The Effect of New Accounting Standards on the Performance of Quantitative Investors*

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Abstract
Quantitative investing relies on stable data generating processes and limited 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 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 skill and judgment to make day-to-day investment decisions. Our result is predictably concentrated among 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 do not find that quantitative investors change their overarching strategies in response to accounting standards, but we do observe excess portfolio turnover. Overall, our results highlight a significant adjustment cost associated with accounting regulation that could become even more significant as more investors rely on quantitative strategies.

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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 computing power, analytical software, and economic data. 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 (i.e., 26% and 14% of hedge fund and mutual fund capital, respectively, 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 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."

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, for at least two reasons. First, without real-time human intervention, the computer systems underlying quantitative trading are limited in their 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 around 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 tend to closely follow market-wide and firm-specific news events such as earnings announcements and 10-K filings, making them more likely to notice and adapt to any changes to the accounting policies underlying firms' financial statement numbers. 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 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 phrases in mutual funds' regulatory filings (e.g., Beggs, Brogaard, and Hill-Kleespie, 2019; 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. To further validate our classification methodology, we follow Abis (2020), a recent study using a related classification based on machine learning, in documenting that quantitative funds are younger and smaller, charge lower fees, and have higher portfolio turnover.

Our main analysis exploits three new U.S. standards affecting the accounting for pensions (2006), noncontrolling interests (2008), and leases (2018). Crucially, each of these standards 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 the issue of 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 3.3%, which is nearly 30% of the average fund's unconditional annual return (of about 11%). This evidence is consistent with revisions to accounting regulation creating incremental adjustment costs for quantitative investors, whose models appear unable to immediately and fully adapt to new accounting conventions.

Of course, not all investors are equally likely to use accounting data and be affected by changing standards as a result. Balance sheet data are a particularly critical ingredient of the value strategy that is so prevalent among fund managers (e.g., in our sample, 21% of fund names include 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 because we expect them to be among

[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 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. As expected, we find that quantitative underperformance is concentrated 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 directly affected by accounting regulations. As a result, a momentum or size component in quantitative funds' models does not need to be updated due to changing accounting standards. Thus, we expect to find no change in the performance difference 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 heterogenous shocks around the time of the standards.

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 six months following the standards and marginal during the next six months, but nonexistent in the second year.

We next investigate the mechanisms through which quantitative investors update their models in response to accounting standards. While we do not find that they are more likely to switch from reliance on accounting-based (i.e., book-to-market) to price-based (i.e., momentum or size) investment strategies, we do find evidence of increased portfolio turnover that may increase trading costs and contribute to the overall underperformance we document. Finally, we further examine the idea that human involvement is useful in navigating new accounting standards. To do so, we examine funds that appear to employ a hybrid of the quantitative and discretionary approach, based on their use of fewer (albeit still greater than zero) quantitative words in their filings. We also exploit variation in management fees, which prior research and intuition suggest are higher for funds that rely more on human managers. Using both of these measures, we find that quantitative funds with more human involvement are less likely to underperform following the accounting standard changes.

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 homogenous, 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., 2019; 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 the preparation and adjustment costs that *firms* would incur as a result of changing standards, our research suggests that such changes also impose costs on other market participants. In particular, the performance of quantitative investors suffers temporarily because it takes them some time to adjust their trading models and strategies in response to changes to accounting standards. Awareness of this adjustment cost facing capital market participants will 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 standards to shareholders complements recent research by Khan, Li, Rajgopal, and Venkatachalam (2018) that suggests the typical FASB 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 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 modern investing regime.

II. LITERATURE REVIEW 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 limited 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., colocation) 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 (Ahmend 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. (2019) 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 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, they 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. Failure to incorporate these differences 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 the quantitative funds that rely heavily on accounting inputs.

However, we acknowledge that accounting changes could plausibly enhance quantitative performance, for example, if the new accounting numbers result in more precise quantitative signals (e.g., financial ratios) 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 or improve 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 first begin with 74 exposure drafts for new accounting standards over the years 2004-2016 (Monsen, 2020). To identify the most material accounting changes, we constrain the set of new accounting standards to the ten that received the highest number of constituent comments.[2] Our decision to focus on a few material standard changes is supported by evidence in Khan et al. (2018) that suggests the majority of accounting standard changes are a non-event from investors' perspective (e.g., no stock market reaction). Since balance sheet numbers constitute such a significant portion of valuation metrics, we further constrain the set of new standards to those that directly impact the balance sheet. 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); 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 these standards also impacted several other parts of the financial statements to some extent, including the income statement and footnotes. Part 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 firms may voluntarily report information for prior years under the new standards. Even if this does occur, quantitative funds' backtests often use more than the three years of data that are commonly presented in firms' financials. Thus, even

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

retroactively applied standard changes could affect quantitative funds, at least in the short term, as we hypothesize in this paper.

2.2.1 Pension

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. It appears that investors do not pay enough attention to pension information disclosed in the footnotes, but completely process information recognized in the financial statements (Picconi, 2006). Researchers thus long urged standard-setters to mandate recognition of pension assets and liabilities in the financial statements (Harper et al., 1987; Coronado et al., 2008).

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.[3] Prior to this standard, information related to the funded status of retirement plans was disclosed in the footnotes but not recognized in the financial statements. The Board 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

[3] 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.

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 Interest

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 total book equity for the average Compustat firm during the post period of 2010 through 2019. 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).

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. Furthermore, the standard requires that any administrative costs incurred to complete the business combination be expensed rather than capitalized as in the previous regime. Both of these requirements likely increased most firms' NCI valuations. 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 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 section of their balance sheets due to the new standard.

III. DATA AND VARIABLE MEASUREMENT

3.1 Sample Selection

We initially collect data on mutual fund performance from 2003 through 2019 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 the following reasons. First, CRSP checks fund prospectuses and contacts fund management to collect voluntarily disclosed holdings more often than Thomson Reuters.[4] 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 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.[5] We remove index funds, ETFs, 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, funds that have less than $5 million in total net assets or hold less than ten common stocks (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.[6] 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

[4] 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

[5] We use the percentage of fund assets invested in common stocks, CRSP variable *per_com,* and take the average over the entire duration of our sample period for each fund.

[6] 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.

this weighting approach for all our numerical variables except *Age*, which we calculate based on the inception date of the oldest fund class.

These criteria result in 360,706 fund-month observations, of which 311,962 have nonmissing data for the variables discussed in Section 3.3. In the next section, we explain how we classify funds as quantitative or discretionary, which further reduces the sample used in our main analyses.

3.2 Mutual Fund Classification: Quantitative vs. Discretionary

To classify funds as quantitative or discretionary, we obtain Form 485APOS and 485BPOS from the SEC's EDGAR database. Mutual funds file a full prospectus, *Form N-1A Registration Statement*, at the time of initial registration, and make subsequent modifications through 485APOS and 485BPOS. 485BPOS forms are filed at least annually with routine updates, while 485APOS forms are filed if there are non-routine amendments (deHaan, Song, Xie, and Zhu, 2019). Both of these forms have a similar structure and include detailed discussions of funds' investment strategies.

