How Fast Do Investors Learn?
Asset Management Investors and Bayesian Learning

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ABSTRACT

We study how fast investors learn about manager skills by examining the speed at which their disagreement converges. Using a novel measure of disagreement, we find that hedge fund investors learn as fast as suggested by Bayes' rule. However, we also find mutual fund investors learn much more slowly than Bayes' rule. Mutual fund investors' slow learning is not caused by investors potentially paying attention to different performance measures, institutional frictions such as loads, or lack of sophistication, but is likely due to a low payoff from learning. Our results suggest learning speed depends on the motivation of financial participants.

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I. Introduction

One difficulty all financial market participants face when making decisions is uncertainty. How investors resolve uncertainty through learning has important implications as it is an essential building block for several theoretical models in a variety of settings. For example, Pastor and Veronesi (2003, 2006) find that learning can explain why higher growth rate uncertainty leads to higher stock prices. Timmerman (1983), Brennan and Xia (2001), and Xia (2001) show that learning by investors can explain why stocks are more volatile than their underlying dividends. In the asset management industry, Berk and Green (2004) assume that mutual fund investors learn about manager skill from past fund performance, which explains why fund flows chase past returns. These models generally assume that investors learn following Bayes' rule. However, little work examines the speed at which financial market participants learn.

Thus, in this paper, we empirically study how quickly learning occurs in the asset management industry. Specifically, we examine how rapidly investors' disagreement about a fund manager's skill converges over time. Investors could have different priors about the skill of a manager; however, as they receive common new information and update their beliefs, their opinions about the skill of a manager should gradually converge. Thus, examining how quickly disagreement declines allows us to draw inferences about how fast investors learn about uncertain financial parameters.

Our novel measure of disagreement is based on fund investor flows. We measure disagreement as the minimum of inflows and outflows. The logic is similar to using trading volume as a proxy for disagreement in the stock market, which measures the minimum of potential buy and sell orders.[1] Money flows likely reflect investors' opinion about the fund. If investors agree

[1] For example, see Harris and Raviv (1993), Kandel and Pearson (1995), and Odean (1998).

that a manager has skill (i.e. is a good manager), we should observe high levels of inflows, but almost no outflows. If investors agree that a manager does not have skill (i.e. is a bad manager), we should observe high levels of outflows, but almost no inflows. If investors disagree about the skill of a manager, we should observe high levels of both inflows and outflows. Thus, the larger the minimum of these two values, the more disagreement there is about manager skill. To validate our measure, we show that index funds, whose performance depends less on manager skill, have lower investor disagreement than active funds.[2]

We then compare the learning speed implied by our disagreement measure against the learning speed implied by Bayes' rule. One well-known fact about Bayes' rule is the impact of new information on investors' beliefs decreases exponentially over time. In other words, the rate of convergence in beliefs has a convex shape with respect to time: The marginal impact of one piece of new information on investor belief is the highest when funds are brand new, and the change of belief with respect to new information goes down over time. This implies our disagreement measure should have a convex shape with respect to time as well.[3]

However, we find that mutual fund investors learn much slower as compared to Bayes' rule. In fact, there is almost no decline in disagreement for mutual fund investors even after observing a decade's worth of performance. In contrast, we find that hedge fund investors learn at approximately the speed of Bayes' Rule, even though learning in this environment should be more difficult given the lower disclosure requirements for hedge funds. These conflicting results suggest

[2] Although managing index funds does not require stock selection skills, index funds can still differ in tracking errors and liquidity management abilities. Thus investors still need to learn about these factors when selecting index funds.

[3] We are not suggesting that flows are only related to disagreement about manager skill as clearly some flows will be due to liquidity needs and so forth. Our assumption is that inflows and outflows due to liquid needs do not go up with fund age to cancel the effect of learning.

that learning speed may depend on the particular investors involved in the financial decisions as well as the conditions of the financial market they are involved in.

For example, learning may be dependent on factors such as investors' sophistication, information availability, and the incentive to learn. To understand how these different factors affect learning, we examine the potential reasons mutual fund investors learn at a much slower pace than what is suggested by Bayes' rule. The first potential explanation is different interpretation of common information. Although mutual fund investors all observe past fund returns, they may not evaluate a fund using the same risk-adjusted performance measure. For example, if a mutual fund manager appears skilled based on her excess style returns but not her four-factor alpha, this could lead to slow learning and persistent disagreement. However, we find that funds with similar performance profiles across various performance measures have the same speed in the decline of disagreement as those whose performance measures disagree.[4]

Another potential explanation is that front and rear loads could impact learning speed. Loads impose a hurdle to invest and divest in a fund, which could lead to less interest in learning about it. Loads also impact our measure since it impacts inflows and outflows. However, we also find no difference in the speed of learning for load and no-load funds. [5] A third explanation is that, on average, mutual fund investors could learn slowly because many mutual fund investors are unsophisticated retail investors. However, we find that funds with larger average account sizes (i.e. more institutional investor dominated funds) provide a similar empirical estimate of learning speed compared to other funds.

[4] In untabulated results, we show that funds' past factor loadings are highly predictive of future loadings. Thus, a lack of learning is also not from investors observing unstable factor loadings.
[5] Loads do affect the level of disagreement, as funds with higher loads tend to have lower inflow and outflows. However, our paper focuses on how fast disagreement goes down with fund ages as a measure of learning, and we find the slope of the disagreement-age curve does not depend on loads.

Another possible way we can detect that mutual fund investors learn about manager skill is by looking at manager changes. At the point of a manager change, the past performance information is not as useful at predicting future skill. Thus, when we observe a change in manager, we should find a jump in disagreement since now there is more uncertainly about future returns. However, we do not find any change in our disagreement measure around manager changes. This suggests that mutual fund investors are not attentive in terms of monitoring their manager and therefore is more evidence that they do not learn about manager skill.

Finally, we examine whether this inattention by mutual fund investors is rational. Although lack of attention suggests a limitation on investors' cognitive ability, investors can still be bounded rational in the sense that they allocate attention to learning about the most value relevant information (Sims (2003), Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016)). In other words, investors will only spend time learning if the effort from learning will be rewarding. We find that, if hedge fund investors invest in the best performing funds based on all historical excess returns compared to the funds with the lowest, they will outperform by 3% per year which is statistically significant.[6] Thus, hedge fund investors spending resources learning is efficient. However, we find that mutual fund investors enjoy no significant performance advantage by investing in the best performing funds rather than the worst performing. Thus, mutual fund investors not learning is rational since learning is not valuable. This could explain why mutual fund investors have poor monitoring – the monitoring is not useful and therefore investors do not put forth effort.

[6] Note this analysis is different than the traditional hedge fund performance persistence test (e.g., Agarwal and Naik (2000) and Baquero, Horst, and Verbeek (2005)). We rank funds by total historical performance t-values rather than just looking at fund performance over the last quarter or last year.

We have performed a number of additional tests as well. For example, we may detect slow learning by mutual fund investors due to consistent contributions to tax-deferred retirement accounts. However, if we split our sample in half by the autocorrelation of inflows, which should be a symptom of these types of contributions, we find similar results. We also examine the impact of return history on learning. If hedge fund investors are learning via Bayes' Rule, we should find that funds with similar standard errors at a point in time but with different return history paths should have the same level of disagreement. Indeed, when we split funds into two groups – one where the standard deviation of returns is higher in the first half of their return series and a second where the opposite occurs – we find no difference between the two groups.[7]

Overall, our results demonstrate that investors can learn as implied by Bayes' Rule, which is assumed by most financial theories based on learning. However, we find that learning depends on whether learning provides value to market participants. In the hedge fund industry, where monitoring is valuable, we find that investors learn via Bayes' rule. However, mutual fund investors learn much more slowly. In fact, after more than a decade, almost no learning has taken place. We find this slow learning is likely due to inattention, which is rational since learning about the skill of a mutual fund manager is not valuable for investors. Thus, assuming that investors learn about parameter uncertainty is only valid when it is clear learning is valuable.

Our findings also have specific implications for the mutual fund industry. Prior research has disagreed about whether mutual fund managers are skilled. Berk and Green (2004) suggest that mutual fund performance is not persistent due to learning about manager skill whereas Fama and French (2010) argue that only a very small percentage of mutual fund managers are skilled.

[7] We perform other robustness checks which are reported later in the paper.

Our findings are consistent with a lack of skill in the industry. Investors learn extremely slowly about performance but yet past performance is uninformative about future performance. This suggests outperformance over time periods is due to luck rather than skill.[8]

Our paper is related to two other papers in the mutual fund space. Both Huang, Wei and Yan (2012) and Choi, Kahrman, and Mukherjee (2016) examine mutual fund investors and learning. Generally, our results are consistent as both papers find that mutual fund investors learn as we do. However, our paper differs from the existing ones in several aspects. First, we focus on the convergence of different opinions as evidence of learning rather than net-flow-performance sensitivity. While documenting investors allocating more capital to past winners is consistent with learning, return-chasing behavior can also be attributed to behavioral biases (Frazzini and Lamont (2008), Bailey, Kumar, and Ng (2011)). Our measure offers an alternative test on whether investors learn, which cannot be captured by net flow.[9] Second, in addition to studying whether mutual fund investors learn, we also examine the speed at which they learn. We find that learning occurs, but mutual fund investors learn very slowly as compared to Bayes' Rule. Finally, our paper also evaluates learning of hedge funds investors and compares that to mutual fund investors.

This paper is structured as follows. Section II describes the data used in our study. Section III defines our disagreement measure and provides some summary information about our measure. Next, Section IV compares the decline in disagreement with the precision in skill measures for both hedge fund and mutual fund investors. Next, Section V examines factors that may impact learning speed while Section VI contains concluding comments.

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[8] Fama and French (2010) argue that only 5% of managers are skilled. This estimate would suggest that investors should not invest significant resources in trying to identify skilled managers, consistent with our findings.
[9] Net flows hide important information about the underlying agreement of investors. While two funds may have 10% net flows, whether or not this occurs with 10% inflows and 0% outflows or 40% inflows and 30% outflows is informative about learning. Our measure captures these differences.

