New Accounting Standards and the Performance of Quantitative Investors*

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November 2021

Abstract
Quantitative investing relies on historical data and limited day-to-day human involvement, which could create short-term inflexibility in the face of changing economic conditions. In this study, we examine quantitative investors' ability to navigate a common and occasionally material change to the financial data generating process: new accounting standards. We find that returns of quantitative mutual funds temporarily decrease following the implementation of standards that change the definition of key accounting variables. The lower performance we document is relative to more traditional "discretionary" funds that rely heavily on human discretion to make investment decisions. Our result is stronger for value funds, which rely heavily on accounting data, and absent among funds slanted towards price-based strategies, including momentum and size. When we further investigate funds' operations, we observe excess portfolio turnover following the implementation of accounting standards. Relatedly, quantitative underperformance is concentrated among funds holding more stocks. Overall, our results highlight a significant adjustment cost associated with accounting regulation that could become even more significant as more investors turn to quantitative strategies.

*We are grateful for helpful comments from Inna Abramova, Sanjeev Bhojraj, Mark Bradshaw, Will Cong, Byoung-Hyoun Hwang, Jinhwan Kim, Hai Lu, Brian Monsen, Suzie Noh, Eric So, Lorien Stice-Lawrence, Baohua Xin, Eric Yeung, and Christina Zhu, as well as seminar participants at the University of Amsterdam, Bocconi University, Boston College, Cornell University, the BYU Accounting Research Symposium, and the Early Insights in Accounting Webinar. We also thank Chris Meredith of O'Shaughnessy Asset Management and Cornell University for helpful discussions about quantitative investing.

"The [AQR Large Cap Multi-Style] fund is unlikely to be successful unless the assumptions underlying the models are realistic and *either remain realistic and relevant in the future or are adjusted to account for changes in the overall market environment*. If such assumptions are inaccurate or become inaccurate and are not promptly adjusted, it is likely that profitable trading signals will not be generated, and major losses may result." (emphasis added)

"Because predictive models are usually constructed based on historical data supplied by third parties, the success of relying on such models may depend heavily on the accuracy and reliability of the supplied historical data."

-AQR Capital Management, 2019 Prospectus

I. INTRODUCTION

In recent years, many investment fund managers have adopted a more quantitative approach to investing as technological advances have increased the availability of economic data, computing power, and analytical software. These technologies facilitate systematic, rules-based strategies that arguably allow for more objective decision-making. However, quantitative funds still only manage a fraction of U.S. equity capital (e.g., roughly 20-30%, according to Harvey, Rattray, Sinclair, and Van Hemert, 2017, and Abis, 2020). Indeed, many market participants remain skeptical of quantitative funds, in large part due to their heavy reliance on past data (Harvey et al., 2017). Of course, such reliance depends on the integrity of the underlying data sources, including a stable data generating process (see, e.g., Ghysels, 1998, and Narang, 2013, pgs. 180-184). In this study, we examine quantitative investing in the context of a common and occasionally material change to the financial data generating process: new accounting standards.

Many popular trading strategies are based on firms' accounting data, such as book values and earnings. For example, quantitative traders typically use backtesting, which involves searching for accounting and other variables, often referred to as "signals," that have historically been correlated with firm value as measured by returns. Trading strategies (or rules) are then formed based on these signals in expectation that historical correlations will continue and trading profits will ensue. In practice, the strategies are programmed into computers that implement trades with human oversight but little or no daily human interaction.

Of course, accounting numbers are governed by regulation and, to a certain extent, by firms' own discretion in selecting accounting procedures. Changes to standards occasionally alter firms' financial accounting procedures (e.g., by including a previously unrecognized transaction), creating time-series variation in accounting numbers that is not due to changes in underlying economics. Thus, users of accounting data are faced with the challenge of determining whether variation reflects real economic factors or accounting factors. In the words of Ball (1972), this raises the concern that if "investors are uninformed of the intricacies of accounting, then they cannot distinguish the real and the accounting influences. Therefore the market might react to each in a like fashion."

There are at least two plausible reasons that quantitative funds could fail to "distinguish the real and the accounting influences," or in other words, appropriately update their models in response to new accounting standards. First, without real-time human intervention, the computer systems underlying quantitative trading have limited ability to recognize that new observations of the same accounting variable may include different economic transactions (Pedersen, 2015, p. 11). Second, even if quantitative funds are aware of accounting standard changes, their reliance on backtesting using data calculated under old accounting rules may temporarily inhibit their ability to update their model's decision-making criteria until sufficient new observations become available. Consistent with this reasoning, we expect and find that quantitative funds' performance decreases after major changes in accounting standards. However, one may have expected the opposite given that standard setters often claim their pronouncements will create more precise and informative accounting numbers (see the examples we provide in Section 2.2).

In examining the effect of changing accounting standards, we contrast quantitative strategies with the more traditional "discretionary" approach. Discretionary investors rely more on human skill and judgment to make day-to-day investment decisions. While this human element may make them more susceptible to behavioral biases such as overconfidence (Odean, 1998), it also makes them inherently more flexible than quantitative managers (Khandani and Lo, 2011; Abis, 2020). In addition, discretionary traders typically analyze a limited number of stocks because their tailored approach is so labor-intensive (Pedersen, 2015). Thus, they tend to closely follow firm-specific events (e.g., earnings announcements and 10-K filings), making them more likely to notice and adapt to any changes to the accounting policies underlying firms' financial statements. Note that while we focus conceptually on model flexibility, which seems particularly relevant when considering a fund's ability to respond to changing accounting rules, we recognize that there are many other differences between the quantitative and discretionary approaches. For example, Harvey et al. (2017) list several common concerns investors express about quantitative funds besides their overreliance on past data, including their homogeneity, complexity, and opacity.

Before discussing our results in detail, we acknowledge that the quantitative and discretionary approaches are not entirely mutually exclusive, preventing a simple binary classification of funds. Thus, we follow recent studies that use textual analysis to identify quantitative words and phrases in mutual funds' regulatory filings (e.g., Beggs, Brogaard, and Hill-Kleespie, 2021; Abis, 2020). Doing so allows us to separate the funds that are most likely to use intensive quantitative methods from those that rely more heavily on human discretion. Consistent with prior studies documenting the rise of quantitative investing, we observe that mutual funds are increasingly likely to describe their investment strategies as quantitative during our sample period (see, e.g., Figure 3). To further validate our classification methodology, we follow Abis (2020), a recent study using a related classification based on machine learning, by documenting that quantitative funds are younger and smaller, charge lower fees, and have higher portfolio turnover.

Our main analyses exploit three recent U.S. standards affecting the accounting for pensions (2006), noncontrolling interests (2008), and leases (2018). Crucially, each of these standards materially affected balance sheet numbers that form the basis of many quantitative (and discretionary) investors' trading decisions.[1] To be specific, two of the standards (pensions and leases) required firms to transition (i.e., recognize) accounting values that were previously disclosed in the footnotes onto the balance sheet (for related reading on disclosure vs. recognition see, e.g., Landsman, 1986; Barth, 1991; Schipper, 2007; Müller et al., 2015). In the third case, noncontrolling interests (NCI) were required to be recognized in the equity section of the balance sheet, whereas firms previously could report NCI in either the liability or "mezzanine" sections.

Our main result is that quantitative fund returns decline significantly relative to discretionary fund returns in the year following each of the three standards. On an annual basis, this underperformance translates to almost 3%, or about 25% of the average fund's unconditional annual return (of 11%). This evidence is consistent with revisions to accounting regulation creating incremental adjustment costs for quantitative investors, whose models appear unable to fully adapt to new accounting conventions on a timely basis.

Of course, not all investors are equally likely to use accounting data and, as a result, be affected by changing standards. Balance sheet data are a particularly critical ingredient of the value strategy that is so prevalent among fund managers (e.g., in our sample, 22% of fund names include

[1] For example, Cong, Tang, Wang, and Zhang (2020) develop a quantitative investing model (which they call "AlphaPortfolio") based on state-of-the-art machine learning techniques. Of the 51 firm-specific variables used as inputs in their model, 27 are calculated using balance sheet numbers. While the standards also affected the income statement, statement of cash flows, and footnotes, we focus on balance sheet effects because of their observed prominence in investors' strategies, and also for parsimony.

the word “value”). For example, in discussing Graham and Dodd’s *Security Analysis*, which laid the foundation for modern value investing, Greenwald (2009) notes, “The special importance that Graham and Dodd placed on *balance sheet valuations* remains one of their most important contributions to the idea of what constitutes a ‘thorough’ analysis of intrinsic value” (emphasis added). Thus, our next analysis focuses on value investors, who we expect to be among the most likely to be impacted by changing accounting standards. We attempt to identify value investors by estimating each fund’s exposure to the book-to-market ratio, variants of which are commonly used to sort value vs. growth firms. Consistent with our expectations, we find evidence that quantitative underperformance is stronger among funds slanted towards high book-to-market stocks.

We next examine momentum and size in a falsification test. Because these strategies are based on stock prices, they are not as directly affected by accounting regulations. As a result, a momentum or size component in quantitative funds’ models likely does not need to be updated due to changing accounting standards. Thus, we expect to find no new differences between quantitative and discretionary funds with high momentum or size exposure following the implementation of new standards. Our findings are consistent with this prediction, which helps rule out alternative explanations for our results, including unobserved differences such as quantitative and discretionary funds facing heterogeneous shocks around the time of the standards.

To better understand the mechanism through which quantitative funds’ performance deteriorates, we investigate changes in observable firm operations. If changes in accounting treatment result in incremental (and potentially unnecessary) trading by quantitative investors, portfolio turnover and transaction costs would increase, thereby decreasing fund returns. Consistent with this explanation, we find evidence of increased portfolio turnover for quantitative investors following changes in accounting standards. Relatedly, we find that quantitative funds’ underperformance is concentrated among funds with a large number of portfolio positions. Intuitively, funds holding more stocks likely face higher portfolio adjustment costs (i.e., turnover) when updating models and position sizes. In addition to turnover-based explanations, we also examine whether funds reduce their reliance on accounting-based (i.e., book-to-market) signals in favor of price-based (i.e., momentum or size) signals. However, there is little evidence that funds change their investment approach in response to changing accounting standards.

Finally, a key component of our conceptual story is that quantitative funds are less flexible, or in other words, take longer to adjust to changing market conditions because they rely on backtesting. If this is the case, the underperformance of quantitative investors likely disappears gradually as they calibrate their models to account for new definitions and calculations of accounting variables. As predicted, the underperformance is substantial during the first year following the standards, but nonexistent in the second year. Similarly, the excess turnover we document only lasts for one year following the standards' implementation.

Our paper contributes to the burgeoning literature on the rise of quantitative investing. As noted previously, common concerns about quantitative funds include that they are homogeneous, complex, and opaque, and that their investing process relies on past data (Harvey et al., 2017). To date, much of the empirical evidence regarding these funds (e.g., Khandani and Lo, 2011; Beggs et al., 2021; Abis, 2020) focuses on the adverse effects of quantitative funds following similar strategies (i.e., "overcrowding"). Our paper complements this prior research by providing evidence about a different cost of quantitative investing. Specifically, compared to more traditional discretionary strategies, rules-based strategies using algorithms and backtesting appear to lack flexibility and be less timely in adjusting to changing accounting policies.

Our results also inform the vast literature on the determinants and consequences of accounting regulations (see Leuz and Wysocki, 2016). While regulators often explicitly account for *firms'* preparation and adjustment costs resulting from changing standards, our research suggests that such changes also impose costs on other market participants. In particular, the performance of quantitative investors appears to deteriorate temporarily because it takes some time to adjust trading models, datasets, and strategies in response to new standards. Awareness of these adjustment costs facing capital market participants should be useful to academics, practitioners, and accounting policy makers alike, especially if the recent trend towards quantitative investing continues. Moreover, our evidence on the costs of *major* accounting standards for quantitative shareholders complements research by Khan, Li, Rajgopal, and Venkatachalam (2018) that suggests the *typical* accounting standard does not add shareholder value.

Relatedly, our paper revisits and updates the age-old debate among accounting academics about how efficiently market participants react to changes in accounting techniques (see, e.g., Ball, 1972, and the several related papers discussed therein). While evidence in Ball (1972) and other early capital markets research in accounting suggests changes in accounting techniques do not mislead the market on average, our evidence suggests this inference does not extend to all investors at all times in the increasingly quantitative modern investing regime.

