}^2}.$$

As shown by Cochrane and Saá-Requejo (2000), this restriction, along with the law of one price condition, makes the set of SDFs close and convex, and thus allows the existence of price bounds.

There exist other restrictions that could be imposed on SDFs to result in price bounds. Hansen and Jagannathan (1991) discuss the no arbitrage condition that excludes non-positive SDFs by ruling out arbitrage opportunities. They show that it restricts further the set of SDFs by increasing the SDF volatility bound. Chen and Knez (1996) demonstrate that it is sufficient to obtain a finite range of performance values, and Ahn, Cao and Chrétien (2009) study no arbitrage performance evaluation bounds for mutual funds. As an alternative, Bernardo and Ledoit (2000) introduce a maximum gain-loss ratio condition that rules out approximate arbitrage opportunities. This ratio measures the attractiveness of opportunities by dividing the expected positive payoff by the absolute value of the expected negative payoff. They argue that it provides a better measure of the attractiveness of opportunities than the Sharpe ratio when returns are not normally distributed. They further show that the condition leads to a restriction on the minimum and maximum SDF values.

In this paper, we select the no good-deal condition over the no arbitrage condition or the maximum gain-loss ratio condition for the following reasons. First, since being introduced by Sharpe (1966), the Sharpe ratio has a long history of relevancy in performance evaluation. Due to its simplicity and great intuitive appeal, the Sharpe ratio is a commonly used measure of performance evaluation, both in practice and in academic studies. Second, the literature offers some guidance on the choice of maximum Sharpe ratio. In contrast, there is little guidance for the maximum gain-loss ratio, and there are often not enough restrictions impose by the no arbitrage condition (so that no arbitrage bounds typically remain too wide). Third, the Sharpe ratio captures approximate arbitrage opportunities as well as the gain-loss ratio when returns are normally distributed, which is reasonable for our sample of monthly equity mutual fund returns. Fourth, the no good-deal framework of Cochrane and Saá-Requejo (2000) offers a closed-form solution for the performance bounds. This solution facilitates and accelerates its implementation in comparison to numerical-only solutions obtained when imposing the no arbitrage condition or the maximum gain-loss ratio condition. This advantage should not be neglected given that our large-scale empirical investigation considers thousands of mutual funds.

2.3. Best Clientele Performance Measure

Considering our basic performance setup and our restrictions on the set of SDFs, the upper bound on performance evaluation can be found by solving the following problem:

$$\bar{\alpha}_{MF} = \sup_{m \in M} E[m\, R_{MF}] - 1,$$

$$\text{subject to } E[m\, \mathbf{R_K}] = \mathbf{1},\ E[m^2] \leq \frac{(1+\bar{h}^2)}{{R_F}^2}.$$

Cochrane and Saá-Requejo (2000) show that this problem has the following solution:

$$\bar{\alpha}_{MF} = E[\bar{m}R_{MF}] - 1,$$

with:

$$\bar{m} = m^* + vw$$

$$m^* = \mathbf{a}'\mathbf{R_K}$$

$$w = R_{MF} - \mathbf{c}'\mathbf{R_K},$$

where:

$$\mathbf{a}' = \mathbf{1}'E[\mathbf{R_K}\,\mathbf{R}'_\mathbf{K}]^{-1}$$

$$\mathbf{c}' = E[R_{MF}\,\mathbf{R}'_\mathbf{K}]\,E[\mathbf{R_K}\,\mathbf{R}'_\mathbf{K}]^{-1}$$

$$v = \sqrt{\frac{\left(\frac{(1+\bar{h}^2)}{R_F{}^2} - E[m^{*2}]\right)}{E[w^2]}}.$$

We call the solution $\bar{\alpha}_{MF}$ the "best clientele performance evaluation or alpha" to refer to our earlier discussion that it indicates whether mutual funds add value from the perspective of their potentially best clientele, the class of investors the most favorable to the mutual fund. Similarly, $\bar{m}$ represents the "best clientele SDF". In this solution, m^* is the SDF identified by Hansen and Jagannathan (1991) as having the minimum volatility under the law of one price condition. It is a linear function of the passive portfolio returns $\mathbf{R_K}$. The error term w represents the difference between the mutual fund return R_{MF} and the best "hedging" or "replicating" payoff $\mathbf{c}'\mathbf{R_K}$ that can be obtained from the passive portfolio returns. Hence, w is the part of the mutual fund return that is not spanned by the passive portfolio returns. Finally, v is the parameter that accounts for the no good-deal restriction and is a function of the maximum Sharpe ratio $\bar{h}$.

We can further understand economically the solution by rewriting it as follow:

$$\bar{\alpha}_{MF} = E[m^* R_{MF}] - 1 + v\, E[w^2].$$

This equation shows that the best clientele alpha can be decomposed into two parts. The first part, $E[m^* R_{MF}] - 1$, is the law of one price (LOP) performance value developed by Chen and Knez (1996), based on the minimum-volatility SDF. Similar to the best clientele performance measure, the LOP measure gives zero performance to the passive portfolios by construction, and thus provide a performance evaluation that does not suffer from the benchmark choice problem. It has also been used by Dahlquist and Söderlind (1999), Farnsworth, Ferson, Jackson and Todd (2002), and Ahn, Cao and Chrétien (2009), among others.

The second part, $v\, E[w^2]$, can be viewed as the maximum investor disagreement between the best clientele alpha and the LOP alpha. This disagreement can come from two distinct sources: the replication error w and the maximum Sharpe ratio restriction $\bar{h}$. With regard to the first source, if the passive portfolios span perfectly the mutual fund returns, so that $w = 0$, then there can be no disagreement in evaluation. Otherwise, the larger is the replication error for a mutual fund (and particularly its volatility), so that the tougher it is for investors to get the same "kind" of opportunities from the passive portfolios, then the wider is the potential valuation disagreement among investors.

With regard to the second source, if the maximum Sharpe ratio allowed corresponds to the maximum Sharpe ratio attainable in the passive portfolios, so that $\bar{h} = h^*$ and $E[\bar{m}^2] = E[m^{*2}]$, then there can be no disagreement in evaluation as $v = 0$. In this case, no opportunities better than the ones in the passive portfolios are deemed reasonable by the investors. Otherwise, the larger the additional opportunities allowed by a higher maximum Sharpe ratio, then the wider is the potential valuation disagreement among investors.

Finally, it is also possible to develop a conditional best clientele performance evaluation by following the scaled payoffs strategy of Cochrane (1996) and Chen and Knez (1996), among others. Specifically, we form public information-managed payoffs, denoted $\mathbf{R_Z}$, by multiplying passive returns with lagged publicly-available information variables. Let $\mathbf{1_Z}$ be the corresponding prices of these payoffs, obtained by multiplying the unit vector by the lagged publicly-available information variables. Then, a conditional best clientele alpha is obtained by replacing $\mathbf{R_K}$ in the previous solution by $\mathbf{R_K^A}$, an augmented set of assets that include both $\mathbf{R_K}$ and $\mathbf{R_Z}$, and by replacing the unit vector $\mathbf{1}$ by $\mathbf{1^A}$, which contains both $\mathbf{1}$ and $\mathbf{1_Z}$.

3. Methodology

3.1. Estimation

The solution for the best clientele performance evaluation measure necessitates the estimation of $2K+1$ parameters for $\bar{\bar{m}}$ ($\mathbf{a}$, $\mathbf{c}$, v), along with the alpha ($\bar{\alpha}_{MF}$). These parameters can be estimated and tested for significance using the generalized method of the moments (GMM) of Hansen (1982). For a sample of T observations, we rely on the following $2K+2$ moments:

$$\frac{1}{T}\sum_{t=1}^{T}[(\mathbf{a}'\mathbf{R_{Kt}})\mathbf{R_{kt}}] - \mathbf{1} = 0, \tag{1}$$

$$\frac{1}{T}\sum_{t=1}^{T}[(R_{MFt} - \mathbf{c}'\mathbf{R_{Kt}})\mathbf{R_{kt}}] = 0, \tag{2}$$

$$\frac{1}{T}\sum_{t=1}^{T}[(\mathbf{a}'\mathbf{R_{Kt}}) + v(R_{MFt} - \mathbf{c}'\mathbf{R_{Kt}})]^2 - \frac{\left(1+\bar{\bar{h}}^2\right)}{{R_F}^2} = 0, \tag{3}$$

$$\frac{1}{T}\sum_{t=1}^{T}\left[\left(\mathbf{a}'\mathbf{R_{Kt}} + v(R_{MFt} - \mathbf{c}'\mathbf{R_{Kt}})\right)R_{MFt}\right] - 1 - \bar{\alpha}_{MF} = 0. \tag{4}$$

The K moments in equation (1) allow the estimation of the LOP SDF $m_t^* = \mathbf{a}'\mathbf{R_{Kt}}$ by ensuring that it prices correctly the K passive portfolio returns. The K moments in equation (2) represent the orthogonality conditions between the replication error term $w_t = R_{MFt} - \mathbf{c}'\mathbf{R_{Kt}}$ and the passive portfolio returns that are needed to estimate the coefficients $\mathbf{c}$ in the best replicating payoff $\mathbf{c}'\mathbf{R_{Kt}}$. The moment in equation (3) imposes the no good-deal condition to estimate the parameter v, which is restricted to be positive in order to obtain an upper bound on performance. In this moment, R_F represents a risk-free rate equivalent and is simply set to one plus the average one-month Treasury bill return in our sample, which is 0.3393%. For consistency, we also include this one-month Treasury bill return as one of the passive portfolio returns, so that the estimated mean SDF corresponds to ${}^{1}/_{R_F}$. Finally, using the estimated best clientele SDF $\overline{m}_t = m_t{}^* + v w_t$, we obtain the upper performance bound for a mutual fund using the moments specified by equation (4).

For comparison with the best clientele alpha, we also examine the LOP performance measure of Chen and Knez (1996), which is based on the SDF with the lowest volatility. Specifically, the LOP alpha can be estimated with the following additional moment:

$$\frac{1}{T}\sum_{t=1}^{T}[(\mathbf{a}'\mathbf{R_{Kt}})R_{MFt}] - 1 - \alpha_{LOP} = 0. \qquad (5)$$

Our estimation system is just identified because the number of parameters equals the number of moments. Hence, the parameter estimates are not influenced by the choice of weighting matrix in GMM. Statistical significance for the parameters is assessed with standard errors adjusted for conditional heteroskedasticity and serial correlation using the method of Newey and West (1987) with three lags.

