Idiosyncratic Volatility and Fund Performance: When Does It Pay to Use Active Managers? *

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November 15, 2020

Abstract

This paper shows that the benchmark-adjusted return of active equity funds is time-varying and highly predictable with the average level of stock idiosyncratic volatilities in the cross-section, the so-called Aggregate Idiosyncratic Volatility (*AIV*). Using the sample of active US equity mutual funds from 1984 to 2020, we document that *AIV* positively predicts benchmark-adjusted fund returns, and its predictive power is stronger for funds deviating more from their benchmarks. In addition, we find that this phenomenon is prevalent around the world using a comprehensive sample of international equity mutual funds. Our preferred explanation for these findings is that *AIV* decreases the risk-bearing capacity of active funds so they require higher rewards for bearing larger tracking errors. Additional tests largely support our story. First, the effect of unexpected *AIV* on contemporaneous benchmark adjusted returns is negative. Second, on average, funds scale back active positions and reduce liquidity provision activity when *AIV* rises. Third, funds that trade against past stock price movements earn greater returns following high *AIV* levels. Overall, our paper answers a critical question: when will active funds generate outperformance for their clients?

Keywords: Active Fund, Performance Evaluation, Idiosyncratic Volatility
JEL Codes: G10, G14, G17, G23

*The author thanks Yan Bai, Yixin Chen, Micheal Gofman, Zhao Jin, Ron Kaniel, Yukun Liu, Alan Moreira, Robert Novy-Marx, Christian Opp, Xuyuanda Qi, Jerry Warner, John Yang, and seminar participants at the University of Rochester, Purdue University, and Tulane University for their helpful comments.

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1. Introduction

Active equity funds invest trillions of dollars on behalf of their clients.[1] The critical role of active funds in financial markets coincides with an extensive literature on their performance. Even though benchmark adjusted returns of active mutual funds varies substantially over time (e.g., Moskowitz, 2000; Kacperczyk, Van Nieuwerburgh, and Veldkamp, 2014), previous literature has not identified power predictors of the time-series of active fund performance. In addition, recent studies suggest that funds deviating more from their benchmarks outperform other funds (e.g., Kacperczyk, Sialm, and Zheng, 2008; Cremers and Petajisto, 2009; Pástor, Stambaugh, and Taylor, 2020). However, there is little research studying whether this cross-sectional relation is dependent on market conditions. Understanding when active mutual funds, especially those with a high degree of deviations from their benchmarks, can generate outperformance is crucial for guiding investors' asset allocation and evaluating market efficiency.

This paper provides an answer to this critical question by showing that Aggregate Idiosyncratic Volatility (*AIV*), measured as the cross-sectional average of idiosyncratic stock return volatilities, is the key determinant of the ability of active mutual funds to outperform their benchmark. Specifically, I document that active mutual funds earn significant positive expected benchmark adjusted returns only during the periods when *AIV* is high. Using the sample of active U.S. equity mutual funds from 1984 through 2020, I find that *AIV* positively predicts average benchmark-adjusted fund returns. In addition, its predictive power is most pronounced among funds that significantly deviate from their benchmarks. I then explore the potential explanations of why *AIV* drives the time variation in expected benchmark adjusted returns. A collection of additional tests supports the story that active funds require a reward for providing liquidity to the stock market and

[1] Despite the growing popularity of passive investing in the US markets, as of 2020, \$4.62 trillion (about 10.8% of U.S. market value) are under the management of active domestic mutual funds in my sample. This number is 4.18 trillion (about 9.8% of U.S. market value) for active domestic mutual funds and exchange-traded funds (see also, Investment Company Fact Book, https://www.icifactbook.org/).

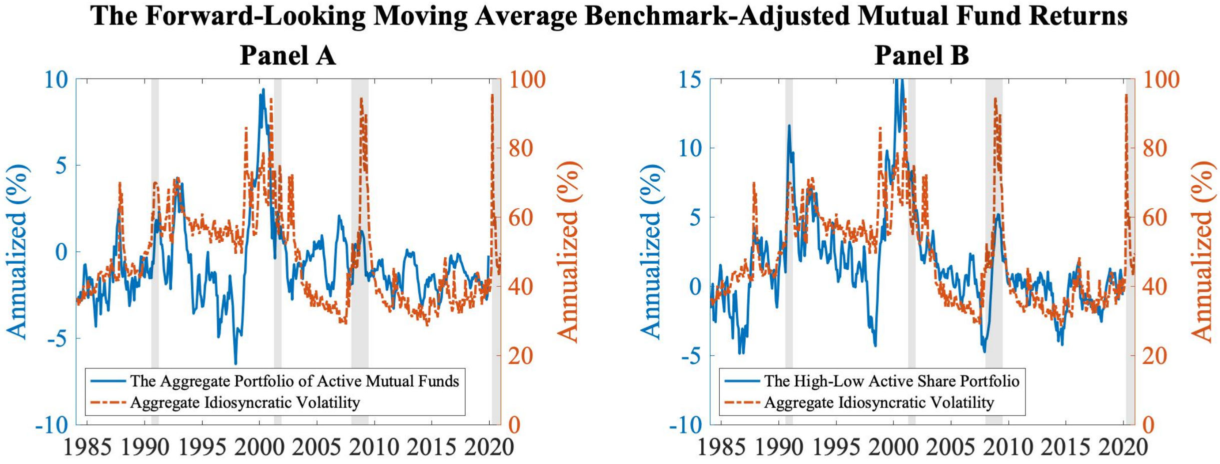

Fig. 1. *AIV* **and Active Mutual Fund Performance**
Panel A plots Aggregate Idiosyncratic Volatility (*AIV*) and the moving average benchmark adjusted returns of the equal weighted portfolio of active mutual funds. Panel B plots *AIV* and the difference of the moving average benchmark adjusted returns between high and low Active Share quintile portfolios. The moving average benchmark adjusted returns are computed over a 12-month forward-looking window. Following Cremers and Petajisto (2009), Active Share measures a fund's degree of deviations from its benchmark, which is the Morningstar Category Benchmark Index. *AIV* is estimated as the equal-weighted average of the Fama-French 3-factor idiosyncratic volatilities. The grey bars represent the NBER recessions. The sample consists of active U.S. equity mutual funds from 1984 to 2020.

AIV decreases their risk-bearing capacity for doing so.

Figure 1 illustrates the predictive ability of *AIV* for benchmark adjusted fund returns. In panel A, the solid line is the forward-looking moving average benchmark-adjusted returns of the equal-weight portfolio of active U.S. equity mutual funds. In panel B, the solid line is the difference of the forward-looking moving average benchmark-adjusted returns between the high and low Active Share quintile portfolios. I also plot the level of *AIV* (the dotted line) in both panels. These plots provide suggestive evidence that *AIV* is positively correlated with expected benchmark-adjusted fund returns, especially for active funds deviating substantially from their benchmarks.

To show the patterns reflected in Figure 1 is a robust feature of data, I begin by analyzing the sample of actively managed U.S. equity mutual funds from 1984 through 2020. I use predictive regressions to formally test the positive relation between *AIV* and subsequent benchmark-adjusted fund returns. My first test focuses on the aggregate portfolio of active equity mutual funds. Specifically, I estimate time-series regressions of the equal-weighted benchmark adjusted fund returns on the previous-month AIV, controlling for various macro variables including the VIX index, the real-time recession probability (Chauvet and Piger, 2008), investor sentiment (Baker and Wurgler, 2006), macro disagreement (Yu, 2011), and illiquidity (Amihud, 2002). The results show that AIV significantly forecasts the average benchmark adjusted returns, both before fund expense and net of expense: a one-standard-deviation rise in AIV is associated with an increase of 1.71% (1.64%) in the annual benchmark adjusted gross (net) return, with a t-statistic of 3.50 (3.30). The adjusted-R^2 from the predictive regression without macro controls for gross and net returns is 2.15% and 1.88%, which are extremely large for predicting monthly asset returns (Campbell and Thompson, 2008). I also find significant results for the value-weighted benchmark adjusted returns, although the economic magnitude of AIV predictive power is lower by 25%. As a comparison, I also examine the aggregate portfolios of passive U.S. equity mutual funds and exchange-traded funds (ETFs). However, I find AIV cannot forecast either equal-weighted or value-weighted benchmark-adjusted returns of passive funds and ETFs.

To outperform the benchmark, a fund manager must take active positions against the benchmark to bet on idiosyncratic stock returns. Because funds deviating less from their benchmarks are essentially closet indexing, AIV's predictability on average benchmark adjusted returns should mainly come from its ability to forecast benchmark adjusted returns of funds with a high degree of deviations. Therefore, my second test focuses on the portfolios formed by sorting active mutual funds into quintiles based on the beginning-of-quarter Active Share. I run predictive regressions of the equal-weighted benchmark adjusted gross returns on the previous month AIV for Active Share quintile portfolios. The results show that the slope coefficient estimates on AIV rise monotonically with Active Share. For the high-minus-low portfolio, a one-standard-deviation rise in AIV is associated with an increase of 2.27% in the annual return with a t-statistic of 4.16. The adjusted-R^2 of 6.61% is remarkably large in monthly predictive regressions. Unconditionally, the high-minus-low portfolio has an average benchmark adjusted return of 1.48%

per year, suggesting that high Active Share funds outperform low Active Share funds only following high levels of *AIV* over the past four decades. This finding contradicts the traditional view that Active Share should persistently predict fund performance in the cross-section as it captures the superior investment talent of fund managers.

I conduct an extensive battery of tests to evaluate the robustness of the predictability of *AIV*. First, the out-of-sample tests confirm that *AIV* significantly forecasts benchmark-adjusted fund returns.[2] The results hold very well after controlling for various priced factors proposed in the recent asset pricing literature. I also find that the odds of *AIV* being a spurious predictor are very low by implementing 10,000 bootstrap simulations based on the method proposed by Stambaugh, Yu, and Yuan (2014). Finally, I run Fama and French (2010) bootstrap simulations for the low and high *AIV* subsamples, respectively. The results are surprising: when *AIV* is high, there are more funds with a significant positive true gross α – the abnormal fund return not explained by the effect of "luck".

After establishing that *AIV* is a powerful predictor of the time-series of benchmark adjusted fund performance, I proceed to explore potential mechanisms underlying this phenomenon. Active mutual funds can earn positive returns relative to their passive benchmark indexes only at the expense of other active investors because the aggregate portfolio of all non-index investors is passive. Suppose there are uninformed investors trading assets for reasons such as biased beliefs or liquidity needs. The aggregate excess demand of uninformed investors could move asset prices away from fundamental values. Active funds may attempt to outperform their benchmark by overweighting (underweighting) underpriced (overpriced) stocks induced by uninformed investor demand. However, by doing so they have to deviate from their benchmarks. If fund managers are risk-averse, then they also want to keep expected tracking errors low to control the risk of substantial under-

[2] The importance of out-of-sample tests has been emphasized in recent return predictability literature. For example, Welch and Goyal (2008) show that, despite significant evidence of in-sample predictability, many popular predictors of the equity risk premium do not show significant predictive power based on out-of-sample tests.

performance. The risk-reward trade-off in the asset management industry suggests that fund managers will require a premium to accommodate uninformed investor demand. This mechanism has been demonstrated in theories of risk-averse liquidity provision (i.g., Shiller, 1984; Grossman and Miller, 1988; Campbell, Grossman, and Wang, 1993). Importantly, these theories predict that fund managers will reduce their liquidity provision activity and require a higher premium when their risk-bearing capacity decreases.

AIV captures the dynamics of the common factor in idiosyncratic stock return volatilities (Herskovic, Kelly, Lustig, and Van Nieuwerburgh, 2016), suggesting that it can decrease the active fund risk-bearing capacity. When *AIV* is high, idiosyncratic stock return volatilities are higher simultaneously, increasing tracking errors a fund manager faces for each dollar position deviating from the benchmark. Therefore, fund managers require a greater premium for bearing larger expected tracking errors during high *AIV* periods. I refer to this explanation as the "risk" story.

This story has additional testable predictions. First, the effect of unexpected *AIV* on contemporaneous benchmark-adjusted returns should be negative since a higher premium will decrease (increase) the current prices of the stocks underweighted (overweighted) by active mutual funds. Second, when *AIV* rises, on average, active funds should scale back their active positions and reduce their liquidity provision. Third, funds that trade against recent stock price movements for providing liquidity can earn larger returns following high *AIV* levels.

Another story is based on the assumption that active fund managers have the superior ability to collect and process information, and they can take advantage of uninformed investors by exploiting their information advantage (e.g., Kyle, 1985). Some movements in idiosyncratic stock returns may be driven by firm-specific news. Fund managers can profit by trading on idiosyncratic returns if they already have private signals about the news or can process the news faster than other investors. Because *AIV* captures the co-movements in idiosyncratic stock return volatilities, it may proxy for the aggregate flows of firms-specific news. When *AIV* is high, there are more profitable investment opportunities for informed fund managers so they can generate substantial outperformance. This explanation is referred to as the "information" story.

However, this story has different implications from the "risk" story for the effects of *AIV* on contemporaneous benchmark adjusted returns and active positions of active mutual funds. Specifically, the "information" story suggests a positive relation between unexpected *AIV* and contemporaneous benchmark adjusted returns because informed traders can realise more profits when there are more firm-specific information for them to collect and process. In addition, when *AIV* rises, this story predicts that active funds expand their active positions to exploit more trading opportunities.

Additional results appear to be more consistent with the risk story.

1. The effect of unexpected *AIV* on contemporaneous benchmark-adjusted fund returns is negative, and the magnitude of this negative relation is stronger for high Active Share portfolio.
2. On average, active mutual funds are liquidity providers – they trade against past stock price movements. They also tend to trade toward their benchmarks when *AIV* rises. More importantly, the sensitivity of liquidity provision to stock price movements decreases during times of high *AIV*.
3. The predictability of *AIV* for benchmark adjusted returns is most pronounced among funds trading against past price movements

It is worth emphasizing that these two stories are non-mutually exclusive. A fund manager may be both risk-averse and informed. She would generate superior performance by simultaneously earning a premium from liquidity provision and making trading profits from information advantage. My results can help us better understand how active fund managers generate outperformance and the critical role of *AIV* in explaining time variation in expected benchmark adjusted returns. However, they are not sufficient to tease out one story from the other. On the other hand, I believe that one single story might not be enough to describe a complete picture of the reality.

The rest of the paper is organized as follows. Section 2 introduces the data and variables. Section 3 provides detailed econometric evidence on the predictability of *AIV* for benchmark adjusted performance of active equity mutual funds. Section 4 conducts additional analyses to explore underlying mechanisms. Section 5 concludes and discusses contributions to the existing literature.

2. Data and Variable Construction

Data in this paper are from several sources. The U.S. and global equity data are from CRSP and Compustat Global. I clean the Compustat Global data following the data appendix in Bessembinder, Chen, Choi, and Wei (2020). The data of actively managed U.S. mutual funds are constructed by merging the CRSP Survivor-Bias-Free Mutual Fund Database, the Morningstar Direct, and the Thomson Reuters Mutual Fund Holding Database. The data cleaning and sample screening exercise based on previous studies (see, Kacperczyk et al., 2008; Cremers and Petajisto, 2009; Berk and van Binsbergen, 2015; Pástor, Stambaugh, and Taylor, 2017) The data of index constituents of passive benchmarks are from the FTSE/Russell. The data of actively managed international mutual funds are from the Morningstar Direct and the FactSet Global Ownership Database. I merge these two databases mainly following (Cremers, Ferreira, Matos, and Starks, 2016). The details of sample construction are described in Appendix.

2.1. U.S. and Global Stocks

The U.S. data include stocks listed in NYSE, AMEX, and NASDAQ from 1984 through 2020. The global data include stocks listed in the 49 largest equity markets, excluding the U.S. markets, from 2001 through 2020. The screening of the equity markets is based on the construction of the international Fama-French five factors Fama and French (2015).[3] Stock prices and returns are converted into U.S. dollars using exchange rates from Compustat.

2.2. *Equity Mutual Funds*

2.2.1. *U.S. Equity Mutual Funds*

I construct a comprehensive sample of U.S. equity mutual funds. Specifically, the sample includes all actively managed mutual funds, passively managed mutual funds, and exchange-traded funds (ETFs). The net fund returns, total net assets, and fund characteristics such as turnover ratio and expense ratio are from the CRSP Survivor-Bias-Free Mutual Fund Database. Other fund information such as the Morningstar Category Benchmark Index and returns of various equity indices are from the Morningstar Direct. The sample period start from January 1984 to address the selection bias problem (Elton, Gruber, and Blake, 2001; Fama and French, 2010). To further address the issue of incubation bias (Evans, 2010), I exclude observations before the reported fund inception date and observations for which the names of the funds are missing in the CRSP. In addition, I only include observations after the fund's total net assets first pass $5 million in the U.S. dollar of 2006. Previous literature mainly relies on the Thomson Reuters database to obtain mutual fund holdings. However, Zhu (2020) show that, from 2008 to 2015, 58% of newly founded U.S. equity mutual fund share classes in the CRSP cannot be matched to the Thomson Reuters database.[4] Thus, I retrieve the mutual fund holdings from Thomson Reuters before August 2008 and CRSP Holding files after September 2008. For funds with multiple share classes, I aggregate fund information at the portfolio level. I sum their total net assets to arrive at the portfolio-level

[3]Specifically, there are 24 developed markets (Australia, Austria, Belgium, Canada, Switzerland, Germany, Denmark, Spain, Finland, France, United Kingdom, Greece, Hong Kong, Ireland, Italy, Japan, Netherlands, Norway, New Zealand, Portugal, Singapore, Sweden) and 26 emerging markets (Argentina, Brazil, Chile, China, Colombia, Czech Republic, Egypt, Greece, Hungary, India, Indonesia, Malaysia, Mexico, Pakistan, Peru, Philippines, Poland, Qatar, Russia, Saudi Arabia, South Africa, South Korea, Thailand, Turkey, United Arab Emirates, Morocco, Taiwan).

