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

Job Market Paper

Please click here for the latest version

Shuaiyu Chen*

University of Rochester

Abstract

This paper shows that aggregate idiosyncratic volatility (*AIV*) is a key determinant of active funds' ability to generate superior performance. Using the sample of active US equity mutual funds from 1984 through 2019, I find that *AIV* positively predicts benchmark-adjusted fund returns, and its predictive power is stronger for funds that deviate more from passive benchmarks. The predictability of *AIV* is also significant in the data of active international mutual funds. I then explore two non-mutually exclusive explanations for these findings: 1) active funds require a reward for accommodating exogenous asset demand and *AIV* drives their risk-bearing capacity (i.e., the risk view); and 2) they profit from private signals about firms' fundamentals and *AIV* proxies for aggregate flows of fundamental news (i.e., the information view). Additional empirical evidence supports the risk view. First, on average, active mutual funds scale back their active positions when *AIV* rises. Second, funds that do not reduce active positions earn larger abnormal returns following high *AIV* levels. Third, a large *AIV* shock leads to a temporary impact on stock prices. The observations during the COVID-19 crisis also corroborate the risk view.

JEL classification: G11, G12, G23

Keywords: Active funds, idiosyncratic volatility

*Simon Business School, University of Rochester. Email: shuaiyu.chen@simon.rochester.edu. I am deeply indebted to my advisors Ron Kaniel and Alan Moreira for their guidance and support. I am grateful for the helpful discussions with my dissertation committee members Robert Novy-Marx and Christian Opp. I also thank Bill Schwert, Jerry Warner, Yixin Chen, Pingle Wang, Zhao Jin, Yucheng (John) Yang, Mykola Pinchuk, and Xuyuanda Qi for suggestions and comments. All errors are my own.

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 and investment strategies. Recent studies suggest that funds significantly deviating from passive benchmarks outperform these benchmarks and other funds (e.g., Kacperczyk, Sialm, and Zheng, 2008; Cremers and Petajisto, 2009; Pástor, Stambaugh, and Taylor, 2020). In addition, there is some evidence that active fund performance is time-varying (e.g., Moskowitz, 2000; Kacperczyk, Van Nieuwerburgh, and Veldkamp, 2014). Understanding the time variation in fund performance, especially for those funds with a high degree of deviations, is crucial for guiding investors' portfolio delegation decisions and evaluating market efficiency. However, there is little research focusing on the question of whether benchmark-adjusted fund returns are predictable, and if so, what are the economic mechanisms driving the fund return predictability.

In this paper, I provide an answer to this important question by showing that aggregate idiosyncratic volatility (*AIV*), measured as the cross-sectional average of idiosyncratic stock return volatilities, is a key determinant of the ability of active funds to generate outperformance. Using the sample of active US equity mutual funds from 1984 through 2019, I find that *AIV* positively predicts benchmark-adjusted fund returns, and its predictive power is stronger for funds that deviate more from their benchmarks. The predictability of *AIV* is also significant for international mutual funds and US hedge funds. To understand the underlying mechanisms, I conduct additional analyses to examine how *AIV* affects fund portfolio allocations and stock prices. A collection of empirical evidence is consistent with the explanation that active managers require a reward for accommodating exogenous asset demands, and *AIV* drives their risk-bearing capacity for doing so.

Figure 1 illustrates the key findings of my paper. In panel A, the solid line is the forward-looking moving average benchmark-adjusted returns on the equal-weight aggregate portfolio

[1] As of 2019, active equity mutual funds worldwide had \$11.5 trillion total net assets (about 13% of global equity market value). Despite the growing popularity of passive investing in the US markets, \$4.3 trillion (about 15% of US market value) are under the management of active domestic mutual funds (see, Investment Company Fact Book, https://www.icifactbook.org/).

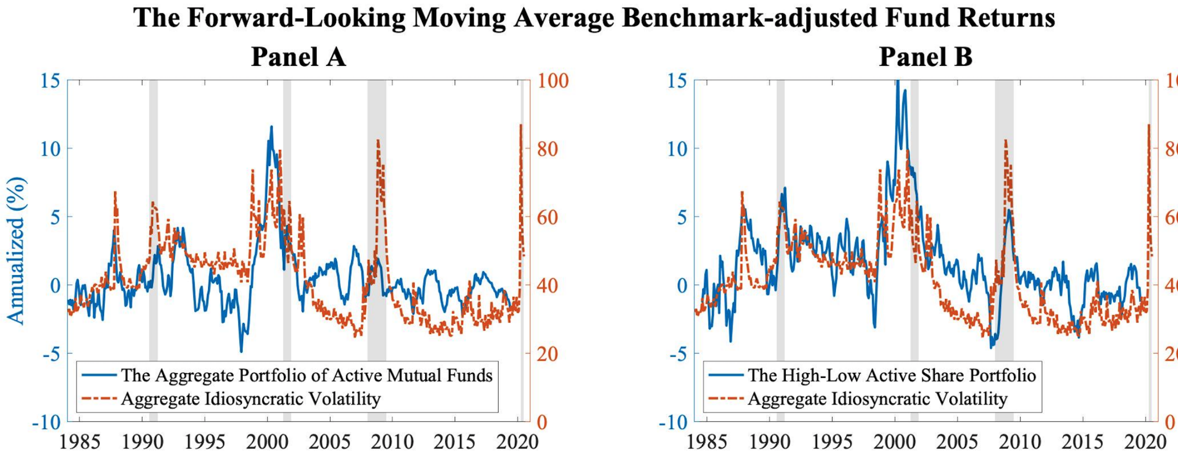

Fig. 1. Panel A plots aggregate idiosyncratic volatility (*AIV*) and the moving average benchmark-adjusted returns on the equal-weight aggregate portfolio of active mutual funds. Panel B plots *AIV* and the difference of the moving average benchmark-adjusted returns between high and low Active Share 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 2019.

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 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 subsequent benchmark-adjusted fund returns, especially for active funds that significantly deviate from their passive benchmarks.

To test the predictive ability of *AIV* on active fund performance, I start by analyzing a sample of actively managed US equity mutual funds from 1984 through 2019. Specifically, I use predictive regressions to formally examine the relation between *AIV* and subsequent benchmark-adjusted fund returns. My initial tests focus on the aggregate portfolios of active mutual funds. I estimate time-series regressions of the equal-weighted (EW) and value-weighted (VW) benchmark-adjusted returns on the beginning-or-period *AIV*, respectively.[2] The results show that the average benchmark-adjusted returns are highly predictable with *AIV*. For example, a one-standard-deviation rise in *AIV* is associated with

[2]Because actively managed mutual funds are evaluated against passive benchmarks, I focus on the average benchmark-adjusted returns as the performance measure of the aggregate portfolio.

an increase of 1% in the EW benchmark-adjusted return per year (t-statistics of 2.84). The R^2 of 2.62% is large in monthly predictive regressions. These results hold qualitatively and quantitatively after controlling for various macro variables such as the VIX index, investor sentiment (Baker and Wurgler, 2006), the real-time recession probability (Chauvet and Piger, 2008), and aggregate liquidity (Pastor and Stambaugh, 2003). I also find significant predictability of AIV on the VW benchmark-adjusted returns, although the economic magnitude is lower by about 35%.

My second tests show that the correlations between AIV and subsequent benchmark-adjusted returns increase with Active Share. Specifically, I sort active mutual funds into quintiles based on the beginning-of-quarter Active Share and then estimate predictive regressions of the EW and VW benchmark-adjusted returns of each quintile portfolio on the previous AIV. Because low Active Share funds track their passive benchmarks closely, the predictability of AIV should be most pronounced among high Active Share portfolio. Consistent with this intuition, I find that the slope coefficients on AIV rise monotonically from the low to high Active Share quintiles. For example, for the high-minus-low portfolio, a one-standard-deviation rise in AIV is associated with an increase of 2.14% in the EW benchmark-adjusted return per year (t-statistics of 3.69), and the R^2 of 5.38% is remarkably large.

An alternative performance measure is information ratio, which effectively captures an active fund's ability to produce abnormal returns per unit of idiosyncratic risk.[3] I find the relations between AIV and benchmark-adjusted returns also hold for information ratios, suggesting that the rise in benchmark-adjusted return with AIV is not just commensurate with an increase in tracking error.

I conduct an extensive battery of tests to evaluate the robustness of the key findings. First, the out-of-sample tests confirm that AIV significantly predicts benchmark-adjusted fund performance.[4] The results are also robust after controlling for various priced factors proposed in the recent literature. In addition, the odds that AIV is a spurious predictor are very low

[3]Information ratio is defined as the ratio between benchmark-adjusted return and tracking error.

[4]The importance of out-of-sample tests has been emphasized in recent 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 in out-of-sample tests.

based on the Stambaugh, Yu, and Yuan (2014) simulations. Furthermore, the Fama and French (2010) bootstrap simulations show that when *AIV* is high, there are more funds with positive gross α, which cannot be explained by "luck".

After establishing that the predictability of *AIV* is a robust feature of the data, I proceed to understand why active mutual funds produce much larger α when *AIV* is high. Theoretically, active funds can earn positive gross α only at the expense of other market participants in two ways. First, suppose some investors have excess asset demands for exogenous reasons such as biased beliefs or liquidity needs. In that case, their demands could move asset prices away from fundamental values. Active funds could earn positive α by taking the other side of those exogenous demands by overweighting (underweighting) underpriced (overpriced) assets (e.g., Shiller, 1984; Grossman and Miller, 1988; Campbell, Grossman, and Wang, 1993). *AIV* can affect active funds because it drives funds' tracking error.[5] Alternatively, *AIV* can serve as a proxy for aggregate flows of firms' fundamental news. If active funds are informed investors, they could trade on their private signals about future firm fundamentals and thus earn positive α (e.g., Kyle, 1985). I refer to the first way as the "risk" view and the second way as the "information" view.

However, these two views have different implications for the effects of *AIV* on active funds' portfolio allocation and asset prices. I conduct several tests to differentiate these two views. First, in response to rises in *AIV*, the risk view suggests that active funds would reduce their active positions to lower the potential increase in tracking errors. In contrast, the information view suggests that active funds would expand their active positions to exploit more informational advantages. Consistent with the risk view, a fund-quarter level analysis provides evidence that active mutual funds, on average, scale back their active positions to track their benchmark more closely when *AIV* rises. I also find that the aggregate active positions are negatively associated with *AIV* based on a stock-quarter level analysis. These results suggest that *AIV* affects an active fund's portfolio allocation by driving time variations in its tracking errors.

Second, funds that hold or even expand active positions when *AIV* rises tend to generate

[5] Herskovic, Kelly, Lustig, and Van Nieuwerburgh (2016) show that idiosyncratic stock return volatilities have a strong factor structure.

greater abnormal returns following high *AIV* levels. In other words, these funds earn more rewards by accommodating asset demands that other funds are not willing to take during periods of high *AIV*.

Third, a positive *AIV* shock would lead to a temporary price effect due to the contraction of active positions from the risk view. In contrast, the information view suggests a permanent price effect due to informed trading. Consistent with the risk view, I find that a substantial *AIV* shock leads to a temporary impact on stock prices. This evidence comes from a non-parametric analysis by assigning stocks into two portfolios based on the beginning-of-quarter active positions and then splitting the sample periods according to the current-quarter *AIV* shocks. In quarters with significant positive *AIV* shocks, the overweight-minus-underweight portfolio has a contemporaneous return of 4.98% per year. It then produces 2.90% and 4.23% in the next two quarters. The pattern of price pressure is also present on each of the two portfolios: 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.

The COVID-19 crisis provides me an extraordinary opportunity to evaluate the effects of *AIV* on fund portfolio allocations and stock prices. Figure 3 shows that *AIV* rose substantially to 85% in March due to the outbreak of COVID-19. Consistent with the risk view, active equity mutual funds reduced their active shares by 1%. More importantly, the high-minus-low decile portfolio formed on the beginning-of-March aggregate active positions (at the stock level) has a return of -2.46% in March (i.e., negative price effect) and a return of 1.97% in April (i.e., reversal). This result is consistent with the risk view, which implies a temporary price impact.

The rest of the paper is organized as follows. Section 2 introduces the data sources. Section 3 provides detailed econometric evidence on the ability of *AIV* to predict the benchmark-adjusted performance of actively managed equity funds. Section 4 conducts additional analyses to understand the relation between *AIV* and performance. Section 5 presents additional results and robustness. Section 6 concludes and discusses contributions to the existing literature.

2. Data

2.1. *Sample*

Data for the empirical analysis are from several sources. The U.S. and global equity data are from CRSP and Compustat Global, respectively. The data of actively managed U.S. mutual funds are from the CRSP Survivor-Bias-Free Mutual Fund Database, the Morningstar Direct, and the Thomson Reuters Mutual Fund Holding Database. The data of index constituents in 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 (formally LionShares). The media-based sentiment scores are from the RavenPack. For the evidence from the COVID-19 crisis, I collect and tabulate the monthly equity holdings of mutual funds from the SEC N-PORT fillings. The details about how I clean and merge these data are in Appendix B.

2.1.1. *U.S. and global stock data*

The U.S. data include stocks listed in NYSE, AMEX, and NASDAQ from January 1980 through June 2020. The global data include stocks listed in the 48 largest equity markets, excluding the U.S. markets.[6] Stock prices and returns are converted into U.S. dollars using exchange rates from Compustat.

2.1.2. *Actively managed U.S. equity mutual funds*

I construct the sample of actively managed U.S. equity mutual funds by merging the CRSP Mutual Fund Database with Morningstar Direct. I clean and combine the CRSP and Morningstar Direct data according to the data appendix in Pástor, Stambaugh, and Taylor (2015). In addition, I screen actively managed equity mutual funds following previous

[6]I select these equity markets according to the construction of the international Fama-French five factors (see the description in the French's website, https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html). 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).

literature (e.g., Kacperczyk, Sialm, and Zheng, 2005; Kacperczyk et al., 2008; Cremers and Pareek, 2016). 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 returns of different 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.

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.[7] 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 total net assets. The monthly total net assets of each share class are available since 1991. 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 actively managed U.S. equity mutual funds includes 4,249 unique 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 period.

2.1.3. *Actively managed 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, Ferreira, Matos, and

[7] 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.

Starks (2016) and Schumacher (2018). The FactSet database includes 83,358 distinct institutions of various types (mutual funds, pension funds, variable annuity funds, etc.) over the sample period 2001 to 2017. I focus on open-end (OEF) active international equity mutual funds that have a broad mandate to invest in multiple markets and that are classified as "Equity" in the Morningstar Global Category Classification. Because there is no linkage table between the Morningstar identifier and Factset identifier, I merge these two databases by first fuzzy matching fund names and then a manual check. I exclude those funds with TNA less than US $5 million and a history of returns less than eight months to address incubation biases. The final sample consists of 8,049 unique active international equity mutual funds. The sample period is January 2001 to December 2017.

2.2. *Empirical Implementation*

2.2.1. *Measuring aggregate idiosyncratic volatility*

The estimation of aggregate idiosyncratic volatility (*AIV*) follows Herskovic et al. (2016). Specifically, *AIV* is constructed as the equal-weighted average of standard deviation of daily residual returns, which are estimated from the time-series regressions of returns on the Fama-French 3 factors within each calendar month. At least 15 daily observations are required in estimation of standard deviation.[8] I also consider alternative estimation methods such as the value-weighting scheme, CAPM/Fama-French 5-factor idiosyncratic volatility, and excluding those micro-cap/low-price stocks. In addition, one plausible forward-looking measure of *AIV* is the difference the average option-implied volatility. It turns out that the key findings of this paper hold qualitatively and quantitatively using these alternative *AIV* measures.

2.2.2. *Mutual fund benchmark index*

I use the Morningstar Category Benchmark Index as passive benchmark for active U.S. equity mutual funds, following suggestions by Sensoy (2009) and Hunter, Kandel, Kandel, and Wermers (2014). Investment advisory companies typically disclose the benchmarks of their active mutual funds in the prospectus. However, these self-reported benchmarks could

[8] For several exceptions such as September 2001, I reduce the required minimum daily observations to 10.

be associated with an agency-conflict issue. Sensoy (2009) show empirically that investment advisory companies have incentives to select easy-to-beat benchmarks. Morningstar addresses this issue by breaking mutual funds into peer groups based on their holdings. Morningstar regularly reviews the category structure and the portfolios within each category to ensure that the system meets the needs of investors. Because some Morningstar category groups have few funds over the sample period, I only focus on the 10 most widely used Morningstar Category 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 sample period.

