Quantitative Investing and Sell-Side Financial Analysts

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Dedication

This dissertation is dedicated to my family.

Abstract

Quantitative mutual funds and ETFs have become an increasingly important part of the equity market, with total assets under management nearly tripling in the last decade. This paper measures the relative percentage of firms' stock owned by quantitative mutual funds and ETFs (hereafter, quantitative ownership) and examines how it impacts the production of information in the capital market, as evidenced by the changing role of financial analysts. Given that the inputs to quantitative investing models are typically not obtained from information in analyst reports, I hypothesize that quantitative investors discourage analysts' information production. In support of this hypothesis, I find that quantitative ownership is negatively correlated with analyst following and this relationship is robust to using an instrument for quantitative ownership based on cases of mutual fund advisory misconduct. I also find that quantitative ownership has an adverse effect on analyst outputs, namely forecast accuracy, the number of dimensions forecasted, the informativeness of analyst forecast revisions, and forecast dispersion. Overall, the paper provides evidence on the impact of quantitative investing on the information environment through its effect on analysts, an important information intermediary.

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"The Quants Run Wall Street Now"

- Gregory Zuckerman and Bradley Hope, *Wall Street Journal*, 2017

1. Introduction

This paper studies whether and how quantitative investing approaches of mutual funds and exchange-traded funds (ETFs) impact the information production of sell-side financial analysts. As key information intermediaries in capital markets, analysts are a vital component of the information environment (Beyer, Cohen, Lys, and Walther 2010; Bradshaw 2011). However, in recent years, the analyst industry has witnessed a decline in analyst coverage (see Figure 1; Armstrong 2018; Drake, Moon, Twedt, and Warren 2019). One potential contributing factor is the rise in quantitative investing, which has reshaped the asset management industry. Practitioners maintain that the lower reliance on analyst services by quantitative investors may have reduced the demand for analysts' information production (e.g., Hamilton 2007; Zuckerman and Hope 2017). Consistent with this argument, Sloan (2018) expresses concern that rule-based investment strategies that ignore fundamental analysis may reduce fundamental information production. To shed light on this issue, this paper studies whether the increase in quantitative investing by mutual funds and ETFs affects the role of sell-side analysts.

Quantitative investing refers to an investment process that relies on pre-fixed rules and proprietary models to identify investment opportunities.[1] For example, a popular quantitative investing strategy, called "smart beta" or "factor investing," identifies investment portfolios based on factors that capture investment opportunities or market

[1] Note that quantitative investing is not algorithmic trading or vice versa. Algorithmic trading refers to a trading process (rather than an investing process) in which orders are executed using automated programs, generally at a high frequency (milliseconds or microseconds).

inefficiencies (Sloan 2018).[2] Due to advances in computational techniques and asset pricing models, this investing approach has become increasingly popular in the asset management industry. For instance, it is extensively used by large investment management companies, including Blackrock, Fidelity, and Vanguard. Moreover, large investment banks, such as J.P. Morgan and Goldman Sachs, have also launched a series of quantitative equity funds in recent years. In terms of size, assets under management of equity mutual funds and ETFs that are quantitatively managed nearly tripled in the last decade, increasing from $302 billion to $806 billion (from 11% to 16% of all U.S. equity mutual funds and ETFs) over the 2010-2017 period (Figure 2). Given the rapid growth of quantitatively managed funds, an important yet unanswered question emerges: How does quantitatively managed ownership impact various aspects of the capital market? This paper focuses on the impact of quantitative investing on a key player in the capital market – the sell-side financial analyst.

Sell-side financial analysts are important information intermediaries in the capital market who provide valuable services to institutional investors. Prior research has documented that analyst following is higher for firms with greater institutional ownership (e.g., Bhushan 1989; O'Brien and Bhushan 1990). Analysts' services provide ex-ante valuation and ex-post stewardship benefits to institutional investors (Beyer, Cohen, Lys, and Walther 2010). Sell-side analysts cater to institutional investors' demand for company-specific information through various channels, including analyst reports, informal meetings, or phone calls (Bradshaw 2011). Consistently, survey evidence in Brown, Call,

[2] Note that some investing strategies labelled "quantitative" may also encompass features of growth investing or technical analyses, while employing a complex modeling framework.

Clement, and Sharp (2015) shows that institutional investors (in particular, hedge funds and mutual funds) are the most important clients of sell-side analysts.

However, the positive association between institutional ownership and analyst following documented by prior studies may not apply to *quantitative* institutional ownership. First, quantitative investors typically form their investment strategies by ranking firms on various indicators, such as size, growth, momentum, and sentiment, and use a modeling approach to analyze the data (Fabozzi, Focardi, and Jonas 2007). Alternative data, back-testing, and proprietary models, rather than analyst reports, give quantitative institutional investors an edge in information processing to make timely investment decisions. Second, quantitative fund managers' fiduciary duties can be fulfilled without acquiring corporate-specific information, leading to reduced demand for information produced by analysts. Consistent with the growing importance of quantitative investing, a survey of 3,368 investment professionals by the National Investor Relations Institute (NIRI) and Clermont Partners reports that only 5% of buy-side clients consider sell-side services to be more important for making investment decisions compared to five years ago (NIRI and Clermont Partners 2017).[3] Because institutional investors are the major consumer of analyst information, the decreased demand from the increasing segment of quantitative institutional investors is likely to discourage information production by sell-side analysts.

I examine the impact of quantitative ownership on analyst coverage and the quantity and quality of analyst outputs. I identify quantitatively managed mutual funds and ETFs and calculate their combined stock ownership for each firm (hereafter, quantitative

[3] National Investor Relations Institute is a professional association of corporate officers and investor relations consultants. Clermont Partners is a strategic communications firm.

ownership). Using this measure, I study the impact of quantitative ownership on analyst coverage, analyst forecast accuracy, and number of dimensions forecasted (EPS, sales, etc.). Finally, I examine how analyst forecast dispersion and investor response to analyst forecast revisions are impacted by quantitative ownership.

I find that quantitative ownership has a significant negative association with analyst coverage after controlling for innovations in trading technology, competition from crowd-sourced forecasts (namely *Estimize*), and other determinants of analyst coverage. The negative association holds for ownership by both actively and passively managed quantitative funds. Moreover, this result is robust when I use a first-difference model, an entropy balanced method, and a propensity score matched sample. Additionally, to mitigate reverse-causality concerns, I introduce an instrumental variable—quantitative ownership affected by mutual fund advisory misconduct. If a mutual fund advisor commits misconduct, mutual fund investors will likely withdraw money from the fund (Wu 2017). As a result, the fund will have to sell off its investments. These actions will create variations in quantitative ownership that are unlikely to be related to corporate attributes that affect analyst following. Using this instrument in a two-stage least squares analysis, I show that, consistent with my main result, fitted quantitative ownership is significantly associated with lower analyst coverage.

Further, I investigate how quantitative ownership affects an individual analyst's outputs, i.e., the number of dimensions forecasted and forecast accuracy. If quantitative mutual funds rely less on sell-side analysts, I would expect sell-side analysts to reduce the quantity and quality of their outputs due to the reduced demand. Consistent with this prediction, I find that analysts forecast fewer dimensions and issue less accurate forecasts for firms with greater quantitative stock ownership. Moreover, I find that quantitative ownership has an adverse impact on the information content of analysts' forecasts - firms with greater quantitative ownership are associated with lower informativeness of analyst revisions and higher forecast dispersion.

To investigate the channel through which quantitative mutual funds affect analyst following, in additional tests, I show that quantitative ownership is associated with a reduction in institutional investors' information acquisition, captured by news readership from the Bloomberg terminal.[4] To the extent that the observed reduction in institutional investors' information acquisition is attributable to quantitative institutions, this evidence corroborates that the decrease in information demand from quantitative funds is the likely mechanism that drives the decline in analysts' information production.

This study makes several contributions. First, the findings contribute to the literature studying sell-side analysts, particularly how institutional investors influence analysts' information production. Prior studies show that analysts are important information intermediaries, who process, produce, and convey valuable information to investors (see Beyer, Cohen, Lys, and Walther 2010 for a review). In general, prior results suggest that institutional ownership is positively correlated with analyst following, because institutional investors increase the need for analyst services, and thus encourage analyst following (Bhushan 1989; O'Brien and Bhushan 1990; Frankel, Kothari, and Weber 2006; Boone and White 2015). I provide evidence suggesting that institutional investors' demand for analyst information is not homogenous and the investing approach used by institutional investors could be an important determinant of analyst following.

[4] About 80% of Bloomberg users work in financial industries (Ben-Rephael, Da, and Israelsen 2017).

Second, my findings provide new insight into the broad literature relating to institutional investor characteristics and their impact on the information environment. Bushee and Noe (2000) classify institutional ownership into three categories (i.e., transient institutions, quasi-indexers, and dedicated investors) based on their trading strategies and examine their impact on corporate disclosures. Several recent studies also show that advances in the asset management industry could have a significant impact on the information environment. For example, index investing has increased the quantity and quality of corporate disclosures (Boone and White 2015; Bird and Karolyi 2016; Schoenfeld 2017). My research focuses on quantitatively managed mutual funds and ETFs, a growing and important segment of the asset management industry, and shows how their investing preferences impact the information environment through their effect on analysts.

Finally, this study contributes to the growing literature on quantitative investing. Prior research examines the performance and style of quantitative funds (Fabozzi, Focardi, and Jonas 2007; Abis 2017), while I focus on *firm-level* quantitative ownership and examine how quantitative funds, as shareholders, affect analyst behavior. My findings broaden our understanding of the consequences of quantitative investing by providing evidence that quantitatively managed funds in the aggregate affect analysts' information production. In a report to Congress, the SEC discusses the increasing usage of quantitative funds and its impact on the capital market.[5] The findings of this paper can inform policymakers about critical issues to consider when developing regulations on the related topics.

[5] Available at: https://www.sec.gov/news/studies/techrp97.htm

The rest of this paper is organized as follows. Section 2 introduces the institutional background and develops the hypotheses. Section 3 describes the data and measurement. Section 4 discusses the sample selection. Section 5 presents the empirical design and results. Section 6 reports additional tests. Section 7 concludes the paper.

2. Institutional Background and Hypothesis Development

2.1 Quantitative Investing

Quantitative investing approaches have become increasingly popular in the asset management industry in the last decade. Quantitative investing is typically defined as an investment process utilizing mathematical models and algorithms to identify investment opportunities. Developments in academic research have provided a foundation for quantitative investing (Sloan 2018). One of the popular quantitative strategies is "smart beta," also called "factor investing" (McGee 2019). It refers to the use of "factors" in investment decision making, where the factors are characteristics that may capture investment opportunities or market inefficiencies (Sloan 2018). One example is the Vanguard U.S. Multifactor Fund, which uses proprietary models sorting stocks on factors.[6] Some fund managers also use quantitative analysis or algorithms to build customized quantitative models. Quantitative investing tries to identify "the best factors to predict returns", unlike traditional investing,[7] which tends to evaluate individual companies' performance using company specific information—e.g., business plans, management team, performance, and product quality (Phillips, Hager & North Investment Management 2016). Quantitative investment strategies usually do not rely on comprehensive approaches to

[6] See https://investor.vanguard.com/mutual-funds/profile/VFMFX
[7] In the paper, I refer to investment styles that are not quantitative as traditional.

evaluate the intrinsic value of underlying securities, and thus could lead to a reduction in fundamental information production (Kok, Ribando, and Sloan 2017; Sloan 2018).