To link the EDGAR filing data with the CRSP MFDB, we follow a multi-step approach based on scraped header information from the 485APOS and 485BPOS filings. We primarily link these data using the fund names and respective CIK numbers listed at the beginning of the fund family's prospectus. Prior to 2006, this header information was not mandatory disclosure. Accordingly, if the SEC header information is absent, we match CRSP fund names to EDGAR fund names. For any unmatched funds, we attempt to fill in the blanks using the CRSP link table crsp_cik_map.[7]

[7] The crsp_cik_map file only reports the most current link between *crsp_fundno* and CIKs. As many funds went through reorganization, such as mergers and acquisitions, the link proves to be incorrect for earlier years in the sample period. We note other researchers have also identified weaknesses with this linking table and attempted to correct

Following Beggs et al. (2019), we classify all funds in a given family as quantitative if their registration documents contain a certain number of quantitative phrases. Appendix B lists the quantitative phrases used in the classification process. We allow the number of quantitative phrases required for classification to change each year to accommodate the drastic increase in funds' propensity to mention quantitative phrases over time. Accordingly, our study classifies funds at or above the 90^{th} percentile of quantitative phrases, in a given year, as quantitative.[8] As an example, we show excerpts from the prospectus of a quantitative fund in Appendix C. We classify funds as discretionary if they use zero quantitative phrases. We exclude funds that use some quantitative phrases but fall below the 90^{th} percentile. While this criterion significantly reduces our sample size, it helps us identify the most quantitative and most discretionary funds and thus increases the power of our tests. Including funds whose strategies are more unclear would likely introduce unnecessary noise into our estimations, as we explain in more detail next.

As is readily apparent, quantitative fund classification is not a straightforward exercise because the quantitative and discretionary approaches are not mutually exclusive. For example, in the mid-2000s, more than half of fund managers reported in interviews that they used a mix of quantitative and fundamental (i.e., discretionary) approaches (Fabozzi et al., 2008). Consistent with conventional wisdom, Figure 2 suggests that quantitative investing has further increased in popularity in recent years, meaning even more funds now incorporate some degree of quantitative screening into their investment decision-making process. That is, the figure shows that the number of quantitative phrases in funds' filings has increased significantly during our sample period.

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them with other matching processes. See the Online Appendix of Chernenko and Sunderam (2020) for details of one such approach.

[8] In later analyses, we use alternative cutoffs and find similar results (see Table 8). However, the economic magnitude of the results decreases as we lower the cutoff. This is expected and is consistent with the most quantitative funds being most affected by the new accounting standards, while funds adopting a "hybrid" quantitative-discretionary approach appear to be able to more quickly adjust to the accounting changes due to greater human involvement.

Specifically, the top decile of funds increased from about 28 quantitative phrases on average in 2003 to about 162 in 2019.

However, casual observation and anecdotal evidence suggest that *quantitative investment* has become a buzzword that funds use to attract investors, even if they are almost entirely discretionary. 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). Thus, excluding the funds that use quantitative phrases but fall below the 90^{th} percentile reduces the chances of including funds in our sample that are largely discretionary but claim to be quants.

We also note that a single prospectus often covers multiple funds belonging to the same fund family (which the SEC refers to as "the registrant"). Of course, classifying funds at the fund family level could result in 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. Fortunately, classifying some discretionary funds as quantitative biases against finding differences between the two groups.

Figure 3 shows the result of our classification. The number of quantitative funds is relatively stable over our sample period. The number of discretionary funds gradually decreased from 576 in 2003 to 411 in 2019. This is consistent with quantitative investing becoming more popular and more funds "check the box" and mention quantitative phrases in the prospectuses. We exclude the middle category of funds (i.e., funds that use quantitative phrases, but are below the 90^{th} percentile) from our analysis to avoid classifying discretionary funds as quantitative. As noted previously, including the middle category of funds in the quantitative group does not materially change our results or inferences (also see Section 4.7).

Starting from the 360,706 fund-month observations that passed our sample selection criteria detailed in section 3.1, we keep observations within the one year pre- and post-period in our difference-in-difference analysis. The total number of fund-month observations from January 2006 to December 2007 (Pension period), January 2008 to December 2009 (NCI period), and January 2018 to December 2019 (Lease period) is 130,678. Next, we drop all funds that are neither quantitative nor discretionary, leaving us with 49,653 fund-month observations (12,765 quantitative and 36,888 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 step reduces our sample size to 35,953 observations (7,408 quantitative and 28,545 discretionary). Removing observations with missing values for key variables reduces the sample size to 33,384 (6,444 quantitative and 26,940 discretionary). Finally, we require that each fund has at least one observation in both the pre- and post-period. These restrictions lead us to the final sample size of 32,036 for our main analysis, out of which 6,027 are observations of quantitative funds and 26,009 are observations of discretionary funds.

3.3 Variable Measurement

To better understand the funds in our sample, we measure a variety of fund-level attributes. 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. Our main dependent variable, *Fund Return*, is fund-level raw returns obtained by value-weighting fund-class-level raw returns using lagged total net assets as the weight.[9] Note that our inclusion of

[9] Monthly fund-class-level raw returns are obtained by adding 1/12 of the annual expense ratio to the monthly fund net return reported by CRSP.

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 dimensions of funds' investment strategy (i.e., value, momentum, and large-cap). In doing so, we sort stocks into quintiles of book-to-market, momentum, and market capitalization. We aggregate these characteristics to the fund-level by summing the product of each stock's quintile rank and its portfolio weight.[10] We then rank the funds every month and use three categorical variables (*Book-to-Market*, *Momentum*, and *Size*) to identify the funds ranked among the bottom 30%, middle 40%, or top 30% of all funds (i.e., -1,0,1).

Other fund characteristics such as *FundFlow*, *FlowVol*, *Turnover*, *Load*, *MgmtFee*, and *ExpRatio* are obtained from value-weighting each fund-class-level measure by lagged total net asset. *Age* is the log of the number of months since the first-offer-date of the oldest fund class within the fund. *FundAssets* is the log of the sum of the total net asset under management. All continuous variables are winsorized at the 1% and 99% levels.

3.4 Descriptive Statistics and Validation of Fund Classification

Table 1 reports descriptive statistics for the quantitative and discretionary funds in our sample and provides some initial insight into differences between the two groups. While quantitative and discretionary funds are about equally likely to be value investors, the former are more heavily slanted towards high momentum stocks and large 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 more assets than the median discretionary fund ($493 million vs. $446 million). However, there are fewer mega-sized quantitative funds than

[10] The weight we use is the CRSP MFDB variable *percent_tna*, the percentage of total assets invested in the security.

discretionary funds (i.e., the 90th percentiles are \$2,186 million and \$7,187 million, respectively).[11] The median discretionary fund is about 15.9 years old, while the median quantitative fund is only 9.3 years old.[12] 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 (0.80 vs. 0.44).

To validate our classification methodology, we compare fund age, size, fee structures, portfolio turnover, and investment strategies between quantitative and discretionary funds in our sample. Table 2 Panel A shows that quantitative funds are younger, smaller, charge lower fees, and have higher turnover. Panel B shows that quantitative funds use more momentum and value investing strategies than discretionary funds, but invest less in small-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-difference design:

$$\begin{aligned} Return_{i,t} = {} & \beta_0 + \beta_1 Quant_{i,t} + \beta_2 Post_{i,t} + \beta_3 Quant_{i,t} \times Post_{i,t} \\ & + Control\_Variables_{i,t} + YearMonth\ FE + Fund\ FE + \varepsilon_{i,t}. \end{aligned} \tag{1}$$

Post is an indicator variable that equals one if month *t* begins after the effective date of the accounting standard change. The effective dates for SFAS 158 (Pension), SFAS 160/141R (NCI), and ASC 842 (Lease) are Dec 15th, 2006, Dec 15th, 2008, and Dec 15th, 2018, respectively. The control variables include fund age (*Age*), fund size (*FundAssets*), fund expenses (*ExpRatio*), front

[11] *FundAssets* is in log of millions of dollars. The above numbers are obtained by: $e^{6.20}$ = 493; $e^{6.10}$ = 446; $e^{7.69}$ = 2,186; $e^{8.88}$ = 7,187

[12] *Age* is in log of months. The above numbers are obtained by: $e^{5.25}/12$ = 15.9; $e^{4.72}/12$ = 9.3

and rear load (*Load*), turnover (*Turnover*), fund flow (*FundFlow*), flow volatility (*FlowVol*), and fund investment strategies (*Book-to-Market*, *Momentum*, and *Size*).

