Performance Evaluation Disagreement: Determinants and Impact on Fund Flows

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Abstract

This paper studies investor disagreement in the performance evaluation of equity mutual funds by comparing two existing approaches and estimating its relations with fund characteristics, active management level and fund flows. We find that investors disagree more about the performance of funds that have higher expense ratio and turnover, lower manager tenure and dividend yield, and that are older, smaller and part of a larger family. Disagreement is also higher for funds that follow riskier investment style strategies and deviate more from their benchmarks. Finally, larger disagreement leads to more net fund flows. These findings suggest that heterogeneous investors do not value funds with aggressive active trading strategies similarly, and that favorable valuations by some clienteles result in positive demands for this type of management.

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Introduction

The 2021 Investment Company Fact Book reports that total worldwide assets invested in regulated open-ended funds are greater than $60 trillion and demand by investors over the past decade has resulted in more than $16 trillion in net fund flows. In consequence, “fund providers have responded to the increasing interest in funds by offering more than 125,000 regulated funds, which provide a vast array of choices for investors.” (Investment Company Institute 2021, p. 15).

One reason why the fund industry offers such a large variety of products is to cater to the multiple needs of their various clienteles. In equity portfolios, differentiation strategies have many dimensions. For examples, they include choices of investment style (value, growth, small-cap, large-cap, etc.), trading activity (turnover, deviations from benchmarks, etc.), risk level (from defensive to aggressive), managerial activity (stock picking, market timing, etc.), clientele-specific needs (low cost, high dividend, tax efficiency, individual versus institutional, etc.), and fund organization (small versus large family, etc.).

In the U.S. alone, mutual funds are owned by more than 100 million individuals, who have different beliefs, constraints and preferences. These differences, along with the large diversity of funds, mean that investors are likely to disagree on what investments are worth the most to them, i.e., their “personal favorites” or “best

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fits". Pioneered by Ferson and Lin (2014), the investor disagreement approach assumes that fund evaluation differs by investors and develops ways to measure the importance of disagreement on performance evaluation. Its empirical findings show a large disagreement effect for equity funds. In particular, Ferson and Lin find that the effect of investor heterogeneity on alpha could be as important as the well documented effects of the benchmark choice or statistical imprecision of alpha estimates. Using another strategy to obtain performance bounds, Chrétien and Kammoun (2017) find that a positive alpha exists for some clienteles for most funds and that disagreement is large enough to change the average alpha of the fund industry from negative to positive, depending on the clienteles.

Given that investor disagreement is one of the current important challenges in fund evaluation (Ferson, 2010), this paper aims to understand better the reasons for disagreement and its effects on behavior. Specifically, we provide an in-depth characterization of disagreement in equity mutual funds by comparing both existing measurement strategies and documenting the relations between disagreement and fund characteristics, active management level and fund flows.

Our analysis has three steps. First, we propose a unified framework that allows for heterogeneity in beliefs and preferences, and in which existing strategies for measuring disagreement can be reconciled. Although Ferson and Lin (2014) and Chrétien and Kammoun (2017) provide two different bounds on investor disagreement because they rely on different restrictions on stochastic discount factors, we derive a constraint based on the no-good-deal condition of Cochrane and Saá-Requejo (2000) that implies their equivalence. Second, we develop testable hypotheses on the signs of the relations between disagreement and variables capturing fund characteristics, active management level and fund flows. To obtain economic predictions, we exploit our theoretical results on the sources of disagreement and the findings from the literature on the link between performance and these variables. Third, we empirically document the sign and significance of the relations and examine if they are consistent with our hypotheses. Our tests rely mainly on the estimation of standard panel regressions. We use a sample of 2791 actively-managed open-ended U.S. equity mutual funds with returns from 1984 to 2016 to estimate disagreement with the generalized method of moments. We show that our results are similar for both disagreement measures, and are robust to various regression specifications and methodological choices.

What types of funds are the most subject to disagreement? Our empirical results find significant relations between disagreement and numerous fund characteristics. Investors disagree more on their evaluation of funds with higher expenses, turnover, longevity, management fees and cost of bundled services, lower manager tenure, size and dividend yield, and that are part of larger fund complexes and follow riskier investment style strategies. Thus, heterogeneous investors do not value similarly funds that represent somewhat risky financial products (i.e., funds that are small, with young managers and with an aggressive and costly active trading strategy) that are well supported by their organization (i.e., funds with a long existence and within a large family).

What is the effect of the level of active management on disagreement? By taking active risk, managers can construct portfolios that differ greatly for their benchmarks. Such relatively unique opportunities allow for greater disagreement by heterogeneous investors who price differently the part of returns not easily replicated by passive portfolios. Our results confirm that future disagreement is positively related to two variables aimed to capture relevant departures from benchmarks by active managers: Active share (Cremers & Petajisto, 2009) and asset selectivity (Amihud & Goyenko, 2013). Average disagreement is more than twice as large for funds in the top versus bottom deciles of asset selectivity or active share.

What is the impact of disagreement on the net demands for funds? High disagreement is associated with large valuation discrepancies. Favorable evaluations should lead investors to large demands for funds, but unfavorable ones should lead to no demand because investors cannot sell the funds short (Ferson & Lin, 2014). Our results support this intuition by finding a positive and statistically significant relation between future net fund flows and disagreement. A one standard deviation increase in disagreement leads to an approximate rise in net fund flows of 0.80% over the next quarter. Thus, favorable evaluations by some clienteles could explain the positive demands for funds with aggressive and costly active trading strategies.

This paper contributes to the growing evidence on investor heterogeneity and clientele effects in mutual funds from studies focusing on specific kinds of clienteles. For examples, these effects are related to investor monitoring and investment advice (James & Karceski, 2006, Bergstresser et al., 2009, Evans & Fahlenbrach, 2012, Del Guercio and Reuter, 2014), taxation (Ivković and Weisbenner, 2009, Sialm and Starks, 2012, Sialm and Zhang, 2020), liquidity and dividend demands (Nanda et al., 2000, Harris et al., 2015), demographics and investor sophistication (Bailey et al., 2011, Evans and Fahlenbrach, 2012), and behavioral biases (Barber et al., 2005, Bailey et al., 2011, Massa and Yadav, 2015, Kronlund et al., 2021).

Many of these studies can be categorized as using a bottom up analysis, since they start from a specific clientele to examine its effects on funds. Our paper follows instead a distinctive top down analysis, as we use aggregate measures of disagreement that implicitly consider multiple clienteles. While the focus of Ferson and Lin (2014) and Chrétien and Kammoun (2017) is on developing these measures and finding their implications for performance evaluation, our paper is the first to provide a comprehensive examination of the determinants and impact on flows of aggregate disagreement.

This paper also adds to the literature on understanding the effects of fund characteristics and investment strategies, and the reasons why money flows into and out of funds. Ippolito (1989, 1992), Elton et al. (1993), Gruber (1996), Carhart (1997) and Sirri and Tufano (1998) are early works in this literature. Recent articles include Ferreira et al. (2012), Barber et al. (2016), Pastor et al. (2015, 2017), Phillips et al. (2018), Song (2020), and Ben-David et al. (2022). Our paper shows that investor disagreement is important to consider for these issues since it is influenced by fund characteristics and investments strategies, and it predicts increased net fund flows.

We proceed as follows. First, we develop our theoretical framework for measuring disagreement. Second, we discuss the relevant literature to develop hypotheses on the relations between disagreement and fund characteristics, active management level and fund flows. Third, we describe the methodology and data for estimation. Fourth, we present our empirical results and assess their robustness. Fifth, concluding remarks are provided.

A Framework for Investor Disagreement in Performance Evaluation

This section develops a framework for measuring maximum disagreement that encompasses two strategies available in the literature. First, we define generally the measurement of investor disagreement in performance evaluation and present the total disagreement obtained from the best and worst clientele alphas of Chrétien and Kammoun (2017) and from the bound on disagreement with a traditional alpha proposed by Ferson and Lin (2014). Second, we relate both disagreement approaches to highlight their differences and obtain a condition for their equivalence.

Total Investor Disagreement Measures in Performance Evaluation

Our framework uses the stochastic discount factor (SDF) approach developed by Glosten and Jagannathan (1994) and Chen and Knez (1996), extended to consider potentially biased investor beliefs, to measure the performance, or (average) alpha, such that:

$$\alpha_{MF,i} = E[m_i \, R_{MF}] - 1, \tag{1}$$

where m_i is the SDF of an investor i interested in valuing the mutual fund with gross return R_{MF}.[3]

[3] In this setup, assuming unbiased beliefs, m_i corresponds to the marginal preference of the investor. If beliefs are biased, then m_i represents a modified SDF which contains an adjustment for biased beliefs. Bondarenko (2003) provides an analysis of the implications of biased beliefs for SDFs. He finds an equivalence relationship between preferences and beliefs, so that the same prices (or alphas in our setup)

According to Ferson (2010), the SDF approach is on the most solid theoretical footing, as it does not require assumptions about utility functions or complete markets and can account for clientele effects and informed managers.

Most performance studies assume unbiased beliefs and a parametric asset pricing model with a representative investor to obtain a unique SDF for evaluation. The investor disagreement approach assumes incomplete markets, resulting in a multiplicity of SDFs and alphas. Using the terminology of Ferson and Lin (2014), m_i is a client-specific SDF and $\alpha_{MF,i}$ is the corresponding client-specific alpha.[4] Without further assumptions, Chen and Knez (1996) demonstrate that there could be an infinite range of alphas in this setup. The investor disagreement approach imposes economically relevant restrictions on SDFs of all investors to obtain a restricted set and identify the fund's most favorable alpha, $\bar{\alpha}_{MF}$, and least favorable alpha, $\underline{\alpha}_{MF}$. From these extreme alphas, this paper defines straightforwardly a bound on total investor disagreement as:

$$DIS_{MF} = \bar{\alpha}_{MF} - \underline{\alpha}_{MF}. \tag{2}$$

Our first measure of investor disagreement, denoted by DISCK, uses the best and worst clientele alphas proposed by Chrétien and Kammoun (2017, 2020). Their idea is to restrict the set of all investor SDFs by imposing two economic restrictions: the law-of-one-price (LOP) condition (Hansen & Jagannathan, 1991), which assumes that investors give zero performance to passive portfolios, and the no-good-deal condition (Cochrane & Saá-Requejo, 2000), which assumes that investors eliminate investment opportunities that have too high Sharpe ratios (so called good deals).[5]

Let $\mathrm{R_K}$ be the vector of (gross) passive portfolio returns. Without loss of generality, we assume that passive portfolios include a risk-free asset with return R_F, which accounts for cash positions and fixes the SDF mean to a relevant value, $E[m_i] = 1/R_F$ (Dahlquist & Söderland, 1999). Let $\bar{h}$ be the maximum allowable Sharpe ratio. The LOP condition implies that $E[m_i\,\mathrm{R_K}] = 1$. The no-good-deal condition implies that $E[m_i^2] \leq \left(1+\bar{h}^2\right)/R_F^2$, or equivalently, $\sigma(m_i) \leq \bar{h}/R_F$. Chrétien and Kammoun (2017) show that these restrictions allow solutions for the best and worst clientele alphas.