II. Data

We use a variety of data sources in this study. For mutual funds, we begin with the CRSP Survivorship Bias Free Mutual Fund database. As with prior mutual fund studies, we retain portfolios whose funds have an equity related style code in CRSP as well as at least 50% of their portfolios invested in equities, valid data for the prior year's December return and net asset fields, turnover, and expenses.[10] Since the style codes we use start in 1991, we only use data prior from CRSP starting in 1991. We then match these funds to their NSAR filings on the SEC's EDGAR website. Since funds are required to file NSAR documents twice per year, we match our fund list against NSARs with an end date in the first half of the year and NSARs with an end date in the second half of the year. NSAR filings are not made based on the calendar year. Rather NSAR disclosures are made as of the halfway point and end of the fiscal year.

Because prior research finds a large amount of errors on the NSAR documents (e.g. Christoffersen et al. (2013), Cashman et al. (2014)), we remove a match if the difference between its NSAR and CRSP net assets is larger than 10%. In a majority of cases, we believe the match is correct, but exclude these data out in an abundance of caution. Across time, the quality of our matching does vary somewhat, although our lowest post-filter match rate is still approximately 87% while our highest post-filter match rate is 94%. Thus, we are able to match a super majority of funds and our sample should be free of any selection bias.

Most of the data used in this study come from the CRSP mutual fund database. However, the advantage of the NSAR filings is that they contain information on the actual dollar inflows and outflows (Question #28) into the fund. This allows us to directly observe the outside demand for

[10] The list of codes we include are: LIPPER_OBJ_CD = "BM", ”CA", "CG", "CS", "EI", "EMN", "FS", “G", "GI", "H", "LSE", "MC", "MR", "S", "SG", "SP", "TK", "TL", "UT", and "GNR" or si_obj_cd = "AGG", "ENV", "FIN", "GMC", "GRI", "GRO", "HLT", "ING", "NTR", "SCG", "SEC", "TEC" or "UTI".

the fund as well as the number of inside investors that left the fund. These data are reported on a monthly basis. Our sample period for the mutual fund analysis is from 1996 to 2014.

For our hedge fund data, we use three sources of data. The first is SEC Form D. Form Ds include several descriptive items, including the name of the issuer, the fund entity type, the types of exemptions claimed, the date of first sale, the minimum investment amount, the total number of investors, and the cumulative amount sold (to all investors, not just U.S. investors). The investor and sales number represent the total history instead of current numbers, such as assets under management (AUM) or current number of investors. Thus, using consecutive filings, we can compute the amount of inflows as the difference between total historical sales from time t and t-1.[11]

We collected the electronic forms from the SEC's website over the January 2009 to June 2016 period. Scanned forms from January to March 2009 were added to our registry to complete the 2009 calendar year. To identify hedge funds, we focus on Form Ds indicating that the offering is within the "pooled investment fund" industry group, with subcategory defined as either "hedge fund" or "other investment fund."

We then match Form D hedge funds to two commercial hedge fund databases - TASS and HFR.[12] We use the February 2016 version of the TASS database, which has 20,069 funds, and the February 2016 version of the HFR database, which has 23,396 funds. Both databases contain live and defunct funds since 1994, which eliminates survivorship bias after that date. Funds that are common to both databases are identified using fund names, with characteristic data defaulting to HFR. The final database consists of 34,078 individual funds.

[11] Jorion and Schwarz (2017) are the first to use Form D to estimate hedge fund flows.
[12] These are widely used databases, as in Ackermann et al. (1999), Liang (2000), Agarwal et al. (2000).

We match funds by fund names. Most of these funds are not in our Form D sample for two reasons. First, most are unavailable since our Form D sample starts in 2009 rather than 1994 like our commercial databases. The second reason is that Form D contains all hedge funds that have at least one external U.S. investor. We match a total of 20,225 Form Ds (22%) to HFR and TASS, related to 4,349 different funds (15%). This coverage is rather low in terms of percentages, even though this is still a large sample of funds.[13] Since we can estimate net flows from commercial databases and have inflow information from the Form D filings, we can also compute outflows for our hedge fund sample (inflows minus net flows). Unlike mutual fund flows which are available on an intra-year basis, our estimates of hedge fund flows are annual.

In summary, we have inflows and outflows for both mutual funds and hedge funds, although we only have annual flows for hedge funds over a shorter time period. In the next section, we describe how we use these data to compute our disagreement measures.

III. Investor Disagreement Measures

We use the inflow and outflow data to construct our measure of disagreement using the following logic. If all investors believe a manager has skill, then we should see many investors buy the fund while no existing investors leave the fund. In other words, we should observe high levels of inflows and almost no outflows. On the other hand, we should observe the opposite if investors believe that a manager does not have skill. Existing investors will leave the fund while no new investors will want to enter the fund. This will lead to high levels of outflows and almost

[13] While we do not match all funds in our commercial databases to a Form D, our match rate is higher than many studies that link commercial database funds to other sources. For example, Aiken et al. (2013) use a sample of approximately 1,500 hedge funds to infer biases about hedge fund returns. Brown et al. (2012) draw conclusions regarding operational risk on approximately 500 hedge funds. In our case, we have close to 4,500 funds (34%) in our linked sample.

no inflows. However, if investors disagree about the skill level of the manager, then we should see investors who think the manager is skilled entering the fund while those who believe the manager is not skilled leaving the fund.

Thus, if investors agree about the skill level of the manager, either inflows or outflows will be close to zero, while if investors disagree, both inflows and outflows will not be close to zero. Our measure of investor disagreement about skill is therefore:

$$IDAS = \frac{MIN(Inflows, Outflows)}{NetAssets}$$

Consistent with the above logic, the more investors disagree about the skill of the manager, the higher IDAS will be.[14] In Table I, we present summary statistics about the IDAS measure for both our mutual fund (Panel A) and hedge fund samples (Panel B) samples. As with IDAS, inflows, outflows, and net flows are indexed by prior month net assets.

<Insert Table I about here>

First looking at the mutual fund IDAS measure, IDAS is right skewed as the average value each year is greater than the median value. In fact, in many years, the 75% percentile and mean are fairly close in value. This is unsurprising given the variable is bounded at zero. The IDAS measure does decline slightly across time; however, the median value in 2014 is close to the median values at the beginning of the sample period.

[14] Our measure assumes that disagreement in investors' prior belief exists, and learning help the disagreement converge. It differs from the mutual fund net flow measure used by Huang, Wei and Yan (2012) to describe the learning behavior of a representative agent.

In Panel B, we see the hedge fund IDAS at first glance is much higher than the mutual fund IDAS measure. However, the mutual fund measure is on a monthly basis while the hedge fund measure is on an annual basis. Thus, as one would expect, hedge funds appear to have slightly less inflows and outflows than mutual funds, although the difference is not very large (24% annualized for mutual funds versus 17% for hedge funds). Otherwise, the measure appears similar in terms of its distributional properties for mutual funds and hedge funds.

While our measure seems like a logical measure of disagreement, there are many reasons investors may make investment or redemption decisions, especially in the mutual fund industry. For example, some investors may simply be investing in a fund for exposure to a particular asset class. Brokers may be pushing a particular fund to their clients. In terms of outflows, investors may leave a fund due to liquidity needs or tax considerations. They may also not leave a fund due to the disposition effect (e.g., Odean (1998)). Therefore, before we use our measure, we validate that our measure is related to investor disagreement about manager skill by examining two specific situations with our mutual fund sample.[15]

First, if our measure is related to investor disagreement about manager skill, then we should see that IDAS is related to extreme returns in the subsequent period. In other words, high levels of disagreement should be for those funds that ex-ante are expected to have high return uncertainty and thus high likelihood of extreme performance. To examine this relation between IDAS and returns, we rank funds by return within their style in quarter t and split the funds into deciles. We then calculate the average IDAS value as well as the average net flow in the prior quarter. In Table II Panel A, we report the average values for the ten deciles.

[15] A third test is simply that our measure is highest for the youngest funds in our sample. We find this is the case as is reported in the next section.

<Insert Table II about here>

We find that IDAS is highest for the lowest and highest performance deciles, which is consistent with IDAS being correlated with investor disagreement about manager skill. Interestingly, net flows cannot predict future extreme performance by mutual funds as net flows are very similar for all ten deciles. This again documents that our measure contains distinct information from net flows.

A second test to validate IDAS as a measure of investor disagreement about manager skill is to examine IDAS levels for active managed mutual funds and passive index mutual funds. It is arguable that index funds are more affected by asset allocation decisions and investor liquidity needs than active funds. Thus, if disagreement is solely due to portfolio rebalancing or liquidity needs, we should observe a higher disagreement for index funds than active fund. However, if our measure is mainly driven by investor disagreement about manager skill, we could see that index funds have lower levels of IDAS as compared to active funds. To control for potential size and age differences, we sort funds into deciles based on size and age and compare active and passive funds within the same deciles. These results are reported in Panel B of Table II.

We find that index funds have lower levels of IDAS than active funds.[16] When examining funds by size, we find that index funds consistently have lower IDAS. These differences are smaller for the very largest funds; however, this is to be expected since large active funds likely more public information about manager skill, either through living for a long time or a lot of

[16] These differences are significant at the 1% level. If investors are using mutual funds as either timing or sector bets, it is much more likely they will do so with index funds. Thus, other flow factors such as liquidity are likely higher for index funds and thus these differences underreport the amount of skill disagreement.

monitoring by current investors, which should lead to lower disagreement. We find that IDAS is very consistent across fund size. Thus, our measure is not driven by either small or large funds.

We find similar results when examining funds by age deciles. Index funds' IDAS declines much more quickly than active funds' IDAS. Since investors in index funds only need to learn about such parameters as the funds' tracking error and fees, it is easier for index fund investors to learn. Active fund investors also have to learn about skill, which is more difficult. Thus, as expected their IDASs decline much more slowly. In summary, these results validate that our IDAS measure captures disagreement by investors concerning manager skills.