In our main analysis, we run equation (1) separately around the Pension, NCI, and Lease accounting standards. While we initially study one year pre- and post-periods, later tests consider different length windows because we expect quantitative funds' lower performance to attenuate as they (or their models) notice lower model performance due to the changing statistical properties of the accounting variables and make appropriate adjustments. β_3 is the coefficient of interest. If accounting standard changes harm quantitative funds more than discretionary funds, the return for quantitative funds will be lower during the post period and β_3 will be negative.

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

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. We adjust fund-specific returns using the average fund return for the month. The average DiD is -0.26%, -0.51%, -0.20%, and -0.32% for the pension, NCI, lease, and combined samples, 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 -0.32% monthly returns from the combined sample translates to about -3.8% on an annual basis.[13] Note that this underperformance represents about 33% of the average fund's unconditional annual return of about 11.4%, which is based on the 90 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.

We estimate a negative coefficient on *Post x Quant* for all three accounting standards. While this coefficient is only marginally statistically significant for the pension standard, the NCI and lease estimates are statistically significant at the one percent level and greater in magnitude. Similarly, the coefficient on *Post x Quant* is highly statistically significant in the final "combined" column. In addition, each of these estimates, which range from -0.19 to -0.48, is economically significant. For example, the -0.28 coefficient in the last column implies that quantitative funds' performance deteriorated by 28 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 3.3%, or about 29% of the average fund's unconditional annual return.

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

[13] $1 - (1-0.0032)^{12} = 0.038$

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 policies and procedures.

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, such as during the financial crisis of 2007-2009 that makes up much of our sample (e.g., Barroso and Santa-Clara, 2015; Israel, Laursen, and Richardson, 2020).

Figure 4 provides a graphical illustration of our main result. Panel A (Panel B) maps out our estimations of incremental (i.e., difference between quantitative and discretionary) returns in event time at the monthly (quarterly) level. Specifically, we replace *Post x Quant* from equation (1) with *Quant* interacted with event-time dummies, one for each of the months (quarters) in the pre- and post-standard period (where the time period directly preceding the standard is the excluded base period). The first takeaway from Figure 4 is that the pre-period indicators are mostly insignificant, with the exception of a few monthly indicators at the beginning of the pre-period. This suggests that there were largely parallel trends between quantitative and discretionary funds before the accounting standards. But, if anything, quantitative performance was improving slightly relative to discretionary funds, which cuts against the significant (and sudden) underperformance following the standards. On that note, the second takeaway from Figure 4 is that the post-standard indicators are significantly negative in the first six months following the standards. We do not find quantitative underperformance after six months, which we discuss in more detail in Section 4.5. Overall, these results are consistent with our findings in Table 3, suggesting that quantitative funds underperform (at least temporarily) relative to discretionary funds following the implementation of major new accounting standards.

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 attempt to 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 this variable with *Post x Quant* as well as the control variables. To be specific, the coefficient on *Post x Quant x 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 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 x Quant x Value Investor* are negative and statistically significant at each standard change (columns 1 through 3) and in the pooled sample (column 4). The -0.44 coefficient in column 4 translates into annualized underperformance of 5.15%. In addition, the insignificant coefficient on *Post x Quant* suggests that non-value quantitative investors do not significantly underperform following 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 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 x Quant x Momentum Investor* or *Post x Quant x Large-cap Investor* is negative and significant. This suggests that the quantitative investors relying most heavily on the momentum and size philosophies are not associated with underperformance following accounting standard updates. In contrast, in both Panels B and C, the coefficients on *Post x Quant* are generally negative and significant, suggesting that the underperformance we documented previously is concentrated among the 70% of quantitative investors that do not substantially rely on 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 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) in our analysis from one to two years. Specifically, to show how quantitative funds' performance evolves during the post-period, we create an indicator for each six-month period during the two years following the new standards.

Table 5 reports the findings of this analysis. We find that quantitative performance decreases substantially for the first six months. When we average over the three standards (i.e., using the result in the final "combined" column), the underperformance in the first six months is 0.37 bps per month, or about 2.20% total. Thereafter, quantitative performance begins to recover quickly. Specifically, the average underperformance during the second six months is only 0.11 bps and is only marginally statistically significant. During the second year, there is no significant quantitative underperformance, which we infer from the coefficients on *Quant x Post(+13,+18)* and *Quant x Post(+19,+24)*. 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 at the very least that their models are dynamic enough to adjust and recover within a few quarters.

4.6 Changes in Fund Operations

In this section, we consider whether significant differences in fund operations arise between quantitative and discretionary funds in addition to the differences in fund returns we have already documented. One possibility is that quantitative funds will be more likely to switch to or from accounting-based strategies as they (or their models) start to notice changes to their accounting data or their performance. Additionally, quantitative funds might incur additional portfolio turnover because changes to accounting standards affect the accounting variables that funds use to rank stocks and estimate model-implied portfolio weights.

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. These regressions, which are reported in Table 6, suggest no difference between quantitative and discretionary funds slant towards the strategies from the pre- to the post-period. That is, none of the *Post x Quant* coefficients are statistically different from zero. As such, we infer that quantitative investors did not change their relative exposure to the book-to-market strategy, which is based on accounting data, or the momentum and size strategies, which are not.

We next test for additional portfolio turnover. This additional turnover could arise due to changing accounting numbers, which of course are inputs in quantitative models, affecting 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 7 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. Moreover, in Panel B of Table 7, we show that this additional turnover was concentrated in the first year following the new standards. This latter result aligns nicely with our finding in Table 5 that quantitative funds more or less fully adjust to the new accounting standards within a year.

4.7 Human Involvement

In making the argument that quantitative investors' performance is likely to suffer, at least temporarily, following changes in accounting standards, we have emphasized the limited human involvement inherent in their approach. At the same time, we acknowledge that many funds adopt a hybrid quantitative-discretionary approach. That is, they combine quantitative techniques, such as reliance on large data sets and statistical modeling, and discretionary techniques, such as having discussions with managers and leaving the ultimate trading decisions to human fund managers. Our analyses in this section exploit variation in fund characteristics that likely reflect human involvement combined with the quantitative approach.

First, we exploit variation in the use of quantitative words in funds' prospectus filings. For the purposes of our main tests, we classify funds as quantitative if their use of quantitative words puts them at or above the 90th percentile. We select such a high cutoff to maximize the power of our tests, or in other words, because we believe that these funds are likely among the very most quantitative and therefore the most likely to be negatively affected by accounting standards. By this same logic, the funds below the 90th percentile, many of which still use some quantitative words, likely incorporate discretionary techniques to a greater extent. We predict that this greater discretionary, or human, reliance will allow these hybrid funds to partially or entirely avoid the negative effects of new accounting standards.

To implement this test, we repeat our analyses using various cutoffs in defining funds as quantitative. To be specific, the first column of Panel A of Table 8 reproduces the last column of

Panel B of Table 3, which shows quantitative underperformance of 0.28 bps per month on average in the year following the accounting standard changes. As expected, in the subsequent columns we find that this underperformance attenuates as we gradually decrease the cutoff to the 80th percentile, 70th percentile, and so on. By the time we reach the classification based on the 50th percentile of quantitative words, the quantitative underperformance more than halves to 0.12 bps per month. Note that the sample size increases as we decrease the percentile cutoff because more funds are classified as "quantitative" and included in the sample. Overall, this result is consistent with less quantitative (or "hybrid") funds being able to more quickly adjust to accounting changes, which mitigates their underperformance relative to the most discretionary funds.