3.2. Maximum Sharpe Ratio Choice

To implement the best clientele performance measure, two choices are particularly important: the passive portfolios and the maximum Sharpe ratio. In the data section, we introduce three different sets of passive portfolios that allow assessing the sensitivity of the results to this choice. This section discusses the maximum Sharpe ratio choice, which we base on the existing literature.

In general, the literature shows that researchers typically impose a subjective constraint on the maximum Sharpe ratio. One early contribution is Ross (1976). To study deviations from the arbitrage pricing theory, he imposes a maximum Sharpe ratio of twice the market Sharpe ratio, leading to a value of 0.25. Considering that the market portfolio should in theory have the highest Sharpe ratio according to the CAPM, he argues that adding the value of its ratio as additional opportunities should reasonably account for all attainable Sharpe ratios. With a related argument that high Sharpe ratios are unlikely from the perspective of risk-based models, MacKinlay (1995) considers that a squared annual Sharpe ratio higher than about 0.6 is implausibly high.

In applying their no good-deal bounds to S&P500 option pricing, Cochrane and Saá-Requejo (2000) select the maximum Sharpe ratio by ruling out opportunities having a Sharpe ratio greater than twice the one of the S&P500 (or equivalently, twice the Sharpe ratio of their basis asset). They explain that this choice is not definitive and that user can change it. Pyo (2011) uses the same assumption in his empirical studies, supposing a maximum Sharpe ratio equal to twice the one of the U.S. stock market index. Huang (2013) develops an upper bound on the predictive *R*-square using the no good-deal bound. He follows Ross (1976) and Cochrane and

Saá-Requejo (2000) and uses twice the market Sharpe ratio as maximum ratio. Floroiu and Pelsser (2013) price real options using no good-deal bounds and they also calibrate the bounds by using twice the Sharpe ratio of the S&P 500.

A few papers consider different values of the maximum Sharpe ratio. Kanamura and Ohashi (2009) use values ranging from two to three times the value of the market Sharpe ratio to find the upper and lower bounds for summer day options. They find that the difference between the two bounds becomes larger as the Sharpe ratio increases. Martin (2013) provides upper bounds on risk aversion by using the no good-deal bounds. He calibrates his bounds by using three different values for the maximum annual Sharpe ratio, 0.75, 1 and 1.25.

Overall, while the maximum Sharpe ratio is somewhat subjectively specified, the literature offers some guidance on its choice. Namely, the most common choice is a maximum Sharpe ratio of twice the one of the underlying basis assets (which oftentimes include only an equity index). Put differently, this choice corresponds to adding the Sharpe ratio of the index to the maximum Sharpe ratio in the basis assets. In this paper, we follow this guidance by adding to the attainable Sharpe ratio of our passive portfolios a value of 0.1262, corresponding to the monthly Sharpe ratio of the market index (the CRSP value-weighted index) in our sample. We denote this choice by $\bar{h} = h^* + hMKT$. More conservatively, we also consider adding half of this value as additional allowable opportunities, so that $\bar{h} = h^* + 0.5hMKT$. While these are our two basic choices, we will also examine the effects on the results of other sensible maximum Sharpe ratio choices, like doubling directly the attainable Sharpe ratio of the passive portfolios.

3.3. Cross-Sectional Performance Statistics

To summarize our estimates of alphas for the mutual funds in our sample, we provide numerous cross-sectional statistics. First, we provide the mean, the standard deviation and selected percentiles of the distributions of the estimated alphas and their corresponding t-statistics, computed as $t = \hat{\alpha}/\sigma_{\hat{\alpha}}$, where $\hat{\alpha}$ is the estimated alpha and $\sigma_{\hat{\alpha}}$ is its Newey-West standard error.

We also present t-statistics to test for the hypothesis that the cross-sectional mean of the estimated alphas is equal to zero. To perform this test, we assume that the cross-sectional distribution of the alphas is multivariate Normal with a mean of zero, a standard deviation equal to the observed cross-sectional standard deviation and a correlation between any two alphas of 0.08. This last value matches the average correlation between fund residuals reported by Barras, Scaillet and Wermers (2010) when discussing the cross-sectional dependence in performance among funds in their sample (which is similar to ours).

We finally compute proportions of estimated alphas that are positive, negative, significantly positive at the 2.5% level and significantly negative at the 2.5% level, and report p-values on the significance of these proportions using the following likelihood ratio test proposed by Christoffersen (1998) based on a binomial distribution[1]:

$$LR = 2Log\left[\frac{\left(1-\frac{n}{N}\right)^{N-n}\left(\frac{n}{N}\right)^{n}}{(1-pr)^{N-n}(pr)^{n}}\right] \sim \chi^2(1),$$

where n is the number of funds that respects a given criteria (i.e. being positive, negative, significantly positive or significantly negative), N is the total number of funds, $\frac{n}{N}$ is the empirical proportion tested and pr is the expected probability under the null.

Furthermore, to control for mutual funds that exhibit significant alphas by luck or "false discoveries", we apply the technique of Barras, Scaillet and Wermers (2010). Their idea consists

[1]A first test examines whether the proportions of positive or negative alphas are equal to 50%. A second test examines whether the proportions of significantly positive alphas or significantly negative alphas are equal to 2.5%.

of adjusting the proportions by counting the number of funds with t-statistics outside the thresholds implied by a significance level, denoted t^- and t^+, and then removing from the count funds that exhibit large estimated alphas by pure luck. The technique thus provides proportions adjusted for false discoveries:

$$\hat{\pi}^- = \widehat{prob}(t < t^-) - \hat{F}^-.$$

$$\hat{\pi}^+ = \widehat{prob}(t > t^+) - \hat{F}^+.$$

In these equations, the probabilities $\widehat{prob}(\quad)$ refer to in-sample proportions. The estimated proportions of "false discoveries" are expressed as follow:

$$\hat{F}^- = \hat{\pi}^0.\widehat{prob^0}(t < t^-),$$

$$\hat{F}^+ = \hat{\pi}^0.\widehat{prob^0}(t > t^+),$$

with

$$\hat{\pi}^0 = \frac{\widehat{prob}(t^- < t < t^+)}{\widehat{prob^0}(t^- < t < t^+)}.$$

where $\widehat{prob^0}(\quad)$ is the null probability of false discoveries under an assumed standard normal distribution for t. Barras, Scaillet and Wermers (2010) show that such adjusted proportions reliably control for false discoveries. They also advocate values of $t^- = -0.5$ and $t^+ = 0.5$ as efficient tresholds to classify adequately the entire population of mutual funds. We thus use their technique to estimate the proportion of unskilled funds ($\hat{\pi}^-$), the proportion of skilled funds ($\hat{\pi}^+$) and the proportion of zero performance funds ($\hat{\pi}^0$)[2].

4. Data

4.1. Mutual Fund Returns

Our fund data consist of monthly returns on actively managed open-ended U.S. equity mutual funds from January 1984 to December 2012. Our data source is the *CRSP Survivor-Bias Free Mutual Fund US* database. Following Kacperczyk, Sialm and Zheng (2008), we exclude bond funds, balanced funds, money market funds, international funds and funds that are not strongly invested in common stocks to focus on U.S. equity funds. Specifically, U.S. equity funds are identified using the following four types of codes: policy codes, Strategic Insight objective codes, Weisenberger objective codes and Lipper objective codes[3]. The four types of codes are useful as each is only available for a part of our sample period. For example, the Lipper objective codes data start from December 1999.

To focus on actively managed funds, we exclude index funds identified by the Lipper objective codes SP and SPSP, and by excluding funds with a name that includes the word "index". We also exclude mutual funds that are not open-ended by consulting the variable "open to investors" in the database. Finally, we keep the funds only if they hold, on average, between 80% and 105% in common stocks.

From this initial sample of funds, we make further sampling decisions to alleviate biases in the CRSP mutual funds database. Survivorship bias is one of the most well documented

[2]Although not explicitly acknowledged by Barras, Scaillet and Wermers (2010), the false discovery adjustment can lead to a negative proportion of unskilled or skilled funds when the unadjusted observed proportion is close to zero. In such instances, we follow Barras, Scaillet and Wermers (2010) by setting the adjusted proportion to zero and readjusted the proportion of zero performance funds so that the proportions sum to one.

[3]As in Kacperczyk, Sialm and Zheng (2008), we identify U.S. equity funds by policy codes: CS; Strategic Insight objective codes: AGC, GMC, GRI, GRO, ING or SCG; Weisenberger objective codes: G, G-I, AGG, GCI, GRO, LTG, MCG or SCG and Lipper objective codes: EIEI, EMN, LCCE, LCGE, LCVE, MATC, MATD, MATH, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, SCGE or SCVE.

problems in mutual funds data. It occurs when only surviving funds are sampled out of a population in which some funds enter and leave. Following Fama and French (2010), we select 1984 as our starting year as the CRSP mutual fund database is free from this bias from then on. This starting year also eliminates a related selection bias in the early years of the database, as discussed by Elton, Gruber and Blake (2001) and Fama and French (2010).

Back-fill and incubation biases are studied by Evans (2010). Back-fill bias arises because the database includes fund returns that are realized prior to the fund database entry. Incubation bias refers to a situation where only the funds that perform well in an incubation period are eventually open to the public and included in the database. To deal with this bias, we follow Elton, Gruber and Blake (2001) and Kacperczyk, Sialm and Zheng (2008). We eliminate observations before the organization date of the funds, funds that do not report their organization date, and funds without a name, since they tend to correspond to incubated funds. We also exclude funds that have total net assets (TNA) inferior to $15 million in the first year of entering the database.

As a last sampling choice, following Barras, Scaillet and Wermers (2010) and others, we consider a minimum fund returns requirement of 60 months. While this requirement introduces a weak survivorship bias, it is common in order to obtain reliable statistical estimates.

Considering all the previous steps, we get a final sample of 2786 actively-managed open-ended U.S. equity mutual funds with returns for at least 60 months between 1984 and 2012.

4.2. Passive Portfolio Returns

The choice of basis assets imposes a trade-off between economic power (i.e. in theory, all assets available to mutual fund investors should be included,) and statistical power (i.e. econometric estimation imposes limitations on the number of assets). We select three different sets of basis assets to represent the passive opportunities available to investors. Our basis assets always include the risk-free rate plus one of the three following sets: (1) ten industry portfolios, (2) six style portfolios and (3) the market portfolio. These assets have been used widely in the empirical asset pricing literature and the mutual fund performance evaluation literature to capture the cross-section of stock returns. Classifications based on industry, style or market sensitivities are also common in practice to categorize equity investments for investors. The inclusion of the risk-free rate accounts for the cash positions in equity mutual funds and fixes the mean of the SDF to a relevant value (Dahlquist and Söderlind (1999)). By varying the number and type of assets included, we aim to examine the sensitivity of our results to these choices, in light of the aforementioned trade-off.