IV. Investor Learning and Precision of Skill Estimates

In this section we examine how the speed of investor learning compares to the speed at which the precision of manager skill estimates increases. To measure the speed of learning, we use the rate at which disagreement of investors declines as the fund ages. To then benchmark how fast we would expect investors to learn based on Bayes' rule, we calculate how quickly the precision of manager skill estimates improve. If investors are Bayesian learning, we should see that disagreement and precision change with the same shape.[17]

To evaluate skill, we use four measures. The first is the Carhart (1997) four factor alpha model, which is commonly used in the mutual fund literature. The second is the one factor model that only includes the excess market return. As Bayesian theories assume that investors consider all past information, we use all of the returns prior to the current month to estimate the fund's

[17] Since we know that flows, especially with mutual funds, have non-skill disagreement components we would not expected our measure to decline to zero. However, we should expect IDAS to decline with the same shape and speed as the decline in the precision of our skill measures.

alpha. We also include two return-based measures, which may be used by the retail investors typical of mutual funds. The first simply uses the raw returns of the fund while the second uses style adjusted returns.[18] To measure the precision of the investors' signal about manager skill, we calculate the standard error of these four performance measures. We focus on standard errors rather than the mean or t-value as the precision of the signal depends on the dispersion, not location.

To begin our analysis, each month, we double sort funds by age and size. For the age sorts, the first decile consists of funds from zero to three years old. We then create eight more groups with each group including the subsequent three years of fund ages. The last group, which does not contain many observations, contains funds that are older than 27 years. With each age group, to control for the fact that age is highly correlated with size, we double sort funds into deciles based on size and age. We first compute the average IDAS as well as the average standard error of all of our four performance measures each period for each group. We then compute averages for the age deciles across the size deciles, and finally across time.

We report these averages in Table III. In Panel A, we report results of our alpha based measures whereas in Panel B we report results of our return-based measures. In addition to reporting the averages of each group, we also report the cumulative decline in the measure as compared to the youngest age group.

<Insert Table III about here>

Overall, we see that the precision of manager skill estimates increases much faster than the disagreement of investors declines. For example, by the time a fund is 16 to 18 years old, the

[18] In untabulated results we also examine the standard error of funds' performance ranking within style, which is used in prior research like Sirri and Tufano (1998). Those results are similar to the return based results reported.

standard errors of the four performance measures declines by at least 93% whereas the IDAS measure only declines by 9%. This disparity between the rate of declines can been seen clearly in Figure 1.

<Insert Figure 1 about here>

While the standard error of the four-factor alpha decreases quickly, IDAS does not begin to decline significantly until the funds are almost 20 years old. The decline of IDAS and standard errors begin to converge at that point, with funds older than 27 years have larger declines in IDAS. Given there is little new information gained from year ten onward, the late rate of decline in IDAS implies it takes investors an extended period of time to learn about manager skill.[19]

We then examine IDAS in the context of hedge funds. We perform a similar analysis with a few small adjustments due to our smaller sample of hedge fund data. We have smaller age bins since hedge funds die quicker than mutual funds. We also use quintiles instead of deciles when sorting by size. We also only look at return based measures of skill since other models have a long return series requirement. As with mutual funds we should see a similar shape in our curves of IDAS and precision of manager skill estimates. We report results in Table IV.

<Insert Table IV about here>

[19] Learning may accelerate at a certain point in time due to an information cascade event (Bikhchandani et al. (1992)). For example, investors could finally give up on a manager after finally observing enough other investors leaving the fund.

Unlike mutual funds, we find that IDAS quickly declines in the hedge fund industry. The decline is much faster when the funds are younger than when the funds are older. In fact, while mutual funds have almost no decline in IDAS by the time they reach 10 years of age, hedge fund disagreement and standard errors have declined by almost the same about by age 10. To see how similar the curves are, we plot the IDAS and skill precision curves in Figure 2.

<Insert Figure 2 about here>

As seen in Table IV, the decline in IDAS and skill estimation error are very similar, indicating hedge fund investors are learning consistent with Bayes' Rule.

As a further validation, we check whether hedge fund investors' learning is path dependent or not. One aspect of Bayes' rule is that the path of returns does not impact learning at a particular moment in time. In other words, if two funds have the same standard error at a particular moment in time, regardless of the path returns took to get there, the disagreement values for the two funds should match. To test this, we split our sample of hedge funds each period into those funds where the first half of the return series has higher volatility than the second half and vice versa. If investors are truly learning via Bayes' Rule, we should see that both groups have similar values. We plot the curves in Figure 3.

<Insert Figure 3 about here>

We find the learning speed is similar for both hedge fund investors regardless of the return path. which is consistent with Bayes' Rule.

To examine the difference in decline rates cross-sectionally, we examine the difference between the decline in disagreement and the decline in the standard errors of our performance measures. We first compute the average IDAS and standard error for each fund each year of its life. We then compute the cumulative decline from the first year of data for the fund in our sample to the current year for both our measures as a percentage of the original values. We then find the difference between these declines and use this value as the dependent variable in a regression. We make two adjustments to this measure. Since we may not observe the first year of data for a fund, we adjust our differences by the average amount of decline in either the IDAS, standard error, or both variables in our sample observed up until the fund is that age.[20,21] The second adjustment we make is we assume a 100% decline in disagreement for mutual funds occurs when IDAS declines by 58% of the original value. This matches the total decline we observe for mutual funds in the data.[22]

The independent variables of interest are fund age in Panel A and then two dummy variables – *Young Fund* and *Middle Age Fund* – in Panel B. For mutual funds (hedge funds), a young fund is less than nine (six) years old and a middle aged fund is between nine (six) and 20 (15) years old. We also include a number of other fund characteristics as controls, such as the fund's net assets, expense ratio, and turnover. We also include the average IDAS for funds in the

[20] This adjustment is necessary because the expected change in our disagreement and standard error measures are dependent on the age of the fund. For example, IDAS may decline more from age one to two should decline by a large amount whereas the decline from 29 to 30 years of age should be very small.

[21] In untabulated results, we performed a number of robustness checks. First, we use funds that started only after 1996 since we have their entire IDAS and return history from birth until death or the end of our sample. Those results are statistically and economically similar to before. We also compare dead and live mutual funds and again find economically similar results. We examine results by style and again find consistent results across styles. Finally, we split out sample by funds with high autocorrelation and low autocorrelation of inflows. This is to test for whether funds that may have consistent inflows from retirement contributes drive our result. However, we again find no difference between groups.

[22] As mentioned previously, we would not expect our measure of disagreement to decline to zero since some inflows and outflows for mutual funds are driven by other factors such as liquidity.

same style and funds in the same management company. We include style and time dummies and cluster standard errors by fund. Results are reported in Table V.

<Insert Table V about here>

The regressions results are similar to the univariate results. We find that the difference between disagreement and standard error decline for mutual funds is largest for young funds and is still statistically larger for middle aged funds than old funds. Thus, this quantifies the slow learning we observe with the prior tables for mutual funds. However, we do not see the same relation for hedge funds. For hedge funds, we do not observe any significant difference between the decline rates, which is again consistent with our prior results.

Overall, we find that hedge fund investors learn as quickly as implied by Bayes' Rule, but mutual fund investors do not. In the next session, we investigate factors that may impact learning speed.

V. Factors that May Impact Investor Learning Speed

In the prior section, we find that investors learn slowly compared to Bayes' rule in the mutual fund industry whereas results in the hedge fund industry are consistent with Bayes' Rule. The question becomes why in the mutual fund industry investors learn slowly relatively to both hedge fund investors and Bayes' Rule. In this section, we investigate some potential reasons that learning could be impeded.

A. Use of Performance Measures

Regardless of which performance measure we examine, mutual fund investors exhibit non-Bayesian learning. One possible reason is that investors use different performance measures to determine skill. For example, some investors may use the one-factor alpha as their skill measure while other investors may use Sharpe ratio as their measure of skill (e.g., Barber et al. (2016)). If these measures paint a different picture, then this could lead to a high level of persistent disagreement by investors. On the other hand, if all measures suggest the same skill level, then the use of different performance measures by investors cannot explain our results.

To examine this possibility, we examine the consistency of three performance measures: the fund's one-factor, four-factor, and Sharpe ratio. Each period, we standardize these measures to a distribution with a mean of zero and standard deviation of one. We then group funds into one of six groups based on the value of the standardized performance measure: greater than 1.96, between 1 and 1.96, between 0 and 1, between -1 and 0, between -1.96 and -1, and finally less than -1.96.[23] We then split funds into two groups. If a fund has all three performance measures within the same group, we label our *Inconsistent* variable as zero and if the performance measures fall into different groups assign one to *Inconsistent*.

We first examine the relation between IDAS decline and standard error decline using our univariate analysis. We graph the IDAS and standard error of the four-factor alpha for both groups in Figure 4.

<Insert Figure 4 about here>

[23] We get similar results using fewer and more splits.

Even if all performance measures provide the same general performance profile for the fund, it appears that the learning speed is still much slower than Bayes' rule would indicate. In fact, there is little difference between the curves of funds with consistent and inconsistent performance measures.

We formally test whether the learning speed between the two groups are statistically different in Table VI. We use the same empirical framework as Table V Panel B. However, in these models we add our *Inconsistent* variable as well as interactions between it and our age variables. If slow learning is caused by inconsistent performance measurements, the non-interacted age variables should be insignificant.

<Insert Table VI about here>

As with the univariate analysis, we find no difference in learning speed between those funds with and without consistent performance information. Thus, the non-Bayesian learning of mutual fund investors appears to not arise due to the use of different performance measures by investors.

B. Impediments to Fund Flows

Another factor that could affect learning speed, as well as our measure, is funds' loads. Both rear loads and front loads are 'in your face' expenses that may cause investors to simply ignore the fund (e.g., Barber et al. (2005)). If this occurs, then learning speed would slow since many investors would not invest the resources needed to learn. Additionally, front and rear loads would also affect our measure of disagreement since IDAS is based on the minimum of inflows and outflows. These loads likely have negative impacts for both inflows and outflows.

To both examine the impact of loads on learning and also ensure our results are not a result of loads, we first segment funds based on whether they have any loads or not. We then perform a univariate analysis and graph the results in Figure 5.

<Insert Figure 5 about here>

While the figure shows funds without loads may have faster learner in their teenage years, the general slower than Bayes' Rule learning still occurs even for those funds without loads. We formally test the learning speed of no-load funds, we run the same models from Table V, except we interact our age variables with our load dummy. As with the prior test, if loads were completely causing the slow learning we observe, we should see the age variables are not significant. Results are reported in Table VII.

<Insert Table VII about here>

We find that funds with no loads have the significantly slow learning. In fact, we find no significant difference between load and no-load funds' learning speed.