2.2.3. Degree of deviation from passive benchmarks

To measure the extent to which an active fund deviates from its benchmark index, I use active share proposed by Cremers and Petajisto (2009), 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,

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

where $w_{i,t}^{fund}$ and $w_{i,t}^{benchmark}$ are the weight in stock i held by an active fund and the weight in the Morningstar Cartogary Benchmark Index, respectively. Active share has a value ranging between zero and one.[9]

[9] Another widely-used measure of the degree of deviation from benchmark is portfolio concentration, constructed 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).

2.2.4. *Benchmark-adjusted performance: benchmark index v.s. priced factors*

Benchmark-adjusted fund return is the difference between a fund gross return and its Morningstar Cartogary Benchmark Index return. Gross returns are computed as the fund's net return plus its monthly expense ratio. To adjust factor exposures of fund returns, the standard method in the mutual fund literature is to estimate time-series regressions with various priced factors such as Carhart four factors (Carhart, 1997). The factor-based regressions are 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. In the robustness, I show the main results of this paper are not sensitive to a variety of priced factors proposed in the recent literature of the cross-section of stock returns.

3. *AIV* and Active Fund Performance

This section presents the key empirical findings of this paper: 1) *AIV* positively predicts the average benchmark-adjusted returns of active equity mutual funds; 2) the predictive ability of *AIV* is stronger for funds that deviate more from passive benchmarks. In this section, I will focus on the sample of actively managed U.S. equity mutual funds from 1984 through 2019.

3.1. *Two-way sort on Active Share and AIV*

I start by considering a simple nonparametric way to examine how subsequent returns and risks of active mutual funds are associated with Active Share and *AIV*. Specifically, I sort active funds into quintiles based on beginning-of-quarter Active Share and then split the sample periods into two groups according to the previous *AIV* levels. I then use a 12-month forward-looking window to compute average benchmark-adjusted returns, tracking errors, and information ratios for each fund. Figure 2 plots the equal-weighted average of these statistics from the two-way sort on Active Share and *AIV*.

[Insert Figure 2 near here]

Panel A shows that, on average, the benchmark-adjusted returns are greater following high *AIV* levels. In addition, the positive cross-sectional relation between Active Share and fund performance is much stronger during the periods of high *AIV*. Specifically, the funds with the highest Active Share have a benchmark-adjusted return of 3.3% per year when *AIV* is high, but only 0.5% when *AIV* is low. The Active Share-performance relation, documented first by Cremers and Petajisto (2009), has motivated a large body of studies that attempt to explain why funds deviating more from passive benchmarks perform better (see, e.g., Van Nieuwerburgh and Veldkamp, 2010). My results from the two-way sort suggest that *AIV* is crucial for understanding this relation.

AIV not only affects benchmark-adjusted fund returns but also tracking errors. Panel B shows that *AIV* positively affects tracking errors, and its effect is stronger for high Active Share funds. It is thus useful to know whether the rise in benchmark-adjusted return with *AIV* is just commensurate with an increase in tracking error or whether the information ratio, which effectively measures the abnormal return per unit of risk, increases as well. Panel C shows that the information ratios increase with both *AIV* and Active Share, suggesting that active funds earn greater returns for bearing per unit of risk during times of high *AIV*.

Next, I will use predictive regressions to provide detailed econometric evidence of the patterns reflected in Figure 2. Specifically, I will first focus on the aggregate portfolio of active equity mutual funds, and then study the portfolios sorted on Active Share.

3.2. Predictive regressions: the aggregate portfolio of active mutual funds

Predictive regressions have been widely used in the time-series asset pricing literature.[10] To formally examine the time-series relation between *AIV* and benchmark-adjusted returns, I estimate the following monthly predictive regressions,

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

[10] For example, Stambaugh, Yu, and Yuan (2012) estimate predictive regressions of monthly returns of various "anomaly" strategies on the previous Baker-Wurgler sentiment index to examine whether the short-sale constraint can cause the asymmetric effect of investor sentiment on the cross-section of stock returns. Nagel (2012) estimate predictive regressions of weekly returns of short-term reversal strategy on previous *VIX* index to identify predictable time-series variation in the expected returns from liquidity provision.

where $R_t^{benchmark-adjusted}$ represents the equal-weighted and value-weighted average benchmark-adjusted fund returns. Because actively managed mutual funds are evaluated against passive benchmarks, I focus on the average benchmark-adjusted returns as the performance measure of the aggregate portfolio.

[Insert Table 1 near here]

Table 1 shows that the average benchmark-adjusted returns are highly predictable with AIV. For example, a one-standard-deviation rise in AIV is associated with an increase of 1% in the EW benchmark-adjusted return per year (t-statistics of 2.84). The R^2 of 2.62% is large in monthly predictive regressions. This result holds qualitatively and quantitatively after controlling for a variety of macro 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).[11] I also find a significant predictability of AIV on the VW benchmark-adjusted returns, although the economic magnitude is lower by about 35%.

3.3. Predictive regressions: the portfolios sorted on Active Share

Next, I show that the correlations between AIV and subsequent benchmark-adjusted returns increase with Active Share. Specifically, I sort active mutual funds into quintiles based on the beginning-of-quarter Active Share, and then estimate predictive regressions of the equal-weighted or value-weighted benchmark-adjusted returns of each quintile portfolio on the previous AIV. Because low Active Share funds track their passive benchmarks closely, the predictive ability of AIV should be most pronounced among high Active Share portfolio.

[11] I control these macro variables for the following reasons. The VIX index and AIV possess substantial common variation, particularly associated with deep recessions (e.g., Bekaert, Hodrick, and Zhang, 2012; Herskovic et al., 2016). Empirical evidence suggests that higher liquidity is accompanied by greater market efficiency (e.g., Chordia, Roll, and Subrahmanyam, 2008, 2011). Mispricing induced by sentiment investors is more likely to occur during the periods that sentiment-driven investors participate more heavily in the stock market (e.g., Baker and Wurgler, 2006; Stambaugh et al., 2012). High market disagreement together with short sale constraints would indicate more mispricing left on the market (e.g., Chen, Hong, and Stein, 2002; Diether, Malloy, and Scherbina, 2002). Active equity mutual funds appear to perform better during recessions (Moskowitz, 2000; Kosowski, 2011; Glode, 2011; Kacperczyk et al., 2014). Previous studies show that fund flows can affect both active funds' portfolio allocation and their portfolio return (e.g., Coval and Stafford, 2007; Lou, 2012; Kaniel and Kondor, 2013).

[Insert Table 2 near here]

Table 2 shows that the slope coefficients on *AIV* rise monotonically from the low to high Active Share quintiles. For the high-minus-low portfolio, for example, a one-standard-deviation rise in *AIV* is associated with an increase of 2.14% in the EW benchmark-adjusted return per year (t-statistics of 3.69), and the R^2 of 5.38% is remarkably large.

3.4. *Predicting conditional information ratios with AIV*

Previous sections examine time variation in the benchmark-adjusted returns of active mutual funds. Table 3 shows that *AIV* is also positively correlated with abnormal returns per unit of risk earned by active mutual funds. The table reports the results from the following monthly time-series predictive regressions,

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

where IR_t is the equal-weighted average conditional information ratios, which is benchmark-adjusted returns standardized by the 12-month rolling standard deviation of benchmark-adjusted returns. The results are qualitatively similar if the conditional information ratio is computed based on the expected tracking errors estimated from the GARCH-type models.

[Insert Table 3 near here]

The table confirms 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. This indicates that active mutual funds earn a higher compensation per unit of risk in times of high *AIV*.

4. Understanding the *AIV*-Performance Relation

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 through holding all the index constituents according to the official index proportions. An active funds attempts to outperform its benchmark by taking active positions against the benchmark. Because passive funds earn zero gross abnormal returns (α), active funds can earn positive gross α only at the expense of outside investors who also hold portfolios that are different from benchmark portfolios.[12]

There are mainly two possibilities that active mutual funds can generate positive α. First, some investors may have excess asset demands for exogenous reasons such as biased beliefs or liquidity needs, which could push asset prices away from fundamental values. Active mutual funds may attempt to overweight (underweight) underpriced (overpriced) assets and thus take the other side of these nonfundamental excess demands. If active fund managers are risk-averse, they will require a reward for bearing tracking errors due to the deviation from passive benchmarks, suggesting that they would not fully correct mispricings. Therefore, active funds effectively perform a liquidity provision role, and their abnormal returns are from the uncorrected mispricings. Second, active funds may profit from informed trading if they have private information about firm fundamentals, and there are noise traders in the financial market.

The ability of *AIV* to predict benchmark-adjusted fund performance would be consistent with both of the interpretations. Because stock idiosyncratic volatilities have a strong factor structure (see, Herskovic et al., 2016), *AIV* drives substantial time variation in tracking error. When *AIV* is high, active funds would be less willing to take active positions against their benchmarks and thus require more compensation for accommodating exogenous demands from other investors. It is also possible that *AIV* proxies for the time-varying aggregate flows

[12] In the absence of outside investors, this assertion also holds in the sense that skilled fund managers earn positive α at the expense of unskilled managers. In this case, active funds play a zero-sum game, which Sharpe (1991) call "the arithmetic of active management."

of private information, so that active funds would make more informed trading profits during the periods of high *AIV*.

In Appendix C, I show theoretically how *AIV* is positively related to expected benchmark-adjusted fund performance under these two economic interpretations. The economic reasons from these theoretical discussions justify the important role of *AIV* as a powerful predictor of the time-series of active mutual fund performance.

To understand how active mutual funds add value for their clients, it is useful to investigate which interpretation is more consistent with data. Even though both arguments support the relation between *AIV* and performance, they have different implications for how *AIV* influences fund portfolio allocations and stock prices. In response to rises in *AIV*, liquidity provision suggests that active funds should hold or scale back their active positions to lower the potential increase in tracking errors, whereas informed trading suggests that they should expand their active positions to exploit more informational advantages. In addition, a positive shock to *AIV* would lead to a temporary price effect due to contraction of liquidity provision, but a permanent price effect due to expansion of informed trading. Furthermore, if some funds attempt to take the opposite side of trades induced by plausible exogenous reasons such as extreme fund flows or media sentiment, the liquidity provision story predicts that they should earn greater abnormal returns during high-*AIV* periods.

Next, I conduct additional analysis to examine these arguments. A collection of empirical evidence largely support the liquidity provision view of how active mutual funds generate abnormal returns.

4.2. Effect of AIV on fund portfolio allocation

This section shows that on average, active equity mutual funds track their benchmarks more closely when *AIV* rises. This evidence is consistent with the economic interpretation that *AIV* is the state variable driving the willingness of active funds to take active positions against mispricings and provide liquidity to investors who have exogenous excess demands.

I first examine the effect of *AIV* on active share, which will be lower if funds reduce their active weights. Specifically, I estimate the following fund-level panel regressions,

$$AS_{j,t} = a_1 AIV_t + a_2 VIX_t + a_3 AggFlow_t + \gamma \mathbf{X_{j,t-1}} + \delta_j + \theta_t + \varepsilon_{j,t},$$

where $AS_{j,t}$ is active share of fund j at the end of quarter t. VIX and $AggFlow$ are the VIX index and aggregate fund flows, respectively. I include VIX in the regression because is shares substantial common variation with AIV, particularly within deep recessions (Herskovic et al., 2016). It is also important to control the potential effect of aggregate fund flows on active share, as recent studies show that fund flows can affect fund managers' portfolio allocation (see, Coval and Stafford, 2007; Lou, 2012). Because investors tend to redeem their shares from active funds during periods of high risk and uncertainty, aggregate fund outflows could be associated with decreases in active share. $\mathbf{X_{j,t-1}}$ represents the fund-level controls including log(total net assets), number of holdings, turnover ratio, and tracking error. I also include fund fixed effects (δ_j) and year fixed effects (θ_t) in the panel regressions. Fund fixed effects are used to absorb time-invariant variation in active share across funds, while year fixed effects account for the lower-frequency time-series co-movement in active share.

Another way to show the effect of AIV on fund portfolio allocation is to investigate whether active funds trade toward their benchmark in response to rises in AIV, in the sense that they sell (buy) stocks that are overweighted (underweighted) at the beginning of periods. To capture this trading activity, I construct a measure called directional turnover, which is defined as follows,

$$DirectionalTunover_{j,t} = \sum_{i=1}^{N} sign\left(w^j_{i,t-1} - w^{benchmark}_{i,t-1}\right) \times \frac{Trade^j_{i,t} \times Price_{i,t-1}}{TNA^j_{t-1}},$$

where $w^j_{i,t-1} - w^{benchmark}_{i,t-1}$ 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, $Price_{i,t-1}$ is stock i's share price, $MTNA_{j,t-1}$ is fund j's total net assets, and $sign(x)$ is a function returning $1(-1)$ if x is positive (negative). Directional turnover will be lower if active funds trade to move toward their benchmarks.

[Insert Table 4 near here]

Table 4 shows the results from the panel regressions in which the dependent variable is active share (Panel A) or directional turnover (Panel B). Column (1) of Panel A reports the coefficient estimate on *AIV* from the specification without VIX and aggregate fund flows. The estimate is negative and statistically significant at the 1% level. The economic magnitude is also large: a one-standard-deviation increase in *AIV* leads to a 0.63% decrease in active share, which is about a one-standard-deviation of the time-series changes in active share. Columns (2) and (3) report the coefficient estimates on VIX and aggregate fund flows, respectively. Active share is negatively correlated with VIX, and positively associated with aggregate fund flows. The regression specifications in column (4) include all three macro variables, from which We can have several important observations. First, the coefficient estimate on *AIV* almost remains the same after controlling for VIX and aggregate fund flows. Second, *AIV* completely explains the negative effect of VIX on active share, suggesting that *AIV* is the key determinant of active funds' portfolio decision. This is consistent with the benchmark-based performance evaluation in active mutual fund industry. Third, even though aggregate fund flows are still positively associated with active share, its economic magnitude is one-half smaller than that in column (3). Therefore, to a large extent, the effect of aggregate fund flows on active share stems from its negative correlation with AIV. Panel B confirms that the effect of *AIV* on directional turnover is very similar to that on active share. The results are significant not only statistically but also economically. For example, column (5) shows that a one-standard-deviation increase in *AIV* leads to a 0.59% decrease in directional turnover, which is about a 1.5 standard deviation of the time-series changes directional turnover. This economic magnitude is also similar to that obtained from active share.

4.3. Effect of AIV on aggregate fund trades

Section 4.2 provides the fund-level evidence 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 construct a stock-level variable called directional trades, which is defined as

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

where $w^{j}_{i,t-1} - w^{benchmark}_{i,t-1}$ 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 to their passive benchmarks.

[Insert Table 5 near here]

Table 4 shows the results from the following stock-level panel regressions,

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

where $\mathbf{X_{i,t-1}}$ represent control variables including log(market capitalization), log(book-to-market), asset growth, gross profit-to-asset, momentum, market beta, and stock idiosyncratic volatility. The specifications also include stock and year fixed effects. The table confirms that *AIV* has a significant effect on the aggregate active fund trades. For example, column (4) shows that a one-standard-deviation increase in *AIV* leads to a 0.13% decrease in directional trades, which is about a one-standard-deviation of the time-series changes directional trades. This economic magnitude is similar to that obtained from the fund-level analysis.

4.4. *Stock price reactions in response to AIV shocks*

I next conduct a non-parametric analysis to show that positive *AIV* shocks result in a sharp price reaction and a subsequent and extended reversals. Specifically, 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 the characteristic-adjusted returns (Daniel, Grinblatt, Titman, and Wermers, 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.

[Insert Table 7 near here]

Table 7 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 during quarter t are due to information about the company's future cash flows, we would expect that these effects are permanent. On the other hand, 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.

4.5. Evidence from the COVID-19 Crisis

[Insert Figure 3 near here]

I also present the novel evidence from the COVID-19 crisis in 2020. Figure 3 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.

4.6. *Do funds that bet against exogenous demands earn large α?*

This section provides evidence that the time-series relation between *AIV* and benchmark-adjusted return is stronger among active funds that attempt to take the other side of excess asset demands which are plausibly induced by exogenous returns. I consider two types of demand shocks that are identified from recent literature: (1) trades proportional to the flows of mutual funds that experience extreme inflows/outflows in the previous quarter (see, Coval and Stafford, 2007; Edmans, Goldstein, and Jiang, 2012); (2) excess demands related to media sentiment (see, Tetlock, 2007).