Second, we follow Abis (2020) and other prior research that finds that quantitative funds tend to charge lower management fees, which is arguably due to their lower reliance on human managers. In other words, human capital is one of funds' most costly resources that investors pay for through management fees. To identify quantitative funds with more human involvement, or similarly more reliance on human capital, we create *High Fee Fund*, an indicator for whether the fund's management fee is in the top 30% of the sample. Following the design of Table 4, we interact this indicator with *Post x Quant* and the control variables. The results are reported in Panel B of Table 8. They suggest that quantitative funds that charge higher management fees, and therefore likely have greater human involvement, outperform quantitative funds with lower management fees following the accounting standards.[14] Taken together, the results in this section

[14] While we use management fees as a measure of human involvement, such fees might also reflect funds' quality or past success. Indeed, in untabulated tests, we find that current management fees and past fund returns are significantly positively associated. Thus, an alternative explanation for our result in Panel B of Table 8 is that the historically "better" funds are able to adapt to accounting regulation faster. To help rule out this alternative explanation, we add past fund returns (over the prior three years) as well as its interactions with *Post*, *Quant*, and *Post x Quant* to the model estimated in Panel B of Table 8. This (untabulated) analysis leads to very similar results and the same inferences.

support and extend our main results by suggesting that they are driven by the aspects of quantitative investing we highlight, especially the lack of human intervention.

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 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 is an economically significant 30% of the average mutual fund's annual return (~11%). Moreover, we find this result for value funds, but not for momentum or 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 no evidence of funds' altering their investment strategies, but do find evidence of additional portfolio turnover following the regulatory events. We also find evidence consistent with the idea that human involvement (or a "hybrid" approach) is one way to mitigate the disadvantages of a quantitative approach.

Our results are subject to important caveats. First, we study a few prominent and dramatic 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 identifying one cost of accounting standards to quantitative 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 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
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 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 (forms 485APOS and 485BPOS). 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.
Post	An indicator variable that equals one if the month begins after the effective date of the accounting standard change. The effective dates for SFAS 158 (Pension), SFAS 160/141R (NCI), and ASC 842 (Lease) are Dec 15th, 2006, Dec 15th, 2008, and Dec 15th, 2018, respectively.
Age	*Age* is the log of the number of months since the first offer date of the oldest fund class.
FundAssets	*FundAssets* is the log of the sum of total net assets for each of the fund class within a fund. The total net asset is in millions of dollars.
ExpRatio	CRSP MFDB variable EXP_RATIO, value weighted by the lagged total net asset of each fund class.
Load	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 value and duration of 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.
Turnover	CRSP MFDB variable TURN_RATIO, value weighted by the lagged total net asset of each fund class.
FundFlow	*FundFlow* is calculated as (TNA_t / TNA_{t-1}) - (1 + Ret_t), following Barber, Huang, and Odean (2016), where Ret is the variable *Return* and TNA is the sum of the total net assets managed under each fund class.
FlowVol	Standard deviation of *FundFlow* over the prior 12 months, calculated on a rolling basis.
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. Preferred shares take on the redemption value (PSTKRQ) if available; 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 (PERCENT_TNA). 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 (PERCENT_TNA). 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 to -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 (PERCENT_TNA). 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.
MgmtFee	CRSP MFDB variable MGMT_FEE, value weighted by lagged total net asset of each fund class.
High Fee Fund	An indicator variable that equals one if a fund's *MgmtFee* is among the top 30% of funds in the sample and zero otherwise. *High Fee Fund* is held constant for each fund during each event period.

Appendix B. Quantitative Phrase List from Beggs et al. (2019)

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 computer valuation, quantitative optimization, quantitatively driven, quantitative studies, quantitative computer valuation, quantitatively assess, quantitative assessment, quantitative research, 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.[15] 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.

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

Figure 1. Detail on Accounting Standard Changes

This figure summarizes key information 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 132(R)	ARB 51; SFAS 140	ASC 840
Effective Date	Dec 15th, 2006	Dec 15th, 2008	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 F/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. Average Number of Quantitative Phrases by Decile

This figure presents the average number of quantitative phrases in fund prospectuses by decile of the selected sample year (i.e., 2003, 2011, and 2019). Decile 10 represents the funds classified as quantitative in our main analysis.

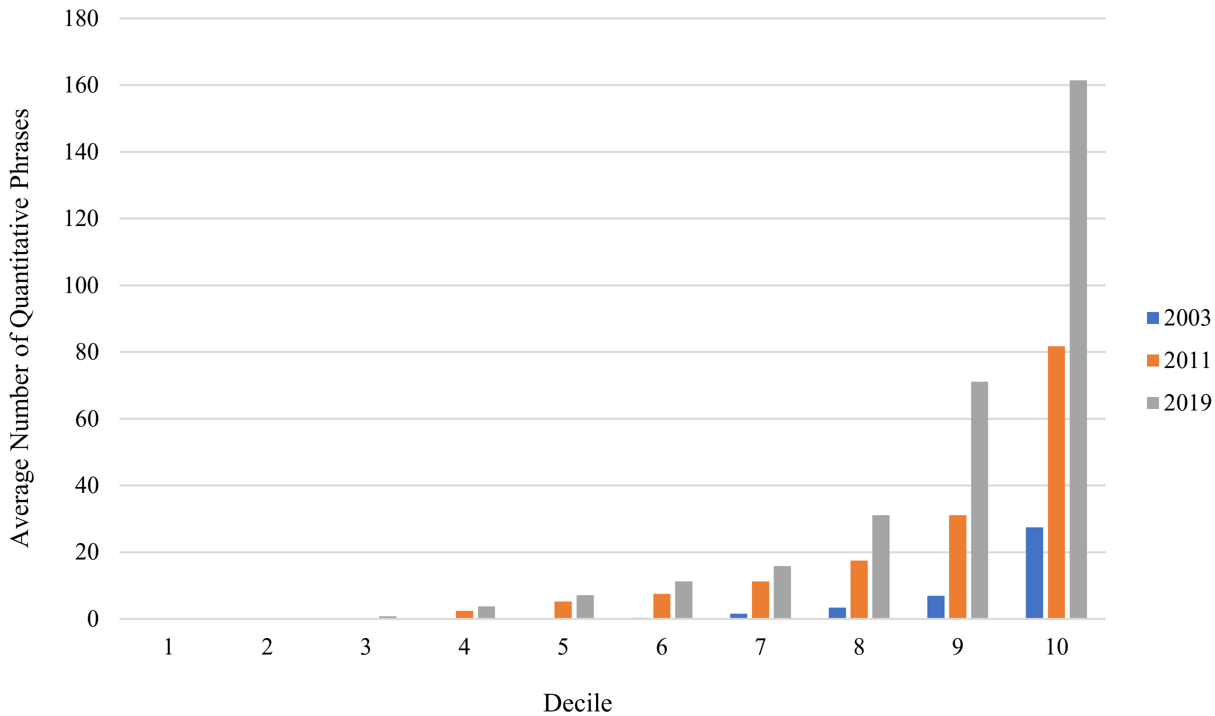
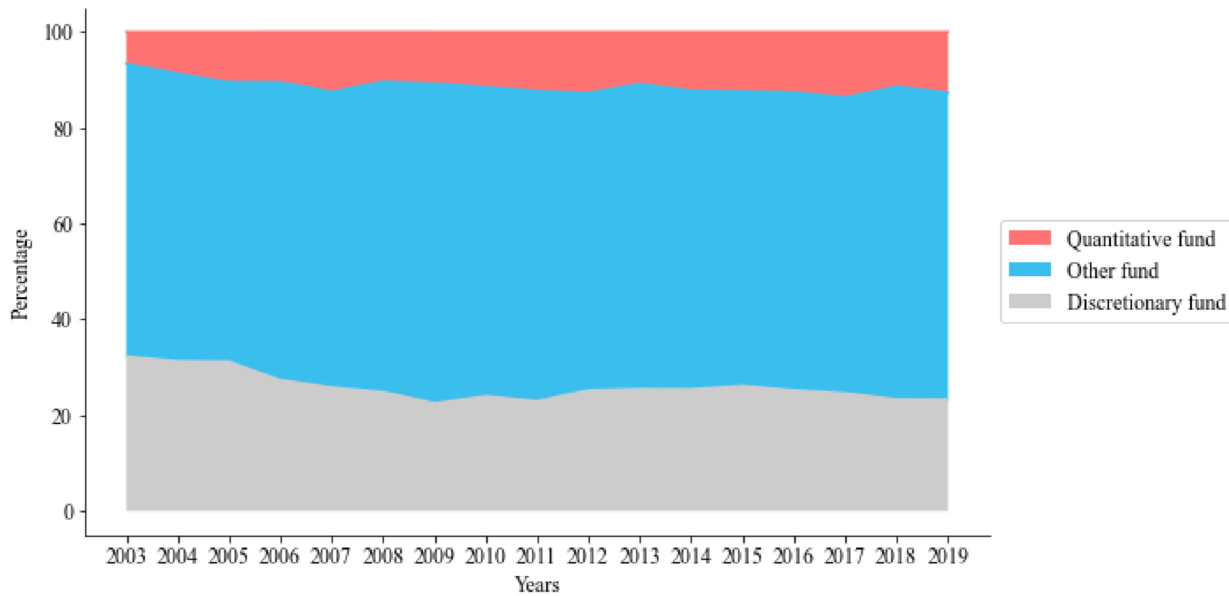