II. INSTITUTIONAL BACKGROUND AND HYPOTHESIS DEVELOPMENT

2.1 Quantitative Investment Funds

Quantitative funds are a large and growing player in the U.S. equity market. They account for 35% of U.S. stock market ownership, 60% of institutional equity assets under management, and 60% of trading volume (The Economist, 2019). Funds are typically classified as quantitative if they delegate some or all investment decision-making to computer models. These investors are often further divided into three groups based on trading frequency and model inputs: fundamental quants, statistical arbitrageurs, and high-frequency traders (Pedersen, 2015). Like the traditional discretionary funds, fundamental quants perform analyses using financial statement information, but they do so systematically with limits imposed on human judgment and oversight. Statistical arbitrageurs identify price discrepancies between similar stocks, such as dual-listed or twin stocks, and hope to profit when the prices level, typically within a few hours or days. High-frequency traders (HFT) invest heavily in engineering and information processing infrastructure (e.g., co-location with an exchange) to create a timing advantage over the rest of the market.

The heightened popularity of quantitative funds has attracted many researchers' attention in recent years. Of particular note, the evidence regarding whether quantitative funds perform better than discretionary funds has been mixed. Specifically, some prior studies find that quantitative small-cap (Ahmed and Nanda, 2005) and macro (Harvey et al., 2017) funds outperform discretionary funds focusing on the same investments. However, others observe that quantitative funds perform worse than discretionary funds (Gregory-Allen et al., 2009), especially during financial crises (Abis, 2020). There have also been debates about whether quantitative funds benefit the overall market. Weller (2018) argues that algorithmic trading results in lower information acquisition prior to earnings announcements, thus impeding price discovery. On the contrary, Birru, Gokkaya, and Liu (2019) find that sell-side analysts with a quantitative background issue higher quality recommendations, which reduces mispricing and improves market efficiency. Furthermore, HFT have been found to impound earnings information into prices (Bhattacharya et al., 2020), improve market liquidity, and enhance price efficiency (Hendershott et al., 2011; Brogaard et al., 2014).

Prior academic studies consider multiple potential explanations for quantitative funds' observed performance and market impact vis-à-vis discretionary funds. One of the most commonly cited benefits of quantitative approaches is their scalable and objective investment decision-making processes. Of course, a large body of research spanning multiple disciplines suggests that behavioral biases hurt investors' returns and that even professional investors do not always avoid common judgment fallacies. For example, human mutual fund managers suffer from the disposition effect, the tendency to sell winning stocks too early and hold losing stocks too long (Shefrin and Statman, 1985; Frazzini, 2006; Cici, 2012). By transacting based on the outputs of impartial computer models, quantitative funds can largely eschew such weaknesses. In fact, the disposition effect gradually decreased among mutual funds from 1980-2010, possibly due to the rise of quantitative funds (Wulfmeyer, 2016).

Of course, quantitative funds' operations are not without their own challenges. The *Quantmare* of August 2007 highlights one such challenge – overlapping strategies. Losses by large financial institutions forced many quantitative hedge funds to liquidate their positions simultaneously. Because so many quantitative funds relied on similar signals, the mass deleveraging caused a liquidity spiral in which many high (low) expected return stocks were sold (bought) to such an extent that a simulated quantitative strategy lost about 25% during a week in which the overall stock market was actually *up* 1.5% (Khandani and Lo, 2007 and 2011; Pedersen, 2009). Beggs et al. (2021) also highlight the risk of correlated trading strategies by providing large-scale evidence that fire sales by quantitative funds destabilize the market much more than fire sales by discretionary funds.

More relevant to this study, quantitative funds also face the risk that the statistical properties of economic data will change over time, which is often referred to as "regime change risk" (Narang, 2013). As Chan (2013) highlights, changes to a country's macroeconomic prospects, a company's management, or a financial market's structure could render patterns and strategies that were successful in the past inapplicable to the future. For example, the 2001 decimalization of U.S. stock markets directly impacted market liquidity in a way that benefitted HFTs and harmed statistical arbitrageurs (Chan, 2013). Similarly, funds betting that the consistent value-growth spread of 2003-2007 would continue were bitterly disappointed during the 2008 financial crisis (Narang, 2013). Many quantitative fund managers use modeling techniques, such as regime-shifting adaptive models, in attempts to mitigate this risk (Fabozzi et al., 2010). However, these studies highlight that quantitative investors cannot completely eliminate the risk because of their limited ability to predict changes to the market environment and adequately adjust their models as changes arise.

New accounting standards, which are the focus of this paper, are a significant type of regime change that could disrupt quantitative models. These standards often change disclosure and recognition requirements, including the location of information in the financial statements and the timing of recognizing economic transactions. These changes can result in past and new accounting data representing different underlying economics or having different relationships with market data. Consistent with this reasoning, Lee and Zhong (2021) provide evidence that changing accounting standards can impose additional processing costs on investors. Specifically, they find that investors use online platforms to ask Chinese firms for more clarification of financial statement information following the adoption of new accounting standards.

Failure to incorporate accounting changes into quantitative models that rely on accounting data would likely produce suboptimal investment choices. For example, excess trading could result from purely accounting effects if quantitative models conflate them with economic shocks (Ball, 1972). Thus, we predict that quantitative funds' performance initially suffers following accounting standard changes, especially among the quantitative funds that rely heavily on accounting inputs.

Anecdotal evidence supports this prediction, and suggests that quantitative investors make investment mistakes resulting from incorrect interpretations of accounting ratios. For example, Sloan (2019) observes that in 2016 quantitative funds were aggressively buying Big Five stock while traditional investors were selling. Sloan argues that the quants' purchases were improper because they resulted from several pitfalls, including (1) ignoring off-balance sheet operating leases, (2) not adjusting for the "old plant trap," and (3) ignoring the timing of inventory purchases. Relatedly, it is common practice for accounting and finance academics to ignore differences in accounting regimes when constructing quantitative models. For example, the machine-learning model in Cong et al. (2020) treats accounting variables, such as leverage and return on assets, the same before and after the recent lease standard. However, they are not alone in this. In fact, other than papers that specifically study regulation, we are not aware of any academic studies (including our own) that adjust variable definitions or functional forms to allow for changes to accounting regulations in their sample periods.

Despite the preceding discussion, we acknowledge that accounting changes could plausibly *enhance* quantitative performance. For example, quantitative forecasts may improve if the new accounting numbers (e.g., financial ratios) result in more precise signals of firm value. This increased precision would be consistent with standard-setters' arguments in support of the new standards we examine, as described in the next section. Thus, whether accounting regime changes hinder, improve, or do not change quantitative performance is ultimately an empirical question that we attempt to answer in this study.

2.2 Changes in Accounting Standards

In this study, we examine changes to accounting standards that significantly influenced firms' balance sheets. To identify our set of new accounting standards, we begin by considering the 74 exposure drafts for new accounting standards over the years 2004-2016 (Monsen, 2021). Evidence in Khan et al. (2018) suggests that many accounting standards are a non-event from investors' perspective (e.g., no stock market reaction). Thus, to identify the most material accounting changes, we further constrain the set of new accounting standards to the ten that received the highest number of constituent comments.[2] Since such a substantial proportion of investors' strategies (both discretionary and quantitative) are based on balance sheet numbers, we further constrain the set of new standards to those that directly impact the balance sheet. Accounting standards that merely require additional supplemental disclosure or only affect a few firms seem less likely to affect investors' trading strategies, which may partially explain the findings of Khan et al. (2018).[3] Lastly, in an attempt to hold the available firm information relatively constant, we constrain the list of accounting standards to those that primarily required firms to recognize accounting information that was previously disclosed. This process results in the selection of the following three new accounting standards: SFAS 158 (pension), SFAS 160/141R (noncontrolling interest), and ASC 842 (leases). Thus, we summarize the primary changes mandated by these accounting standards in this section, as well as in Figure 1.

Note that our discussion focuses on balance sheet numbers because of their observed prominence in investors' strategies (Cong et al., 2020), and also for parsimony. However, we recognize that the three selected standards also impacted several other parts of the financial

[2] We thank Brian Monsen for graciously sharing this data with us.

[3] To illustrate using recent standards, SFAS 161 merely required additional disclosure on derivative instruments and hedging activities. Besides not changing accounting procedures underlying the financial statements, this standard only applies to the subset of firms that use derivatives and hedging. Similarly, SFAS 163 affects the accounting for financial guarantee insurance contracts, which only applies to insurance companies (one of the 49 Fama-French industries).

statements to some extent, including the income statement and footnotes. The wide-reaching and complex impact of these accounting standards on various aspects of the financial statements actually works in our favor. That is, a central component of our argument is that such varied, nuanced, and intricate changes would be easier for a discretionary fund to identify and account for, relative to quantitative funds who rely on past data and search over more firms and variables. Additionally, while we are unaware of systematic retrospective disclosures for these new standards, we acknowledge the possibility that some firms may voluntarily report information for prior years under the new standards. Even if this does occur, backtesting would be problematic to the extent that retrospective application is inconsistent across firms (i.e., selection concerns). Thus, even retroactively applied standard changes could affect quantitative funds, at least in the short term, as we hypothesize in this paper.

2.2.1 Pensions

Both regulators and researchers have closely examined the value relevance and information quality of pension disclosures. Prior studies find that stock prices incorporate information about pension obligations and expenses (Barth, 1991; Barth et al., 1992), albeit not immediately (Landsman and Ohlson, 1990). Relatedly, Franzoni and Marin (2006) find that a portfolio created by taking long positions in overfunded companies and short positions in underfunded companies earns economically significant abnormal returns, suggesting investors overvalue underfunded firms. Thus, it appears that some investors may not pay enough attention to pension information disclosed in the footnotes, but completely process information recognized in the financial statements (Picconi, 2006).

In September 2006, the FASB released SFAS No. 158, which requires firms to recognize the overfunded (underfunded) status of their defined benefit postretirement plans as an asset (liability) in the balance sheet, with any changes to the funded status being recognized in comprehensive income.[4] Prior to this standard, information related to the funded status of retirement plans was disclosed in the footnotes and reconciled to the plan asset or liability in the financial statements. The FASB argued that the prior standards "failed to communicate the funded status of those plans in a complete and understandable way" (FASB, 2006), and that the new approach would result in more complete, timely, and understandable financial statements. Poor stock market performance due to the bursting of the tech bubble in the early 2000s led to significant decreases in pension plan asset values, which resulted in high aggregate underfunding (Franzoni and Marin, 2006). Thus, SFAS 158 required a significant number of firms to recognize liabilities on the balance sheet that were previously disclosed in the footnotes, thereby reducing the book value of their equity.

2.2.2 Noncontrolling Interests

SFAS 160 was issued by the FASB in December 2007, requiring *Minority Interest* to be renamed *Noncontrolling Interest* (NCI) and recognized in the equity section of the balance sheet. Previous standards left firms with considerable flexibility in reporting NCI. Some chose to recognize NCI under the liability section, while others recorded NCI under the mezzanine section between liability and equity. The FASB argued that the inconsistency of treatment increased investors' costs of acquiring comparable information across companies.

Some companies thus experienced an increase in the book value of their equity. Moreover, this increase appears to have been economically significant. That is, NCI is about four percent of

[4] Note that the Pension Protection Act (PPA) was enacted contemporaneously, i.e., in August 2006. The PPA Act requires firms to fully fund their pension plans within seven years (previous law gave firms 30 years to fund 90%). The PPA also increases the contribution level for tax deductibility from 100% of the projected benefit obligation to 150%. Campbell et al. (2010) find that firms with underfunded plans and those with high levels of capital investments are negatively impacted by the PPA, while those with higher marginal tax rates benefited from the higher deductible level. Unlike SFAS 158, the PPA resulted in actual economic transactions, many of which occurred in future periods well after the brief window we study in our paper.

total book equity for the average Compustat firm during the post-implementation period of 2010 through 2020. Additionally, those firms that previously recorded NCI in the liability section also experienced a decrease in liabilities. Although the underlying economic prospects of these firms did not change, their debt-to-equity ratio decreased, which appears to have allowed some firms with binding debt covenants and other financial constraints to take on more debt (Cohen et al., 2019). Of course, such changes could also affect quantitative (and other) strategies that incorporate debt-to-equity and related accounting metrics.