4.6.1. *Flow-driven trades*

Coval and Stafford (2007) find that substantial purchase/redemption by mutual fund investors cause individual stocks held across various mutual funds to experience significant unanticipated buying/selling pressures. By modifying the measures of Coval and Stafford (2007), Edmans et al. (2012) document the pattern of price impacts and reversals associated with large mutual fund redemption. Following a similar methodology, I construct a measure, betting against flow-driven trading (*BAFT*), to capture the extent to which a fund buys (sells) stocks that are sold (purchased) by the other mutual funds due to extreme flows. Specifically, *BAFT* is defined as

$$BAFT_t^j = -\sum_{i=1}^{N} Trade_{i,t}^j \times \left(InFlows_{i,t}^{-j} - OutFlows_{i,t}^{-j}\right),$$

where $Trade^{j}_{i,t}$ is fund j's trade on stock i in quarter t, and $InFlows^{-j}_{i,t}$ ($OutFlows^{-j}_{i,t}$) is the trade aggregated across funds (excluding fund j) that experience extreme inflows (outflows). Similar to the construction proposed by Edmans et al. (2012), $InFlows^{-j}_{i,t}$ is computed as

$$InFlows^{-j}_{i,t} = \frac{\sum_{k=1,k\neq j}^{M} \left(Shares^{k}_{i,t-1} \times Price_{i,t-1} \times NetFlows^{k}_{t} \middle| NetFlows^{k}_{t} > 5\% \right)}{DollarVolume_{i,t}},$$

and $OutFlows^{-j}_{i,t}$ is computed conditional on $NetFlows^{k}_{t} < -5\%$. $Shares^{k}_{i,t-1}$ denotes shares held by fund k at the end of quarter $t-1$. $NetFlows^{k}_{t}$ is fund k's net flows in quarter t. *Price* and *DollarVolume* are stock price and dollar trading volume.

I form portfolios from dependent sorts on *BAFT* and active share. Table A10 shows the results for the equal-weighted average of benchmark-adjusted return of these portfolios. The table shows that active funds that aggressively take the opposite side of flow-driven trades (the lower right corner) generate much larger abnormal expected returns when *AIV* is high. A one-standard-deviation increase in *AIV* leads to a rise of annualized 4.06 percentage points in the benchmark-adjusted return of the high *BAFT* and active share portfolio. However, for those funds that deviate from their benchmark but don't appear to accommodate the demand shocks (the upper right corner), their benchmark-adjusted performance is less related to *AIV*.

4.6.2. Media sentiment

It has been documented that media content is likely to be related to investor sentiment. For example, Tetlock (2007) provide empirical evidence that high media pessimism is associated with low investor sentiment, resulting in downward pressure on prices. If some mutual funds overweight (underweight) stocks with media pessimism (optimism), they are likely to trade against sentiment-investor excess demand and thus earn a large premium as compensation during periods of high *AIV*. To test whether the positive *AIV*-performance relation is stronger among these funds, I construct a measure, betting against media sentiment (*BAMS*), to captures the extent to which a fund overweights/underweights stocks with high media pessimism/optimism. Specifically, *BAMS* of fund k in quarter t is constructed as

$$BAMS_t^k = -\frac{1}{N}\sum_{i=1}^{N} sign\left(w_{i,t}^j - w_{i,t}^{benchmark}\right) \times sign(ESS - 50),$$

where $sign(x)$ is a function returning 1 (-1) if $x > 0 (< 0)$, and ESS is the RavenPack Event Sentiment Score which is classified to be media optimism (pessimism) if it is larger (smaller) than 50.

I form portfolios from dependent sorts on *BAMS* and active share. Table A11 shows the results for the equal-weighted average of benchmark-adjusted return of these portfolios. The table shows that active funds that aggressively bet against media-sentiment stocks (the lower right corner) generate much larger abnormal expected returns when *AIV* is high. A one-standard-deviation increase in *AIV* leads to a rise of annualized 10.11 percentage points in the benchmark-adjusted return of the high *BAMS* and active share portfolio. However, for those funds that deviate from their benchmark but bet in the same direction of media sentiment (the upper right corner), their benchmark-adjusted performance is much less related to *AIV*.

4.7. Discussion on alternative explanations

I identify two alternative explanations on the time-varying fund performance, but none is consistent with the empirical observations. First, Glode (2011) develop a model showing that fund clients are willing to pay more for active returns in bad states when their marginal utility of consumption is high, so fund managers optimally work hard in bad states but allocate less effort in good states. However, the high active share funds don't underperform when *AIV* is low.[13] Second, 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. Using the same skill measures proposed by Kacperczyk et al. (2014), I instead find that it is stock picking that allows the high active share funds to earn a large return following high *AIV*

[13]Even though the low-*AIV* state is undoubtedly a good state, there is a debate on whether the high-*AIV* state is bad for investors. Herskovic et al. (2016) argue that increases in *AIV* adversely affect the marginal utility of investors because they represent increase in consumption risk for the average household.

levels. Cremers and Petajisto (2009) have shown that active share mainly reflects managers' stock picking rather than factor timing activities.

5. Additional Results and Robustness

5.1. Out-of-sample tests

Recent empirical asset pricing literature has emphasized the importance of out-of-sample tests in return predictability.[14] To examine the robustness of the in-sample results, I conduct out-of-sample tests on the predictability of *AIV* for benchmark-adjusted fund performance. 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 reduction 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

[14] 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.

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 $H_A : R^2_{OOS} > 0$).

[Insert Table 10 near here]

Table 10 shows that the R^2_{OOS} statistics rise from 0.92% to 6.54% from the low to high active share quintiles. For the high-minus-low active share portfolio, the R^2_{OOS} is 5.11% and statistically significant.

5.2. *Controlling for various price factors*

So far, active mutual funds' performance is compared with its Morningstar Category Benchmark Index, which is a common practice in the active asset management industry. However, the academic literature typically uses the factor-based regression approach to adjust factor exposures of fund returns. For example, the Fama-French-Carhart four-factor model is arguably the most widely used model to evaluate active mutual fund performance. Controlling priced factors also alleviates the concern that *AIV* captures some factors ignored in the regression specifications (Chen and Petkova, 2012). If fund managers trade on these factors to generate abnormal returns, then *AIV* would predict subsequent fund performance due to its association with these factors. I thus 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; (2) the 4-factor model augmented with liquidity factor (Pastor and Stambaugh, 2003) and betting-against-beta factor (Frazzini and Pedersen, 2014); (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. Table 12 shows that the coefficient estimates on *AIV* are consistent across different regression specifications, and importantly, are similar those reported in Table 2.

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

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 432 months for the full sample, 216 months for the low-AIV subsample, and 216 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 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.[15] I then compare the values of $t(\alpha)$ at selected percentiles of the cumulative density function (CDF) of the $t(\alpha)$ estimates from actual fund returns with the averages across the 10,000 simulation runs of the $t(\alpha)$ estimates at the same percentiles. Figure A3 plots the probability density functions of 4-factor $t(\alpha)$. 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. Therefore, mutual funds' ability of generating alpha appear to be varying significantly with *AIV* over time.

5.4. *Other activeness measures*

A growing line of literature shows that fund "activeness" is positively correlated with fund performance in the cross-section. Even though the constructions of these "activeness" measures are different, they all essentially capture how far an active fund deviates from a passive portfolio. Therefore, I expect that the cross-sectional relations between these measures and performance are stronger during the periods of high *AIV*. I test this prediction for three

[15] Fama and French (2010) focus on $t(\alpha)$, rather than estimates of α, to control for differences in precision due to differences in residual variance and in the number of months funds are in a simulation run. The simulated returns have the same properties of actual fund returns, except the in-sample α estimates are subtracted from actual returns for each fund. Therefore, the simulated cross-sections describe the distribution of α estimates when alpha is zero.

well-known "activeness" measures from the mutual fund literature: portfolio concentration (HHI) (Table A2), industry concentration index (Kacperczyk et al., 2005) (Table A3) and fund activeness (Pástor et al., 2020) (Table A4). I find that *AIV* also strongly predicts benchmark-adjusted returns of the high (high-minus-low) portfolios formed on these measures, and the economic magnitude is very similar to that obtained from the portfolios sorted on active share (see, Table 2).

5.5. *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.[16] 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 A7 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*.

5.6. *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 funds. The time-varying *AIV* is a phenomenon not only in the US but also in other equity markets. Figure A2 plots *AIV* in the 48 equity markets around the world, including 23 developed markets (including US) and 25 emerging markets. For each equity market, *AIV* is computed as the equal-weighted average of standard deviations of daily residual returns, estimated from time-series regressions of stock returns on the market excess returns and the

[16] For example, Ferson, Sarkissian, and Simin (2003) find 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 only 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.

Fama-French international 3 factors of the market's corresponding region. The figure confirms that *AIV* fluctuates significantly over time and across equity markets. Importantly, even though there are co-movement in *AIV* across the developed markets (Guo and Savickas, 2008; Bekaert et al., 2012), Figure A2 shows that the time-series variation of *AIV* among emerging markets are largely different from that of developed markets.

I extend the evidence to the sample of active international equity mutual funds. Specifically, I conduct the following panel predictive regressions,

$$R_{i,j,t}^{characteristic-adjusted} = bAIV_{j,t-1} + \gamma \mathbf{X_{i,t-1}} + \phi \mathbf{Y_{j,t-1}} + \delta_{\mathrm{j}} + \delta_{\mathrm{i}} + \theta_{\mathrm{t}} + \varepsilon_{\mathrm{i,j,t}}$$

where $R_{i,j,t}^{characteristic-adjusted}$ is the weighted-average characteristic-adjusted return earned by fund i from market j based on quarterly equity holdings. $AIV_{j,t}$ is the equal-weighted average of standard deviation of daily residual returns estimated from the Fama-French international 3-factor model within each quarter. $\mathbf{X_{i,t-1}}$ represents the fund-level controls including log(total net assets), turnover ratio, return volatility, and number of equity holdings. $\mathbf{Y_{j,t-1}}$ represents the market-level controls including market volatility and the value-weighted averages of book-to-market, asset growth, and institutional ownership.

[Insert Table 13 near here]

Table 13 shows a significant positive correlation between *AIV* and subsequent characteristic-adjusted return from the panel regressions with various fixed effects and controls. The economic magnitude of the coefficient estimates on *AIV* from the international sample is comparable with that estimated from the US sample.

6. Conclusions

This paper explores the effects of aggregate idiosyncratic volatility (*AIV*) on active equity mutual funds. I find that when *AIV* is high, funds that deviate more from the benchmark generate much higher subsequent returns than those with less deviation. However, when *AIV* is low, this difference in fund performance disappears. These findings suggest that risk-averse fund managers require a reward for taking the other side of exogenous demands and *AIV* drives their risk-bearing capacity. I provide a collection of empirical evidence consistent with this interpretation. First, on average, fund managers scale back their active positions to lower the potential increase in tracking error due to rising *AIV*. Second, these reduced active positions result in price pressure: stocks that are initially overweighted (underweighted) by active mutual funds have a negative (positive) contemporaneous abnormal return but a positive (negative) subsequent return. I also provide corroborating evidence from the COVID-19 crisis. Third, a subset of funds that attempt to accommodate exogenous trades due to extreme flows or media sentiment earn great returns during high *AIV* periods.

The results in this paper have several implications. First, numerous empirical papers relate performance to fund "activeness" in the cross-section (e.g., Kacperczyk et al., 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 performance to business cycles (e.g., Moskowitz, 2000; Kosowski, 2011; Glode, 2011; Kacperczyk et al., 2014). The empirical findings of this paper show that *AIV* drives the variation of fund performance in both the cross-section and the time series.

Idiosyncratic volatility has been studied in the asset pricing literature. Campbell, Lettau, Malkiel, and Xu (2001) and Brandt, Brav, Graham, and Kumar (2010) examine secular variation in average idiosyncratic volatility. Herskovic et al. (2016) show that shocks to the common factor in idiosyncratic volatility are priced. Guo and Savickas (2008) and Bekaert et al. (2012) find comovement in *AIV* across developed countries. This paper instead explores the effects of *AIV* on active mutual fund performance.

An extensive empirical research focuses on whether institutional demand can result in price pressure. Previous studies document a sharp price reaction and a subsequent and more extended reversal in response to the mutual fund flow-driven demand shock (e.g., Coval and Stafford, 2007; Edmans et al., 2012; Khan, Kogan, and Serafeim, 2012; Lou, 2012). Duffie (2010) provide various examples of price reactions to demand shocks and discuss different models of price pressure and reversals. Koijen and Yogo (2018) develop an asset pricing model with flexible heterogeneity in asset demand across investors. They estimate the price impact of latent institutional demand using 13-F institutional holdings data. This paper documents novel evidence of price pressure caused by mutual fund demand shock due to managers' risk-reward trade-off and the strong time variation in AIV.

References

Amihud, Y., Goyenko, R., 2013. Mutual Fund's R2 as Predictor of Performance. Rev Financ Stud 26, 667–694.

Baker, M., Wurgler, J., 2006. Investor Sentiment and the Cross-Section of Stock Returns. The Journal of Finance 61, 1645–1680.

Bekaert, G., Hodrick, R. J., Zhang, X., 2012. Aggregate Idiosyncratic Volatility. Journal of Financial and Quantitative Analysis 47, 1155–1185, publisher: Cambridge University Press.

Berk, J. B., van Binsbergen, J. H., 2015. Measuring skill in the mutual fund industry. Journal of Financial Economics 118, 1–20.

Bessembinder, H., Chen, T.-F., Choi, G., Wei, K. C. J., 2019. Do Global Stocks Outperform US Treasury Bills? SSRN Scholarly Paper ID 3415739, Social Science Research Network, Rochester, NY.

Brandt, M. W., Brav, A., Graham, J. R., Kumar, A., 2010. The Idiosyncratic Volatility Puzzle: Time Trend or Speculative Episodes? Rev Financ Stud 23, 863–899.

Campbell, J. Y., Grossman, S. J., Wang, J., 1993. Trading Volume and Serial Correlation in Stock Returns. Q J Econ 108, 905–939, publisher: Oxford Academic.

Campbell, J. Y., Lettau, M., Malkiel, B. G., Xu, Y., 2001. Have Individual Stocks Become More Volatile? An Empirical Exploration of Idiosyncratic Risk. The Journal of Finance 56, 1–43.

Campbell, J. Y., Thompson, S. B., 2008. Predicting Excess Stock Returns Out of Sample: Can Anything Beat the Historical Average? Rev Financ Stud 21, 1509–1531.

Carhart, M. M., 1997. On Persistence in Mutual Fund Performance. The Journal of Finance 52, 57–82.

Chauvet, M., Piger, J., 2008. A Comparison of the Real-Time Performance of Business Cycle Dating Methods. Journal of Business & Economic Statistics 26, 42–49, publisher: Taylor & Francis _eprint: https://doi.org/10.1198/073500107000000296.

Chen, J., Hong, H., Stein, J. C., 2002. Breadth of ownership and stock returns. Journal of Financial Economics 66, 171–205.

Chen, Z., Petkova, R., 2012. Does Idiosyncratic Volatility Proxy for Risk Exposure? Rev Financ Stud 25, 2745–2787, publisher: Oxford Academic.

Chordia, T., Roll, R., Subrahmanyam, A., 2008. Liquidity and market efficiency. Journal of Financial Economics 87, 249–268.

Chordia, T., Roll, R., Subrahmanyam, A., 2011. Recent trends in trading activity and market quality. Journal of Financial Economics 101, 243–263.

Clark, T. E., West, K. D., 2007. Approximately normal tests for equal predictive accuracy in nested models. Journal of Econometrics 138, 291–311.

Cohen, R. B., Coval, J. D., Pástor, , 2005. Judging Fund Managers by the Company They Keep. The Journal of Finance 60, 1057–1096.

Coval, J., Stafford, E., 2007. Asset fire sales (and purchases) in equity markets. Journal of Financial Economics 86, 479–512.

Cremers, K. J. M., Petajisto, A., 2009. How Active Is Your Fund Manager? A New Measure That Predicts Performance. Rev Financ Stud 22, 3329–3365.

Cremers, M., Ferreira, M. A., Matos, P., Starks, L., 2016. Indexing and active fund management: International evidence. Journal of Financial Economics 120, 539–560.

Cremers, M., Pareek, A., 2016. Patient capital outperformance: The investment skill of high active share managers who trade infrequently. Journal of Financial Economics 122, 288–306.

Daniel, K., Grinblatt, M., Titman, S., Wermers, R., 1997. Measuring Mutual Fund Performance with Characteristic-Based Benchmarks. The Journal of Finance 52, 1035–1058.

Daniel, K., Hirshleifer, D., Sun, L., 2020. Short- and Long-Horizon Behavioral Factors. Rev Financ Stud 33, 1673–1736, publisher: Oxford Academic.