Figure 3. Distribution of Classified Funds

This figure presents the mixture of mutual funds classified as quantitative, discretionary, and other. Other represents funds with some quantitative phrases in their prospectus, but not enough to be classified as a quantitative fund. We exclude funds classified as other from the main analyses, but examine some of them in additional tests (see Table 8). Panel A shows the percentage of quantitative and discretionary mutual funds as a percentage of the total number of funds in the sample. Panel B shows the distribution of the number of different types of funds over the sample period.

Panel A: Distribution of Funds, Percentage



Panel B: Distribution of Funds, Count

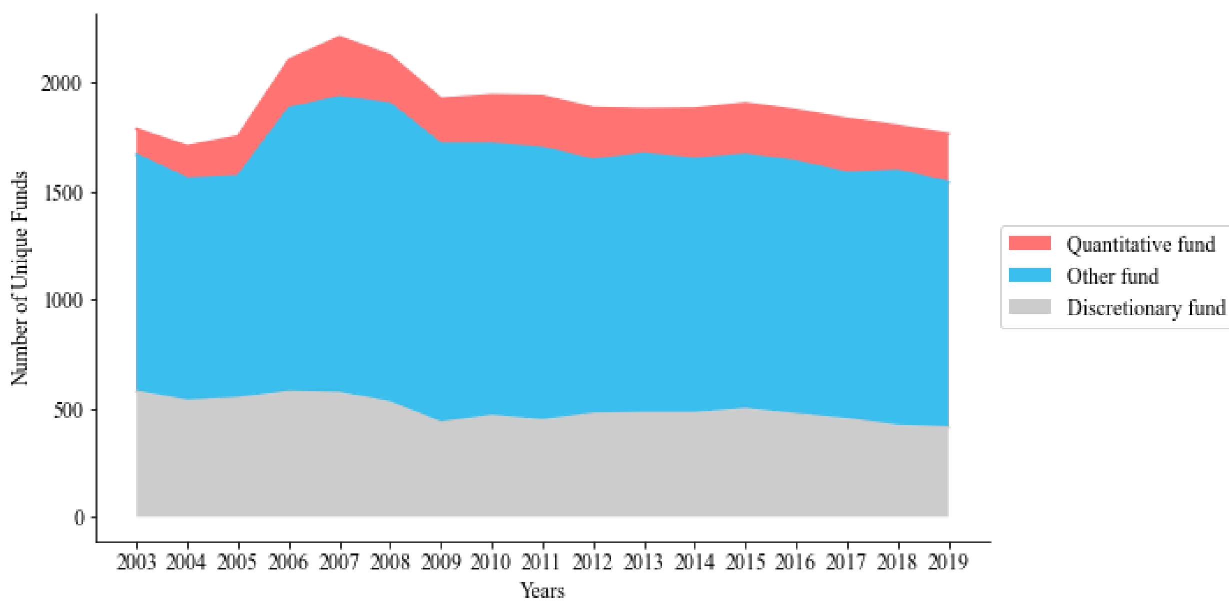
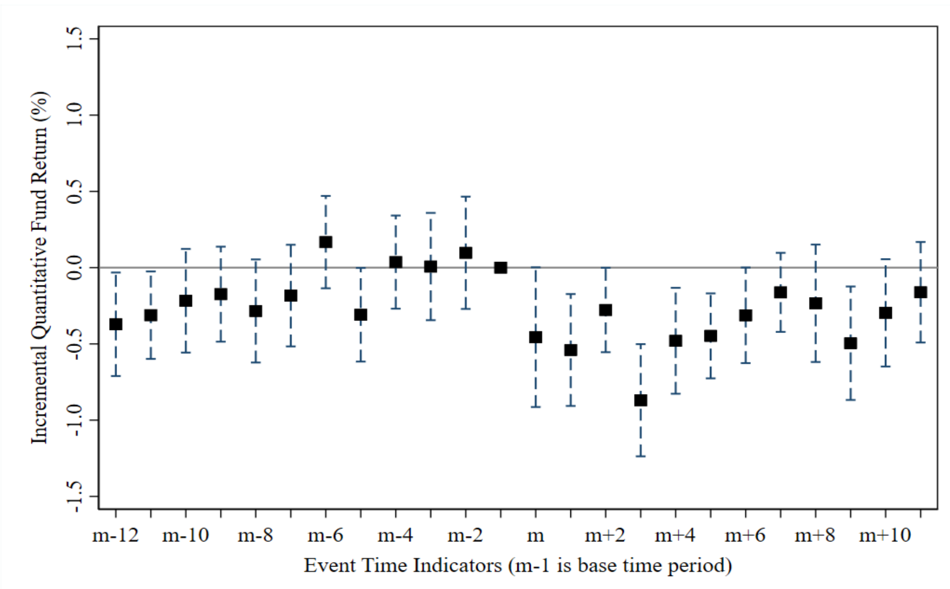


Figure 4. Effect of Accounting Standards in Event Time

Panel A (Panel B) of this figure presents the estimated time-series pattern in monthly (quarterly) returns for quantitative and discretionary mutual funds around accounting standard changes. The figure presents the incremental (i.e., difference between quantitative and discretionary) returns for the combined sample used in the primary analyses (i.e., last column of Table 3 Panel B). The Panel A (Panel B) regression replaces *Post x Quant* from equation (1) with *Quant* interacted with event-time dummies, one for each of the months (quarters) in the period, where the month (quarter) directly preceding the standard change is the excluded base time period. Other than these specific substitutions, the regressions are the same as in the last column of Table 3, Panel B (i.e., same controls, fixed effects, clustering, etc.). Each black dot on the graph represents the regression coefficient for the respective event-time dummy interacted with the *Quant* indicator. Each dashed line bar represents a 95% confidence interval.