The ten industry portfolios are used for our main results and the data are from Ken French's website. They consist of consumer nondurables, consumer durables, manufacturing, energy, high technology, telecommunication, shops, healthcare, utilities, and other industries. The six style portfolios are also from Ken French's website. The portfolios are constructed from two market equity capitalisation (size) sorts (big or small) and three book-to-market (value) sorts (low, medium or high). The market portfolio is the CRSP value-weighted index of NYSE/AMEX/NASDAQ stocks and the risk-free rate returns are taken from the CRSP database.

4.3. Information Variables

For conditional performance evaluation, we consider lagged values of four public information variables that are commonly used in the literature and were first introduced by Keim and Stambaugh (1986), Campbell (1987), Campbell and Shiller (1988) and Fama and French (1989). We use: the dividend yield of the S&P500 Index (DIV) from the Datastream database, which is computed as the difference between the log of the twelve-month moving sum of dividends paid on the S&P500 and the log of its lagged value, the yield on the three-month U.S. Treasury bill (YLD) from the FRED database at the Federal Reserve Bank at St. Louis, the term spread

(TERM), which is the difference between the long-term yield on government bonds (from Datastream) and the yield on the three-month Treasury bills; the default spread (DEF), which is the difference between BAA- and AAA-rated corporate bond yields from the FRED database.

With these lagged information variables, we construct four public information-managed payoffs by combining them with the market portfolio returns. We then add these four managed payoffs to each set of basis assets described previously to obtain the augmented sets R_K^A used for conditional performance evaluation.

4.4. Summary Statistics

Table 1 presents summary statistics for the monthly returns of our sample of actively-managed open-ended U.S. equity mutual funds (panel A), and for the monthly returns of the basis assets and the values of the information variables (panel B).

[INSERT TABLE 1 AROUND HERE]

In panel A, the monthly equity fund averages of returns (net of fees) have a mean of 0.73% and standard deviation of 0.3% across funds. The averages of returns range from -4.83% to 2.09% while the standard deviations of returns range from 0.92% to 16.92%. The monthly Sharpe ratios vary between -0.4640 and 0.3787, with a mean of 0.0857 and a standard deviation of 0.0532.

In panel B, the industry portfolios and style portfolios both have mean monthly returns around 1%. Industry portfolios have mean returns between 0.83% and 1.17%, and standard deviations between 3.99% and 7.22%. Style portfolios have monthly mean returns between 0.80% and 1.22%, and standard deviations between 4.58% and 6.76%. The Sharpe ratios vary between 0.0698 and 0.1962 for the industry portfolios, and between 0.0685 and 0.1487 for the style portfolios. Statistics for the market portfolio returns, the risk-free returns and the information variables are as expected.

To illustrate the investment opportunities captured by the basis assets, figure 1 shows the efficient frontiers of returns from the set based on the industry portfolios (RF + 10I), the set based on the style portfolios (RF + 6S), and the set based on the market portfolio (RF + MKT). As expected, the market portfolio set provides less investment opportunities than the other sets.

[INSERT FIGURE 1 AROUND HERE]

5. Empirical Results

5.1. Best Clientele Performance Results

Table 2 presents our main empirical results. Using the risk-free rate and the ten industry portfolios as basis assets, it shows statistics on the cross-sectional distribution of SDF alphas estimated with two best clientele performance measures, allowing for maximum Sharpe ratios of $\bar{h} = h^{*} + 0.5hMKT$ and $\bar{h} = h^{*} + hMKT$. Results for the LOP measure of Chen and Knez (1996) (denoted by h^{*}) are also reported for comparison. Figure 2 illustrates these results by presenting histograms on the distributions of the LOP alphas and either the best clientele alphas for $\bar{h} = h^{*} + 0.5hMKT$ (figure 2a) or the best clientele alphas for $\bar{h} = h^{*} + hMKT$ (figure 2b).

[INSERT TABLE 2 AROUND HERE]

[INSERT FIGURE 2 AROUND HERE]

In panel A of table 2, we provide the mean, the standard deviation and selected percentiles of the distributions of the estimated alphas (columns under Performance) and their corresponding t-statistics (columns under t-statistics). We also report t-statistics on the significance of the cross-sectional mean of estimated alphas (see t-stat). As discussed in section 3.3, the tests account for the cross-sectional dependence in performance among funds by assuming that the distribution of the alphas is multivariate Normal with a mean of zero, a standard deviation equal to the observed cross-sectional standard deviation and a correlation between any two alphas of 0.08.

The cross-sectional distribution of SDF alphas from the best clientele performance measure with $\bar{h} = h^{*} + hMKT$ has a mean of 0.4414% and a standard deviation of 0.4173%. When $\bar{h} = h^{*} + 0.5hMKT$, the mean and standard deviation decrease to 0.2327% and 0.3332%, respectively. Both means are statistically different from zero, with respective t-statistics of 2.46 and 3.73. For comparison, the average alpha from the LOP measure of Chen and Knez (1996), which does not attempt to capture the potentially best clientele's evaluation by ruling out investor disagreement (as $v = 0$), is -0.1789% (t-stat. = -2.33). This negative performance is similar to the empirical results typically found in the mutual fund performance literature, which also does not account for investor disagreement by focusing on a representative investor's evaluation.

As Ferson and Lin (2013), our results thus support an economically important divergence in performance evaluation between clienteles. For example, the magnitude of disagreement between the LOP alpha and the best clientele alpha with $\bar{h} = h^{*} + 0.5hMKT$ is 0.4116%. This value is comparable to the magnitude of investor disagreement documented by Ferson and Lin (2013), who obtain a value of 0.38% when they used index funds as passive portfolios. The divergence in alphas is well illustrated by the alpha distributions in figure 2.

The distribution of the cross-sectional distribution of the t-statistics in panel A of table 2 confirms that the increased alpha values when more investment opportunities are allowed through a higher maximum Sharpe ratio result in more significantly positive alphas and less significantly negative alphas. Panel B studies this issue further. It gives the proportions of estimated alphas that are positive ($\%\bar{\alpha}_{MF} > 0$), negative ($\%\bar{\alpha}_{MF} < 0$), significantly positive ($\%\bar{\alpha}_{MF} signif > 0$), and significantly negative ($\%\bar{\alpha}_{MF} signif < 0$). We also provide proportions adjusted for false discoveries with the technique of Barras, Scaillet and Wermers (2010), namely the proportion $\hat{\pi}^-$ of unskilled funds, the proportion $\hat{\pi}^+$ of skilled funds and the proportion $\hat{\pi}^0$ of zero performance funds. We finally present p-values for likelihood ratio tests (described in section 3.3) that the proportions of positive estimated alphas are equal to 50%, and that the proportions of significantly positive and significantly negative funds are equal to 2.5%.

Panel B shows that the proportions of positive and significantly positive alphas increase when allowing for more disagreement, going from 20.32% to 91.46% for positive alphas and from 1.04% to 47.09% for significantly positive alphas. Accordingly, the proportions of negative and significantly negative alphas decrease when the maximum Sharpe ratio allowed increases, from 79.68% to 8.54% for negative alphas and from 29.54% to 0.47% for significantly negative alphas. The p-values confirm the significance of these results. Furthermore, the proportions of funds that are skilled from the point of view of their best clientele increase considerably with the maximum Sharpe ratio. Inversely, the proportion of funds that are unskilled from the point of view of their best clientele disappears once controlling for false discoveries.

Again, accounting for investor disagreement and focusing on the potentially best clientele are keys to understanding the difference between our results and the existing literature on the value added by active management. For example, the findings from the LOP measure are typical of the literature, with around 20% (80%) of the funds with positive (negative) values. Interestingly, increasing allowable opportunities by half the Sharpe ratio of the market index is sufficient to obtain approximately the opposite result. This is consistent with Ahn, Cao and Chrétien (2009) who argue that more than 80% of the mutual funds could be given a positive performance value by some investors.

To gain more insights on the best clientele performance evaluation, figure 3 presents the best clientele and LOP alphas for decile portfolios of the 2786 mutual funds sorted in increasing order of their average return (figure 3a), in increasing order of their standard deviation of returns (figure 3b), and in increasing order of their Sharpe ratio (figure 3c). Figures 3a and 3c show that alphas are increasing with average returns and Sharpe ratios for the decile portfolios. Thus, not surprisingly, a fund with higher average return or higher Sharpe ratio is generally given a higher best clientele alpha. Figure 3b reveals that the best clientele alphas are also increasing with standard deviations of returns, especially for funds with high standard deviation, a relation not observed for the LOP alphas. While investor disagreement appears relatively stable across portfolios formed on average returns and Sharpe ratios, it is greatly increasing with the standard deviation of mutual fund returns. As passive portfolio returns have more difficulty replicating the returns of mutual funds with large volatility, so that these funds represent somewhat "unique" opportunities, it allows for large valuation disagreements for the potentially best clienteles.

[INSERT FIGURE 3 AROUND HERE]

Overall, we thus find that an increase in admissible investment opportunities equivalent to half the Sharpe ratio of the market index leads to generally positive performance for the best clientele. As stipulated by Chen and Knez (1996) and Ferson and Lin (2013), if the SDF alpha is positive, then there exists some investor that would want to buy the fund. Our best clientele alpha results suggest that there is a clientele that would want to buy a majority of the mutual funds, consistent with the real-life continued investments in mutual funds.

5.2. Conditional Performance Results

Ferson and Schadt (1996) argue that accounting for the effect of public information results in improved performance measures. We implement a conditional version of our performance measure that considers a mutual fund's best potential clientele in incomplete market with investor disagreement. To do so, we use the risk-free rate, the ten industry portfolios and the public information-managed payoffs to form an augmented set of basis assets for estimation purpose.

[INSERT TABLE 3 AROUND HERE]

Table 3 presents the cross-sectional performance statistics of the conditional version of the best clientele alphas. The table shows that our unconditional findings of the previous section extend to the conditional results. The inclusion of conditioning information does not alter our conclusion on the importance of investor disagreement and best clienteles.

5.3. Sensitivity to Passive Portfolio Choice

Tables 4 and 5 allow an examination of the sensitivity of the results to the choice of basis assets. They show unconditional performance results using the basis assets based on the six style portfolios (table 4) and the market portfolio (table 5). In the latter case, it is interesting to note the the LOP measure is equivalent to the CAPM measure as the SDF is linear in the market return, $m^{*} = a_1 R_F + a_2 R_{MKT}$.