Diether, K. B., Malloy, C. J., Scherbina, A., 2002. Differences of Opinion and the Cross Section of Stock Returns. The Journal of Finance 57, 2113–2141, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/0022-1082.00490.

Doshi, H., Elkamhi, R., Simutin, M., 2015. Managerial Activeness and Mutual Fund Performance. Rev Asset Pric Stud 5, 156–184.

Duffie, D., 2010. Presidential Address: Asset Price Dynamics with Slow-Moving Capital. The Journal of Finance 65, 1237–1267, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.2010.01569.x.

Edmans, A., Goldstein, I., Jiang, W., 2012. The Real Effects of Financial Markets: The Impact of Prices on Takeovers. The Journal of Finance 67, 933–971, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.2012.01738.x.

Elton, E. J., Gruber, M. J., Blake, C. R., 2001. A First Look at the Accuracy of the CRSP Mutual Fund Database and a Comparison of the CRSP and Morningstar Mutual Fund Databases. The Journal of Finance 56, 2415–2430.

Evans, R. B., 2010. Mutual Fund Incubation. The Journal of Finance 65, 1581–1611.

Fama, E. F., French, K. R., 2010. Luck versus Skill in the Cross-Section of Mutual Fund Returns. The Journal of Finance 65, 1915–1947.

Fama, E. F., French, K. R., 2015. A five-factor asset pricing model. Journal of Financial Economics 116, 1–22.

Fama, E. F., French, K. R., 2017. International tests of a five-factor asset pricing model. Journal of Financial Economics 123, 441–463.

Ferson, W. E., Sarkissian, S., Simin, T. T., 2003. Spurious Regressions in Financial Economics? The Journal of Finance 58, 1393–1413.

Frazzini, A., Pedersen, L. H., 2014. Betting against beta. Journal of Financial Economics 111, 1–25.

Glode, V., 2011. Why mutual funds "underperform". Journal of Financial Economics 99, 546–559.

Grossman, S. J., Miller, M. H., 1988. Liquidity and Market Structure. The Journal of Finance 43, 617–633, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.1988.tb04594.x.

Guo, H., Savickas, R., 2008. Average Idiosyncratic Volatility in G7 Countries. Rev Financ Stud 21, 1259–1296, publisher: Oxford Academic.

Herskovic, B., Kelly, B., Lustig, H., Van Nieuwerburgh, S., 2016. The common factor in idiosyncratic volatility: Quantitative asset pricing implications. Journal of Financial Economics 119, 249–283.

Hou, K., Mo, H., Xue, C., Zhang, L., 2020. An Augmented q-Factor Model with Expected Growth*. Review of Finance .

Hunter, D., Kandel, E., Kandel, S., Wermers, R., 2014. Mutual fund performance evaluation with active peer benchmarks. Journal of Financial Economics 112, 1–29.

Kacperczyk, M., Sialm, C., Zheng, L., 2005. On the Industry Concentration of Actively Managed Equity Mutual Funds. The Journal of Finance 60, 1983–2011.

Kacperczyk, M., Sialm, C., Zheng, L., 2008. Unobserved Actions of Mutual Funds. Rev Financ Stud 21, 2379–2416.

Kacperczyk, M., Van Nieuwerburgh, S. V., Veldkamp, L., 2014. Time-Varying Fund Manager Skill. The Journal of Finance 69, 1455–1484.

Kacperczyk, M., Van Nieuwerburgh, S. V., Veldkamp, L., 2016. A Rational Theory of Mutual Funds' Attention Allocation. Econometrica 84, 571–626, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.3982/ECTA11412.

Kaniel, R., Kondor, P., 2013. The Delegated Lucas Tree. Rev Financ Stud 26, 929–984.

Khan, M., Kogan, L., Serafeim, G., 2012. Mutual Fund Trading Pressure: Firm-Level Stock Price Impact and Timing of SEOs. The Journal of Finance 67, 1371–1395, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.2012.01750.x.

Koijen, R. S. J., Yogo, M., 2018. A Demand System Approach to Asset Pricing. Journal of Political Economy 127, 1475–1515.

Kosowski, R., 2011. Do Mutual Funds Perform When It Matters Most to Investors? US Mutual Fund Performance and Risk in Recessions and Expansions. Quart. J. of Fin. 01, 607–664.

Kozak, S., Nagel, S., Santosh, S., 2018. Interpreting Factor Models. The Journal of Finance 73, 1183–1223.

Kyle, A. S., 1985. Continuous Auctions and Insider Trading. Econometrica 53, 1315–1335, publisher: [Wiley, Econometric Society].

Lou, D., 2012. A Flow-Based Explanation for Return Predictability. Rev Financ Stud 25, 3457–3489, publisher: Oxford Academic.

Moskowitz, T. J., 2000. Mutual Fund Performance: An Empirical Decomposition into Stock-Picking Talent, Style, Transactions Costs, and Expenses: Discussion. The Journal of Finance 55, 1695–1703.

Nagel, S., 2012. Evaporating Liquidity. Rev Financ Stud 25, 2005–2039, publisher: Oxford Academic.

Newey, W. K., West, K. D., 1987. A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. Econometrica 55, 703–708.

Novy-Marx, R., 2014. Predicting anomaly performance with politics, the weather, global warming, sunspots, and the stars. Journal of Financial Economics 112, 137–146.

Pastor, , Stambaugh, R., 2003. Liquidity Risk and Expected Stock Returns. Journal of Political Economy 111, 642–685.

Pástor, , Stambaugh, R. F., Taylor, L. A., 2015. Scale and skill in active management. Journal of Financial Economics 116, 23–45.

Pástor, , Stambaugh, R. F., Taylor, L. A., 2017. Do Funds Make More When They Trade More? The Journal of Finance 72, 1483–1528.

Pástor, , Stambaugh, R. F., Taylor, L. A., 2020. Fund tradeoffs. Journal of Financial Economics .

Schumacher, D., 2018. Home Bias Abroad: Domestic Industries and Foreign Portfolio Choice. Rev Financ Stud 31, 1654–1706, publisher: Oxford Academic.

Sensoy, B. A., 2009. Performance evaluation and self-designated benchmark indexes in the mutual fund industry. Journal of Financial Economics 92, 25–39.

Sharpe, W. F., 1991. The Arithmetic of Active Management. Financial Analysts Journal 47, 7–9, publisher: CFA Institute.

Shiller, R. J., 1984. Stock Prices and Social Dynamics. Brookings Papers on Economic Activity 1984, 457–510, publisher: Brookings Institution Press.

Stambaugh, R. F., 2014. Presidential Address: Investment Noise and Trends. The Journal of Finance 69, 1415–1453, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jofi.12174.

Stambaugh, R. F., Yu, J., Yuan, Y., 2012. The short of it: Investor sentiment and anomalies. Journal of Financial Economics 104, 288–302.

Stambaugh, R. F., Yu, J., Yuan, Y., 2014. The long of it: Odds that investor sentiment spuriously predicts anomaly returns. Journal of Financial Economics 114, 613–619.

Stambaugh, R. F., Yuan, Y., 2017. Mispricing Factors. Rev Financ Stud 30, 1270–1315.

Tetlock, P. C., 2007. Giving Content to Investor Sentiment: The Role of Media in the Stock Market. The Journal of Finance 62, 1139–1168, _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.2007.01232.x.

Van Nieuwerburgh, S., Veldkamp, L., 2010. Information Acquisition and Under-Diversification. Rev Econ Stud 77, 779–805, publisher: Oxford Academic.

Welch, I., Goyal, A., 2008. A Comprehensive Look at The Empirical Performance of Equity Premium Prediction. Rev Financ Stud 21, 1455–1508.

Yu, J., 2011. Disagreement and return predictability of stock portfolios. Journal of Financial Economics 99, 162–183.

Zhu, Q., 2020. The Missing New Funds. Management Science 66, 1193–1204, publisher: INFORMS.

Tables and Figures

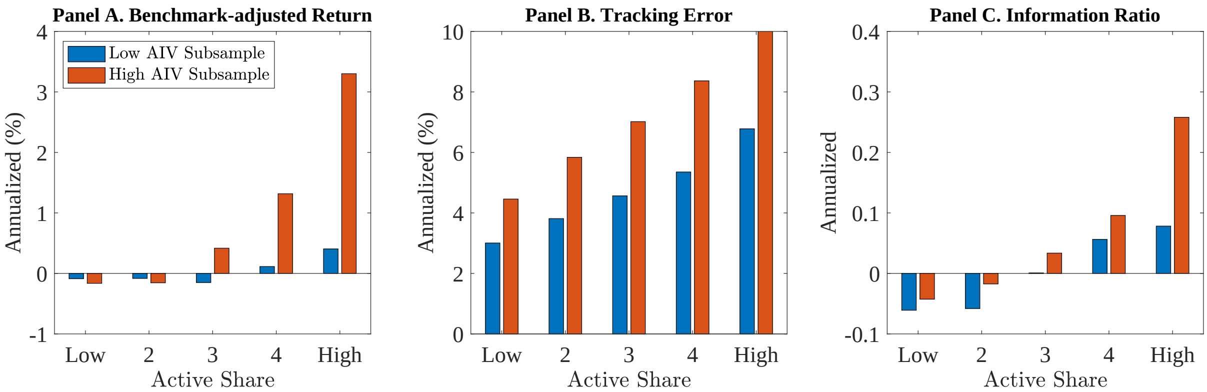

Fig. 2. This figure shows how the subsequent return and risk of active mutual funds are related to beginning-of-quarter active share and *AIV*. Specifically, I sort funds into quintiles according to active share and then split the sample periods equally into the low and high *AIV* subsamples. For each 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 from 1984 through 2019.

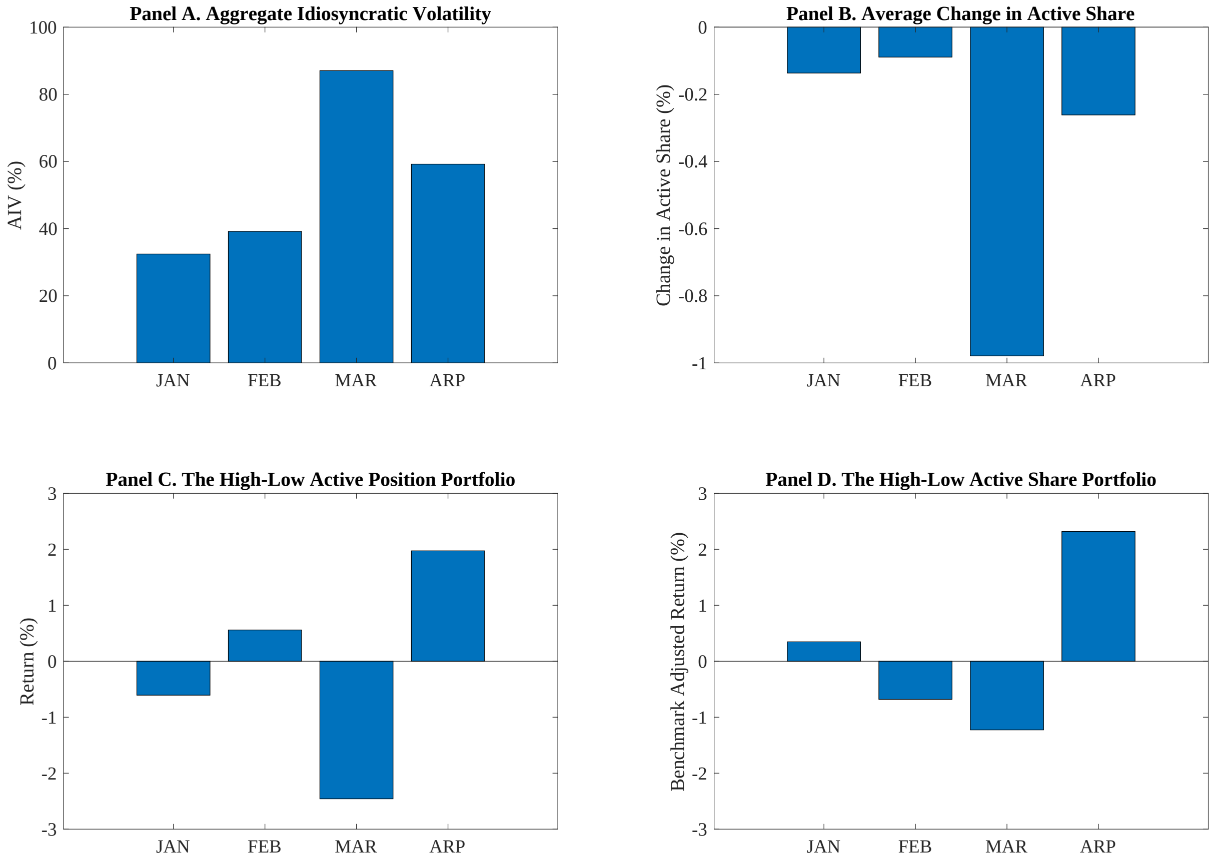

Fig. 3. This figure provides evidence from the COVID-19 period, January through April in 2020. Panel A plots aggregate idiosyncratic volatility (*AIV*), and panel B plots the equal-weighted average of active share changes across active mutual funds. Panel C plots the difference of characteristic-adjusted 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 1: **Predictive regressions: the aggregate portfolios of active mutual funds**

This table shows that Aggregate Idiosyncratic Volatility (AIV) positively predicts benchmark-adjusted returns on the aggregate portfolio of active equity mutual funds. 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 average benchmark-adjusted returns using equal weights (EW) or value weights (VW). A fund's benchmark-adjusted return is the fund's gross return (net return plus expense ratio) minus the return on the Morningstar Category Benchmark Index (Pástor et al., 2017). 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), the VIX index, 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 sample consists of active U.S. equity mutual funds from 1984 to 2019. 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 predictive ability on benchmark-adjusted fund return.

Slope coefficients and [t-statistics] for the aggregate portfolio of active mutual funds from the time-series predictive regressions $R_t^{benchmark-adjusted} = a + bAIV_{t-1} + \gamma X_{t-1} + \epsilon_t$

	(1)	(2)	(3)	(4)
	The EW aggregate portfolio		The VW aggregate portfolio	
AIV	1.00	1.44	0.66	1.07
	[2.84]	[3.59]	[1.82]	[2.25]
Recessions		0.11		0.32
		[0.30]		[0.64]
VIX		-1.44		-1.52
		[-2.74]		[-2.59]
Sentiment		0.82		0.75
		[1.76]		[1.26]
Disagreement		1.04		1.01
		[2.78]		[1.88]
Liquidity		-0.45		-0.75
		[-0.77]		[-1.08]
Adjusted-R^2(%)	2.62	8.76	1.34	4.65

Table 2: **Predictive regressions: the portfolios sorted on Active Share**

This table shows that the predictive ability of Aggregate Idiosyncratic Volatility (*AIV*) on benchmark-adjusted fund return is increasing with Active Share, a measure that captures a fund's degree of deviations from its own benchmark (Cremers and Petajisto, 2009). I sort active mutual funds into quintile portfolios according to beginning-of-quarter Active Share. 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 equal-weighted or value-weighted average benchmark-adjusted returns on the Active Share quintile portfolios. Active Share is defined as $\frac{1}{2}\sum_{i=1}^{N}\left|w_{i,t}^{fund} - w_{i,t}^{benchmark}\right|$, 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 X. See the caption in Table 1 for the definitions of *AIV* and control variables. Newey and West (1987) heteroskedasticity-and-autocorrelation-robust t-statistics with three lags are reported in the bracket. The sample consists of active U.S. equity mutual funds from 1984 to 2019. 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 predictive ability on benchmark-adjusted fund return.