2.2 Related Literature and Hypothesis Development

2.2.1 Related Literature

Several studies have examined the relationship between stock ownership characteristics and the information environment. One stream of literature studies the relation between the information environment and institutional investors' trading strategies. For example, Bushee and Noe (2000) find that (1) transient institutions prefer firms with more disclosures due to liquidity concerns, (2) quasi-indexers are likely to demand more disclosures to monitor firm operations, and (3) dedicated investors—who are more likely to have proprietary information—may be indifferent to corporate transparency. Furthermore, several studies examine the influence of index investing on disclosure and find that the frequency and content of disclosures increase after a firm is included in a major index (Boone and White 2015; Bird and Karolyi 2016; Schoenfeld 2017). Boone and White (2015) suggest that indexers demand enhanced information to minimize transaction and monitoring costs. In recent years, a growing body of literature has centered on how changes in the asset management industry (e.g., ETF ownership) impact the information environment. Israeli, Lee, and Sridharan (2017) investigate ETF ownership and pricing efficiency of underlying securities and ascertain that past ETF ownership decreases future information efficiency of underlying securities. On the other hand, Glosten, Nallareddy, and Zou (2021) document contemporaneous increases in information efficiency for firms with increases in ETF ownership.

Another stream of literature examines the relation between institutional investors and security analysts (e.g., Bhushan 1989; O'Brien and Bhushan 1990), finding that firms with greater institutional ownership tend to have greater analyst coverage. Sell-side analysts' survey responses state that institutional investors are their most important clients (Brown et al. 2015) who can pay for their research through "soft dollar" arrangements (Gokkaya, Liu, Pool, Xie, and Zhang 2021). However, recent years have witnessed a sharp decline in analysts' information production. Studies have offered several reasons for this shift in the analyst industry, such as regulation changes, the popularization of digital media, and the rise in crowdsourced earnings forecasts (Banker et al. 2017; Drake et al. 2019; Fang et al. 2020; Ott, Subramanyam, and Zhang 2021). For example, Fang et al. (2020) document that Markets in Financial Instruments Directive (MiFID) II, a regulation requiring investment firms to separate investment research costs from other service costs, leads to a decrease in analyst following. In examining the effect of digital media, Drake et al. (2019) find that analysts' forecasts released after articles on Seeking Alpha elicit lower market reactions.[8] Banker et al. (2017) examine firms covered by Estimize, a platform providing crowdsourced earnings forecasts, and find that IBES earnings forecasts of covered firms become more timely as a result of increased competition from Estimize forecasters. This paper focuses on another change in the financial landscape, the rise in quantitative investing in the asset management industry, and examines how it affects analyst behavior.

2.2.2 Hypothesis Development

[8] Seeking Alpha is an online platform posting articles on crowdsourced financial research.

There is limited research on how the investment style of institutional investors impacts analysts' information production. Inputs to investment decisions are different for quantitative versus traditional investing approaches. Traditional investing relies on analysts' reports, financial statements, private meetings, and media to understand company specifics and industry trends. On the other hand, quantitative investing utilizes proprietary models, that sort and rank stocks on factors (e.g., size, momentum, growth) to identify trading opportunities. The machine-based approach of quantitative investors depends less on analyst forecasts to make trading decisions. This study examines whether and how quantitative investing alters the information environment via changes in analyst coverage and analyst outputs.

There are several reasons why quantitative ownership may be associated with a reduction in analysts' information production. Analysts convey their analysis via formal analyst reports and informal channels (Bradshaw 2011). The informal channels include presentations to major clients, private communication to clients, meetings between investors and firm managers, industry conferences, etc. Institutions such as mutual funds require information to satisfy their fiduciary duties, so the use of analyst reports could be viewed as evidence of care when investing. However, quantitative funds have less need for analyst information, as they rely more on algorithms using various matrices rather than company-specific information and depend on well-designed and well-tested models to satisfy their fiduciary duties. Because analyst decisions about which firms to follow are affected by institutional demand for information (O'Brien and Bhushan 1990; Beyer, Cohen, Lys, and Walther 2010), a decrease in information demand from quantitative institutional investors may lead to a decrease in analyst following. On the other hand, it is also possible that the growth in quantitative ownership may not impact analysts' information production. Because quantitative funds are well-diversified (Abis 2017), the aggregate ownership of these funds in a particular firm may not be significant enough to change analysts' coverage decisions. Thus, whether quantitative ownership has an impact on analysts' activities is an empirical question. My first hypothesis is as follows:

H1: *Quantitative ownership is negatively associated with analyst following.*

My second hypothesis examines the effect of quantitative ownership on the output of analysts. Due to the reduced demand from quantitative investors, analysts may decrease their forecasting effort for firms with greater quantitative ownership. As a result, we may observe a reduction in the quantity and quality of forecast outputs at the individual analyst level. I examine the number of dimensions forecasted per analyst (*Dimension*) and forecast accuracy (*Accuracy*) to assess whether analysts exert less effort in response to lower information demand. Analysts typically forecast many performance dimensions of a firm—such as sales, earnings, and cash flows—and the number of dimensions forecasted is likely to be positively correlated with analyst effort (Shroff, Venkataraman, and Xin 2014). Thus, if analysts exert lower effort for firms with high quantitative ownership, we will observe a reduction in the number of dimensions forecasted and lower forecast accuracy. The second hypothesis is as follows:

H2: *Quantitative ownership is negatively associated with analysts' output, measured as the number of dimensions forecasted by an analyst and forecast accuracy.*

Next, I examine whether quantitative ownership affects the information content of analyst forecasts. Frankel, Kothari, and Weber (2006) document that institutional ownership positively contributes to the informativeness of analysts' reports. However, the investment process of quantitative investing does not rely as much on information from analysts. Therefore, more quantitative ownership may be associated with reduced informativeness of analysts' reports. In addition, analysts' forecasts may be more dispersed as a result of the lower effort exerted by analysts. Thus, my third hypothesis is as follows:

H3: *Quantitative ownership is negatively associated with the informativeness of analysts' revisions and positively associated with analyst forecast dispersion.*

3. Variable Measurement

3.1 Quantitative Ownership

I obtain the sample of mutual funds and ETFs from the CRSP Survivor-Bias-Free U.S. Mutual Fund Database. Following Kacperczyk, Sialm, and Zheng (2008) and Abis (2017), I select U.S. domestic equity mutual funds and ETFs using Strategic Insights, Wiesenberger, and Lipper objective codes and policy codes in the dataset.[9] I exclude variable annuity underlying funds and funds without a valid fund name or starting year. To focus on funds with more accurate holdings data, I also restrict the sample to funds with (1) assets-under-management in excess of $5 million, (2) holdings of more than 10 stocks on average, (3) equity holdings between 80 and 105 percent. I then group share classes of a fund into one fund (portfolio).[10]

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[9] Equity fund selection starts with choosing funds whose crsp_obj_cd is ED. If a funds' crsp_obj_cd is missing, I select funds whose Lipper Classification code is one of the following options: EIEI, LCCE, LCGE, LCVE, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, SCCE, SCGE, or SCVE. If both crsp_obj_cd and Lipper Classification code are not available, I choose funds whose Strategic Insights objective codes is one of the following options: AGG, GMC, GRI, GRO, ING, or SCG. When all the above codes are missing, I select funds whose Wiesenberger objective codes equal to G, G-I, G-I-S, G-S, I-G, I-S-G, GCI, LTG, MCG, IEQ or SCG. When all the above codes are missing, funds with a policy code of CS were classified as equity funds. During this process, I also exclude funds with the following policy codes: Canadian and international balanced funds, Bonds and preferred stocks, Bonds, Government securities, Preferred stocks, Money market funds, or Tax-free money market funds.

[10] When grouping, for each fund, I keep the qualitative information (e.g., name of fund) from the first issued share class, compute total net assets by aggregating across all share classes, and calculate weighted average returns (weighted by lagged total net assets).

I obtain textual information about funds' investment process from prospectuses filed in the Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system. I rely on the fund name to match prospectuses with the CRSP mutual fund database and exclude those without valid investment process disclosures.[11] This process generates 2,477 unique mutual funds and ETFs during the sample period between 2011 and 2017.

To classify a mutual fund or ETF as either quantitative or traditional, I initially utilize the "smart beta" ETF list on the www.etf.com to classify quantitative ETFs. For the rest of the funds, I read investment process descriptions from their prospectus to identify quantitative funds.[12] Usually, the disclosures of the investment process are in the "Principal Investment Strategies" section of Form N1-A. Appendix B presents examples of such disclosures.

In the final step, I calculate quantitative ownership for each firm using holdings information compiled by CRSP. Specifically, the measure of quantitative ownership equals the number of shares held by quantitative funds divided by the total number of shares held by all U.S. equity mutual funds and ETFs.[13] This scaled measure helps to capture the relative importance of quantitative investing among mutual funds and ETFs, and alleviates the concern that it simply reflects the increase in assets under management for mutual funds and ETFs over the past decade.

[11] I remove special purpose funds (dividend funds, ESG funds, tax-managed funds, and exchange-traded notes) in this process, because these funds are likely to demand more firm specifics when making investment decisions.
[12] Of the 2,477 funds with investment strategy disclosures, 205 funds contain descriptions of both traditional and quantitative strategies. These 205 funds are classified based on their dominating strategy, resulting in the classification of 39 funds as quantitative. My results continue to hold when I exclude these 205 funds from my analysis.
[13] I replace negative quantitative ownership with zero, since a negative number of shares in the holding dataset represents short-selling activities of funds.

3.2 Quantitative Investor Characteristics

A comparison of the characteristics of quantitative funds with traditional funds is presented in Table 1. On average, quantitative funds have lower net assets under management, lower management fees, lower expense ratios, and higher turnover ratios. Examining portfolio characteristics, quantitative funds invest less in each stock and have a lower percentage of assets held longer than two years. These statistics are consistent with prior literature (Abis 2017) and anecdotes which reflect that quantitative funds tend to have lower expense ratios, more diversified portfolios, and higher turnover ratios.

One key assumption in this paper is that quantitative funds rely less on analyst forecasts. To provide direct evidence on this assumption, I test whether the association between fund portfolio changes and analyst recommendations differs across quantitative and traditional funds. I follow the procedure described in Kacperczyk and Seru (2007)[14] to calculate the association measure and find that quantitative fund holdings are less associated with analyst recommendations than traditional fund holdings. Specifically, the average association is 0.20 for quantitative funds, relative to 0.31 for traditional funds. A two-sample t-test of the mean suggests that the difference is statistically significant at the 1% level, with a t-statistic of 36.97 (see the last row of Table 1). This result is consistent with my assumption that quantitative funds demand less information from analysts, compared with the traditional funds.