By taking the difference between these alphas, we obtain the DISCK measure:

$$DISCK_{MF} = 2vE[w_{MF}^2], \tag{3}$$

where

$$v = \sqrt{\frac{\left(\frac{(1+\bar{h}^2)}{{R_F}^2} - E[m_{LOP}^2]\right)}{E[w_{MF}^2]}}, \tag{4}$$

$$w_{MF} = R_{MF} - \mathrm{c}'\mathrm{R_K}, \tag{5}$$

$$m_{LOP} = \mathrm{a}'\mathrm{R_K}. \tag{6}$$

In these equations, the parameter v is an increasing function of the maximum allowable Sharpe ratio $\bar{h}$. The replication error term w_{MF} is the residual from a linear projection of the fund return onto passive portfolio returns. The SDF m_{LOP} is the minimum volatility SDF under the LOP condition. It is a linear function of passive portfolio returns $\mathrm{R_K}$. Hansen and Jagannathan (1991) show that $E[m_{LOP}^2] = \left(1+{h^*}^2\right)/R_F^2$, or

can result from either preference choices or biased beliefs (or some combination of the two). An econometrician cannot distinguish between both possibilities unless specific assumptions on beliefs and preferences are made.

[4] In their rational expectations equilibrium analysis of mutual funds, Berk and Green (2004) and Berk and van Binsgergen (2015, 2017) argue that alpha is not a good measure of ability as skilled managers can extract rents from investors (in the form of fees) to bring fund value added to zero. In this paper, following Ferson and Lin (2014), alpha represents an investor-specific evaluation or personal value added, and is thus not a general measure of skill or value added.

[5] Hansen and Jagannathan (1991) and Cochrane and Saá-Requejo (2000) also consider the no-arbitrage (NA) condition that excludes negative SDFs by ruling out arbitrage opportunities. However, this condition imposes negligible restrictions on SDFs in the evaluation of equity funds. Ahn et al. (2009) find that performance bounds under the LOP and NA conditions are typically wide. Chrétien and Kammoun (2017) show that empirical SDFs are almost always positive under the LOP and no-good-deal conditions.

equivalently, $\sigma(m_{LOP}) = h^*/R_F$, where h^* is the maximum Sharpe ratio obtained from the passive portfolios. Thus, in the DISCK measure, disagreement is greater if investors are willing to allow more good deals and if fund returns are more difficult to span with passive portfolio returns.

Our second measure of investor disagreement, denoted by DISFL, is derived from the bound on disagreement with a traditional alpha proposed by Ferson and Lin (2014). Their approach also assumes the LOP condition, but it does not impose the no-good-deal condition. Instead, it assumes a restriction on the correlations that SDFs can have, specifically, $\left|\rho_{m_i,\varepsilon_{MF}}/\rho_{m_i,R^*}\right| \leq 1$, where R^* is the passive portfolio return that achieves the maximum Sharpe ratio h^* and ε_{MF} is the error term in a linear regression of excess fund return, $R_{MF} - R_F$, on excess passive portfolio returns:

$$R_{MF} - R_F = a_{MF} + \mathrm{b}'(\mathrm{R}_{\mathrm{K}^-} - R_F 1) + \varepsilon_{MF}. \quad (7)$$

with $\mathrm{R}_{\mathrm{K}^-}$ being the vector of passive portfolio returns *excluding* the risk-free return, a_{MF} being the traditional (Jensen's) alpha that would be obtained if excess returns on the passive portfolios are the benchmark returns in a factor model, b being the vector of factor loadings, and $E[\varepsilon_{MF}] = E[\,\varepsilon_{MF}\,\mathrm{R}_{\mathrm{K}^-}] = 0$. This restriction means that, for all SDFs, the magnitude of their correlations with the part of fund return not captured by passive portfolio returns is smaller than the magnitude of their correlations with the passive portfolio return with the maximum Sharpe ratio.

Using the implications of the bound of Ferson and Lin (2014) for the maximum and minimum SDF alphas, we obtain the following DISFL disagreement measure:

$$DISFL_{MF} = \frac{2h^*}{R_F}\sigma(\varepsilon_{MF}). \quad (8)$$

This measure indicates that maximum disagreement depends on the maximum Sharpe ratio obtained from the passive portfolios, h^*, and the standard deviation of the regression error term, $\sigma(\varepsilon_{MF})$. Disagreement is thus greater if the minimum volatility SDF is higher and if fund return is more difficult to explain with passive portfolio returns.

Relation between the Disagreement Measures

The DISCK and DISFL measures are general as they do not require complete markets, parametric assumptions on beliefs, and preferences or representative investors. They have different bounds on disagreement because they rely on different restrictions on SDFs. The DISCK measure uses an exogenous maximum allowable Sharpe ratio $\bar{h}$. As discussed by Chrétien and Kammoun (2017), Sharpe ratios have a long history in performance studies and there is guidance on $\bar{h}$ as the no-good-deal restriction has been used in various contexts (e.g., Ross, 1976; MacKinlay, 1995; Cochrane & Saá-Requejo, 2000; Pettenuzzo et al., 2014). In contrast, the DISFL measure avoids the specification of $\bar{h}$, but imposes a constraint on the correlations that SDFs can have. This restriction is difficult to interpret economically and is not made elsewhere in the literature.[6]

To understand better the relation between the measures, we can rewrite the DISCK measure in a way that is more comparable to the DISFL measure by making two changes. First, the projection error term w_{MF} and the regression error term ε_{MF} are similar since we include a (constant) risk-free return in the passive portfolio returns used in the projection. Hence, $E[w_{MF}^2] = E[\varepsilon_{MF}^2] = \sigma^2(\varepsilon_{MF})$. Second, since $E[m_{LOP}^2] = \left(1 + h^{*2}\right)/R_F^2$, the parameter v can be written as:

$$v = \sqrt{\frac{\left(\frac{(1+\bar{h}^2)}{{R_F}^2} - \frac{(1+h^{*2})}{R_F^2}\right)}{E[w_{MF}^2]}} = \sqrt{\frac{(\bar{h}^2 - h^{*2})}{{R_F}^2\, E[w_{MF}^2]}}. \quad (9)$$

Using these results, we can rewrite the DISCK measure as follows:

$$DISCK_{MF} = 2vE[w_{MF}^2] = \frac{2\sqrt{(\bar{h}^2 - h^{*2})}}{R_F}\sigma(\varepsilon_{MF}) = \frac{\sqrt{(\bar{h}^2 - h^{*2})}}{h^*} DISFL_{MF}. \quad (10)$$

[6] The only other constraint on SDF correlations in the literature is the bound on the autocorrelation of SDFs of Chrétien (2012), which restricts the admissible economic time variation across two periods.

This expression clarifies the relation between the DISCK and DISFL measures. When $\overline{h} = \sqrt{2}\, h^*$, the measures are equivalent. When $\overline{h} > \sqrt{2}\, h^*$ $\left(\overline{h} < \sqrt{2}\, h^*\right)$, $DISCK_{MF} > DISFL_{MF}$ $(DISCK_{MF} < DISFL_{MF})$. Thus, the restriction on SDF correlations assumed for the DISFL measure has an effect similar to assuming that the maximum allowable Sharpe ratio (or maximum allowable SDF standard deviation) is 41.4% higher than the maximum Sharpe ratio obtained from the passive portfolios (or the minimum SDF standard deviation). Empirically, given the different methodological choices of Chrétien and Kammoun (2017) and Ferson and Lin (2014), the results will show that the DISCK and DISFL measures are not equivalent, but are closely related, although the highest estimates can come from either measure, depending on the set of passive portfolios and period used for estimation.

Investor Disagreement Across Funds: Hypotheses Development

This paper's main objective is to investigate the relations between investor disagreement and three types of variables: fund characteristics, active management level and fund flows. The literature offers relevant empirical findings to develop hypotheses on these relations in two ways. First, we show disagreement as a difference between upper and lower performance values. The literature on the links between performance and the variables investigated is thus relevant. Second, we show that disagreement is larger for funds with returns that are more difficult to replicate. Because such returns belong to managers who deviate more from their benchmarks, the literature studying active trading and managerial skills is also useful for hypotheses development.

Fund Characteristics

We consider a large number of relevant fund characteristics. This section shortly reviews the literature on these variables to formulate hypotheses on their relations with disagreement. When the literature yields mixed predictions, we rely on the best evidence or economic intuition to determine the likely relations. We discuss the most commonly used characteristics in the first subsection and some other relevant characteristics in second subsection.

Most Common Fund Characteristics

The sign and significance of the relations between the most commonly used characteristics and performance are often not robust across studies.

Expenses. Prather et al. (2004) find a positive relation between expenses and abnormal fund returns, while Ippolito (1989) and Chen et al. (2004) show that there is no relation between the two variables. In contrast, Carhart (1997) and Cremers and Petajisto (2009) report a negative effect of expenses on performance.

Turnover. Some studies (Ippolito, 1989, Prather et al., 2004, Chen et al., 2004, Huang et al., 2011) find no link between turnover and performance. Other studies report negative (Carhart, 1997, Massa & Patgiri, 2009) or positive (Grinblatt & Titman, 1994, Pastor et al., 2017) relations.

Age. According to some authors (Prather et al., 2004, Chen et al., 2004, Huang et al., 2011, Ferreira et al., 2012, Agnesens, 2013), there is no relation between fund age and performance. However, Cremers and Petajisto (2009) and Massa and Patgiri (2009) find that fund age has a positive and statistically significant effect on performance.

Manager tenure. Golec (1996) suggests that manager tenure is generally associated with positive excess returns. Prather et al. (2004), however, find no significant relationship between performance and manager tenure.

Size. Carhart (1997), Prather et al. (2004) and Phillips et al. (2018) argue that there is no relation between performance and size, measured by total net assets (TNA). Chen et al. (2004), Ferreira et al. (2012), Pastor et al. (2015) and Song (2020) find instead that size tends to have a negative impact on fund returns.

Given these conflicting results, it is difficult to formulate clear predictions on the relations between these variables and investor disagreement. Amihud and Goyenko (2013) provide an helpful analysis to clarify our predictions. They study the determinants of the R^2 obtained from a regression of fund returns on returns of benchmarks from a multifactor model. Lower R^2 suggests that a fund deviates more from the benchmarks and should correspond to higher $E[w_{MF}^2]$ and $\sigma^2(\varepsilon_{MF})$, and thus larger investor disagreement. Amihud and Goyenko (2013) find that funds with high expense ratio, high turnover, high age, high manager tenure and low TNA typically deviate more from their benchmarks. These results suggest the following relations across funds.

H1a: There is a positive relation between future disagreement and expenses.

H1b: There is a positive relation between future disagreement and turnover.

H1c: There is a positive relation between future disagreement and age.

H1d: There is a positive relation between future disagreement and manager tenure.

H1e: There is a negative relation between future disagreement and size.

Other Relevant Fund Characteristics

The literature identifies many fund characteristics as cross-sectional determinants of performance. We select additional variables that could be relevant given the evidence on investor heterogeneity and clientele effects discussed in the introduction. Specifically, we consider fund expense components, tax burden, dividend yield, family size, factor exposures and style as additional possible determinants of investor disagreement.

Expense components. Expenses include management fees, advertising expenses (12b-1) and the costs of bundled services. Golec (1996) finds that management fees do not decrease performance, but Wermers (2000) documents that they have a negative impact. Ferris and Chance (1987) report a negative effect of 12b-1 fees on performance. Since H1a predicts a positive relation between disagreement and expenses, we expect a similar result between disagreement and management fees or the costs of bundled services. However, by providing information that can help investors in their evaluation, advertising expenses are expected to reduce disagreement.