[4]Funds that are missing from the Thomson Reuters tend to be smaller, have higher turnover ratios, receive higher fund flows, and have higher four-factor alphas.

total net assets. I retain the largest fund's observation for qualitative characteristics of funds such as investment objectives and inception dates. For quantitative attributes of funds, I take the weighted average by lagged total net assets. Finally, I exclude funds with less than eight observations of fund net returns (Fama and French, 2010).

The sample of U.S. equity funds includes 4,021 actively managed funds, 536 passively managed funds, and 478 ETFs. The total number of funds increases from 218 in January 1984 to 2,535 in December 2020. Figure A1 plots the total net assets across funds for each fund category (scaled by the total value of the U.S. equity market) over the sample period.

2.2.2. International Equity Mutual Funds

I construct the sample of active international equity mutual funds by combining the Morningstar Direct and FactSet Global Ownership following Cremers et al. (2016) and Schumacher (2018). The FactSet database includes institutions of various types (mutual funds, pension funds, variable annuity funds, etc.) over the sample period December 2001 to December 2020. I focus on open-end (OEF) mutual funds and that are classified as "Equity" in the Morningstar Global Category Classification. I merge the Morningstar and Factset first by matching fund ISIN identifier and then by fuzzy matching fund names with a manual check. I only include observations after the fund's total net assets first pass $5 million in the U.S. dollar of 2006. I also exclude funds with a history of returns less than 12 months to address incubation biases. The final sample consists of 56,038 unique international equity mutual funds. The total number of funds increases from 12,128 in December 2001 to 24,476 in December 2020. These funds are domiciled in 47 countries and invest in the 50 equity markets (see Section 2.1).

2.3. *Empirical Implementation*

2.3.1. *Measuring Aggregate Idiosyncratic Volatility*

The estimation of Aggregate Idiosyncratic Volatility (AIV) is similar to the methods in Bekaert, Hodrick, and Zhang (2012) and Herskovic et al. (2016). Specifically, AIV is computed as the equal-weighted average of standard deviations of daily residual returns, which are estimated from the time-series regressions of daily stock returns on the Fama-French 3 factors within each calendar month. At least 15 daily observations are required in estimation of standard deviation.[5] The main finding that AIV is a powerful predictor of the time-series of benchmark-adjusted returns is robust to alternative estimation methods.[6]

2.3.2. *Mutual Fund Benchmark Index*

I use the Morningstar Category Benchmark Index as the passive benchmark for active U.S. equity mutual funds, following the suggestions by Sensoy (2009) and Hunter, Kandel, Kandel, and Wermers (2014). Even though investment advisory companies typically disclose the benchmarks of their active mutual funds in the prospectus, these self-reported benchmarks likely have an agency-conflict issue. Sensoy (2009) find that investment advisory companies have incentives to select easy-to-beat benchmarks as their prospectus benchmark. Morningstar addresses this issue by breaking mutual funds into peer groups based on their holdings. Because some Morningstar categories have few funds over the sample period, I select the 10 most widely used benchmarks in practice: S&P 500, Russell 1000, Russell 1000 Value, Russell 1000 Growth, Russell Midcap, Russell Midcap Value, Russell Midcap Growth, Russell 2000, Russell 2000 Value, and Russell 2000 Growth. Table A1 shows the number of funds in each of these benchmark categories over the

[5]For several exceptions (i.e., September 2001), I reduce the required minimum daily observations to 10.

[6]Speficially, I estimate AIV using alternative methods such as the value-weighting average, CAPM/Fama-French 5-factor model, and excluding those micro-cap/low-price stocks. I also consider the difference between the average option-implied volatility and the VIX index as a forward-looking measure of AIV.

sample period.

The benchmark-adjusted return of an active fund is based on the Morningstar Category Benchmark Index. Specifically, it is computed as the fund return before expense, minus its Morningstar Category Benchmark Index return. In this paper, I mainly use benchmark adjusted returns as a performance measure of active mutual funds. However, the traditional method is to run time-series regressions of fund returns on various priced factors to adjust factor exposures (i.g. Carhart, 1997). The factor-based method is popular because, unlike the Morningstar data, they are freely available or can be easily constructed. The disadvantage, however, is that these priced factors are long-short portfolios whose returns cannot be costlessly achieved by active fund managers Berk and van Binsbergen (2015). The main results of this paper are robust to a variety of priced factors proposed in the recent asset pricing literature (see Section 3.4).

2.3.3. *Degree of Deviation from Benchmarks*

To measure the extent to which an active fund deviates from its benchmark index, I use Cremers and Petajisto (2009) Active Share, which has been popular in both academia and industry. Active Share represents the fraction of portfolio holdings that are different from those of the benchmark index. Specifically, it is computed as

$$AS_t = \frac{1}{2}\sum_{i=1}^{N}\left|w_{i,t}^{fund} - w_{i,t}^{benchmark}\right|$$

where $w_{i,t}^{fund}$ is the weight on stock i in an active fund portfolio and $w_{i,t}^{benchmark}$ is the weight in the Morningstar Cartogary Benchmark Index. Active Share has a value ranging between zero and one.[7]

[7]Another widely-used measure of the degree of deviations from benchmark is portfolio concentration, defined as the Herfindahl-Hirschman Index (HHI) of active weights,

$$HHI_t = \sum_{i=1}^{N}\left(w_{i,t}^{fund} - w_{i,t}^{benchmark}\right)^2.$$

It turns out the time-series average of cross-sectional correlation between Active Share and portfolio concentration is very high (about 0.95).

3. Main Results

This section shows that Aggregate Idiosyncratic Volatility (*AIV*) is a powerful time-series predictor of benchmark adjusted returns of active equity mutual funds. I begin by focusing on the data of U.S. equity mutual funds from 1984 through 2020. Using time-series predictive regressions, I document that *AIV* significantly positively forecasts average benchmark adjusted returns of active mutual funds. However, *AIV* does not predict average benchmark adjusted returns of passive funds and exchange-traded funds. In addition, I show that the predictive ability of *AIV* is most pronounced among high Active Share funds. In particular, only those funds with both high persistent and temporary components of Active Share earn greater returns following high levels of *AIV*. Finally, I find that *AIV*'s predictability is persistent within a 1-year horizon.

3.1. *AIV and Aggregate Fund Portfolios*

A large body of evidence shows that, unconditionally, the average active fund cannot outperform the market index before the expense and significantly underperforms the market index net of expense. However, this evidence does not mean that average benchmark adjusted fund returns are constant and thus unpredictable. As shown in Figure 1, the equal-weighted benchmark adjusted fund returns vary substantially over time, and more importantly, the time variation in expected benchmark adjusted returns is highly correlated with *AIV*. To formally test whether *AIV* is a significant predictor of average benchmark adjusted fund returns, I estimate the following monthly time-series predictive regressions,

$$R_t^{benchmark-adjusted} = a + bAIV_{t-1} + \gamma X_{t-1} + \epsilon_t,$$

where $R_t^{benchmark-adjusted}$ represents the equal-weighted average of benchmark-adjusted fund returns.[8] In particular, I form the aggregate portfolio for active funds, as well as for passive funds and exchange-traded funds. By examining active funds and passive funds simultaneously, I can investigate whether the predictability AIV for benchmark-adjusted returns is unique to active funds.

Table 1 presents the results from the predictive regressions. Panel A provides strong evidence that the average benchmark-adjusted returns of active equity mutual funds are highly predictable with AIV. Column (1) shows that a one-standard-deviation rise in AIV is associated with an increase of 0.97% in the annual benchmark-adjusted returns before expense. The magnitude is only slightly lower for the benchmark-adjusted return net of expense (0.91%). In addition, the estimated coefficients on AIV are statistically significant, with t-statistics well above 2. The R^2 of 2% is extremely large in predictive regressions for monthly asset returns (Campbell and Thompson, 2008). These results are not driven by other macro variables either. In fact, the predictive power of AIV becomes even stronger after controlling for a variety of variables: the real-time recession probability (Chauvet and Piger, 2008), the VIX index, investor sentiment (Baker and Wurgler, 2006), market disagreement (Yu, 2011), and aggregate liquidity (Pastor and Stambaugh, 2003).[9] This result suggests that AIV plays a unique role in driving the expected benchmark adjusted fund returns. Table A2 in the appendix shows that the predictability of AIV is statistically and economically significant for the value-weighted portfolios as

[8]Predictive regressions have been widely used in the time-series asset pricing literature. For example, Stambaugh, Yu, and Yuan (2012) test the asymmetric effect of investor sentiment on the cross-section of stock returns by running predictive regressions of monthly returns to "anomaly" strategies on the previous Baker-Wurgler sentiment index. To identify predictable time variation in the expected returns from liquidity provision, Nagel (2012) estimate predictive regressions of weekly returns to the short-term reversal strategy on previous VIX.

[9]I control these macro variables because they may be correlated with AIV or subsequent fund performance. Previous studies find some evidence that active equity mutual funds appear to perform better during recessions (Moskowitz, 2000; Kosowski, 2011; Kacperczyk et al., 2014). As shown by Bekaert et al. (2012) and Herskovic et al. (2016), VIX and AIV possess substantial common variation, particularly during deep economic recessions. Investor sentiment is a key driver of the expected stock returns (e.g., Baker and Wurgler, 2006; Stambaugh et al., 2012), suggesting a possibility that it also drives benchmark adjusted fund returns. Similarly, high market disagreement together with short sale constraints often induces overpricing in financial markets (e.g., Chen, Hong, and Stein, 2002; Diether, Malloy, and Scherbina, 2002). Market liquidity would also be negatively associated with market efficiency (e.g., Chordia, Roll, and Subrahmanyam, 2008, 2011).

Table 1: **Aggregate Idiosyncratic Volatility and Aggregate Fund Portfolios**

This table shows that Aggregate Idiosyncratic Volatility (AIV) positively predicts benchmark adjusted returns of the aggregate portfolio of active U.S. equity mutual funds, but it does not predict benchmark adjusted returns of the aggregate portfolio of passive funds and exchange-traded funds. The table reports the slope coefficient estimate, t-statistic, and adjusted-R^2 from the monthly time-series predictive regressions,

$$R_t^{benchmark-adjusted} = a + bAIV_{t-1} + \gamma X_{t-1} + \epsilon_t,$$

where $R_t^{benchmark-adjusted}$ represents the equal-weighted average of benchmark adjusted fund returns. Panel A shows the results for active equity mutual funds and Panel B shows the results for passive mutual funds and exchange-traded funds (ETFs). A fund's benchmark adjusted return is the fund's return minus the return on the Morningstar Category Benchmark Index (Pástor et al., 2017). The table reports results for benchmark adjusted returns both before expense and net of expense. AIV is computed as the equal-weighted average of idiosyncratic volatilities, estimated from time-series regressions of daily stock returns on the Fama-French three factors within each month. X represents macro control variables including Recessions (the real-time recession probability (Chauvet and Piger, 2008)), VIX, Sentiment (the investor sentiment index (Baker and Wurgler, 2006)), Disagreement (the macro disagreement index (Yu, 2011)), and Illiquidity (the cross-sectional average of Amihud illiquidity (Amihud, 2002)). Newey and West (1987) heteroskedasticity-and-autocorrelation-robust t-statistics with three lags are reported in the bracket. The return is annualized and in percentages. AIV is standardized to have zero mean and unit standard deviation. The slope coefficient estimate on AIV means the increase in expected benchmark-adjusted fund returns per year associated with a one-standard-deviation increase in AIV. The sample consists of U.S. equity funds in both CRSP and Morningstar from 1984 to 2020.

Panel A. Estimates and [t-statistics] for the equal-weighted portfolio of active mutual funds from the monthly time-series predictive regressions, $R_t^{benchmark-adjusted} = a + bAIV_{t-1} + \gamma X_{t-1} + \epsilon_t$

	(1)	(2)	(3)	(4)
	Before expense		Net of expense	
AIV	0.85	1.71	0.80	1.64
	[2.42]	[3.50]	[2.25]	[3.30]
Recessions		0.22		0.24
		[0.58]		[0.59]
VIX		-1.60		-1.62
		[-3.16]		[-3.15]
Sentiment		0.72		0.74
		[1.59]		[1.60]
Disagreement		1.04		1.09
		[2.59]		[2.66]
Illiquidity		-0.39		-0.33
		[-1.68]		[-1.40]
Adj-R^2 (%)	2.15	10.05	1.88	9.65

Panel B. Estimates and [t-statistics] for the equal-weighted portfolio of passive funds and ETFs from the monthly time-series predictive regressions, $R_t^{benchmark-adjusted} = a + bAIV_{t-1} + \gamma X_{t-1} + \epsilon_t$				
	(1)	(2)	(3)	(4)
	Before expense		Net of expense	
AIV	0.27	0.45	0.13	0.35
	[0.75]	[0.73]	[0.34]	[0.57]
Recessions		-0.01		-0.03
		[-0.03]		[-0.08]
VIX		-0.52		-0.55
		[-1.25]		[-1.35]
Sentiment		0.72		0.73
		[2.03]		[2.01]
Disagreement		0.53		0.68
		[1.23]		[1.55]
Illiquidity		-0.17		-0.22
		[-0.81]		[-1.04]
Adj-R^2 (%)	0.26	3.50	0.05	4.03

well.

In contrast, Panel B shows that *AIV* has no predictive power on the average benchmark-adjusted returns of passive and exchange-traded funds. Unlike actively managed funds that attempt to beat their benchmarks, passive funds aim to track their benchmarks closely at a low management and transaction cost. Therefore, to understand the relation between *AIV* and active fund performance, it is crucial to investigate the investment behaviors of active mutual funds. In particular, the degree of deviations from the benchmark would be of great importance for explaining the time variation in benchmark adjusted returns.

3.2. *AIV and Portfolios Formed by Active Share*

In this section, I proceed to explore whether the predictive ability of *AIV* for a fund's benchmark adjusted returns depends on the extent to which the fund deviates from its benchmark. The motivation behind this investigation is a simple intuition: an active fund manager can beat her passive benchmark only by holding a portfolio sufficiently different from the benchmark portfolio. In other words, deviating from her benchmark is the necessary condition for her to beat the benchmark. Therefore, I hypothesize that the predictive ability of *AIV* is mainly concentrated on funds significantly deviating from their benchmarks.

3.2.1. Benchmark Adjusted Returns of Active Share Quintile Portfolios

Next, I use Active Share to measure the degree of deviation of a fund's portfolio weights from its benchmark index weights. Active Share has seen a growing popularity in both academics and practitioners as a cross-sectional predictor of active fund performance because of its simple construction and substantial predictive power. Cremers and Petajisto (2009) document a significant positive relation between Active Share and fund performance in the cross-section. This relation has motivated a large body of academic studies to explain why funds deviating more from their benchmarks can generate outperformance (e.g., Van Nieuwerburgh and Veldkamp, 2010). Because high Active Share funds are more likely to produce great returns, an important question is whether they do so mainly following high AIV levels. Answering this question is obviously crucial for understanding both the time-series and cross-section of active fund performance.

I first sort active mutual funds into quintiles by the beginning-of-quarter Active Share and then compute the equal-weighted average of benchmark-adjusted returns in each quintile. Next, I run predictive regressions of average benchmark-adjusted returns on the previous AIV for all quintile portfolios. Because a fund with lower Active Share tends to track its benchmarks more closely, we should expect that the predictive ability of AIV monotonically increases with Active Share. Consistent with the hypothesis, Table 2 shows that the slope coefficients on AIV rise monotonically from the low to high Active Share quintiles. Panel A shows that for the high-minus-low Active Share portfolio, a one-standard-deviation rise in AIV is associated with an increase of 2.27% in the annual benchmark-adjusted return (t-statistics of 4.16), and the R^2 of 6.61% is remarkably large. In addition, the predictive power of AIV is most pronounced for the highest Active Share quintile. These results suggest that active funds can generate higher expected benchmark adjusted returns by deviating from their benchmark only during the periods of high AIV.

Table 2: *AIV* **and Active Share Quintile Portfolios**

This table shows that the predictability of Aggregate Idiosyncratic Volatility (*AIV*) is most pronounced among funds with high Active Share (*AS*) (Cremers and Petajisto, 2009).
The table reports the slope coefficient estimate, t-statistic, and adjusted-R^2 from the monthly time-series predictive regressions,

$$R_t^{benchmark-adjusted} = a + bAIV_{t-1} + \gamma X_{t-1} + \epsilon_t,$$

where $R_t^{benchmark-adjusted}$ represents the equal-weighted benchmark adjusted returns for the portfolios formed by sorting active mutual funds into quintiles on beginning-of-quarter Active Share. Active Share is computed by $\frac{1}{2}\sum_{i=1}^{N}\left|w_{i,t}^{fund} - w_{i,t}^{benchmark}\right|$, where $w_{i,t}^{fund}$ denotes an active fund's weight on stock i and $w_{i,t}^{benchmark}$ denotes the weight on stock i in the Morningstar Category Benchmark Index. Panel A (B) presents the results from the regression specification without (with) control variables. See the caption in Table 1 for the definitions of *AIV* and macro control variables. Newey and West (1987) heteroskedasticity-and-autocorrelation-robust t-statistics with three lags are reported in the bracket. The return is annualized and in percentages. *AIV* is standardized to have zero mean and unit standard deviation. The slope coefficient estimate on *AIV* means the increase in expected benchmark-adjusted fund returns per year associated with a one-standard-deviation increase in *AIV*. The sample consists of active U.S. equity mutual funds in both CRSP and Morningstar from 1984 through 2020.