SFAS 141R, which was issued contemporaneously with SFAS 160, affected the accounting for business combinations by requiring that assets, liabilities, and noncontrolling interests be recognized at their *fair value*, instead of *historical values* used under earlier standards. This change likely increased many firms' NCI valuations due to the tendency for asset prices to increase over time. Furthermore, the standard requires that any administrative costs incurred to complete a business combination be expensed rather than capitalized as in the previous regime. Of course, expensing (to equity) versus capitalizing (to assets and liabilities) would affect ratios such as debt-to-equity. Note that both SFAS 160 and SFAS 141R mandated several more minor changes, including additional footnote disclosure, that we do not detail here for brevity. Together, these standards imposed several nuanced and intricate changes to the valuation and recognition of NCI, which in turn affected firms' financial metrics.

2.2.3 Leases

The FASB released ASC 842 in July 2018. The new standard mandates that operating and capital leases be recognized on the lessee's balance sheet for the vast majority of leases. Prior to this standard, operating leases were not recognized on the balance sheet. Instead, footnote disclosures were sufficient, resulting in a considerable source of off-balance sheet financing for many firms. Specifically, the standard results in a new (or larger) lease asset and lease liability on the balance sheet. The FASB also mandated more detailed disclosure about the "amount, timing and uncertainty" of lease-related cash flows, aiming to improve investors' understanding of the cost and benefits associated with the leases (FASB, 2016).

This standard could have a significant impact on capital markets due to the vastly altered balance sheet presentation. For example, the IASB estimated that listed companies using IFRS or US GAAP had about $3.3 trillion of lease commitments in 2014, of which over 85% did not appear on the balance sheet (IFRS, 2016). Many key financial metrics, such as the debt-to-equity and return-on-assets ratios, changed substantially as firms added billions of dollars to the assets and liabilities sections of their balance sheets following the new standard.[5]

III. DATA AND VARIABLE MEASUREMENT

3.1 Mutual Fund Data

We initially collect data on mutual fund performance from 2003 through 2020 using the CRSP Survivorship-Bias-Free Mutual Fund Database (CRSP MFDB). We obtain fund holdings from CRSP MFDB instead of from Thomson Reuters Mutual Fund Holdings for several reasons. First, CRSP checks fund prospectuses and contacts fund management to collect voluntarily disclosed holdings more often than Thomson Reuters.[6] The more frequently updated holdings positions are helpful because our analyses are at the monthly level, while many holdings are reported only at the semi-annual or quarterly level. Second, Thomson Reuters misses many new U.S. equity mutual fund share classes after 2008 (Zhu, 2020). This is particularly important for

[5] From an income statement perspective, the location of expenses resulting from operating leases changed. Previously, operating leases generated rent expense that was typically included in SG&A. Now, the leased asset is depreciated over time. Of note, depreciation expense is often excluded in analysis of ratios that include income statement data. The same is true of free cash flow analysis. Thus, metrics based on non-balance sheet data were also affected.
[6] https://wrds-www.wharton.upenn.edu/pages/support/support-articles/crsp/mutual-fund/tfn-mutual-fund-holding-vs-crsp-mutual-fund-holdings/?_ga=2.8750065.514058509.1606764681-1628130839.1581111764

our study because many quantitative funds are relatively new. Third, CRSP reports short positions, which we want to include because quantitative funds short sell securities more often than discretionary funds (Abis, 2020).

We focus on U.S. domestic equity mutual funds investing at least 80% of fund assets in common equities because these funds have the highest probability of being impacted by accounting standard changes.[7] We remove variable annuities, international funds, and sector funds. To mitigate incubation bias, we remove observations prior to the funds' first year of offering, observations with missing fund names, and observations with less than $5 million in total net assets or less than ten common stock positions (Elton, Gruber, and Blake, 2001; Kacperczyk, Sialm, and Zheng, 2008).

The CRSP MFDB reports fund characteristics and returns at the fund-class level. Some mutual funds have multiple fund classes to target various groups of investors.[8] The fund classes share the same portfolio, but can have different returns due to differential fee structures. To obtain fund-level attributes, we value-weight class-level measures by lagged total net assets. We follow this weighting approach for all our numerical variables except *Fund Age*, which we calculate based on the inception date of the oldest fund class.

These criteria result in 461,487 fund-month observations. In the next section, we explain our quantitative vs. discretionary classification, which further reduces the sample used in our main analyses.

[7] For each fund, we calculate the average of the percentage of fund assets invested in common stocks (CRSP variable *per_com)* over the duration of our sample period.
[8] For example, Class A, B, and C typically target retail investors and charge higher fees, while Class I is usually geared towards institutional investors with lower fees but higher dollar investment requirements.

3.2 Mutual Fund Classification: Quantitative vs. Discretionary

To classify funds as quantitative or discretionary, we obtain statutory and summary prospectuses (i.e., Forms 497K, 485APOS, and 485BPOS) from SEC's EDGAR database. Form 497K is a summary prospectus filed for individual funds, whereas 485APOS and 485BPOS are full prospectuses that often pertain to multiple funds (e.g., a fund family). Because we are interested in individual funds' investment strategies, and there could be substantial variation in strategy within a fund family, the 497Ks are ideal for our purposes. With 497Ks, we are able to automate the identification and extraction of the *Principal Investment Strategies* (PIS) section for thousands of funds in our sample. As the name suggests, the PIS discusses the fund's strategy, including the extent to which they are quantitative or not, more directly than any other part of the prospectus.

To determine the extent to which a fund is quantitative, we count the instances of words such as 'quantitative,' 'algorithm,' 'alpha,' and 'analytics' that appear in the PIS of the 497K. A complete list of the words (and associated word stems) we use is provided in Appendix B.1. We compiled this list by (1) referring to prior work on quantitative investing (e.g., Pedersen, 2015, and Beggs et al., 2021) and (2) reading 100 randomly selected prospectuses to identify the words funds commonly use to describe their quantitative investing methods.[9]

Panel A of Figure 2 uses a word cloud to illustrate the most common words in the PIS of Form 497K for all funds in our sample. As expected, both quantitative and discretionary funds often use words such as "securities," "stock," and "market" within their strategy descriptions.

[9] Our algorithm further ensures that the keyword occurs in the context of investment strategies by requiring the keyword not to be preceded or followed by certain words that are usually unrelated to investment strategies. For example, we require "model" not to be preceded by "business." Also, the list originally included the keyword "factor." However, after carefully reading many descriptions of investment strategies, we find that the word "factor" is often used in contexts different from factor investing. For example, funds often say things like, "we consider many factors in making investment decisions." Thus, we exclude the word "factor" from the keyword list when it appears alone, but include references to "multi-factor" models.

Panel B of Figure 2 uses a word cloud to show differences in word choices across the funds we classify as quantitative and discretionary. In particular, it includes the words that are in the top five hundred most used words by quantitative funds but are not in the top five hundred most used words by discretionary funds. We have used the color red to denote the words from our keywords list (e.g., “quantitative,” “proprietary,” and “score”). By construction, many of these red words feature prominently (i.e., because we used their occurrence to split the sample).

In Figure 3, we plot key aspects of the time series distribution of the number of quantitative word stems identified in the PIS of Form 497K. While the average fund used just over one quantitative word stem in its PIS in 2010, the mean gradually and significantly increases about 50% to nearly two by 2020. This increase is consistent with conventional wisdom that suggests quantitative investing approaches have increased in popularity over time (e.g., Zuckerman and Hope, 2017).[10] Figure 3 also shows that the 75th percentile is two during most of this period. Thus, to match prior research that suggests quantitative funds make up roughly 20-30% of the population (e.g., Harvey et al., 2017; Zuckerman and Hope, 2017; Abis, 2020; Beggs et al., 2021), we classify a fund as quantitative if its PIS contains at least two of the keywords listed in Appendix B.1. Otherwise, the fund is classified as discretionary.

Unfortunately, Form 497Ks were not required until the SEC issued Rule No. 33-8998 in 2009. Thus, this document is only available surrounding the implementation of the lease standard (i.e., in 2018-2019). For the pension and NCI standards that were implemented before 2009, we must instead rely on Forms 485APOS and 485BPOS. Mutual funds must file these forms on a

[10] Casual observation and anecdotal evidence suggest that quantitative investment has become a buzzword that funds use to attract investors. In other words, many funds appear to be simply “checking the box,” while not effectively integrating quantitative managers and analysts, suggesting that their primary investment strategy does not rely on quantitative methods in any material way (Kishan, 2016). To the extent that these funds are improperly classified as quantitative in our analyses, it would bias against finding differences between quantitative and discretionary investors.

regular basis, as well as whenever they make modifications to the prospectus (i.e., Form N-1A Registration Statement) they filed at the time of initial registration. Specifically, Form 485BPOS is filed at least annually with routine updates, while form 485APOS is filed if there are non-routine amendments (deHaan, Song, Xie, and Zhu, 2021). Both of these forms have a similar structure and include detailed discussions of funds' investment strategies. However, as noted previously, these forms often pertain to multiple funds. Also, due to more archaic file conventions and formatting, we are unable to cleanly separate either (1) the section pertaining to each individual fund or (2) the PIS section of each individual fund. Accordingly, we analyze the entire document for these filings and assign quantitative classifications to the entire fund family.

Another shortcoming of using forms 485 is that quantitative keywords, such as 'analytical,' 'data,' and 'model,' are frequently used in other parts of the prospectus that are not directly related to funds' investment strategies. As a result, classifying funds based on keywords in the entire 485 filing results in an over-classification of quantitative funds (i.e., type I classification error). Accordingly, we perform two steps to mitigate this error. First, we adopt a *phrase-based* approach based on quantitative phrases used in Beggs et al. (2021), as this should help distinguish strategy-related discussions from irrelevant quantitative words found in other parts of the prospectus.[11] Second, we classify all funds in a given fund family as quantitative if their registration documents are among the top decile of documents using quantitative phrases in a given year. We classify funds as discretionary if they use zero quantitative phrases, and exclude funds that use some quantitative phrases but fall below the top decile. While this criterion significantly reduces our sample size, it helps us identify the most quantitative and most discretionary funds and thus

[11] The full list of quantitative phrases is provided in Appendix B.2. This list matches the list provided in Appendix B of Beggs et al. (2021), except for a few minor adjustments we made to avoid double counting due to redundancies.

increases the power of our tests. Including funds whose strategies are more unclear would likely introduce unnecessary noise into our estimations.[12]

Crucially, the two different classification approaches (for forms 497K and forms 485) lead to a sample and classification that passes the validation tests we present in Table 2, which we discuss in more detail below. That is, the funds we classify as quantitative have the characteristics that theory and prior research predict, relative to more discretionary funds. To illustrate funds' usage of quantitative terminology, Appendix C includes excerpts from the 2019 prospectus of AQR Capital Management, a well-known quantitative fund.

Starting with the 461,487 fund-month observations that passed the sample selection criteria detailed in Section 3.1, we retain observations within the two-year event windows that are centered on the adoption of the three accounting standards we study. In particular, there are 177,128 fund-month observations during January 2006 through December 2007 (pension period), April 2008 through March 2010 (NCI period), and April 2018 through March 2020 (lease period). Next, we drop all funds that are neither quantitative nor discretionary (which applies to the first two standards only, given the different documents available during our sample period), leaving 107,512 fund-month observations (36,530 quantitative and 70,982 discretionary). Considering each accounting standard separately, we require that a fund's quantitative vs. discretionary classification did not change from before to after the event. This criterion reduces our sample size to 71,519 observations (49,606 quantitative and 21,913 discretionary). Removing observations with missing values for key variables (which we describe in the next section) further reduces the sample size to

[12] As noted previously, the part of our sample that relies on 485 filings is likely subject to some misclassification to the extent fund families include both quantitative and discretionary funds. This is not an issue for the discretionary group because their filings have zero quantitative phrases, suggesting that none of the funds in the family are quantitative. However, some of the funds we classify as quantitative may be discretionary funds from highly quantitative fund families. Of course, classifying some discretionary funds as quantitative biases against finding differences between the two groups, which mitigates this classification concern.