Tax burden. Some authors (Barclay et al., 1998, Gibson et al., 2000, Bergstresser and Poterba, 2002, Ivković and Weisbenner, 2009, Sialm and Zhang, 2020) report negative effects of taxes on fund performance. Sialm and Starks (2012), however, find no significant relationship between performance and taxes. We predict a positive relation between disagreement and tax burden as there is heterogeneity on the effect of taxation on investors. This is consistent with the expected positive relation between disagreement and turnover (H1b).

Dividend yield. Harris et al. (2015) find that buying stocks before dividend payments, called juicing, reduces fund performance. But Jiang and Sun (2020) report a positive effect of dividend yield on performance. Nanda et al. (2000) show a dividend clientele effect since liquidity demands differ across fund investors. Given that dividends reduce uncertainty in returns, there should be less disagreement on funds with high dividend yield.

Family size. Many authors (Chen et al., 2004, Pollet and Wilson, 2008, Ferreira et al., 2012, Agnesens, 2013, Jun et al., 2014) find a positive relation between performance and the size of the fund family. But Bhojraj et al. (2012) show that this result disappears after regulatory changes (i.e., Regulation Fair Disclosure and the Global Settlement) and increased scrutiny because of scandals. Massa (2003) finds evidence of family driven heterogeneity among funds. In large families, product differentiation for clienteles can lead to niche funds that please or displease investors. We thus predict a positive relation between disagreement and family size.

Factor exposures. Factor exposures consist of loadings on size (β_{SMB}), value (β_{HML}) and momentum (β_{UMD}), and are helpful to understand factor tilts. Gruber (1996) and Carhart (1997), among others, show that these factors are relevant in explaining fund returns. The literature offers conflicting explanations on the premium associated with these factors. Value, small-cap and winner stocks could be either riskier or more neglected than growth, large-cap and loser stocks. As there is arguably more disagreement in riskier or neglected stocks than in safer or glamour stocks, we expect positive relations between disagreement and factor exposures.

Styles. Styles are important and highly publicized in the fund industry. Barberis and Shleifer (2003) discuss the interest of financial service firms to understand style preferences and there is a literature that studies the economic differences between style clienteles (Bailey et al. 2011, Cronqvist et al., 2015, Betermier et al., 2017, Chrétien & Kammoun, 2019). Although different styles could please different clienteles, styles associated with more aggressive investing are more difficult to evaluate. We thus expect disagreement to differ by style, with more disagreement for funds following more aggressive styles (like micro-cap funds) and less disagreement for funds following more defensive styles (like equity income funds).

In summary, our hypotheses for these additional variables are as follows.

> H1f: There is a positive relation between future disagreement and management fees or the costs of bundled services. There is a negative relation between future disagreement and advertising expenses.
>
> H1g: There is a positive relation between future disagreement and tax burden.
>
> H1h: There is a negative relation between future disagreement and dividend yield.
>
> H1i: There is a positive relation between future disagreement and family size.
>
> H1j: There are positive relations between future disagreement and factor exposures.
>
> H1k: There is a significant relation between future disagreement and styles, with larger disagreement for funds following aggressive styles and smaller disagreement for funds following defensive styles.

Active Management Variables

Many studies argue that performance is significantly related to numerous active management skills (see Cremers et al. (2019) for a recent review). A manager with those skills should exploit them to take active positions in his portfolio. However, taking active risk is not rewarded similarly by heterogeneous investors, leading to investor disagreement. We can thus conjecture that disagreement should be positively related to active management skills.

We consider two measures of relevant departures from benchmarks to establish this relation. Amihud and Goyenko (2013) develop *Asset selectivity*, a measure computed as $1 - R^2$, with R^2 estimated by regressing fund returns on the returns of benchmarks. Cremers and Petajisto (2009) propose *Active share*, a measure of the importance of the fund's active bets, which are deviations of the fund's stock holdings from those of its benchmark. Both measures aim to capture the level of active management as their values increase when the managed portfolio deviates more from benchmarks. They aggregate into one general indicator (all possible managerial skills) since any ability should lead the manager to deviate from the benchmarks. We examine the following hypotheses for asset selectivity and active share.

> H2a: There is a positive relation between future disagreement and asset selectivity.
>
> H2b: There is a positive relation between future disagreement and active share.

Fund Flows

Many studies (e.g., Ippolito (1992), Gruber (1996), Chevalier & Ellison (1997), and Sirri & Tufano (1998)) find that investors chase past performance. There is also evidence of clientele effects in the flow-performance relationship (Sawicki, 2001, Del Guercio & Tkac, 2002, Huang et al., 2007, Nanda et al., 2009, Jun et al., 2014, Barber et al., 2016, Ben-David et al., 2022). This literature does not relate flows to investor disagreement directly, but Ferson and Lin (2014) suggest that the effect of heterogeneity on flows is positive. In general, high disagreement means that some investors have high alphas while others have low alphas, leaving the net effect of their demands unclear. However, this ambiguity is resolved when investors face trading constraints. Because they cannot sell short funds, those with negative alphas cannot easily act on their evaluation. The demand by those with favorable evaluations should then generate a positive relation between disagreement and net flows. Ferson and Lin (2014) provide evidence that higher heterogeneity results in higher flows, but they rely on heterogeneity in electricity consumption across U.S. states to compute their admittedly "crude" proxy. This paper uses disagreement estimates to test the following hypothesis on the relation between disagreement and net flows.

H3: There is a positive relation between past disagreement and net fund flows.

Methodology and Data

This section first presents the methodology for estimating the disagreement measures. Then, it discusses the panel regressions used to estimate the relations with fund characteristics, active management levels and net fund flows. It also describes the data and provides summary statistics.

Estimation of the Disagreement Measures

We estimate the DISCK and DISFL measures by translating their solutions into empirical moments and applying the generalized method of moments (GMM) of Hansen (1982). Chen and Knez (1996) and Dahlquist and Söderland (1999) are the first to use GMM for SDF performance evaluation. We follow closely Chrétien and Kammoun (2017) and Ferson and Lin (2014) for the implementation of their respective measure. Let T be the number of monthly observations.

For the DISCK measure, similar to Chrétien and Kammoun (2017, 2020), we use the following set of moments.

$$\frac{1}{T}\sum_{t=1}^{T}[(\mathrm{a}'\mathrm{R}_{\mathrm{Kt}})\mathrm{R}_{\mathrm{Kt}}] - 1 = 0, \tag{11}$$

$$\frac{1}{T}\sum_{t=1}^{T}[(R_{MFt} - \mathrm{c}'\mathrm{R}_{\mathrm{Kt}})\mathrm{R}_{\mathrm{Kt}}] = 0, \tag{12}$$

$$\frac{1}{T}\sum_{t=1}^{T}[(\mathrm{a}'\mathrm{R}_{\mathrm{Kt}}) + v(R_{MFt} - \mathrm{c}'\mathrm{R}_{\mathrm{Kt}})]^2 - \frac{\left(1+\bar{h}^2\right)}{R_F{}^2} = 0, \tag{13}$$

$$\frac{1}{T}\sum_{t=1}^{T}[2v \times (R_{MFt} - \mathrm{c}'\mathrm{R}_{\mathrm{Kt}})^2] - DISCK_{MF} = 0. \tag{14}$$

Equations (11) to (14) represent a system of $2K + 2$ moments with $2K + 2$ parameters, where K is the number of passive portfolios. The K moments in equation (11) allow for the estimation of the parameters a of the minimum volatility SDF under the LOP condition, $m_{LOPt} = \mathrm{a}'\mathrm{R}_{\mathrm{Kt}}$, by ensuring that it prices correctly the passive portfolio returns R_{Kt}. The K moments in equation (12) are the orthogonality conditions between the replication error term, $w_{MFt} = R_{MFt} - \mathrm{c}'\mathrm{R}_{\mathrm{Kt}}$, and the passive portfolio returns, needed to estimate the projection parameters c. The moment in equation (13) imposes the no-good-deal condition to estimate v, which is restricted to be positive. In this moment, we set $\bar{h} = h^* + 0.5$, following Chrétien and Kammoun (2017), who show the relevancy of this choice in the literature and empirically. 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 0.2986%. Finally, using w_{MFt} and v, we obtain the disagreement estimate $DISCK_{MF}$ with the moment specified by equation (14).

For the DISFL measure, we use the following set of moments.

$$\frac{1}{T}\sum_{t=1}^{T}\left[\left(R_{MF,t} - R_{Ft}\right) - \left(a + \mathrm{b}'(\mathrm{R}_{\mathrm{K^-t}} - R_{Ft})\right)\right] = 0, \tag{15}$$

$$\frac{1}{T}\sum_{t=1}^{T}\left[\left(\left(R_{MF,t} - R_{Ft}\right) - \left(a + \mathrm{b}'(\mathrm{R}_{\mathrm{K^-t}} - R_{Ft})\right)\right) \times (\mathrm{R}_{\mathrm{K^-t}} - R_{Ft})\right] = 0, \tag{16}$$

$$\frac{1}{T}\sum_{t=1}^{T}[(\mathrm{a}'\mathrm{R}_{\mathrm{Kt}})\mathrm{R}_{\mathrm{Kt}}] - 1 = 0, \tag{17}$$

$$\frac{1}{T}\sum_{t=1}^{T}[(\mathrm{a}'\mathrm{R}_{\mathrm{Kt}})]^2 - \frac{\left(1+h^{*2}\right)}{R_F{}^2} = 0, \tag{18}$$

$$\frac{1}{T}\sum_{t=1}^{T}\left[\frac{2h_a^*}{R_F} \times \left(\left(R_{MF,t} - R_{Ft}\right) - \left(a + \mathrm{b}'(\mathrm{R}_{\mathrm{K^-t}} - R_{Ft})\right)\right)^2\right] - DISFL_{MF} = 0. \tag{19}$$

Equations (15) to (19) also represent a system of $2K + 2$ moments with $2K + 2$ parameters. The K moments in equations (15) and (16) allow for the estimation of the linear regression in equation (7). Equation (17) is the same as equation (11) and estimates the parameters of $m_{LOPt} = \mathrm{a}'\mathrm{R}_{\mathrm{Kt}}$ by ensuring that it correctly prices the passive portfolio returns. The moment in equation (18) allows the estimation of the maximum Sharpe ratio obtained from the passive portfolios h^*. Following Ferson and Lin (2014), we the compute h_a^* to adjust h^* for the bias investigated by Ferson and Siegel (2003).[7] Finally, using the regression error term $\varepsilon_{MFt} = (R_{MF,t} - R_{Ft}) - (a + \mathrm{b}'(\mathrm{R}_{\mathrm{K^-t}} - R_{Ft}))$ and h_a^*, we obtain the disagreement estimate $DISFL_{MF}$ with the moment specified by equation (19).

To construct a full panel useful for the panel regressions proposed in the next section, we estimate disagreement with the previous systems every quarter by using a rolling estimation window made of the previous 60 monthly observations. Amihud and Goyenko (2013) and others follow a similar strategy to construct their panel data. We check the robustness of the results to this choice by also using a 36-month rolling estimation window. For inferences, we use Newey and West (1987) standard errors to account for the autocorrelation and heteroskedasticity in residuals.

Estimation of the Panel Regressions

To examine the previously stated hypotheses, we run various panel regressions and report the coefficient estimates and their corresponding *t*-statistics, with standard errors clustered by time and by fund. Amihud and Goyenko (2013), Ferson and Lin (2014), Doshi et al. (2015) and many others use similar methodologies.

To test the hypotheses H1 on the relations between future disagreement and fund characteristics, we regress the disagreement estimates on the previously identified characteristics. To test the hypotheses H2 on the relation between future disagreement and active management variables, we add estimates of asset selectivity or active share to some of the previous regressions.