Estimates and [t-statistics] for the equal-weighted Active Share (*AS*) quintile portfolios from the monthly time-series predictive regressions $R_t^{benchmark-adjusted} = a + bAIV_{t-1} + \gamma X_{t-1} + \epsilon_t$						
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Predictive regressions without controls X_{t-1}					
	Low *AS*	2	3	4	High *AS*	H-L
AIV	0.15	0.37	0.77	0.79	2.42	2.27
	[0.51]	[1.13]	[2.04]	[1.90]	[3.83]	[4.16]
Adj-R^2 (%)	0.08	0.38	1.30	1.17	6.14	6.61
	Panel B. Predictive regressions with controls X_{t-1}					
	Low *AS*	2	3	4	High *AS*	H-L
AIV	0.54	0.86	1.65	1.95	3.78	3.24
	[1.34]	[1.77]	[2.88]	[2.90]	[3.90]	[3.43]
Recessions	0.55	0.16	0.12	-0.16	0.21	-0.35
	[1.88]	[0.50]	[0.31]	[-0.30]	[0.27]	[-0.51]
VIX	-0.86	-1.06	-1.59	-1.71	-2.98	-2.13
	[-2.09]	[-2.24]	[-2.93]	[-2.60]	[-3.79]	[-3.61]
Sentiment	0.56	0.60	0.44	0.42	1.52	0.96
	[1.32]	[1.28]	[0.90]	[0.84]	[2.28]	[1.61]
Disagreement	0.61	0.64	1.06	0.89	2.26	1.65
	[1.69]	[1.68]	[2.29]	[1.98]	[3.23]	[2.75]
Illiquidity	-0.50	-0.14	-0.30	-0.67	-0.09	0.41
	[-2.66]	[-0.72]	[-1.07]	[-1.93]	[-0.15]	[0.68]
Adj-R^2 (%)	4.56	3.85	5.90	7.04	14.48	11.66

Table 3: **Fund's Holdings Return and Return Gap**

This table shows that Aggregate Idiosyncratic Volatility (AIV) predicts both the fund's holdings return and return gap. A fund's holdings return is the return of a hypothetical portfolio investing in the fund's recently disclosed holdings. The return gap is a fund return before expense minus its holdings return (Kacperczyk et al., 2008).
Panel A reports the slope coefficient estimate, t-statistic, and adjusted-R^2 from the monthly time-series predictive regressions,

$$HR_t = a + bAIV_{t-1} + \gamma X_{t-1} + \epsilon_t,$$

where HR_t represents the equal-weighted benchmark adjusted returns of the fund holdings for Active Share quintile portfolios. Panel B reports the results from the regressions,

$$RG_t = a + bAIV_{t-1} + \gamma X_{t-1} + \epsilon_t,$$

where RG_t represents the equal-weighted return gaps for Active Share quintile portfolios. SEC requires mutual funds to disclose quarterly holdings no later than 60 days after the report date. I thus form the hypothetical portfolio of the fund's holdings two months after the report date. See the captions in Table 1 and Table 2 for the definitions of AIV, Active Share, and macro control variables. Newey and West (1987) heteroskedasticity-and-autocorrelation-robust t-statistics with three lags are reported in the bracket. The return is annualized and in percentages. AIV is standardized to have zero mean and unit standard deviation. The slope coefficient estimate on AIV means the increase in expected returns per year associated with a one-standard-deviation increase in AIV. The sample consists of active U.S. equity mutual funds in both CRSP and Morningstar from 1984 through 2020.

	Estimates and [t-statistics] for Active Share (AS) quintile portfolios from the monthly time-series predictive regressions $Y_t = a + bAIV_{t-1} + \gamma X_{t-1} + \epsilon_t$					
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Y_t: the fund's holdings return (HR_t)					
	Low AS	2	3	4	High AS	H-L
AIV	0.82	0.95	1.39	1.00	2.74	1.92
	[1.60]	[2.02]	[2.12]	[1.41]	[2.89]	[2.40]
Adj-R^2 (%)	6.85	5.83	5.05	4.60	10.82	6.55
	Panel B. Y_t: the return gap (RG_t)					
	Low AS	2	3	4	High AS	H-L
AIV	-0.18	0.09	0.39	0.99	1.07	1.24
	[-0.47]	[0.28]	[1.16]	[2.38]	[2.69]	[2.44]
Adj-R^2 (%)	3.19	4.16	4.15	5.38	4.42	3.10

3.2.2. Fund's Holdings Return and Return Gap

Mutual funds are required by SEC to disclose their equity holdings only at a quarterly frequency, so we do not observe all actions of fund managers. It is thus interesting to explore whether *AIV* forecasts the returns generated by unobserved interim actions of fund managers within the quarter, or the returns of observed quarterly equity holdings, or both. This exercise can also help us answer the question of whether the outperformance of high Active Share funds come from their options or other derivatives holdings.[10]

To answer this questions, I compute the fund's holdings return and return gap. A fund's holdings return is the return of a hypothetical portfolio investing in the fund's recently disclosed holdings. The return gap is a fund return before expense minus its holdings return, which can capture the hidden profits from the fund's interim trades within the quarter (Kacperczyk et al., 2008). SEC requires mutual funds to disclose quarterly holdings no later than 60 days after the report date. I thus form the hypothetical portfolio of the fund's holdings two months after the report date.

Table 3 shows the results from the predictive regressions of the fund's holdings return (in excess of benchmark index return) or return gap on previous *AIV* for Active Share quintile portfolios. There are two important observations from this table. First, the slope coefficient estimates on *AIV* monotonically increase with Active Share for both the fund's holdings return and return gap. Second, *AIV* significantly forecasts both the fund's holdings return and return gap for the high Active Share quintile. However, the magnitude of its predictive power on the fund holdings' return is roughly two times larger than that on the return gap. Therefore, 70% of *AIV*'s predictability is on the returns of observed quarterly equity holdings. In other words, the positive relation between *AIV* and expected benchmark adjusted returns can only partially explained by 1) the short-term trading activity of active

[10] Even a small fraction of the fund's portfolio on derivatives is sufficient to generate substantial profits due to the non-linear payoff structure and impeded leverage in derivative contracts.

Table 4: **Persistent and Temporary Components of Active Share**
This table shows that the predictability of AIV for subsequent benchmark-adjusted fund returns is most pronounced among funds with both high persistent and temporary components of Active Share. The persistent component of Active Share ($\overline{AS}$) is the 12-quarter rolling average of Active Share over the window $[t-13, t-1]$. The temporary component (ΔAS) is the quarter-t Active Share minus the persistent component.
The table reports the coefficient estimates and t-statistics from the monthly predictive regressions

$$R_t^{benchmark-adjusted} = a + bAIV_{t-1} + \gamma X_{t-1} + \epsilon_t,$$

where $R_t^{benchmark-adjusted}$ is the equal-weighted benchmark adjusted returns for the portfolios formed by independently sorting active funds on the persistent and temporary components of Active Share. See the captions in Table 1 and Table 2 for the definitions of AIV, Active Share, and macro control variables. Newey and West (1987) heteroskedasticity-and-autocorrelation-robust t-statistics with three lags are reported in the bracket. The return is annualized and in percentages. AIV is standardized to have zero mean and unit standard deviation. The slope coefficient estimate on AIV means the increase in expected returns per year associated with a one-standard-deviation increase in AIV. The sample consists of active U.S. equity mutual funds in both CRSP and Morningstar from 1987 through 2020.

Estimates and [t-statistics] for portfolios sorted independently on persistent and temporary Active Share from the monthly time-series predictive regressions $R_t^{benchmark-adjusted} = a + bAIV_{t-1} + \gamma X_{t-1} + \epsilon_t$

	Persistent Active Share ($\overline{AS}$)					
Temporary Active Share (ΔAS)	Low $\overline{AS}$	2	3	4	High $\overline{AS}$	H-L
Low	0.51	1.10	1.66	1.18	0.14	-0.37
	[0.93]	[1.38]	[2.70]	[1.21]	[0.10]	[-0.23]
2	0.85	0.96	0.93	1.18	0.09	-0.77
	[1.21]	[1.38]	[1.66]	[1.14]	[0.05]	[-0.40]
3	-0.38	2.21	1.24	1.55	1.77	2.14
	[-0.47]	[3.39]	[1.81]	[1.74]	[1.26]	[1.68]
4	1.47	0.19	3.40	2.08	3.16	1.69
	[1.63]	[0.21]	[2.87]	[1.79]	[2.58]	[1.32]
High	0.52	1.60	2.39	4.34	10.46	9.94
	[0.63]	[1.29]	[1.70]	[3.08]	[3.12]	[3.04]
H-L	0.00	0.50	0.73	3.16	10.32	
	[0.01]	[0.42]	[0.50]	[2.24]	[2.80]	

funds; 2) the potential options and derivatives holdings. Because quarterly equity holdings play the most important role in driving predictable benchmark adjusted returns, I next explore how the AIV-performance relation is associated with fund investment behaviors at a quarterly frequency.

3.2.3. Persistent and Temporary Active Share

It is helpful to decompose Active Share into the persistent and temporary components and investigate which parts are driving the results in Table 2. The persistent component of Active Share might be associated with the intent of active funds to bet on factor exposures or (negatively) proxies for fund manager risk aversion. In contrast, the temporary component captures the attempt of active funds to take short-term investment opportunities, such as liquidity provision or private information. The persistent component of Active Share ($\overline{AS}$) is the 12-quarter rolling average of Active Share over the window $[t-13, t-1]$. The temporary component (ΔAS) is the quarter-t Active Share minus the persistent component. Table 4 presents the estimates from the independent sorts on the permanent and temporary components. It shows that the positive AIV-performance relation is most pronounced among funds with both high persistent and temporary components. For example, for the high $\overline{AS}$ - high ΔAS portfolio, a one-standard-deviation rise in AIV is associated with an increase of 10.32% in the annual benchmark-adjusted return (t-statistics of 3.12), about five times larger than that for the high Active Share quintile in Table 2. Importantly, for the high $\overline{AS}$ - low ΔAS portfolio, AIV does not show any predictive ability for benchmark adjusted returns. This result suggests that less risk-averse fund managers are able to exploit some profitable short-term opportunities during periods of high AIV. Section 4 explores potential mechanisms related to this thought in more detail.

3.2.4. Horizons of Predictability of AIV

The previous analyses focus on the one-month ahead predictability of AIV for benchmark-adjusted fund returns. It is also important to examine over what horizons the predictive power of AIV is persistent and significant. The relevant horizon can give us more useful information to investigate the underlying mechanism. The results from Sections 3.2.2 and 3.2.3 point to the possibility that active funds generate greater returns by exploiting short-term opportunities during times of high AIV. One potential case is that active funds earn a reward for providing liquidity to uninformed investors. When AIV is high, it's riskier for them to accommodate uninformed investor demand so they require higher rewards for bearing larger tracking errors. I will postpone more detailed discussions on this story in Section 4.

To test the horizons of the predictability of AIV, I compute the benchmark ad-

Table 5: **Horizons of Predictability of** *AIV*

This table shows that the predictability of *AIV* on benchmark-adjusted holdings returns is significant within a 9-months horizon.

The table reports the slope coefficient estimate, t-statistic, and adjusted-R^2 from the monthly time-series predictive regressions,

$$HR_t^{[3(k-1),3k]} = a + bAIV_{t-1} + \epsilon_t,$$

where $HR_t^{[3(k-1),3k]}$ represents the equal-weighted benchmark adjusted holdings returns at different horizons for the portfolios formed by Active Share at time t. $HR_t^{[3(k-1),3k]}$ of an active fund is computed as

$$HR_t^{[3(k-1),3k]} = \sum (w_{i,t}^{fund} - w_{i,t}^{benchmark}) \times r_{i,t}^{[3(k-1),3k]},$$

where $r_{i,t}^{[3(k-1),3k]}$ is the return of stock i over $[3(k-1), 3k]$ and $w_{i,t}^{fund} - w_{i,t}^{benchmark}$ denotes the fund's weight minus its benchmark index weight on stock i. Newey and West (1987) heteroskedasticity-and-autocorrelation-robust t-statistics with six lags are reported in the bracket. The return is annualized and in percentages. *AIV* is standardized to have zero mean and unit standard deviation. The slope coefficient estimate on *AIV* means the increase in expected returns per year associated with a one-standard-deviation increase in *AIV*. The sample consists of active U.S. equity mutual funds in both CRSP and Morningstar from 1984 through 2020.

Estimates and [t-statistics] for the portfolios formed by the quarter-t Active Share (AS) from the monthly time-series predictive regressions $HR_{t+3(k-1),t+3k} = a + bAIV_{t-1} + \epsilon_t$						
	Low AS	2	3	4	High AS	H-L
			1-3 months ahead ($k=1$)			
AIV	-0.53	0.23	0.69	0.90	2.28	2.81
	[-0.98]	[0.81]	[1.38]	[1.65]	[2.02]	[2.25]
Adj-R^2 (%)	0.63	0.38	2.09	2.80	9.36	9.03
			4-6 months ahead ($k=2$)			
AIV	-0.77	-0.05	0.40	0.37	1.67	2.45
	[-1.26]	[-0.20]	[0.77]	[0.68]	[2.01]	[2.31]
Adj-R^2 (%)	1.32	0.02	0.82	0.54	5.19	6.89
			7-9 months ahead ($k=3$)			
AIV	-0.56	-0.09	0.50	0.54	1.61	2.17
	[-1.14]	[-0.26]	[0.96]	[1.04]	[1.74]	[2.04]
Adj-R^2 (%)	0.65	0.05	1.23	1.38	5.43	5.78
			10-12 months ahead ($k=4$)			
AIV	-0.71	-0.39	0.32	0.32	1.01	1.73
	[-1.57]	[-1.31]	[0.81]	[0.68]	[1.46]	[1.87]
Adj-R^2 (%)	1.15	1.13	0.59	0.47	2.16	3.11
			13-15 months ahead ($k=5$)			
AIV	-0.73	-0.09	0.05	0.12	0.61	1.34
	[-1.53]	[-0.51]	[0.15]	[0.29]	[0.87]	[1.49]
Adj-R^2 (%)	0.91	0.07	0.02	0.08	0.71	1.94

justed holdings returns k-months ahead generated by an active fund's current active weights – the fund's portfolio weights relative to the benchmark index weights. Specifically, the benchmark adjusted holdings return of an active fund is computed over the 3-month window at different horizons $[3(k-1), 3k]$ (k = 1,2,3,4,5),

$$HR_t^{[3(k-1),3k]} = \sum (w_{i,t}^{fund} - w_{i,t}^{benchmark}) \times r_{i,t}^{[3(k-1),3k]},$$

where $r_{i,t}^{[3(k-1),3k]}$ is the return of stock i over $[3(k-1), 3k]$ and $w_{i,t}^{fund} - w_{i,t}^{benchmark}$ denotes the fund's weight minus its benchmark index weight on stock i. I then estimate the following monthly time-series predictive regressions,

$$HR_t^{[3(k-1),3k]} = a + bAIV_{t-1} + \epsilon_t,$$

where $HR_t^{[3(k-1),3k]}$ represents the equal-weighted benchmark adjusted holdings returns at different horizons for the portfolios formed by Active Share at time t. Table 5 shows that the predictability of AIV for subsequent benchmark-adjusted holdings returns decreases monotonically and becomes insignificant at a 1-year horizon, suggesting that liquidity provision would be a potential explanation for how active funds generate positive benchmark adjusted returns and why they can do so particularly following high AIV levels.

3.3. *Additional Results and Robustness*

3.3.1. *Out-of-Sample Tests*

Recent literature has emphasized the importance of out-of-sample tests in return predictability.[11] To examine the robustness of the in-sample results, in this section I conduct out-of-sample tests on the predictability of AIV for benchmark-adjusted fund returns. Specifically, I compute the out-of-sample R^2 (R^2_{OOS}) proposed by Campbell and Thompson (2008). The R^2_{OOS} is defined as the proportional reduc-

[11] For example, Welch and Goyal (2008) show that the in-sample predictive ability of various plausible return predictors of aggregate stock returns generally does not hold up in out-of-sample tests.

Table 6: **Out-of-Sample Tests**

This table shows that the predictability of *AIV* for benchmark adjusted fund returns is robust in out-of-sample tests.