[14] The association between fund portfolio changes and analyst recommendations is calculated as the unadjusted R^2 from regressing the change in fund holdings on the change in analysts' recommendations for each fund. Specifically, the following model is estimated:

$$\Delta Holdings_{i,j,t} = \beta_1 \Delta Recommendation_{i,t-1} + \beta_2 \Delta Recommendation_{i,t-2} + \beta_3 \Delta Recommendation_{i,t-3} + \beta_4 \Delta Recommendation_{i,t-4} + \epsilon$$

3.3 Measurement of Analyst Following and Properties of Analyst Forecasts

I use analyst following to capture analysts' activities because it reflects aggregated analysts' effort on each firm (O'Brien and Bhushan 1990; Lang and Lundholm 1996; Lehavy et al. 2011). Analyst following is defined as the number of analysts that forecast one-year ahead annual EPS for a firm in a given year.

Analyst following captures the aggregate effort of analysts per firm. I examine two measures of individual analyst effort – the number of dimensions forecasted per analyst (*Dimension*) and forecast accuracy (*Accuracy*). Analysts may forecast a series of items, such as earnings, sales, and cash flows, in their reports. The number of dimensions forecasted in an analyst's report is likely to be correlated with the analyst's effort. To avoid the problem of double counting, I classify forecasted items that are similar in nature as one dimension (Shroff, Venkataraman, and Xin 2014). For example, book value per share, enterprise value, and net asset value are considered as one dimension. Appendix A specifies the items in each of the eight dimensions studied. I examine the impact of quantitative ownership on forecast accuracy, another proxy for analyst effort (Harford, Jiang, Wang, and Xie 2019). Forecast accuracy (*Accuracy*) is defined as minus one times the absolute difference between actual and forecasted annual EPS, scaled by the stock price 90 days before the annual earnings announcement.[15]

To measure the impact of quantitative funds on the information production by analysts, I follow prior literature and use the following two measures: informativeness of analyst forecast revisions (*1-Day Return*) and forecast dispersion (*Dispersion*). Specifically,

[15] I focus on forecasts made in a shorter window (90-day window before the earnings announcement) to make forecast accuracy comparable across analysts. Forecasts that are made in a period closer to earnings announcement are likely to be more accurate because of greater information availability. By focusing on a shorter window, I am better able to control for unobserved time effects.

I utilize the absolute magnitude of the stock price reaction to analysts' annual EPS forecast revisions to capture forecast informativeness, following Frankel, Kothari, and Weber (2006) and Lehavy et al. (2011).[16] Similar to prior research (e.g., Behn et al. 2008; Lehavy et al. 2011), forecast dispersion (*Dispersion*) is defined as the standard deviation of annual EPS forecasts, scaled by the stock price 90 days before the earnings announcement.[17]

4. Sample Selection and Descriptive Statistics

I begin the sample construction with all U.S. firms, traded by U.S. equity open-end funds, in COMPUSTAT and CRSP between 2011 and 2017.[18] I then restrict the observations to those with a share type (shrcd) of 10 or 11. I merge this sample with Thomson Reuters 13F database to obtain institutional ownership information. All other control variables are calculated using data from COMPUSTAT, CRSP, SEC Market Information Data Analytics System (MIDAS), and Estimize.[19] I further exclude observations with a non-positive equity value, total assets of less than $100 million, and missing control variables. I obtain data on analysts' outputs from I/B/E/S. Consistent with Barth et al. (2001) and Lehavy et al. (2011), I set missing analyst coverage to zero.

As shown in Table 2, Panel A, I retain 14,178 firm-year observations, corresponding to 2,696 firms from 2011 to 2017. On average, mutual funds own 33.2% of sample-firm stocks, and quantitative funds represent 16.6% of mutual fund ownership.

[16] Specifically, informativeness of analysts' reports is defined as: the sum of one-day absolute size-adjusted returns on the forecast revision days scaled by the sum of one-day absolute size-adjusted returns over the year.
[17] The standard deviation is computed using one-year-ahead EPS forecasts made during a 90-day window before the annual earnings announcement. For analysts who make multiple one-year-ahead EPS forecasts, the last forecast is used to calculate the standard deviation.
[18] My sample begins in 2011 to enhance the accuracy of mutual fund holdings data. Schwarz and Potter (2016) find inaccuracies in CRSP holding reports data prior to 2008. Starting from 2010, CRSP uses a new data vendor for mutual fund holding.
[19] I thank Jacob Ott for generously sharing the Estimize data.

Sample firms are followed by 10.2 analysts on average in a given year. Table 2, Panel B, displays the sample distribution by year. The table reveals an increase in quantitative ownership over the sample period, from 14.6% in 2011 to 18.9% in 2017. Panel C provides the Pearson correlation coefficients among key variables.

Table 2, Panel D, reports the univariate relationship between quantitative ownership and variables that capture analysts' information production. I partition the sample into above- and below-median quantitative ownership and compare the variables related to analysts' information production across the two subsamples. Consistent with my hypotheses, I find that firms with higher quantitative ownership have (1) lower analyst coverage, (2) fewer dimensions forecasted per analyst, (3) lower forecast accuracy, (4) lower informativeness of forecast revisions, and (5) higher forecast dispersion. The t-tests show that the two sample means are significantly different at the 1% level.

5. Empirical Analyses and Results

5.1 Analyst Following

5.1.1 Multivariate Regression Model

In this section, I empirically test *H1— Quantitative ownership is negatively associated with analyst following*— using the following specification:

$$AnalystFollowing_{i,t+1} = \alpha_0 + \beta_1 \, Quant_{i,t} + \gamma \, X_{i,t} + FE + \varepsilon_{i,t+1} \qquad (1)$$

where i indexes firms and t indexes years. $Quant_{i,t}$ is the quantitative funds ownership for firm i in year t as defined in section 3.1. X is a vector of control variables. The regression is estimated with firm and year/industry-year fixed effects.

I include firm-specific and time-varying control variables that could affect firms' information environment. Consistent with Lehavy et al. (2011), I include firm size (*Size*), institutional ownership (*InstOwnership*), advertising expenses (*AdvExp*), R&D expenses (*RDExp*), growth opportunities (*Growth*), standard deviation of stock returns (*Std_Ret*), and number of segments (*Segment*) as my control variables. I also include total stock ownership by mutual funds (*MFOwnership*) for each firm to control for growth in mutual fund ownership. More importantly, I use algorithmic trading (*AlgoTrading*) and Estimize coverage (*Estimize*) to control for innovations in trading technology and competition from crowd-sourced forecasts that could impact analyst following. Firm fixed effects and year/industry-year fixed effects are included to control for unobserved time-invariant firm characteristics and changes in analyst activities affected by industry shocks and the macro environment.

Hypothesis *H1* predicts a negative association between quantitative ownership and analyst following. I test this prediction by examining whether the coefficient on quantitative ownership (*Quant*) is less than zero, i.e., $\beta_1 < 0$. The results of estimating Equation (1) are presented in Table 3, Panel A. Column (1) reports the results with firm and year fixed effects and column (2) reports the results using firm and industry-year fixed effects. In support of H1, I find that quantitative ownership is negatively associated with analyst following. Specifically, the coefficients on *Quant* in columns (1) and (2) are negative and statistically significant at the 1% level. The coefficient estimate suggests that a one standard deviation (8.77%) increase in quantitative ownership is associated with a reduction of 0.38 (0.36) analysts in the following year. Consistent with prior literature (e.g., Lang and Lundholm 1996; Lehavy et al. 2011), *Size* is positively correlated with analyst following. Among other control variables, *Growth* and *MFOwnership* are positively correlated with analyst following, while *Std_Ret* is negatively correlated with analyst following.

5.1.2 First-difference Model

To test the robustness of the main result, I use a first-difference model to estimate the relationship between the change in quantitative ownership and lead change in analyst following. Specifically, I estimate the following model:

$$\Delta AnalystFollowing_{i,t+1} = \alpha_0 + \beta_1 \Delta(Quant)_{i,t} + \gamma \Delta(X)_{i,t} + FE + \varepsilon_{i,t+1} \quad (2)$$

The results are reported in Table 3, Panel B. Column (1) reveals that there is a significantly negative association between changes in quantitative ownership and lead changes in analyst following. Column (2) shows that the relation does not alter after controlling for yearly industry trend. In support of H1, I find that an increase in quantitative ownership is accompanied by a decrease in analyst following.

5.1.3 Instrumental Variables

There is a concern that these results may be subject to reverse-causality or omitted variable bias, if quantitative funds select firms with lower information production or with certain characteristics that are correlated with information production. To mitigate this concern, I exploit the variation in ownership affected by quantitative mutual fund advisory misconduct and assess the impact of quantitative funds on analyst following.

To be a valid instrument, the variable has to meet two conditions: relevance and exclusion restriction (e.g., Larcker and Rusticus 2010; Roberts and Whited 2013). Wu (2017) shows that on average one case of mutual fund advisory misconduct leads to an abnormal reduction of 5% inflows. Due to this outflow pressure, mutual funds have to sell the stocks they own. As a result, firms with higher ownership exposure to quantitative fund advisory misconduct would have a lower level of quantitative ownership in the future, thus satisfying the relevance requirement of instruments. I verify this relationship using my sample. This instrumental variable also meets the exclusion restriction requirement. Mutual fund advisory misconduct caused by investment advisers' negligent or unethical behavior is unlikely to be directly related to analyst following other than through the reduction in quantitative ownership. I, therefore, expect that mutual fund advisory misconduct can only affect analyst following via its impact on quantitative ownership of firms.

Specifically, the instrument is calculated in two steps. I first extract information about mutual fund advisory misconduct from Form ADV, a report filed by mutual fund advisors on an annual basis. Typically, the misconduct includes transactions (e.g., market timing, unauthorized trading, or late trading behavior), omissions of material disclosure, or violations of a compliance requirement (Wu 2017). As an example of mutual fund advisory misconduct, on August 27, 2018, the SEC sanctioned quantitative investment managers, Transamerica Asset Management Inc. and Transamerica Financial Advisors Inc., because their investment model did not work as intended and because of insufficient oversight and disclosures.[20]

After identifying the quantitative funds impacted by advisory misconduct, I obtain their holdings information from the CRSP mutual fund dataset and aggregate the holdings into firm-year observations. I then divide this variable by the number of shares held by U.S. equity mutual funds and ETFs for each firm in a given year.[21] I denote the instrumental variable as *QuantMiscdt*. I first establish that the instrument is strongly associated with a

[20] Available at: https://www.sec.gov/news/press-release/2018-167
[21] For consistency, I use the same denominator used to calculate quantitative ownership.

future decrease in quantitative ownership using the following equation—which is the first stage of the two-stage least squares (2SLS) regression analysis:

$$\Delta Quant_{i,t+1} = \alpha_0 + \beta_1\ QuantMiscdt_{i,t} + \gamma\ \Delta(X)_{i,t} + FE + \varepsilon_{i,t+1} \qquad (3)$$

where $\Delta Quant_{t+1}$ is the change in quantitative ownership from year *t* to year *t+1*. The results are reported in Appendix C. As expected, β_1 is negative and significant, indicating that the *QuantMiscdt* is associated with a subsequent decrease in quantitative ownership. The Cragg-Donald F-statistics exceed the critical values proposed by Stock and Yogo (2005), indicating that it is not a weak instrument. Then using the $Fitted(\Delta Quant_{t+1})$ obtained from the first-stage regression, I estimate the second stage of the 2SLS analysis:

$$\begin{aligned}\Delta AnalystFollowing_{i,t+2} & \qquad (4)\\ = \alpha_0 + \lambda_1\ Fitted(\Delta Quant)_{i,t+1} + \gamma\ \Delta(X)_{i,t} + FE + \varepsilon_{i,t+1}\end{aligned}$$

Table 3, Panel C, reports the results of Equation (4). Consistent with H1 and the results in panel A, λ_1 is negative and significant, suggesting that an increase in quantitative ownership leads to a reduction in analyst coverage. Thus, the main results are robust to using the instrumental variable approach.