C. *Inattention*

Another possible reason for the slow decline in disagreement is that investors do not pay attention to less salient information. For example, Sirri and Tufano (1998) document that investors have an overwhelming number of funds to choose from and that advertising helps reduce search costs for investors. Barber et al. (2005) find that investors pay attention to fund loads more than expenses because they are more obvious to investors. Investors may also exert resources learning about the fund when they make their initial investment, but then not check on the fund and cease learning. For example, Bergstresser and Poterba (2002), Johnson (2010), and Cashman et al. (2014) all find that mutual fund redemptions are invariant to performance.

One event that should lead to a large change in disagreement about manager skill is when the fund manager changes. Obviously, when the manager changes, the prior performance information of the fund is no longer relevant as an estimate for the new manager's skill.[24] Thus, if investors are paying attention to less salient information like the fund manager, we should see investor disagreement rise after a fund manager change.[25]

To examine this issue, we use the CRSP manager date to detect fund manager changes. We calculate the average IDAS for the 12 months prior to the manager change and then the 12 months after the manager change. We then compare the average difference between the IDAS before and after the change to those funds that did not change managers. We both report univariate results (Panel A) as well as results from a regression (Panel B) where we control for time and style as well as other fund characteristics. We report these results in Table VIII.

<Insert Table VIII about here>

[24] If the new manager has previously managed a fund or is currently managing a fund, investors would have more information than if the manager was a completely new manager. While we do not control for this possibility in our analysis, we should still see an average effect for two reasons. First, the industry clearly has introduced new managers. Thus, many new managers will not fall under this category. Second, while the history for the other funds will help reduce uncertainty, investors will need to learn whether this new manager will have the same investment strategy and skill in the new fund.

[25] Although the manager of the fund may be important for the fund itself, that information is less likely to be in 'the face' of investors. For example, the name of the manager is not listed in the summary information of mutual funds on Yahoo! Finance while performance information is.

We find no evidence disagreement increases after a manager change. The decline in our IDAS measure is the same over the 12-month period for both those funds with and without manager change. Thus, it appears that part of slow learning may be due to inattention by investors.

D. Investor Type

Unlike hedge funds, mutual funds are dominated by retail investors, who are assumed to be unsophisticated.[26] Thus, it may not be surprising these investors do not pay attention to information events like manager changes. It could be, however, that institutional mutual fund investors pay more attention to their funds, which would enable them to learn at the speed implied by Bayesian learning. If so, funds dominated by large, institutional type investors may show faster learning speeds than those funds with more retail investors.

We therefore examine mutual funds that likely have high institutional ownership separately from those funds likely dominated by retail investors. Using the number of account information available on NSAR filings, we calculate the average account size for each mutual fund. We then rank funds by their average account size. Note for the interpretation of the variable, we inversely rank funds such that the fund with the largest account size has a rank of zero. We then interact this variable with our age related variables and report results in Table IX.

<Insert Table IX about here>

[26] For example, retail investors are essentially forbidden to invest in hedge funds due to large income and net worth requirements.

Overall, we find that funds dominated by institutional investors have the same learning speed as funds dominated by retail investors. The non-interacted variables are still significant and positive. Thus, the funds with the largest accounts have slow learning similar to funds with smaller average accounts.

E. *Impact of New Information on Disagreement*

If investors are learning about performance over time, then the impact of new performance information on disagreement should subside when the fund gets older. In other words, if there is currently eight years of information about performance versus only one year of performance, we should find the impact of new performance information on disagreement to be greater for the one-year fund if investors are learning over time.

To test whether or not investors are acting in this way, each month we compute the change in our disagreement measure. We also compute the prior month's return ranking for funds. We regress the changes in disagreement with the prior month's return rankings. If investors are learning, we should see that the impact of new performance is highest for young funds and almost non-existent for older funds. We report the disagreement-current performance relation for the three age groups in Table X.

<Insert Table X about here>

We find that regardless of fund age the impact of a change in disagreement is the same. This result is again inconsistent with investor learning through observing the history of fund performance.[27]

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[27] Huang, Wei, and Hong (2012) examine next flows and find that the flow-performance relation is more mooted for older funds as compared to younger funds. They use this as evidence that investors are learning. However, this may

F. Value to Learning

So far, the most likely reason we have identified for mutual fund investors' slow learning is inattention. This does not seem rational as one would expect that mutual fund investors are motivated to learn about manager skill. To examine how strong this motivation is, we examine the value to learning for both hedge fund and mutual fund investors. Each period, we rank funds by the t-value of their performance measure using all available returns. We then sort funds into deciles based on these t-values and find the difference between the highest and lowest deciles. While similar to performance persistence tests run previously in the literature, our tests use all prior returns rather than returns over a shorter-term period like one quarter or one year. We report results in Figure 6.

<Insert Figure 6 about here>

We find that mutual fund investors have little reason to learn. Over the entire 15-year period, the cumulative difference between the best and worse t-value funds is approximately 12%. This translate to a performance difference of 0.2% per quarter, which is insignificant. On the other hand, hedge funds have a cumulative performance difference of 45% over the same period, or 0.8% per quarter. This difference is significant at the 1% level. Thus, hedge fund investors have an incentive to learn.

Overall, these results can explain the learning difference between hedge fund and mutual fund investors. Mutual fund investors do not pay attention to fund performance because there is

be due to the distribution of size, age, and performance. For example, if we look at the smallest 10% of funds, funds that are younger than three years old and older than 14 years old have similar flow-performance sensitivities.

no value to learning. On the other hand, hedge fund investors are motivated to learn and therefore do so as efficiently as possible.

V. Conclusion

Many models in finance assume that investors learn over time. These models help explain a number of empirical anomalies. For example, learning can explain why mutual fund performance does not persist, even if managers are skilled. Most of these models expect investors to learn according to Bayes' rule. However, little evidence exists concerning whether investors learn that quickly.

In this paper, we use a new measure of disagreement to examine how quickly investors learn. We provide evidence that hedge fund investors can learn as quickly as Bayes' Rule implies. However, we also document mutual fund investors lean much more slowly than Bayes' rule. While the precision of manager skill estimates increases substantially over the first ten years of a fund's life, investor disagreement does not decline significantly over this same time period. Only after a fund is in existence more than ten years does the declines in disagreement and performance standard errors become more aligned for mutual fund investors.

Since learning speed is heterogeneous, we then investigate why mutual fund investors learn relatively slowly as compared to Bayes' Rule. We show this slow decline in disagreement is not due to investors using different performance measures or due to investor frictions like front and rear loads. Rather, we find evidence slow learning is due to inattention. While one may assume inattention is due to retail investors, we find that even funds dominated by institutional investors have slow learning. However, we show that inattention by mutual fund investors is rational. While hedge fund investors gain value from learning, learning about mutual fund manager skill is not valuable.

Overall, our results suggest that learning speed is heterogeneous across different environments. Specifically, investors will not spend time learning if that learning does not have any payoff. More specifically to the mutual fund industry, our slow learning results suggest that investor learning likely cannot explain the lack of performance persistent in the mutual fund industry. Rather the lack of persistence is likely due to no manager skill.

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Figure 1: Disagreement Level and Alpha Error

In this table, we compare the speed of disagreement decline and four factor alpha standard error. We group funds into bins based on their age. Except for the final bin, each bucket is three years wide. We then report the average IDAS value for that age bucket as well as the average standard error of alpha from a Carhart (1997) regression using all available data prior to that year. The x-axis is the age of the fund (in years) represented by the bin. The left y-axis is the IDAS average whereas the right y-axis is the alpha standard error.

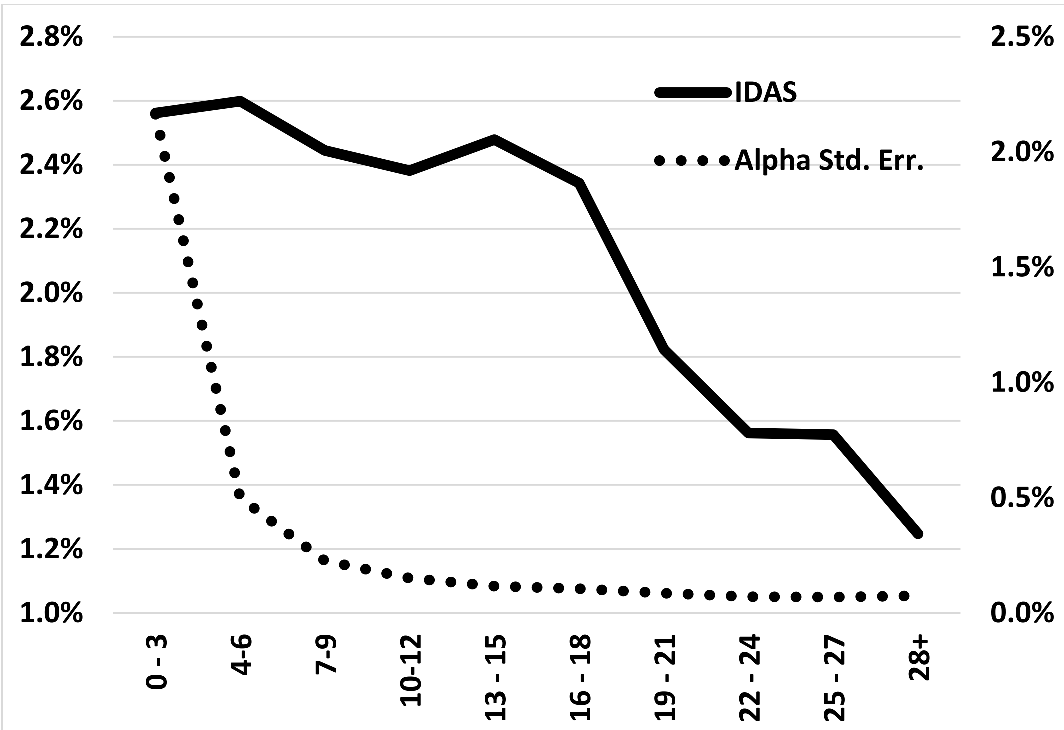

Figure 2: Disagreement Level and Alpha Error

In this table, we compare the speed of disagreement decline and four factor alpha standard error. We group funds into bins based on their age. Except for the final bin, each bucket is three years wide. We then report the average IDAS value for that age bucket as well as the average standard error of alpha from a Carhart (1997) regression using all available data prior to that year. The x-axis is the age of the fund (in years) represented by the bin. The left y-axis is the IDAS average whereas the right y-axis is the alpha standard error.