The table reports the out-of-sample R-squared (R^2_{OOS}) (Campbell and Thompson, 2008) and the associated $CW-$statistics (Clark and West, 2007). R^2_{OOS} is the proportional reduction in mean squared forecast error for the predictive regression forecast vis-á-vis the prevailing mean forecast. The predictive regression forecast is computed as

$$\widehat{R_t} = \widehat{a}_{t-1} + \widehat{b}_{t-1} AIV_{t-1},$$

where $\widehat{a}_{t-1}$ and $\widehat{b}_{t-1}$ are estimated from $R_t^{benchmark-adjusted} = a + bAIV_{t-1} + \epsilon_t$, based on data from the beginning of the sample through t. The prevailing mean forecast is computed as

$$\overline{R_t} = \frac{1}{t} \sum_{k=1}^{t} R_k^{benchmark-adjusted},$$

under the assumption that benchmark-adjusted returns are not predictable. R^2_{OOS} is defined by

$$R^2_{OOS} = 1 - \frac{\sum_{t=1}^{T} \left(R_t^{benchmark-adjusted} - \widehat{R_t} \right)^2}{\sum_{t=1}^{T} \left(R_t^{benchmark-adjusted} - \overline{R_t} \right)^2}.$$

$CW-$statistic tests the null hypothesis $R^2_{OOS} \leq 0$ against the alternative hypothesis $R^2_{OOS} > 0$. The null hypothesis is rejected at a one-sided 5% test if $CW-$statistic is larger than 1.96. The sample consists of active U.S. equity mutual funds in both CRSP and Morningstar from 1984 through 2020. The forecast evaluation period starts from 1994 to have 10-year data to estimate both forecasts.

	The Campbell and Thompson (2008) R^2_{OOS} and Clark and West (2007) statistics					
	(1)	(2)	(3)	(4)	(5)	(6)
	Low *AS*	2	3	4	High *AS*	H-L
R^2_{OOS}	-0.13	-0.87	-0.48	2.08	6.05	5.02
	[0.59]	[0.83]	[1.48]	[2.11]	[3.49]	[3.67]

tion in mean squared forecast error (MSFE) for the predictive regression forecast based on AIV vis-á-vis the prevailing mean forecast. The predictive regression forecast is computed as

$$\widehat{R_t} = \widehat{a}_{t-1} + \widehat{b}_{t-1} AIV_{t-1},$$

where $\widehat{a}_{t-1}$ and $\widehat{b}_{t-1}$ are the coefficient estimates from $R_t^{benchmark-adjusted} = a + bAIV_{t-1} + \epsilon_t$, based on data from the beginning of the sample through month t. The prevailing mean forecast is computed as

$$\overline{R_t} = \frac{1}{t} \sum_{k=1}^{t} R_k^{benchmark-adjusted},$$

under the assumption that benchmark-adjusted fund returns are not predictable. The R^2_{OOS} is then computed as

$$R^2_{OOS} = 1 - \frac{\sum_{t=1}^{T} \left(R_t^{benchmark-adjusted} - \widehat{R_t} \right)^2}{\sum_{t=1}^{T} \left(R_t^{benchmark-adjusted} - \overline{R_t} \right)^2}.$$

I start the forecast evaluation period from 1994 to ensure that there are at least 10-year data to estimate both forecasts. It is useful to know whether the predictive regression forecast delivers a statistically significant improvement in MSFE. Therefore, I also report the $CW-$statistics proposed by Clark and West (2007) for testing the null hypothesis that the prevailing mean MSFE is less than or equal to the predictive regression MSFE against the alternative hypothesis that the prevailing mean MSFE is greater than the predictive regression MSFE (corresponding to $H_0 : R^2_{OOS} \leq 0$ against $H_A : R^2_{OOS} > 0$). Table 6 shows that the R^2_{OOS} statistics rise from -0.13% to 6.05% from the low to high Active Share quintiles. For the high-minus-low Active Share portfolio, the R^2_{OOS} is 5.02% with a CW-statistic of 3.67, meaning that the null hypothesis can be rejected at a one-sided 1% test.

Table 7: **Time Variation in Market Timing and Stock Picking**

This table shows that Aggregate Idiosyncratic Volatility (AIV) is positively correlated with time variation in expected returns generated by fund manager stock picking but not market timing skill.
Panel A reports the slope coefficient estimate, t-statistic, and adjusted-R^2 from the monthly time-series predictive regressions,

$$Picking_t = a + bAIV_{t-1} + \gamma X_{t-1} + \epsilon_t,$$

where $Picking_t$ represents the equal-weighted stock picking skill for Active Share quintile portfolios.
Panel B reports the results from the regressions,

$$Timing_t = a + bAIV_{t-1} + \gamma X_{t-1} + \epsilon_t,$$

where $Timing_t$ represents the equal-weighted market timing skill for Active Share quintile portfolios. Following Kacperczyk et al. (2014), the stock picking and market timing skills measure the returns generated by fund manager skill based on their portfolio holdings. See the captions in Table 1 and Table 2 for the definitions of AIV, Active Share, and macro control variables. Newey and West (1987) heteroskedasticity-and-autocorrelation-robust t-statistics with three lags are reported in the bracket. The return is annualized and in percentages. AIV is standardized to have zero mean and unit standard deviation so the slope coefficient estimate on AIV means the increase in expected return generated by manager skill associated with a one-standard-deviation increase in AIV. The sample consists of active U.S. equity mutual funds in both CRSP and Morningstar from 1984 through 2020.

	Estimates and [t-statistics] for Active Share (AS) quintile portfolios from monthly time-series predictive regressions $Y_t = a + bAIV_{t-1} + \gamma X_{t-1} + \epsilon_t$					
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. Y_t: stock picking ($Picking_t$)					
	Low AS	2	3	4	High AS	H-L
AIV	1.47	2.12	4.25	6.03	8.20	6.74
	[1.45]	[2.12]	[3.15]	[2.89]	[3.95]	[2.99]
Adj-R^2 (%)	4.85	6.03	8.01	6.08	8.45	6.76
	Panel B. Y_t: market timing ($Timing_t$)					
	Low AS	2	3	4	High AS	H-L
AIV	-2.86	-3.18	-3.34	-3.66	-4.02	-1.16
	[-0.70]	[-0.78]	[-0.80]	[-0.85]	[-1.05]	[-1.18]
Adj-R^2 (%)	8.17	8.33	8.72	8.95	8.40	3.04

3.3.2. Time-Varying Timing and Picking Skills

Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016) show theoretically that skilled managers can pick stocks well in booms and time the market well in recessions because they rationally allocate their limited attention over different market conditions. And Kacperczyk et al. (2014) provide consistent empirical evidence from the sample of active U.S. equity mutual funds. Using the same skill measures proposed by Kacperczyk et al. (2014), Table 7 shows that it is stock picking that allows the high Active Share funds to earn greater returns following high *AIV* levels. This is also consistent with the evidence in Cremers and Petajisto (2009) showing that Active Share mainly reflects managers' stock picking rather than factor timing activities.

3.3.3. Spurious Regression

Highly autocorrelated regressor as a predictor for asset return could probably result in the spurious regression bias: If the unobserved expected return is time-varying and persistent, another persistent variable having no real relationship with the expected return can appear to have the predictive ability in a finite sample.[12] I investigate how large the chance that a randomly generated spurious regressor supports these two features by implementing simulations proposed in Stambaugh et al. (2014). Table A3 shows that, out of 1 million simulations of a randomly generated spurious regressor, only one of 1,179 simulated spurious regressors can predict the benchmark-adjusted return of the high-low Active Share portfolio as strongly as *AIV*.

[12] Ferson, Sarkissian, and Simin (2003) show that the combination of spurious regression and data mining substantially increases the chance of finding a persistent regressor that appears to have predictive power for stock returns but does so spuriously. Novy-Marx (2014) provides many examples that the regressors such as sunspots and planetary positions can predict returns of various anomalies at usual statistically significance level.

3.4. *Controlling for Price Factors*

So far, the performance of an active fund is evaluated against its Morningstar Category Benchmark Index, which is a common practice in the asset management industry. In contrast, the academic literature typically uses the factor-based regression approach to adjust factor exposures of fund returns. For example, the Carhart four-factor model is probably the most widely used model to evaluate active mutual fund performance. Controlling various priced factors also alleviates the concern that *AIV* captures factors ignored in the regression specifications (Chen and Petkova, 2012). If fund managers trade on these factors, then *AIV* would predict subsequent fund performance because of its association with these factors. Table A4 shows that the coefficient estimates on *AIV* are significant from predictive regressions augmented with various priced factors and the economic magnitudes are similar to those reported in Table 2.[13] These results suggest that the predictability of *AIV* is not likely result from the model misspecification.

3.4.1. *Fama-French (2010) Bootstrap Simulations*

Finally, I employ the Fama and French (2010) bootstrap simulations to investigate how the cross-section of mutual fund α shifts when *AIV* rises. Specifically, I construct the cross-sections of actual estimates and the simulated of Carhart 4-factors $t(\alpha)$ for the full sample, the low-*AIV* subsample, and the high-*AIV* subsample. A simulation run is a random sample (with replacement) of 444 months for the full sample, 222 months for the low-AIV subsample, and 222 months for the high-*AIV* subsample. I estimate $t(\alpha)$ fund by fund from each simulation draw of months. I then compare (i) the values of $t(\alpha)$ at selected percentiles of the CDF of the $t(\alpha)$ estimates from actual fund returns and (ii) the averages across the 10,000

[13] I control the following priced factors proposed in the recent literature of the cross-section of the stock returns: (1) the Carhart (1997) 4-factor model augmented with liquidity factor (Pastor and Stambaugh, 2003); (2) the CAPM augmented with the CIV factor (Herskovic et al., 2016); (3) the Fama and French (2015) 5-factor model; (4) the Stambaugh and Yuan (2017) 4-factor model; (5) the Daniel, Hirshleifer, and Sun (2020) 3-factor model augmented with the size factor (SMB); (6) the Hou, Mo, Xue, and Zhang (2020) 5-factor model.

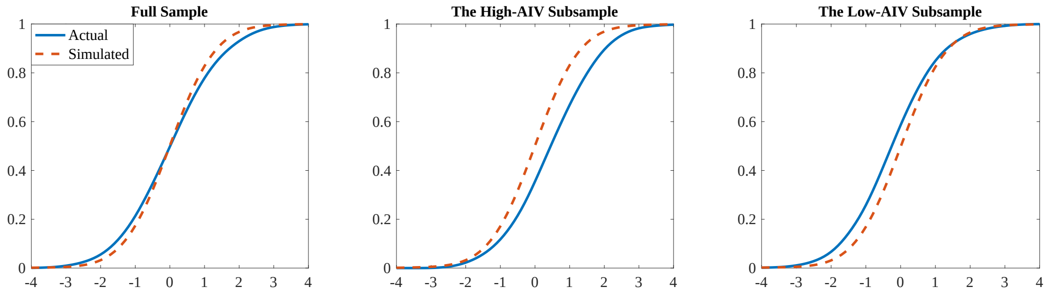

Fig. 2. **Fama-French (2010) Bootstrap Simulations**
This figure plots the actual and simulated cumulative density functions of t-statistics of the Fama-French-Carhart gross α based on the Fama and French (2010) bootstrap simulations. I run 10,000 bootstrap simulations for the full sample (444 months), the low-*AIV* sub-sample (222 months), and the high-*AIV* sub-sample (222 months), respectively. I estimate $t(\alpha)$ fund by fund from each simulation draw of months. I then compare (i) the values of $t(\alpha)$ at selected percentiles of the CDF of the $t(\alpha)$ estimates from actual fund returns and (ii) the averages across the 10,000 simulation runs of the $t(\alpha)$ estimates at the same percentiles. The fat right (left) tail in the cross-sectional distribution of the actual $t(\alpha)$ relative to the simulated $t(\alpha)$ indicates the existence of funds with positive (negative) α. The sample consists of active U.S. equity mutual funds in both CRSP and Morningstar from 1984 through 2020.

simulation runs of the $t(\alpha)$ estimates at the same percentiles. The fat right (left) tail in the cross-sectional distribution of the actual $t(\alpha)$ relative to the simulated $t(\alpha)$ indicates the existence of funds who are able to generate positive (negative) α. Figure 2 plots the probability density functions of 4-factor $t(\alpha)$.[14] The bootstrap simulations from the two subsamples produce very different patterns of $t(\alpha)$. In the high (low) -*AIV* subsample, the CDF of actual $t(\alpha)$ shifts almost entirely to the right (left) of the average of the simulated CDFs. The results from the Fama and French (2010) bootstrap simulations strongly support that *AIV* is the key driver of the ability of active funds to outperform passive strategies.

4. Exploring The Mechanism

Section 3 provides robust empirical evidence that high Aggregate Idiosyncratic Volatility (*AIV*) forecasts high benchmark-adjusted returns of active equity mutual funds. This section explores potential mechanisms to understand why *AIV* drives time variation in expected benchmark-adjusted fund returns. I first identify two

[14]Table A5 in Appendix reports the values of $t(\alpha)$ at selected percentiles of the cumulative density function (CDF) for the actual $t(\alpha)$ estimates and the averages across the 10,000 simulation runs of the $t(\alpha)$ estimates.

non-mutually exclusive stories: 1) active funds are compensated for providing liquidity to the stock market and *AIV* decreases their risk-bearing capacity for doing so (i.e., the risk story); and 2) active fund managers are skilled at collecting and processing information and *AIV* proxies for the aggregate flow of firm-specific news (i.e., the information story). Then I conduct a collection of tests to evaluate these two stories. I find empirical evidence is more consistent with the risk story.

4.1. *Why Does* AIV *Predict Benchmark Adjusted Fund Performance?*

Delegated portfolio management contains two categories: passive funds and active funds. A passive fund aims to replicate the return on a benchmark index by holding all the index constituents according to the official index proportions. On the other hand, an active fund attempts to outperform its benchmark by taking active positions against the benchmark. Because passive funds earn zero benchmark-adjusted returns, active funds can earn positive benchmark-adjusted returns only at the expense of other active investors.[15]

Suppose there are uninformed investors trading assets for reasons such as biased beliefs or liquidity needs. The aggregate excess demand of uninformed investors could move asset prices away from fundamental values. Active funds may attempt to exploit this opportunity by taking the other side of uninformed investor demand. If fund managers are risk-averse, then they also want to keep expected tracking errors low to control the risk of substantial underperformance. This risk-reward trade-off in the asset management industry suggests that fund managers will require a premium for accommodating uninformed investor demand. This mechanism has been demonstrated in theories of risk-averse liquidity provision (i.g., Shiller, 1984; Grossman and Miller, 1988; Campbell et al., 1993). These theories predict that fund managers will reduce their liquidity provision activity and re-

[15]In the absence of other investors, skilled portfolio managers can earn positive α only at the expense of unskilled portfolio managers. In other words, active funds as a whole play a zero-sum game, which Sharpe (1991) call "the arithmetic of active management." However, this is not consistent with the empirical finding in Section 3.1 where we observe that the average active fund generates significant expected benchmark-adjusted returns when *AIV* is high.

quire a higher premium when their risk-bearing capacity decreases.[16] *AIV* captures the dynamics of the common factor in idiosyncratic stock return volatilities (Herskovic et al., 2016). This phenomenon suggests that *AIV* can decrease active fund risk-bearing capacity because it increases tracking errors a fund manager faces for each dollar position deviating from its benchmark. When *AIV* is high, idiosyncratic stock return volatilities are higher simultaneously, increasing the fund's risk of taking active positions against the benchmark. Therefore, fund managers require a greater premium for bearing larger expected tracking errors during high *AIV* periods. I refer to this explanation as the "risk" story. This story has additional testable predictions. First, the effect of unexpected *AIV* on contemporaneous benchmark-adjusted returns should be negative since a higher premium will decrease (increase) the current prices of the stocks underweighted (overweighted) by active mutual funds. Second, when *AIV* rises, on average, active funds should scale back their active positions and reduce their liquidity provision. Third, funds that trade against recent stock price movements for providing liquidity can earn larger returns following high *AIV* levels.

Another story is based on the assumption that active fund managers have the superior ability to collect and process information, and they can take advantage of uninformed investors by exploiting their information advantage (e.g., Kyle, 1985). Some movements in idiosyncratic stock returns may be driven by firm-specific news. Fund managers can profit by trading on idiosyncratic returns if they already have private signals about the news or can process the news faster than other investors. Because *AIV* captures the co-movements in idiosyncratic stock return volatilities, it may proxy for the aggregate flows of firms-specific news. When *AIV* is high, there are more profitable investment opportunities for informed fund managers so they can generate substantial outperformance. This explanation is referred to as the "information" story. This story, however, has different implications for the effects of *AIV* on contemporaneous benchmark adjusted returns and active positions of ac-

[16]In appendix 5, I develop a simple theoretical framework to deliver this mechanism.

Table 8: **Active Fund Performance and Contemporaneous Shocks to** *AIV*
This table shows a significant negative effect of *AIV* on unexpected contemporaneous benchmark adjusted fund returns and the magnitude of this negative effect increases with Active Share.
The table reports the slope coefficient estimate, t-statistic, and adjusted-R^2 from the monthly time-series regressions,

$$R_t^{benchmark-adjusted} = a + bAIV_t^{unexpected} + cAIV_{t-1} + \epsilon_t,$$

where $R_t^{benchmark-adjusted}$ is the equal-weighted average benchmark-adjusted returns for Active Share quintile portfolios. $AIV^{unexpected}$ is estimated as the AR(1) residuals of *AIV*. See the captions in Tables 1 and 2 for the definitions of *AIV* and Active Share. Newey and West (1987) heteroskedasticity-and-autocorrelation-robust t-statistics with three lags are reported in the bracket. The return is annualized and in percentages. Both $AIV^{unexpected}$ and *AIV* are standardized to have unit standard deviation. The sample consists of active U.S. equity mutual funds in both CRSP and Morningstar from 1984 through 2020.