5.1.4 Results by Type of Quantitative Ownership

There could be a concern that the above results are driven by passively managed funds rather than quantitative investing approaches. I study how the effect of quantitative ownership on analyst coverage varies with different types of mutual fund ownership. I partition quantitative ownership into actively (*Active Quant*) and passively managed (*Passive Quant*), and test whether my results are driven by passively managed funds.[22]

[22] In the sample, about 60% of quantitative ownership is passively managed and 40% of quantitative ownership is actively managed.

Column (1) and (2) of panel D in Table 3 report the results. I find that the coefficients on *Active Quant* and *Passive Quant* are both negative and significant at the 1% level. This finding illustrates that it is the funds' quantitative investing approach that affects analyst following, rather than their passive managerial style.

Because Israeli, Lee, Sridharan (2017) has documented that ETFs can have a negative impact on analyst coverage, to test whether my results are driven by ETF ownership, I partition quantitative ownership into non-ETF quantitative ownership (*Non-ETF Quant)* and ETF quantitative ownership (*ETF Quant*), and re-estimate Equation (1). Columns (3) and (4) of panel D present the results. I find that the coefficients on *Non-ETF Quant* are negative and significant at the 1% level, while the coefficients on *ETF Quant* are negative but insignificant, alleviating the concern that my results are driven by ETF ownership.

5.2 Properties of Analyst Forecasts

5.2.1 Outputs of Individual Analysts

To test H2 (i.e., quantitative ownership is negatively associated with analysts' output), I employ two measures—the number of dimensions forecasted by an analyst and forecast accuracy—and estimate the following equations:

$$Dimension_{i,j,t+1} = \alpha_0 + \beta_1\, Quant_{i,j,t} + \gamma\, X_{i,j,t} + FE + \varepsilon_{i,j,t+1} \tag{5}$$

$$Accuracy_{i,j,t+1} = \alpha_0 + \beta_1\, Quant_{i,j,t} + \gamma\, X_{i,j,t} + FE + \varepsilon_{i,j,t+1} \tag{6}$$

where *i* indexes firms, *j* indexes analysts, and *t* indexes years. *Dimension* and *Accuracy* are calculated for each analyst-firm-year. More detailed variable definitions are provided in Appendix A. The regressions include (1) analyst, firm, industry-year or (2) analyst-firm, industry-year fixed effects.

Columns (1) and (2) of Table 4 report the results of estimating Equation (5). The coefficients on *Quant* are negative and statistically significant at the 1% level when (1) analyst, firm, and year fixed effects, or (2) analyst-firm and industry-year fixed effects are controlled for. This evidence suggests that more quantitative ownership is associated with fewer dimensions forecasted by an analyst, leading to lower information production. Thus, my results show that, not only fewer analysts follow firms with more quantitative ownership, but also the information produced (or effort exerted) by individual analysts decreases with quantitative ownership.

Columns (3) and (4) of Table 4 report the results of estimating Equation (6). The coefficients on *Quant* are negative and statistically significant at the 5% (10%) level when analyst, firm, and industry-year fixed effects (analyst-firm and industry-year fixed effects) are included. These results indicate that analysts generate less accurate forecasts for firms with high quantitative ownership. It is possible that the lower accuracy of forecasts is due to higher quality analysts discontinuing coverage of firms with high quantitative ownership. I find evidence inconsistent with this explanation. Untabulated results show that, for firms with high quantitative ownership, analysts that terminate coverage of a firm are in fact less accurate forecasters in the preceding year relative to analysts that continue coverage (difference in *Accuracy* = 0.16, significant at the 1% level).

5.2.2 Information Content of Forecasts

H3 predicts that quantitative ownership is negatively associated with the informativeness of analysts' revisions and positively associated with forecast dispersion. To test this hypothesis, I estimate the following equations:

$$1\text{-}Day\ Return_{i,t+1} = \alpha_0 + \beta_1\, Quant_{i,t} + \gamma\, X_{i,t} + FE + \varepsilon_{i,t+1} \qquad (7)$$

$$Dispersion_{i,t+1} = \alpha_0 + \ \beta_1 \ Quant_{i,t} + \ \gamma \ X_{i,t} + FE + \varepsilon_{i,t+1} \tag{8}$$

where 1-$Day \ Return$ is the one-day absolute size-adjusted returns on the release of an analyst's revisions summed over all analysts following a firm during the year, scaled by the sum of one-day absolute size-adjusted returns over the year (Frankel, Kothari, and Weber 2006; Lehavy et al. 2011). $Dispersion$ is the standard deviation of annual earnings forecasts made during a 90-day window before the annual earnings announcement, scaled by the stock price 90 days before the earnings announcement. Other variable definitions are identical to those in Equation (1).

Columns (1) and (2) of Table 5 report the OLS estimates of Equation (7). Consistent with H3, the coefficients on *Quant* are negative and statistically significant at the 5% level, thus suggesting that the informativeness of analyst forecasts is decreasing in the firms' quantitative ownership level. This evidence supports the idea that analysts produce lower quality forecasts when the firm has higher quantitative ownership.

Columns (3) and (4) of Table 5 report the results of estimating Equation (8). The coefficients on *Quant* are positive and significant at the 5% level, hence indicating that firms with high quantitative ownership are associated with more dispersed analyst forecasts. Overall, this evidence is consistent with quantitative ownership being associated with less analysts' information production.

In further analysis, I examine whether the effect of quantitative ownership on analyst forecast accuracy and dispersion varies with firm size. Since large firms have many information sources in addition to the information produced by analysts, I expect a lower effect of *Quant* on analysts' forecast accuracy and dispersion for large firms relative to small. To test this cross-sectional effect, I interact *Quant* with a firm size indicator variable in regressions (6) and (8). Consistent with my expectation, I find that the effect of *Quant* on forecast accuracy and dispersion is significantly stronger for small firms relative to large (untabulated).

6. Additional Analyses

I perform several additional tests in this section. In section 5.1, I perform robustness tests using entropy balancing and propensity score matching techniques. In section 5.2, I examine whether quantitative ownership is associated with less institutional investor information acquisition, to shed light on the channel through which quantitative ownership could impact analysts' information production.

6.1 Entropy Balancing and Propensity Score Matching

6.1.1 Entropy Balancing

I perform robustness tests using an entropy balanced sample for high and low quantitative ownership. I first define a binary variable *High Quant* that equals one if the quantitative ownership is greater or equal to the sample median, and zero otherwise. Then I perform entropy balancing by reweighting the sample to adjust for the differences in control variables between firms with high and low quantitative ownership. The summary statistics before and after entropy balancing are presented in Appendix D. Next, I examine the relationship between quantitative ownership and analysts' information production before and after entropy balancing. The results for analyst following, analyst outputs, and the information content are reported in Table 6, Panels A, B, and C, respectively. The regression results are similar for the sample with and without entropy balancing, and consistent with the main findings.

6.1.2 Propensity Score Matching

I perform propensity score matching in this section, because propensity score matching is an efficient method to reduce selection bias. I matched on all control variables (i.e., size, institutional ownership, advertising expenses, R&D expenses, growth, number of segments, return volatility, mutual fund ownership, algorithmic trading, and Estimize coverage) and industry fixed effects.

I perform propensity score matched pairs analyses using all observations in the sample that with analyst forecast properties (i.e., analyst following, number of dimensions forecasted, accuracy, informativeness, and dispersion) available. Observations with higher (lower) than median quantitative ownership are classified as “High Quant” (“Low Quant”). I match observations in the “High Quant” category with observations in the “Low Quant” category and retain the top 2,000 matches.

Table 7 reports the results. Panel A presents pairwise differences in means and the associated t-tests on the matching variables. The pairwise t-tests suggest the matching variables are not statistically different between the high quantitative ownership and low quantitative ownership categories, indicating the propensity score matching is efficient. Panel B reports pairwise differences in means and the associated pairwise t-tests on the analyst forecast characteristics between high and low quantitative ownership categories. I find evidence that observations with high quantitative ownership have significantly less analyst following, both statistically and economically. Additionally, observations with high quantitative ownership are associated with low quality of analyst reports, evidenced by number of dimensions forecasted, accuracy, informativeness, and dispersion.

6.2 Institutional Investor Information Acquisition

One possible mechanism is that quantitative ownership reduces demand for information and suppliers of information (analysts) respond to the lower demand with less information production. A direct test of institutional investors' informational demand is to examine the institutional investors' attention to firms. If quantitative funds indeed demand less information, I should observe a negative relationship between quantitative ownership and institutional investors' information acquisition.

I formally test the above notion using the institutional investors' information acquisition measure proposed by Ben-Rephael et al. (2017). The measure is based on the news searching and reading frequency from the Bloomberg terminal. Bloomberg creates a firm-level daily index for news readership based on the number of times news articles are read and searched on Bloomberg terminals.[23] Ben-Rephael et al. (2017) suggest that this index measures institutional attention, as terminals are primarily used by institutional investors. If quantitative funds exert less effort to acquire firm-specific information, I expect to find lower institutional attention for firms with higher quantitative ownership.

Table 8 presents the results. After controlling for firm and year/industry-year fixed effects, I find institutional investor attention is negatively correlated with quantitative ownership, indicating institutional investors' information acquisition is lower for firms with high quantitative ownership. This evidence corroborates my premise that lower informational demand from quantitative investors leads to lower information production by analysts.

[23] I aggregate the measure to an annual frequency by taking the average of the daily index.