[INSERT TABLE 4 AROUND HERE]

[INSERT TABLE 5 AROUND HERE]

The previous results are confirmed when using the basis assets based on the six style portfolios or the market portfolio. An increase in admissible investment opportunities equivalent to half the Sharpe ratio of the market index leads to generally positive best clientele performance values for both alternative sets of basis assets. For example, the SDF alphas estimated from the best clientele performance measure with $\bar{h} = h^{*} + 0.5hMKT$ have a mean of 0.2862% (*t*-stat. = 2.94) for the six style portfolios and 0.2650% (*t*-stat. = 3.09) for the market portfolio. These values are slightly greater than the mean of 0.2327% for the ten industry portfolios. This result along with a general comparison of the cross-sectional distributions of the alphas from the three sets suggest that the benchmarks implicit from the six style portfolios or the market portfolio appear to be slightly easier to "beat" on a risk-adjusted basis.

As before, the means of the distributions of SDF alphas indicate an economically important divergence in performance evaluation between clienteles. For example, the magnitudes of disagreement between the LOP alphas of Chen and Knez (1996) and the best clientele alphas with $\bar{h} = h^{*} + 0.5hMKT$ are comparable across different basis assets (i.e., 0.4116% for the ten industry portfolios, 0.3701% for the six style portfolios and 0.3283% for the market). The higher disagreement found with the ten industry portfolios suggests that the fund returns are slightly less well spanned by this set than by the two other sets, or that the choice of maximum Sharpe ratio results in a higher disagreement parameter for this set than the two other sets.

5.4. Alternative Maximum Sharpe Ratio Choices

Table 6 presents the empirical results for other sensible choices of maximum Sharpe ratios using ten industry portfolios as basis assets. We provide the mean, the standard deviation and selected percentiles of the distributions of the estimated alphas (six columns under Performance) and their corresponding *t*-statistics (six columns under *t*-statistics). As discussed earlier, several papers argue that calibrating the maximum Sharpe ratio constraint is a subjective choice. We consider three additional cases.

In the first case, we consider a maximum Sharpe ratio as a multiple of the attainable Sharpe ratio of the passive portfolios. This case is in line with the previously reviewed literature that uses twice the Sharpe ratio of their basis assets as choice. To perform this analysis, two maximum Sharpe ratios are taken: $\bar{h} = 2h^*$ or $\bar{h} = 1.5h^*$. A problem with this case is that the in-sample optimal basis asset Sharpe ratio h^* can be close to zero or unusually high, especially for mutual funds that have a limited time series. Taking a multiple of a potentially unrealistic h^* might lead to an unrealistic maximum Sharpe ratio. In the second case, we thus *add* to h^* a multiple of the optimal basis asset Sharpe ratio. The maximum Sharpe ratios become $\bar{h} = h^* + 0.5hT$ and $\bar{h} = h^* + hT$, where hT represents the optimal Sharpe ratio of the basis assets in the full sample. In the third case, as the sample optimal Sharpe ratio is biased upward, we use an adjusted Sharpe ratio hTa following the bias correction proposed by Ferson and Siegel (2003)[4]. The maximum Sharpe ratios are then $\bar{h} = h^* + 0.5hTa$ and $\bar{h} = h^* + hTa$.

[INSERT TABLE 6 AROUND HERE]

The empirical results in table 6 show that the SDF alphas estimated from the best clientele performance measure have means varying from 0.2944% (*t*-stat. = 2.92) for $\bar{h} = h^* +$

[4]As discussed by Ferson and Siegel (2003), the sample optimal Sharpe ratios are biased upward when the number of basis assets (*K*) is large relative to number of observations (*T*). We adjust the full-sample optimal Sharpe ratio of basis assets using their proposed correction: $hTa = \sqrt{\frac{(hT)^2\,(T-K-2)}{T} - \frac{K}{T}}$.

$0.5hTa$ to 0.7924% (t-stat. = 4.72) for $\bar{h} = 2h^*$. All maximum Sharpe ratios investigated lead to best clientele performance values that are generally positive and increasing with the importance of the additional opportunities allowed with the choice of $\bar{h}$. Average investor disagreements, which can be calculated from the difference between the mean alphas in table 6 and the mean LOP alpha in table 2 (for h^*), continue to be economically important. For example, when the maximum Sharpe ratio is $\bar{h} = h^* + 0.5hTa$, we obtain a disagreement between the best clientele measure and the no disagreement LOP measure of 0.4733%. Overall, these results show that the maximum Sharpe ratio of $\bar{h} = h^* + 0.5hMKT$ investigated in previous tables is the most conservative choice as it adds less investment opportunities than the other sensible maximum Sharpe ratios considered. Appendix A confirms these findings for the sets of basis assets based on the six style portfolios and the market portfolio.

5.5. Zero-Alpha Implied Maximum Sharpe Ratios

Our analysis has thus far relied on an exogenous choice for the maximum Sharpe ratio. Previously, we show that although this choice is somewhat subjectively specified, the literature offers some guidance, providing a justification for our selections. Yet given the importance of this choice, this section investigates an alternative estimation strategy that does not require the selection of a maximum Sharpe ratio and leads to a measure of the allowable investment opportunities needed for the mutual funds to be fairly evaluated by their potentially best clientele.

To understand this strategy, notice that the selection of $\bar{h}$ allows the estimation of the disagreement variable v in equation (3). Then, v is needed for the estimation of $\bar{\alpha}_{MF}$ with equation (4). In this section, we proceed reversely. Specifically, we set a value for alpha that implies that the best clientele gives zero value to a mutual fund, $\bar{\alpha}_{MF} = 0$. This choice leads to the estimation of the disagreement variable v with equation (4), which then allows for the estimation of the maximum Sharpe ratio $\bar{h}$ with equation (3). We call the resulting estimated $\bar{h}$ the zero-alpha implied maximum Sharpe ratio. The difference between this value for a fund and the corresponding optimal basis asset Sharpe ratio for its sample, $\bar{h} - h^*$, gives a measure of how much additional allowable opportunities are sufficient to find a potential clientele who gives a nonnegative value to a fund.

Table 7 shows the cross-sectional distributions of the implied Sharpe ratios estimated when fixing the best clientele alpha at zero, the attainable optimal Sharpe ratios of the passive portfolios and the differences between both Sharpe ratios. For all three sets of basis assets, the average differences are small, so that only a small increase in admissible opportunities is needed to change the negative mean LOP alpha into zero mean best clientele alpha. For example, when considering the ten industry portfolios as basis assets, augmenting Sharpe ratio opportunities by only 0.0412 (about a third of the sample market Sharpe ratio) is sufficient for the evaluation to become nil on average. Even less additional opportunities are needed for the passive portfolios based on the six style portfolio (0.0296) and the market index (0.0335).

[INSERT TABLE 7 AROUND HERE]

The distributions show that mutual funds require different levels of investor disagreement to be valued fairly. For example, with the basis assets based on the ten industry portfolios, zero-alpha implied Sharpe ratios vary between 0.1488 and 0.7507 and Sharpe ratio differences vary between 0.000 and 0.4596. Nevertheless, these findings suggest that our conclusion on the generally positive performance values for the mutual fund's best potential clientele would hold unless an unreasonably low value for the maximum Sharpe ratio is selected.

6. Conclusion

In this paper, we apply the no good-deal approach of Cochrane and Saá-Requejo (2000) to measure mutual fund performance from the point of view of the most favourable clientele. We use a large cross-section of actively managed open-ended U.S. equity mutual funds to provide the first comprehensive performance evaluation exercise from the point of view of each fund's potentially most favourable clientele.

Our empirical results suggest that the long-standing issue of actively managed mutual fund underperformance might be due to the implicit use of a unique representative investor in standard performance measures. Considering investor disagreement and focusing on the best clients result in mutual funds performing better, with the cross-sectional average of alphas increasing with additional admissible investment opportunities in incomplete market. These results are robust to the use of different basis assets and conditioning information, and to adjustments for false discoveries. Overall, they support the findings of Ahn, Cao and Chrétien (2009) and Ferson and Lin (2013) on the importance of heterogeneous preferences and investor disagreement in mutual fund evaluation.

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Table 1: Summary Statistics

Table 1 presents summary statistics for our monthly data from January 1984 to December 2012. Panel A shows cross-sectional summary statistics (average (Mean), standard deviation (StdDev) and selected percentiles) on the distributions of the average (Mean), standard deviation (StdDev), minimum (Min), maximum (Max) and Sharpe ratio (h) for the returns on 2786 actively managed open-ended U.S. equity mutual funds. Panel B gives the average (Mean), standard deviation (StdDev), minimum (Min), maximum (Max) and Sharpe ratio (h) for the passive portfolio returns and information variables. The passive portfolios include ten industry portfolios (consumer nondurables (NoDur), consumer durables (Dur), manufacturing (Manuf), energy (Enrgy), high technology (HiTec), telecommunication (Telcm), shops (Shops), healthcare (Hlth), utilities (Utils), and other industries (Other)), six Fama-French style portfolios based on two market equity capitalisation (size) sorts (big (B) or small (S)) and three book-to-market (value) sorts (low (L), medium (M) or high (H)), the market portfolio (MKT) based on the CRSP value-weighted index, and the risk free asset (RF) based on the one-month Treasury bill. The information variables are lagged values of the dividend yield on the S&P500 Index (DIV), the yield on the three-month Treasury bill (YLD), the term spread (TERM) and the default spread (DEF). All statistics are in percentage except for the Sharpe ratios.