Because disagreement is estimated over 60 months, we use non-overlapping periods of 60 months to form a partial panel for these regressions, similar to Amihud and Goyenko (2013). Specifically, we keep observations from the complete panel for which disagreement is estimated independently, starting with the last available disagreement estimates (December 2016) and moving back in time by leaps of five years. Characteristics and active management variables are as of the end of the year before the beginning of the 60-month estimation period or the last available observation. Hence, we match disagreement estimated for the five-year period ending in December 2016 with data for the explanatory variables in December 2011. We repeat this procedure until the sample beginning, which yields a partial panel that starts with disagreement estimated with data up to December 1991 matched with December 1986 data for the explanatory variables.[8]

In addition to the regression results, we provide visual representations of the relations by using a sorting procedure. Specifically, to obtain further economic insights on our findings for H1 and H2, we categorize funds into deciles based on the average value of their characteristics or active management variables, and examine graphically if average disagreement varies by groups.

Finally, we test hypothesis H3 by regressing net fund flows on lagged values of disagreement estimates and control variables, using all available quarterly observations in the full panel. The net flow for a given quarter is the percentage growth in TNA under management between the beginning and end of the quarter, adjusted for fund return. Lagged disagreement estimates are the estimates for the five-year period ending in the previous quarter. Control variables include three variables similar to those used by Ferson and Lin (2014), namely past performance, measured by the LOP alpha (which uses m_{LOPt} for evaluation), fund return volatility and fund

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[7] They show that the sample maximum Sharpe ratio is biased upward when the number of basis assets (*K*) is large relative to number of observations (*T*). They propose a bias correction to obtain an adjusted maximum Sharpe ratio given by $h_a^* = \sqrt{(h^*)^2\ (T-K-2)/T-K/T}$.

[8] The partial panel has six points in time, so that our results are driven mainly by the cross section of funds and not the time series. Following Amihud and Goyenko (2013), Doshi et al. (2015) and others, we take characteristics and active management variables at the start of the period used for estimating disagreement to check if observable variables are helpful to determine the types of funds the most subject to future disagreement. Our estimation strategy also follows the literature on the relation between characteristics and performance by ignoring the additional error generated from estimating the disagreement measures.

return first-order autocorrelation, plus the most common fund characteristics identified earlier and the tax burden, dividend yield and family size variables.

Data and Summary Statistics

Mutual Funds

This paper uses monthly data on actively managed open-ended U.S. equity mutual funds from the *CRSP Survivor Bias Free US Mutual Fund Database*, for the period from 1984 to 2016. We account for known biases in the CRSP fund database. We start in 1984 because Elton et al. (2001) and Fama and French (2010) show that survivorship bias is problematic in prior years. To deal with back-fill and incubation biases, we eliminate observations before the fund organization date, or funds without a name, with no reported organization date or with TNA inferior to $15 million in the first year of entering the database (Elton et al., 2001, Kacperczyk et al., 2008, and Evans, 2010). To ensure that only actively managed open-ended U.S. equity funds are in our sample, we follow the selection criteria of Kacperczyk et al. (2008) and Chrétien and Kammoun (2017).[9] We obtain a final sample of 2791 funds. Table 1 shows statistics for net-of-expenses monthly fund returns. On average across funds, the mean monthly fund return (net of fees) is 0.75% and the standard deviation is 5.24%. Overall, the sample of fund returns is similar to those in the literature (e.g., Kacperczyk et al., 2008 and Chrétien & Kammoun, 2017).

Passive portfolios

To estimate disagreement, we use three sets of passive portfolios, which allow an examination of the sensitivity of our results. The three sets include the risk-free return (RF) from CRSP. Our main choice follows Chrétien and Kammoun (2017) by using ten industry portfolios from Kenneth R. French's website. The classifications are consumer nondurables (NoDur), consumer durables (Durbl), manufacturing (Manuf), energy (Enrgy), high technology (HiTec), telecommunication (Telcm), shops (Shops), healthcare (Hlth), utilities (Utils) and other sectors (Others). Our second choice uses the same five passive ETFs as Ferson and Lin (2014). Their tickers (underlying indices) are SPY (S&P 500 Index), MDY (S&P Mid Cap 400 Index), IJR (S&P Small Cap 600 Index), QQQ (Nasdaq 100 Index) and IYR (Dow Jones U.S. Real Estate Index), and their returns come from *Morningstar*. Our third choice is the 11 benchmark Vanguard index funds proposed by Berk and van Binsbergen (2015). The tickers (Vanguard names) are VFINX (S&P 500 Index), VEXMX (Extended Market Index), NAESX (Small-Cap Index), VEURX (European Stock Index), VPACX (Pacific Stock Index), VVIAX (Value Index), VBINX (Balanced Index), VEIEX (Emerging Markets Stock Index), VIMSX (Mid-Cap Index), VISGX (Small-Cap Growth Index) and VISVX (Small-Cap Value Index).

[9] Specifically, 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. Then, we exclude index funds identified by the Lipper objective codes SP and SPSP, and funds with a name that includes "index". We also use the database variable "Open to Investors" to exclude funds that are not open-ended. Finally, we keep the funds only if they hold between 80% and 105% in common stocks on average.

Table 1. Summary Statistics for the Mutual Fund Returns

	Mean	StdDev	Min	Max
Mean	0.750	5.237	-19.963	16.388
StdDev	0.306	1.551	5.779	7.766
Max	2.097	16.921	0.000	89.667
99%	1.442	10.364	-4.977	41.579
95%	1.146	8.065	-12.810	32.585
90%	1.050	7.072	-14.433	27.063
75%	0.913	5.895	-16.568	18.581
Median	0.768	4.917	-19.381	14.088
25%	0.625	4.314	-22.874	11.453
10%	0.434	3.870	-26.297	9.970
5%	0.287	3.491	-28.950	9.076
1%	-0.114	1.565	-36.895	5.201
Min	-4.833	0.150	-100.000	0.493

Table 1 presents summary statistics for the monthly returns on 2791 actively managed open-ended U.S. equity mutual funds from January 1984 to December 2016. It 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), and maximum (Max) for the fund returns in percentage. For each fund, we first compute the average, standard deviation, minimum and maximum for its monthly returns. Then, across the 2791 values for each of these statistics, we compute the average, standard deviation and selected percentiles.

The three sets of passive portfolios are hereafter identified as 10I, ETFs and Vanguard. The data for 10I cover the same period as the data for mutual funds, but the data for ETFs and Vanguard start in 2005 and 2003, respectively, instead of 1984. Table 2 presents monthly statistics. The 10I portfolios have mean returns from 0.87% (for consumer durables) to 1.17% (for consumer nondurables), with standard deviations from 3.94% (for utilities) to 6.89% (for high technology). The ETFs have mean returns from 0.70% (for the Nasdaq 100 Index ETF) to 1.06% (for the S&P Mid Cap 400 Index ETF), with standard deviations from 4.16% (for the S&P 500 Index ETF) to 7.28% (for the Nasdaq 100 Index ETF). The Vanguard funds have mean returns from 0.34% (for the Value Index) to 0.99% (for the Extended Market Index), with standard deviations from 2.59% (for the Balanced Index) to 6.78% (for the Emerging Markets Stock Index).

Fund Characteristics, Active Management Variables, and Net Flows

The data for fund characteristics, active management variables, net fund flows and other control variables generally come from the CRSP fund database. Cremers and Petajisto (2009), Amihud and Goyenko (2013) and Ferson and Lin (2014) provide details on their computation.

Table 2. Summary Statistics for the Passive Portfolio Returns

Passive portfolios		Mean	StdDev	Min	Max
10I	NoDur	1.166	4.110	-21.030	14.630
	Durbl	0.869	6.815	-32.630	42.630
	Manuf	1.069	4.932	-27.330	17.510
	Enrgy	1.027	5.380	-18.330	19.030
	HiTec	0.985	6.892	-26.010	20.780
	Telcm	0.997	5.076	-16.220	21.340
	Shpos	1.051	4.902	-28.250	13.280
	Hlth	1.140	4.659	-20.460	16.470
	Utils	0.949	3.942	-12.650	11.720
	Other	0.951	5.165	-23.600	16.420
ETFs	SPY	0.814	4.164	-16.790	10.890
	MDY	1.055	5.021	-21.740	14.820
	IYR	0.987	6.137	-31.200	29.510
	QQQ	0.699	7.275	-26.410	24.980
	IJR	0.956	5.403	-20.190	17.450
Vanguard	VFINX	0.941	4.326	-21.727	13.267
	VEXMX	0.985	5.170	-21.508	15.838
	NAESX	0.874	5.646	-32.203	18.254
	VEURX	0.643	5.055	-21.772	14.048
	VPACX	0.842	4.233	-16.552	10.393
	VVIAX	0.344	5.491	-18.397	20.735
	VBINX	0.667	2.587	-11.593	6.978
	VEIEX	0.664	6.781	-27.667	18.266
	VIMSX	0.896	5.140	-21.927	14.180
	VISGX	0.846	6.005	-22.149	20.996
	VISVX	0.856	5.483	-21.090	19.760
	RF	0.299	0.231	0.000	1.000

Table 2 presents summary statistics for the monthly returns on three sets of passive portfolios. It shows the average (Mean), standard deviation (StdDev), minimum (Min), and maximum (Max) for each passive portfolio. The set 10I includes 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)), with data from January 1984 to December 2016. The set ETFs includes five exchange traded funds (large-cap (SPY), mid-cap (MDY), small-cap (IJR), NASDAQ 100 (QQQ), and Mortgage/Real Estate (IYR)), with data from January 2005 to December 2016. The set Vanguard includes 11 Vanguard index funds (VFINX (S&P 500 Index), VEXMX (Extended Market Index), NAESX (Small-Cap Index), VEURX (European Stock Index), VPACX (Pacific Stock Index), VVIAX (Value Index), VBINX (Balanced Index), VEIEX (Emerging Markets Stock Index), VIMSX (Mid-Cap Index), VISGX (Small-Cap Growth Index) and VISVX (Small-Cap Value Index)), with data from January 2003 to December 2016. All three sets include the risk-free asset (RF) based on the one-month Treasury bill.

Fund characteristics are defined as follows. Expenses are measured by the expense ratio, the fraction of total investment that shareholders pay for the fund's operating expenses. Turnover is the minimum of aggregate sales or aggregate purchases of securities divided by the average twelve-month TNA of the fund. Age is the difference in years between current date and the date the fund was first offered. Manager tenure is the difference in years between the current date and the date when the current manager took control. Size is given by TNAs. The fund expenses components provided by CRSP are management fees, advertising expenses (12b-1) and the costs of bundled services (bundled). Tax burden is the weighted average of the tax rates of investors in different income brackets, where the weights correspond to the declared amounts of dividends and capital gains.[10] Dividend yield is the amount of annual dividends per share paid by the fund, divided by the end-of-year net asset value per share (see Harris et al. (2015)). Family size is the number of funds in the family to which the fund belongs in each quarter.[11] Factor exposures are loadings on size (β_{SMB}), value (β_{HML}), and momentum (β_{UMD}), estimated from regressions of the fund excess returns on the factors over a 60-month window.

Fund styles are determined as in Amihud and Goyienko (2013), who consider nine categories: aggressive growth (AG), equity income (EI), growth (G), long-term growth (LTG), growth and income (GI), mid-cap (MC), micro-cap (MRC), small cap (SC) and maximum capital gains (MCG). The CRSP fund database provides investment objective codes from three sources: Wiesenberger (from 1962 to 1993), Strategic Insight (from 1993 to 1998) and Lipper (since 1998). We assign a fund to one style using the three sources. If no code is available for a period, we assign the style from the previous period. We exclude non-identified funds from the sample.