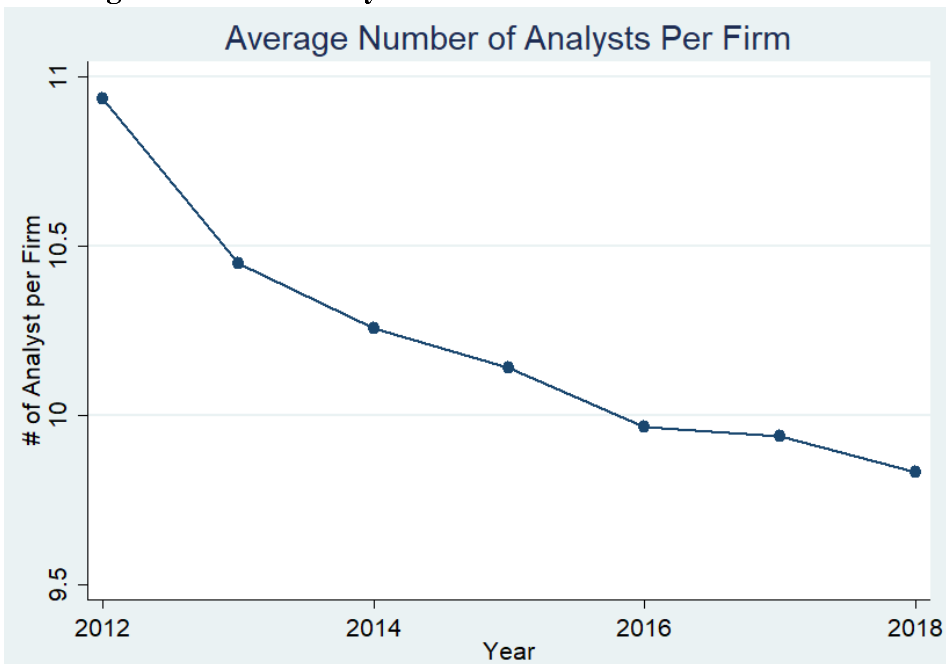
7. Conclusion

The analyst industry has witnessed a decline in analyst coverage in recent years. This paper investigates a possible contributing factor—the rise of quantitative investing—that reduces the demand for analyst information. Because quantitative investing models mainly rely on algorithms using various matrices rather than firm-specific information from analyst reports, I hypothesize that quantitative investors discourage analysts' information production. Consistent with my hypothesis, the results suggest that stock ownership by quantitative mutual funds and ETFs is associated with lower analyst coverage, lower quantity and quality of analysts' forecasts.

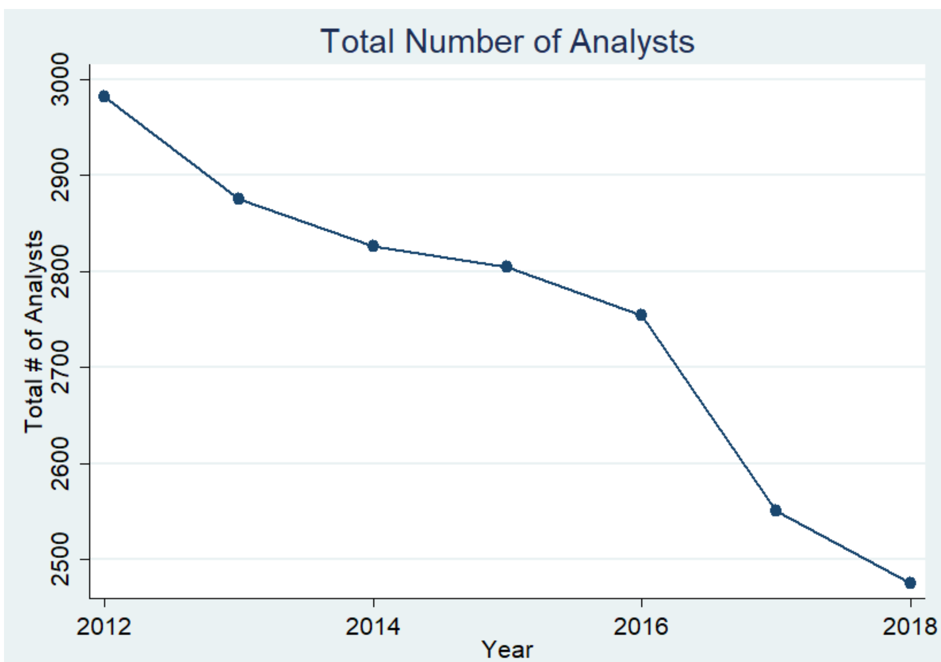
In contrast with prior literature, which has documented that institutional investors encourage more information production from analysts, this paper provides evidence that quantitative mutual fund investors have less informational demand, and analysts reduce their effort in response to the decline in demand. This study provides insight into how institutional investors' investing approach influences the analysts' information environment, as well as expands our understanding of the effect of quantitative investing on the capital markets.

Figure 1: Yearly Trend in Analyst Coverage

Panel A: Average Number of Analysts Per Firm



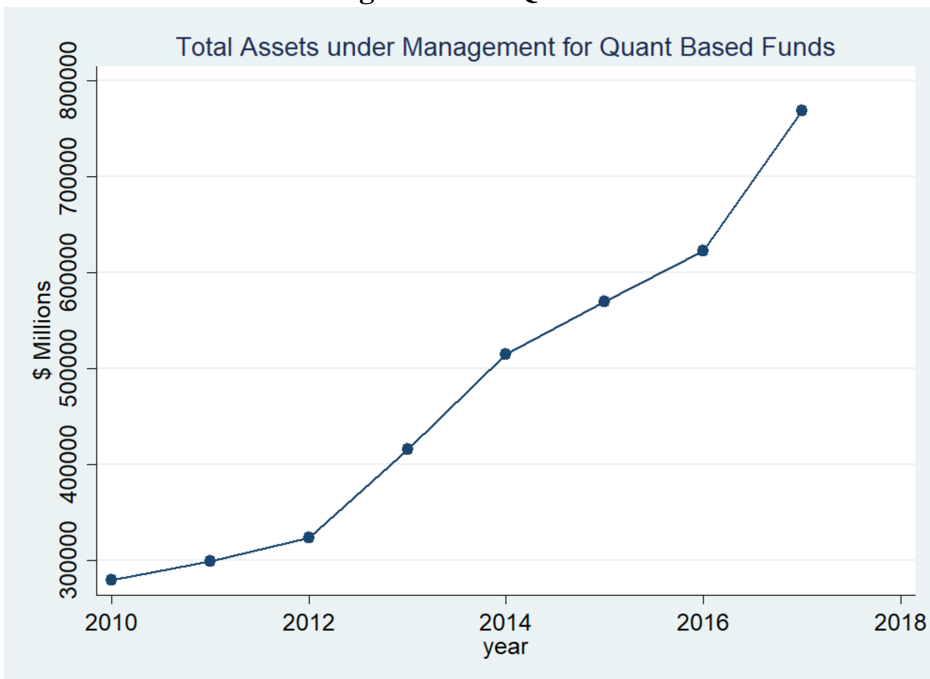
Panel B: Total Number of Analysts



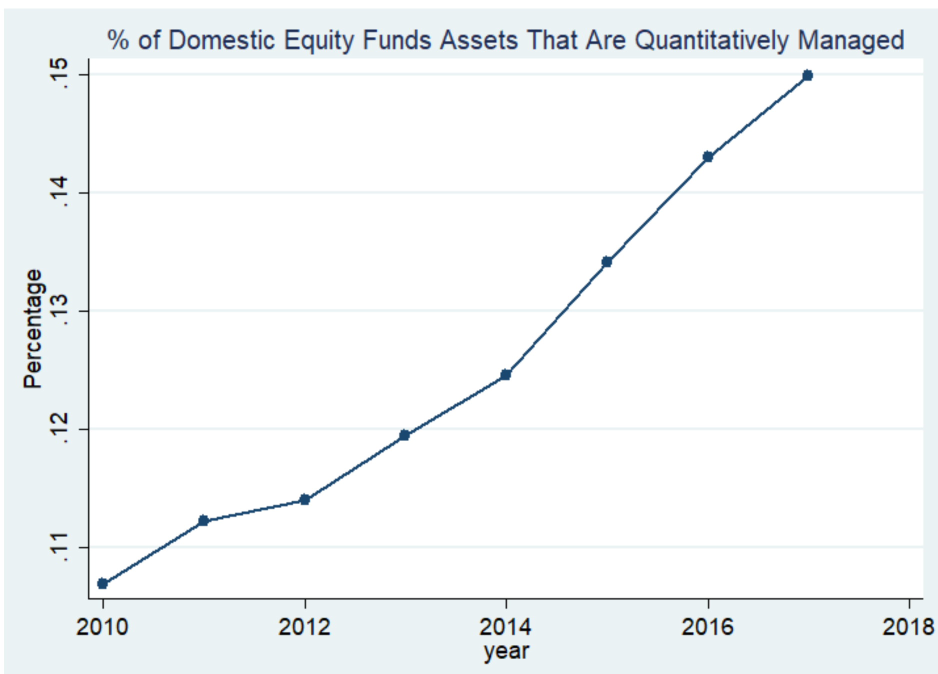
Panel A (B) plots the yearly average number of analysts per firm (total number of unique analysts) in the sample between 2012 and 2018. The sample construction is detailed in Section 4.

Figure 2: Yearly Trend in Quantitative Funds

Panel A: Total Assets under Management for Quant based funds



Panel B: Percentage of domestic equity fund assets that are quantitatively managed



Panel A plots the assets under management in quantitatively managed funds. Panel B presents the percentage of domestic equity funds' assets under management between 2010 and 2017 in quantitatively managed. Section 3.1 details the procedure to identify the quantitative funds.

Table 1: Characteristics of Quantitative Funds

	(1) *TraditionalFunds*		(2) *QuantitativeFunds*		(3) *Difference*	
	Mean	Std.Dev.	Mean	Std.Dev.	Diff.	t-Statistics
Total Net Assets (MM)	1,942.193	6,623.402	1,351.580	4,292.938	590.613***	(15.577)
Expense Ratio	0.012	0.004	0.008	0.005	0.004***	(107.920)
Management Fee (%)	0.722	0.237	0.501	0.289	0.221***	(103.568)
Fund Turnover Ratio	0.631	0.531	0.909	1.383	-0.278***	(-30.435)
Avg $ Invested in Each Stock (MM)	17.870	33.297	6.273	15.862	11.597***	(69.800)
Stability of Holdings (%)	13.167	31.048	6.119	19.760	7.048***	(38.687)
Association between fund portfolio changes and analyst recommendations	0.306	0.306	0.199	0.249	0.108***	(36.967)

The sample consists of fund-quarter observations from the CRSP Survivor-Bias-Free US Mutual Fund Database. Column (1) presents the statistics for traditional (non-quantitative) funds. Column (2) presents the statistics for quantitative funds. Column (3) reports the difference and the two sample t-test of difference in means of quantitative and traditional funds. All variables are winsorized at the 0.01 and 0.99 levels. *, **, and *** indicate significance at 0.1, 0.05, and 0.01 levels, respectively. Appendix A provides the variable definitions.