65,598 (19,613 quantitative and 45,985 discretionary). Finally, we require that each fund has at least one observation in both the pre- and post-period. These restrictions lead to a final sample size of 63,163 observations for our main analysis, of which 18,648 (30%) are quantitative and 44,515 (70%) are discretionary. As discussed above, recent research suggests that roughly 20-30% of funds are quantitative, so it is reassuring that our classification and sample selection criteria also result in a final sample that is 30% quantitative funds.

3.3 Variable Measurement

The key independent variable in our analysis is $Quant_{i,t}$, which is set to one if the approach described in the prior section classifies fund *i* as quantitative in period *t*, and zero otherwise. This measure requires us to link the CRSP MFDB with EDGAR filing data. We do so using a multi-step approach based on header information that we scrape from the 497K, 485APOS, and 485BPOS filings. To be specific, we first attempt to link the CRSP fund identification number (crsp_fundno) to CIK numbers using the CRSP linking table (crsp_cik_map). For any remaining unmatched funds, we match using the fund names and CIK numbers listed at the beginning of the prospectus.[13] Our main dependent variable, $Fund\ Return_{i,t}$, is fund-level raw returns obtained by value-weighting fund-class-level raw returns using lagged total net assets as the weight. Note that our inclusion of time fixed effects, which we discuss in more detail below, allows our return estimates to be interpreted as abnormal returns for the period.

We also measure funds' slant towards popular investment strategies (i.e., value, momentum, and size). In doing so, we first sort stocks into quintiles of book-to-market,

[13] The crsp_cik_map file only reports the most current link between *crsp_fundno* and CIKs. Since many funds undergo reorganization, such as mergers and acquisitions, the link often proves to be incorrect for earlier years in the sample period. Other researchers have also identified weaknesses with this linking table and attempted to correct them with other matching processes. See the Online Appendix of Chernenko and Sunderam (2020) for details of one such approach.

momentum, and market capitalization. We then aggregate these characteristics to the fund-level by summing the product of each stock's quintile rank and portfolio weight. Next, we rank the funds each month and use three categorical variables (*Book-to-Market*, *Momentum*, and *Size*) to identify funds ranked among the bottom 30%, middle 40%, or top 30% of all funds (i.e., -1,0,1).

Other fund characteristics such as *Fund Flow*, *Flow Vol*, *Turnover*, *Load*, and *Exp Ratio* are obtained from value-weighting each fund-class-level measure by lagged total net assets. *Fund Age* is the number of months since the oldest fund class within the fund was first offered. *Fund Assets* is the sum of the total net assets under management. All fund-level continuous variables are winsorized at the 1% and 99% levels and standardized for ease of interpretation.

Since prior research shows that overall market conditions influence the performance of quantitative funds, we also control for current and expected market volatility. In particular, *Market Volatility* is the standard deviation of the difference between the market return and the risk-free return over the previous 120 trading days, and *VIX* is the monthly average of the daily VIX index obtained from the Chicago Board Options Exchange.

3.4 Descriptive Statistics and Validation of Fund Classification

Table 1 reports descriptive statistics for the funds in our sample. Panel A presents descriptive statistics for the full sample, and Panel B splits the sample on our quantitative vs. discretionary classification to provide some initial insight into differences between the two groups. While quantitative and discretionary funds are about equally likely to be large-cap investors, the former are more heavily slanted towards high momentum stocks and value stocks. Quantitative funds have more funds per family, are younger, have more volatile flows, have higher turnover, and charge lower fees. The median quantitative fund manages less assets than the median discretionary fund ($358.45 million vs. $582.70 million). There are also fewer mega-sized quantitative funds than discretionary funds (i.e., the 90th percentiles are \$3,180.30 million and \$8,649.40 million, respectively). The median discretionary fund is about 16.3 years old, while the median quantitative fund is only 10.4 years old.[14] Quantitative funds also have much higher turnover than discretionary funds. The median *Turnover* of quantitative funds is almost double the median *Turnover* of discretionary funds (0.61 vs. 0.37).

To further validate our classification methodology, we next use regression analysis to compare fund age, size, expense ratio, portfolio turnover, and investment strategies across the quantitative and discretionary funds in our sample. Panel A of Table 2 provides additional evidence that quantitative funds are younger, smaller, charge lower fees, and have higher turnover. Panel B suggests that quantitative funds use more momentum and value investing strategies than discretionary funds, and invest more in large-cap stocks. These differences are highly significant and are consistent with contemporary studies on quantitative mutual funds (see Abis, 2020).

IV. EMPIRICAL DESIGN AND RESULTS

4.1 Research Design

To evaluate the performance of quantitative funds (relative to discretionary funds) around periods of accounting change, we use the following difference-in-differences design:

$$Return_{i,t} = \beta_0 + \beta_1 \times Post_t \times Quant_{i,t} + \lambda \times \text{Control Variables}_{i,t} + \text{Year-Month FE} + \text{Fund FE} + \varepsilon_{i,t} \quad (1)$$

$Post_t$ is an indicator variable that equals one if month t is within the effective period of the accounting standard change. The pension standard is effective for fiscal years *ending* after December 15th, 2006. The NCI and lease standards are effective for fiscal periods (including

[14] *Fund Age* is reported in months. The above numbers are obtained as follows: 196/12 = 16.3; 125/12 = 10.4;

interim periods, e.g., quarters) *beginning* on or after December 15th, 2008, and December 15th, 2018, respectively. Thus, for the pension (NCI) [lease] standard, we set *Post* to one starting on January 1, 2007 (April 1, 2009) [April 1, 2019], which captures when firms start to disclose financial statements prepared using the new standards.

The control variables include fund age (*Fund Age*), fund size (*Fund Assets*), fund expenses (*Exp Ratio*), front and rear loads (*Load*), fund flows (*Fund Flow*), flow volatility (*Flow Vol*), and fund investment strategies (*Book-to-Market*, *Momentum*, and *Size*). Because prior research shows that overall market conditions impact the performance of quantitative funds (Abis, 2020), we also control for *Quant* × *Market Volatility* and *Quant* × *VIX*.

In our main analysis, we estimate equation (1) separately around the pension, NCI, and lease standards. While we initially study one year pre- and post-periods, later tests consider a longer window because we expect quantitative funds' lower performance to attenuate as they (or their models) begin to make adjustments upon noticing lower model performance, the changing statistical properties of the accounting variables, or both. β_1 is the coefficient of interest. Specifically, if new accounting standards harm quantitative funds more than discretionary funds, the return for quantitative funds will be lower during the post period and β_1 will be negative.

We include year-month and fund fixed effects to control for time-invariant fund characteristics and month-specific factors, respectively. As a result, the main effects for *Quant* and *Post* are excluded from equation (1). Standard errors are clustered at the fund level to account for likely correlation among returns of the same fund. As noted previously, we only keep observations that do not switch type (i.e., quantitative vs. discretionary) from the respective pre- to post-period, which increases our chances of satisfying the stable unit treatment value assumption of the difference-in-differences model.

4.2 Main Result

In Table 3, we report the outcome of the main analysis, which compares changes in monthly returns of quantitative and discretionary funds from before to after new accounting standards. Specifically, Panel A reports difference-in-differences (DiD) estimates of average returns for the three accounting standard changes individually as well as after combining the three standards into a pooled sample. Because this univariate analysis does not include time fixed effects, we adjust fund-specific returns using the average fund return for the month. The average DiD is -0.22%, -0.26%, -0.12%, and -0.18% for the pension, NCI, lease, and the combined sample, respectively. These estimates are statistically significant, suggesting a decrease in quantitative relative to discretionary performance following all three accounting standard changes. The estimates are also economically significant. For example, the estimated -0.18% monthly returns from the combined sample translates to about -2.14% on an annual basis.[15] Note that this underperformance represents about 19% of the average fund's unconditional annual return of about 11%, which is based on the 88 bps per month reported in Panel A of Table 1.

Panel B presents a similar regression-based analysis that allows for the inclusion of control variables and fixed effects. This analysis helps us establish whether the effect of accounting standards is incremental to established and observable determinants of fund returns, as well as fixed fund-specific and period-specific unobservables. Columns (1), (2), and (3) report our estimates of equation (1) for the pension, NCI, and lease accounting changes, respectively. The final column reports estimates from a regression using the pooled sample of all three standards, where we weight all three events equally.[16]

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[15] $1 - (1-0.0018)^{12} = 0.0214$

[16] Our results are similar and inferences are unchanged if we instead weight each event by the number of available observations.

We estimate a statistically significant negative coefficient on *Post* × *Quant* for all three accounting standards and the combined analysis. In addition, each of these estimates, which range from -0.10 to -0.46, is economically significant. For example, the -0.23 coefficient in the last column implies that quantitative funds' performance deteriorated by 23 basis points (bps) per month relative to discretionary funds in the year after the standards came into effect. On an annual basis, this underperformance translates to 2.73%, or about 25% of the average fund's unconditional annual return.[17]

These results are consistent with our main hypothesis that quantitative investors are less able to immediately adjust to accounting standard changes, experiencing lower performance as a result. The fact that we document this phenomenon around multiple recent accounting regime changes is consistent with this being a persistent and robust result that occurs each time there is a major change to financial statement preparation.

In addition, we find this result after controlling for several key determinants of fund performance. While few of the control variables are consistently significant in one direction or the other, this could be due to limited time-series variation in many of the controls coupled with our inclusion of fund fixed effects. The notable exceptions are the coefficients on the book-to-market, momentum, and size factors, which are statistically significant across all events. Given the vast prior literature on these factors, it is initially surprising that funds slanted towards high book-to-market and high momentum stocks underperform and funds slanted towards large firms outperform. However, we note that several studies have found that the performance of these factors has diminished in recent years during several notable episodes, such as the financial crisis of 2007-

[17] $1 - (1-0.0023)^{12} = 0.0273$; 2.73%/11% = 25%

2009 that makes up much of our sample (e.g., Barroso and Santa-Clara, 2015; Israel, Laursen, and Richardson, 2020).

4.3 Intensity of Treatment

While the results in the previous section are consistent with quantitative funds underperforming following accounting standard changes on average, the strategies and operations of quantitative funds vary substantially, as we explained in Section 2.1. For example, fundamental quantitative investors seem much more likely to rely on accounting data and be adversely affected by changing accounting standards than statistical arbitrageurs or HFT. In addition, even within the subset of fundamental quantitative funds, there is likely substantial variation in the extent to which their models rely on accounting information instead of other types of data, such as market prices. Therefore, in this section, we attempt to identify funds that are more intensely exposed to the treatment effect of the accounting standard changes.

We first focus on value investors because they make up such a significant proportion of the investment industry and because balance sheet data are a particularly critical ingredient of their approach, which focuses on identifying stocks with low prices but strong fundamentals. This approach is typically implemented by measuring fundamental strength using accounting variables, which are then compared to market prices, as in the popular book-to-market ratio. Thus, we expect value investors to be among the most likely to be impacted by accounting standard changes.

Following the prior value investing literature, we identify value investors by estimating each fund's exposure to the book-to-market ratio. Specifically, we create the indicator variable *Value Investor*, which is set to one if the value-weighted book-to-market ratio of the stocks held by the fund is in the top 30% of the sample. We then augment equation (1) by interacting *Post* × *Quant* with *Value Investor*. To be specific, the coefficient on *Post* × *Quant* × *Value Investor* represents our estimate of the change in the performance difference between quantitative and discretionary funds using book-to-market investment strategies from the pre-period to the post-period.

The results of this expanded regression are presented in Panel A of Table 4. As expected, we find some evidence that quantitative investors' underperformance relative to discretionary investors is concentrated among funds slanted towards high book-to-market stocks. In particular, the coefficients on *Post* × *Quant* × *Value Investor* are negative and statistically significant for two of the standards, and marginally significant for the combined sample. The -0.17 coefficient in column 4 translates into *incremental* annualized underperformance of about 2%. In addition, the insignificant coefficients on *Post* × *Quant* following the pension and lease events suggest that non-value quantitative investors did not significantly underperform following the new accounting standards. This result is consistent with our hypothesis that value quantitative funds' reliance on accounting data results in their performance deteriorating more than other quantitative funds following standard changes.