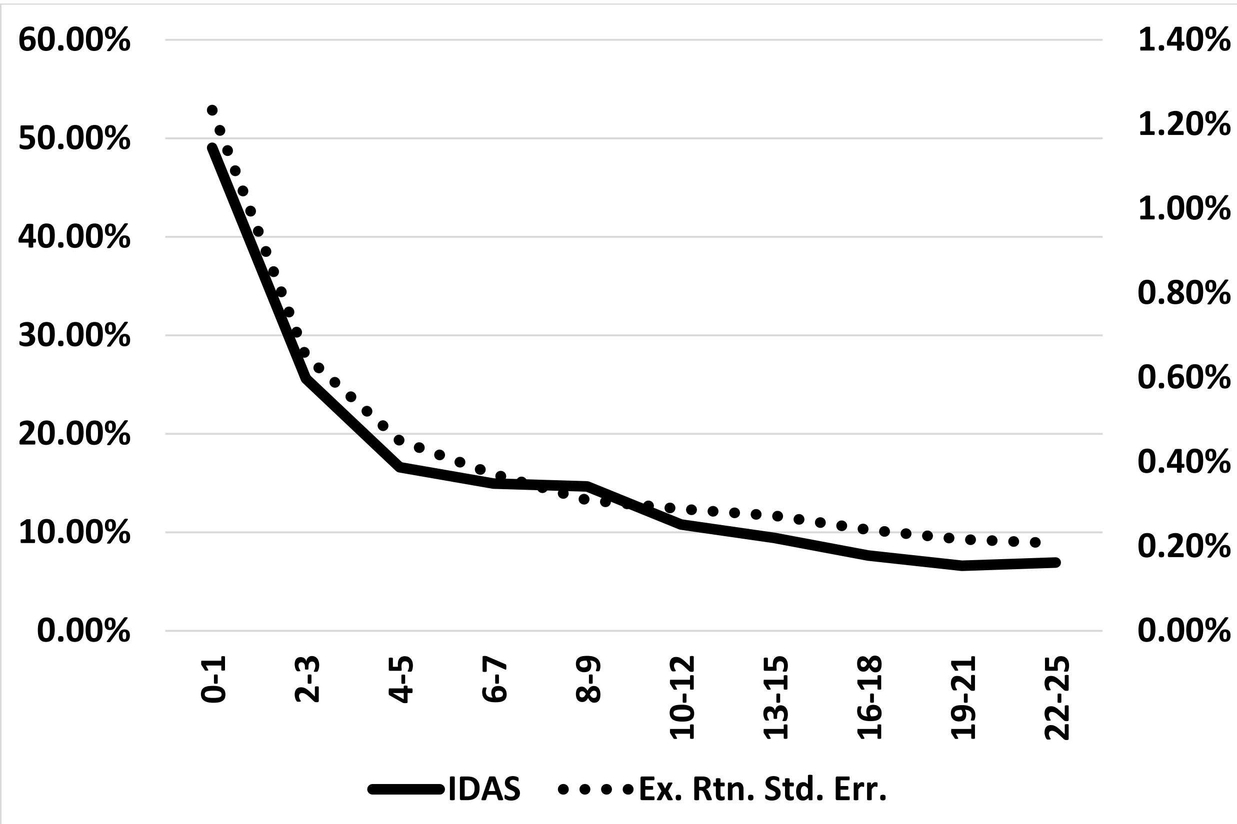

Figure 3: Path Dependence and Learning Speed for Hedge Funds

In this table, we compare the speed of disagreement decline and return standard error. We split the sample into two groups – those whose return series has higher volatility in the first half (*High/Low*) and those whose return series has lower volatility in the first half (*Low/High*). We perform an analysis similar to prior Figures. The x-axis is the age of the fund (in years) represented by the bin. The left y-axis is the IDAS average whereas the right y-axis is the alpha standard error.

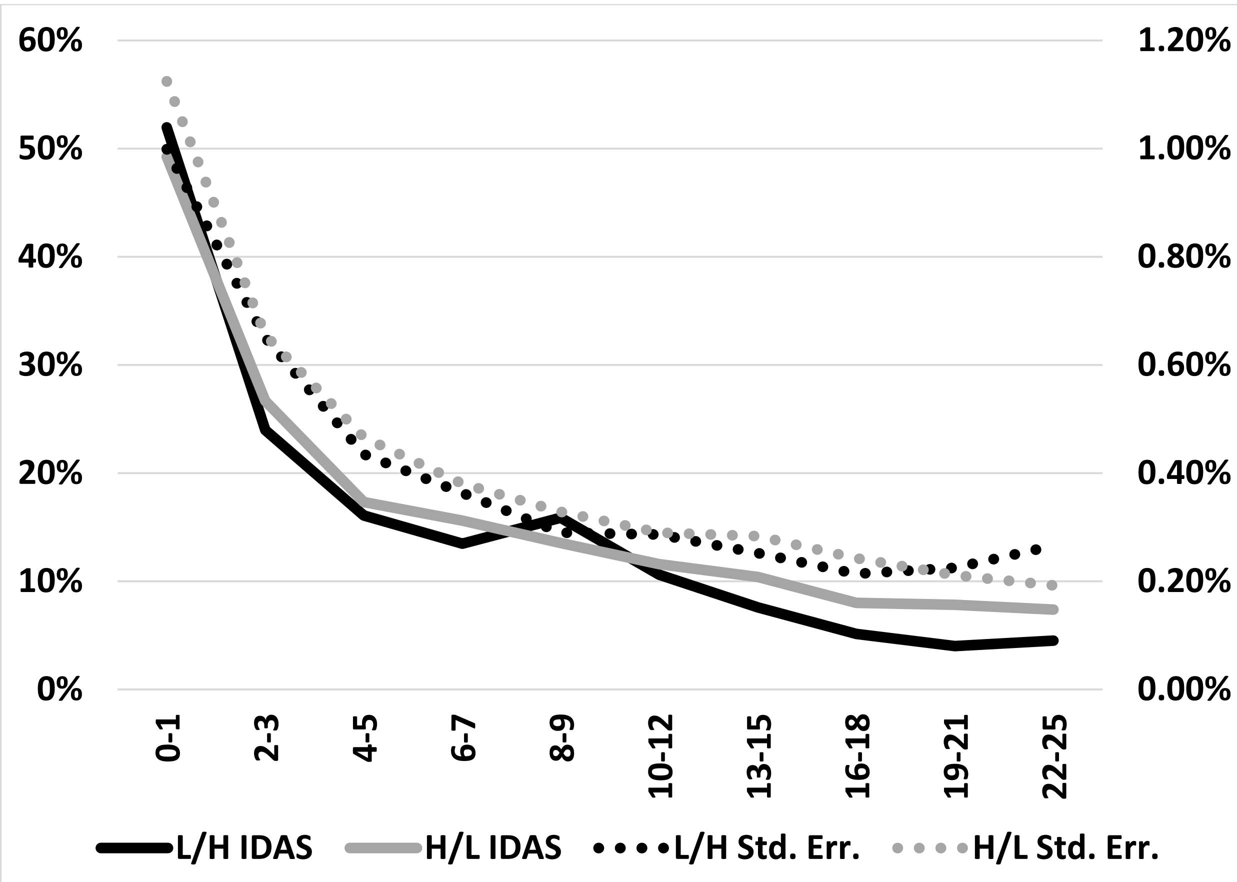

Figure 4: Performance Measure Consistency and Learning Speed

In this table, we compare the speed of disagreement decline and four factor alpha standard error. We split the sample into two groups – those whose performance characteristics are similar across performance measures and those whose performance measures are not consistent. For each one of these groups, we place funds into bins based on their age. Except for the final bin, each bucket is three years wide. We then report the average IDAS value for that age bucket as well as the average standard error of alpha from a Carhart (1997) regression using all available data prior to that year. The x-axis is the age of the fund (in years) represented by the bin. The left y-axis is the IDAS average whereas the right y-axis is the alpha standard error.