Estimates and [t-statistics] for Active Share (*AS*) quintile portfolios from the monthly time-series regressions $R_t^{benchmark-adjusted} = a + bAIV_t^{unexpected} + cAIV_{t-1} + \epsilon_t$						
	(1)	(2)	(3)	(4)	(5)	(6)
	Low *AS*	2	3	4	High *AS*	H-L
$AIV_t^{unexpected}$	-0.04	-0.05	-1.31	-1.24	-3.34	-3.30
	[-0.05]	[-0.05]	[-1.32]	[-1.16]	[-2.51]	[-3.87]
AIV_{t-1}	0.19	0.41	1.96	1.91	5.47	5.28
	[0.26]	[0.47]	[2.29]	[2.01]	[4.51]	[6.24]
Adj-R^2 (%)	0.08	0.38	1.94	1.66	8.11	8.98

tive mutual funds. Specifically, the "information" story suggests a positive relation between unexpected *AIV* and contemporaneous benchmark adjusted returns because informed traders can realise more profits when there are more firm-specific information for them to collect and process. In addition, when *AIV* rises, this story predicts that active funds expand their active positions to exploit more trading opportunities.

4.2. *Evidence*

4.2.1. *Unexpected AIV and Contemporaneous Benchmark Adjusted Returns*

My first test focuses on the relationship between unexpected changes in *AIV* and contemporaneous benchmark-adjusted fund returns. A negative relation provides evidence supporting the risk story. Suppose this month's *AIV* is larger than predicted. Then active fund managers will revise the predicted *AIV* upward for all future periods. If they accommodate uninformed demand and earn a premium, which is positively related to *AIV*, then the premium will also be larger for all future periods. Therefore, we should expect that stocks initially overweighted (underweighted) by an active mutual fund will have lower (higher) current prices, suggesting a negative correlation between AIV shocks and contemporaneous benchmark-adjusted fund returns. In addition, the magnitude of this negative correlation should be increasing with the fund's deviation from its benchmarks. To test this hypothesis, I estimate the following time-series regressions for Active Share quintile portfolios,

$$R_t^{benchmark-adjusted} = a + bAIV_t^{unexpected} + cAIV_{t-1} + \epsilon_t,$$

where $AIV_t^{unexpected}$ represents the unexpected AIV, which is estimated as the AR(1) residuals of AIV. Table 8 shows that there is a negative effect of unexpected AIV on benchmark-adjusted fund returns for all Active Share quintile portfolios. The magnitude of this negative effect increases with Active Share and statistically significant for the high Active Share portfolio.

4.2.2. Evidence on Liquidity Provision of Active Funds

I proceed to test whether AIV decreases the willingness of active funds to deviate from their benchmarks for providing liquidity. Because AIV increases idiosyncratic volatilities of all stocks simultaneously, it is riskier for fund managers to deviate from their benchmarks to provide liquidity when AIV is high. As a result, active funds should seek to scale back their active positions and reduce their liquidity provision. I thus examine how active funds adjust their active positions in response to the contemporaneous rises of AIV. To test this hypothesis, I construct a variable to capture the trading behaviors of an active fund, called Directional Trades (DT), as follows,

$$DT_t = \sum_{i=1}^{N} sign\left(w_{i,t-1} - w_{i,t-1}^{benchmark}\right) \times \frac{Trade_{i,t} \times Price_{i,t-1}}{TotalNetAsset_{t-1}},$$

where $w_{i,t} - w_{i,t}^{benchmark}$ denotes the fund's active weight on stock i against its Morningstar Category Benchmark index, $Trade_{i,t}$ is shares traded by the fund in quarter t, $Price_{i,t-1}$ is stock i's share price, and $sign(x)$ is a function returning $1(-1)$ if x is

Table 9: *AIV* **and Liquidity Provision Activity of Active Mutual Funds**

This table shows that active mutual funds scale back their active positions and reduce their liquidity provision when contemporaneous *AIV* rises. The trading behavior of an active fund is measured by Directional Trades (*DT*),

$$DT_t = \sum_{i=1}^{N} sign\left(w_{i,t-1} - w_{i,t-1}^{benchmark}\right) \times \frac{Trade_{i,t} \times Price_{i,t-1}}{TotalNetAsset_{t-1}},$$

where $w_{i,t} - w_{i,t}^{benchmark}$ denotes the fund's active weight on stock i against its Morningstar Category Benchmark index, $Trade_{i,t}$ is shares traded by the fund in quarter t, $Price_{i,t-1}$ is stock i's share price, and $sign(x)$ is a function returning $1(-1)$ if x is positive (negative). DT is lower if the fund trades toward its benchmark index. The past stock price movement associated with the fund's liquidity provision is measured by Return Deviation (RD),

$$RD_t^{[0,k]} = \sum_{i=1}^{N} sign\left(w_{i,t-1} - w_{i,t-1}^{benchmark}\right) \times AR_{i,t}^{[0,k]}$$

where $AR_{i,t}^{[0,k]}$ is the characteristic-adjusted returns (Daniel et al., 1997) of stock i over the backward-looking window of k horizon $[t-k,t]$. $RD_t^{[0,k]}$ is higher if the prices of the fund's holdings move in the same direction of its active weights over $[t-k,t]$.

The table reports the results from the fund-quarter level panel regressions,

$$DT_{j,t} = a_1 AIV_t + a_2 RD_{j,t}^{[0,k]} + a_3 AIV_t \times RD_{j,t}^{[0,k]} + \gamma \mathbf{X}_{\mathbf{j,t-1}} + \varepsilon_{j,t},$$

where $\mathbf{X}_{\mathbf{j,t-1}}$ includes both macro control variables (see Table 1) and the following fund-level variables: log(total net assets), number of holdings, turnover ratio, tracking error, and quarterly fund-level flow. The panel regressions include fund×year fixed effects. Robust t-statistics are clustered by fund and quarter and are reported in parentheses, where *, **, *** denote significance at the 10%, 5%, and 1% level, respectively. Directional Trades and Return Deviation are in percentages. *AIV* is standardized to have zero mean and unit standard deviation. The sample consists of active U.S. equity mutual funds in CRSP and Morningstar from 1984 to 2020.

	Dependent variable: $DT_{j,t}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AIV_t	-0.741***	-0.732***	-0.706***	-0.613**	-0.660***	-0.527**	-0.758***	-0.611**
	[-3.12]	[-3.06]	[-3.01]	[-2.53]	[-2.85]	[-2.33]	[-3.14]	[-2.51]
$RD_{j,t}^{[0,3]}$	-0.226***	-0.230***						
	[-3.15]	[-3.26]						
$AIV_t \times RD_{j,t}^{[0,3]}$		0.063**						
		[2.23]						
$RD_{j,t}^{[0,6]}$			-0.215***	-0.235***				
			[-4.48]	[-5.08]				
$AIV_t \times RD_{j,t}^{[0,6]}$				0.070**				
				[2.42]				
$RD_{j,t}^{[0,9]}$					-0.193***	-0.199***		
					[-4.33]	[-4.65]		
$AIV_t \times RD_{j,t}^{[0,9]}$						0.082***		
						[2.98]		
$RD_{j,t}^{[0,12]}$							-0.136***	-0.148***
							[-3.79]	[-4.20]
$AIV_t \times RD_{j,t}^{[0,12]}$								0.048**
								[2.61]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund×Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	94,282	94,282	94,282	94,282	94,282	94,282	94,282	94,282
R^2	0.525	0.525	0.525	0.525	0.525	0.525	0.525	0.525

positive (negative). DT is lower if the fund trade toward its benchmark index.

The past stock price movements associated with the fund's liquidity provision is measured by Return Deviation (RD),

$$RD_t^{[0,k]} = \sum_{i=1}^{N} sign\left(w_{i,t-1} - w_{i,t-1}^{benchmark}\right) \times AR_{i,t}^{[0,k]}$$

where $AR_{i,t}^{[0,k]}$ is the characteristic-adjusted returns (Daniel et al., 1997) of stock i over the backward-looking window of k horizon $[t-k,t]$. $RD^{[0,k]}$ is higher if the prices of the fund's holdings move in the opposite direction of its active weights over $[t-k,t]$. I then estimate the following fund-quarter level panel regressions,

$$DT_{j,t} = a_1 AIV_t + a_2 RD_{j,t}^{[0,k]} + a_3 AIV_t \times RD^{[0,k]} + \gamma \mathbf{X_{j,t-1}} + \varepsilon_{j,t},$$

where $\mathrm{X_{j,t-1}}$ includes both macro control variables (see Table 1) and the following fund-level variables: $\log$(total net assets), number of holdings, turnover ratio, tracking error, and quarterly fund-level flow. The panel regressions include fund×year fixed effects.

The results presented in Table 9 deliver three important observations. First, the coefficient on AIV is significantly negative, meaning that active mutual funds track their benchmark more closely when AIV rises. This result supports the hypothesis that the risk-bearing capacity of active mutual funds decreases when AIV is high. In addition, we observe a significantly negative coefficients on Return Deviation, consistent with the liquidity provision role of active mutual funds. Third, the coefficients on the interaction between AIV and Return Deviation is significantly positive, suggesting that the sensitivity of liquidity provision to past stock price movements decreases during episodes of high AIV.

If active fund managers are risk-averse and perform a liquidity provision role in the stock market, then they should require a premium particularly when their risk-bearing capacity becomes worse. Because AIV increases idiosyncratic volatilities of all stocks simultaneously, it should be riskier for fund managers to deviate from

Table 10: AIV **and Returns to Liquidity Provision of Active Funds**

This table shows that the predictability of AIV for benchmark adjusted fund returns is most pronounced among funds providing liquidity to the stock market. Liquidity Provision (LP) of an active fund is defined as

$$LP_t^{[0,k]} = -\frac{\sum_i DollarTrades_{i,t} \times AR_{i,t}^{[0,k]}}{TotalNetAssets_{t-1}}, k = 3, 6, 9, 12,$$

where $AR_{i,t}^{[0,k]}$ is the characteristic-adjusted returns (Daniel et al., 1997) of stock i over the backward-looking window of k horizon $[t-k, t]$, and $DollarTrades_{i,t}$ is the value of the shares of stock i traded by an active fund at time t. High $LP^{[0,k]}$ funds buy (sell) stocks with negative (positive) abnormal returns over past k months.

The table reports the slope coefficient estimate, t-statistic, and adjusted-R^2 from the monthly time-series predictive regressions, $R_t^{benchmark-adjusted} = a + bAIV_{t-1} + \epsilon_t$, where $R_t^{benchmark-adjusted}$ represents the equal-weighted benchmark adjusted returns for the portfolios formed by sorting active funds into quintiles on Liquidity Provision of different horizons. Newey and West (1987) heteroskedasticity-and-autocorrelation-robust t-statistics with six lags are reported in the bracket. The return is annualized and in percentages. AIV is standardized to have zero mean and unit standard deviation. The slope coefficient estimate on AIV means the increase in expected returns per year associated with a one-standard-deviation increase in AIV. The sample consists of active U.S. equity mutual funds in both CRSP and Morningstar from 1984 through 2020.

Estimates and [t-statistics] for the portfolios sorted on the k-month-horizon Liquidity Provision ($LP^{[0,k]}$) from the monthly time-series regressions $R_t^{benchmark-adjusted} = a + bAIV_{t-1} + \epsilon_t$

	3-month-horizon Liquidity provision					
	Low $LP^{[0,3]}$	2	3	4	High $LP^{[0,3]}$	H-L
AIV	0.46	0.18	0.91	0.59	1.73	1.27
	[1.00]	[0.40]	[2.20]	[1.36]	[3.97]	[2.56]
Adj-R^2 (%)	0.37	0.06	2.27	0.87	5.52	2.77
	6-month-horizon Liquidity provision					
	Low $LP^{[0,6]}$	2	3	4	High $LP^{[0,6]}$	H-L
AIV	0.14	-0.09	0.90	0.86	1.63	1.50
	[0.27]	[-0.18]	[2.20]	[1.87]	[3.65]	[2.62]
Adj-R^2 (%)	0.03	0.02	2.26	1.61	5.42	3.17
	9-month-horizon Liquidity provision					
	Low $LP^{[0,9]}$	2	3	4	High $LP^{[0,9]}$	H-L
AIV	0.24	0.19	0.90	0.91	1.52	1.27
	[0.50]	[0.29]	[2.11]	[1.90]	[3.38]	[2.25]
Adj-R^2 (%)	0.10	0.07	2.09	1.78	4.74	2.92
	12-month-horizon Liquidity provision					
	Low $LP^{[0,12]}$	2	3	4	High $LP^{[0,12]}$	H-L
AIV	0.25	0.05	0.84	0.93	1.47	1.22
	[0.50]	[0.12]	[2.01]	[1.82]	[3.35]	[2.32]
Adj-R^2 (%)	0.10	0.01	2.01	1.76	4.15	2.60

their benchmarks to provide liquidity. Next, I examine whether the returns to the liquidity provision of active mutual funds are positively predicted with AIV. To capture the liquidity provision activity of an active fund, I construct the following fund-level measure,

$$LP_t^{[0,k]} = -\frac{\sum_i DollarTrades_{i,t} \times AR_{i,t}^{[0,k]}}{TotalNetAssets_{t-1}}, k = 3, 6, 9, 12,$$

where $AR_{i,t}^{[0,k]}$ is the characteristic-adjusted returns (Daniel et al., 1997) of stock i over the backward-looking window of k horizon $[t-k, t]$, and $DollarTrades_{i,t}$ is the value of the shares of stock i traded by an active fund at time t. High $LP^{[0,k]}$ means a fund buys (sells) stocks with negative (positive) abnormal returns over past k months.

Table 10 shows that the predictability of AIV for benchmark adjusted fund returns is most pronounced among funds providing liquidity to the stock market. Specifically, I sort funds into quintiles according to their liquidity provision measure and then regress the equal-weighted average benchmark-adjusted returns on the previous AIV for each quintile portfolio. For liquidity provision at all horizons, AIV positively predicts benchmark adjusted returns of the high LP portfolio. In addition, this predictability decreases and disappears for the low liquidity provision portfolio.

4.2.3. Variation in Tracking Errors and Information Ratios

The decreases in the risk-bearing capacity could result from a decline in mutual fund managers' risk aversion. If this is the case, then AIV should also increase the premium per unit of risk earned by active mutual funds. The quantity of risk is usually measured by tracking errors, which is the standard deviation of benchmark adjusted returns. The premium per unit of risk can be captured by information ratios, which is the ratio of average benchmark-adjusted returns to tracking errors.

To test this hypothesis, I start by considering a simple nonparametric way to ex-

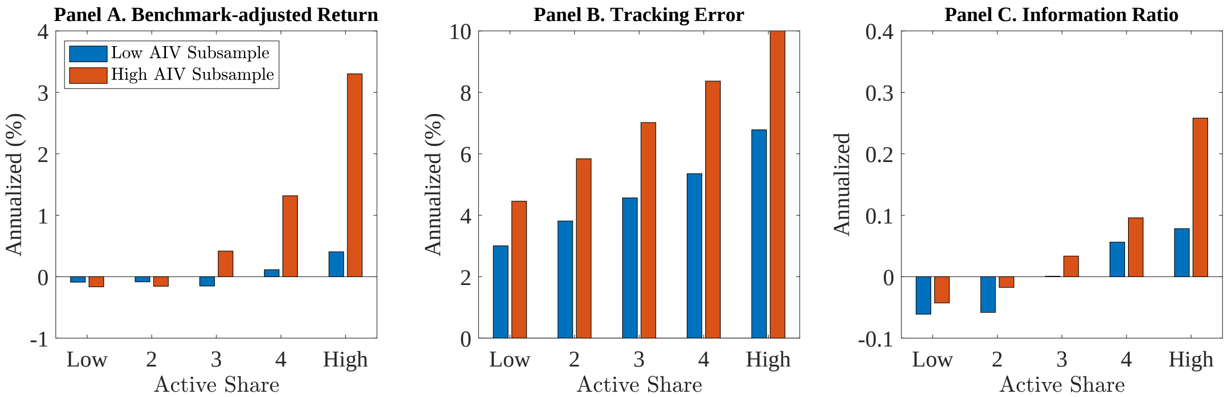

Fig. 3. **Two-way Sorts on *AIV* and Active Share**
This figure shows how the subsequent benchmark-adjusted returns, tracking errors, and information ratios of active mutual funds are related to beginning-of-quarter active share and *AIV*. I sort funds into quintiles according to active share and then split the sample periods equally into the low and high *AIV* sub-samples. For each fund, I compute subsequent average benchmark-adjusted returns, tracking errors, and information ratios over a 12-month forward-looking window. The figure plots the equal-weighted average of these statistics in the two-way sorts of active share and *AIV*. The sample consists of active U.S. equity mutual funds in both CRSP and Morningstar from 1984 through 2020.

amine how tracking errors and information ratios are associated with the previous Active Share and *AIV*. I sort active funds into quintiles based on beginning-of-quarter Active Share and then split all months into two groups according to the previous *AIV* levels. I then use a 12-month forward-looking window to compute subsequent benchmark-adjusted returns, tracking errors, and information ratios for each fund. Figure 3 plots the equal-weighted average of these statistics for each bin. The figure shows that *AIV* is positively correlated with both expected tracking errors and information ratios, suggesting that *AIV* decreases the risk-bearing capacity of an active fund, and the fund requires greater returns per unit of risk.