4.4 Falsification

To increase confidence that the accounting changes are the underlying reason for the deteriorating quantitative fund performance in the post period, we perform a falsification test using momentum and size. Like value, these firm-level variables are extremely popular among investment professionals, and a vast literature on empirical asset pricing supports their utility (see, e.g., Fama and French, 1993, and Jegadeesh and Titman, 1993). Yet unlike value, these variables are based on market prices instead of accounting data. Therefore, they are less likely to be affected by new accounting standards. Thus, funds that rely heavily on momentum and size are ideal candidates for falsification tests.

To be specific, we repeat the test described in Section 4.3 after replacing *Value Investor* with *Momentum Investor* and *Large-cap Investor*. These momentum and size indicators are defined analogously to the value indicator, i.e., to indicate funds whose slant towards momentum or size is in the top 30% of the sample. We follow Carhart (1997) in calculating stock level momentum as the cumulative return over the prior year, excluding the most recent month. Size is the product of stock price and shares outstanding.

Panels B and C of Table 4 report the outcome of our falsification tests. As expected, none of the coefficients on *Post* × *Quant* × *Momentum Investor* or *Post* × *Quant* × *Large-cap Investor* is negative and significant. This suggests that the quantitative investors relying most heavily on momentum and size do not underperform following accounting standard updates. In contrast, in both Panels B and C, the coefficients on *Post* × *Quant* are consistently negative and significant, suggesting that the underperformance we documented previously is concentrated among the 70% of quantitative investors that are not substantially slanted towards momentum or size. Overall, the results in Table 4 are consistent with the idea that quantitative investors' use of accounting data subjects them to underperformance following accounting regime changes. This evidence also helps rule out alternative explanations for the underperformance we find, such as a liquidity crisis affecting the entire universe of quantitative funds (e.g., Khandani and Lo, 2007).

4.5 Mechanism Tests

To better understand the mechanism through which quantitative funds' performance deteriorates, we test whether quantitative funds have excessive portfolio turnover in the post-period and whether the effect is concentrated in funds holding more common stocks. Additional turnover could arise if changing accounting numbers, which of course are inputs in quantitative models, affect the outputs and resulting trading decisions of quantitative models. In this test, we use fund turnover as the dependent variable in equation (1) instead of fund returns. Panel A of Table 5 provides evidence that quantitative funds' turnover did significantly increase relative to discretionary funds following the NCI and lease standards, as well as in the combined sample. This suggests that at least part of the return underperformance we documented earlier could be due to increased trading costs resulting from excessive turnover.

If the change in the performance of quantitative funds is due to additional turnover following the accounting standard changes, we expect funds holding more common stocks to have the largest decline in returns in the post period. To test this, we include the interaction term *Post* × *Quant* × *Many Stocks* in our initial return regression, where *Many Stocks* is an indicator variable that equals 1 if the number of common stocks a fund holds is among the top 30% of all funds in our sample. Consistent with our expectation, Panel B of Table 5 shows that quantitative equity funds holding more common stocks performed worse in the post-period than quantitative funds holding fewer stocks *and* discretionary funds. The magnitude of the coefficient on *Post* × *Quant* × *Many Stocks* is -0.32, which is about 40% larger than the coefficient on *Post* × *Quant* in the main difference-in-difference analysis shown in the last column of Table 3. The smaller, but still significant, coefficients on *Post* × *Quant* in Panel B of Table 5 indicate that the other quantitative funds still performed worse in the post-periods than discretionary funds, but to a lesser extent than the quantitative funds holding more common equities.

Beyond changes in fund turnover, we further consider whether quantitative funds' performance deteriorates because of shifts in fund strategy. One possibility is that quantitative funds switch to or from accounting-based strategies as they (or their models) start to notice changes to their accounting data or their performance. To better understand potential shifts in strategy, we again examine the major investment signals used by quantitative and discretionary investors, namely book-to-market, momentum, and size. In previous tests, we classified funds based on their slant towards a particular strategy as of the end of the pre-period; however, in this analysis, we test for changes in strategy from the pre- to the post-period. Specifically, we calculate each fund's slant towards each of the three strategies in each month of the sample period. We then regress these strategy variables on *Post, Quant,* controls, and fixed effects as in earlier tests.

The first regression reported in Table 6 suggests no difference between the slant of quantitative and discretionary funds towards book-to-market following the new accounting standards. This result is consistent with funds not shying away from, or slanting more heavily towards, accounting information as a result of the standard change. In other words, the costs of adjusting to the accounting standards does not appear to affect quantitative funds' willingness to incorporate accounting information in their investment processes. Our estimate is insignificant in the momentum regression and negative in the size regression, suggesting quants shifted away from large-cap stocks to an extent following the accounting standards. However, we do not have strong predictions about how the accounting standards would affect momentum and size investing, since they are not directly based on accounting metrics.

4.6 Persistence of Results

We next consider how long it takes for quantitative fund managers to adjust their models to accommodate new accounting conventions and eliminate the resulting underperformance. Because quantitative managers are aware that they need to continually conduct research and modify their models to accommodate the evolving market (Narang, 2013), we expect quantitative performance to eventually rebound. To quantify this adjustment, we extend the post-period (as well as the pre-period, to maintain symmetry) from one to two years. Specifically, to show how quantitative funds' performance evolves during the post-period, we create two indicator variables, *Post (Year 1)* and *Post (Year 2),* to indicate the first and second years, respectively, after the effective date of the new standards.

Table 7 reports the findings of this analysis for both the fund return and fund turnover regressions. For both of these tests, we use the combined sample for brevity. We first find that quantitative performance decreases substantially within the first year, but the effect is not present in the second year. In particular, the underperformance in the first year is 0.16 bps per month, or about 2%. During the second year, there is no significant quantitative underperformance, which we infer from the coefficient on *Quant* × *Post (Year 2)*. While this test cannot speak to whether quantitative fund managers ever realize accounting standards are the underlying reason for the temporary reduction in returns, it suggests that, at the very least, their models are dynamic enough to adjust and recover within a year.

Consistent with the mechanism test detailed in the previous section, we observe that quantitative funds' turnover is also higher in the first year, but not the second year, following the accounting standards. Specifically, the turnover ratio of quantitative funds during the first year in the post-period increases about 0.04 relative to discretionary funds, or about 5.7% of the unconditional sample mean.

This persistence test also allows us to better interpret our main results. For example, one alternative interpretation of our main results is that quantitative funds outperformed discretionary investors in the pre-period precisely because the former could better extract information from footnote disclosures (e.g., by using textual analysis) than the latter. The new standards we examine forced additional accounting recognition, which may have leveled the playing field between quantitative and discretionary investors (e.g., making it easier for discretionary investors to evaluate the firm, and improving their performance as a result). If this alternative interpretation is true, then the performance difference we document between the pre- and the post-periods should be permanent. Instead, we observe that the effect is temporary, consistent with quantitative funds updating their models to ameliorate temporary underperformance.

V. CONCLUSION

Quantitative investment methods rely on stable data generating processes and minimal human involvement, which could create lower flexibility in the face of changing economic conditions. In this study, we examine quantitative investors' ability to navigate a common and occasionally material change to the financial data generating process: new accounting standards. We find that quantitative mutual fund performance deteriorates relative to discretionary mutual funds in the year following new accounting standards, but recovers thereafter. This result is consistent with quantitative funds' systematic, rules-based approach, which relies on past data, creating inflexibility relative to more traditional investing techniques during these times. This one-time (or in other words, one year) adjustment cost of nearly 3% is an economically significant 25% of the average mutual fund's annual return (which is about 11% in our sample). Moreover, we find this result is stronger for quantitative value funds, and absent for quantitative momentum and size funds, which helps increase confidence that our results reflect costly efforts to incorporate accounting intricacies into quantitative trading models.

In addition, we provide evidence on how quantitative investors ultimately adjust operations around these standard changes. We find little evidence of funds' altering their reliance on popular investment signals, but do find evidence of additional portfolio turnover following the regulatory changes. We also find that our results are concentrated among funds holding more stocks, meaning they likely must engage in more transactions when adjusting their models.

Our results are subject to important caveats. First, we study a few prominent accounting standard changes, so the costs we document might not generalize to the typical standard. Second, fund underperformance only matters to investors to the extent that maximizing returns is a principal fund objective. If fund operations are instead meant to facilitate hedging, diversification, liquidity, or social impact, then the documented underperformance may be less meaningful. Third, we are only studying one cost of accounting standards to a specific type of investors, and cannot speak conclusively to the overall cost-benefit tradeoff. Fourth, we only consider mutual fund performance. It is possible that the documented underperformance may not generalize to other types of market participants, such as more sophisticated hedge funds. Nonetheless, our study provides novel evidence on an occasional cost that accounting standards impose on a significant subset of modern investors, who increasingly rely on quantitative trading methods.

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Appendix A. Variable Descriptions

Variable	Description
Fund Return	Value-weighed monthly raw return of the fund, calculated by adding back 1/12 * EXP_RATIO to the monthly net return (CRSP MFDB variable MRET). The fund class raw return is then value-weighted by lagged total net asset to obtain a fund-level raw return.
Quant	An indicator variable that equals one if a fund has been classified as a quantitative fund and zero if a fund has been classified as a discretionary fund. The classification is based on the fund prospectuses (Form 485APOS and 485BPOS) during the pension and NCI period. If the number of quantitative phrases in a fund's prospectus is ranked among the top 10% of all funds for a given year in our sample, the fund is classified as a quantitative fund. If there are zero quantitative phrases in a fund's prospectus, the fund is classified as a discretionary fund. In the lease period, the classification is based on the fund summary prospectuses (Form 497K). If there are at least two unique quantitative words in the Principal Investment Strategy section of the summary prospectus, the fund is classified as a quantitative fund. Otherwise, the fund is classified as a discretionary fund.
Post	An indicator variable that equals one if the month is in the effective period of the respective accounting standard change. The pension standard is effective for fiscal years ending after December 15th, 2006. The NCI (lease) standards are effective for fiscal periods beginning on or after December 15th, 2008 (December 15th, 2018). Thus, for the pension (NCI) [lease] standard, we set *Post* to one starting on January 1, 2007 (April 1, 2009) [April 1, 2019].
Fund Age	*Age* is the standardized number of months since the first offer date of the oldest fund class. In all regression analyses, we take the log of the standardized value. *Fund Age* is winsorized at the 1% and 99% levels and standardized. Table 1 Descriptive Statistics shows the value before standardization.
Fund Assets	*FundAssets* is the standardized sum of total net assets for each of the fund classes within a fund. The total net asset is in millions of dollars. In all regression analyses, we take the log of the standardized value. *FundAssets* is winsorized at the 1% and 99% levels and standardized. Table 1 Descriptive Statistics shows the value before standardization.
Exp Ratio	*Exp Ratio* is the fund-level expense ratio, obtained from value-weighting the CRSP MFDB fund class-level variable EXP_RATIO by the lagged total net asset of each fund class. *ExpRatio* is winsorized at the 1% and 99% levels and standardized.
Load	*Load* is the sum of the fund's value-weighted mean front load and value-weighted mean rear load. Funds charge different levels of front load and rear load for different values and durations of the investment. Mean front (rear) load is calculated as the simple average of front (rear) load ratios of all investment levels for a fund class. To obtain the fund-level *Load*, the mean front load and the mean rear load for the fund classes are value-weighted by lagged total net asset. *Load* is winsorized at the 1% and 99% levels and standardized.
Turnover	CRSP MFDB variable TURN_RATIO, value weighted by the lagged total net asset of each fund class. *Turnover* is winsorized at the 1% and 99% levels.
Fund Flow	*FundFlow* is calculated as (TNA_t / TNA_{t-1}) - (1 + Ret_t), following Barber, Huang, and Odean (2016), where Ret is the variable *Fund Return* and TNA is the sum of the total net assets managed under each fund class. *FundFlow* is winsorized at the 1% and 99% levels and standardized.
Flow Vol	*FlowVol* is the standard deviation of *FundFlow* over the prior 12 months, calculated on a rolling basis. *FlowVol* is winsorized at the 1% and 99% levels and standardized.