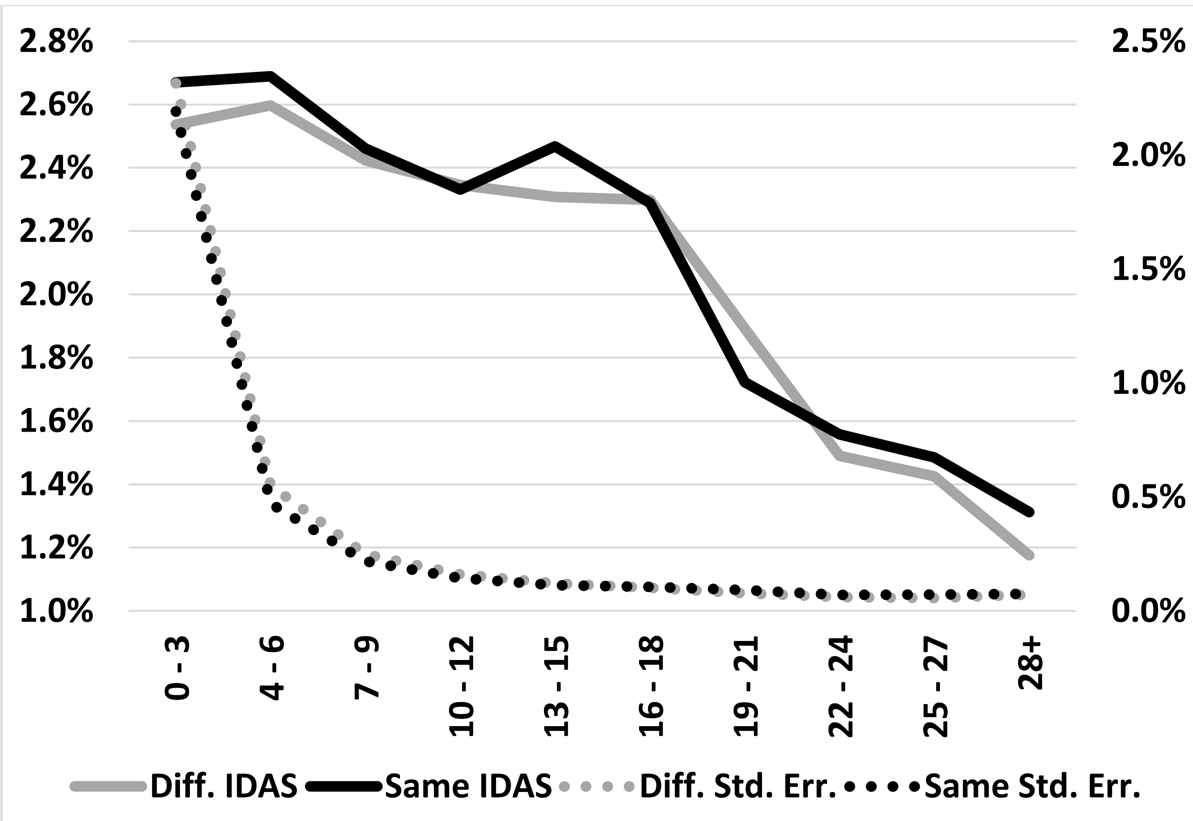

Figure 5: Loads and Learning Speed

In this table, we compare the speed of disagreement decline and four factor alpha standard error. We split the sample into two groups – those whose performance characteristics are similar across performance measures and those whose performance is not consistent. For each one of these groups, we place funds into bins based on their age. Except for the final bin, each bucket is three years wide. We then report the average IDAS value for that age bucket as well as the average standard error of alpha from a Carhart (1997) regression using all available data prior to that year. The x-axis is the age of the fund (in years) represented by the bin. The left y-axis is the IDAS average whereas the right y-axis is the alpha standard error.

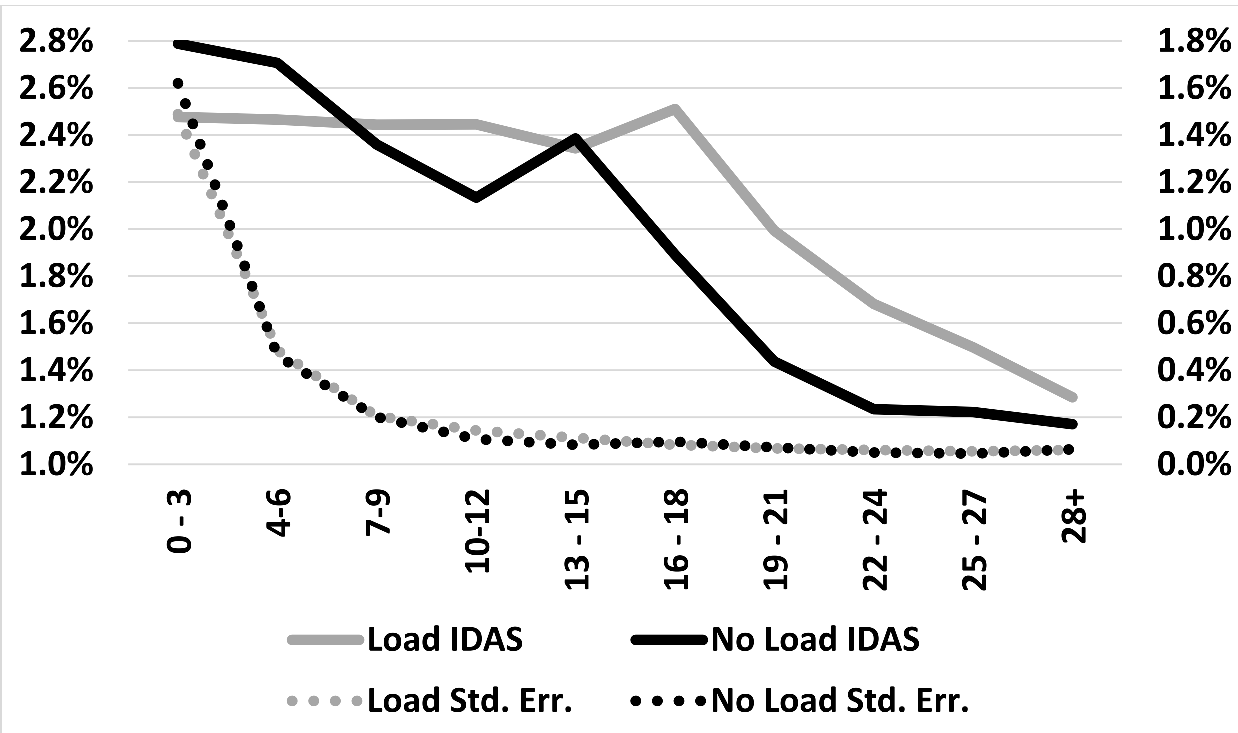

Figure 6: Value to Learning

In this figure, we plot the returns from learning. Each quarter, we compute all funds historical excess return t-values. We then group funds into deciles based on these t-values. We then compute the following quarter returns of the top minus bottom decile. This figure displays the cumulative returns from this strategy for both hedge funds and mutual funds.

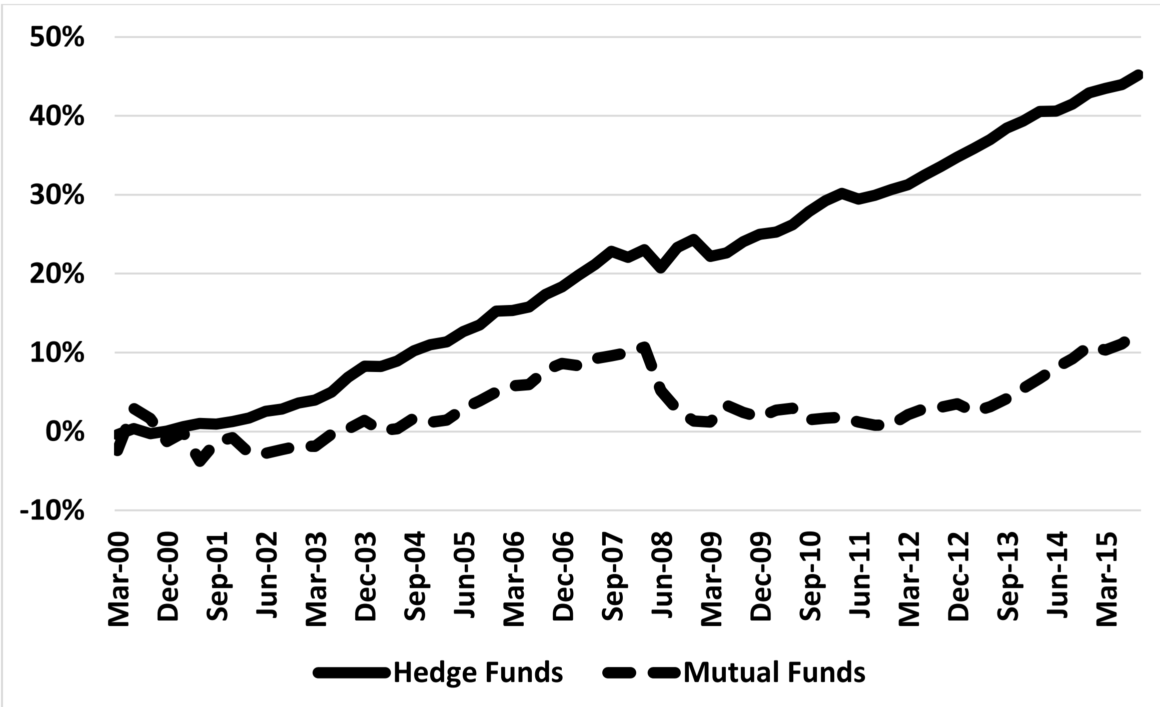

Table I: Summary Statistics

In this table, we present summary statistics of our investor flow data. Each quarter for each fund, we sum the monthly inflow and outflow data from NSAR forms and scale those values by the fund's net assets at the end of the prior quarter. Net flows is the difference of inflows and reinvestments minus outflows. The mutual fund disagreement measure is the minimum of inflows and outflows. The top and bottom one percent of all measures are winsorized to control for outliers. Reported values are the simply average for that year.

Panel A: Mutual Fund IDAS Distribution

Year	Mean	Q1	Median	Q3
1996	2.73%	0.81%	1.49%	2.81%
1997	2.90%	0.88%	1.60%	3.16%
1998	3.06%	1.00%	1.76%	3.36%
1999	3.11%	0.93%	1.77%	3.35%
2000	3.08%	0.88%	1.70%	3.29%
2001	2.72%	0.85%	1.59%	2.80%
2002	2.69%	0.83%	1.59%	2.73%
2003	2.39%	0.84%	1.47%	2.37%
2004	1.90%	0.69%	1.23%	1.94%
2005	1.93%	0.64%	1.18%	1.83%
2006	1.71%	0.68%	1.21%	1.86%
2007	1.72%	0.66%	1.20%	1.86%
2008	1.92%	0.71%	1.30%	2.12%
2009	1.88%	0.72%	1.32%	2.09%
2010	2.03%	0.57%	1.19%	1.96%
2011	2.02%	0.54%	1.19%	2.00%
2012	1.89%	0.46%	1.06%	1.81%
2013	2.02%	0.52%	1.16%	1.84%
2014	1.84%	0.47%	1.03%	1.72%

Panel B: Hedge Fund IDAS Distribution

Year	Mean	Q1	Median	Q3
2009	12.7%	0.0%	1.3%	10.6%
2010	22.1%	0.1%	5.1%	19.0%
2011	17.0%	0.1%	4.4%	15.5%
2012	18.5%	0.3%	4.5%	15.2%
2013	17.6%	0.1%	3.5%	14.8%
2014	18.4%	0.1%	4.2%	14.7%
2015	15.5%	0.0%	3.0%	12.2%

Table II: Validating the IDAS Measure

In this table, we present results relating IDAS to investor disagreement. In Panel A, we rank funds based on their quarter (t) performance within their styles and then group the funds into deciles. We then report the IDAS and Net Flows in the prior quarter. In Panel B, we rank funds into deicals based on their size or age. We then report the average IDAS for actively managed (*Active*) and index funds (*Index*) within those decials as well as the difference. The last two decials for age are omitted as both actively and passively funds did not exist.