Panel A: Mutual Fund Returns

	Mean	StdDev	Min	Max	h
Mean	0.7338	5.3400	-19.9976	16.4080	0.0857
StdDev	0.3008	1.5632	5.6560	7.8772	0.0532
Max	2.0906	16.9206	-2.1401	101.6191	0.3787
99%	1.3677	10.3594	-5.5453	41.5517	0.1990
95%	1.1405	8.2353	-12.8253	32.5704	0.1593
90%	1.0453	7.2002	-14.4430	27.0565	0.1427
75%	0.9044	6.0719	-16.5652	18.5645	0.1178
Median	0.7464	5.0272	-19.4020	14.1103	0.0900
25%	0.5946	4.3865	-22.9302	11.4669	0.0613
10%	0.4232	3.8968	-26.3190	9.9918	0.0229
5%	0.2943	3.4811	-29.0886	9.0829	-0.0033
1%	-0.1139	1.6197	-36.9313	5.3715	-0.0827
Min	-4.8327	0.9168	-86.9707	2.4218	-0.4640

Table 1: Summary Statistics (continued)

Panel B: Passive Portfolio Returns and Information Variables					
	Mean	StdDev	Min	Max	h
Industry Portfolios					
NoDur	1.1713	4.3493	-21.0300	14.7400	0.1962
Durbl	0.8311	7.0347	-32.8900	42.9200	0.0698
Manuf	1.0667	5.1203	-27.3200	17.7800	0.1420
Enrgy	1.1223	5.3691	-18.3900	19.1300	0.1459
HiTec	0.9338	7.2260	-26.1500	20.4600	0.0822
Telcm	0.9689	5.2612	-15.5600	22.1200	0.1199
Shops	1.0394	5.0898	-28.3100	13.3800	0.1375
Hlth	1.1140	4.7552	-20.4700	16.5400	0.1636
Utils	0.9444	3.9952	-12.6500	11.7600	0.1521
Other	0.8829	5.3165	-23.6800	16.1100	0.1024
Style Portfolios, Market Portfolio and Risk-Free Asset					
B/L	0.9403	4.7004	-23.1900	14.4500	0.1281
B/M	0.9705	4.5832	-20.3200	14.8500	0.1378
B/H	0.9279	5.2367	-24.4700	22.1600	0.1126
S/L	0.8037	6.7657	-32.3400	27.0200	0.0685
S/M	1.1221	5.2548	-27.5700	18.8700	0.1487
S/H	1.2282	6.2180	-28.0500	38.3900	0.1426
MKT	0.9174	4.5814	-22.5363	12.8496	0.1262
RF	0.3393	0.2166	0.0000	1.0000	-
Information Variables					
DIV	2.4649	0.9204	1.0800	4.9900	-
YLD	4.1264	2.6038	0.0100	10.4700	-
TERM	1.9419	1.1392	-0.5300	3.7600	-
DEF	1.0255	0.4046	0.5500	3.3800	-

Table 2: Best Clientele Alphas Using the RF + 10I Passive Portfolio Set

Table 2 shows statistics on the cross-sectional distribution of monthly SDF alphas estimated with two best clientele performance measures, allowing for maximum Sharpe ratios of $h^* + 0.5hMKT$ and $h^* + hMKT$ (see definition in section 3.2), and for the LOP measure (denoted by h^*), using the risk-free rate and the ten industry portfolios (RF + 10I) as basis assets. Panel A provides the mean, the standard deviation (StdDev) and selected percentiles of the distributions of the estimated alphas (columns under Performance) and their corresponding *t*-statistics (columns under *t*-statistics). It also reports *t*-statistics (*t*-stat) on the significance of the mean of estimated alphas using a test that accounts for the cross-sectional dependence in performance among funds (see description in section 3.3). Panel B gives the proportions of estimated alphas that are positive ($\%\bar{\alpha}_{MF} > 0$), negative ($\%\bar{\alpha}_{MF} < 0$), significantly positive ($\%\bar{\alpha}_{MF} signif > 0$), and significantly negative ($\%\bar{\alpha}_{MF} signif < 0$). It also provides proportions adjusted for false discoveries (see description in section 3.3), namely the proportion of zero alpha, unskilled and skilled funds. It finally presents *p*-values (in parentheses) for likelihood ratio tests (described in section 3.3) that the proportions of positive estimated alphas are equal to 50%, and that the proportions of significantly positive and significantly negative funds are equal to 2.5%. The data (see description in table 1) cover the period January 1984-December 2012. All statistics are in percentage except *t*-statistics.

Panel A: Performance and t-statistics of Individual Mutual Funds

	Performance			t-statistics		
	h^*	$h^* + 0.5hMKT$	$h^* + hMKT$	h^*	$h^* + 0.5hMKT$	$h^* + hMKT$
Mean	-0.1789	0.2327	0.4414	-1.2291	1.0067	1.8948
StdDev	0.2707	0.3332	0.4173	1.4743	1.4339	1.4011
(t-stat)	(-2.3317)	(2.4643)	(3.7323)			
Max	0.6322	1.8723	2.6371	3.8044	6.5340	7.4785
99%	0.3580	1.2642	1.8322	2.0211	4.4775	5.4440
95%	0.1787	0.7800	1.1538	1.0473	3.3425	4.2471
90%	0.0967	0.6400	0.9722	0.5435	2.7363	3.5796
75%	-0.0364	0.4195	0.6779	-0.2258	1.9288	2.7555
Median	-0.1630	0.1814	0.3556	-1.1398	1.0517	1.8852
25%	-0.2854	0.0205	0.1478	-2.1715	0.1564	1.0578
10%	-0.4501	-0.1055	0.0170	-3.1627	-0.8412	0.1501
5%	-0.5978	-0.1934	-0.0725	-3.6814	-1.4442	-0.4675
1%	-0.9247	-0.4376	-0.2408	-4.8763	-2.6243	-1.5068
Min	-5.5072	-3.1462	-2.0639	-8.7615	-6.2206	-4.6528

Panel B: Performance Proportions

		h^*	$h^* + 0.5hMKT$	$h^* + hMKT$
Performance	$\%\bar{\alpha}_{MF} > 0$	20.32 (0.00)	78.07 (0.00)	91.46 (0.00)
Sign	$\%\bar{\alpha}_{MF} < 0$	79.68	21.93	8.54
Performance	$\%\bar{\alpha}_{MF} signif > 0$	1.04 (0.00)	23.87 (0.00)	47.09 (0.00)
Significance	$\%\bar{\alpha}_{MF} signif < 0$	29.54 (0.00)	2.26 (41.22)	0.47 (0.00)
Classifications	Zero alpha	48.30	48.38	21.81
Adjusted for	Unskilled	51.70	0.00	0.00
False Discoveries	Skilled	0.00	51.62	78.19

Table 3: Conditional Best Clientele Alphas Using the RF + 10I + RZ Passive Portfolio Set

Table 3 shows statistics on the cross-sectional distribution of monthly SDF alphas estimated with two best clientele performance measures, allowing for maximum Sharpe ratios of $h^* + 0.5hMKT$ and $h^* + hMKT$ (see definition in section 3.2), and for the LOP measure (denoted by h^*), using the risk-free rate, the ten industry portfolios and the public information-managed payoffs (RF + 10I + RZ) as basis assets. Panel A provides the mean, the standard deviation (StdDev) and selected percentiles of the distributions of the estimated alphas (columns under Performance) and their corresponding *t*-statistics (columns under *t*-statistics). It also reports *t*-statistics (*t*-stat) on the significance of the mean of estimated alphas using a test that accounts for the cross-sectional dependence in performance among funds (see description in section 3.3). Panel B gives the proportions of estimated alphas that are positive ($\%\bar{\alpha}_{MF} > 0$), negative ($\%\bar{\alpha}_{MF} < 0$), significantly positive ($\%\bar{\alpha}_{MF} signif > 0$), and significantly negative ($\%\bar{\alpha}_{MF} signif < 0$). It also provides proportions adjusted for false discoveries (see description in section 3.3), namely the proportion of zero alpha, unskilled and skilled funds. It finally presents *p*-values (in parentheses) for likelihood ratio tests (described in section 3.3) that the proportions of positive estimated alphas are equal to 50%, and that the proportions of significantly positive and negative funds are equal to 2.5%. The data (see description in table 1) cover the period January 1984-December 2012. All statistics are in percentage except *t*-statistics.

Panel A: Performance and T-statistics of Individual Mutual Funds

	Performance			T-statistics		
	h^*	$h^* + 0.5hMKT$	$h^* + hMKT$	h^*	$h^* + 0.5hMKT$	$h^* + hMKT$
Mean	-0.1795	0.2298	0.4347	-1.2283	1.0138	1.8980
Std Dev	0.2684	0.3322	0.4145	1.4582	1.4399	1.4186
(t-stat)	(-2.3599)	(2.4400)	(3.7001)			
Max	0.6336	1.8905	2.6412	3.7486	6.4917	7.4375
99%	0.3637	1.2341	1.7043	2.0194	4.4468	5.4256
95%	0.1776	0.7733	1.1227	1.0437	3.3427	4.2652
90%	0.0930	0.6331	0.9584	0.5195	2.7619	3.6294
75%	-0.0385	0.4152	0.6726	-0.2333	1.9380	2.7706
Median	-0.1642	0.1813	0.3524	-1.1368	1.0528	1.8940
25%	-0.2854	0.0199	0.1454	-2.1637	0.1545	1.0447
10%	-0.4496	-0.1089	0.0140	-3.1277	-0.8763	0.1234
5%	-0.5927	-0.1928	-0.0769	-3.6879	-1.4396	-0.5121
1%	-0.9102	-0.4385	-0.2469	-4.8902	-2.5426	-1.5287
Min	-5.5066	-3.5894	-2.7198	-8.3928	-5.9284	-4.4862

Panel B: Performance Proportions

		h^*	$h^* + 0.5hMKT$	$h^* + hMKT$
Performance	$\%\bar{\alpha}_{MF} > 0$	19.81 (0.00)	77.93 (0.00)	91.03 (0.00)
Sign	$\%\bar{\alpha}_{MF} < 0$	80.19	22.07	8.97
Performance	$\%\bar{\alpha}_{MF} signif > 0$	1.01 (0.00)	24.23 (0.00)	47.67 (0.00)
Significance	$\%\bar{\alpha}_{MF} signif < 0$	29.40 (0.00)	2.15 (23.05)	0.36 (0.00)
Classifications	Zero alpha	47.86	48.45	22.07
Adjusted for	Unskilled	52.14	0.00	0.00
False Discoveries	Skilled	0.00	51.55	77.93

Table 4: Best Clientele Alphas Using the RF + 6S Passive Portfolio Set

Table 4 shows statistics on the cross-sectional distribution of monthly SDF alphas estimated with two best clientele performance measures, allowing for maximum Sharpe ratios of $h^* + 0.5hMKT$ and $h^* + hMKT$ (see definition in section 3.2), and for the LOP measure (denoted by h^*), using the risk-free rate and the six style portfolios (RF + 6S) as basis assets. Panel A provides the mean, the standard deviation (StdDev) and selected percentiles of the distributions of the estimated alphas (columns under Performance) and their corresponding *t*-statistics (columns under *t*-statistics). It also reports *t*-statistics (*t*-stat) on the significance of the mean of estimated alphas using a test that accounts for the cross-sectional dependence in performance among funds (see description in section 3.3). Panel B gives the proportions of estimated alphas that are positive ($\%\bar{\alpha}_{MF} > 0$), negative ($\%\bar{\alpha}_{MF} < 0$), significantly positive ($\%\bar{\alpha}_{MF} signif > 0$), and significantly negative ($\%\bar{\alpha}_{MF} signif < 0$). It also provides proportions adjusted for false discoveries (see description in section 3.3), namely the proportion of zero alpha, unskilled and skilled funds. It finally presents *p*-values (in parentheses) for likelihood ratio tests (described in section 3.3) that the proportions of positive estimated alphas are equal to 50%, and that the proportions of significantly positive and significantly negative funds are equal to 2.5%. The data (see description in table 1) cover the period January 1984-December 2012. All statistics are in percentage except *t*-statistics.