Market Volatility	Standardized market volatility, computed as the moving standard deviation of the market return less risk-free return over the previous 120 trading days.
VIX	The daily VIX index is obtained from the Chicago Board Options Exchange. We take the average daily VIX index to obtain a monthly VIX index. The monthly VIX index is then standardized.
Book-to-Market	An indicator variable that equals -1, 0, or 1 if the fund's value-weighted book-to-market measure is among the bottom 30%, middle 40%, or top 30% of all funds in our sample, respectively. Stock-level book-to-market is calculated as book equity over market equity, where book equity is common shareholder's equity plus deferred taxes and investment tax credit (TXDITCQ) and minus the preferred shares (PS). Common shareholder's equity is SEQQ, CEQQ+PS, or ATQ-LTQ, in the stated order based on data availability. If available, preferred shares take on the redemption value (PSTKRQ); otherwise, the total preferred stock value (PSTKQ) is used. Stock-level market equity is calculated as the absolute value of price (PRC) times the number of shares outstanding (SHROUT). Using quantile breakpoints based on NYSE common stocks (SHRCD=10 or 11), we assign a score of 1-5 to each stock. The fund-level book-to-market measure is obtained by value-weighting stock-level book-to-market using the percentage of total net assets invested in the stock. Finally, all funds are ranked each month based on the value-weighted book-to-market measure and assigned a value of -1, 0, or 1 if they are among the bottom 30%, middle 40%, or top 30% of all funds in our sample.
Value Investor	An indicator variable that equals one if a fund's *Book-to-Market* is equal to one in the last month during the pre-period and zero otherwise. *Value Investor* is held constant for each fund during each event period.
Momentum	An indicator variable that equals -1, 0, or 1 if a fund's value-weighted momentum is among the bottom 30%, middle 40%, or top 30% of all funds in our sample. Stock-level momentum is calculated based on the 12-2 approach. We assign a score of 1-5 for each stock using the quintile momentum breakpoints provided on Ken French's website. The fund-level momentum is obtained by value-weighting stock-level momentum using the percentage of total net assets invested in the stock. Finally, all funds are ranked each month based on the value-weighted momentum and assigned a value of -1, 0, or 1 if they are among the bottom 30%, middle 40%, or top 30% of all funds in our sample.
Momentum Investor	An indicator variable that equals one if a fund's *Momentum* is equal to one in the last month during the pre-period and zero otherwise. *Momentum Investor* is held constant for each fund during each event period.
Size	An indicator variable that equals -1, 0, or 1 if the fund's value-weighted size strategy is among the bottom 30%, middle 40%, or top 30% of all funds in our sample, respectively. Stock-level market equity is calculated as the absolute value of price (PRC) times the number of shares outstanding (SHROUT). We assign a score of 1-5 to each stock based on the quintile market equity breakpoints provided on Ken French's website. The fund-level size is obtained by value-weighting stock-level size using the percentage of total net assets invested in the stock. Finally, all funds are ranked each month based on the value-weighted size and assigned a value of -1, 0, or 1 if they are among the bottom 30%, middle 40%, or top 30% of all funds in our sample.
Large-cap Investor	An indicator variable that equals one if a fund's *Size* is equal to one in the last month during the pre-period and zero otherwise. *Large-cap Investor* is held constant for each fund during each event period.
Many Stocks	An indicator variable that equals one if a fund's number of common stocks held in the last month during the period is among the top 30% of all funds in the sample, and 0 otherwise.

Appendix B. Quantitative Terms

This appendix provides the lists of words and phrases we use to identify funds that use quantitative investment methods. In paragraph B.1, we provide the word stems used in analyzing the Principal Investment Strategies sections extracted from Form 497K filings, which are available from 2010 through 2020. The "." in some of the stems is a coding convention that allows us to extract hyphenated and unhyphenated compound word forms (e.g., "multi-factor" is treated the same as "multi factor"). In paragraph B.2, we provide the phrases used in analyzing the entire Form 485APOS and Form 485BPOS filings, which we use for the period 2003 through 2009.

B.1 Quantitative Word Stems

quantitative, algorithm, alpha, analytic, anchor, beta, calculat, computer, data, econometric, math, model, multi.factor, optimiz, probabilit, proprietary, rank, ratio, rules.based, score, screen, signal, statistic, style, systematic

B.2 Beggs et al. (2021) Quantitative Phrases

quantitative investment, quantitative model, quantitative analysis, quantitative process, quantitative tools, quantitative formula, quantitative computer, statistically driven, statistical methods, quantitative methodology, quantitative management, quantitative method, quantitative models, quantitative analytics, quantitatively-driven, quantitatively-derived, quantitative approach, quantitative value, quantitative statistics, quantitatively investing, quantitative measures, quantitative techniques, quantitative research, quantitative methods, factor-based, quantitative three factor, quantitative approaches, quantitative optimization, quantitatively driven, quantitative studies, quantitatively assess, quantitative assessment, quantitatively-oriented, multi-factor, multifactor, multi factor

Appendix C. Excerpts from a Quantitative Fund's Prospectus

The following fund strategy description and investment risk disclosures come from the statutory prospectus filed by AQR Large Cap Multi-Style Fund on January 28, 2019.[18] This prospectus included 200 quantitative references, placing it in the top 3% of mutual funds in the year. Sentences related to regime change risk and the use of accounting metrics are bolded for emphasis.

Principal Investment Strategies of the Fund

The Fund combines multiple investment styles, primarily including value, momentum and quality, using an integrated approach. In managing the Fund, the Adviser seeks to invest in attractively valued companies with positive momentum and stable businesses. **Companies are considered to be good value investments if they appear cheap based on multiple fundamental measures, including price-to-book and price-to-earnings ratios relative to other securities in its relevant universe at the time of purchase**. In assessing positive momentum, the Adviser favors securities with strong medium-term performance relative to other securities in its relevant universe at the time of purchase. Further, the Adviser favors stable companies in good business health, including those with strong profitability and stable earnings. The Adviser may add to or modify the economic factors employed in selecting securities. There is no guarantee that the Fund's objective will be met.

Principal Risks of Investing in the Fund

Model and Data Risk: Given the complexity of the investments and strategies of the Fund, the Adviser relies heavily on quantitative models and information and data supplied by third parties ("Models and Data"). Models and Data are used to construct sets of transactions and investments, to provide risk management insights, and to assist in hedging the Fund's investments.

When Models and Data prove to be incorrect or incomplete, any decisions made in reliance thereon expose the Fund to potential risks. Similarly, any hedging based on faulty Models and Data may prove to be unsuccessful. Some of the models used by the Adviser for the Fund are predictive in nature. The use of predictive models has inherent risks. **Because predictive models are usually constructed based on historical data supplied by third parties, the success of relying on such models may depend heavily on the accuracy and reliability of the supplied historical data.** The Fund bears the risk that the quantitative models used by the Adviser will not be successful in selecting companies for investment or in determining the weighting of investment positions that will enable the Fund to achieve its investment objective.

All models rely on correct data inputs. If incorrect data is entered into even a well-founded model, the resulting information will be incorrect. **However, even if data is inputted correctly, "model prices" will often differ substantially from market prices, especially for instruments with complex characteristics, such as derivative instruments.**

The Fund is unlikely to be successful unless the assumptions underlying the models are realistic and either remain realistic and relevant in the future or are adjusted to account for changes in the overall market environment. If such assumptions are inaccurate or become inaccurate and are not promptly adjusted, it is likely that profitable trading signals will not be generated, and major losses may result.

The Adviser, in its sole discretion, will continue to test, evaluate and add new models, which may result in the modification of existing models from time to time. There can be no assurance that model modifications will enable the Fund to achieve its investment objective.

[18] For the full prospectus, please refer to: https://www.sec.gov/Archives/edgar/data/1444822/000119312519018978/d676698d485bpos.htm.

Figure 1. Accounting Standard Changes

This figure summarizes key details about the accounting standards we examine in the paper, including the effective date, what the accounting standard changed, and whether the accounting standard required financial statement recognition of previously disclosed footnote information.

	Pension	NCI	Lease
FASB Standard	SFAS 158	SFAS 160; SFAS 141R	ASC 842
Superseded Standards	SFAS 87, SFAS 88, SFAS 106, SFAS 132I	ARB 51; SFAS 140	ASC 840
Effective Period	Fiscal years ending after Dec 15th, 2006	Fiscal years, and interim periods within those fiscal years, beginning on or after Dec 15th, 2008	Fiscal years, and interim periods within those fiscal years, beginning on or after Dec 15th, 2018
Description of Change	Recognize the funding status of defined benefit pension plans in the financial statements. Recognize as OCI for the period of change.	SFAS 160: NCI needs to be presented in the equity section of the B/S (previously, this was often recognized under the liabilities section); Consolidated Net Income should be before deduction of income attributed to NCI. SFAS 141R: Main change related to NCI is the recognition of NCI at fair value as of the purchase date.	The lessee should recognize the asset and liabilities of operating leases on the balance sheet.
Was information previously disclosed but not recognized?	Yes	No	Yes

Figure 2. Word Clouds

This figure uses word clouds to illustrate the most frequently used words from the Principal Investment Strategy (PIS) section of funds' Form 497K (i.e., the Summary Prospectus). The size of each word in the cloud is proportional to the frequency of the word in the strategy descriptions. The word cloud in Panel A is based on the strategy description of both quantitative and discretionary funds. The word cloud in Panel B shows words that are within the top five hundred most frequently-used words in quantitative funds' PIS, but are not within the top five hundred most frequently-used words in discretionary funds' PIS. In Panel B, we use the color red to denote words that are included in our quantitative word stem list (see Appendix B.1).

Panel A: Frequently-Used Words: All Funds

Panel B: Frequently-Used Words: Quantitative but not Discretionary Funds

Figure 3. Distribution of the Number of Quantitative Words

This figure presents the time-series distribution of the number of quantitative word stems from the Principal Investment Strategy (PIS) section of funds' Form 497K filings from 2010 to 2020. The quantitative word stems are listed in Appendix B.1.

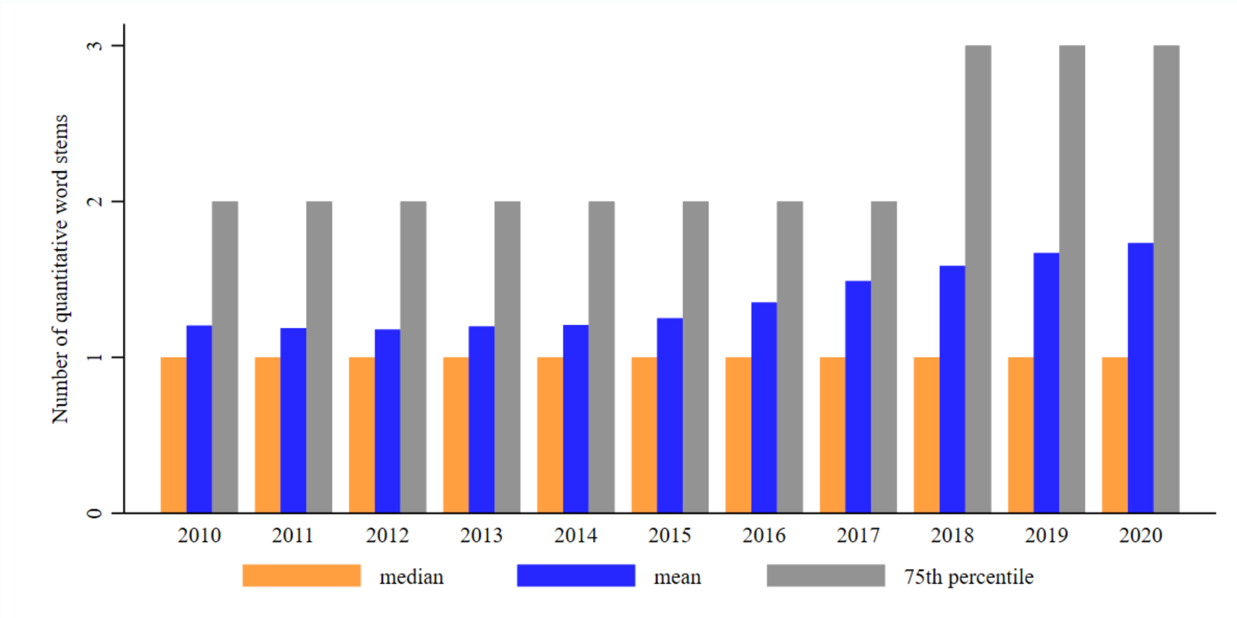

Table 1. Descriptive Statistics

This table provides the descriptive statistics for the funds in our sample. Panel A shows the descriptive statistics for all funds from 2003 to 2020, including quantitative funds, discretionary funds, and other funds not used in our analyses. Panel B focuses on quantitative and discretionary funds within the one year pre- and post-event period for our difference-in-difference analyses. Variable definitions are as follows: investment strategy categorical variables (*Book-to-Market, Momentum,* and *Size*) that equal -1, 0, or 1 if the value-weighted (using portfolio weights) average *Book-to-Market, Momentum,* and *Size* quintile of the stocks in the fund's portfolio is among the bottom 30%, middle 40%, or top 30% of all funds, TNA-weighted fund raw return in percentage terms (*Fund Return*), the number of funds under each fund family (*Funds per Family*), total asset under management for each fund (*Fund Assets),* the number of months since the first-offer-date of the oldest fund class (*Fund Age),* net fund flows adjusted by fund returns (*Fund Flow*), standard deviation of fund flow over the past 12 months (*Flow Vol*), fund turnover ratio (*Turnover)*, fund expense ratio (*Exp Ratio)*, the sum of the fund's value-weighted mean front load and value-weighted mean rear load (*Load*), the standard deviation of the market excess return over the previous 120 days (*Market Volatility*), and the monthly-level VIX index (*VIX*). *Turnover*, *Exp Ratio*, and *Load* are obtained by value-weighting fund class measures with lagged total net assets, and all other fund measures are measured directly at the fund level. All fund-level continuous variables are winsorized at the 1% and 99% levels.