Table 11 provides econometric evidence on the positive relation between *AIV* and conditional information ratios. Specifically, it reports the estimates from the following monthly time-series predictive regressions for Active Share quintile portfolios,

$$IR_t = a + bAIV_{t-1} + \gamma X_{t-1} + \epsilon_t,$$

where IR_t is the equal-weighted average conditional information ratios, which is benchmark-adjusted returns standardized by the 12-month rolling standard de-

Table 11: *AIV* **and Conditional Information Ratios**

This table shows that Aggregate Idiosyncratic Volatility (AIV) is positively associated with conditional information ratios of active funds and this relation is stronger for high Active Share (AS) funds. Information ratio effectively measures abnormal return per unit of idiosyncratic risk earned by an active fund.

The table reports the slope coefficient estimates, t-statistics, and adjusted-R^2 from the monthly time-series predictive regressions,

$$IR_t = a + bAIV_{t-1} + \gamma X_{t-1} + \epsilon_t,$$

where IR_t represents the equal-weighted conditional information ratios for Active Share quintile portfolios. The conditional information ratio is computed by its benchmark-adjusted return standardized by the 12-month rolling standard deviation of benchmark-adjusted returns. See the captions in Table 1 and Table 2 for the definitions of AIV, Active Share, and macro control variables. Newey and West (1987) heteroskedasticity-and-autocorrelation-robust t-statistics with three lags are reported in the bracket. The information ratio is annualized and in percentages. AIV is standardized to have zero mean and unit standard deviation so the slope coefficient estimate on AIV means the increase in conditional information ratio per year associated with a one-standard-deviation increase in AIV. The sample consists of active U.S. equity mutual funds in both CRSP and Morningstar from 1984 through 2020.

	Estimates and [t-statistics] for Active Share (AS) quintile portfolios from the monthly time-series predictive regressions $IR_t = a + bAIV_{t-1} + \gamma X_{t-1} + \epsilon_t$					
	(1)	(2)	(3)	(4)	(5)	(6)
	Low AS	2	3	4	High AS	H-L
AIV	0.05	0.07	0.18	0.16	0.26	0.21
	[0.61]	[0.77]	[1.95]	[1.84]	[2.91]	[2.02]
Recessions	0.16	0.06	0.08	0.03	0.06	-0.10
	[2.21]	[1.05]	[1.46]	[0.35]	[0.71]	[-1.28]
VIX	-0.18	-0.18	-0.24	-0.24	-0.30	-0.12
	[-1.70]	[-1.83]	[-2.80]	[-2.69]	[-3.40]	[-1.40]
Sentiment	0.08	0.10	0.07	0.06	0.09	0.00
	[1.14]	[1.54]	[1.14]	[1.16]	[1.60]	[0.06]
Disagreement	0.05	0.05	0.11	0.06	0.10	0.05
	[0.70]	[0.75]	[1.51]	[0.99]	[1.54]	[0.58]
Illiquidity	-0.12	-0.01	-0.06	-0.08	-0.02	0.10
	[-2.55]	[-0.16]	[-1.27]	[-1.82]	[-0.37]	[1.48]
Adj-R^2 (%)	2.66	2.20	3.92	4.71	5.63	2.57

Table 12: **International Evidence**
This table presents international evidence on the positive relation between *AIV* and the subsequent abnormal return of active equity mutual funds. In addition, this relation is stronger for countries with lower institutional ownership and higher sentiment.
The table reports the estimates from the quarter-fund-market level panel predictive regressions where the dependent variable is the weighted-average market-adjusted stock return earned by an active fund from one of the stock markets based on its quarterly stock holdings. *AIV* is the equal-weighted average of the standard deviation of daily residual returns from the regressions of daily stock returns on the market excess returns within each quarter. I include the following fund-level control variables: log(total net assets), turnover ratio, return volatility, and the number of equity holdings. The t-statistics are computed based on the standard errors clustered by market and quarter. Robust t-statistics are clustered by fund and quarter and are reported in parentheses, where *, **, *** denote significance at the 10%, 5%, and 1% level, respectively. The return is annualized and in percentages. *AIV* is standardized to have zero mean and unit standard deviation. The sample consists of actively managed international equity mutual funds in 47 equity markets (excluding the US) from 2001 through 2020.

	Dependent variable: $\tilde{r}_{i,j,t}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$AIV_{j,t}$	1.655**	1.633**	2.269**	1.499**	1.165	1.500**	1.509*
	[2.55]	[2.45]	[2.60]	[2.15]	[1.42]	[2.13]	[1.96]
Institutional Ownership$_{j,t}$		-0.603	2.018				
		[-0.41]	[0.89]				
$AIV_{j,t}$ × Institutional Ownership$_{j,t}$			-5.101**				
			[-2.12]				
Sentiment$_{j,t}$				-0.135	-0.281		
				[-0.98]	[-1.40]		
$AIV_{j,t}$ × Sentiment$_{j,t}$					0.479**		
					[2.26]		
Illiquidity$_{j,t}$						0.002	0.002
						[1.50]	[1.62]
$AIV_{j,t}$ × Illiquidity$_{j,t}$							0.037*
							[1.76]
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund× Market FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	9,197,823	9,197,823	9,197,823	9,196,456	9,196,456	9,195,794	9,195,794
R^2	0.060	0.060	0.060	0.060	0.061	0.060	0.060

viation of benchmark-adjusted returns. The results confirm that the conditional information ratios increase with *AIV*. For example, a one-standard-deviation rise in *AIV* leads to an increase of 0.15 (0.12) in the annualized information ratio of the high (high-minus-low) active share portfolio.

4.3. Additional Implications

4.3.1. International Evidence

The empirical evidence from the sample of active US equity mutual funds demonstrates that *AIV* drives substantial time variation in the expected benchmark-adjusted return of active mutual funds. Next, I extend this finding to the sample of active international equity mutual funds. The international data also allows me to conduct additional tests on the two stories. Specifically, the risk story predicts that the relation between *AIV* and subsequent fund performance is stronger for the market with more retail investors, high sentiment, and low liquidity. Table 12 shows a significant positive correlation between *AIV* and subsequent characteristic-adjusted return from the panel regressions with various fixed effects and controls. In addition, this correlation is stronger when institutional ownership is lower, sentiment is higher, and liquidity is lower. All of these results support the risk story.

4.3.2. *Effect of AIV on Aggregate Fund Trades*

I've shown that when *AIV* rises, active equity mutual funds track their benchmarks more closely by scaling back their active positions. One question is whether these reduced active positions are offset after aggregation at the stock level or still have a significant effect. For example, if one fund overweights a stock and the other fund underweights the same stock, they could both lower their active weights in response to rises in *AIV* but trade in the opposite direction so that there would be no net effect of *AIV* on the stock-level fund positions.

To examine this question, I Aggregate Directional Trades across funds at a stock-level,

$$AggregateDT_{i,t} = \sum_{j=1}^{M} sign\left(w_{i,t-1}^{j} - w_{i,t-1}^{benchmark}\right) \times \frac{Trades_{i,t}^{j}}{SharesOutstanding_{i,t-1}},$$

where $w_{i,t-1}^{j} - w_{i,t-1}^{benchmark}$ is fund j's active weight on stock i at the end of quarter $t-1$, $Trade_{i,t}^{j}$ is shares traded by fund j in quarter t, $SharesOutstanding_{i,t-1}$ is shares outstanding, and $sign(x)$ is a function returning $1(-1)$ if x is positive (negative). Aggregate Directional Trades will be lower if active mutual funds, in the aggregate, move toward to their passive benchmarks. Table A6 shows that *AIV* has a significant effect on the aggregate trades of active mutual funds. For example, column (4) shows that a one-standard-deviation increase in *AIV* leads to a 0.13% decrease in Aggregate Directional Trades. This economic magnitude is similar to that obtained from the fund-level analysis.

4.3.3. *Stock Price Reactions to AIV Shocks*

The effect of unexpected *AIV* on stock prices is also consistent with the results from active mutual funds. Specifically, I find a negative contemporaneous relation between unexpected *AIV* and the returns of the long-short portfolio formed by sorting stocks on the aggregate active positions across all active mutual funds. In addition, high *AIV* positively predicts high returns of the long-short portfolio. In quarter t, I form two portfolios according to beginning-of-quarter active position. If a stock's active position is positive (negative), then the stock is assigned to the overweight (underweight) portfolio. I then record stock returns in quarter t, t+1, and t+2 and compute the value-weighted average of characteristic-adjusted returns (Daniel et al., 1997) for each portfolio. I also compute the difference of returns between the overweight and underweight portfolios. To identify the effect of *AIV* shocks on the returns of these two portfolios, I assign the highest 25% ΔAIV_t quarters into the high ΔAIV group and other quarters into the low ΔAIV group.

Table A7 shows that when *AIV* rises substantially in quarter t, the *Difference* portfolio has a negative return in quarter t and has subsequent positive returns in the next two quarters. Panel A shows that for quarters with the largest increases in *AIV*, the *Difference* portfolio has an average return of –4.74% per year. This negative return alone does not, of course, indicate that stock prices are affected by mutual fund demand shift. If the price changes are due to the contraction of active positions in response to *AIV* shocks, the effects should be temporary and stock prices would reverse in the following quarters. As shown in panel B and C, we observe the reversals of 2.75% and 4.22% in the next two quarters, suggesting the the second channel is consistent with the data. The pattern of a sharp price reaction and a subsequent and more extended reversal is also present in the overweight and underweight portfolios separately. Specifically, the sequences of returns are -2.62%, 1.69%, 2.39% for the overweight portfolio, and 2.12%, -1.07%, -1.86% for the underweight portfolio.

4.3.4. Evidence from the COVID-19 Crisis in 2020

I also present the novel evidence from the COVID-19 crisis in 2020. Figure A2 shows that *AIV* substantially rose from 40% in February to 85% in March, about a four-standard-deviation increase over the past four decades. In response to this extremely large *AIV* shock, active equity mutual funds, on average, reduced 1% of their active share. Accordingly, the stocks that were overweighted by active mutual funds at the end of February experienced a -2.46% return in March compared to those underweighted stocks. Later in April, we observe a price reversal with a similar magnitude of 1.97%. At the same time, high active share funds, on average, generated a benchmark-adjusted return higher than those low active share funds by 2.32%. These observations are largely consistent with the findings in the previous sections, and also support the interpretation that *AIV* drives the risk-bearing capacity of active mutual funds and thus could result in temporary price effects.

5. Conclusions

This paper shows that Aggregate Idiosyncratic Volatility (*AIV*) is a powerful predictor of benchmark adjusted returns of active equity mutual funds. I find that active mutual funds earn significant expected benchmark adjusted returns only when *AIV* is high. In addition, the predictability of *AIV* is most pronounced among funds deviating from their benchmarks and betting against past stock price movements. I also find that when *AIV* rises, funds scale back their active positions and reduce their liquidity provision. These results are consistent with the explanation that risk-averse fund managers require a reward for providing liquidity to the stock market, and *AIV* decreases their risk-bearing capacity.

A large body of research attempts to understand active fund performance. Numerous empirical papers relate fund performance to fund "activeness" in the cross-section (e.g., Kacperczyk, Sialm, and Zheng, 2005; Cremers and Petajisto, 2009; Amihud and Goyenko, 2013; Doshi, Elkamhi, and Simutin, 2015; Cremers and Pareek, 2016; Pástor et al., 2020). Other papers relate time variation in fund performance to business cycles (e.g., Moskowitz, 2000; Kosowski, 2011; Glode, 2011; Kacperczyk et al., 2014). Aggregate Idiosyncratic Volatility has been extensively studied in the asset pricing literature (Campbell, Lettau, Malkiel, and Xu, 2001; Guo and Savickas, 2008; Brandt, Brav, Graham, and Kumar, 2010; Bekaert et al., 2012). However, no paper has recognized the important role of *AIV* in explaining active fund performance. My paper provides novel and robust evidence showing that *AIV* is the key driver of benchmark adjusted fund returns in both cross section and time series.

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Appendix

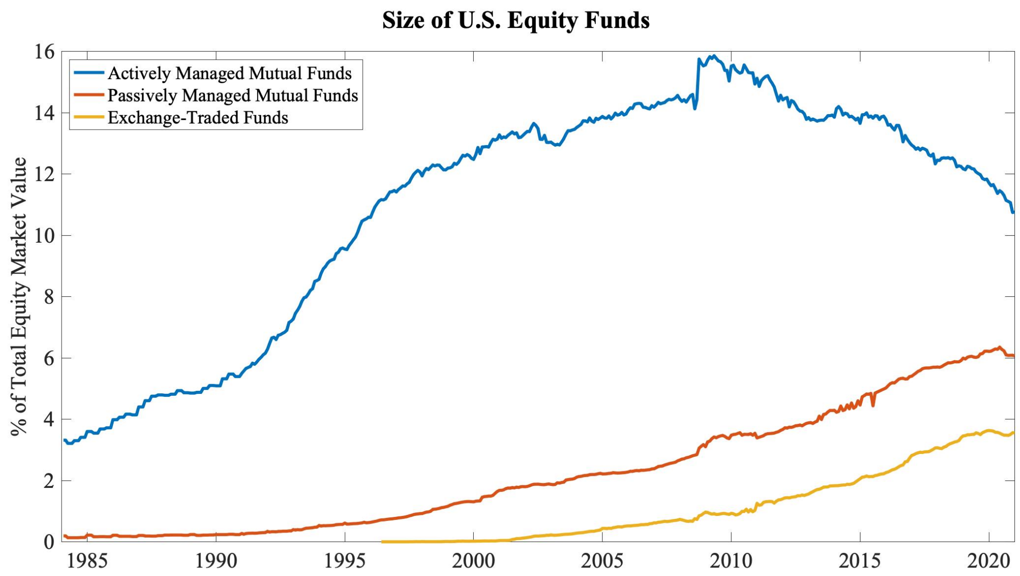

Fig. A1. **Total Net Assets of U.S. Equity Funds Scaled by Total Value of U.S. Equity Market**
This figure plots the total net assets of U.S. equity funds scaled by the total value of equity market from 1984 through 2020.

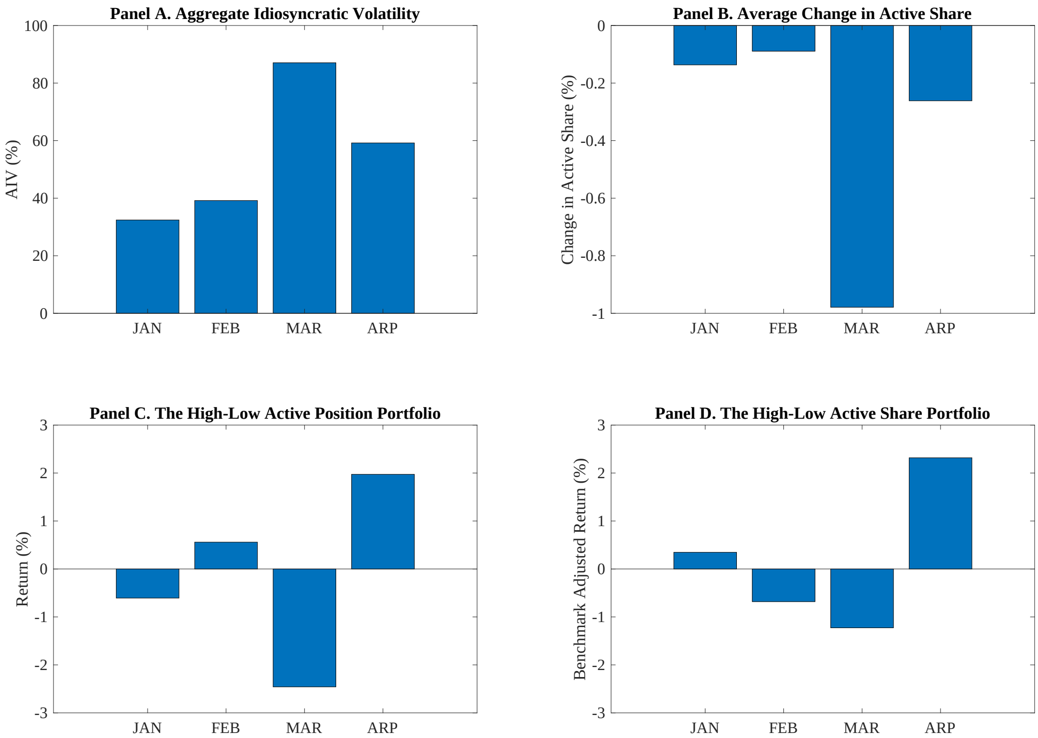

Fig. A2. **The COVID-19 Period**
This figure provides evidence from the COVID-19 period from January through April in 2020. Panel A plots aggregate idiosyncratic volatility (*AIV*), and panel B plots the equal-weighted average of active share changes across active mutual funds. Panel C plots the difference of characteristic-adjusted returns between the high and low stock portfolios formed on active positions. Panel D plots the difference of benchmark-adjusted returns between the high and low fund portfolios formed on active share. *AIV* is annualized and in percentages. The stock and fund returns are monthly and in percentages.

Table A1: **Number of Actively Managed Mutual Funds Tracking Each Benchmark Index**
This table reports the number of funds tracking each benchmark index. I consider two types of benchmark categories: the Morningstar Category Benchmark (panel A) and the Prospectus Benchmark (panel B). The sample consists of actively managed U.S. equity mutual funds from 1980 to 2020.