The active management variables are defined as follows. Asset selectivity is computed as $1 - R^2$, with R^2 estimated by regressing fund returns on the returns of a set of benchmarks, which we assume to be the 10I passive portfolios in our base case. Active share is obtained from *Morningstar* and is equal to $\frac{1}{2}\sum_{i=1}^{N}\left|\omega_{Fund,i} - \omega_{Index,i}\right|$, where $\omega_{Fund,i} - \omega_{Index,i}$ is the deviation of the fund's holdings in stock i from those of its main benchmark index.

Net fund flows are equal to $\left[TNA_{MF,t} - TNA_{MF,t-1}R_{MF,t}\right]/TNA_{MF,t-1}$, where $TNA_{MF,t}$ is the fund TNA at quarter t and $R_{MF,t}$ is the quarterly fund return. Other control variables in the fund flow regressions include lagged values of LOP alpha, estimated using the 10I passive portfolios, fund return volatility VOL, and fund return first-order autocorrelation AR. These variables are computed with a 60-month rolling estimation window ending in the previous quarter.

Table 3 gives quarterly summary statistics for the fund characteristics, active management variables, fund flows and other control variables. The means (across funds and time) for the most common fund characteristics are 1.35% for the expense ratio, 87.22% for the turnover, 13.05 years for fund age, 4.83 years for manager tenure and $1136.94 million for fund size. Fund expense components have means of 0.72% for management fees, 0.43% for advertising expenses and 0.64% for the costs of bundled services. Means for tax burden, dividend yield and family size are 0.020%, 2.10% and 23.6 funds, respectively. Factor exposures have means of 0.38 for size, -0.36 for value and -0.12 for momentum. Means for asset selectivity, active share and net fund flows are 14.44%, 78.23% and -1.10%, respectively.[12] Finally, means for LOP alpha, fund return volatility and fund return autocorrelation are -0.14%, 0.30% and 0.072, respectively.

[10] We thank Clemens Sialm for providing time series of the tax rates on dividends (DIV), short-term capital gains (SCG), and long-term capital gains (LCG). We follow Sialm and Zhang (2020) to compute tax burden.
[11] Following Pollet and Wilson (2008), we treat funds with the same management company name as belonging to the same family of funds.

[12] Active share has a maximum of 211.90%, which is unusually high. It should be below 100% unless a fund has important short selling activities and extreme equity portfolio weights (potentially a sign of derivatives positions). We investigate the data series and find that less than 1% of observations have active share values above 100%. Our results are robust to the exclusion of these observations.

Table 3. Summary Statistics for the Fund Characteristics, Active Management Variables, Net Fund Flows, and Other Control Variables

		Mean	StdDev	Min	Max
Most common fund characteristics	Expenses (%)	1.350	0.970	0.000	102.440
	Turnover (%)	87.220	111.330	0.040	9150.000
	Age (years)	13.053	13.263	0.036	87.460
	Manager tenure (years)	4.834	5.280	0.074	61.910
	Fund size (in millions $)	1136.937	4191.458	0.001	109073.000
Other relevant fund characteristics	Management fees (%)	0.720	0.270	0.000	6.670
	Advertising expenses (%)	0.430	0.400	0.000	1.600
	Bundled (%)	0.640	0.870	0.000	102.440
	Tax burden (%)	0.020	0.020	0.000	1.020
	Dividend yield (%)	2.100	0.760	1.110	4.920
	Family size (number of funds)	23.558	25.309	1.000	112.000
	β_{SMB}	0.378	0.491	-1.322	2.810
	β_{HML}	-0.360	0.585	-4.169	2.624
	β_{UMD}	-0.124	0.282	-1.963	1.403
Active management	Asset selectivity (%)	14.440	13.560	0.060	94.500
	Active share (%)	78.227	13.586	3.141	211.898
	Fund flows (%)	-1.100	21.320	-101.940	3144.950
Other control variables	LOP alpha (%)	-0.140	0.390	-6.650	2.770
	VOL (%)	0.300	0.250	0.000	6.060
	AR	0.072	0.142	-0.477	0.896

Table 3 presents quarterly summary statistics for the fund characteristics, active management variables, net fund flows and other control variables, using data from January 1984 to December 2016. It shows the average (Mean), standard deviation (StdDev), minimum (Min), and maximum (Max) for each variable. The most common characteristics variables include Expenses (the annual expense ratio), Turnover (the minimum of aggregated sales or aggregated purchases of securities divided by the average twelve-month TNA of the fund), Age (the number of years since the fund was first offered), Manager tenure (the number of years since the current manager took control) and Fund size (the TNA in millions $). Other relevant characteristics variables include Management fees, Advertising expenses (12b-1 fees), Bundled (the cost of bundled services), Tax burden (the weighted average of the tax rates of investors in different income brackets, where the weights correspond to the declared amounts of dividends and capital gains), Dividend yield (the annual yield of dividend payments by the fund), Family size (the number of funds in the family to which the fund belongs in each quarter), and the betas β_{SMB}, β_{HML} and β_{UMD} (the factor exposures on size, value and momentum from the Carhart (1997) model). The active management variables are Asset selectivity (computed as $1 - R^2$, with R^2 estimated by regressing fund returns on the returns of a set of benchmarks) and Active share (a measure of the deviations of the fund' stock holdings from those of its main benchmark). The net fund flow variable is Fund Flows (the quarter-to-quarter growth in TNA). Other control variables are LOP alpha (the performance based on the minimum volatility SDF and estimated using ten industry passive portfolios), VOL (the fund return volatility) and AR (the first-order autocorrelation of fund returns). LOP alpha, VOL and AR are estimated with a rolling estimation window made to the previous 60 monthly observations. The unit of measure is given in parentheses.

Empirical Results

This section presents the empirical results. First, we compare the DISCK and DISFL disagreement estimates. Then, we examine their relations with past fund characteristics or active management variables. Finally, we document the impact of investor disagreement on future net fund flows.

Investor Disagreement Estimates

Table 4 reports cross-sectional statistics on the disagreement estimates. The first two columns show results for disagreement estimated every quarter using the 10I passive portfolios and a rolling estimation window made of the previous 60 monthly observations. The DISCK estimates have a mean of 0.881% and a standard deviation of 0.626%, and the DISFL estimates have a mean of 0.889% and a standard deviation of 0.484%. Both means are statistically different from zero. These values are similar to the total disagreement implied by the results of Ferson and Lin (2014) and Chrétien and Kammoun (2017), who use data from 1984 to 2012. The correlation between both measures is high at 0.936, which is expected given that they are closely related, as demonstrated the theoretical section.[13]

To assess robustness to the estimation window length, the third and fourth columns report results for disagreement estimated with a window made of the previous 36 monthly observations. The results are qualitatively similar to those using the 60-month window. Furthermore, when we investigate the relations between disagreement and fund characteristics, active management level and fund flows, we find that the results are robust to this variation in the estimation window.

Finally, to check the sensitivity of our results to the choice of passive portfolios, the last four columns of table 4 give results for disagreement estimated using either the ETFs or Vanguard passive portfolios (and a rolling estimation window of 60 observations). The estimates have lower means when using the alternative sets of passive portfolios, especially when using ETFs. This finding suggests that fund returns are easier to span with ETFs or Vanguard index funds than with industry portfolios.

One likely reason for this difference is that data for ETFs and Vanguard funds start in 2005 and 2003, respectively, instead of 1984 for the 10I portfolios. To nullify the impact of the starting dates, we re-estimate disagreement using the common sample from 2005 to 2016. For the 10I portfolios, we find that the mean DISCK (DISFL) estimate becomes equal to 0.578% (0.678%). The correlations between the different estimates vary from 0.276 to 0.892. Hence, estimated in their common sample, disagreement values are closer, but still show important differences.

[13] We show that when $\overline{h} = \sqrt{2}\, h^*$, the measures are equivalent. Following Chrétien and Kammoun (2017), our estimation sets $\overline{h} = h^* + 0.5$ for the DISCK measure. Hence, the disagreement estimates should be similar when $h^* = 1.21$. However, following Ferson and Lin (2014), we use h_a^* instead of h^* for the DISFL measure. The bias correction in h_a^* increases with K and decreases with T. This implies $h^* > 1.21$ for equivalence, with a value closer to 1.21 when T increases or when K decreases. In the data, the estimated h^* varies according to the set of passive portfolios and period used for estimation. This variation leads to a non-perfect correlation between the disagreement estimates, and empirical results in which the highest estimates can come from either the DISCK or the DISFL measures.

Table 4. Investor Performance Disagreement

	DISCK (10I)	DISFL (10I)	DISCK (10I, 36M)	DISFL (10I, 36M)	DISCK (ETFs)	DISFL (ETFs)	DISCK (Vanguard)	DISFL (Vanguard)
Mean	0.881	0.889	0.908	0.918	0.442	0.461	0.602	0.792
StdDev	0.626	0.484	0.648	0.543	0.336	0.392	0.437	0.631
(t-stat)	(323.06)	(356.33)	(346.55)	(428.57)	(212.96)	(203.58)	(247.17)	(237.12)
Max	8.554	8.254	9.264	11.126	7.194	10.457	9.108	12.571
99%	3.493	2.380	3.563	3.155	1.838	1.805	2.519	3.008
95%	2.028	1.723	2.117	1.853	0.901	0.982	1.281	1.753
90%	1.564	1.504	1.635	1.571	0.723	0.789	0.999	1.356
75%	1.070	0.947	1.105	0.990	0.512	0.628	0.701	0.923
Median	0.708	0.735	0.727	0.737	0.365	0.382	0.499	0.697
25%	0.484	0.637	0.494	0.637	0.269	0.198	0.367	0.452
10%	0.365	0.594	0.372	0.588	0.205	0.092	0.270	0.270
5%	0.314	0.344	0.318	0.343	0.172	0.071	0.218	0.203
1%	0.236	0.318	0.239	0.314	0.08	0.041	0.114	0.100
Min	0.014	0.144	0.012	0.069	0.005	0.000	0.006	0.034

Table 4 shows statistics on the cross-sectional distribution of monthly performance disagreement estimates. DISCK is the disagreement from the best and worst clientele alphas proposed by Chrétien and Kammoun (2017). DISFL is the disagreement from the bound with a traditional alpha proposed by Ferson and Lin (2014). The table provides the mean, standard deviation (StdDev) and selected percentiles of the distributions of the disagreement estimates. It also reports the *t*-statistics (t-stat) on the significance of the mean of the disagreement estimates. In the base cases (columns 'DISCK (10I)' and 'DISFL (10I)'), we estimate disagreement every quarter using ten industry passive portfolios (10I) and a rolling estimation window made to the previous 60 monthly observations. In columns 'DISCK (10I, 36M)' and 'DISFL (10I, 36M)', the rolling estimation window is the previous 36 monthly observations. In columns 'DISCK (ETFs)', 'DISFL (ETFs)', 'DISCK (Vanguard)' and 'DISFL (Vanguard)', the estimates use either the ETF passive portfolios (ETFs) or the Vanguard index fund passive portfolios (Vanguard) (and a rolling estimation window made to the previous 60 monthly observations). The data (see description in tables 1 and 2) cover the period January 1984-December 2016 when using the 10I passive portfolios, January 2005-December 2016 when using the ETFs passive portfolios and January 2003-December 2016 when using the Vanguard passive portfolios. All statistics are in percentage except the t-statistics.