Panel A: Monthly Level



Panel B: Quarterly Level

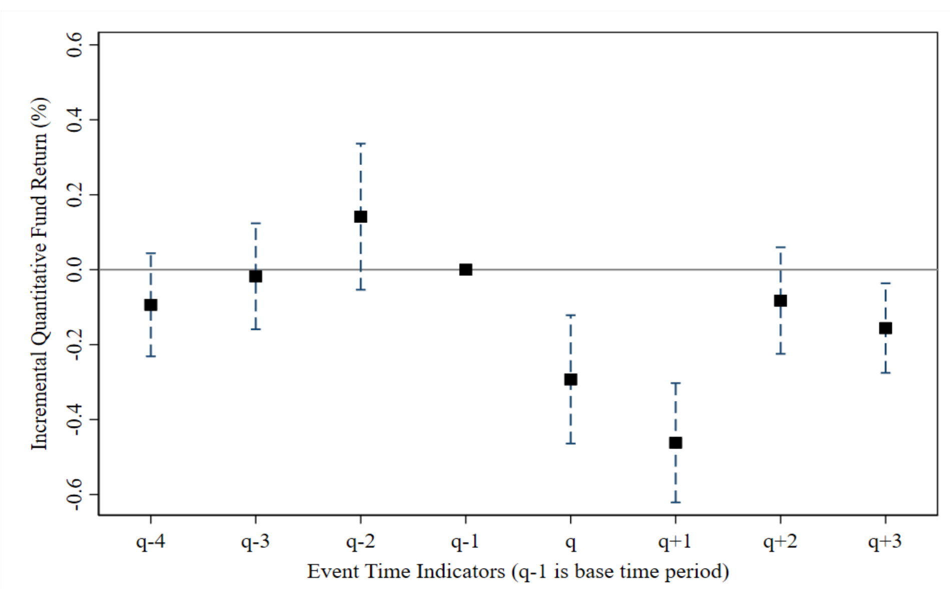


Table 1. Descriptive Statistics

This table provides the descriptive statistics for the funds in our sample. Panel A shows the descriptive statistics for all funds from 2003 to 2019, 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. Variables: fund investment strategy indicator variables that equals one if a fund's strategy is among the top 30% of funds and held constant for each fund during each event (*Value Investor, Momentum Investor, and Large-cap Investor*), investment strategy indicator variables that equals -1, 0, or 1 if a fund's investment strategy is among the bottom 30%, middle 40%, or top 30% of all funds and updated on a monthly basis (*Book-to-Market, Momentum,* and *Size*), TNA-weighted fund raw return in percentage terms (*Return*), the number of funds under each fund family (*Funds per Family*), the log of the total asset under management for each fund (*FundAssets),* the log of the number of months since the first-offer-date of the oldest fund class (*Age),* net fund flows adjusted by fund returns (*FundFlow*), standard deviation of fund flow over the past 12 months (*FlowVol*), fund turnover ratio (*Turnover)*, fund expense ratio (*ExpRatio),* fund management fee *(MgmtFee)*, and indicator variable that equals one if the fund's *MgmtFee* is among the top 30% of funds and held constant for each fund during each event (*High Fee Fund*). *Turnover, ExpRatio, MgmtFee* are obtained by value-weighting fund class measures with lagged total net asset; all other measures are measured directly at the fund level. All continuous variables are winsorized at the 1% and 99% levels.

Panel A: All Funds 2003-2019

	N	Mean	Std.	10th	50th	90th
Investment Strategies:						
Book-to-Market	311,962	0.01	0.77	-1	0	1
Momentum	311,962	0.00	0.77	-1	0	1
Size	311,962	-0.01	0.77	-1	0	1
Fund Characteristics:						
Return	311,962	0.90	4.44	-5.08	1.31	6.05
Funds per Family	311,962	7.04	6.14	1	5	16
FundAssets	311,962	5.65	1.86	3.19	5.60	8.12
Age	311,962	4.94	0.82	3.81	5.03	5.87
FundFlow	311,962	0.00	0.04	-0.03	-0.01	0.03
FlowVol	311,962	0.04	0.08	0.01	0.02	0.09
Turnover	311,962	0.72	0.61	0.17	0.56	1.47
ExpRatio	311,962	0.01	0.00	0.01	0.01	0.02
MgmtFee	311,962	0.71	0.30	0.37	0.73	1.02

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:															
Value Investor	6,027	0.32	0.47	0	0	1	26,009	0.30	0.46	0	0	1	32,036	0.02	3.46
Momentum Investor	6,027	0.39	0.49	0	0	1	26,009	0.23	0.42	0	0	1	32,036	0.16	25.78
Large-cap Investor	6,027	0.36	0.48	0	0	1	26,009	0.26	0.44	0	0	1	32,036	0.09	14.37
Book-to-Market	6,027	-0.01	0.80	-1	0	1	26,009	-0.01	0.77	-1	0	1	32,036	0.00	0.04
Momentum	6,027	0.13	0.74	-1	0	1	26,009	-0.13	0.78	-1	0	1	32,036	0.26	23.89
Size	6,027	0.11	0.78	-1	0	1	26,009	-0.01	0.74	-1	0	1	32,036	0.11	10.68
Fund Characteristics:															
Return	6,027	0.35	5.35	-7.17	1.26	6.03	26,009	0.49	5.47	-6.96	1.29	6.21	32,036	-0.14	-1.82
Funds per Family	6,027	15.83	7.90	7	16	27	26,009	4.07	4.59	1	2	13	32,036	11.76	153.31
FundAssets	6,027	5.94	1.50	3.72	6.20	7.69	26,009	6.06	2.13	3.21	6.10	8.88	32,036	-0.12	-4.07
Age	6,027	4.74	0.82	3.61	4.72	5.77	26,009	5.19	0.78	4.16	5.25	6.13	32,036	-0.45	-39.71
FundFlow	6,027	0.00	0.05	-0.03	-0.01	0.03	26,009	0.00	0.04	-0.03	-0.01	0.03	32,036	0.00	-0.01
FlowVol	6,027	0.06	0.11	0.01	0.02	0.12	26,009	0.03	0.06	0.00	0.01	0.06	32,036	0.03	26.21
Turnover	6,027	0.88	0.50	0.29	0.80	1.53	26,009	0.68	0.74	0.11	0.44	1.47	32,036	0.20	19.94
ExpRatio	6,027	0.01	0.00	0.00	0.01	0.01	26,009	0.01	0.00	0.01	0.01	0.02	32,036	0.00	-32.42
MgmtFee	6,027	0.64	0.32	0.27	0.70	0.99	26,009	0.71	0.30	0.35	0.70	1.05	32,036	-0.07	-14.96
High Fee Fund	6,027	0.27	0.44	0	0	1	26,009	0.32	0.47	0	0	1	32,036	-0.05	-7.72

Table 2. Validation of Quantitative Fund Classification

Panel A shows the age, size, fees, and turnover of quantitative funds. Panel B shows the investment strategies of quantitative funds. Variables: log of the number of months since the first-offer-date of the oldest fund class (*Age*), log of the total net asset under management of all fund classes (*FundAsset*), fund expense ratio (*ExpRatio)* in percentage terms, management fee ratio (*MgmtFee)* in percentage terms, fund turnover ratio (*Turnover)*, an indicator variable that equals one if the fund has been classified as quantitative (*Quant)*, sum of the fund's mean front load and mean rear load (*Load),* net fund flows adjusted by fund returns (*FundFlow*), standard deviation of fund flow over the past 12 months (*FlowVol*), and investment strategy indicator variables that equal -1, 0, or 1 if a fund's investment strategy is among the bottom 30%, middle 40%, or top 30% of all funds and updated on a monthly basis (*Book-to-Market, Momentum,* and *Size*). *Turnover, ExpRatio, MgmtFee, and Load* are obtained by value-weighting fund class measures with lagged total net asset; all other measures are measured directly at the fund level. All continuous variables are winsorized at the 1% and 99% levels. 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.