Panel A: Performance and t-statistics of Individual Mutual Funds

	Performance			t-statistics		
	h^*	$h^* + 0.5hMKT$	$h^* + hMKT$	h^*	$h^* + 0.5hMKT$	$h^* + hMKT$
Mean	-0.0839	0.2862	0.4706	-0.7286	1.5803	2.4612
StdDev	0.2680	0.3437	0.4160	1.5176	1.4566	1.4437
(t-stat)	(-1.1044)	(2.9374)	(3.9911)			
Max	1.0492	2.3782	3.3233	4.0599	6.6859	7.8838
99%	0.5424	1.4120	1.9870	2.7262	5.0187	6.0269
95%	0.3215	0.8695	1.1591	1.8065	3.9518	4.8682
90%	0.2063	0.7023	0.9601	1.2286	3.4588	4.3490
75%	0.0364	0.4355	0.6485	0.2899	2.5605	3.4162
Median	-0.0866	0.2152	0.3737	-0.7565	1.5089	2.3984
25%	-0.2015	0.0813	0.2109	-1.7059	0.6564	1.5210
10%	-0.3333	-0.0261	0.0939	-2.6708	-0.1962	0.7080
5%	-0.4451	-0.1104	0.0194	-3.2540	-0.8161	0.1489
1%	-0.7944	-0.3458	-0.1718	-4.3803	-1.9112	-0.9276
Min	-5.5400	-3.2703	-2.2134	-7.2184	-5.2881	-4.0278

Panel B: Performance Proportions

		h^*	$h^* + 0.5hMKT$	$h^* + hMKT$
Performance	$\%\bar{\alpha}_{MF} > 0$	31.19 (0.00)	87.62 (0.00)	95.84 (0.00)
Sign	$\%\bar{\alpha}_{MF} < 0$	68.81	12.38	4.16
Performance	$\%\bar{\alpha}_{MF} signif > 0$	3.73 (0.01)	38.62 (0.00)	63.17 (0.00)
Significance	$\%\bar{\alpha}_{MF} signif < 0$	20.03 (0.00)	0.93 (0.00)	0.29 (0.00)
Classifications	Zero alpha	56.44	32.07	12.19
Adjusted for	Unskilled	39.53	0.00	0.00
False Discoveries	Skilled	4.03	67.93	87.81

Table 5: Best Clientele Alphas Using the RF + MKT Passive Portfolio Set

Table 5 shows statistics on the cross-sectional distribution of monthly SDF alphas estimated with two best clientele performance measures, allowing for maximum Sharpe ratios of $h^* + 0.5hMKT$ and $h^* + hMKT$ (see definition in section 3.2), and for the LOP measure (denoted by h^*), using the risk-free rate and the market portfolio (RF + MKT) as basis assets. Panel A provides the mean, the standard deviation (StdDev) and selected percentiles of the distributions of the estimated alphas (columns under Performance) and their corresponding *t*-statistics (columns under *t*-statistics). It also reports *t*-statistics (*t*-stat) on the significance of the mean of estimated alphas using a test that accounts for the cross-sectional dependence in performance among funds (see description in section 3.3). Panel B gives the proportions of estimated alphas that are positive ($\%\bar{\alpha}_{MF} > 0$), negative ($\%\bar{\alpha}_{MF} < 0$), significantly positive ($\%\bar{\alpha}_{MF} signif > 0$), and significantly negative ($\%\bar{\alpha}_{MF} signif < 0$). It also provides proportions adjusted for false discoveries (see description in section 3.3), namely the proportion of zero alpha, unskilled and skilled funds. It finally presents *p*-values (in parentheses) for likelihood ratio tests (described in section 3.3) that the proportions of positive estimated alphas are equal to 50%, and that the proportions of significantly positive and significantly negative funds are equal to 2.5%. The data (see description in table 1) cover the period January 1984-December 2012. All statistics are in percentage except *t*-statistics.

Panel A: Performance and t-statistics of Individual Mutual Funds

	Performance			t-statistics		
	h^*	$h^* + 0.5hMKT$	$h^* + hMKT$	h^*	$h^* + 0.5hMKT$	$h^* + hMKT$
Mean	-0.0683	0.2650	0.4669	-0.3830	1.1588	1.8902
StdDev	0.2747	0.3021	0.3643	1.1960	1.1834	1.1832
(t-stat)	(-0.8770)	(3.0949)	(4.5216)			
Max	0.8317	1.7586	2.4727	3.8707	5.8038	6.5530
99%	0.4663	1.0932	1.6397	2.2969	3.9204	4.8390
95%	0.2957	0.7488	1.0485	1.4196	3.0261	3.8575
90%	0.2171	0.6173	0.8953	1.0338	2.5927	3.3893
75%	0.0767	0.4369	0.6785	0.4046	1.9226	2.6338
Median	-0.0515	0.2480	0.4339	-0.3137	1.1965	1.8705
25%	-0.1845	0.0740	0.2117	-1.1147	0.4390	1.1558
10%	-0.3458	-0.0425	0.0806	-1.8898	-0.2548	0.5083
5%	-0.4818	-0.1477	-0.0027	-2.4349	-0.8276	-0.0276
1%	-0.8637	-0.4154	-0.2719	-3.7594	-2.0091	-1.1446
Min	-5.5151	-3.5756	-2.6251	-5.7317	-4.3505	-2.5594

Panel B: Performance Proportions

		h^*	$h^* + 0.5hMKT$	$h^* + hMKT$
Performance	$\%\bar{\alpha}_{MF} > 0$	39.63 (0.00)	85.53 (0.00)	94.83 (0.00)
Sign	$\%\bar{\alpha}_{MF} < 0$	60.37	14.47	5.17
Performance	$\%\bar{\alpha}_{MF} signif > 0$	1.87 (2.50)	23.58 (0.00)	46.95 (0.00)
Significance	$\%\bar{\alpha}_{MF} signif < 0$	9.37 (0.00)	1.11 (0.00)	0.22 (0.00)
Classifications	Zero alpha	82.53	41.50	14.99
Adjusted for	Unskilled	17.47	0.00	0.00
False Discoveries	Skilled	0.00	58.50	85.01

Table 6: Best Clientele Alphas for Alternative Maximum Sharpe Ratio Choices Using the RF + 10I Passive Portfolio Set

Table 6 shows statistics on the cross-sectional distribution of monthly SDF alphas estimated with six best clientele performance measures, allowing for maximum Sharpe ratios of $1.5h^*$, $2h^*$, $h^* + 0.5hT$, $h^* + hT$, $h^* + 0.5hTa$ and $h^* + hTa$ (see definition in section 5.4), using the risk-free rate and the ten industry portfolios (RF + 10I) as basis assets. It provides the mean, the standard deviation (StdDev) and selected percentiles of the distributions of the estimated alphas (columns under Performance) and their corresponding t-statistics (columns under t-statistics). It also reports t-statistics (t-stat) on the significance of the mean of estimated alphas using a test that accounts for the cross-sectional dependence in performance among funds (see description in section 3.3). The data (see description in table 1) cover the period January 1984-December 2012. All statistics are in percentage except t-statistics.

Performance and t-statistics of Individual Mutual Funds												
	Performance						t-statistics					
	$1.5h^*$	$2h^*$	$h^* + 0.5hT$	$h^* + hT$	$h^* + 0.5hTa$	$h^* + hTa$	$1.5h^*$	$2h^*$	$h^* + 0.5hT$	$h^* + hT$	$h^* + 0.5hTa$	$h^* + hTa$
Mean	0.4470	0.7924	0.4291	0.7653	0.2944	0.5408	1.8992	2.9912	1.8475	2.9343	1.2885	2.2544
StdDev	0.4187	0.5928	0.4118	0.5736	0.3559	0.4629	1.3904	1.3829	1.4029	1.3969	1.4224	1.3935
(t-stat)	(3.767)	(4.716)	(3.676)	(4.708)	(2.918)	(4.122)						
Max	2.5955	4.0642	2.5875	4.0642	2.0885	3.0632	7.4293	8.4645	7.4293	8.4645	6.8413	7.8374
99%	1.8157	2.8743	1.7965	2.7621	1.4158	2.1153	5.3752	6.5508	5.3915	6.5649	4.7813	5.8407
95%	1.1627	1.8458	1.1277	1.7651	0.8909	1.3344	4.2162	5.4591	4.1971	5.4185	3.6220	4.6805
90%	0.9751	1.5478	0.9536	1.4949	0.7297	1.1338	3.5910	4.7720	3.5271	4.7642	3.0196	3.9938
75%	0.6799	1.1101	0.6634	1.0722	0.4957	0.7989	2.7540	3.8087	2.7106	3.7921	2.1894	3.0884
Median	0.3674	0.6577	0.3454	0.6404	0.2313	0.4436	1.9043	2.9037	1.8437	2.8403	1.3193	2.2164
25%	0.1504	0.3505	0.1404	0.3353	0.0576	0.2065	1.0661	2.1143	1.0109	2.0385	0.4439	1.4055
10%	0.0184	0.1929	0.0104	0.1886	-0.0696	0.0687	0.1583	1.3561	0.0952	1.2518	-0.5294	0.5421
5%	-0.0594	0.1210	-0.0808	0.1165	-0.1558	-0.0055	-0.4163	0.8092	-0.5177	0.7181	-1.1387	-0.0418
1%	-0.2580	-0.0343	-0.2524	-0.0201	-0.3901	-0.1551	-1.4775	-0.1965	-1.5631	-0.1087	-2.2620	-0.9930
Min	-1.2139	-0.3974	-2.1284	-0.4196	-2.8250	-1.5544	-4.5998	-2.2393	-4.7455	-2.4432	-5.7557	-3.9321

Table 7: Zero-Alpha Implied Maximum Sharpe Ratios

Table 7 shows statistics on the cross-sectional distribution of monthly Maximum Sharpe ratios implied when fixing the best clientele alpha at zero (denoted by $\bar{\alpha}_{MF} = 0$), the attainable monthly optimal Sharpe ratios of the passive portfolios (denoted by Basis Assets), and the differences between both Sharpe ratios (denoted by Difference), using the risk-free rate and either the ten industry portfolios, the six style portfolios or the market portfolio as basis assets. It provides the mean, the standard deviation (StdDev) and selected percentiles of the distributions of the values. The data (see description in table 1) cover the period January 1984-December 2012.