Table 2: Descriptive Statistics

Panel A: Summary Statistics

	Count	Mean	Std.Dev.	P25	P50	P75
Quant	14,178	0.166	0.087	0.107	0.157	0.217
Size	14,178	7.170	1.877	5.780	7.036	8.434
InstOwnership	14,178	0.654	0.285	0.498	0.746	0.878
AdvExp	14,178	0.014	0.028	0.000	0.000	0.016
RDExp	14,178	0.047	0.116	0.000	0.000	0.027
Growth	14,178	1.084	0.236	0.970	1.046	1.140
Segment	14,178	2.469	1.978	1.000	1.000	4.000
Std_Ret	14,178	0.091	0.050	0.056	0.079	0.112
MFOwnership	14,178	0.332	0.163	0.210	0.350	0.456
AlgoTrading	14,178	-0.219	1.148	-0.836	-0.184	0.398
Estimize	14,178	0.410	0.492	0.000	0.000	1.000
AnalystFollowing	14,178	10.207	9.424	3.000	7.000	15.000
Observations	14,178					

Panel B: Quantitative Ownership by Year

	2011	***2012***	***2013***	***2014***	***2015***	***2016***	***2017***
Num of Obs	2,121	2,196	2,154	2,103	1,954	1,941	1,709
Quant	0.146	0.154	0.163	0.163	0.172	0.183	0.189

Panel C: Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)Quant	1										
(2)AnalystFollowing	-0.09***	1									
(3)Size	0.06***	0.76***	1								
(4)InstOwnership	0.07***	0.33***	0.45***	1							
(5)AdvExp	-0.04***	0.10***	0.07***	-0.01	1						
(6)RDExp	-0.07***	0.10***	0.06***	0.09***	-0.04***	1					
(7)Growth	-0.01	0.08***	0.02	0.00	-0.01	0.13***	1				
(8)Segment	0.08***	0.09***	0.23***	0.12***	-0.09***	-0.10***	-0.03***	1			
(9)Std_Ret	0.07***	-0.15***	-0.35***	-0.12***	-0.04***	0.23***	0.14***	-0.08***	1		
(10)MFOwnership	0.03***	0.34***	0.42***	0.68***	-0.07***	0.10***	0.03**	0.12***	-0.07***	1	
(11)AlgoTrading	0.01	0.23***	0.10***	0.01	0.02	0.24***	0.08***	0.03***	0.27***	0.05***	1
(12)Estimize	0.06***	0.41***	0.52***	0.36***	0.06***	0.13***	0.06***	0.10***	-0.11***	0.35***	0.08***

Panel D: Univariate Analysis

	(1)		(2)		(3)	
	Low Quant		***High Quant***		***Difference***	
	Mean	Std.Dev.	Mean	Std.Dev.	Diff.	t-Statistics
AnalystFollowing	11.313	10.650	9.103	7.861	2.210***	(14.060)
Dimension	4.616	1.068	4.531	1.108	0.084***	(4.333)
Accuracy	-0.005	0.013	-0.007	0.018	0.002***	(6.449)
1-Day Return	0.148	0.116	0.127	0.093	0.021***	(11.434)
Dispersion	0.004	0.013	0.006	0.017	-0.001***	(-4.008)

Panel A presents the summary statistics for variables used in the main specification of this paper. Ownership and control variables are measured from 2011 to 2017. Outcome variables are measured from 2012 to 2018. Panel B reports the distribution (mean) of quantitative ownership by year. Panel C shows Pearson correlations among the key variables. Panel D reports the univariate relationship between quantitative ownership and characteristics of analysts' information production in the following year. Column (1) presents the statistics for firms with below-median quantitative ownership. Column (2) presents the statistics for firms with above-median quantitative ownership. Column (3) reports the difference and t-statistics of the two sample t-test of difference in means between columns (1) and (2). *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively. All continuous variables are winsorized at the 0.01 and 0.99 levels. Appendix A provides the variable definitions.

Table 3: Quantitative Ownership and Analyst Following

Panel A: Multivariate Regression Model

	(1) *AnalystFollowing*	(2) *AnalystFollowing*
Quant	-4.332***	-4.157***
	(-7.33)	(-6.97)
Size	1.726***	1.816***
	(15.19)	(16.42)
InstOwnership	-0.134	-0.134
	(-0.34)	(-0.36)
AdvExp	0.768	0.438
	(0.20)	(0.10)
RDExp	1.176	1.285
	(0.68)	(0.74)
Growth	0.470***	0.362**
	(2.59)	(1.97)
Segment	0.055	0.043
	(1.17)	(0.94)
Std_Ret	-2.916***	-3.008***
	(-3.03)	(-3.14)
MFOwnership	4.930***	4.882***
	(6.11)	(6.27)
AlgoTrading	0.022	-0.043
	(0.31)	(-0.60)
Estimize	0.160*	0.096
	(1.65)	(0.95)
Observations	14,178	14,116
Adj R-square	0.90	0.90
Fixed Effects	Firm, Year	Firm, Ind-Year

Panel B: First-Difference Model

	(1) Δ*AnalystFollowing*	(2) Δ*AnalystFollowing*
Δ*Quant*	-1.542***	-1.548***
	(-4.16)	(-4.21)
Δ*Size*	1.023***	1.068***
	(16.93)	(16.98)
Δ*InstOwnership*	0.420**	0.521**
	(2.06)	(2.55)
Δ*AdvExp*	0.481	0.299
	(0.11)	(0.07)
Δ*RDExp*	1.260	1.966
	(0.65)	(1.00)
Δ*Growth*	0.097	0.137
	(0.91)	(1.21)
Δ*Segment*	-0.006	-0.013
	(-0.25)	(-0.51)
Δ*Std_Ret*	-1.055**	-1.064**
	(-2.20)	(-2.20)
Δ*MFOwnership*	2.724***	2.634***
	(8.48)	(8.29)
Δ*AlgoTrading*	0.153**	0.101*
	(2.56)	(1.72)
Δ*Estimize*	0.004	-0.017
	(0.07)	(-0.29)
Observations	11,694	11,662
Adj R-square	0.05	0.09
Fixed Effects	Year	Ind-Year

Panel C: Instrumental Variables

	(1) ΔAnalystFollowing	(2) ΔAnalystFollowing
Fitted(ΔQuant)	-26.882*	-25.165*
	(-1.83)	(-1.71)
ΔSize	0.755***	0.801***
	(6.26)	(6.93)
ΔInstOwnership	0.515*	0.413
	(1.71)	(1.42)
ΔAdvExp	-10.568*	-9.181
	(-1.72)	(-1.45)
ΔRDExp	-3.866	-3.270
	(-1.25)	(-1.06)
ΔGrowth	0.064	-0.072
	(0.41)	(-0.47)
ΔSegment	0.005	0.008
	(0.15)	(0.25)
ΔStd_Ret	0.683	0.699
	(0.85)	(0.90)
ΔMFOwnership	-1.200	-1.004
	(-1.19)	(-1.02)
ΔAlgoTrading	-0.037	-0.042
	(-0.48)	(-0.56)
ΔEstimize	0.210*	0.207
	(1.67)	(1.52)
Observations	9,105	9.084
Cragg-Donald F-stat	11.30	10.37
Fixed Effects	Year	Ind-Year

Panel D: Quantitative Ownership and Analyst Following - Partition

	(1) *AnalystFollowing*	(2) *AnalystFollowing*	(3) *AnalystFollowing*	(4) *AnalystFollowing*
Active Quant	-2.620***	-2.413***		
	(-3.74)	(-3.38)		
Passive Quant	-7.903***	-7.906***		
	(-7.43)	(-7.38)		
Non-ETF Quant			-4.368***	-4.199***
			(-7.49)	(-7.10)
ETF Quant			-6.468	-7.313
			(-0.43)	(-0.45)
Observations	14,178	14,116	14,178	14,116
Adj R-square	0.90	0.90	0.90	0.90
Controls	Included	Included	Included	Included
Fixed effect	Firm, Year	Firm, Ind-Year	Firm, Year	Firm, Ind-Year

Panel A of this table reports the results of regression (1) estimating the relation between quantitative ownership and analyst following in the subsequent year. Panel B reports the results of the regression of lead changes in analyst following on changes in quantitative ownership. Panel C reports results of the two-stage least squares (2SLS) regression analysis using *QuantMiscdt* as an instrumental variable. Panel D reports the regression results of the relation between types of quantitative ownership and analyst following in the subsequent year. Industries are defined following the Fama-French 30 industry classification. Standard errors are clustered by firm. T-statistics are in parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively. Appendix A provides the variable definitions.

Table 4: Quantitative Ownership and Outputs of Analyst Forecasts

	(1) *Dimension*	(2) *Dimension*	(3) *Accuracy*	(4) *Accuracy*
Quant	-1.027***	-0.944***	-0.008**	-0.008*
	(-3.78)	(-3.15)	(-2.09)	(-1.93)
Size	0.278***	0.269***	0.007***	0.007***
	(7.87)	(6.61)	(9.21)	(8.76)
InstOwnership	-0.106	-0.256*	0.003*	0.002
	(-0.93)	(-1.89)	(1.89)	(1.27)
AdvExp	1.553	1.900	0.051***	0.048***
	(1.11)	(1.20)	(3.73)	(3.38)
RDExp	-0.418	0.121	-0.000	0.004
	(-0.75)	(0.18)	(-0.04)	(0.66)
Growth	-0.041	0.060	-0.000	-0.000
	(-0.75)	(0.94)	(-0.15)	(-0.18)
Segment	0.017	0.017	-0.000	-0.000
	(1.43)	(1.32)	(-0.61)	(-0.55)
Std_Ret	-0.854**	-1.343***	-0.008	-0.008
	(-2.07)	(-3.02)	(-1.22)	(-1.18)
MFownership	0.797***	0.979***	-0.005	-0.002
	(3.43)	(3.76)	(-1.57)	(-0.70)
AlgoTrading	-0.071***	-0.092***	-0.001***	-0.001***
	(-2.68)	(-2.84)	(-2.93)	(-2.73)
Estimize	0.025	0.027	-0.000	-0.000
	(0.78)	(0.79)	(-0.75)	(-0.79)
Observations	174,602	162,012	124,357	111,696
Adj R-Squared	0.41	0.38	0.48	0.44
Fixed Effects	Analyst, Firm, Ind-Year	Analyst-Firm, Ind-Year	Analyst, Firm, Ind-Year	Analyst-Firm, Ind-Year

This table reports the regression results of the relation between quantitative ownership and outputs of analysts in the following year. Columns (1) and (2) report the relation between quantitative ownership and the number of dimensions forecasted by an analyst, and columns (3) and (4) report the relation between quantitative ownership and forecast accuracy. Industries are defined following the Fama-French 30 industry classification. Standard errors are clustered by firms. T-statistics are in parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively. Appendix A provides the variable definitions.