Panel A. Slope coefficients and [t-statistics] for each Active Share quintile portfolio from the time-series predictive regressions $R_t^{benchmark-adjusted} = a + bAIV_{t-1} + \epsilon_t$

	(1)	(2)	(3)	(4)	(5)	(6)
	The EW portfolios sorted on Active Share					
	Low	2	3	4	High	H-L
AIV	0.28	0.44	0.78	0.84	2.42	2.14
	[0.90]	[1.25]	[1.75]	[2.08]	[3.51]	[3.69]
Adjusted-R^2(%)	0.03	0.30	0.92	1.28	5.63	5.38
	The VW portfolios sorted on Active Share					
	Low	2	3	4	High	H-L
AIV	0.29	0.99	0.80	1.12	2.30	2.01
	[0.63]	[1.29]	[1.39]	[1.82]	[2.58]	[3.17]
Adjusted-R^2(%)	0.07	0.51	0.90	0.98	3.60	4.02

Panel B. Slope coefficients and [t-statistics] for each Active Share quintile portfolio from the time-series predictive regressions $R_t^{benchmark-adjusted} = a + bAIV_{t-1} + \gamma X_{t-1} + \epsilon_t$

	(1)	(2)	(3)	(4)	(5)	(6)
	The EW portfolios sorted on Active Share					
	Low	2	3	4	High	H-L
AIV	0.41	0.94	1.39	1.67	3.74	3.33
	[1.14]	[1.97]	[2.63]	[2.50]	[4.18]	[3.92]
Recessions	0.39	0.13	0.14	-0.29	0.04	-0.35
	[1.37]	[0.40]	[0.37]	[-0.55]	[0.05]	[-0.49]
VIX	-1.00	-1.24	-1.51	-1.70	-3.15	-2.15
	[-2.26]	[-2.70]	[-2.91]	[-2.74]	[-3.78]	[-3.54]
Sentiment	0.71	0.58	0.67	0.41	1.51	0.80
	[1.78]	[1.26]	[1.37]	[0.80]	[2.27]	[1.37]
Disagreement	0.81	0.87	1.10	1.01	2.31	1.50
	[2.34]	[2.13]	[2.44]	[2.17]	[3.20]	[2.42]
Liquidity	-0.56	-0.33	-0.27	-0.19	-0.84	-0.29
	[-1.00]	[-0.59]	[-0.48]	[-0.29]	[-1.14]	[-0.59]
Adjusted-R^2(%)	3.00	3.64	4.32	4.42	13.52	9.60
	The VW portfolios sorted on Active Share					
	Low	2	3	4	High	H-L
AIV	0.50	1.34	1.96	2.34	3.39	2.89
	[0.90]	[1.49]	[1.90]	[2.07]	[2.95]	[3.01]
Recessions	0.53	-0.03	0.27	0.49	0.27	-0.26
	[1.26]	[-0.04]	[0.53]	[0.62]	[0.25]	[-0.32]
VIX	-1.58	-2.53	-1.97	-2.06	-3.37	-1.79
	[-2.50]	[-2.75]	[-2.48]	[-2.44]	[-3.10]	[-2.40]
Sentiment	1.23	0.62	-0.06	0.49	2.19	0.96
	[2.07]	[0.73]	[-0.09]	[0.68]	[2.44]	[1.60]
Disagreement	1.15	1.59	1.38	0.74	2.62	1.47
	[2.24]	[1.43]	[1.95]	[1.25]	[2.79]	[2.15]
Liquidity	-0.94	-1.11	-0.41	-0.38	-1.33	-0.40
	[-1.22]	[-1.14]	[-0.73]	[-0.55]	[-1.36]	[-0.72]
Adjusted-R^2(%)	1.97	2.11	4.33	5.17	12.13	6.91

Table 3: AIV **and the information ratios of active mutual funds**

This table shows that Aggregate Idiosyncratic Volatility (AIV) is positively associated with funds' information ratios and this relationship is stronger for high Active Share funds. Information ratio is benchmark-adjusted return standardized by tracking error, which effectively measures abnormal return per unit of idiosyncratic risk. 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 average conditional information ratios on the Active Share quintile portfolios. A fund's conditional information ratio is computed as its benchmark-adjusted return standardized by the 12-month rolling standard deviation of benchmark-adjusted returns. Panel A (B) presents the results from regression specifications without (with) control variables X. See the captions in Table 1 and Table 2 for the definitions of AIV, and Active Share, control variables. Newey and West (1987) heteroskedasticity-and-autocorrelation-robust t-statistics with three lags are reported in the bracket. The sample consists of actively managed U.S. equity mutual funds from 1984 to 2019. The information ratio is annualized. AIV is standardized to have zero mean and unit standard deviation to interpret the economic magnitude of its predictive ability on conditional information ratios.

Panel A. Slope coefficients and [t-statistics] for each Active Share quintile portfolio from the time-series predictive regressions $IR_t = a + bAIV_{t-1} + \epsilon_t$

	The portfolios sorted on Active Share					
	Low	2	3	4	High	H-L
AIV	0.03	0.02	0.07	0.05	0.15	0.12
	[0.47]	[0.41]	[1.14]	[0.77]	[2.42]	[2.20]
Adjusted-R^2(%)	0.18	0.24	0.24	0.26	1.33	0.41

Panel B. Slope coefficients and [t-statistics] for each Active Share quintile portfolio from the time-series predictive regressions $IR_t = a + bAIV_{t-1} + \gamma X_{t-1} + \epsilon_t$

	The portfolios sorted on Active Share					
	Low	2	3	4	High	H-L
AIV	0.01	0.10	0.13	0.12	0.25	0.24
	[0.16]	[1.16]	[1.56]	[1.41]	[2.92]	[2.55]
Recessions	0.13	0.06	0.08	0.01	0.04	-0.09
	[1.78]	[1.03]	[1.43]	[0.17]	[0.46]	[-1.08]
VIX	-0.15	-0.19	-0.21	-0.22	-0.29	-0.14
	[-1.58]	[-2.14]	[-2.61]	[-2.69]	[-3.46]	[-1.74]
Sentiment	0.13	0.09	0.09	0.07	0.08	-0.06
	[1.85]	[1.41]	[1.45]	[1.33]	[1.46]	[-0.73]
Disagreement	0.09	0.08	0.10	0.07	0.10	0.01
	[1.23]	[1.22]	[1.51]	[1.31]	[1.63]	[0.20]
Liquidity	0.02	0.01	-0.00	-0.00	-0.01	-0.03
	[0.18]	[0.09]	[-0.03]	[-0.07]	[-0.25]	[-0.37]
Adjusted-R^2(%)	0.47	0.80	1.78	2.35	3.89	0.30

Table 4: **Effect of *AIV* on fund-level portfolio allocation**

This table shows that active mutual funds scale back their active positions to track passive benchmarks more closely when *AIV* rises. The table reports the results from the fund-quarter level panel regressions,

$$Y_{j,t} = a_1 AIV_t + a_2 VIX_t + a_3 AggFlow_t + \gamma \mathbf{X}_{\mathbf{j,t-1}} + \delta_j + \theta_t + \varepsilon_{j,t},$$

where dependent variable is Active Share or Directional Turnover, both of which are lower if funds reduce their active positions. Fund j's Active Share in quarter t is computed as $\frac{1}{2}\sum_{i=1}^{N}\left|w_{i,t}^{j} - w_{i,t}^{benchmark}\right|$, where $w_{i,t}^{j}$ denotes the fund's weight on stock i and $w_{i,t}^{benchmark}$ denotes the stock's weight in the Morningstar Category Benchmark. Directional Turnover in quarter t is computed as $\sum_{i=1}^{N} sign\left(w_{i,t-1}^{j} - w_{i,t-1}^{benchmark}\right) \times \frac{Trade_{i,t}^{j} \times Price_{i,t-1}}{TNA_{t-1}^{j}}$, where $Trade_{i,t}^{j}$ is shares traded by fund j in quarter t, $Price_{i,t-1}$ is stock i's share price, $MTNA_{j,t-1}$ is the fund's total net assets, and $sign(x)$ is a function returning $1(-1)$ if x is positive (negative). *AggFlow* denotes the aggregate fund flow. $\mathbf{X}_{\mathbf{j,t-1}}$ represents the fund-level control variables including log(total net assets), number of holdings, turnover ratio, tracking error, and quarterly fund flow. The panel regressions include both fund and 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. The sample consists of active U.S. equity mutual funds from 1990 to 2019. Active Share and Directional Turnover 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)	(5)	(6)	(7)	(8)
	Dependent variable: Active Share				Dependent variable: Directional Turnover			
AIV	-0.634***			-0.747***	-0.588***			-0.706**
	(-8.10)			(-6.06)	(-4.73)			(-2.56)
VIX		-0.283***		0.143		-0.272***		0.296
		(-3.24)		(1.56)		(-2.98)		(1.47)
Aggregate fund flow			0.283**	0.119			0.611***	0.567***
			(2.09)	(1.17)			(4.96)	(3.57)
Fund-level control	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N (fund-quarter)	95,269	95,269	95,269	95,269	85,993	85,993	85,993	85,993

Table 5: **Effect of AIV on aggregate fund 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,

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

where directional trades is defined as

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

$w_{i,t-1}^{j} - w_{i,t-1}^{benchmark}$ 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). 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. $\mathbf{X_{i,t-1}}$ 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 2019. 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 6: **Double sorts on Active Share and the sensitivity of Active Share to** *AIV*

This table shows that the positive relation between *AIV* and subsequent benchmark-adjusted return is most pronounced among funds that do not scale back their active positions when *AIV* rises. The table reports the coefficient estimates b and t-statistics from the predictive regressions

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

where $R_t^{benchmark-adjusted}$ is the equal-weighted average benchmark-adjusted returns on the portfolios from an independent sort on Active Share and the sensitivity of Active Share to *AIV*. I estimate the sensitivity of Active Share to *AIV* from time-series regressions of Active Share on *AIV* using a three-year rolling window. High (low) sensitivity means that active funds expand (reduce) their active positions to move toward (away from) their benchmarks. The Newey and West (1987) heteroskedasticity-and-autocorrelation-robust t-statistics with three lags are reported in the bracket. Bold numbers indicate the t-statistics with an absolute value greater than 2. The sample consists of active U.S. equity mutual funds from 1984 to 2019. The return is annualized and in percentages. *AIV* is standardized to have zero mean and unit standard deviation to interpret the economic magnitude of the coefficient estimates.

Slope coefficient b and [t-statistics] from predictive regressions
$R_t^{benchmark-adjusted} = a + bAIV_{t-1} + \epsilon_t$

	Active Share					
Sensitivity of Active Share to *AIV*	Low	2	3	4	High	H-L
Low	-0.28	-0.07	-0.14	0.56	-0.72	-0.43
	[-0.69]	[-0.16]	[-0.17]	[0.71]	[-0.46]	[-0.28]
2	-0.24	0.00	-0.53	0.58	1.58	1.82
	[-0.84]	[0.00]	[-0.80]	[1.03]	[0.61]	[0.73]
3	-0.68	0.19	0.77	0.01	0.13	0.81
	[-1.68]	[0.56]	[1.44]	[0.02]	[0.18]	[1.18]
4	-0.44	0.79	0.54	0.42	**1.71**	**2.14**
	[-0.79]	[1.67]	[1.54]	[0.76]	[2.58]	[2.61]
High	0.45	0.20	0.68	1.87	**2.62**	**2.17**
	[1.39]	[0.48]	[1.59]	[1.06]	[3.08]	[2.80]
H-L	0.74	0.27	0.82	1.31	**3.34**	
	[1.55]	[0.45]	[1.02]	[0.56]	[2.20]	

Table 7: **Stock price reactions in response to positive *AIV* shocks**

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 2019.

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]

Table 8: **Fund return decomposition: the holdings return and the return gap**

This table shows the relations between Aggregate Idiosyncratic Volatility (*AIV*) and the fund return components: the holdings return and the return gap. A fund's holdings return is the return to the portfolio that invests in the previously disclosed fund holdings. The return gap is the difference between the gross return (the reported net return plus expense ratio), and the holdings return (Kacperczyk et al., 2008). Panel A reports the slope coefficient estimates, t-statistics, 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 average benchmark-adjusted holdings returns on the Active Share quintile portfolios. Panel B reports the results from the predictive regressions,

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

where RG_t represents the equal-weighted average return gap on the Active Share quintile portfolios. To compute a fund's holdings return, I form the hypothetical portfolio of holdings two months after the fund's disclosure because mutual funds are required to file quarterly holdings to SEC no later than 60 days. See the captions in Table 1 and Table 2 for the definitions of *AIV*, Active Share, and control variables. Newey and West (1987) heteroskedasticity-and-autocorrelation-robust t-statistics with three lags are reported in the bracket. The sample consists of active U.S. equity mutual funds from 1990 to 2019. 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 predictive ability on the fund return components.

Panel A. Slope coefficients and [t-statistics] for each Active Share quintile portfolio from the time-series predictive regressions $HR_t = a + bAIV_{t-1} + \gamma X_{t-1} + \epsilon_t$

	(1)	(2)	(3)	(4)	(5)	(6)
	The portfolios sorted on Active Share					
	Low	2	3	4	High	H-L
AIV	0.39	0.62	0.80	0.97	2.80	2.41
	[1.12]	[1.75]	[1.55]	[1.99]	[3.22]	[2.89]
Recessions	0.69	0.52	0.67	0.39	0.73	0.04
	[1.89]	[1.38]	[1.18]	[0.67]	[0.80]	[0.04]
VIX	-0.86	-0.87	-1.11	-1.17	-1.83	-0.97
	[-1.90]	[-2.15]	[-2.25]	[-2.07]	[-2.39]	[-1.55]
Sentiment	0.85	0.55	0.62	0.42	1.33	0.47
	[1.64]	[1.06]	[1.00]	[0.74]	[1.89]	[0.77]
Disagreement	0.79	0.74	0.96	0.67	1.60	0.81
	[1.96]	[1.77]	[1.78]	[1.27]	[2.17]	[1.47]
Liquidity	-0.85	-0.11	0.10	0.39	-0.15	0.70
	[-1.43]	[-0.24]	[0.19]	[0.80]	[-0.22]	[1.78]
Adjusted-R^2(%)	1.61	1.96	1.90	2.30	6.99	4.01

Panel B. Slope coefficients and [t-statistics] for each Active Share quintile portfolio from the time-series predictive regressions $RG_t = a + bAIV_{t-1} + \gamma X_{t-1} + \epsilon_t$

	(1)	(2)	(3)	(4)	(5)	(6)
	The portfolios sorted on Active Share					
	Low	2	3	4	High	H-L
AIV	-0.03	-0.05	0.27	0.69	0.81	0.84
	[-0.13]	[-0.18]	[1.00]	[1.90]	[2.34]	[2.08]
Recessions	-0.31	-0.35	-0.53	-0.67	-0.64	-0.32
	[-0.92]	[-0.97]	[-1.27]	[-1.19]	[-1.00]	[-0.56]
VIX	-0.10	-0.14	-0.12	-0.30	-0.74	-0.65
	[-0.34]	[-0.39]	[-0.35]	[-0.63]	[-1.61]	[-1.57]
Sentiment	-0.13	0.15	0.16	0.04	0.32	0.44
	[-0.51]	[0.62]	[0.57]	[0.11]	[0.96]	[1.46]
Disagreement	-0.03	-0.04	-0.01	0.21	0.34	0.37
	[-0.09]	[-0.12]	[-0.04]	[0.55]	[0.92]	[1.11]
Liquidity	0.28	-0.25	-0.38	-0.51	-0.73	-1.01
	[1.00]	[-0.88]	[-1.41]	[-1.53]	[-2.25]	[-2.81]
Adjusted-R^2(%)	0.02	0.30	0.81	1.33	2.96	3.96

Table 9: **Fund flows and fee revenues**

This table shows the relations between Aggregate Idiosyncratic Volatility (*AIV*) and mutual fund flows and fee revenues, respectively. The fund flow is defined as $Flow = \frac{TNA_t - TNA_{t-1} \times (1+NetReturn_t)}{TNA_{t-1}}$, and the fee revenue is defined as $Revenue = TNA_t \times ExpenseRatio$, where TNA denotes total net assets. The flows and fee revenues are subtracted by their aggregate levels to remove the potential time trends in these variables. The Panel A reports the results from the monthly time-series regressions, $Flow_t = a + bAIV_{t-1} + \epsilon_t$, where $Flow_t$ represents the flows of the Active Share quintile portfolios. Panel B reports the results from the monthly time-series regressions, $Revenue_t = a + bAIV_{t-1} + \epsilon_t$, where $Revenue_t$ represents the fee revenues of the Active Share quintile portfolios. See the captions in Table 1 and Table 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 monthly total net assets are available in CRSP after 1990 so the sample period is from 1990 to 2019. The flows and fee revenues are annualized. The flow is in percentages and the fee revenue is in a million. *AIV* is standardized to have zero mean and unit standard deviation to interpret the economic magnitude of its effect on fund flow and fee revenue.