Panel A: All Funds 2003-2020

	N.	Mean	Std.	10th	50th	90th
Investment Strategies:						
Book-to-Market	386,545	0.01	0.78	-1	0	1
Momentum	386,545	0.00	0.77	-1	0	1
Size	386,545	-0.01	0.78	-1	0	1
Fund Characteristics:						
Fund Return	386,545	0.88	4.62	-5.31	1.31	6.12
Funds per Family	386,545	8.59	8.69	1	6	18
Fund Assets	386,545	1,729.97	4,640.12	24.70	292.10	3,824.20
Fund Age	386,545	178.72	148.16	41	145	333
Fund Flow	386,545	0.00	0.05	-0.03	0.00	0.03
Flow Vol	386,545	0.05	0.11	0.01	0.02	0.10
Turnover	386,545	0.70	0.68	0.13	0.51	1.44
Exp Ratio	386,545	1.03	0.45	0.36	1.05	1.56
Load	386,545	0.64	0.89	0.00	0.15	2.23
Market Environment:						
Market Volatility	386,545	1.05	0.59	0.61	0.85	1.69
VIX	386,545	18.76	8.57	11.87	16.17	27.65

Panel B: Quantitative and Discretionary Funds within 1-Year Pre-Post Event Period

	Quantitative Mutual Funds						Discretionary Mutual Funds						Difference		
	N	Mean	Std.	10th	50th	90th	N	Mean	Std.	10th	50th	90th	N	Mean	T-stat
Investment Strategies:															
Book-to-Market	18,648	0.04	0.77	-1	0	1	44,515	-0.03	0.77	-1	0	1	63,163	0.07	10.97
Momentum	18,648	0.04	0.76	-1	0	1	44,515	-0.08	0.77	-1	0	1	63,163	0.12	17.59
Size	18,648	0.02	0.75	-1	0	1	44,515	0.00	0.77	-1	0	1	63,163	0.02	2.96
Fund Characteristics:															
Fund Return	18,648	0.00	6.00	-8.68	1.35	6.08	44,515	0.34	5.77	-8.06	1.45	6.23	63,163	-0.34	-6.74
Funds per Family	18,648	13.18	11.31	2	10	26	44,515	8.07	10.63	1	4	18	63,163	5.11	54.06
Fund Assets	18,648	1,432.33	3,822.36	33.40	358.45	3,180.30	44,515	3,866.19	10,357.03	29.40	582.70	8,649.40	63,163	-2433.86	-31.21
Fund Age	18,648	163.17	148.43	37	125	321	44,515	225.25	167.74	58	196	415	63,163	-62.08	-43.85
Fund Flow	18,648	0.00	0.05	-0.04	0.00	0.04	44,515	0.00	0.04	-0.03	-0.01	0.03	63,163	0.00	3.30
Flow Vol	18,648	0.05	0.09	0.01	0.02	0.12	44,515	0.04	0.08	0.00	0.02	0.08	63,163	0.01	20.69
Turnover	18,648	0.78	0.63	0.19	0.61	1.52	44,515	0.57	0.65	0.09	0.37	1.21	63,163	0.21	36.42
Exp Ratio	18,648	0.82	0.40	0.25	0.86	1.30	44,515	0.98	0.47	0.25	1.00	1.50	63,163	-0.16	-39.92
Load	18,648	0.47	0.75	0.00	0.00	1.68	44,515	0.59	0.87	0	0.12	2.11	63,163	-0.12	-16.68

Table 2. Validation of Quantitative Fund Classification

Panel A regresses age, size, expense ratio, and turnover on other fund characteristics. Panel B regresses investment strategies on other fund characteristics. Variable definitions are as follows: the number of months since the first-offer-date of the oldest fund class (*Fund Age*), the total net asset under management of all fund classes (*Fund Assets*), fund expense ratio (*Exp Ratio)* in percentage terms, fund turnover ratio (*Turnover)*, an indicator variable that equals one if the fund has been classified as quantitative (*Quant)*, the sum of the fund's mean front load and mean rear load (*Load),* net fund flows adjusted by fund returns (*Fund Flow*), the standard deviation of fund flow over the past 12 months (*Flow Vol*), and investment strategy categorical variables (*Book-to-Market, Momentum,* and *Size*) that equal -1, 0, or 1 if the value-weighted (using portfolio weights) average *Book-to-Market*, *Momentum*, and *Size* quintile of the stocks in the fund's portfolio is among the bottom 30%, middle 40%, or top 30% of all funds. *Turnover, Exp Ratio*, and *Load* are obtained by value-weighting fund class measures with lagged total net asset, and all other measures are measured directly at the fund level. All fund-level continuous variables are winsorized at the 1% and 99% levels and standardized. Sample observations are at the monthly level, with standard errors clustered at the fund and year-month level. t-statistics are included in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent two-tailed level, respectively.

Panel A: Fund Age, Size, Expense Ratio, and Turnover

Dependent Variable =	***Age***	***FundAssets***	***ExpRatio***	***Turnover***
	(1)	(2)	(3)	(5)
Quant	-0.37***	-0.09**	-0.27***	0.33***
	(-6.23)	(-2.01)	(-6.11)	(6.75)
Fund Age	---	0.34***	0.15***	-0.02
		(14.25)	(5.40)	(-0.94)
Fund Assets	0.43***	---	-0.50***	-0.06**
	(15.46)		(-20.43)	(-2.25)
Exp Ratio	0.19***	-0.53***	---	0.27***
	(5.70)	(-22.72)		(7.56)
Turnover	-0.02	-0.04**	0.17***	---
	(-0.95)	(-2.21)	(9.07)	
Load	0.13***	0.15***	0.32***	-0.02
	(4.85)	(5.91)	(15.36)	(-0.60)
Fund Flow	-0.12***	0.04***	-0.03***	-0.04***
	(-9.98)	(5.67)	(-3.40)	(-3.23)
Flow Vol	-0.12***	-0.06***	-0.09***	0.11***
	(-6.35)	(-3.10)	(-3.47)	(3.45)
Book-to-Market	-0.05	0.04	-0.04*	-0.07**
	(-1.61)	(1.32)	(-1.74)	(-2.32)
Momentum	0.04*	0.01	-0.04*	0.21***
	(1.70)	(0.26)	(-1.86)	(7.78)
Size	0.09***	0.04	-0.18***	-0.08**
	(2.72)	(1.52)	(-6.26)	(-2.62)
R-squared	0.29	0.42	0.46	0.16
Observations	63,163	63,163	63,163	63,163

Panel B: Fund Investment Strategies

Dependent Variable =	***Book-to-Market***	***Momentum***	***Size***
	(1)	(2)	(3)
Quant	0.14***	0.18***	0.09**
	(3.62)	(5.88)	(2.08)
Fund Age	-0.03	0.03*	0.06***
	(-1.63)	(1.69)	(2.79)
Fund Assets	0.03	0.00	0.04
	(1.31)	(0.26)	(1.52)
Exp Ratio	-0.04*	-0.03*	-0.16***
	(-1.73)	(-1.86)	(-6.36)
Turnover	-0.03**	0.10***	-0.04**
	(-2.26)	(7.25)	(-2.49)
Load	0.04**	0.02*	0.05**
	(2.10)	(1.72)	(2.23)
Fund Flow	-0.01**	0.04***	-0.01
	(-2.00)	(4.53)	(-0.96)
Flow Vol	0.01	0.01	-0.01
	(0.59)	(1.16)	(-0.66)
Book-to-Market	---	-0.46***	-0.24***
		(-16.09)	(-8.99)
Momentum	-0.45***	---	0.00
	(-16.15)		(0.11)
Size	-0.21***	0.00	---
	(-8.43)	(0.11)	
R-squared	0.28	0.26	0.13
Observations	63,163	63,163	63,163

Table 3. Fund Returns and Accounting Standard Changes

Panel A presents univariate difference-in-differences estimates of quantitative mutual funds' returns around accounting standard changes relative to discretionary funds. Panel B presents a regression-based version of this analysis that allows for the inclusion of control variables and fixed effects. The dependent variable, *Fund Return (%),* is the TNA-weighted monthly fund return in percentage terms. In Panel A, raw fund-specific returns are adjusted using the average fund return. A similar adjustment is accomplished in Panel B by including time fixed effects. *Pension*, *NCI*, and *Lease* refer to the accounting standard changes detailed in Figure 1. *Combined* denotes an equal-weighted pooled analysis of all three standard changes. *Post* is an indicator variable that equals one if the month is after the effective date of the accounting standard change. *Quant* is an indicator variable that equals one if the fund is classified as a quantitative fund. *Fund Age* is the log of the number of months since the first-offer-date of the oldest fund class. *Fund Assets* is the log of the sum of total net asset for all fund classes*, Exp Ratio* is the fund expense ratio, *Load* is the sum of the fund's mean front load and mean rear load, *Fund Flow* is the net fund flows adjusted by fund returns, *Flow Vol* is the standard deviation of fund flow over the past 12 months. *Book-to-Market*, *Momentum*, and *Size* are (-1, 0, 1) categorical variables that represent the bottom 30%, middle 40%, or top 30% of all funds based on their value, momentum, and size slants, respectively. *Market Volatility* is the moving standard deviation of the market return less the risk-free return over the previous 120 days. *VIX* is the monthly-level VIX index obtained from averaging the CBOE daily VIX index. All fund-level continuous variables are winsorized at the 1% and 99% levels and standardized. All regressions are at the monthly level with year-month and fund fixed effects. Standard errors are clustered at the fund level. t-statistics are included in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent two-tailed level, respectively.