Table 5: Quantitative Ownership and Information Content of Analyst Forecasts

	(1) *1-Day Return*	(2) *1-Day Return*	(3) *Dispersion*	(4) *Dispersion*
Quant	-0.020**	-0.018**	0.010**	0.011**
	(-2.51)	(-2.34)	(1.98)	(2.20)
Size	0.026***	0.026***	-0.006***	-0.005***
	(17.68)	(18.19)	(-5.97)	(-5.15)
InstOwnership	0.007*	0.005	-0.003	-0.005**
	(1.65)	(1.37)	(-1.41)	(-2.02)
AdvExp	0.038	0.026	-0.037**	-0.051***
	(0.75)	(0.50)	(-2.30)	(-2.69)
RDExp	0.011	0.011	0.006	0.010
	(0.54)	(0.58)	(0.80)	(1.41)
Growth	0.007***	0.005*	0.002	0.002
	(2.61)	(1.95)	(1.31)	(1.02)
Segment	0.001	0.001	0.000	0.000
	(1.16)	(0.95)	(0.56)	(1.17)
Std_Ret	-0.079***	-0.063***	0.011	0.013
	(-5.86)	(-4.67)	(1.19)	(1.36)
MFOwnership	0.010	0.011	0.012**	0.012**
	(1.22)	(1.48)	(2.18)	(2.32)
AlgoTrading	0.000	0.001	0.001	0.001**
	(0.24)	(0.91)	(1.16)	(2.28)
Estimize	0.000	-0.001	0.000	0.000
	(0.05)	(-0.62)	(0.37)	(0.40)
Observations	12,390	12,357	7,079	7,054
Adj R-square	0.87	0.88	0.30	0.33
Fixed Effects	Firm, Year	Firm, Ind-Year	Firm, Year	Firm, Ind-Year

This table reports the regression results of the relation between quantitative ownership and the information content of analyst forecasts in the following year. Columns (1) and (2) report the relation between quantitative ownership and the 1-day market reaction to analyst revisions, and columns (3) and (4) report the relation between quantitative ownership and forecast dispersion. Industries are defined following the Fama-French 30 industry classification. Standard errors are clustered by firms. T-statistics are in parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively. Appendix A provides the variable definitions.

Table 6: Entropy Balancing

Panel A: Analyst Following

	(1) **No Entropy Balancing**	(2) **Entropy Balancing**
	AnalystFollowing	*AnalystFollowing*
High Quant	-0.512***	-0.470***
	(-5.72)	(-5.29)
Size	1.708***	1.682***
	(15.04)	(13.77)
InstOwnership	-0.192	-0.273
	(-0.48)	(-0.64)
AdvExp	0.631	1.402
	(0.16)	(0.35)
RDExp	1.095	1.479
	(0.64)	(0.83)
Growth	0.407**	0.524**
	(2.29)	(2.47)
Segment	0.054	0.060
	(1.15)	(1.25)
Std_Ret	-3.207***	-3.074***
	(-3.32)	(-2.98)
MFOwnership	5.090***	5.416***
	(6.30)	(6.56)
AlgoTrading	0.022	0.043
	(0.31)	(0.61)
Estimize	0.167*	0.242***
	(1.72)	(2.59)
Observations	14,178	14,178
Adj R-Squared	0.90	0.89
Fixed Effects	Firm, Year	Firm, Year

Panel B: Analyst Outputs

	(1) **No Entropy Balancing** *Dimension*	(2) **Entropy Balancing** *Dimension*	(3) **No Entropy Balancing** *Accuracy*	(4) **Entropy Balancing** *Accuracy*
High Quant	-0.050**	-0.065***	-0.001**	-0.001***
	(-2.30)	(-2.82)	(-2.21)	(-2.70)
Size	0.066***	0.069***	0.006***	0.007***
	(2.75)	(2.69)	(6.97)	(6.48)
InstOwnership	0.137*	0.135*	0.003*	0.004*
	(1.80)	(1.68)	(1.69)	(1.88)
AdvExp	0.803	1.306	0.030**	0.029*
	(0.87)	(1.32)	(2.10)	(1.93)
RDExp	0.362	0.640	-0.007	0.006
	(0.90)	(1.16)	(-0.62)	(0.22)
Growth	-0.009	0.002	-0.001	-0.001
	(-0.23)	(0.04)	(-0.64)	(-0.70)
Segment	0.018*	0.019	-0.000	-0.000
	(1.70)	(1.63)	(-0.93)	(-0.90)
Std_Ret	-0.072	-0.044	-0.013	-0.010
	(-0.29)	(-0.17)	(-1.64)	(-1.25)
MFOwnership	0.162	0.103	-0.007	-0.010**
	(1.11)	(0.69)	(-1.52)	(-1.98)
AlgoTrading	0.018	0.022	-0.000	-0.000
	(0.84)	(0.91)	(-0.82)	(-0.95)
Estimize	-0.056**	-0.053*	-0.000	0.000
	(-2.21)	(-1.90)	(-0.29)	(0.13)
Observations	12,344	12,344	8,052	8,052
Adj R-Squared	0.68	0.69	0.34	0.35
Fixed Effects	Firm, Year	Firm, Year	Firm, Year	Firm, Year

Panel C: Information Content of Analyst Forecasts

	(1) **No Entropy Balancing**	(2) **Entropy Balancing**	(3) **No Entropy Balancing**	(4) **Entropy Balancing**
	1-Day Return	*1-Day Return*	*Dispersion*	*Dispersion*
High Quant	-0.003**	-0.003**	0.001	0.001
	(-2.56)	(-2.33)	(1.37)	(1.52)
Size	0.026***	0.028***	-0.006***	-0.006***
	(17.67)	(16.44)	(-5.98)	(-5.07)
InstOwnership	0.007	0.003	-0.003	-0.004
	(1.59)	(0.73)	(-1.37)	(-1.48)
AdvExp	0.038	0.022	-0.038**	-0.032**
	(0.75)	(0.38)	(-2.32)	(-1.97)
RDExp	0.010	0.028	0.006	0.014
	(0.52)	(1.30)	(0.76)	(1.14)
Growth	0.006**	0.006*	0.002	0.002
	(2.40)	(1.96)	(1.38)	(1.14)
Segment	0.001	0.000	0.000	-0.000
	(1.16)	(0.80)	(0.59)	(-0.46)
Std_Ret	-0.079***	-0.081***	0.011	0.012
	(-5.91)	(-5.35)	(1.21)	(1.14)
MFOwnership	0.010	0.020**	0.011**	0.012*
	(1.25)	(2.30)	(2.05)	(1.95)
AlgoTrading	0.000	0.001	0.001	0.001
	(0.23)	(0.60)	(1.16)	(0.81)
Estimize	0.000	-0.000	0.000	0.000
	(0.08)	(-0.06)	(0.37)	(0.57)
Observations	12,390	12,390	7,079	7,079
Adj R-Squared	0.87	0.86	0.30	0.29
Fixed Effects	Firm, Year	Firm, Year	Firm, Year	Firm, Year

This table presents the regression analyses of the relation between quantitative ownership and analysts' information production with and without the entropy balanced sample. Industries are defined following the Fama-French 30 industry classification. Standard errors are clustered by firm. T-statistics are in parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively. Appendix A provides the variable definitions.

Table 7: Propensity Score Matching

Panel A: Univariate Comparison of Control Variables after Matching

	(1)	(2)	(3)	
	Low Quant	***High Quant***	***Difference***	
	Mean	Mean	Diff.	t-Statistics
Size	8.088	8.107	-0.019	(-0.4)
InstOwnership	0.732	0.731	0.001	(0.2)
AdvExp	0.013	0.014	-0.001	(-0.9)
RDExp	0.036	0.040	-0.003	(-1.15)
Growth	1.092	1.085	0.007	(1.00)
Segment	2.662	2.684	-0.023	(-0.35)
Std_Ret	0.086	0.085	0.001	(0.85)
MFOwnership	0.384	0.379	0.006	(1.45)
AlgoTrading	-0.038	-0.071	0.033	(1)
Estimize	0.549	0.528	0.021	(1.3)

Panel B: Univariate Comparison of Analysts' Information Production after Matching

	(1)	(2)	(3)	
	Low Quant	***High Quant***	***Difference***	
	Mean	Mean	Diff.	t-Statistics
AnalystFollowing	16.266	14.229	2.037***	(8.05)
Dimension	4.797	4.694	0.103***	(3.85)
Accuracy	-0.005	-0.006	0.001**	(3.10)
1-Day Return	0.190	0.180	0.010**	(3.25)
Dispersion	0.005	0.005	-0.001**	(-2.10)

This table reports the matched sample results of univariate comparisons between quantitative ownership and characteristics of analysts' information production in the following year. I define matched pairs by propensity score matching based on the control variables and industry fixed effects. I use the top 2,000 matched pairs for the analysis. Panel A presents the comparison of control variables after matching. Panel B presents the comparison of analysts' information production variables after matching. Column (1) presents the statistics for observations with below-median quantitative ownership. Column (2) presents the statistics for observations with above-median quantitative ownership. Column (3) reports the difference and t-statistics of the pairwise t-test of means across columns (1) and (2). *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively. Appendix A provides the variable definitions.

Table 8: Institutional Investors' Information Acquisition

	(1) *InstitutionInfoAcq*	(2) *InstitutionInfoAcq*
Quant	-0.032*	-0.034*
	(-1.83)	(-1.96)
Size	0.030***	0.028***
	(12.01)	(10.60)
InstOwnership	0.043***	0.041***
	(4.49)	(4.30)
AdvExp	0.087	0.110
	(0.75)	(0.96)
RDExp	0.156***	0.137***
	(3.41)	(3.03)
Growth	0.001	-0.001
	(0.11)	(-0.14)
Segment	0.002	0.002*
	(1.42)	(1.69)
Std_Ret	0.079***	0.070**
	(2.71)	(2.39)
MFOwnership	0.023	0.001
	(1.39)	(0.05)
AlgoTrading	0.003	0.007***
	(1.48)	(3.28)
Estimize	-0.001	-0.000
	(-0.18)	(-0.07)
Observations	9,640	9,617
Adj R-square	0.91	0.92
Fixed effects	Firm, Year	Firm, Ind-Year

This table reports the regression results of the relation between quantitative ownership and institutional information acquisition through the Bloomberg terminals in the following year. *InstitutionInfoAcq* is a measure of corporate news reading and searching frequency on the Bloomberg terminals. Industries are defined following the Fama-French 30 industry classification. Standard errors are clustered by firm. T-statistics are in parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively. Appendix A provides the variable definitions.