Panel A. The Morningstar Category Benchmark

Period	Russell 1000	Russell 1000 Growth	Russell 1000 Value	Russell 2000	Russell 2000 Growth	Russell 2000 Value	Russell Midcap	Russell Midcap Growth	Russell Midcap Value	S&P 500
1980-1984	62	80	34	4	8	2	6	32	5	1
1985-1989	86	101	58	7	16	8	9	42	9	2
1990-1994	134	144	114	22	37	14	19	61	20	3
1995-1999	245	264	190	66	114	39	50	115	37	4
2000-2004	334	434	271	111	194	68	80	196	65	10
2005-2009	351	450	319	151	230	94	102	220	95	19
2010-2014	317	400	295	165	196	95	100	181	98	30
2015-2019	289	357	297	185	182	105	99	168	100	30

Panel B. The Prospectus Benchmark

Period	Russell 1000	Russell 1000 Growth	Russell 1000 Value	Russell 2000	Russell 2000 Growth	Russell 2000 Value	Russell Midcap	Russell Midcap Growth	Russell Midcap Value	S&P 500
1980-1984	5	30	23	6	4	2	2	16	5	120
1985-1989	6	38	36	10	11	6	4	22	6	182
1990-1994	11	59	65	27	24	15	8	34	13	275
1995-1999	17	111	109	74	64	40	22	61	25	445
2000-2004	31	185	169	123	108	73	36	99	47	619
2005-2009	47	214	215	150	138	108	48	117	76	660
2010-2014	50	195	195	152	126	114	47	96	76	618
2015-2019	57	163	183	161	114	127	48	83	75	580

Table A2: *AIV* **and Value-Weighted Fund Portfolios**

The table reports the slope coefficient estimates, t-statistics, and adjusted-R^2 from the monthly time-series predictive regressions,

$$R_t^{benchmark-adjusted} = a + bAIV_{t-1} + \gamma X_{t-1} + \epsilon_t,$$

where $R_t^{benchmark-adjusted}$ represents the value-weighted average of benchmark-adjusted fund returns. A fund's benchmark-adjusted return is the fund's return minus the return on the Morningstar Category Benchmark Index (Pástor et al., 2017). The table includes benchmark-adjusted returns both before expense and after expense. *AIV* is computed as the equal-weighted average of idiosyncratic stock return volatilities, which are estimated from time-series regressions of daily returns on the Fama-French three factors within each month. X represents control variables including Recessions (Chauvet and Piger, 2008), *VIX*, Sentiment (Baker and Wurgler, 2006), Disagreement (Yu, 2011), and Liquidity (Pastor and Stambaugh, 2003). Newey and West (1987) heteroskedasticity-and-autocorrelation-robust t-statistics with three lags are reported in the bracket. The return is annualized and in percentages. *AIV* is standardized to have zero mean and unit standard deviation to interpret the economic magnitude of its predictability for subsequent benchmark-adjusted returns. The sample consists of U.S. equity funds in both CRSP and Morningstar from 1984 through 2020.

Slope coefficients and [t-statistics] for the equal-weighted fund portfolios from the time-series predictive regressions, $R_t^{benchmark-adjusted} = a + bAIV_{t-1} + \gamma X_{t-1} + \epsilon_t$				
	(1) Before expense	(2) After expense	(3) Before expense	(4) After expense
	Active funds		Passive funds and ETFs	
AIV	1.28	1.27	0.50	0.43
	[2.01]	[1.98]	[1.10]	[0.95]
Recessions	0.52	0.52	-0.46	-0.44
	[1.00]	[0.99]	[-1.29]	[-1.21]
VIX	-1.72	-1.76	-0.03	-0.02
	[-2.79]	[-2.84]	[-0.07]	[-0.05]
Sentiment	0.71	0.69	-0.03	-0.04
	[1.14]	[1.11]	[-0.09]	[-0.12]
Disagreement	0.92	0.96	0.01	0.14
	[1.81]	[1.89]	[0.03]	[0.39]
Illiquidity	-0.40	-0.36	-0.66	-0.68
	[-1.16]	[-1.03]	[-2.11]	[-2.09]
Adj-R^2 (%)	5.70	5.68	2.22	2.39

Table A3: **Robustness: Odds of AIV Being Spurious**

This table reports the estimated number of randomly generated regressors with at least one regressor that has predictive power as strong as AIV, based on the simulation approach proposed by Stambaugh et al. (2014). Specifically, a randomly generated regressor x_{t-1} replaces AIV_{t-1} in the predictive regression, $R_t^{benchmark-adjusted} = a + bAIV_{t-1} + \epsilon_t$, where $R_t^{benchmark-adjusted}$ is the equal-weighted average benchmark-adjusted returns for Active Share quintile portfolios. The regressors are generated from a first-order autoregressive process with autocorrelation of 0.92 (the sample autocorrelation of AIV). Let t_{AIV} (t_x) denote the t-statistic of the coefficient estimate $\hat{b}$ of AIV_{t-1} (x_{t-1}). I then compute the reciprocal of the frequency of $t_{AIV} \leq t_x$.

Number of randomly generated predictors required to obtain one predictor that produces results as strong as AIV					
(1)	(2)	(3)	(4)	(5)	(6)
Low AS	2	3	4	High AS	H-L
4	6	17	10	258	1179

Table A4: **Robustness: Controlling for Priced Factors**

This table reports the coefficient estimates b, t-statistics, and adjusted R^2 from the monthly time-series predictive regressions,

$$R_t^{benchmark} = a + bAIV_{t-1} + \gamma X_{t-1} + \beta \mathrm{F_t} + \epsilon_t,$$

where $R_t^{benchmark}$ represents the equal-weighted average benchmark adjusted returns for Active Share quintile portfolios. F_t represents different factor models. Each row presents the estimates from the regression specification in which F_t is one of the following models: 1) the Carhart (1997) model augmented with liquidity factor (Pastor and Stambaugh, 2003); 2) the CAPM augmented with the CIV factor (Herskovic et al., 2016); 3) the Fama and French (2015) five factors; 4) the Stambaugh and Yuan (2017) four factors; 5) the Daniel et al. (2020) three factors augmented with the size factor (SMB); (6) the Hou et al. (2020) five factors. See the captions in Table 1 and Table 2 for the definitions of AIV, Active Share, and macro control variables. Newey and West (1987) heteroskedasticity-and-autocorrelation-robust t-statistics with three lags are reported in the bracket. The return is annualized and in percentages. AIV is standardized to have zero mean and unit standard deviation so the slope coefficient estimate on AIV means the increase in expected returns per year associated with a one-standard-deviation increase in AIV. The sample consists of active U.S. equity mutual funds in both CRSP and Morningstar from 1984 through 2020.

Slope coefficient estimates and [t-statistics] for the equal-weighted Active Share (AS) quintile portfolios from the monthly time-series regressions $R_t^{benchmark} = a + bAIV_{t-1} + \gamma X_{t-1} + \beta \mathrm{F_t} + \epsilon_t$

	(1)	(2)	(3)	(4)	(5)	(6)
	Low AS	2	3	4	High AS	H-L
Carhart+Liquidity	0.15	0.30	1.07	1.63	3.12	2.97
	[0.47]	[0.78]	[2.03]	[2.35]	[3.72]	[3.64]
Herskovic-Kelly-Lustig-Van Nieuwerburgh (2016)	0.24	0.69	1.44	1.76	3.12	2.88
	[0.62]	[1.39]	[2.55]	[2.59]	[3.63]	[3.16]
Fama-French (2015)	0.01	0.19	1.00	1.52	3.41	3.40
	[0.03]	[0.41]	[1.80]	[2.05]	[4.40]	[4.07]
Stambaugh-Yu (2017)	0.27	0.47	1.33	1.82	3.56	3.29
	[0.76]	[1.20]	[2.54]	[2.69]	[3.62]	[3.31]
Daniel-Hirshleifer-Sun (2020)	0.08	0.30	1.02	1.54	3.47	3.40
	[0.22]	[0.70]	[1.78]	[2.14]	[3.83]	[3.77]
Hou-Mo-Xue-Zhang (2020)	0.10	0.28	1.18	1.72	3.68	3.58
	[0.25]	[0.71]	[2.46]	[2.58]	[3.88]	[3.35]

Table A5: **Fama and French (2010) Bootstrap Simulations**
This table reports the results from the Fama and French (2010) bootstrap simulations for the full sample (Panel A), the low-AIV sub-sample (Panel B), and the high-AIV sub-sample (Panel C), respectively. In each panel, the first column presents values of Fama-French-Carhart 4-factor $t(\alpha)$ at selected percentiles of the cross-sectional distribution of $t(\alpha)$ estimates for actual gross returns. The second column shows the average value of $t(\alpha)$ at the selected percentiles from the simulations. The third column shows the percentile of the 100,000 simulation runs that produce lower values of $t(\alpha)$ than those observed for actual fund returns ($\% \leq Actual$). The sample consists of active U.S. equity mutual funds from 1984 through 2020.

	Panel A. Full sample			Panel B. Low *AIV* subsample			Panel C. High *AIV* subsample		
Percentiles	Actual	Simulated	% ≤Actual	Actual	Simulated	% ≤Actual	Actual	Simulated	% ≤Actual
1	-3.22	-2.55	1.39	-3.44	-2.56	0.36	-2.41	-2.66	67.13
2	-2.81	-2.19	1.41	-2.97	-2.20	0.50	-2.03	-2.25	68.62
3	-2.57	-1.99	1.58	-2.80	-1.99	0.31	-1.85	-2.03	65.64
4	-2.37	-1.84	1.98	-2.66	-1.84	0.20	-1.65	-1.87	70.56
5	-2.22	-1.72	2.41	-2.50	-1.72	0.22	-1.41	-1.74	83.35
10	-1.76	-1.33	3.32	-2.07	-1.32	0.18	-1.03	-1.34	82.68
20	-1.27	-0.87	3.09	-1.52	-0.85	0.19	-0.46	-0.87	92.64
30	-0.88	-0.54	4.36	-1.14	-0.52	0.16	-0.03	-0.55	97.45
40	-0.53	-0.26	7.90	-0.81	-0.24	0.16	0.30	-0.27	98.48
50	-0.23	-0.00	11.80	-0.51	0.02	0.16	0.65	-0.01	99.20
60	0.12	0.26	24.51	-0.19	0.28	0.32	0.92	0.24	99.09
70	0.49	0.54	42.10	0.14	0.56	0.67	1.26	0.52	99.17
80	0.92	0.86	64.12	0.53	0.90	2.10	1.67	0.84	99.30
90	1.58	1.33	87.61	1.16	1.37	17.23	2.28	1.30	99.53
95	2.10	1.72	93.85	1.72	1.77	46.16	2.89	1.69	99.79
96	2.27	1.84	95.34	1.86	1.89	50.02	3.02	1.81	99.77
97	2.49	1.98	96.88	2.03	2.04	52.31	3.15	1.96	99.68
98	2.75	2.18	97.58	2.23	2.25	51.63	3.34	2.17	99.43
99	3.08	2.52	96.91	2.60	2.60	54.67	3.83	2.55	99.03

Table A6: *AIV* **and Aggregate Directional Trades**

This table shows that aggregate active mutual funds sell (buy) stocks that are initially overweighted (underweighted) when *AIV* rises.

The table reports the results estimated from the following firm-quarter level panel regressions,

$$AggregateDirectionalTrades_{i,t} = a_1 AIV_t + a_2 VIX_t + a_3 AggFlow_t + \gamma \mathbf{X}_{\mathbf{i,t-1}} + \delta_i + \theta_t + \varepsilon_{i,t},$$

where Aggregate Directional Trades is defined as

$$AggregateDirectionalTrades_{i,t} = \sum_{j=1}^{M} sign\left(w^{j}_{i,t-1} - w^{benchmark}_{i,t-1}\right) \times \frac{Trades^{j}_{i,t}}{SharesOutstanding_{i,t-1}},$$

$w^{j}_{i,t-1} - w^{benchmark}_{i,t-1}$ is fund j's active weight on stock i at the end of quarter $t-1$, $Trade^{j}_{i,t}$ is shares traded by fund j in quarter t, $SharesOutstanding_{i,t-1}$ is shares outstanding, and $sign(x)$ is a function returning $1(-1)$ if x is positive (negative). Directional trades will be lower if active mutual funds, in the aggregate, move toward their passive benchmarks. *VIX* and *AggFlow* are the *VIX* index and aggregate fund flows, respectively. $\mathbf{X}_{\mathbf{i,t-1}}$ represents the stock-level controls including log(market capitalization), log(book-to-market), asset growth, gross profit-to-asset, momentum, market beta, and stock idiosyncratic volatility. The specifications in the first four columns include stock and year fixed effects, and the last column includes interacted stock-year fixed effects. Robust t-statistics are clustered by stock and quarter and are reported in parentheses, where *, **, *** denote significance at the 10%, 5%, and 1% level, respectively. The sample consists of active U.S. equity mutual funds from 1990 to 2020. Directional trades are in percentages. *AIV*, *VIX*, and *AggFlow* are standardized to have zero mean and unit standard deviation to interpret the economic magnitude of the coefficient estimates.

	(1)	(2)	(3)	(4)
	Dependent variable: Directional Trades			
AIV	-0.084***			-0.134***
	(-5.40)			(-5.81)
VIX		-0.012		0.054*
		(-0.68)		(1.91)
Aggregate fund flows			0.012	0.007
			(0.57)	(0.39)
Firm-level control	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N (firm-quarter)	374,378	374,378	374,378	374,378

Table A7: **Stock Price Reactions To Unexpected** *AIV*

The table shows the pattern of price pressure and subsequent reversals in response to positive *AIV* shocks (ΔAIV). In quarter t, I form two portfolios according to the beginning-of-quarter active position. If a stock's active position is positive (negative), then the stock is assigned to the overweight (underweight) portfolio. I then record stock returns in quarter t, t+1, and t+2 and compute the value-weighted average of the characteristic-adjusted returns (Daniel et al., 1997) for each portfolio. I also compute the difference in returns between the overweight and underweight portfolios. To identify the effect of *AIV* shocks on the returns to these two portfolios, I assign the highest 25% ΔAIV_t quarters into the high ΔAIV group and other quarters into the low ΔAIV group. The return is annualized and in percentages. t-statistics are reported in brackets. Bold numbers indicate that the t-statistic is greater than 2 in absolute value. The sample consists of stocks in NYSE, Amex, and Nasdaq from 1984 to 2020.

Characteristic-adjusted returns and [t-statistics] in quarter t, t+1, t+2 from two-way sorts on active position at the beginning of quarter t and *AIV* shock in quarter t									
	Panel A. Quarter t			Panel B. Quarter $t+1$			Panel C. Quarter $t+2$		
ΔAIV_t	Underweight	Overweight	Difference	Underweight	Overweight	Difference	Underweight	Overweight	Difference
Low (bottom 75%)	**-1.26**	**1.72**	**2.98**	-0.56	0.79	1.35	-0.20	0.48	0.68
	[-3.28]	[3.58]	[3.47]	[-1.37]	[1.63]	[1.52]	[-0.43]	[0.94]	[0.71]
High (top 25%)	**2.12**	**-2.62**	**-4.74**	-1.07	1.69	2.75	-1.86	2.36	**4.22**
	[2.06]	[-2.14]	[-2.19]	[-0.93]	[1.30]	[1.15]	[-1.85]	[1.94]	[2.06]

A Simple Theoretical Framework

Assets

Consider an economy with discrete time $t = 0, 1, 2, \ldots$ There are N stocks, indexed by $i = 1, \ldots, N$, and a risk-free bond in the market. The total supply of each stock equals one and the risk-free bond has an infinitely elastic supply at a gross interest rate of $r_f > 1$. Stock i has share price $p_{i,t}$ at the beginning of the period t and payoff $\tilde{y}_{i,t+1}$ (including dividends) at the end of the period. A share in the market portfolio, therefore, has payoff $\tilde{y}_{m,t+1} = (1/N)\sum_{i=1}^{N}\tilde{y}_{i,t+1}$ and price $\tilde{p}_{m,t} = (1/N)\sum_{i=1}^{N}p_{i,t}$.