Panel A: Return Forecasting

Return Decile (t)	IDAS (t-1)	Net Flows (t-1)
1	3.24%	0.36%
2	2.54%	0.77%
3	2.22%	0.25%
4	2.18%	-0.46%
5	2.12%	1.62%
6	2.18%	0.52%
7	2.17%	0.40%
8	2.30%	0.85%
9	2.55%	0.91%
10	3.34%	0.81%

Panel B: Active versus Passive Funds

	By Size			By Age		
Decile	Active	Index	Diff.	Active	Index	Diff.
1	2.20%	1.85%	0.35%	2.76%	1.81%	0.95%
2	2.28%	1.55%	0.73%	2.72%	2.19%	0.53%
3	2.17%	1.50%	0.67%	2.47%	2.64%	-0.17%
4	2.36%	2.01%	0.35%	2.41%	2.12%	0.29%
5	2.50%	1.65%	0.85%	2.41%	1.76%	0.65%
6	2.27%	1.49%	0.78%	2.41%	1.65%	0.76%
7	2.27%	1.57%	0.70%	1.93%	1.39%	0.54%
8	2.46%	1.66%	0.80%	1.55%	0.94%	0.61%
9	2.34%	2.09%	0.25%	1.41%	1.16%	0.25%
10	1.95%	2.13%	-0.18%	1.03%	1.18%	-0.15%

Table III: Change in IDAS and Performance Measurement Precision

In this table, we report results comparing the cumulative decline in our disagreement measure (*IDAS*) and four measures of skill precision. Each month we split funds into ten age groups, ranging from *0 – 3* years of age to those funds older than 27 years. To control for potential size effects, we double sort on size and age. We then compute average values for all funds within each age group across the size deciles in each period and finally average these values across time. *IDAS* is our measure of disagreement. *1-F Alpha Std. Err.* is the standard error of the intercept from the one factor market model. *4-F Alpha Std. Err.* is the standard error of the intercept from the four factor Carhart model. *Return Std. Err.* is the standard error of raw returns while *Ex. Return Std. Err.* is the standard error of style adjusted returns. All return standard errors are based on all returns available prior to the date. *Chg.* is the total cumulative decline over the life of the fund.

Panel A: Alpha Based

Fund Age	IDAS	Chg.	1-F Alpha Std. Err.	Chg.	4-F Alpha Std. Err.	Chg.
0 – 3	2.56%		1.48%		2.16%	
4 – 6	2.60%	1%	0.38%	-74%	0.50%	-77%
7 – 9	2.44%	-5%	0.20%	-87%	0.23%	-90%
10 – 12	2.38%	-7%	0.15%	-90%	0.15%	-93%
13 – 15	2.48%	-3%	0.12%	-92%	0.12%	-95%
16 – 18	2.34%	-9%	0.11%	-93%	0.11%	-95%
19 – 21	1.82%	-29%	0.09%	-94%	0.09%	-96%
22 – 24	1.56%	-39%	0.08%	-95%	0.07%	-97%
24 – 27	1.56%	-39%	0.07%	-95%	0.07%	-97%
> 27	1.25%	-51%	0.08%	-94%	0.07%	-97%

Panel B: Return Based

Fund Age	IDAS	Chg.	Return Std. Err.	Chg.	Ex. Return Std. Err.	Chg.
0 – 3	2.56%		1.99%		1.08%	
4 – 6	2.60%	1%	0.60%	-70%	0.33%	-70%
7 – 9	2.44%	-5%	0.33%	-83%	0.17%	-84%
10 – 12	2.38%	-7%	0.23%	-88%	0.12%	-88%
13 – 15	2.48%	-3%	0.18%	-91%	0.10%	-91%
16 – 18	2.34%	-9%	0.16%	-92%	0.09%	-92%
19 – 21	1.82%	-29%	0.13%	-93%	0.08%	-93%
22 – 24	1.56%	-39%	0.12%	-94%	0.06%	-94%
24 – 27	1.56%	-39%	0.10%	-95%	0.06%	-95%
> 27	1.25%	-51%	0.12%	-94%	0.06%	-94%

Table IV: Change in HFID and Performance Measurement Precision

In this table, we report results comparing the cumulative decline in our disagreement measure (*HFID*) for hedge funds and four measures of skill precision. Each month we split funds into 10 age groups, ranging from *0 – 1* years of age to those funds that are 25 years. We then compute average values for all funds within each group in each period and finally average these values across time. *IDAS* is our measure of disagreement. *Return Std. Err.* is the standard error of raw returns while *Ex. Return Std. Err.* is the standard error of style adjusted returns. All return standard errors are based on all returns available prior to the date. *Chg.* is the total cumulative decline over the life of the fund.

Fund Age	IDAS	Chg.	Return Std. Err.	Chg.	Ex. Return Std. Err.	Chg.
0-1	49.04%		1.30%		1.23%	
2-3	25.60%	-48%	0.71%	-45%	0.65%	-47%
4-5	16.59%	-66%	0.51%	-60%	0.45%	-63%
6-7	14.93%	-70%	0.43%	-67%	0.37%	-70%
8-9	14.65%	-70%	0.37%	-72%	0.31%	-75%
10-12	10.79%	-78%	0.34%	-74%	0.29%	-77%
13-15	9.42%	-81%	0.32%	-75%	0.27%	-78%
16-18	7.64%	-84%	0.29%	-78%	0.24%	-81%
19-21	6.58%	-87%	0.26%	-80%	0.22%	-82%
22-25	6.93%	-86%	0.23%	-82%	0.21%	-83%

Table V: Relation between Learning Speed, Alpha Precision, and Fund Age

In this table, we report results examining the relation between the difference in cumulative investment disagreement changes and standard error changes and fund age. Each fund age year, we compute the average the IDAS and standard error estimates. We then compute the differences between the cumulative decline in the *IDAS* measure and our four estimates of manager skill and use these differences as our dependent variable. We regress these dependent variables against *Age*, which is the fund age in years. *Exp. Ratio* and *Turnover* are the fund's expense ratio and portfolio turnover in percent. *Style Avg. IDAS* (*Company Avg. IDAS*) is style (fund management company) average level of disagreement. Finally, *Lag Log(TNA)* is the fund's net assets and *Avg. Acct. Size* is the average investor's investment size. In Panel B, we regress the differences on young fund and middle aged fund dummies. For mutual funds (hedge funds), a young fund is less than nine (six) years old and a middle aged fund is between nine (six) and 20 (15) years old. ** and * represent significance at the 1% and 5%, levels respectively.

Panel A: Age as Linear Variable

	MF 4-Factor Alpha		MF 1-Factor Alpha		MF Style Adj. Returns		HF Style Adj. Returns	
	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value
Age	-0.093	-13.54**	-0.087	-12.67**	-0.081	-11.93**	0.006	1.73
Log(TNA)	0.001	0.04	-0.001	-0.02	-0.002	-0.07	0.004	0.27
Exp. Ratio/Mfee	-13.627	-1.30	-13.619	-1.30	-13.570	-1.31	-0.041	-1.07
Loads (1/0)	0.357	3.73***	0.355	3.70**	0.355	3.72**		
Incentive Fee							-0.005	-0.90
Turnover	-0.137	-5.22**	-0.138	-5.30**	-0.140	-5.34**		
Avg. Acct. Size	0.108	4.45**	0.108	4.46**	0.109	4.52**		
Style Avg. IDAS	10.695	2.17*	9.887	2.01*	9.608	1.96		
Company Avg. IDAS	6.757	6.01**	6.770	6.01**	6.826	6.06**		
High Water Mark							0.011	0.12
Min. Investment							-0.040	-1.56
Lockup Period							-0.111	-0.36
Redemption Period							-0.109	-1.69
Subscription Period							-0.106	-1.61
Time Dummies	Y		Y		Y		Y	
Style Dummies	Y		Y		Y		Y	

	MF 4-Factor Alpha		MF 1-Factor Alpha		MF Style Adj. Returns		HF Style Adj. Returns	
R-Sq.	6.90%		6.44%		6.09%		1.93%	
Obs	25,154		25,154		25,154		4,249	

Panel B: Age Groups

	MF 4-Factor Alpha		MF 1-Factor Alpha		MF Style Adj. Returns		HF Style Adj. Returns	
	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value
Young Fund	1.653	14.72**	1.583	14.13**	1.510	13.52**	-0.068	-1.21
Middle Age Fund	0.934	11.05**	0.924	10.93**	0.908	10.76**	0.073	1.38
Log(TNA)	-0.021	-0.77	-0.021	-0.77	-0.022	-0.80	-0.004	-0.30
Exp. Ratio/Mfee	-11.096	-1.06	-11.302	-1.08	-11.023	-1.06	-0.042	-1.13
Loads (1/0)	0.364	3.80**	0.360	3.76**	0.360	3.77**		
Incentive Fee							-0.006	-0.90
Turnover	-0.135	-5.17**	-0.136	-5.24**	-0.136	-5.22**		
Avg. Acct. Size	0.118	4.87**	0.117	4.85**	0.117	4.86**		
Style Avg. IDAS	14.408	2.99**	13.321	2.77**	13.068	2.72**		
Company Avg. IDAS	6.938	6.18**	6.924	6.16**	6.952	6.18**		
High Water Mark							0.008	0.09
Min. Investment							-0.037	-1.50
Lockup							-0.084	-0.27
Redemption Period							-0.107	-1.68
Subscription Period							-0.097	-1.69
Time Dummies	Y		Y		Y		Y	
Style Dummies	Y		Y		Y		Y	
R-Sq.	6.33%		5.98%		5.66%		2.49%	
Obs	25,154		25,154		25,154		25,154	

Table VI: Performance Measure Consistency and Learning Speed

In this table, we report results examining the relation between the difference in cumulative investment disagreement changes and standard error changes and fund age. Each fund age year, we compute the average of the IDAS and standard error estimates. We then compute the differences between the cumulative decline in the IDAS measure and our three performance measures and use these differences as our dependent variable. We regress these dependent variables against young fund and middle aged fund dummies. A young fund is less than nine years old and a middle aged fund is between nine and 20 years old. We include a dummy variable that is one if the performance measures are consistent in that period and zero otherwise (Consistent). We then interact this variable with both *Young* (*Young*Consistent*) and *Middle* (*Middle*Consistent*). *Exp. Ratio* and *Turnover* are the fund's expense ratio and portfolio turnover in percent. *Front* (*Rear*) *Load* is the maximum front (rear) load for the fund. *Style Avg. IDAS* (*Company Avg. IDAS*) is style (fund management company) average level of disagreement. Finally, *Log(TNA)* is the fund's net assets and *Avg. Acct. Size* is the average investor's investment size. ** and * represent significance at the 1% and 5%, levels respectively.