Panel A. Slope coefficients and [t-statistics] for each Active Share quintile portfolio from the time-series regressions $Flow_t = a + bAIV_{t-1} + \epsilon_t$

	(1)	(2)	(3)	(4)	(5)	(6)
	The portfolios sorted on Active Share					
	Low	2	3	4	High	H-L
AIV	-1.11	0.53	1.01	0.62	3.89	4.99
	[-3.31]	[1.47]	[1.77]	[0.76]	[2.84]	[3.28]
Adjusted-R^2(%)	5.21	1.88	3.37	1.36	8.03	9.91

Panel B. Slope coefficients and [t-statistics] for each Active Share quintile portfolio from the time-series regressions $Revenue_t = a + bAIV_{t-1} + \epsilon_t$

	(1)	(2)	(3)	(4)	(5)	(6)
	The portfolios sorted on Active Share					
	Low	2	3	4	High	H-L
AIV	-1.26	0.42	0.07	0.30	1.22	2.48
	[-2.44]	[1.25]	[0.85]	[1.43]	[3.74]	[3.05]
Adjusted-R^2(%)	4.28	8.31	3.57	7.06	16.52	8.05

Table 10: **Robustness: out-of-sample tests**

This table shows that the in-sample predictability of *AIV* 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 $CW-$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 fund returns are not predictable. The R^2_{OOS} is computed as

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

The $CW-$statistics are used to test the null hypothesis $H_0 : R^2_{OOS} \leq 0$ against the alternative hypothesis $H_A : R^2_{OOS} > 0$. Bold numbers indicate that the null hypothesis is rejected at a one-sided 5% test. The sample consists of active U.S. equity mutual funds from 1984 to 2019. The forecast evaluation period starts from 1994 so that there are at least 10-year data to estimate both forecasts.

The Campbell and Thompson (2008) R^2_{OOS} and the Clark and West (2007) statistics						
	(1)	(2)	(3)	(4)	(5)	(6)
	The portfolios sorted on Active Share					
	Low	2	3	4	High	H-L
R^2_{OOS}	0.92	0.34	0.75	**3.16**	**6.54**	**5.11**
CW-statistics	[1.17]	[0.96]	[1.52]	[2.24]	[3.57]	[3.75]

Table 11: **Robustness: *AIV* and the aggregate portfolio, controlling for priced factors**

This table shows that Aggregate Idiosyncratic Volatility (*AIV*) positively predicts factor-adjusted returns on the aggregate portfolio of active equity mutual funds. The table reports the coefficient estimates, t-statistics, and adjusted-R^2 from the following monthly time-series predictive regressions,

$$R_t^{excess} = a + bAIV_{t-1} + \gamma X_{t-1} + \eta F_t + \epsilon_t,$$

where R_t^{excess} represents the equal-weighted or value-weighted average of excess returns. A fund's excess return is the fund's gross return minus the one-month Treasury bill rate. *AIV* is computed as the equal-weighted average of idiosyncratic volatilities, which are estimated from time-series regressions of daily stock returns on the Fama-French three factors within each month. F_t represents the Carhart four factors (Carhart, 1997). Newey and West (1987) heteroskedasticity-and-autocorrelation-robust t-statistics with three lags are reported in the bracket. Bold numbers indicate the t-statistics with an absolute value greater than 2. The sample consists of actively managed U.S. equity mutual funds from 1984 to 2019. The *VIX* index is available from CBOE after 1990. The return is annualized and in percentages. *AIV* and *VIX* are standardized to have zero mean and unit standard deviation to interpret the economic magnitude of the coefficient estimates.

Slope coefficients and [t-statistics] for the aggregate portfolio of active mutual funds from the time-series predictive regressions $R_t^{excess} = a + bAIV_{t-1} + \gamma X_{t-1} + \eta F_t + \epsilon_t$				
	(1)	(2)	(3)	(4)
	The EW aggregate portfolio		The VW aggregate portfolio	
AIV	1.92	2.62	1.36	1.95
	[3.26]	[2.66]	[3.10]	[2.82]
Recessions		-0.64		-0.59
		[-0.85]		[-0.75]
VIX		-1.26		-1.08
		[-2.19]		[-2.36]
Sentiment		0.76		0.28
		[1.48]		[0.69]
Disagreement		0.56		-0.07
		[0.78]		[-0.13]
Liquidity		-0.33		-0.24
		[-0.56]		[-0.53]
MKT	1.00	1.00	1.00	1.00
	[87.36]	[98.07]	[96.72]	[123.21]
SMB	0.19	0.20	0.07	0.07
	[9.10]	[9.30]	[6.16]	[6.76]
HML	0.04	0.03	-0.01	-0.01
	[2.01]	[1.42]	[-0.43]	[-0.86]
UMD	0.02	0.01	0.02	0.01
	[1.27]	[0.61]	[2.11]	[1.22]
Adjusted-R^2(%)	98.22	98.23	98.64	98.66

Table 12: **Robustness: *AIV* and the Active Share sorted portfolios, controlling for priced factors**

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

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

where R_t^{excess} represents the average excess returns on the Active Share quintile portfolios. See the caption in Table 1 for the definitions of *AIV* and control variables, and the caption in Table 2 for the construction of Active Share. 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) four factors; (2) the Carhart (1997) model augmented with liquidity factor (Pastor and Stambaugh, 2003) and betting-against-beta factor (Frazzini and Pedersen, 2014); (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. Newey and West (1987) heteroskedasticity-and-autocorrelation-robust t-statistics with six lags are reported in the bracket. The sample consists of actively managed U.S. equity mutual funds from 1990 to 2019. 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 predictive ability on factor-adjusted fund return.

Slope coefficients b, [t-statistics], and adjusted R^2 from time-series regressions
$R_t^{excess} = a + bAIV_{t-1} + \gamma X_{t-1} + \beta \mathbf{F_t} + \epsilon_t$

	The EW portfolios sorted on Active Share					
	Low	2	3	4	High	H-L
Carhart (1997)	0.64	0.86	1.40	1.65	2.73	2.09
	[1.28]	[1.39]	[1.49]	[1.43]	[2.24]	[2.09]
Carhart+Liquidity+BAB	0.65	0.88	1.44	1.69	2.79	2.14
	[1.29]	[1.41]	[1.52]	[1.45]	[2.29]	[2.26]
Fama-French (2015)	0.60	0.83	1.34	1.54	2.91	2.31
	[1.16]	[1.32]	[1.38]	[1.26]	[2.48]	[2.48]
Stambaugh and Yu (2017)	0.74	1.05	1.80	2.21	3.72	2.98
	[1.30]	[1.63]	[2.10]	[2.38]	[3.31]	[2.92]
Daniel-Hirshleifer-Sun (2020)	0.53	0.87	1.48	1.68	3.49	2.96
	[1.01]	[1.32]	[1.44]	[1.36]	[2.34]	[2.39]
Hou-Mo-Xue-Zhang (2020)	0.62	0.93	1.53	1.78	3.25	2.63
	[1.15]	[1.47]	[1.62]	[1.61]	[2.47]	[2.37]

Table 13: *AIV* **and the performance of active international equity mutual funds**

This table presents international evidence on the positive relation between *AIV* and subsequent abnormal return of active equity mutual funds. The table reports the coefficient estimates b and t-statistics from the following quarter-fund-market level panel predictive regressions,

$$R_{i,j,t}^{characteristic-adjusted} = bAIV_{j,t-1} + \gamma \mathbf{X}_{\mathbf{i,t-1}} + \phi \mathbf{Y}_{\mathbf{j,t-1}} + \delta_{\mathrm{j}} + \delta_{\mathrm{i}} + \theta_{\mathrm{t}} + \varepsilon_{\mathrm{i,j,t}}$$

where $R_{i,j,t}^{characteristic-adjusted}$ is the weighted-average characteristic-adjusted stock return earned by fund i from market j based on quarterly stock holdings. The characteristic-adjusted stock return is computed following Daniel et al. (1997). $AIV_{j,t}$ is the equal-weighted average of standard deviation of daily residual returns, which are estimated from the Fama-French international 3-factor model within each quarter. $\mathbf{X}_{\mathbf{i,t-1}}$ represents the fund-level controls including log(total net assets), turnover ratio, return volatility, and number of equity holdings. $\mathbf{Y}_{\mathbf{j,t-1}}$ represents the market-level controls including market volatility and the value-weighted averages of book-to-market, asset growth, and institutional ownership. The t-statistics are computed based on the standard errors clustered by market and quarter. Bold numbers indicate the t-statistics with an absolute value greater than 2. The sample consists of actively managed international equity mutual funds from 2001 through 2017. I focus on 47 worldwide equity markets (excluding US). The return is annualized and in percentages. *AIV* is standardized to have zero mean and unit standard deviation to interpret the economic magnitude of the coefficient estimates.

	Slope coefficients b and (t-statistics) from panel predictive regressions $R_{i,j,t}^{characteristic-adjusted} = bAIV_{j,t-1} + \gamma \mathrm{X}_{\mathrm{i,t-1}} + \phi \mathrm{Y}_{\mathrm{j,t-1}} + \delta_{\mathrm{j}} + \delta_{\mathrm{i}} + \theta_{\mathrm{t}} + \varepsilon_{\mathrm{i,j,t}}$				
	(1)	(2)	(3)	(4)	(5)
AIV	2.797***	3.081***	3.270***	3.260***	4.113**
	(3.54)	(4.14)	(2.91)	(2.84)	(2.43)
Market control	No	No	No	No	Yes
Fund control	No	No	No	Yes	Yes
Quarter FE	No	No	Yes	Yes	Yes
Fund FE	No	Yes	Yes	Yes	Yes
Market FE	Yes	No	Yes	Yes	Yes
N (quarter-fund-market)	1,801,028	1,801,028	1,801,028	1,801,028	1,801,028

Table 14: *AIV* **and the performance of US equity hedge funds**

This table shows that Aggregate Idiosyncratic Volatility (*AIV*) positively predicts factor-adjusted returns on the aggregate portfolio of equity hedge funds. The table reports the coefficient estimates, t-statistics, and adjusted-R^2 from the following monthly time-series predictive regressions,

$$R_t^{excess} = a + bAIV_{t-1} + \gamma X_{t-1} + \eta F_t + \epsilon_t,$$

where R_t^{excess} represents the equal-weighted or value-weighted average of excess returns. A fund's excess return is the fund's gross return minus the one-month Treasury bill rate. *AIV* is computed as the equal-weighted average of idiosyncratic volatilities, which are estimated from time-series regressions of daily stock returns on the Fama-French three factors within each month. F_t represents the Carhart four-factor model (Carhart, 1997). The Newey and West (1987) heteroskedasticity-and-autocorrelation-robust t-statistics with three lags are reported in the bracket. The sample consists of U.S. equity hedge funds from 1995 to 2019. The return is annualized and in percentages. *AIV* is standardized to have zero mean and unit standard deviation to interpret the economic magnitude of the coefficient estimates.

Slope coefficients, [t-statistics], and adjusted-R^2 from time-series regressions $R_t^{excess} = a + bAIV_{t-1} + \gamma X_{t-1} + \eta F_t + \epsilon_t$				
	The equal-weight portfolio		The value-weight portfolio	
AIV	2.71	4.63	1.96	4.32
	[3.14]	[3.72]	[2.20]	[3.27]
Recessions		-1.47		-0.73
		[-0.77]		[-0.33]
VIX		-1.93		-4.00
		[-1.31]		[-2.07]
Sentiment		-1.55		-1.50
		[-1.80]		[-1.68]
Disagreement		-0.69		-0.43
		[-0.78]		[-0.49]
Liquidity		-0.31		-0.33
		[-0.35]		[-0.33]
Adjusted-R^2(%)	67.13	67.83	53.42	55.18

Appendix A. Additional Figures and Tables

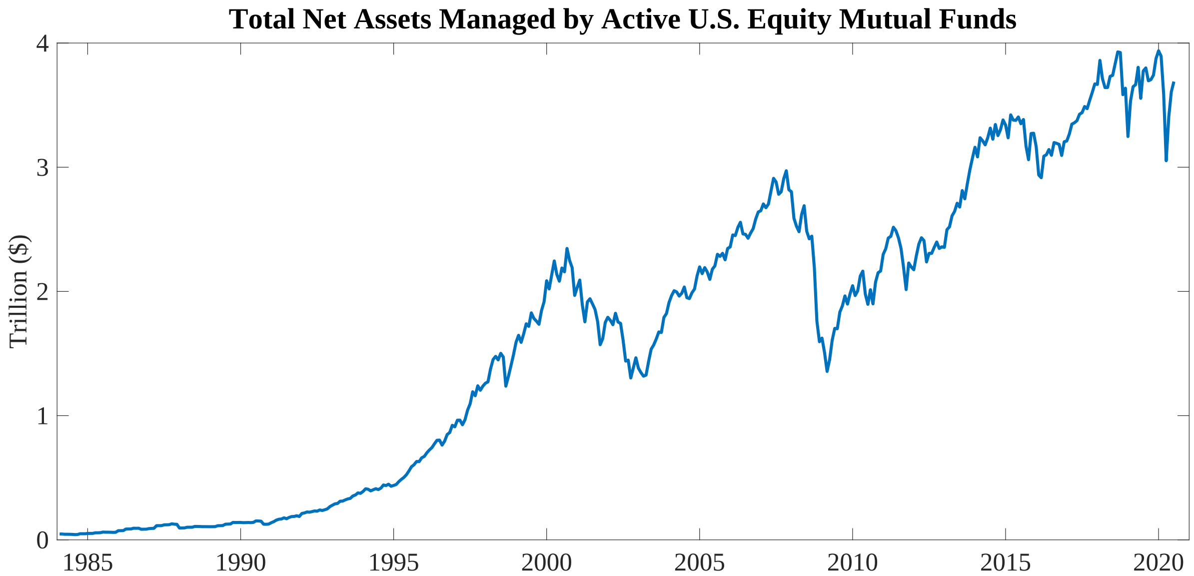

Fig. A1. This figure plots the total net assets managed by actively managed U.S. equity mutual funds from January 1984 through June 2020.

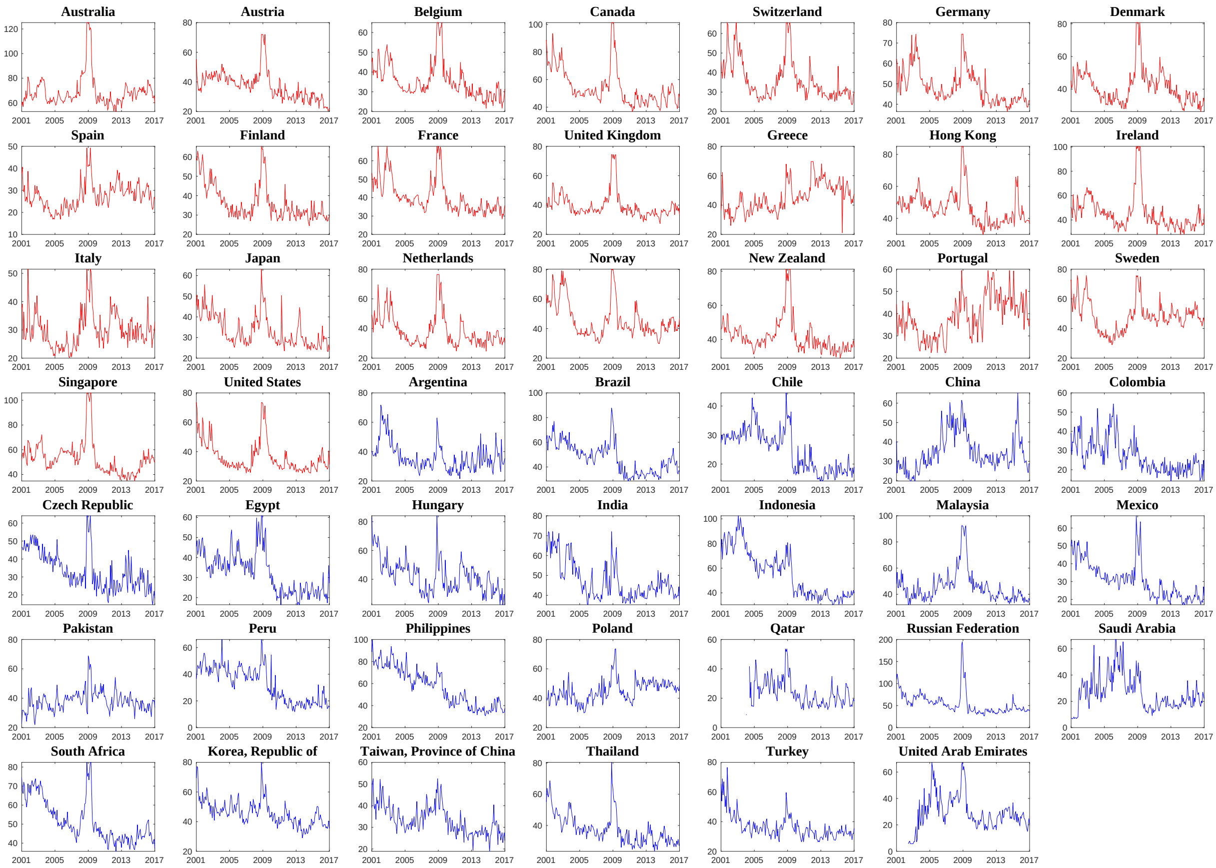

Fig. A2. This figure plots *AIV* in 48 equity markets from January 2001 through December 2017. The red (blue) lines represent developed (emerging) markets based on the classifications from the Kenneth French's website. *AIV* is the equal-weighted average of standard deviation of daily residual returns, estimated from time-series regression of daily stock returns on the market excess returns and the Fama-French international size and value factors within each calendar month. *AIV* is annualized and in percentages.