In the rest of the analysis, we rely mainly on disagreement estimated using the 10I portfolios and an estimation window of 60 months. However, given the differences between estimates obtained from different sets of passive portfolios, we also discuss our findings when using ETFs or Vanguard funds. In general, the results are robust to the choice of passive portfolios.

Investor Disagreement and Fund Characteristics

Table 5 study the relations between investor disagreement and past fund characteristics, with panels A and B focusing on the DISCK and DISFL measures, respectively. We consider six models to investigate the impact of characteristics. For each model, we report the coefficient estimate and *t*-statistic associated with each included variable, along with the number of observations and R^2 of the regression. In all models, we find that the results are similar for both disagreement measures.

Our first model considers the most commonly studied determinants of performance, namely expenses, turnover, age, manager tenure and size. The second model replaces expenses with their components (management fees, advertising expenses (12b-1) and the costs of bundled services). The third model replaces turnover with tax burden as suggested by Sialm and Zhang (2020). The fourth model considers dividend yield, family size and factor exposures. The fifth model examines fund styles. The last model includes all characteristics except expenses and turnover.

Table 5 shows that performance disagreement is higher for funds with higher expenses, turnover and age. It is also generally higher for funds with younger managers, although this relation is not robust across models. Positive and negative coefficients on log(Fund Size) and log(Fund Size^2) indicate that investor disagreement is a concave function of fund size (in logarithm). The coefficient values suggest that there is a negative relation between disagreement and size for most funds, except the smallest ones. Disagreement is higher for funds with higher management fees and costs of bundled services. There is some evidence that advertising reduces disagreement, although the negative relation is oftentimes not statistically significant.

There is also evidence of a positive relation between disagreement and tax burden, although the relation loses its statistical significance once dividend yield, family size and factor exposures are included. Funds with higher dividend yields have significantly lower disagreement, supporting the idea that dividends reduce uncertainty in returns. We find a positive relation between disagreement and family size, suggesting that there is family driven heterogeneity among funds that are part of a large family. However, this relation becomes insignificant once style dummies are considered. There is a positive relation between disagreement and exposure to the size factor, but the evidence is mixed for exposures to value and momentum factors. Finally, as expected, disagreement is larger for funds following aggressive styles (micro-cap funds, maximum capital gain funds and small-cap funds, growth funds and mid-cap funds) and smaller for funds following defensive styles (equity income funds and growth and income funds).

To ensure that these results are not specific to disagreement estimated with the 10I passive portfolios, we examine the relations with estimates using either ETFs or Vanguard funds. In results not included, we find that the sign and significance of the relations are mostly the same. We can report only two notable differences. First, tax burden is never statistically significant. Second, the positive relation between disagreement and family size always stays statistically significant.

Table 5. Relations between Future Disagreement and Fund Characteristics

Panel A. DISCK													
		Model (1)		Model (2)		Model (3)		Model (4)		Model (5)		Model (6)	
Expenses		0.2883	(7.41)			0.3875	(14.80)			0.1679	(5.38)		
Turnover		0.0005	(3.54)	0.0003	(1.72)					0.0002	(2.42)		
Log(Age)		0.0007	(2.02)	0.0019	(3.59)	0.0002	(0.50)	0.0033	(5.54)	-0.0006	(-1.53)	0.0037	(5.47)
Log(Manager tenure)		-0.0008	(-3.93)	-0.0006	(-2.54)	-0.0012	(-4.96)	0.0000	(0.22)	-0.0012	(-6.32)	-0.0002	(-0.99)
Log(Fund size)		0.0034	(6.80)	0.0018	(6.54)	0.0026	(6.50)	0.0031	(7.59)	0.0000	(0.16)	0.0010	(3.22)
Log(Fund size^2)		-0.0007	(-5.64)	-0.0004	(-5.07)	-0.0004	(-4.81)	-0.0006	(-6.85)	0.0000	(-0.54)	-0.0002	(-2.78)
Management fees				0.3966	(7.87)			0.5189	(10.66)			0.2934	(5.53)
Advertising expenses				-0.0500	(-2.02)			-0.0173	(-0.63)			-0.0210	(-0.83)
Bundled				0.2518	(2.56)			0.4439	(7.59)			0.3404	(5.55)
Tax burden						1.5639	(2.20)	0.4100	(1.08)			0.2311	(0.93)
Dividend yield								-0.5014	(-9.59)			-1.0102	(-12.61)
log(Family size)								0.0011	(4.72)			0.0003	(1.28)
β_{SMB}								0.0044	(26.35)			0.0060	(16.38)
β_{HML}								-0.0005	(-0.98)			0.0011	(2.38)
β_{UMD}								0.0009	(0.96)			0.0022	(2.48)
Style dummies	AG									0.0064	(7.53)	0.0139	(12.20)
	EI									0.0043	(5.35)	0.0127	(12.10)
	G									0.0087	(12.18)	0.0157	(13.17)
	LTG									0.0071	(8.48)	0.0124	(11.92)
	GI									0.0048	(6.13)	0.0128	(12.34)
	MC									0.0080	(9.80)	0.0140	(13.60)
	MRC									0.0113	(11.45)	0.0141	(12.04)
	SC									0.0093	(11.70)	0.0132	(14.13)
	MCG									0.0096	(11.52)	0.0128	(12.33)
N		6681		4492		5230		3492		6681		3492	
R^2		0.6755		0.7227		0.6706		0.7626		0.7205		0.7929	

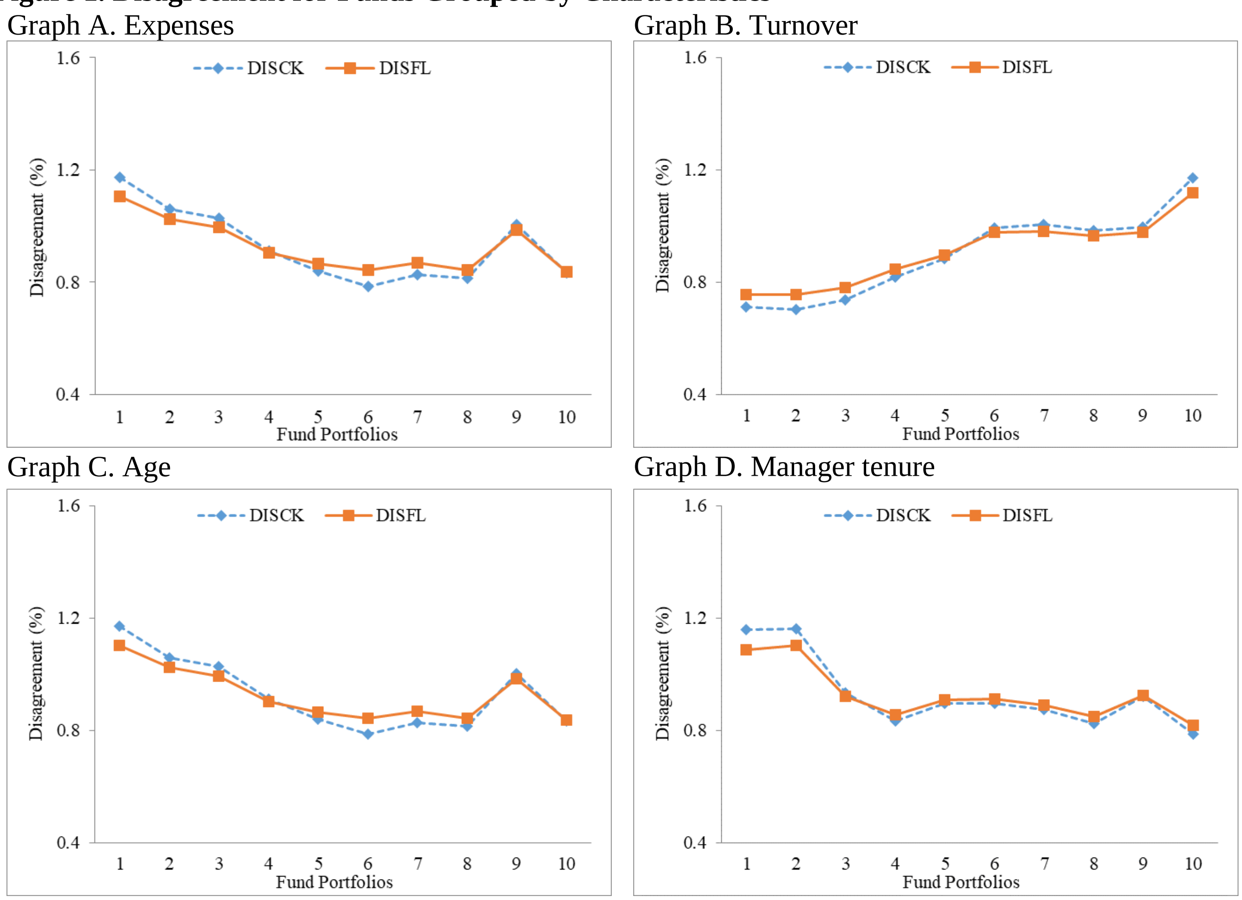
Table 5. Relations between Future Disagreement and Fund Characteristics (continued)

Panel B. DISFL													
		Model (1)		Model (2)		Model (3)		Model (4)		Model (5)		Model (6)	
Expenses		0.2406	(7.11)			0.3332	(17.64)			0.1280	(5.74)		
Turnover		0.0004	(3.45)	0.0002	(1.52)					0.0001	(1.93)		
Log(Age)		0.0016	(5.62)	0.0032	(7.25)	0.0012	(4.23)	0.0032	(5.64)	0.0006	(1.87)	0.0033	(5.46)
Log(Manager tenure)		-0.0005	(-2.65)	-0.0003	(-1.26)	-0.0008	(-4.10)	0.0000	(-0.19)	-0.0008	(-5.30)	-0.0003	(-1.49)
Log(Fund size)		0.0032	(7.51)	0.0016	(6.68)	0.0025	(7.64)	0.0029	(7.03)	0.0001	(0.26)	0.0008	(2.81)
Log(Fund size^2)		-0.0006	(-6.05)	-0.0004	(-5.68)	-0.0004	(-5.51)	-0.0005	(-6.59)	0.0000	(-0.59)	-0.0001	(-2.33)
Management fees				0.3459	(8.17)			0.4732	(10.18)			0.2517	(5.46)
Advertising expenses				-0.0301	(-1.38)			-0.0052	(-0.20)			-0.0084	(-0.35)
Bundled				0.1789	(2.42)			0.3341	(6.83)			0.2299	(5.51)
Tax burden						1.3342	(2.23)	0.4386	(1.35)			0.2690	(1.13)
Dividend yield								-0.4164	(-8.16)			-0.9502	(-10.97)
log(Family size)								0.0010	(4.39)			0.0001	(0.71)
β_{SMB}								0.0041	(24.23)			0.0060	(14.96)
β_{HML}								0.0003	(0.56)			0.0019	(3.63)
β_{UMD}								-0.0024	(-2.34)			-0.0009	(-0.88)
Style dummies	AG									0.0064	(9.63)	0.0146	(12.05)
	EI									0.0043	(6.89)	0.0132	(11.96)
	G									0.0079	(14.87)	0.0163	(12.61)
	LTG									0.0062	(9.48)	0.0132	(12.36)
	GI									0.0046	(7.62)	0.0134	(12.06)
	MC									0.0075	(12.10)	0.0145	(13.38)
	MRC									0.0103	(12.90)	0.0142	(12.47)
	SC									0.0085	(13.81)	0.0134	(14.62)
	MCG									0.0079	(11.73)	0.0135	(12.64)
N		6681		4492		5230		3492		6681		3492	
R^2		0.7458		0.7603		0.7371		0.7960		0.7814		0.8227	

Table 5 shows the results from the panel regressions of the disagreement estimates DISCK (Panel A) and DISFL (Panel B) on lagged fund characteristics. We estimate DISCK and DISFL every quarter using ten industry passive portfolios and a rolling estimation window made of the previous 60 monthly observations. We then use non-overlapping periods of 60 months to form partial panels for the regressions. The fund characteristics are as the end of the year before the beginning of the 60-month estimation period or the last available observation if missing. The fund characteristic variables are defined in table 3, except for the nine style dummy variables, which are AG (aggressive growth), EI (equity income), G (growth), LTG (long-term growth), GI (growth and income), MC (mid-cap), MRC (micro-cap), SC (small cap) and MCG (maximum capital gains). The data cover the period from January 1984 to December 2016. We present the estimated coefficients with their t-statistics in parentheses, and the number of observations (N) and R^2 of the regressions.