I assume that the stock payoffs are given by

$$\tilde{y}_{i,t+1} = y_{i,t} + p_{i,t}\tilde{\eta}_{i,t+1} \tag{A.1}$$

$$\tilde{\eta}_{i,t+1} = \tilde{z}_{t+1} + \tilde{\epsilon}_{i,t+1}, \quad i = 1, \ldots, N \tag{A.2}$$

where $\mathrm{E}(\tilde{z}_{t+1}) = \mathrm{E}(\tilde{\epsilon}_{i,t+1}) = 0$, $\mathrm{Cov}(\tilde{\epsilon}_{i,t+1}, \tilde{\epsilon}_{j,t+1}) = 0$ for all $i \neq j$, and end-of-period-t expected variance of $\tilde{\epsilon}_{i,t+1}$, denoted by $\sigma_{i,t}$, has a one-factor structure

$$\sigma_{i,t} = \sigma_i + f_t, \quad i = 1, \ldots, N \tag{A.3}$$

where f_t is the common factor in idiosyncratic volatilities, which serves as the aggregate idiosyncratic volatility in the model.[17]

Under the assumption that $(1/N)\sum_{i=1}^{N}p_{i,t}\epsilon_{i,t+1} \approx 0$, the rate of return on the market portfolio is well approximated as

$$\tilde{r}_{m,t+1} = \mu_{m,t} + \tilde{z}_{t+1} - 1, \quad i = 1, \ldots, N \tag{A.4}$$

where $\mu_{m,t} = y_{m,t}/p_{m,t}$, with $y_{m,t} = (1/N)\sum_{i=1}^{N}y_{i,t}$. The rate of return on stock i at the end of period t is given by

$$\tilde{r}_{i,t+1} = \frac{\tilde{y}_{i,t+1}}{p_{i,t}} - 1 = \frac{y_{i,t}}{p_{i,t}} + \tilde{z}_{t+1} + \tilde{\eta}_{i,t+1} - 1 \tag{A.5}$$

from which we know that $\beta_{i,t} = \mathrm{Cov}(\tilde{\epsilon}_{i,t+1}, \tilde{\epsilon}_{m,t+1})/\mathrm{Var}(\tilde{\epsilon}_{m,t+1}) = 1$, and the market-adjusted return on stock i is

$$\tilde{R}_{i,t+1} = \tilde{r}_{i,t+1} - \tilde{r}_{m,t+1} = \alpha_{i,t} + \tilde{\epsilon}_{i,t+1} \tag{A.6}$$

where $\alpha_{i,t} = y_{i,t}/p_{i,t} - \mu_{m,t}$ is the alpha, or expected market-adjusted return, for stock i.

Active Funds

There are M rational active funds, each managing the same amount of assets. I assume M is finite but large enough so that each individual fund takes $\alpha_{i,t}$ and $\sigma_{i,t}$ as given when deciding their optimal portfolio weights. There are N skilled managers (S) and $M - N$ unskilled managers (U). I assume the perceived stock $\alpha_{i,t}$

[17] Without of generality, I assume that $f_t = N^{-1}\sum_{i=1}^{N}\sigma_{i,t}$.

of the skilled managers are correct, but the unskilled managers are not able to distinguish alphas of different stocks so are lack of stock-picking skill. Denote the skill for manager j as ρ^j, where $\rho^S = 0$ for $j = 1, \ldots m$ and $\rho^U = 1$ for $j = 1 + m, \ldots, M$.[18]

To deliver high benchmark-adjusted performance, it is necessary for a fund manager to hold portfolio weights that are different from the market portfolio weights. Define the active weight of fund j at the beginning of period t as

$$\phi^j_{i,t} = w^j_{i,t} - w^m_{i,t} \tag{A.7}$$

where $w^j_{i,t}$ is manager j's weight in stock i, and $w^m_{i,t}$ is stock i's weight in the market portfolio. Note that $\sum_{i=1}^N \phi^j_{i,t} = 0$ since $\sum_{i=1}^N w^j_{i,t} = \sum_{i=1}^N w^m_{i,t} = 1$.

The manager's benchmark-adjusted rate of return is

$$\tilde{R}^j_{i,t} = \sum_{i=1}^N w^j_{i,t} \tilde{R}_{i,t+1} = \sum_{i=1}^N \phi^j_{i,t} \tilde{R}_{i,t+1} \tag{A.8}$$

The second equality comes from the identity that $\sum_{i=1}^N w^m_{i,t} \tilde{R}_{i,t+1} = 0$. Denote the fund j's objective alpha and tracking error by $ALPHA^j_t$ and TE^j_t, respectively,

$$ALPHA^j_t = \sum_{i=1}^N \phi^j_{i,t} \alpha_{i,t} \tag{A.9}$$

$$TE^j_t = \sum_{i=1}^N (\phi^j_{i,t})^2 \sigma_{i,t} \tag{A.10}$$

Active manager j maximizes the following one-period subjective mean-variance objective, taking $\alpha_{i,t}$ and $\sigma_{i,t}$, $i = 1, \ldots, N$ as given,[19]

$$\max_{\phi^j_{i,t}} \rho^j \sum_{i=1}^N \phi^j_{i,t} \alpha_{i,t} - \frac{\gamma}{2} \sum_{i=1}^N (\phi^j_{i,t})^2 \sigma_{i,t}, \quad \text{subject to} \quad \sum_{i=1}^N \phi^j_{i,t} = 0 \tag{A.11}$$

[18] The managers' perception of stock alpha can be endogenously generated by the their Bayesian learning based on the trading signals. The skilled (unskilled) managers are endowed with accurate (inaccurate) signals (Cohen, Coval, and Pástor, 2005).

[19] I first solve the optimization problem (A.12) by forming the corresponding Lagrangian, obtaining

$$\mathcal{L} = \rho^j \left[\sum_{i=1}^N \phi^j_{i,t} \alpha_{i,t} - \xi \sum_{i=1}^N \phi^j_{i,t} \right] - \frac{\gamma}{2} \sum_{i=1}^N (\phi^j_{i,t})^2 (\sigma_i + f_t)$$

Differentiating with respect to $\phi^j_{i,t}$ gives the optimal portfolio weights

$$\phi^{j*}_{i,t} = \rho^j \frac{\alpha_{i,t} - \xi}{\gamma(\sigma_i + f_t)}$$

where ξ is the scaled Lagrangian multiplier of portfolio manager j. Since $\sum_{i=1}^N \phi^{j*}_{i,t} = 0$, we have $\xi = \sum_{i=1}^N \frac{(\sigma_i + f_t)^{-1}}{\sum_{i=1}^N (\sigma_i + f_t)^{-1}} \alpha_{i,t}$. Note that ξ is the weighted average of stocks' alpha with the inverse of idiosyncratic variances as weights, and is the same across active fund managers. As shown later, $\xi = 0$ under certain assumptions in the equilibrium. Without loss of generality, I ignore it in Equation (A.12).

Solving this problem gives the manager's optimal active weights $\phi_{i,t}^{j*}$

$$\phi_{i,t}^{j*} = \rho^j \frac{\alpha_{i,t}}{\gamma(\sigma_i + f_t)} \tag{A.12}$$

Equation (A.12) shows that the active manager optimally adjusts his active weight according to the stock's alpha-idiosyncratic risk trade-off. In particular, during the periods of high aggregate idiosyncratic volatility, large active weights indicate the high-alpha opportunities identified by the skilled manager. For an unskilled manager, the active weights will always be zero so he is essentially an "index closer".

Uninformed Investors

Uninformed investors invest directly in individual stocks. The uninformed-investor excess demand is assumed to be exogenous. Denote the excess weights aggregate across uninformed investors in stock j as $x_{i,t}$.[20] In addition, I assume $\sum_{i=1}^{N} w_{i,t}^{m} x_{i,t} = 0$, so that there is no distortion of uninformed-investor excess demand on the price of the market portfolio. Given this assumption, the model is most sensibly applied in the cross-sectional asset pricing.

Equilibrium Pricing

To highlight the effect of aggregate idiosyncratic volatility f_t on asset prices and active fund performance in the equilibrium, I assume $\sigma_i = 0$ for all stocks. From equation (A.12) we have the active weights aggregated across active funds,[21] $\phi_{i,t}^{F}$, as

$$\phi_{i,t}^{F} = \frac{m}{M} \frac{\alpha_{i,t}}{\gamma f_t} \tag{A.13}$$

The market clearing condition is

$$\phi_{i,t}^{F} + h x_{i,t} = 0 \tag{A.14}$$

where h is the fraction of the market held by uninformed investors relative to the fraction of the market held by active fund managers.[22]

From equations (A.13) and (A.14), we can have the following equilibrium asset pricing equation,

Proposition 1. *The abnormal return on stock i in the equilibrium is given by the following equation,*

$$\alpha_{i,t} = -\left(\frac{m}{M}\right)^{-1} \left(h x_{i,t}\right) \left(\gamma f_t\right) \tag{A.15}$$

[20] A similar assumption has also been used in Stambaugh (2014); Kozak, Nagel, and Santosh (2018). Notice that $\sum_{i=1}^{N} x_{i,t} = 0$ and $i = 1, \ldots, N$.

[21] Note that ξ reduces to $N^{-1} \sum_{i=1}^{N} \alpha_{i,t}$, the equal-weighted average of stock alphas. Since $\sum_{i=1}^{N} w_{i,t}^{m} \alpha_{i,t} = 0$ and $\sum_{i=1}^{N} w_{i,t}^{m} x_{i,t} = 0$, $\xi = 0$ for all active funds in the equilibrium. For simplification I ignore it here.

[22] If the total assets managed by active funds is A and the total wealth invested by uninformed investors is B, then $h = B/A$.

The abnormal return of stock i is determined by three economic components: 1) m/M, the fraction of skilled active managers; 2) $hx_{i,t}$, the excess demand from uninformed investors, scaled by the relative wealth of uninformed investors to active funds; 3) γf_t, aggregate idiosyncratic volatility multiplied by active managers' risk-aversion parameter. Intuitively, assets with negative (positive) uninformed excess demand ($x_{i,t}$) have positive (negative) expected abnormal returns. Importantly, the magnitude of cross-sectional mispricing increases with aggregate idiosyncratic volatility (f_t) and decreases with the fraction of skilled active managers (m/M).

Define a measure of cross-sectional mispricing as the sum of squared stocks' information ratios adjusted by managers' risk aversion,

$$\begin{aligned}\psi_t &= \sum_{i=1}^{N}\left(\frac{\alpha_{i,t}}{\sqrt{\gamma f_t}}\right)^2 \\ &= \left(\frac{m}{M}\right)^{-2}\left[\sum_{i=1}^{N}(hx_{i,t})^2\right](\gamma f_t) \end{aligned} \tag{A.16}$$

which is positively associated with the commonality in idiosyncratic volatility f_t and the cross-sectional dispersion of uninformed excess demand $\sum_{i=1}^{N}(hx_{i,t})^2$.

It is easy to show that the benchmark-adjusted return generated by skilled active manager α_t^S is the multiple of the benchmark-adjusted return on the aggregate portfolio of all active mutual funds α_t^F,

$$\alpha_t^S = \left(\frac{m}{M}\right)^{-1}\alpha_t^F \tag{A.17}$$

The next proposition says that α_t^F can be interpreted as a proxy for the magnitude of uncorrected price distortion.

Proposition 2. *The benchmark-adjusted return on the aggregate portfolio of all active equity funds is given by*

$$\begin{aligned}\alpha_t^F &= \sum_{i=1}^{N}\phi_{i,t}^{f}\alpha_{i,t} \\ &= \left(\frac{m}{M}\right)^{-1}\left[\sum_{i=1}^{N}(hx_{i,t})^2\right](\gamma f_t) \\ &= \left(\frac{m}{M}\right)\psi_t \end{aligned} \tag{A.18}$$

Data Cleansing

Stock

This section of cleaning equity data mainly follows the data appendix in Bessembinder et al. (2020). For U.S.firms, data are from the CRSP monthly/daily stock files. For Canadian firms, data is obtained from Compustat/North America. For firms in other countries, data is from Compustat/Global. I focus on firms from the 48 markets which are used in the construction of the Fama-French international five factors (Fama and French, 2017). Specifically, there are 23 developed markets countries (Australia, Austria, Belgium, Canada, Switzerland, Germany, Denmark, Spain, Finland, France, United Kingdom, Greece, Hong Kong, Ireland, Italy, Japan, Netherlands, Norway, New Zealand, Portugal, Sweden, Singapore, United States) and 25 emerging markets/countries (Argentina, Brazil, Chile, China, Colombia, Czech Republic, Egypt, Hungary, India, Indonesia, Malaysia, Mexico, Pakistan, Peru, Philippines, Poland, Qatar, Russia, Saudi Arabia, South Africa, South Korea, Taiwan, Thailand, Turkey, United Arab Emirates). Local currency stock prices and returns are converted into US dollars using exchange rates from Compustat.

I clean Compustat Global data mainly following the procedures described in the data appendix of Bessembinder, Chen, Choi, and Wei (2019). I retrieve the following data files from Compustat Global: Security Daily library (secd) for Canadian stocks, Security Daily library (gsecd) for other countries, Country (r_country), Exchange Trading Codes (r_ex_codes), Global Industry Codes (r_giccd), security descriptor (security), and company descriptor (company).

I identify U.S. common stocks based on the CRSP sharecode variable, SHRCD = 10, 11. To identify common stocks outside the U.S., I first select securities with Compustat Issue Type TPCI = '0' as well as ADR stocks with TPCI = 'F'. I then exclude securities that contain the "%" symbol in the DSCI field (as they are likely preferred stocks with a fixed dividend), and also exclude stocks where the EXCHG field contains "Broker", "Fund Manager", "Fund Managers", "OTC", "OTC Bulletin Board", "Other-OTC", "Subsidiary/Private", "Unlisted Evaluated Equity", "Unlisted Securities Market", "Non-traded Company or Security", or "Stock Connect".

The remaining set of non-US securities with Issue Type TPCI = '0' contains a substantial number of investment funds and trusts, including mutual funds, hedge funds, and exchange-traded funds. I then attempt to exclude these securities as follows:

1. Securities that are likely to be Real Estate Investment Trusts, based on GSUBIND = 40401010 or GIND = 404020.
2. Securities that are likely to be funds or trusts, based on their company name variables. In particular, we focus on securities for which CONM or CONML contains " fund", " trust", "venture capital trust", " vct", or " reit".

The variable CSHOC (shares outstanding at the security level) is not available prior to April 1998 in the Compustat North America data, which I rely on for Canadian stocks. As a consequence, I download shares outstanding from Datastream to fill the missing data before 1998.

Mutual Funds

The sample of actively managed US equity mutual funds is constructed by merging the CRSP Mutual Fund Database and Morningstar Direct. I clean and combine the CRSP data and the Morningstar Direct data mainly following the procedure described in the data appendix of Berk and van Binsbergen (2015) and Pástor et al. (2017). I screen actively managed equity funds following the common practice in literature (e.g., Kacperczyk et al., 2005, 2008; Cremers and Pareek, 2016). First, I require the Lipper Prospectus objective code, the Strategic Insight objective code, and the Weisenberger objective code to indicate that the fund is pursuing an active US equity strategy that is not focusing on one or more particular industries or sectors. I require the Lipper Prospectus objective code to be equal to EI, EIEI, ELCC, G, GI, LCCE, LCGE, LCVE, LSE, MC, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, MR, S, SCCE, SCGE, SCVE, SESE, SG, or missing; I require the Strategic Insight objective code to be equal to AGG, GMC, GRI, GRO, ING, SCG, or missing; I require the Weisenberger objective code to be equal to GCI, IEQ, IFL, LTG, MCG, SCG, G, G-I, G-I-S, G-S, G-S-I, GS, I, I-G, I-G-S, I-S, I-S–G, S, S-G-I, S-I, S-I-G, or missing; and I require the CDA/Spectrum code to be equal to 2, 3 ,4, or missing. Second, I exclude index funds and Exchange Traded Funds as indicated by CRSP or fund name. Third, to ensure the fund is primarily focusing on US equities, I require the percentage of stocks in the portfolio as reported by CRSP to be between 50% and 150%. For funds where this variable is missing, I calculate and use the ratio of the total assets calculated from holdings in the Thomson Reuters to the total net assets from CRSP.

I use net fund returns, total net assets, and fund characteristics such as turnover ratio and expense ratio from CRSP. Other fund information such as the Morningstar Category Benchmark Index and total return prices of different equity indices are from Morningstar Direct. The sample period start from January 1984 to address the selection bias problem (Elton et al., 2001; Fama and French, 2010). To further address the issue of incubation bias (Evans, 2010), I exclude observations prior to the reported fund inception date as well as observations for which the names of the funds are missing in the CRSP.

Literature mainly relies on the Thomson Reuters database to obtain mutual fund holdings. However, Zhu (2020) shows that, from 2008 to 2015, 58% of newly founded US equity mutual fund share classes in the CRSP cannot be matched to the Thomson Reuters database.[23] Following the paper's suggestions, I retrieve the mutual fund holdings from Thomson Reuters before August 2008 and from CRSP Holding files after September 2008. For funds with multiple share classes, I aggregate fund information at portfolio level. Because I use two different holdings database before and after 2008, I make an unified portfolio-level identifier by combining WFICN and CRSP_PORTNO, which are portfolio identifiers from Thomson Reuters and CRSP, respectively. I sum their total net assets to arrive at the portfolio-level total net assets. The monthly total net assets of each share class are available since 1991. For the qualitative attributes of funds such as objectives and inception dates, I retain the observation of the largest fund. For the quantitative attributes of funds, I take the weighted average with the lagged total net assets

[23] Funds that are missing from the Thomson Reuters tend to be smaller, have higher turnover ratios, receive higher fund flows, and have higher four-factor alphas.

as weight. Finally, I exclude funds with less than 8 observations of valid fund net returns (Fama and French, 2010).

The sample of actively managed US equity mutual fund includes 4,249 distinct funds and 690,369 fund-month observations. The number of funds in each month varies between 212 in January 1984 and 1,988 in December 2019. Figure A1 plots the sum of total net assets across all funds in the sample.

The sample of active equity international mutual fund are constructed by combining the Morningstar Direct and Factset Global Ownership mainly following the procedure described in Cremers et al. (2016) and Schumacher (2018). Because there is no linkage table between Morningstar identifier and Factset identifier, I merge these two database by fuzzy matching fund names and then a manual check. I further exclude funds with TNA less than US $5 million and a performance history of less than 1 years to address concerns about incubation biases. The final sample includes 5,106 distinct international funds. The sample of country funds is used to construct actively managed country benchmarks for the analysis of fund performance. The sample period December 2000 to December 2020.