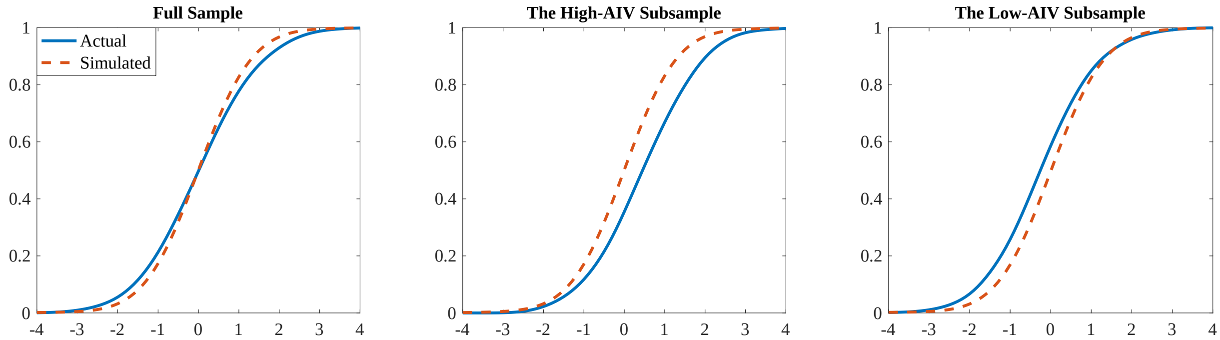

Fig. A3. This figure plots the actual and simulated cumulative density functions of t-statistics of the Fama-French-Carhart gross α based on the Fama and French (2010) bootstrap simulations. I run 10,000 bootstrap simulations for the full sample (432 months), the low-*AIV* sub-sample (216 months), and the high-*AIV* sub-sample (216 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 actively managed U.S. equity mutual funds from January 1984 to December 2019.

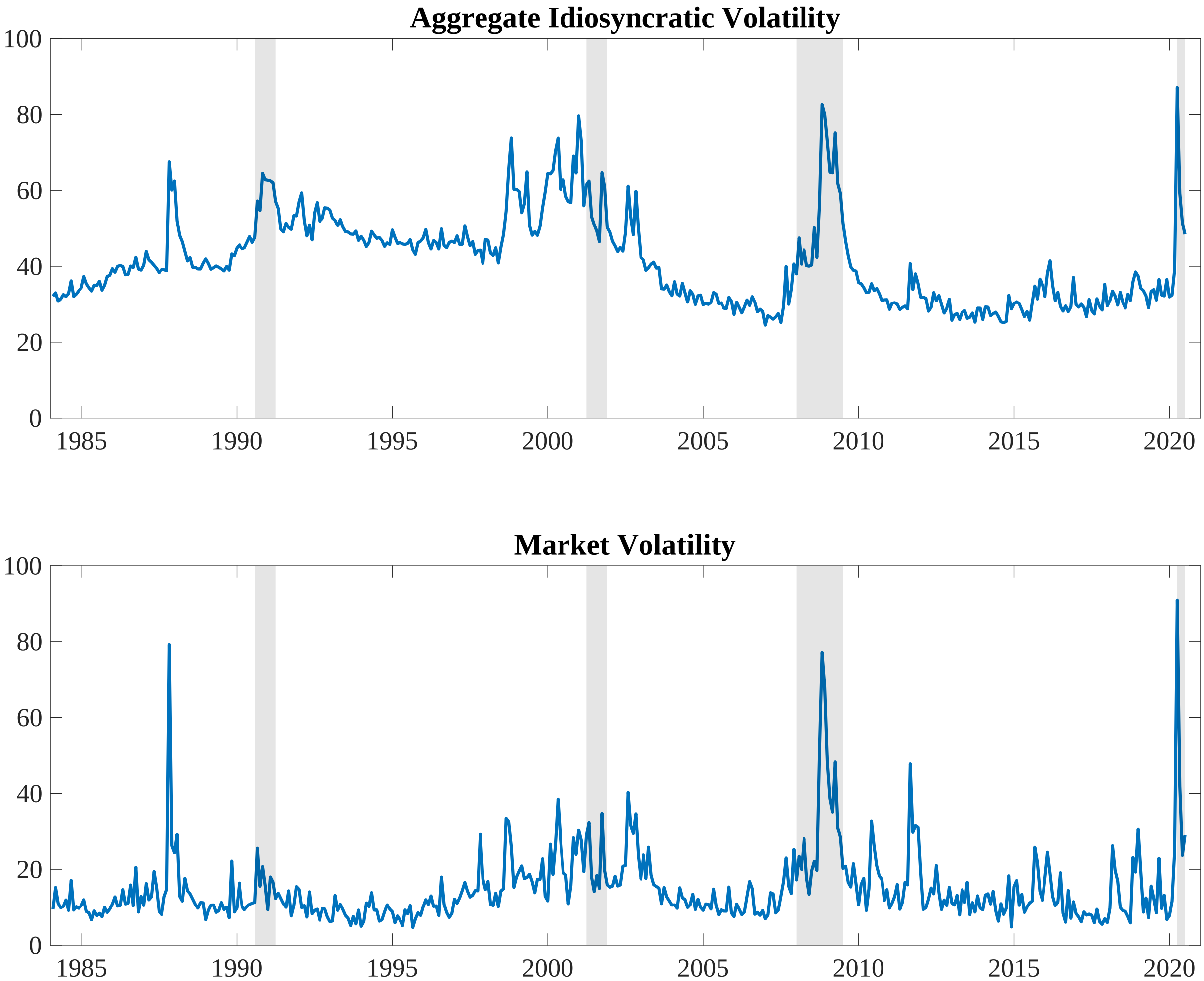

Fig. A4. This figure plots aggregate idiosyncratic volatility (*AIV*) and market volatility (*MV*) from January 1984 through June 2020. *AIV* is estimated as the equal-weighted average of stock idiosyncratic volatilities. Idiosyncratic volatility is estimated from time-series regressions of daily stock returns on the Fama-French three factors within each calendar month. *MV* is estimated as the standard deviation of daily market returns within each calendar month. Both *AIV* and *MV* are annualized 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 2019.

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: **Portfolios sorted on portfolio concentration**

This table shows that *AIV* positively predicts benchmark-adjusted fund performance of portfolios formed on portfolio concentration (HHI) at the previous-quarter end. I also construct the high-minus-low HHI portfolio and the aggregate portfolio of active mutual funds. Panel A reports the coefficient estimates b and c, t-statistics, and adjusted-R^2 from the predictive regressions,

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

where the left-hand side variable is the equal-weighted average of the benchmark-adjusted returns of HHI sorted portfolios. Panel B reports the estimates from the predictive regressions

$$\frac{R_t^{benchmark-adjusted}}{\sigma_{t-1}\left(R_t^{benchmark-adjusted}\right)} = a + bAIV_{t-1} + \epsilon_t,$$

where the left-hand side variable is the equal-weighted average of the conditional information ratios of ICI sorted portfolios. The Newey and West (1987) heteroskedasticity-and-autocorrelation-robust t-statistics with six lags are reported in the bracket. Bold numbers indicate the t-statistics with an absolute value greater than 2. The sample consists of active U.S. equity mutual funds from 1984 to 2019. The return and information ratio are annualized and in percentages. *AIV* is standardized to have zero mean and unit standard deviation to interpret the economic magnitude of the coefficient estimates.

Panel A. Slope coefficients b, [t-statistics], and adjusted-R^2 from predictive regressions
$R_t^{benchmark-adjusted} = a + bAIV_{t-1} + \epsilon_t$

		Equal-weighted portfolios sorted on portfolio concentration					
	Aggregate	Low	2	3	4	High	H-L
b	**1.01**	0.58	0.66	0.77	0.96	**2.09**	**1.50**
	[2.63]	[1.81]	[1.75]	[1.80]	[1.94]	[4.00]	[4.37]
adjusted-R^2(%)	2.67	0.85	0.63	1.30	1.37	5.78	4.29

Panel B. Slope coefficients b, [t-statistics], and adjusted-R^2 from predictive regressions
$\frac{R_t^{benchmark-adjusted}}{\sigma_{t-1}\left(R_t^{benchmark-adjusted}\right)} = a + bAIV_{t-1} + \epsilon_t$

		Equal-weighted portfolios sorted on portfolio concentration					
	Aggregate	Low	2	3	4	High	H-L
b	0.06	0.01	0.07	0.03	0.05	**0.18**	**0.17**
	[1.23]	[0.17]	[1.03]	[0.59]	[0.75]	[3.40]	[4.03]
adjusted-R^2(%)	0.19	-0.23	-0.02	-0.13	-0.07	2.55	2.30

Table A3: **Portfolios sorted on industry concentration index (Kacperczyk et al., 2005)**

This table shows that *AIV* positively predicts benchmark-adjusted fund performance of portfolios formed on industry concentration index (ICI) (Kacperczyk et al., 2005) at the previous-quarter end. I also construct the high-minus-low ICI portfolio and the aggregate portfolio of active mutual funds. Panel A reports the coefficient estimates b and c, t-statistics, and adjusted-R^2 from the predictive regressions,

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

where the left-hand side variable is the equal-weighted average of the benchmark-adjusted returns of ICI sorted portfolios. Panel B reports the estimates from the predictive regressions

$$\frac{R_t^{benchmark-adjusted}}{\sigma_{t-1}\left(R_t^{benchmark-adjusted}\right)} = a + bAIV_{t-1} + \epsilon_t,$$

where the left-hand side variable is the equal-weighted average of the conditional information ratios of ICI sorted portfolios. The Newey and West (1987) heteroskedasticity-and-autocorrelation-robust t-statistics with six lags are reported in the bracket. Bold numbers indicate the t-statistics with an absolute value greater than 2. The sample consists of active U.S. equity mutual funds from 1984 to 2019. The return and information ratio are annualized and in percentages. *AIV* is standardized to have zero mean and unit standard deviation to interpret the economic magnitude of the coefficient estimates.

Panel A. Slope coefficients b, [t-statistics], and adjusted-R^2 from predictive regressions $R_t^{benchmark-adjusted} = a + bAIV_{t-1} + \epsilon_t$

		Equal-weighted portfolios sorted on industry concentration index					
	Aggregate	Low	2	3	4	High	H-L
b	**1.01**	0.35	0.92	**1.11**	**1.13**	**1.71**	**1.36**
	[2.63]	[0.91]	[1.93]	[2.59]	[2.47]	[3.14]	[2.42]
adjusted-R^2(%)	2.67	0.18	1.47	2.62	2.14	2.96	1.70

Panel B. Slope coefficients b, [t-statistics], and adjusted-R^2 from predictive regressions $\frac{R_t^{benchmark-adjusted}}{\sigma_{t-1}\left(R_t^{benchmark-adjusted}\right)} = a + bAIV_{t-1} + \epsilon_t$

		Equal-weighted portfolios sorted on industry concentration index					
	Aggregate	Low	2	3	4	High	H-L
b	0.06	0.03	0.07	0.06	0.08	**0.11**	0.08
	[1.22]	[0.44]	[1.11]	[1.12]	[1.45]	[2.09]	[1.42]
adjusted-R^2(%)	0.20	-0.17	0.07	0.13	0.27	0.75	0.21

Table A4: **Portfolios sorted on activeness (Pástor et al., 2020)**

This table shows that *AIV* positively predicts benchmark-adjusted fund performance of portfolios formed on activeness (Pástor et al., 2020) at the previous-quarter end. I also construct the high-minus-low activeness portfolio and the aggregate portfolio of active mutual funds. Panel A reports the coefficient estimates b and c, t-statistics, and adjusted-R^2 from the predictive regressions,

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

where the left-hand side variable is the equal-weighted average of the benchmark-adjusted returns of activeness sorted portfolios. Panel B reports the estimates from the predictive regressions

$$\frac{R_t^{benchmark-adjusted}}{\sigma_{t-1}\left(R_t^{benchmark-adjusted}\right)} = a + bAIV_{t-1} + \epsilon_t,$$

where the left-hand side variable is the equal-weighted average of the conditional information ratios of activeness sorted portfolios. The Newey and West (1987) heteroskedasticity-and-autocorrelation-robust t-statistics with six lags are reported in the bracket. Bold numbers indicate the t-statistics with an absolute value greater than 2. The sample consists of active U.S. equity mutual funds from 1984 to 2019. The return and information ratio are annualized and in percentages. *AIV* is standardized to have zero mean and unit standard deviation to interpret the economic magnitude of the coefficient estimates.

Panel A. Slope coefficients b, [t-statistics], and adjusted-R^2 from predictive regressions $R_t^{benchmark-adjusted} = a + bAIV_{t-1} + \epsilon_t$

		Equal-weighted portfolios sorted on activeness					
	Aggregate	Low	2	3	4	High	H-L
b	**1.01**	0.37	0.54	**0.93**	**1.01**	**2.26**	**1.89**
	[2.63]	[1.08]	[1.38]	[2.02]	[2.42]	[4.20]	[3.96]
adjusted-R^2(%)	2.67	0.07	0.44	1.99	1.71	6.23	3.81

Panel B. Slope coefficients b, [t-statistics], and adjusted-R^2 from predictive regressions $\frac{R_t^{benchmark-adjusted}}{\sigma_{t-1}\left(R_t^{benchmark-adjusted}\right)} = a + bAIV_{t-1} + \epsilon_t$

		Equal-weighted portfolios sorted on activeness					
	Aggregate	Low	2	3	4	High	H-L
b	0.06	-0.04	0.02	0.06	0.09	**0.21**	**0.25**
	[1.23]	[-0.75]	[0.28]	[1.04]	[1.52]	[3.38]	[3.89]
adjusted-R^2(%)	0.19	-0.11	-0.22	0.11	0.35	2.58	2.83

Table A5: **Fama and French (2010) simulations from the low and high-*AIV* subsamples**

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 2019. I split the full sample period (432 months) into two partitions according to the previous-month *AIV* (216 months).

	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: **Evidence from the large developed markets**

The table provides international evidence from the sample of actively managed international equity funds whose investment area is one of the following six large developed markets: Canada, United Kingdom, France, Germany, Japan, and Hong Kong. The table reports the slope coefficients b_1 and b_2, the associated t-statistics, and the adjusted $R^2(\%)$ for each market from predictive regressions

$$R_t^{H-L} = b_0 + b_1 AIV_{t-1} + b_2 MV_{t-1} + \epsilon_t$$

where R_t^{H-L} is the high-low equal-weighted tercile portfolio formed on portfolio concentration PC, which is constructed as the Herfindahl-Hirschman Index of a mutual fund's active weights against the corresponding market index, $\sum_{i=1}^{N}\left(w_{i,t}^{active} - w_{i,t}^{Country}\right)^2$. AIV is measured as the equal-weighted average of standard deviation of daily stock residual returns, which are estimated from the time-series regressions of return on daily market excess return within each calendar month. To reduce the effect of abnormally high idiosyncratic volatilities, I exclude the stocks with the previous-month price below the 20%. MV is estimated as the standard deviation of daily market index returns within each calendar month. The Newey and West (1987) heteroskedasticity-and-autocorrelation-robust t-statistics with maximum 12 lags are reported in the bracket. Bold number means the t-statistic is greater than 1.96 in absolute value. The sample period is from January 2001 through December 2017.
Both the long-short return and volatility are annualized to have one percentage point for interpreting the economic magnitude. For example, for the high-low PC tercile portfolio in Canada, an increase of 10 percentage points in the annualized AIV is associated with an increase of 3.9 percentage points in the annualized benchmark-adjusted return.