Figure 1 illustrates if average disagreement varies by groups by categorizing all funds into deciles based on average values of selected characteristics. Positive slopes for expenses and turnover (see Figures 1a and 1b) and negative slopes for manager tenure and fund size (see Figures 1d and 1e) reinforce the results in table 4 and show that the impact of these characteristics can be economically large. Average disagreement is at least 45% higher for funds in the top versus bottom deciles of expenses (1.23% versus 0.66%) or turnover (1.17% versus 0.71%), or for funds in the bottom versus top deciles of manager tenure (1.16% versus 0.79%) or size (1.08% versus 0.72%). While table 4 documents positive relations between disagreement and fund age, Figure 1c shows U-shape relations in which younger and older funds face more disagreement than middle-aged funds. Flat slopes for tax burden (Figure 1f) and family size (Figure 1h) are consistent with the unreliable significance of these variables in table 4, and the ones for dividend yield (Figure 1g) suggest that its negative relation is significant because other variables are in the regressions.

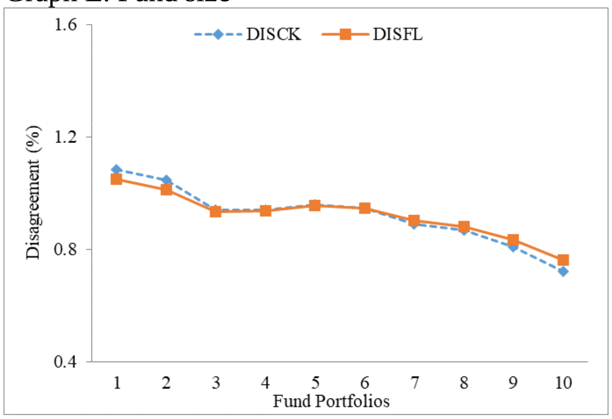
Figure 1. Disagreement for Funds Grouped by Characteristics[14]



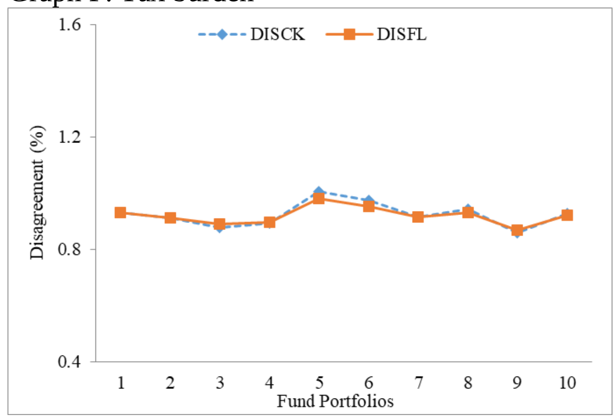
[14] Figure 1 displays the mean monthly DISCK and DISFL disagreement estimates for mutual funds grouped into decile portfolios according to the average value of selected fund characteristics. In graph A, funds are sorted in increasing order of their average expenses. In graph B, funds are sorted in increasing order of their average turnover. In graph C, funds are sorted in increasing order of their average age. In graph D, funds are sorted in increasing order of their average manager tenure. In graph E, funds are sorted in increasing order of their size. In graph F, funds are sorted in increasing order of their average tax burden. In graph G, funds are sorted in increasing order of their average dividend yield. In graph H, funds are sorted in increasing order of their average family size.

Figure 1. Disagreement for Funds Grouped by Characteristics (continued)

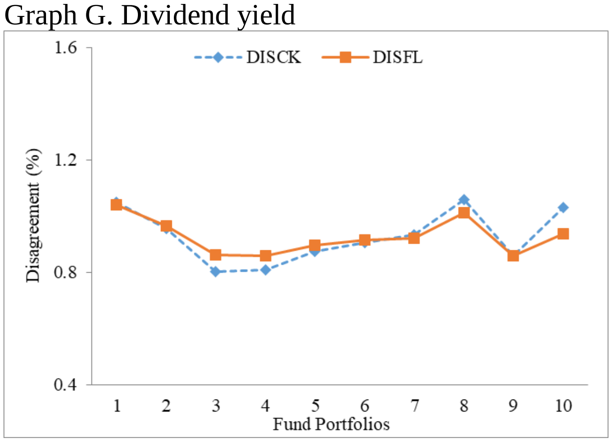
Graph E. Fund size



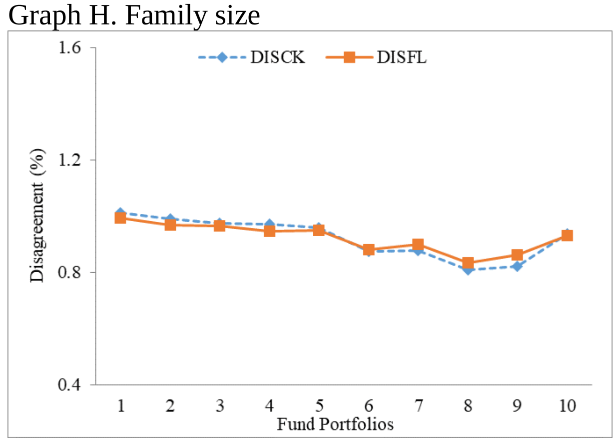
Graph F. Tax burden



Graph G. Dividend yield



Graph H. Family size



In summary, except for manager tenure, results are consistent with the hypotheses developed previously and are robust to different model specifications and sets of passive portfolios. Investor disagreement is significantly related to numerous fund characteristics, which can be used to identify the types of funds that can be subject to large discrepancies in evaluation.

Investor Disagreement and Active Management Variables

Table 6 documents the relations between future investor disagreement and active management variables, controlling for fund characteristics, with panels A and B focusing on the DISCK and DISFL measures, respectively. We consider six regression models. The first three models consider the most commonly studied determinants of performance (as in model 1 of table 5) and add asset selectivity, active share or both. The last three models replace expenses with their components (management fees, advertising expenses (12b-1) and the costs of bundled services), turnover with tax burden, and include dividend yield, family size and factor exposures (as in model 4 of table 5).

Table 6. Relations between Future Disagreement and Active Management Variables

Panel A. DISCK												
	Model (1)		Model (2)		Model (3)		Model (4)		Model (5)		Model (6)	
Expenses	0.1214	(4.62)	0.0544	(2.40)	0.0503	(2.89)						
Turnover	-0.0003	(-1.50)	0.0007	(6.23)	0.0003	(2.66)						
Log(Age)	0.0022	(8.31)	-0.0012	(-5.20)	0.0002	(0.62)	0.0010	(3.40)	0.0011	(3.19)	0.0006	(2.71)
Log(Manager tenure)	-0.0002	(-1.35)	-0.0006	(-4.26)	-0.0002	(-1.57)	0.0000	(0.05)	-0.0001	(-0.65)	-0.0000	(-0.20)
Log(Fund size)	0.0006	(1.29)	-0.0014	(-5.58)	-0.0010	(-4.65)	0.0001	(0.46)	0.0008	(2.91)	-0.0000	(-0.02)
Log(Fund size^2)	-0.0001	(-1.58)	0.0003	(5.08)	0.0002	(4.03)	0.0000	(-0.16)	-0.0001	(-2.49)	-0.0000	(-0.13)
Management fees							0.0740	(1.66)	0.1986	(5.21)	0.0641	(2.77)
Advertising expenses							-0.0215	(-1.18)	0.0025	(0.17)	0.0025	(0.20)
Bundled							0.2310	(4.27)	0.1485	(3.90)	0.0452	(1.78)
Tax burden							0.2637	(1.48)	0.0106	(0.09)	0.0464	(0.60)
Dividend yield							-0.0817	(-2.04)	-0.4310	(-13.36)	-0.1430	(-5.44)
log(Family size)							0.0004	(2.50)	0.0002	(1.82)	-0.0000	(-0.32)
β_{SMB}							0.0027	(10.65)	0.0040	(33.15)	0.0031	(24.12)
β_{HML}							-0.0006	(-1.82)	-0.0016	(-7.68)	-0.0018	(-11.45)
β_{UMD}							-0.0029	(-7.05)	-0.0022	(-6.33)	-0.0037	(-13.98)
Asset selectivity	**0.0279**	**(13.42)**			**0.0157**	**(12.37)**	**0.0278**	**(9.14)**			**0.0159**	**(9.03)**
Active share			**0.0113**	**(22.34)**	**0.0069**	**(11.49)**			**0.0091**	**(15.52)**	**0.0044**	**(5.87)**
N	5360		3412		3216		3492		2661		2661	
R^2	0.8115		0.8730		0.8981		0.8582		0.9115		0.9307	

Table 6. Relations between Future Disagreement and Active Management Variables (continued)

Panel B. DISFL												
	Model (1)		Model (2)		Model (3)		Model (4)		Model (5)		Model (6)	
Expenses	0.1032	(4.93)	0.0417	(2.87)	0.0402	(3.84)						
Turnover	-0.0002	(-1.42)	0.0005	(4.44)	0.0002	(1.86)						
Log(Age)	0.0029	(11.66)	0.0004	(2.02)	0.0010	(3.65)	0.0011	(3.74)	0.0012	(3.45)	0.0008	(3.05)
Log(Manager tenure)	0.0000	(0.23)	-0.0003	(-2.26)	-0.0001	(-0.75)	-0.0001	(-0.44)	-0.0001	(-0.400)	-0.0000	(-0.03)
Log(Fund size)	0.0011	(3.14)	-0.0008	(-3.75)	-0.0006	(-2.76)	0.0003	(1.11)	0.0009	(3.22)	0.0003	(1.28)
Log(Fund size^2)	-0.0002	(-3.43)	0.0002	(3.09)	0.0001	(2.08)	0.0000	(-0.81)	-0.0002	(-2.84)	-0.0001	(-1.30)
Management fees							0.0790	(1.97)	0.1837	(4.83)	0.0726	(2.56)
Advertising expenses							-0.0090	(-0.49)	0.0016	(0.11)	0.0017	(0.12)
Bundled							0.1456	(4.48)	0.1364	(4.14)	0.0510	(2.15)
Tax burden							0.3090	(1.78)	0.0891	(0.74)	0.1187	(1.23)
Dividend yield							-0.0445	(-1.37)	-0.3600	(-11.02)	-0.1220	(-4.06)
log(Family size)							0.0003	(2.26)	0.0002	(1.56)	-0.0000	(-0.12)
β_{SMB}							0.0026	(11.63)	0.0039	(29.07)	0.0031	(21.20)
β_{HML}							0.0001	(0.35)	-0.0011	(-4.92)	-0.0013	(-7.05)
β_{UMD}							-0.0057	(-11.26)	-0.0057	(-14.88)	-0.0070	(-22.28)
Asset selectivity	**0.0216**	**(11.77)**			**0.0100**	**(7.40)**	**0.0246**	**(8.80)**			**0.0131**	**(7.31)**
Active share			**0.0097**	**(22.40)**	**0.0074**	**(11.75)**			**0.0076**	**(13.37)**	**0.0037**	**(5.09)**
N	5360		3412		3216		3492		2661		2661	
R^2	0.8261		0.8713		0.8787		0.8606		0.9154		0.9257	