	4-Factor Alpha		1-Factor Alpha		Style Adj. Returns	
	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value
Young Fund	1.373	7.05**	1.323	6.80**	1.263	6.49**
Middle Age Fund	0.854	5.34**	0.844	5.28**	0.833	5.21**
Young*Inconsistent	0.362	1.84	0.338	1.72	0.333	1.70
Middle*Inconsistent	0.117	0.66	0.117	0.67	0.117	0.67
Inconsistent	-0.166	-0.97	0.163	0.96	0.163	0.96
Log(TNA)	-0.019	-0.67	-0.019	-0.69	-0.019	-0.70
Exp. Ratio	-12.026	-1.15	-12.241	-1.17	-12.308	-1.19
Loads (1/0)	0.372	3.87**	0.368	3.83**	0.367	3.84**
Turnover	-0.132	-5.11**	-0.133	-5.18**	-0.134	-5.22**
Avg. Acct. Size	0.120	4.93**	0.119	4.91**	0.119	4.94**
Style Avg. IDAS	14.884	3.08**	13.781	2.85**	13.271	2.76**
Company Avg. IDAS	6.696	6.02**	6.681	6.00**	6.729	6.03**
Time Dummies	Y		Y		Y	
Style Dummies	Y		Y		Y	
R-Sq.	6.36%		6.00%		5.71%	
Obs	24,559		24,559		24,559	

Table VII: Loads and Mutual Fund Learning Speed

In this table, we report results examining the relation between the difference in cumulative investment disagreement changes and standard error changes and fund age. Each fund age year, we compute the average the IDAS and standard error estimates. We then compute the differences between the cumulative decline in the *IDAS* measure and our four estimates of manager skill and use these differences as our dependent variable. We regress these dependent variables against young fund and middle aged fund dummies. A young fund is less than nine years old and a middle aged fund is between nine and 20 years old. We include a dummy variable that is one if the fund does not have a front and rear load and zero otherwise (*No Load*). We then interact this variable with both *Young* (*Young* Load*) and *Middle* (*Middle* Load*). *Exp. Ratio* and *Turnover* are the fund's expense ratio and portfolio turnover in percent. *Style Avg. IDAS* (*Company Avg. IDAS*) is style (fund management company) average level of disagreement. *Front* (*Rear*) *Load* is the maximum front (rear) load for the fund. Finally, *Log(TNA)* is the fund's net assets and *Avg. Acct. Size* is the average investor's investment size. ** and * represent significance at the 1% and 5%, levels respectively.

	4-Factor Alpha		1-Factor Alpha		Style Adj. Returns	
	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value
Young Fund	1.520	8.78**	1.454	8.40**	1.391	8.06**
Middle Age Fund	0.975	6.79**	0.965	6.71**	0.955	6.65**
Young*Loads	0.206	1.03	0.200	1.00	0.198	0.99
Middle*Loads	-0.063	-0.36	-0.064	-0.37	-0.065	-0.37
Log(TNA)	-0.023	-0.81	-0.023	-0.82	-0.023	-0.83
Exp. Ratio	-11.787	-1.12	-11.978	-1.15	-12.081	-1.17
Loads (1/0)	0.304	1.72	0.303	1.71	0.304	1.72
Turnover	-0.134	-5.15**	-0.136	-5.22**	-0.137	-5.25**
Avg. Acct. Size	0.119	4.94**	0.118	4.91**	0.119	4.95**
Style Avg. IDAS	14.595	3.02**	13.504	2.80**	13.030	2.72**
Company Avg. IDAS	6.985	6.22**	6.971	6.20**	7.014	6.23**
Time Dummies	Y		Y		Y	
Style Dummies	Y		Y		Y	
R-Sq.	6.38%		6.03%		5.75%	
Obs	25,154		25,154		25,154	

Table VIII: Mutual Fund Manager Changes and Investor Disagreement

In this table, we examine changes in investment disagreement around manager changes. We compute a fund's average IDAS over the prior and subsequent twelve months. We then categorize funds into those funds that experience a manager change that month and those that do not. In Panel A, we report univariate averages in both periods as well as the change. *t*-values are computed using clustering by fund. In Panel B, we performance a multivate analysis. The depending variable is the change over the two twelve month periods. We regress these dependent variables against young fund and middle aged fund dummies. A young fund is less than nine years old and a middle aged fund is between nine and 20 years old. We include a dummy variable that is one if the fund does experiences a manager change that month and zero otherwise (*Mgr. Change*). *Exp. Ratio* and *Turnover* are the fund's expense ratio and portfolio turnover in percent. *Style Avg. IDAS* (*Company Avg. IDAS*) is style (fund management company) average level of disagreement. *Front* (*Rear*) *Load* is the maximum front (rear) load for the fund. Finally, *Log(TNA)* is the fund's net assets and *Avg. Acct. Size* is the average investor's investment size. ** and * represent significance at the 1% and 5%, levels respectively.

Panel A: Univariate Analysis

	Pre-Chg.	Post-Chg.	Difference	t-value
No Mgr. Chg.	2.37%	2.22%	-0.15%	-18.44**
Mgr. Chg.	2.74%	2.56%	-0.19%	-5.36**
Difference	0.37%	0.34%	-0.04%	
t-value	4.11**	3.88**	-1.04	

Panel B: Multivariate Analysis

	Model 1		Model 2	
	Coeff.	*t*-value	Coeff.	*t*-value
Mgr. Change	-0.024	-0.71	-0.009	-0.26
Young Fund			-0.061	-1.48
Middle Age Fund			-0.029	-0.73
Exp. Ratio			-12.445	-3.56**
Log(TNA)			-0.055	-8.43**
Loads (1/0)			0.037	1.68
Turnover			0.040	2.67**
Avg. Acct.			-0.030	-0.97
Style Avg. IDAS			0.908	0.54
Company Avg. IDAS			-4.252	-5.27**
Time Dummies	Y		Y	
Style Dummies	Y		Y	
R-Sq.	0.99%		1.79%	
Obs	204,575		202,152	

Table IX: Investor Type and Mutual Fund Learning Speed

In this table, we report results examining the relation between the difference in cumulative investment disagreement changes and standard error changes and fund age. Each fund age year, we compute the average the IDAS and standard error estimates. We then compute the differences between the cumulative decline in the *IDAS* measure and our four estimates of manager skill and use these differences as our dependent variable. We regress these dependent variables against young fund and middle aged fund dummies. A young fund is less than nine years old and a middle aged fund is between nine and 20 years old. We include a dummy variable that is one if the fund's average account size is in the top 10% of all funds and zero otherwise (*Institutional Fund*). We then interact this variable with both *Young* (*Young*Inst. Fund*) and *Middle* (*Middle*Inst. Fund*). *Exp. Ratio* and *Turnover* are the fund's expense ratio and portfolio turnover in percent. *Front* (*Rear*) *Load* is the maximum front (rear) load for the fund. *Style Avg. IDAS* (*Company Avg. IDAS*) is style (fund management company) average level of disagreement. Finally, *Log(TNA)* is the fund's net assets. ** and * represent significance at the 1% and 5%, levels respectively.

	MF 4-Factor Alpha		MF 1-Factor Alpha		MF Style Adj. Returns	
	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value
Young Fund	1.313	5.18**	1.246	4.92**	1.181	4.66**
Middle Age Fund	0.860	3.82**	0.846	3.76**	0.834	3.71**
Young* Acct. Size	0.633	1.70	0.626	1.68	0.628	1.69
Middle* Acct. Size	0.088	0.27	0.095	0.29	0.098	0.30
Log(TNA)	-0.012	-0.43	-0.012	-0.43	-0.012	-0.44
Exp. Ratio	-8.640	-0.83	-8.738	-0.84	-9.000	-0.87
Loads (1/0)	0.374	3.91**	0.371	3.88**	0.369	3.88**
Turnover	-0.136	-5.21**	-0.137	-5.29**	-0.138	-5.32**
Acct. Size	-1.343	-3.87**	-1.341	-3.87**	-1.340	-3.86**
Style Avg. IDAS	13.616	2.84**	12.539	2.62**	12.045	2.52*
Company Avg. IDAS	6.785	6.00**	6.773	5.98**	6.814	6.00**
Time Dummies	Y		Y		Y	
Style Dummies	Y		Y		Y	
R-Sq.	6.71%		6.36%		6.08%	
Obs	25,154		25,154		25,154	

Table X: Fund Age and Impact on Fund Performance

In this table, we example the impact of fund age on the effect of new performance information on mutual fund investor disagreement. A young fund is less than nine years old and a middle aged fund is between nine and 20 years old. We report the five piecewise variables related to current performance, similar to Sirri and Tufano (1998). *Low Perf.* is the minimum of the fund's current performance rank and 0.2. *Mid1 Perf.* through *Mid3 Perf.* are piecewise linear variables that are 0.2 in width each that cover the 0.2 – 0.8 performance rank region. *High Perf.* represents the piecewise linear variable for performance above the 0.8 performance rank. ** and * represent significance at the 1% and 5%, levels respectively.

	All Changes		Top Decile		Bottom Decile	
	Coeff.	*t*-value	Coeff.	*t*-value	Coeff.	*t*-value
Young Fund	-0.003	-0.61	0.001	0.02	0.047	1.10
Middle Age Fund	-0.003	-0.87	0.044	1.29	0.012	0.36
Log(TNA)	-0.006	-5.13**	-0.021	-1.69	0.002	0.13
Exp. Ratio	-0.732	-1.35	10.307	1.93	-8.296	-1.83
Loads (1/0)	-0.010	-3.02**	-0.064	-1.57	0.009	0.21
Turnover	-0.001	-0.26	0.023	1.58	-0.036	-2.57*
Avg. Acct. Size	0.052	5.54**	0.147	1.57	0.094	1.15
Time Dummies	Y		Y		Y	
Style Dummies	Y		Y		Y	
R-Sq.	0.96%		1.63%		1.75%	
Obs	328,327		32,911		32,611	