Slope coefficients b_1 and b_2, [t-statistics], and the adjusted $R^2(\%)$ from predictive regressions $R_t^{H-L} = b_0 + b_1 AIV_{t-1} + b_2 MV_{t-1} + \epsilon_t$

Canada			Japan			Hong Kong		
AIV	MV	R^2	AIV	MV	R^2	AIV	MV	R^2
0.39	-0.26	7.97	0.16	-0.03	0.32	**0.70**	**-0.55**	5.09
[2.34]	[-1.52]		[0.76]	[-0.14]		[3.10]	[-2.74]	
United Kingdom			**France**			**Germany**		
AIV	MV	R^2	AIV	MV	R^2	AIV	MV	R^2
0.33	**-0.30**	3.09	**0.44**	-0.21	1.54	**0.86**	**-0.95**	9.38
[1.98]	[-2.10]		[2.13]	[-1.64]		[3.41]	[-4.74]	

Table A7: **Odds that *AIV* is a spurious predictor**

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 of benchmark-adjusted returns of portfolios sorted on active share. 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*					
Equal-weighted portfolios sorted on active share					
Low	2	3	4	High	H-L
4	6	17	10	258	1179

Table A8: **Predicting benchmark-adjusted return with the option-implied volatility**

This table reports the coefficient estimates b and c, t-statistics, and adjusted-R^2 from the following predictive regressions,

$$R_t^{benchmark-adjusted} = a + bIV_{t-1} + cVIX_{t-1} + \epsilon_t.$$

I form portfolios by sorting active funds into quintiles according to the previous-quarter-end active share. I also form the high-minus-low active share portfolio and the aggregate portfolio of active mutual funds. Panel A reports the estimates from the equal-weighted benchmark-adjusted returns of these portfolios. Panel B reports the estimates from the value-weighted benchmark-adjusted returns. IV is the equal-weighted average of option-implied volatility. The Newey and West (1987) heteroskedasticity-and-autocorrelation-robust t-statistics with six lags are reported in the bracket. Bold numbers indicate the t-statistics with an absolute value greater than 2. The sample consists of active U.S. equity mutual funds from 1984 to 2019. The return is annualized and in percentages.

Slope coefficients b and c, [t-statistics], and adjusted-R^2 from predictive regressions $R_t^{benchmark-adjusted} = a + bIV_{t-1} + cVIX_{t-1} + \epsilon_t$

		Panel A. Equal-weighted portfolios sorted on active share					
	Aggregate	Low	2	3	4	High	H-L
b	**2.28**	**1.42**	**1.75**	**2.08**	**2.36**	**4.14**	**2.73**
	[4.22]	[2.91]	[3.20]	[3.59]	[4.19]	[4.12]	[3.59]
c	**-1.41**	**-0.91**	**-1.30**	**-1.33**	**-1.71**	**-2.04**	-1.13
	[-2.63]	[-2.22]	[-2.67]	[-2.00]	[-2.91]	[-2.31]	[-1.64]
adjusted-R^2(%)	8.74	3.77	4.79	5.38	6.19	10.43	5.49

		Panel B. Value-weighted portfolios sorted on active share					
	Aggregate	Low	2	3	4	High	H-L
b	**2.28**	**1.84**	2.77	**2.07**	**1.77**	**3.72**	1.88
	[4.22]	[2.15]	[1.54]	[2.23]	[2.16]	[2.03]	[1.69]
c	**-1.41**	**-1.36**	-1.87	-1.22	-1.06	-1.53	-0.17
	[-2.63]	[-2.15]	[-1.79]	[-1.45]	[-1.24]	[-1.15]	[-0.21]
adjusted-R^2(%)	8.74	3.69	4.14	2.64	1.77	6.16	2.81

Table A9: **Double sorts on Active Share and quarterly net flows**

the time-series relation between *AIV* and performance is stronger among active funds that bet against media sentiment. I construct portfolios from dependent sorts on betting against media sentiment (*BAMS*) and active share. *BAMS* captures the extent to which an active fund overweights/underweights stocks with high media pessimism/optimism (Tetlock, 2007). Specifically, *BAMS* is defined as

$$BAMS_t^k = -\frac{1}{N}\sum_{i=1}^{N} sign\left(w_{i,t}^j - w_{i,t}^{benchmark}\right) \times sign(ESS - 50),$$

where $sign(x)$ is a function returning 1 (-1) if $x > 0 (< 0)$, and *ESS* is the RavenPack Event Sentiment Score which indicates media optimism (pessimism) if it is larger (smaller) than 50. The table reports the coefficient estimates b and t-statistics from the predictive regressions

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

where $R_t^{benchmark-adjusted}$ is the equal-weighted average of benchmark-adjusted return of the sorted portfolios. $\mathbf{Control_{t-1}}$ represents macro controls including VIX, aggregate fund flows, and the real-time recession probability (Chauvet and Piger, 2008). The Newey and West (1987) heteroskedasticity-and-autocorrelation-robust t-statistics with six lags are reported in the bracket. Bold numbers indicate the t-statistics with an absolute value greater than 2. The sample consists of active U.S. equity mutual funds from 2001 to 2019 when the RavenPack data is available. The return is annualized and in percentages. *AIV* is standardized to have zero mean and unit standard deviation to interpret the economic magnitude of the coefficient estimates.

Slope coefficient b and [t-statistics] from predictive regressions $R_t^{benchmark-adjusted} = a + bAIV_{t-1} + \epsilon_t$

	Active Share					
Net flows	Low	2	3	4	High	H-L
Low	0.25	0.25	0.34	0.41	1.75	1.50
	[0.78]	[0.74]	[0.68]	[0.65]	[1.79]	[1.66]
2	0.33	0.31	0.17	0.45	**2.41**	**2.08**
	[0.96]	[0.76]	[0.37]	[0.64]	[2.25]	[2.12]
3	0.25	0.73	0.68	0.45	**2.24**	**1.99**
	[0.72]	[1.42]	[1.41]	[0.82]	[2.87]	[2.76]
4	0.16	0.48	0.95	0.99	**2.85**	**2.69**
	[0.38]	[1.31]	[1.70]	[1.31]	[4.40]	[4.52]
High	-0.19	0.63	**1.82**	1.13	**3.22**	**3.41**
	[-0.49]	[1.06]	[2.97]	[1.92]	[4.16]	[4.64]
H-L	-0.44	0.37	1.48	0.72	1.48	
	[-1.16]	[0.60]	[1.98]	[0.84]	[1.34]	

Table A10: **Cross-sectional test: betting against flow-driven trading**

The table shows that the time-series relation between *AIV* and performance is stronger among active funds that take the other side of flow-driven trades. I construct portfolios from dependent sorts on betting against flow-driven trading (*BAFT*) and active share. *BAFT* captures the extent to which a fund buys (sells) stocks that are sold (purchased) by other mutual funds due to extreme fund flows. Specifically, *BAFT* is defined as

$$BAFT_t^j = -\sum_{i=1}^{N} Trade_{i,t}^j \times \left(InFlows_{i,t}^{-j} - OutFlows_{i,t}^{-j}\right),$$

where $Trade_{i,t}^j$ is fund j's trade on stock i in quarter t, and $InFlows_{i,t}^{-j}$ ($OutFlows_{i,t}^{-j}$) is the trade aggregated across funds (excluding fund j) that experience extreme inflows (outflows). Similar to the construction proposed by Edmans et al. (2012), $InFlows_{i,t}^{-j}$ is computed as

$$InFlows_{i,t}^{-j} = \frac{\sum_{k=1,k\neq j}^{M}\left(Shares_{i,t-1}^k \times Price_{i,t-1} \times NetFlows_t^k \middle| NetFlows_t^k > 5\%\right)}{DollarVolume_{i,t}},$$

and $OutFlows_{i,t}^{-j}$ is computed conditional on $NetFlows_t^k < -5\%$. $Shares_{i,t-1}^k$ denotes shares held by fund k at the end of quarter $t-1$. $NetFlows_t^k$ is fund k's net flows in quarter t. *Price* and *DollarVolume* are stock price and dollar trading volume.
The table reports the coefficient estimates b and t-statistics from the predictive regressions

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

where $R_t^{benchmark-adjusted}$ is the equal-weighted average of benchmark-adjusted return of the sorted portfolios. $\mathbf{Control_{t-1}}$ represents macro controls including *VIX*, aggregate fund flows, and the real-time recession probability (Chauvet and Piger, 2008). The Newey and West (1987) heteroskedasticity-and-autocorrelation-robust t-statistics with six lags are reported in the bracket. Bold numbers indicate the t-statistics with an absolute value greater than 2. The sample consists of active U.S. equity mutual funds from 1984 to 2019. The return is annualized and in percentages. *AIV* is standardized to have zero mean and unit standard deviation to interpret the economic magnitude of the coefficient estimates.

Slope coefficients b and [t-statistics] from predictive regressions
$R_t^{benchmark-adjusted} = a + bAIV_{t-1} + \gamma\mathbf{Control}_{t-1} + \epsilon_t$

	Active share					
Betting against flow-driven trading	Low	2	3	4	High	H-L
Low	0.13	0.84	1.11	0.94	1.36	1.23
	[0.27]	[1.27]	[1.56]	[1.66]	[1.49]	[1.80]
2	0.06	0.26	0.88	1.37	1.99	1.93
	[0.18]	[0.43]	[1.36]	[1.91]	[1.56]	[1.75]
3	0.09	0.22	0.64	1.14	1.95	1.86
	[0.34]	[0.49]	[1.23]	[1.91]	[1.79]	[1.88]
4	-0.18	-0.38	0.56	1.11	**3.14**	**3.32**
	[-0.30]	[-0.48]	[0.61]	[1.22]	[2.21]	[3.02]
High	-0.44	-0.73	0.24	1.27	**4.06**	**4.50**
	[-0.73]	[-0.94]	[0.38]	[1.92]	[3.65]	[3.86]

Table A11: **Cross-sectional test: betting against media sentiment**

the time-series relation between *AIV* and performance is stronger among active funds that bet against media sentiment. I construct portfolios from dependent sorts on betting against media sentiment (*BAMS*) and active share. *BAMS* captures the extent to which an active fund overweights/underweights stocks with high media pessimism/optimism (Tetlock, 2007). Specifically, *BAMS* is defined as

$$BAMS_t^k = -\frac{1}{N}\sum_{i=1}^{N} sign\left(w_{i,t}^j - w_{i,t}^{benchmark}\right) \times sign(ESS - 50),$$

where $sign(x)$ is a function returning 1 (-1) if $x > 0 (< 0)$, and *ESS* is the RavenPack Event Sentiment Score which indicates media optimism (pessimism) if it is larger (smaller) than 50. The table reports the coefficient estimates b and t-statistics from the predictive regressions

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

where $R_t^{benchmark-adjusted}$ is the equal-weighted average of benchmark-adjusted return of the sorted portfolios. $\mathbf{Control_{t-1}}$ represents macro controls including VIX, aggregate fund flows, and the real-time recession probability (Chauvet and Piger, 2008). The Newey and West (1987) heteroskedasticity-and-autocorrelation-robust t-statistics with six lags are reported in the bracket. Bold numbers indicate the t-statistics with an absolute value greater than 2. The sample consists of active U.S. equity mutual funds from 2001 to 2019 when the RavenPack data is available. The return is annualized and in percentages. *AIV* is standardized to have zero mean and unit standard deviation to interpret the economic magnitude of the coefficient estimates.

Slope coefficient b and [t-statistics] from predictive regressions
$R_t^{benchmark-adjusted} = a + bAIV_{t-1} + \gamma \mathbf{Control_{t-1}} + \epsilon_t$

	Active share					
Betting against media sentiment	Low	2	3	4	High	H-L
Low	0.18	0.70	0.97	0.72	3.62	3.44
	[0.34]	[0.45]	[0.73]	[0.82]	[1.42]	[1.47]
2	0.69	0.99	0.33	0.39	**3.51**	2.83
	[0.70]	[1.12]	[0.50]	[0.33]	[2.67]	[1.80]
3	1.78	1.01	0.09	2.15	**6.91**	**5.13**
	[1.47]	[1.12]	[0.06]	[1.11]	[8.71]	[3.91]
4	**1.59**	1.00	**3.95**	1.75	**6.85**	**5.26**
	[2.04]	[1.27]	[2.91]	[1.18]	[3.22]	[2.86]
High	2.77	**3.75**	**4.47**	**5.00**	**10.11**	**7.34**
	[1.83]	[2.25]	[2.82]	[5.36]	[5.63]	[5.56]

Table A12: **Predicting benchmark-adjusted fund returns, net of expense**

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

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

where $R_t^{benchmark-adjusted}$ represents the average benchmark-adjusted returns on the Active Share quintile portfolios using equal weights or value weights. Panel A (B) reports the results from the predictive regression with (without) the VIX index. Following Pástor et al. (2017), a fund's benchmark-adjusted return is the fund's net return minus the return on the benchmark designated by Morningstar Category. See the caption in Table 2 for the definitions of Active Share and AIV. The Newey and West (1987) heteroskedasticity-and-autocorrelation-robust t-statistics with three lags are reported in the bracket. Bold numbers indicate the t-statistics with an absolute value greater than 2. The sample is from 1990 to 2019 because the VIX index is available after 1990. The return is annualized and in percentages. AIV and VIX are standardized to have zero mean and unit standard deviation to interpret the economic magnitude of the coefficient estimates.

Panel B. Slope coefficients b and c, [t-statistics], and adjusted-R^2 from time-series regressions $R_t^{benchmark-adjusted} = a + bAIV_{t-1} + cVIX_{t-1} + \epsilon_t$

	The equal-weight Active Share quintile portfolios					
	Low	2	3	4	High	H-L
AIV	0.41	0.78	**1.17**	**1.27**	**3.29**	**2.88**
	[1.23]	[1.97]	[2.61]	[2.64]	[4.25]	[4.71]
VIX	-0.51	**-0.90**	**-1.10**	**-1.44**	**-2.29**	**-1.78**
	[-1.42]	[-2.41]	[-2.42]	[-2.88]	[-3.53]	[-3.51]
Adjusted-R^2(%)	0.26	1.53	2.50	3.33	8.33	7.71

	The value-weight Active Share quintile portfolios					
	Low	2	3	4	High	H-L
AIV	0.60	1.13	**1.28**	**1.28**	**3.11**	**2.51**
	[1.11]	[1.81]	[2.05]	[2.06]	[3.04]	[3.32]
VIX	-0.91	-1.08	-1.11	**-1.60**	**-2.35**	**-1.44**
	[-1.82]	[-1.67]	[-1.76]	[-2.33]	[-2.77]	[-2.25]
Adjusted-R^2(%)	0.64	1.41	1.30	2.12	5.59	5.02

Appendix B. Data Sources, Sample Construction, and Filters

B.1. Stock Data

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.

B.1.1. Actively Managed US Equity 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.[17] 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 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

[17] 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.

all funds in the sample.

B.1.2. *Actively Managed International Equity Mutual Funds*

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 2017.

Appendix C. Theoretical Framework

C.1. 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

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

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

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

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

where f_t is the common factor in idiosyncratic volatilities, which serves as the aggregate idiosyncratic volatility in the model.[18]

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

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

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

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

period t is given by

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

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

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

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

C.2. *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 $\alpha_{i,t}$ 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 $j = 1 + m, \ldots, M$.[19]

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

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

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 $\sum_{i=1}^N w^j_{i,t} = \sum_{i=1}^N w^m_{i,t} = 1$.

[19]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).

The manager's benchmark-adjusted rate of return is

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

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,

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

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

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,[20]

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

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

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

Equation (B.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

[20] I first solve the optimization problem (B.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 (B.12).

identified by the skilled manager. For an unskilled manager, the active weights will always be zero so he is essentially an ”index closer”.

C.3. Sentiment Investors

Sentiment investors invest directly in individual stocks. The sentiment-investor excess demand is assumed to be exogenous. Denote the excess weights aggregate across sentiment investors in stock j as $x_{i,t}$.[21] In addition, I assume $\sum_{i=1}^{N} w_{i,t}^{m} x_{i,t} = 0$, so that there is no distortion of sentiment-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.

C.4. 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 (B.12) we have the active weights aggregated across active funds,[22] $\phi_{i,t}^{F}$, as

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

The market clearing condition is

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

where h is the fraction of the market held by sentiment investors relative to the fraction of the market held by active fund managers.[23]

From equations (B.13) and (B.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*

[21] 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 $i = 1, \ldots, N$.

[22] 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.

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

equation,

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

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 sentiment investors, scaled by the relative wealth of sentiment investors to active funds; 3) γf_t, aggregate idiosyncratic volatility multiplied by active managers' risk-aversion parameter. Intuitively, assets with negative (positive) sentiment 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,

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

which is positively associated with the commonality in idiosyncratic volatility f_t and the cross-sectional dispersion of sentiment 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,

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

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*

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