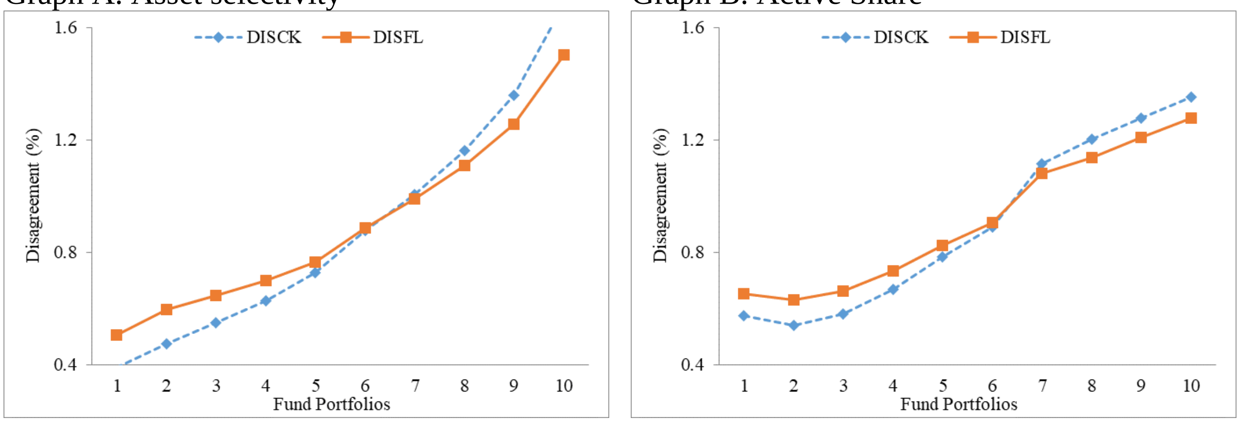
Table 6 shows the results from the panel regressions of the disagreement estimates DISCK (Panel A) and DISFL (Panel B) on lagged active management variables (Asset Selectivity and Active Share, in bold) and fund characteristics. We estimate DISCK and DISFL every quarter using ten industry passive portfolios and a rolling estimation window made of the previous 60 monthly observations. We then use non-overlapping periods of 60 months to form partial panels for the regressions. The active management variables and fund characteristics are as the end of the year before the beginning of the 60-month estimation period or the last available observation if missing. The active management variables and fund characteristics are defined in table 3. The data cover the period from January 1984 to December 2016. We present the estimated coefficients with their t-statistics in parentheses, and the number of observations (N) and R^2 of the regressions.

We expect a positive relation between future disagreement and the level of active management, since taking active risk should not be rewarded similarly by heterogeneous investors. Funds with a higher level of active management differ more from benchmarks. Hence, their returns represent relatively "unique" opportunities to investors because they cannot be spanned easily by passive portfolio returns. This uniqueness allows for greater disagreement. Table 6 confirms positive and statistically significant relations for both asset selectivity and active share across all models and for both disagreement measures.[15] In results not included, we also find that the relations are robust to the choice of passive portfolios. Figure 2 illustrates this positive relation by looking at average disagreement for decile portfolios of funds sorted by asset selectivity (Figure 2a) and active share (Figure 2b). Average disagreement is more than twice as large for funds in the top versus bottom deciles of asset selectivity (1.69% versus 0.39% for DISCK; 1.50% versus 0.51% for DISFL) or active share (1.35% versus 0.57% for DISCK; 1.28% versus 0.65% for DISFL).

Figure 2. Disagreement for Funds Grouped by Active Management Variables[16]

Graph A. Asset selectivity

Graph B. Active Share



Investor Disagreement and Net Fund Flows

Table 7 examines the relation between investor disagreement and future net fund flows to understand the effect of differences in evaluation on the net demands for funds. The regressions include controls for three variables used by Ferson and Lin (2014) as potentially relevant to predict fund flows, namely past performance (captured by the LOP alpha), fund return volatility and fund return first-order autocorrelation. Models 1, 2, and 3 also consider the most common fund characteristics (as in model 1 of table 5) and add the DISCK estimates, the DISFL estimates or both. Models 4, 5 and 6 remove turnover and include tax burden, dividend yield and family size.

[15] Table 6 also shows that results for most characteristics are robust to the inclusion of active management variables, as they are similar to those documented in table 5. Exceptions are turnover (insignificant coefficient in model 1), fund size (disagreement is a convex function of size in models 2 and 3) and the value and momentum factor exposures (significantly negative coefficients in models 4, 5 and 6).

[16] Figure 2 displays the mean monthly DISCK and DISFL disagreement estimates for mutual funds grouped into decile portfolios according to the average value of their active management variables. Funds are sorted in increasing order of their average asset selectivity (graph A) or their average active share (graph B).

Table 7. Relations between Future Net Fund Flows and Disagreement

	Model (1)		Model (2)		Model (3)		Model (4)		Model (5)		Model (6)	
LOP alpha	4.371	(16.11)	4.3845	(16.18)	4.382	(16.29)	4.790	(15.01)	4.813	(15.02)	4.791	(15.02)
DISCK	**1.362**	**(6.80)**			**0.075**	**(0.20)**	**1.032**	**(4.70)**			**0.841**	**(2.13)**
DISFL			**1.6479**	**(7.65)**	**1.577**	**(4.11)**			**1.036**	**(4.87)**	**0.233**	**(0.62)**
Expenses	-0.432	(-2.86)	-0.5142	(-3.39)	-0.514	(-3.39)	-1.480	(-7.71)	-1.471	(-7.66)	-1.485	(-7.72)
Turnover	0.002	(2.35)	0.0019	(2.23)	0.002	(2.23)						
Log(Age)	0.023	(9.09)	0.0216	(8.57)	0.022	(8.69)	0.004	(1.58)	0.004	(1.43)	0.004	(1.54)
Log(Manager	-0.003	(-1.17)	-0.0033	(-1.25)	-0.003	(-1.25)	-0.004	(-1.40)	-0.004	(-1.47)	-0.004	(-1.41)
Log(Fund size)	-0.015	(-13.93)	-0.0157	(-14.21)	-0.016	(-14.09)	-0.020	(-14.43)	-0.020	(-14.48)	-0.020	(-14.43)
VOL	-1.429	(-3.28)	-1.3328	(-3.28)	-1.365	(-3.15)	-1.156	(-2.20)	-0.790	(-1.77)	-1.143	(-2.18)
AR	0.009	(1.64)	0.0118	(2.06)	0.012	(2.04)	0.016	(2.56)	0.017	(2.70)	0.017	(2.59)
Tax burden							4.135	(1.20)	4.236	(1.22)	4.147	(1.21)
Dividend yield							2.195	(10.73)	2.149	(10.49)	2.182	(10.69)
Log (Family size)							0.009	(5.55)	0.009	(5.37)	0.009	(5.51)
N	94255		94255		94255		76719		76719		76719	
R^2	0.0157		0.0159		0.0159		0.0180		0.0180		0.0180	

Table 7 shows the results from the panel regressions of net fund flows on lagged disagreement estimates (DISCK and DISFL, in bold) and control variables. Net fund flows are defined as the quarter-to-quarter growth in TNA in excess of fund returns. Every quarter, we compute net fund flows, estimate DISCK and DISFL using ten industry passive portfolios and a rolling estimation window made of the previous 60 monthly observations, and obtain the control variables. We then form the panels for the regressions by matching fund flows in a quarter with the values for the disagreement estimates and the control variables in the previous quarter. Control variables include fund characteristics (Expenses, Turnover, Age, Fund Size, Tax Burden, Dividend Yield and Family Size) and other control variables (LOP Alpha, VOL and AR) defined in table 3. The data cover the period from January 1984 to December 2016. We present the estimated coefficients with their t-statistics in parentheses, and the number of observations (N) and R^2 of the regressions.

As discussed previously, we predict a positive relation between future net fund flows and disagreement. High disagreement is associated with extreme valuations for a fund. Investors with highly positive alphas should have high demands for the fund, but those with negative alphas cannot sell the fund short and so should have no demand, leading to a positive relation between net fund flows and disagreement. As expected, and consistent with the findings of Ferson and Lin (2014), table 7 documents positive and statistically significant relations for both disagreement measures, when included individually.[17] The coefficients imply economically important relations. When disagreement rises by one standard deviation, net fund flows increase by 0.85% (for DISCK) or 0.80% (for DISFL) over the next quarter. However, when we consider both measures jointly, their significance decreases as they are strongly correlated. In results not included, we find that these relations are robust to the set of passive portfolios.

Conclusion

The vast array of choices in the mutual fund industry is a strong indication that fund providers consider the multiple needs of investors who have different beliefs, constraints and preferences. Because some funds are better "fits" for them, investors are likely to disagree with each other on their evaluation. This paper provides new insights on investor disagreement in equity mutual funds. We develop a theoretical framework that allows for heterogeneity in beliefs and preferences, and use it to highlight the similarities and differences between the strategies of Ferson and Lin (2014) and Chrétien and Kammoun (2017) for measuring disagreement. We then study the relations between disagreement and fund characteristics, active management level and fund flows.

Empirically, we find that funds that are the most subject to disagreement are risky financial products that appear well supported by their organizations. These funds are small with young managers. They tend to follow aggressive and costly active trading strategies, with large deviations from their benchmarks. However, they have a long existence and are part of large fund families. We also find that higher disagreement is associated with higher future net fund flows. High disagreement means that some investors have favorable evaluations, and our results are consistent with such evaluations leading to positive demands. Overall, our empirical findings thus suggest that these somewhat risky financial products could have their dedicated clienteles.

Ferson (2010) and Ferson and Lin (2014) call for more research on investor disagreement and clientele effects in performance evaluation. This paper contributes to the growing evidence on investor heterogeneity and clientele effects in mutual funds by using aggregate measures of disagreement, instead of focusing on specific kinds of clienteles (like individual versus institutional investors, value versus growth investors, taxable versus tax-free investors, etc.). It also shows that disagreement is important for understanding the effects of fund characteristics and investment strategies, and the reasons why money flows into and out of funds.

There are many avenues for future research. For examples, it would be insightful to develop new disagreement measures by using restrictions on heterogeneity based on our understanding of specific kinds of clienteles. Also it would be important to investigate the particular roles of heterogeneity in beliefs, preferences and constraints in generating aggregate disagreement. Finally, it would be interesting to adapt existing fund performance analyses to study disagreement, like whether disagreement is persistent and exploitable in an investment strategy.

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[17] Table 7 also finds that future net flows are positively related to past performance, turnover, age, fund return autocorrelation, dividend yield and family size, and negatively related to expenses, fund size and fund return volatility. Hence, money tends to flow into funds for which there is a large disagreement and that have high past performance, low expenses, high turnover, low volatility, high autocorrelation and high dividend yield, that are older and smaller, and that belong to a large family.

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