Panel A: Univariate Difference-in-Differences Estimates in Monthly Fund Returns

Pension

	Pre	*Post*	*Post - Pre*
Discretionary	0.02%	0.02%	0.01%
Quant	0.01%	-0.20%	-0.21%
Quant - Discretionary	-0.01%	-0.23%	**-0.22%**
		t-statistic (DiD) =	**(-3.01)**

NCI

	Pre	*Post*	*Post - Pre*
Discretionary	0.02%	0.13%	0.11%
Quant	0.07%	-0.08%	-0.15%
Quant - Discretionary	0.05%	-0.21%	**-0.26%**
		t-statistic (DiD) =	**(-2.47)**

Lease

	Pre	*Post*	*Post - Pre*
Discretionary	0.05%	0.09%	0.04%
Quant	-0.07%	-0.15%	-0.08%
Quant - Discretionary	-0.11%	-0.24%	**-0.12%**
		t-statistic (DiD) =	**(-2.86)**

Combined

	Pre	*Post*	*Post - Pre*
Discretionary	0.02%	0.08%	0.05%
Quant	-0.01%	-0.14%	-0.13%
Quant - Discretionary	-0.04%	-0.22%	**-0.18%**
		t-statistic (DiD) =	**(-4.61)**

Panel B: Regression-Based Difference-in-Differences Estimates in Monthly Fund Returns

	Y = ***Return*** **(%)**			
	(1)	(2)	(3)	(1) – (3)
	Pension	**NCI**	**Lease**	**Combined**
Post × Quant	-0.24**	-0.46***	-0.10***	-0.23***
	(-2.16)	(-3.75)	(-2.88)	(-4.22)
Fund Age	-0.70**	0.36	-0.60***	-0.44***
	(-2.46)	(1.02)	(-3.40)	(-2.97)
Fund Assets	0.31	-0.53*	1.83***	0.60***
	(1.59)	(-1.78)	(9.81)	(4.57)
Exp Ratio	0.04	0.16	0.28*	0.20
	(0.20)	(0.68)	(1.85)	(1.44)
Load	0.05	-0.17	0.48***	0.04
	(0.30)	(-1.07)	(3.77)	(0.35)
Fund Flow	0.17***	0.04	-0.02	0.05***
	(7.09)	(1.47)	(-0.89)	(3.70)
Flow Vol	0.03	0.04	-0.02	0.01
	(1.30)	(1.14)	(-1.14)	(0.92)
Book-to-Market	-0.44***	-0.51***	-0.63***	-0.49***
	(-8.08)	(-5.65)	(-13.31)	(-10.75)
Momentum	-0.22***	-0.51***	-0.25***	-0.35***
	(-7.35)	(-13.24)	(-11.55)	(-17.30)
Size	0.24***	0.23*	0.42***	0.29***
	(3.13)	(1.66)	(6.19)	(4.51)
Quant × Market Volatility	-0.22	-0.45***	-0.39***	-0.38***
	(-1.02)	(-3.29)	(-5.57)	(-4.37)
Quant × VIX	0.24	0.26*	0.10	0.17**
	(1.12)	(1.83)	(1.40)	(2.12)
Year × Month FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
R-squared	0.76	0.91	0.90	0.89
Observations	12,796	11,384	38,983	63,163

Table 4. Intensity of Treatment Tests

This table presents the results for the intensity of treatment tests. Panel A focuses on the quantitative funds using book-to-market investment strategies. Panel B and Panel C show the results of two falsification tests using funds relying more on momentum and size strategies, respectively. The dependent variable, *Fund Return (%),* is the TNA-weighted monthly fund return in percentage terms. Pension, NCI, and Lease refer to the accounting standard changes detailed in Figure 1. The final column in each panel is the equal-weighted pooled analysis of all three standard changes. *Post* is an indicator variable that equals one if the month is after the effective date of the accounting standard change. *Quant* is an indicator variable that equals one if the fund has been classified as a quantitative fund. The control variables, which are defined in Table 1, are *Fund Age*, *Fund Assets*, *Exp Ratio*, *Load*, *Fund Flow*, *Flow Vol*, *Book-to-Market*, *Momentum, Size*, *Quant* × *Market Volatility,* and *Quant* × *VIX*. We exclude *Book-to-Market* (*Momentum*) [*Size*] from the controls in Panel A (Panel B) [Panel C] to avoid multicollinearity. All fund-level continuous variables are winsorized at the 1% and 99% levels and standardized. All regressions are at the monthly level with year-month and fund fixed effects. Standard errors are clustered at the fund level. t-statistics are included in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent two-tailed level, respectively.

Panel A: Value Investors

	Y = ***Fund Return*** **(%)**			
	(1) **Pension**	(2) **NCI**	(3) **Lease**	(1) – (3) **Combined**
Post × *Quant*	0.05	-0.48***	-0.03	-0.17***
	(0.38)	(-3.58)	(-0.71)	(-2.70)
Post × *Quant* × *Value Investor*	-0.37**	0.08	-0.21**	-0.17*
	(-2.41)	(0.35)	(-2.52)	(-1.68)
Controls	Yes	Yes	Yes	Yes
Year × *Month* FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
R-squared	0.76	0.91	0.90	0.89
Observations	12,796	11,384	38,983	63,163

Panel B: Falsification Test #1 – Momentum Investors

	Y = ***Fund Return*** **(%)**			
	(1) **Pension**	(2) **NCI**	(3) **Lease**	(1) – (3) **Combined**
Post × *Quant*	-0.27**	-0.21*	-0.14***	-0.19***
	(-1.99)	(-1.65)	(-3.39)	(-3.44)
Post × *Quant* × *Momentum Investor*	-0.26	-0.02	0.09	-0.01
	(-1.13)	(-0.07)	(1.11)	(-0.12)
Controls	Yes	Yes	Yes	Yes
Year × *Month* FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
R-squared	0.76	0.91	0.90	0.89
Observations	12,796	11,384	38,983	63,163

Panel C: Falsification Test #2 – Large-cap Investors

	Y = ***Fund Return*** **(%)**			
	(1) **Pension**	(2) **NCI**	(3) **Lease**	(1) – (3) **Combined**
Post × *Quant*	-0.26*	-0.24*	-0.11***	-0.22***
	(-1.78)	(-1.68)	(-2.61)	(-3.58)
Post × *Quant* × *Large-cap Investor*	-0.04	-0.39	0.06	-0.04
	(-0.18)	(-1.60)	(0.81)	(-0.41)
Controls	Yes	Yes	Yes	Yes
Year × *Month* FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
R-squared	0.76	0.91	0.90	0.89
Observations	12,796	11,384	38,983	63,163

Table 5. Mechanism Test – Increased Turnover

This table examines turnover as a mechanism through which quantitative funds' performance changes relative to discretionary funds around accounting standard changes. The dependent variable in Panel A, *Turnover*, is obtained by value-weighting fund class level turnover with lagged total net asset. The dependent variable in Panel B, *Fund Return (%),* is the TNA-weighted monthly fund return in percentage terms. *Pension*, *NCI*, and *Lease* refer to the accounting changes detailed in Figure 1. *Combined* denotes an equal-weighted pooled analysis of all three standard changes. *Quant* is an indicator variable that equals one if the fund has been classified as a quantitative fund. *Many Stocks* is an indicator variable that equals one if the number of common stocks the fund holds during the last month in the pre-period is among the top 30% of all funds in the sample, and zero otherwise. In both panels, we control for *Age*, *FundAssets*, *ExpRatio*, *Load*, *FundFlow*, *FlowVol*, *Size*, *Momentum*, *Book-to-Market*, *Quant* × *Market Volatility,* and *Quant* × *VIX*. We also control for *Fund Return* when *Turnover* is the dependent variable. All variables are defined in Table 1. Coefficients of control variables are omitted for brevity. All fund-level continuous variables are winsorized at the 1% and 99% levels. Regressions are at the monthly level with year-month and fund fixed effects. Standard errors are clustered at the fund level. t-statistics are included in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent two-tailed level, respectively.

Panel A: Fund Turnover

	Y = *Turnover*			
	(1)	(2)	(3)	(1) – (3)
	Pension	**NCI**	**Lease**	**Combined**
Post × *Quant*	0.02	0.12***	0.02**	0.05***
	(0.81)	(3.43)	(2.34)	(3.84)
Controls	Yes	Yes	Yes	Yes
Year × *Month* FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
R-squared	0.90	0.93	0.94	0.93
Observations	12,796	11,384	38,983	63,163

Panel B: Common Stocks

	Y = *Fund Return* (%)			
	(1)	(2)	(3)	(1) – (3)
	Pension	**NCI**	**Lease**	**Combined**
Post × *Quant*	0.03	-0.40**	-0.06	-0.12*
	(0.19)	(-2.48)	(-1.24)	(-1.80)
Post × *Quant* × *Many Stocks*	-0.58***	-0.43*	-0.06	-0.32***
	(-2.91)	(-1.68)	(-0.83)	(-3.25)
Controls	Yes	Yes	Yes	Yes
Year × *Month* FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
R-squared	0.76	0.91	0.90	0.89
Observations	12,796	11,384	38,983	63,163

Table 6. Mechanism Test - Fund Strategies

This table presents estimates of whether funds change investment strategies around accounting standard changes. The dependent variables *Book-to-Market*, *Momentum*, and *Size* are (-1, 0, 1) categorical variables that represent the bottom 30%, middle 40%, or top 30% of all funds based on their value, momentum, and size slants, respectively, and are updated on a monthly basis. *Post* is an indicator variable that equals one if the month is after the effective date of the accounting standard change. *Quant* is an indicator variable that equals one if a fund has been classified as quantitative. *Fund Age* is the number of months since the first-offer-date of the oldest fund class. *Fund Assets* is the sum of the total net asset for all fund classes, *Exp Ratio* is the fund expense ratio, *Load* is the sum of the fund's mean front load and mean rear load, *Fund Flow* is the net fund flows adjusted by fund returns, *Flow Vol* is the standard deviation of fund flow over the past 12 months. *Market Volatility* is the moving standard deviation of the market return less the risk-free return over the previous 120 days. *VIX* is the monthly-level VIX index obtained from averaging the CBOE daily VIX index. *Exp Ratio* and *Load* are obtained by value-weighting fund class measures with lagged total net asset, and all other measures are measured directly at the fund level. All fund-level continuous variables are winsorized at the 1% and 99% levels and standardized. Sample observations are at the monthly level, with standard errors clustered at the fund level. t-statistics are included in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent two-tailed level, respectively.

Dependent Variable =	***Book-to-Market***	***Momentum***	***Size***
	(1)	(2)	(3)
Post × *Quant*	0.00	-0.00	-0.03***
	(0.25)	(-0.21)	(-2.71)
Fund Age	0.05	-0.13*	0.02
	(1.18)	(-1.78)	(0.56)
Fund Assets	-0.12***	0.35***	0.00
	(-3.08)	(5.80)	(0.15)
Exp Ratio	0.05**	0.01	-0.03
	(2.17)	(0.19)	(-1.36)
Load	-0.03	0.06	-0.04*
	(-1.14)	(1.55)	(-1.82)
Fund Flow	-0.00**	0.02***	0.00
	(-2.37)	(5.19)	(0.63)
Flow Vol	-0.00	0.01	-0.00
	(-0.66)	(1.00)	(-1.12)
Book-to-Market	--	-0.26***	-0.04***
		(-14.84)	(-4.94)
Momentum	-0.08***	--	0.01***
	(-14.00)		(2.97)
Size	-0.09***	0.07***	--
	(-5.06)	(3.04)	
Quant × *Market Volatility*	-0.01	0.10***	-0.00
	(-0.53)	(3.30)	(-0.21)
Quant × *VIX*	-0.01	-0.05***	0.00
	(-0.93)	(-3.56)	(0.56)
Year × *Month* FE	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
R-squared	0.88	0.60	0.93
Observations	63,163	63,163	63,163

Table 7. Time Varying Effects

This table shows quantitative funds' performance and turnover over multiple years relative to discretionary funds around accounting standard changes. The dependent variable in the first column is *Fund Return (%),* the TNA-weighted monthly fund return in percentage terms. The dependent variable in the second column is *Turnover*, obtained by value-weighting fund class level turnover with lagged total net asset. *Quant* is an indicator variable that equals one if a fund has been classified as quantitative. *Post (Year 1)* and *Post (Year 2)* are indicator variables that equal one if the month is within the first or second year after the effective date of the accounting standard change, respectively. Note that here we expand our difference-in-difference model from one year pre-post to two years pre-post. Thus, the sample size is greater than in the prior analyses. The control variables for both columns are *Fund Age*, *Fund Assets*, *Exp Ratio*, *Load*, *Fund Flow*, *Flow Vol*, *Size*, *Momentum*, *Book-to-Market, Quant* × *Market Volatility,* and *Quant* × *VIX*. We also control for *Fund Return* when *Turnover* is the dependent variable. All variables are defined in Table 1. Coefficients of control variables are omitted for brevity. All fund-level continuous variables are winsorized at the 1% and 99% levels. Regressions are at the monthly level with year-month and fund fixed effects. Standard errors are clustered at the fund level. t-statistics are included in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent two-tailed level, respectively.

Dependent Variable =	***Fund Return (%)***	***Turnover***
	(1)	(2)
Quant × *Post (Year 1)*	-0.16***	0.04***
	(-4.02)	(2.68)
Quant × *Post (Year 2)*	0.07	0.03
	(1.42)	(1.19)
Controls	Yes	Yes
Year × *Month* FE	Yes	Yes
Fund FE	Yes	Yes
R-squared	0.89	0.88
Observations	109,456	109,456