Panel A: Fund Age, Size, Fees, and Turnover

Dependent Variable =	***Age***	***FundAssets***	***ExpRatio***	***MgmtFee***	***Turnover***
	(1)	(2)	(3)	(4)	(5)
Quant	-0.40***	-0.21***	-0.18***	-0.04***	0.20***
	(-34.25)	(-9.09)	(-37.22)	(-8.51)	(23.45)
Age	---	0.69***	0.01***	0.01***	-0.06***
		(57.07)	(2.98)	(2.66)	(-12.90)
FundAssets	0.14***	---	-0.10***	-0.01***	-0.01***
	(55.96)		(-96.88)	(-12.50)	(-4.75)
ExpRatio	4.31***	-270.02***	---	---	38.31***
	(2.98)	(-113.90)			(26.29)
Turnover	-0.07***	-0.06***	0.08***	-0.01**	---
	(-12.79)	(-4.75)	(29.59)	(-2.15)	
Load	10.16***	35.77***	13.67***	-1.37***	1.68***
	(23.12)	(36.93)	(75.69)	(-8.84)	(3.45)
FundFlow	-2.77***	2.30***	-0.14***	0.02	-0.54***
	(-21.28)	(9.97)	(-3.14)	(0.41)	(-4.74)
FlowVol	-1.26***	-1.88***	-0.29***	-0.22***	0.46***
	(-9.84)	(-6.04)	(-5.31)	(-6.49)	(5.67)
Book-to-Market	-0.04***	0.03*	-0.02***	-0.01***	-0.06***
	(-5.84)	(1.93)	(-7.31)	(-4.40)	(-12.10)
Momentum	0.07***	-0.05***	-0.03***	-0.02***	0.16***
	(10.87)	(-3.96)	(-11.50)	(-9.48)	(25.86)
Size	0.08***	0.01	-0.09***	-0.11***	-0.05***
	(15.06)	(0.55)	(-37.64)	(-46.40)	(-9.61)
R-squared	0.25	0.41	0.47	0.09	0.13
Observations	32,036	32,036	32,036	32,036	32,036

Panel B: Fund Investment Strategies

Dependent Variable =	***Book-to-Market***	***Momentum***	***Size***
	(1)	(2)	(3)
Quant	0.14***	0.23***	0.08***
	(13.02)	(22.49)	(7.36)
Age	-0.03***	0.06***	0.08***
	(-5.84)	(10.82)	(15.16)
FundAssets	0.00*	-0.01***	0.00
	(1.93)	(-3.95)	(0.55)
ExpRatio	-8.61***	-14.21***	-47.79***
	(-7.27)	(-11.62)	(-36.68)
Load	3.78***	1.78***	5.61***
	(9.04)	(4.02)	(11.82)
Turnover	-0.06***	0.15***	-0.05***
	(-12.21)	(25.10)	(-9.22)
FundFlow	-0.08	1.26***	-0.12
	(-0.81)	(12.20)	(-1.26)
FlowVol	-0.08	0.24***	-0.11*
	(-1.35)	(4.85)	(-1.89)
Book-to-Market	---	-0.48***	-0.22***
		(-99.02)	(-38.43)
Momentum	-0.48***	---	-0.01
	(-98.84)		(-1.19)
Size	-0.20***	-0.01	---
	(-37.99)	(-1.19)	
R-squared	0.30	0.30	0.14
Observations	32,036	32,036	32,036

Table 3. Fund Returns and Accounting Standard Changes

Panel A presents univariate difference-in-difference 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 a 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. *Age* is the log of the number of months since the first-offer-date of the oldest fund class. *FundAssets* is the log of the sum of total net asset for all fund classes*,* *ExpRatio* is the fund expense ratio, *Load* is the sum of the fund's mean front load and mean rear load, *Turnover* is the fund turnover ratio, *FundFlow* is the net fund flows adjusted by fund returns, *FlowVol* is the standard deviation of fund flow over the past 12 months. *Size*, *Momentum*, and *Book-to-Market* are (-1, 0, 1) indicator variables that represent the bottom 30%, middle 40%, or top 30% of all funds' size, momentum, and value investment strategies, respectively, and is rebalanced on a monthly basis. All other variables are as defined in Table 2 and all continuous variables are winsorized at the 1% and 99% levels. 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%	0.04%	0.02%
Quant	0.01%	-0.23%	-0.24%
Quant - Discretionary	-0.01%	-0.27%	**-0.26%**
		t-statistic (DiD) =	**(-3.27)**

NCI

	Pre	*Post*	*Post - Pre*
Discretionary	-0.01%	0.18%	0.20%
Quant	0.14%	-0.17%	-0.31%
Quant - Discretionary	0.16%	-0.35%	**-0.51%**
		t-statistic (DiD) =	**(-4.15)**

Lease

	Pre	*Post*	*Post - Pre*
Discretionary	-0.01%	0.07%	0.08%
Quant	0.00%	-0.12%	-0.12%
Quant - Discretionary	0.01%	-0.19%	**-0.20%**
		t-statistic (DiD) =	**(-2.27)**

Combined

	Pre	*Post*	*Post - Pre*
Discretionary	0.00%	0.10%	0.10%
Quant	0.05%	-0.17%	-0.22%
Quant - Discretionary	0.05%	-0.27%	**-0.32%**
		t-statistic (DiD) =	**(-5.60)**

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

	Y = ***Fund Return*** **(%)**			
	(1)	(2)	(3)	(1) – (3)
	Pension	**NCI**	**Lease**	**Combined**
Post × Quant	-0.19*	-0.48***	-0.21***	-0.28***
	(-1.69)	(-2.89)	(-3.66)	(-3.70)
Age	-0.96**	0.30	0.61**	-0.23
	(-2.50)	(0.61)	(2.20)	(-0.98)
FundAssets	0.15	-0.38***	-0.11	-0.11
	(1.48)	(-2.76)	(-0.79)	(-1.49)
ExpRatio	29.37	68.90	10.47	49.62
	(0.71)	(1.15)	(0.20)	(1.53)
Load	6.39	-22.91	80.79***	-0.16
	(0.33)	(-1.37)	(3.86)	(-0.01)
Turnover	-0.03	-0.19*	-0.06	-0.07
	(-0.27)	(-1.85)	(-0.48)	(-0.93)
FundFlow	3.45***	0.38	-0.03	1.66***
	(6.40)	(0.48)	(-0.03)	(3.57)
FlowVol	0.05	0.53	-0.01	0.22
	(0.22)	(1.29)	(-0.02)	(0.97)
Book-to-Market	-0.36***	-0.58***	-0.52***	-0.47***
	(-5.69)	(-5.84)	(-8.11)	(-9.32)
Momentum	-0.22***	-0.64***	-0.32***	-0.41***
	(-6.68)	(-14.13)	(-7.90)	(-17.24)
Size	0.25***	0.18	0.26***	0.23***
	(3.18)	(1.41)	(2.68)	(3.59)
Year × Month FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
R-squared	0.75	0.90	0.86	0.88
Observations	11,191	10,297	10,548	32,036

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 right-most column is the 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 are *Age*, *FundAssets*, *ExpRatio*, *Load*, *Turnover*, *FundFlow*, *FlowVol*, *Size*, *Momentum*, *Book-to-Market*, plus each of these controls interacted with *Value Investor* (*Momentum Investors*) [*Large-cap Investors*]. All continuous variables are winsorized at the 1% and 99% levels. 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*	0.13	-0.23	-0.15**	-0.14
	(1.12)	(-1.21)	(-2.00)	(-1.60)
Post × *Quant* × *Value Investor*	-0.45***	-1.00***	-0.24*	-0.44***
	(-2.74)	(-3.06)	(-1.90)	(-3.14)
Controls + Controls × *Value Investor*	Yes	Yes	Yes	Yes
Year × *Month* FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
R-squared	0.76	0.90	0.86	0.88
Observations	11,191	10,297	10,548	32,036