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Appendix A. Variable Definitions

Variable	Definition
Ownership Measures	
Quant	Number of shares of a firm held by quantitative mutual funds and ETFs, divided by the number of shares held by all U.S. equity mutual funds and ETFs.
QuantMiscdt	Number of shares held by quantitative mutual funds and ETFs with at least one case of advisory misconduct, scaled by the number of shares held by all U.S. equity mutual funds and ETFs.
Fund Characteristics	
Total Net Assets (MM)	Total assets under management, measured in millions of dollars.
Expense Ratio	The expense ratio as of the fiscal year-end.
Management Fee (%)	Percentage management fee. Negative values are dropped.
Fund Turnover Ratio	Minimum of total sales or purchases of securities scaled by the 12-month average total net assets.
Avg $ Invested in Each Stock(MM)	Market value of total equity holdings divided by the number of stocks owned by a fund, measured in millions of dollars.
Stability of Holdings (%)	Percentage of investment in stocks that are held longer than 2 years.
Association between Fund Portfolio Changes and Analyst Recommendations	Unadjusted R^2 from regressing the change in fund holdings on the change in analysts' recommendations for each fund in each quarter. Specifically, the following model is estimated: $\Delta Holdings_{i,t} = \beta_1 \Delta Recommendation_{i,t-1} + \beta_2 \Delta Recommendation_{i,t-2} + \beta_3 \Delta Recommendation_{i,t-3} + \beta_4 \Delta Recommendation_{i,t-4} + \epsilon$
Outcome Variables	
AnalystFollowing	Number of analysts issuing one-year ahead annual EPS forecasts in a year.
Dimension	The number of dimensions forecasted by an analyst. Items are aggregated into the following dimensions: (1) Book Value Per Share, Enterprise Value, Net Asset Value (2) Cash Flow Per Share, Cash Earnings Per Share, Funds from Operations (3) Capital Expenditures (4) Dividend Per Share (5) Earnings Per Share - Before Goodwill, Earnings Per Share - Alternate, GAAP/Earnings Per Share - Fully Reported, Net Income, Operating Profit, Pre-tax Profit, EBIT, EBITDA Per Share, EBITDA (6) Net Debt (7) Revenue (8) Return on Assets, Return on Equity, Gross Margin
Accuracy	Minus one times the absolute difference between actual annual EPS and analyst's EPS forecast made during a 90-day window before the annual earnings announcement for the fiscal year-end, scaled by the stock price 90 days before the earnings announcement.
1-Day Return	The sum of one-day absolute size-adjusted returns on the analyst forecast revision days scaled by the sum of one-day absolute size-adjusted returns over the year. The size-adjusted returns are based on CRSP daily size decile portfolios.
Dispersion	Standard deviation of annual earnings forecasts made during a 90-day window before the earnings announcement for the fiscal year-end. It is scaled by the stock price 90 days before the earnings announcement.
InstitutionInfoAcq	The news heat index from Bloomberg. The index is based on news searching and reading frequency on Bloomberg Terminals.

Control Variables	
Size	Natural logarithm of market value of equity at the fiscal year end.
InstOwnership	Number of shares held by institutional investors scaled by total shares outstanding at the year-end.
Std_Ret	Standard deviation of monthly stock returns in a year.
AdvExp	Advertising expenses (Compustat item xad), scaled by operating expenses (Compustat item xopr). Missing xad is replaced by zero.
RDExp	R&D investment (Compustat item xrd), scaled by operating expenses. Missing xrd is replaced by zero.
Growth	Average sales growth rate over the prior 3-5 years.
Segment	Number of business segments. Missing values are replaced by one.
MFOwnership	Number of shares held by mutual funds and ETFs scaled by total shares outstanding at the year-end.
AlgoTrading	The first principal component of the odd lot volume ratio, the trade-to-order volume ratio, the cancel-to-trade ratio, and the average trade size (Weller 2018). The value in 2011 is assigned to be the value in 2012. Missing value is replaced by the industry average, with industry defined by Fama-French 30 industry classification.
Estimize	An indicator variable that equals one if a firm has Estimize coverage in the year, and zero otherwise. Missing values are replaced by zero.

Appendix B. Principal Investment Strategies Disclosures

Quantitative Funds

Some excerpts of investment styles of quantitative funds are extracted from "Principal Investment Strategies" section of their Form N1-A and provided below.

Example 1: AQR Large Cap Momentum Style Fund

The Fund pursues a momentum investment style by investing primarily in equity or equity-related securities (including, but not limited to, exchange-traded funds, equity index futures, and depositary receipts) of large-cap companies traded on a principal U.S. exchange or over-the-counter market that the Adviser determines to have positive momentum. The Adviser considers a security to have positive momentum primarily if it has outperformed other securities on a relative basis over a recent time period. Relative performance may be based on price momentum, earnings momentum, or other types of momentum, and will generally be measured over time periods ranging from one to twelve months. The criteria the Adviser uses for determining positive momentum may change from time to time.

The Adviser determines the weight of each security in the portfolio using a combination of the market capitalization of the security and the Adviser's determination of the attractiveness of the security based on the Adviser's assessment of the security's momentum and additional criteria that form part of the Adviser's security selection process.

Example 2: Allianz Funds: AGIC Mid-Cap Growth Fund

The portfolio managers use a growth-oriented, dynamic quantitative process combined with a fundamentals-based, actively-managed security selection process to make individual security and industry sector selection decisions. The investment philosophy is focused on investing in companies undergoing positive change with sustainable growth characteristics and timely market recognition will result in outperformance. The process is built upon a proprietary multi-factor model that analyzes securities in the investment universe. This multi-factor model employs an array of criteria to make these stock selection recommendations. The team qualitatively reviews each of the model's investment recommendations to determine suitability. The integrated relationship between research and portfolio management combines the latest research from the academic and investment management community with real-world portfolio management experience to maximize excess return opportunities within a risk-controlled framework. The approach is quantitative in nature, therefore the majority of research conducted is model research to improve current or develop new factors to enhance the quantitative model's stock-selection capabilities. The portfolio managers consider whether to sell a particular security when any of the model's multi-factors materially change or when a more attractive total return candidate is identified.

Example 3: Goldman Sachs ActiveBeta US Small Cap Equity ETF

The Index is designed to deliver exposure to equity securities of small capitalization U.S. issuers. The Index is constructed using the patented ActiveBeta® Portfolio Construction Methodology, which was developed to provide exposure to the factors (or characteristics) that are commonly tied to a stock's outperformance relative to market returns. These factors include value (i.e., how attractively a stock is priced relative to its fundamentals, such as book value and free cash flow), momentum (i.e., whether a company's share price is trending up or down), quality (i.e., profitability) and low volatility (i.e., a relatively low degree of fluctuation in a company's share price over time). Given the Fund's investment objective of attempting to track its Index, the Fund does not follow traditional methods of active investment management, which may involve buying and selling securities based upon analysis of economic and market factors.

Goldman Sachs Asset Management, L.P. (the "Index Provider") constructs the Index in accordance with a rules-based methodology that involves two steps.

Step 1

In the first step, individual factor subindexes for value, momentum, quality and low volatility (the ActiveBeta® Factor Subindexes") are created from the constituents of the Russell 2000® Index (the "Reference Index"), a market capitalization-weighted index. To construct each ActiveBeta® Factor Subindex, all constituents in the Reference Index are assigned a "factor score" based on certain specified measurements (for example, in the case of the value factor, the factor score is based on a composite of book value-to-price, sales-to-price and free cash flow-to-price). Securities with a factor score that is above a fixed "Cut-off Score" receive an overweight in the applicable ActiveBeta® Factor Subindex relative to the Reference Index and securities with a factor score that is below the Cut-off Score receive an underweight in the ActiveBeta® Factor Subindex relative to the Reference Index. Accordingly, the magnitude of overweight or underweight that a security receives in constructing the applicable ActiveBeta® Factor Subindex is determined by its attractiveness when evaluated based on the relevant factor. The Index only includes long positions (i.e., short positions are impermissible), so the smallest weight for any given security is zero.

Step 2

The ActiveBeta® Factor Subindexes are combined in equal weights to form the Index.

Traditional Funds

Example: AMCAP Fund

The investment adviser uses a system of multiple portfolio managers in managing the fund's assets. Under this approach, the portfolio of the fund is divided into segments managed by individual managers who decide how their respective segments will be invested. The fund relies on the professional judgment of its investment adviser to make decisions about the fund's portfolio investments. The basic investment philosophy of the investment adviser is to seek to invest in attractively valued companies that, in its opinion, represent good, long-term investment opportunities. The investment adviser believes that an important way to accomplish this is through fundamental analysis, which may include meeting with company executives and employees, suppliers, customers and competitors. Securities may be sold when the investment adviser believes that they no longer represent relatively attractive investment opportunities.

Appendix C: First Stage of IV Regression - Advisory Misconduct

	(1) Δ*Quant*	(2) Δ*Quant*
QuantMiscdt	-0.010***	-0.010***
	(-3.09)	(-2.98)
Δ*Size*	-0.005**	-0.005**
	(-2.54)	(-2.20)
Δ*InstOwnership*	0.001	-0.001
	(0.23)	(-0.18)
Δ*AdvExp*	-0.102	-0.105
	(-0.95)	(-0.95)
Δ*RDExp*	-0.102*	-0.101*
	(-1.89)	(-1.86)
Δ*Growth*	0.004	0.004
	(1.43)	(1.19)
Δ*Segment*	-0.001	-0.000
	(-0.75)	(-0.46)
Δ*Std_Ret*	0.025	0.023
	(1.51)	(1.30)
Δ*MFOwnership*	-0.061***	-0.059***
	(-7.17)	(-6.90)
Δ*AlgoTrading*	-0.002	-0.002
	(-1.26)	(-1.34)
Δ*Estimize*	0.007***	0.008***
	(3.92)	(4.20)
Observations	9,105	9,084
R-square	0.02	0.04
Fixed Effects	Year	Ind-Year

This table reports the regression results of the relation between ownership that is affected by quantitative mutual fund advisory misconduct (IV) and the lead change in quantitative ownership. Industries are defined following the Fama-French 30 industry classification. Standard errors are clustered by firm. T-statistics are in parentheses. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively. Appendix A provides the variable definitions.

Appendix D: Covariate Balance Before and After Entropy Balancing

Panel A: Means *Before* Entropy Balancing

	High Quant	***Low Quant***	***Difference in Means***	***p-value***
	(1)	(2)	(3)	(4)
Size	7.193	7.146	0.047	0.140
InstOwnership	0.663	0.645	0.019***	0.000
AdvExp	0.013	0.015	-0.002***	0.000
RDExp	0.039	0.055	-0.016***	0.000
Growth	1.077	1.091	-0.015***	0.000
Segment	2.599	2.338	0.261***	0.000
Std_Ret	0.093	0.090	0.003**	0.001
MFOwnership	0.334	0.329	0.005	0.058
Algorithmic Trading	-0.231	-0.206	-0.025	0.193
Estimize	0.435	0.384	0.052***	0.000

Panel B: Means *After* Entropy Balancing

	High Quant	***Low Quant***	***Difference in Means***	***p-value***
	(1)	(2)	(3)	(4)
Size	7.193	7.192	0.001	0.987
InstOwnership	0.663	0.663	0.000	0.989
AdvExp	0.013	0.013	0.000	0.997
RDExp	0.039	0.039	0.000	0.997
Growth	1.077	1.077	0.000	0.987
Segment	2.599	2.599	0.000	0.994
Std_Ret	0.093	0.093	0.000	0.992
MFOwnership	0.334	0.334	0.000	0.989
Algorithmic Trading	-0.231	-0.231	0.000	0.999
Estimize	0.435	0.435	0.000	0.995

This appendix shows the variable means of control variables before and after entropy balancing for observations with high quantitative ownership (*High Quant*) in column (1) and low quantitative ownership (*Low Quant*) in column (2). Column (3) shows the difference between columns (1) and (2), and column (4) shows the p-value from a t-test of the difference between columns (1) and (2). Panel A shows the summary statistics *before* entropy balancing, and Panel B shows the summary statistics *after* entropy balancing. *, **, and *** indicate significance at the 0.1, 0.05, and 0.01 levels, respectively.