	Sharpe Ratios								
	Ten Industry Portfolios			Six Style Portfolios			MKT		
	$\bar{\alpha}_{MF} = 0$	Basis Assets	Difference	$\bar{\alpha}_{MF} = 0$	Basis Assets	Difference	$\bar{\alpha}_{MF} = 0$	Basis Assets	Difference
Mean	0.2983	0.2571	0.0412	0.3087	0.2790	0.0296	0.1480	0.1146	0.0335
StdDev	0.0718	0.0408	0.0576	0.0556	0.0275	0.0449	0.0588	0.0383	0.0485
Max	0.7507	0.5453	0.4596	0.7093	0.5962	0.4188	0.6025	0.3500	0.3736
99%	0.5746	0.4628	0.2591	0.5384	0.3643	0.2186	0.3510	0.2713	0.2549
95%	0.4527	0.3002	0.1622	0.4119	0.3267	0.1135	0.2648	0.1626	0.1305
90%	0.3868	0.2838	0.1136	0.3676	0.3103	0.0763	0.2158	0.1484	0.0869
75%	0.3169	0.2692	0.0538	0.3223	0.2847	0.0373	0.1665	0.1270	0.0428
Median	0.2765	0.2528	0.0182	0.2924	0.2761	0.0134	0.1334	0.1171	0.0150
25%	0.2539	0.2364	0.0038	0.2777	0.2677	0.0033	0.1170	0.0965	0.0034
10%	0.2397	0.2214	0.0006	0.2674	0.2515	0.0005	0.0944	0.0700	0.0006
5%	0.2293	0.2147	0.0002	0.2540	0.2367	0.0001	0.0788	0.0593	0.0001
1%	0.2135	0.1895	0.0000	0.2356	0.2276	0.0000	0.0522	0.0100	0.0000
Min	0.1488	0.1433	0.0000	0.2183	0.2068	0.0000	0.0066	0.0012	0.0000

Appendix A: Additional Results on Alternative Maximum Sharpe Ratio Choices

Table A1: Best Clientele Alphas for Alternative Maximum Sharpe Ratio Choices Using the RF + 6S Passive Portfolio Set

Table A1 shows statistics on the cross-sectional distribution of monthly SDF alphas estimated with six best clientele performance measures, allowing for maximum Sharpe ratios of $1.5h^*$, $2h^*$, $h^* + 0.5hT$, $h^* + hT$, $h^* + 0.5hTa$ and $h^* + hTa$ (see definition in section 5.4), using the risk-free rate and the six style portfolios (RF + 6S) as basis assets. It provides the mean, the standard deviation (StdDev) and selected percentiles of the distributions of the estimated alphas (columns under Performance) and their corresponding t-statistics (columns under t-statistics). It also reports t-statistics (t-stat) on the significance of the mean of estimated alphas using a test that accounts for the cross-sectional dependence in performance among funds (see description in section 3.3). The data (see description in table 1) cover the period January 1984-December 2012. All statistics are in percentage except t-statistics.

Performance and t-statistics of Individual Mutual Funds												
	Performance						T-statistics					
	$1.5h^*$	$2h^*$	$h^* + 0.5hT$	$h^* + hT$	$h^* + 0.5hTa$	$h^* + hTa$	$1.5h^*$	$2h^*$	$h^* + 0.5hT$	$h^* + hT$	$h^* + 0.5hTa$	$h^* + hTa$
Mean	0.5052	0.8323	0.5015	0.8261	0.4441	0.7286	2.5983	3.6655	2.5896	3.6564	2.3469	3.3845
StdDev	0.4282	0.5819	0.4293	0.5810	0.4048	0.5336	1.4314	1.4605	1.4439	1.4731	1.4441	1.4605
(t-stat)	(4.163)	(5.046)	(4.122)	(5.017)	(3.870)	(4.818)						
Max	3.3586	5.1028	3.4822	5.1584	3.1873	4.6537	8.0564	9.3876	8.0564	9.3876	7.7290	9.0726
99%	2.0487	3.0433	2.0613	2.9721	1.9252	2.6720	6.1868	7.4125	6.1717	7.3722	5.8978	7.0302
95%	1.2569	1.8182	1.2244	1.7971	1.1244	1.6183	5.0026	6.1283	4.9949	6.1416	4.7395	5.7971
90%	1.0045	1.4760	1.0059	1.4710	0.9197	1.3299	4.4807	5.5964	4.4834	5.6031	4.2265	5.3140
75%	0.6869	1.0641	0.6852	1.0535	0.6182	0.9435	3.5124	4.5654	3.5404	4.5659	3.3080	4.3176
Median	0.4060	0.6924	0.4012	0.6892	0.3511	0.6021	2.5324	3.6028	2.5288	3.5963	2.2839	3.3384
25%	0.2358	0.4580	0.2315	0.4536	0.1919	0.3891	1.6543	2.6662	1.6421	2.6354	1.4200	2.3874
10%	0.1146	0.3094	0.1123	0.3028	0.0792	0.2476	0.8436	1.8477	0.8226	1.8309	0.5980	1.5906
5%	0.0496	0.2355	0.0383	0.2291	0.0039	0.1739	0.3072	1.4173	0.3001	1.3432	0.0228	1.1036
1%	-0.1155	0.0956	-0.1464	0.0641	-0.1936	0.0147	-0.7123	0.5586	-0.7630	0.4189	-1.0708	0.1167
Min	-1.7755	-0.3027	-2.0357	-0.3890	-2.3656	-0.7319	-4.2285	-2.2839	-3.8108	-1.6470	-4.2132	-2.2599

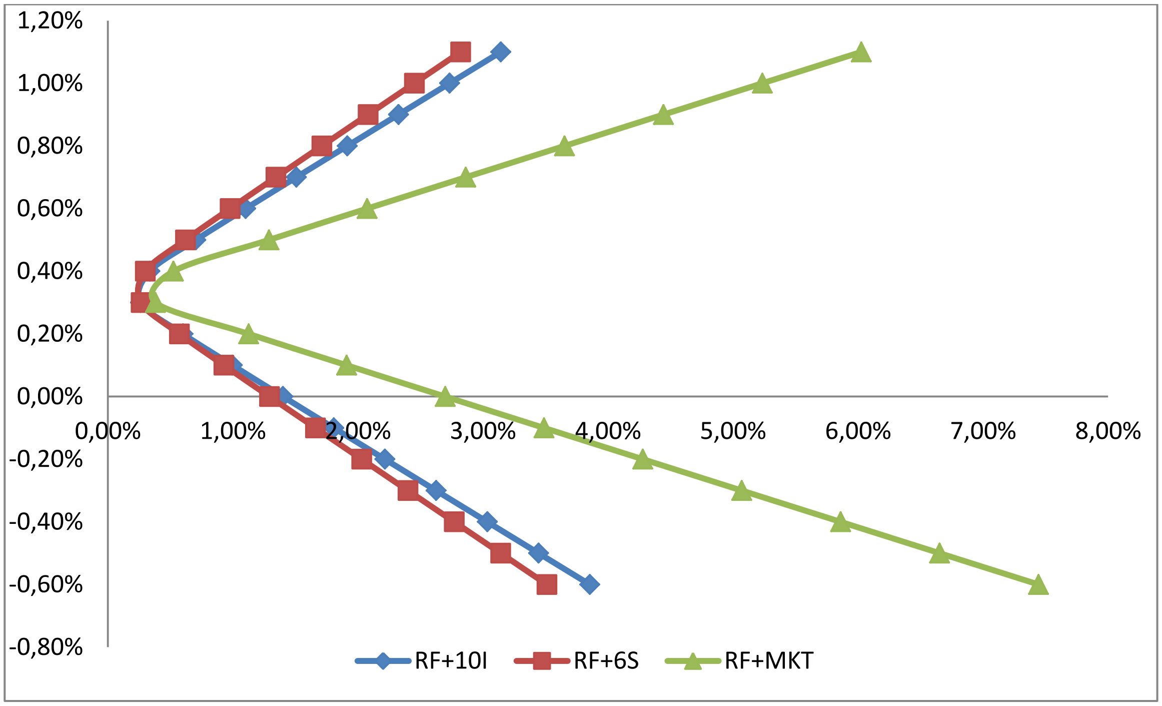
Table A2: Best Clientele Alphas for Alternative Maximum Sharpe Ratio Choices Using the RF + MKT Passive Portfolio Set

Table A2 shows statistics on the cross-sectional distribution of monthly SDF alphas estimated with two best clientele performance measures, allowing for maximum Sharpe ratios of $1.5h^*$ and $2h^*$ (see definition in section 5.4), using the risk-free rate and the market portfolio (RF + MKT) as basis assets. It provides the mean, the standard deviation (StdDev) and selected percentiles of the distributions of the estimated alphas (columns under Performance) and their corresponding *t*-statistics (columns under *t*-statistics). It also reports *t*-statistics (*t*-stat) on the significance of the mean of estimated alphas using a test that accounts for the cross-sectional dependence in performance among funds (see description in section 3.3). The data (see description in table 1) cover the period January 1984-December 2012. All statistics are in percentage except *t*-statistics.

Performance and t-statistics of Individual Mutual Funds

	Performance		t-statistics	
	$1.5h^*$	$2h^*$	$1.5h^*$	$2h^*$
Mean	0.2444	0.4317	1.0863	1.7768
StdDev	0.3041	0.3750	1.2153	1.2575
(t-stat)	(2.835)	(4.062)		
Max	1.9137	2.9479	5.8772	6.6439
99%	1.1193	1.6253	3.9233	4.8328
95%	0.7190	1.0164	2.9936	3.8091
90%	0.5922	0.8684	2.5507	3.3670
75%	0.4146	0.6332	1.8655	2.5770
Median	0.2234	0.3972	1.1145	1.7632
25%	0.0561	0.1813	0.3410	1.0069
10%	-0.0674	0.0477	-0.3672	0.2550
5%	-0.1686	-0.0554	-0.9204	-0.3227
1%	-0.4904	-0.3862	-2.2712	-1.6296
Min	-3.0077	-1.6592	-3.8140	-3.3445

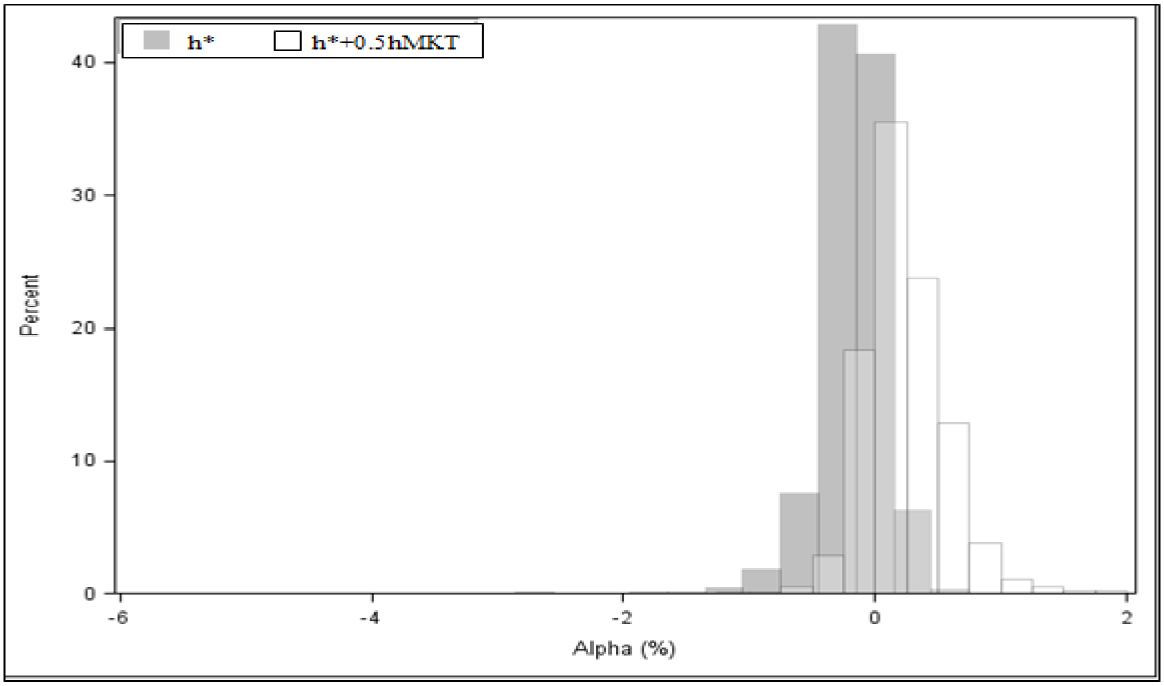
Figure 1: Mean-Standard Deviation Frontiers from the Sets of Passive Portfolio Returns



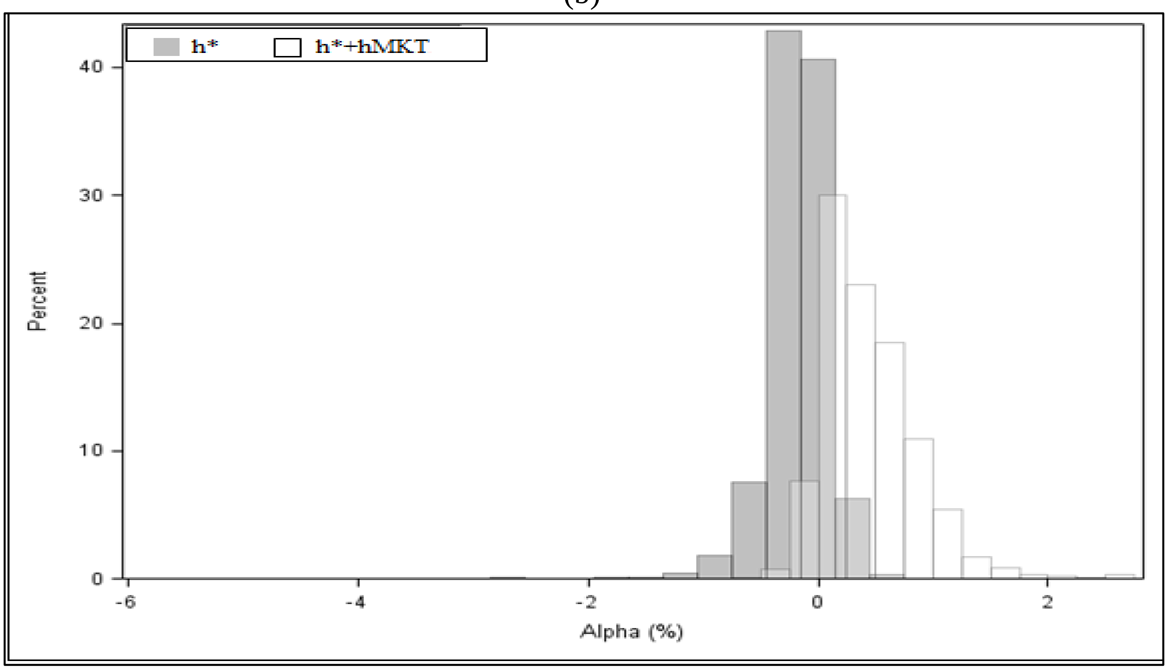
Notes: Figure 1 presents the mean-standard deviation frontiers of investment opportunities from the risk-free rate and either the ten industry portfolios (RF+10I), the six style portfolios (RF+6S) or the market portfolio (RF+MKT) as passive portfolios.

Figure 2: Histogram of the Best Cliente and LOP Alphas

(a)



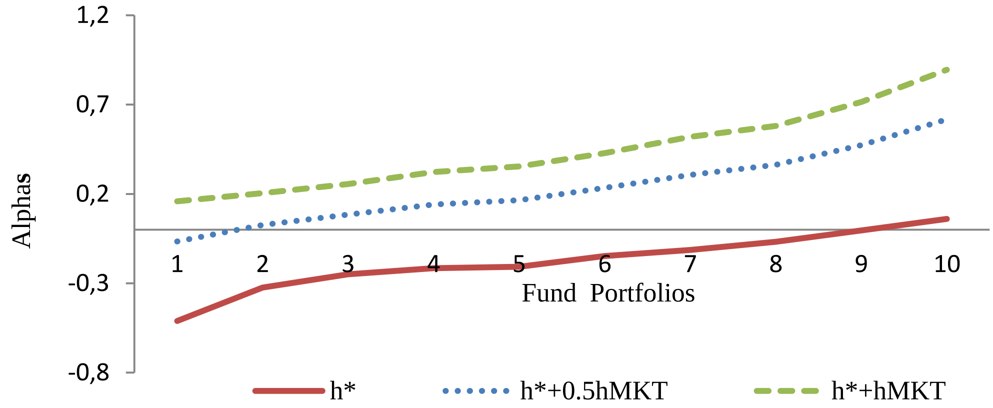
(b)



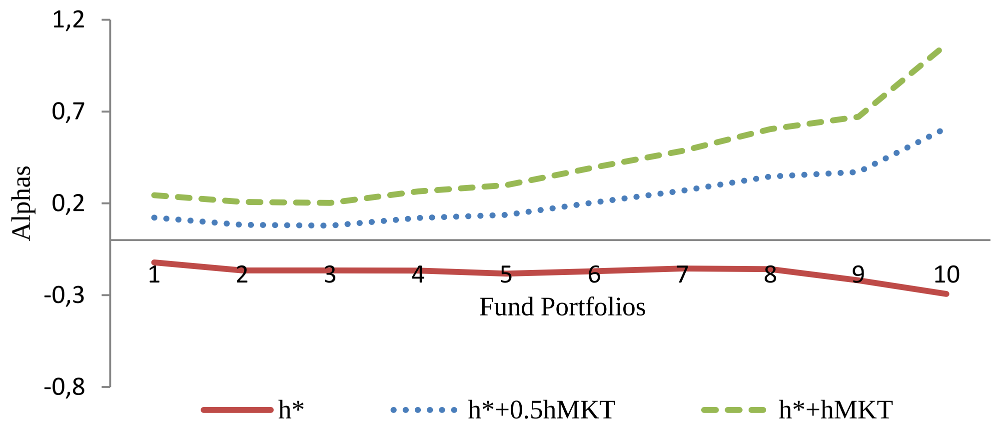
Notes: Figure 2 presents histograms illustrating the distributions of the best clientele and LOP alphas. Figure 2a illustrates the LOP alphas (denoted h^*) and the best clientele alpha allowing for a maximum Sharpe ratio of $h^* + 0.5hMKT$. Figure 2b illustrates the LOP alphas (denoted h^*) and the best clientele alpha allowing for a maximum Sharpe ratio of $h^* + hMKT$.

Figure 3: Best Clientele and LOP Alphas for Decile Fund Portfolios

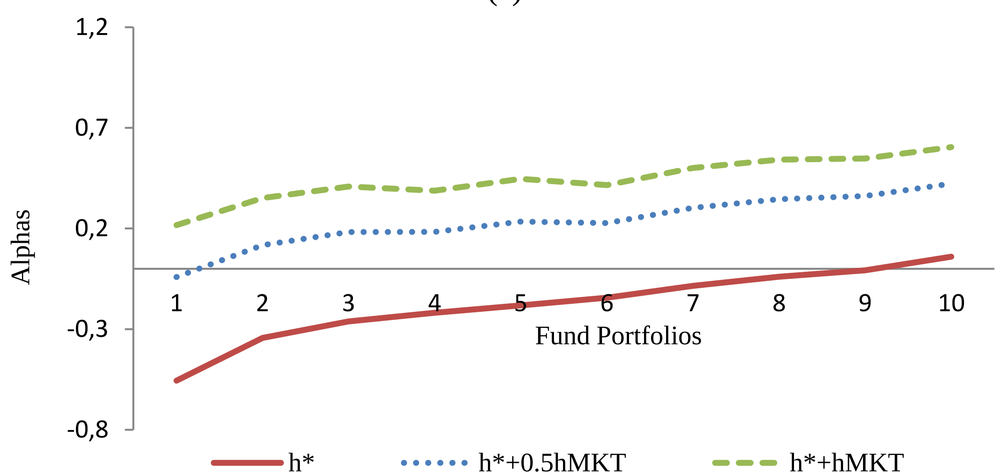
(a)



(b)



(c)



Notes: Figure 3 presents the best clientele and LOP alphas for mutual funds grouped in decile portfolios. In figure 3a, the funds are sorted in increasing order of their average return. In figure 3b, the funds are sorted in increasing order of their standard deviation of returns. In figure 3c, the funds are sorted in increasing order of their Sharpe ratio.