Panel B: Falsification Test #1 – Momentum Investors

	Y = ***Fund Return*** **(%)**			
	(1) **Pension**	(2) **NCI**	(3) **Lease**	(1) – (3) **Combined**
Post × *Quant*	-0.27**	-0.43**	-0.30***	-0.30***
	(-1.97)	(-2.14)	(-4.20)	(-3.42)
Post × *Quant* × *Momentum Investor*	-0.19	0.13	0.34***	0.14
	(-0.78)	(0.38)	(2.60)	(1.00)
Controls + Controls × *Momentum Investor*	Yes	Yes	Yes	Yes
Year × *Month* FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
R-squared	0.75	0.90	0.86	0.88
Observations	11,191	10,297	10,548	32,036

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

	Y = ***Fund Return*** **(%)**			
	(1) **Pension**	(2) **NCI**	(3) **Lease**	(1) – (3) **Combined**
Post × *Quant*	-0.18	-0.43**	-0.16**	-0.24**
	(-1.20)	(-2.19)	(-2.15)	(-2.50)
Post × *Quant* × *Large-cap Investor*	-0.06	0.11	-0.10	-0.05
	(-0.28)	(0.31)	(-0.73)	(-0.35)
Controls + Controls × *Large-cap Investor*	Yes	Yes	Yes	Yes
Year × *Month* FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
R-squared	0.75	0.90	0.86	0.88
Observations	11,191	10,297	10,548	32,036

Table 5. Diminishing Effect of Quantitative Fund Underperformance

This table examines the evolution of quantitative funds' performance relative to discretionary funds around accounting standard changes. The dependent variable, *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 a 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. *Post(+n,+m)* represents an indicator variable that equals one if the month is between *n* and *m* months after the effective date of the accounting standard change. The control variables are *Age*, *FundAssets*, *ExpRatio*, *Load*, *Turnover*, *FundFlow*, *FlowVol*, *Size*, *Momentum*, and *Book-to-Market*. Coefficients of control variables are omitted for clarity but available upon request. Note that in this test, we expand our difference-in-difference model from one year pre-post to two years pre-post. Thus, the sample size increased relative to the main analyses. The coefficients in front of *Quant* × *Post(+13,+18)* and *Quant* × *Post(+19,+24)* are missing for the lease column because the lease standard became effective in January 2019; at the time of writing, we do not yet have the data for the second year following the lease standard, fiscal 2020. All 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.

	Y = ***Fund Return*** **(%)**			
	(1)	(2)	(3)	(1) – (3)
	Pension	**NCI**	**Lease**	**Combined**
Quant × *Post(+1,+6)*	-0.14**	-0.71***	-0.27***	-0.37***
	(-2.05)	(-4.25)	(-4.10)	(-5.33)
Quant × *Post(+7,+12)*	-0.26*	-0.03	-0.02	-0.11*
	(-1.67)	(-0.27)	(-0.39)	(-1.92)
Quant × *Post(+13,+18)*	0.12	-0.16	---	-0.01
	(1.13)	(-1.42)		(-0.12)
Quant × *Post(+19,+24)*	0.24	-0.03	---	0.13
	(1.17)	(-0.26)		(1.24)
Controls	Yes	Yes	Yes	Yes
Year × *Month* FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
R-squared	0.86	0.90	0.84	0.88
Observations	21,050	19,724	15,696	56,470

Table 6. 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) indicator variables that represent the bottom 30%, middle 40%, or top 30% of all funds' value, momentum, and size investment strategies 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. *Age* is the log of the number of months since the first-offer-date of the oldest fund class. *FundAssets* is the log of the sum of the total net asset for all fund classes, *ExpRatio* is the fund expense ratio, *Load* is the sum of the fund's mean front load and mean rear load, *Turnover* is the fund turnover ratio, *FundFlow* is the net fund flows adjusted by fund returns, *FlowVol* is the standard deviation of fund flow over the past 12 months. *Turnover, ExpRatio, and Load* are obtained by value-weighting fund class measures with lagged total net asset; all other measures are measured directly at the fund level. All continuous variables are winsorized at the 1% and 99% levels. 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	0.04	-0.02
	(0.18)	(1.51)	(-1.38)
Age	-0.05	-0.24**	-0.02
	(-0.70)	(-2.00)	(-0.42)
FundAssets	-0.06**	0.11***	0.02
	(-2.48)	(3.22)	(1.21)
Load	-0.80	10.00**	-4.99**
	(-0.22)	(2.25)	(-2.35)
ExpRatio	2.45	-13.01	-8.00
	(0.32)	(-0.88)	(-1.21)
Turnover	0.02	0.05	-0.04**
	(0.82)	(1.38)	(-2.48)
FundFlow	-0.20***	0.54***	-0.01
	(-3.36)	(4.15)	(-0.12)
FlowVol	-0.02	0.16	-0.07
	(-0.28)	(1.43)	(-1.26)
Book-to-Market	---	-0.26***	-0.04***
		(-15.04)	(-2.84)
Momentum	-0.09***	---	0.01**
	(-12.91)		(2.53)
Size	-0.07***	0.06**	---
	(-2.90)	(2.56)	
Year × Month FE	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes
R-squared	0.88	0.64	0.93
Observations	32,036	32,036	32,036

Table 7. Fund Turnover

This table presents estimates of changes in fund turnover around accounting standard changes. Panel A presents a difference-in-difference analysis of quantitative funds relative to discretionary funds around accounting standard changes. Panel B examines the time-series evolution of quantitative funds' turnover relative to discretionary funds around accounting standard changes. The dependent variable in both panels is fund turnover ratio, obtained by value-weighting fund class level turnover with lagged total net asset. *Pension*, *NCI*, and *Lease* refer to the accounting changes detailed in Figure 1. *Combined* denotes a pooled analysis of all three standard changes. *Quant* is an indicator variable that equals one if a fund has been classified as quantitative. *Post(+n,+m)* represents an indicator variable that equals one if the month is between *n* and *m* months after the effective date of the accounting standard change. Note that in Panel B, we expand our difference-in-difference model from one year pre-post to two years pre-post. Thus, the sample size in Panel B is greater than in Panel A. The coefficients in front of *Quant* × *Post(+13,+18)* and *Quant* × *Post(+19,+24)* are missing for the lease column because the lease standard became effective in January 2019; at the time of writing, we do not yet have the data for the second year following the lease standard, fiscal 2020. The control variables for both panels are *Age*, *FundAssets*, *ExpRatio*, *Load*, *FundFlow*, *FlowVol*, *Return*, *Size*, *Momentum*, and *Book-to-Market*. All 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 and Accounting Standard Changes

	Y = *Turnover*			
	(1)	(2)	(3)	(1) – (3)
	Pension	**NCI**	**Lease**	**Combined**
Post × *Quant*	0.01	0.16***	0.06*	0.07***
	(0.29)	(3.75)	(1.87)	(3.66)
Controls	Yes	Yes	Yes	Yes
Year × *Month* FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
R-squared	0.90	0.93	0.93	0.92
Observations	11,191	10,297	10,548	32,036

Panel B: Diminishing Effect of Quantitative Fund Turnover

	Y = *Turnover*
	(1)
	Combined
Quant × *Post(+1,+6)*	0.05**
	(2.11)
Quant × *Post(+7,+12)*	0.06**
	(2.43)
Quant × *Post(+13,+18)*	0.02
	(0.50)
Quant × *Post(+19,+24)*	0.02
	(0.48)
Controls	Yes
Year × *Month* FE	Yes
Fund FE	Yes
R-squared	0.86
Observations	56,470

Table 8. Human Involvement

This table presents the differential performance changes of quantitative funds depending on the degree of human involvement. The dependent variable for both panels, *Fund Return (%),* is the TNA-weighted monthly fund return in percentage terms. The analysis in Panel A column (1) is the same as the right-most column of Table 3, Panel B. In Panel A column (2) to (5), we lower the threshold used in selecting quantitative funds. The percentile refers to the cutoff based on the number of quantitative keywords in fund prospectuses. The sample size increases because more funds are classified as quantitative funds and brought into the analysis as we relax the selection criteria. The control variables in Panel A are the same as in Table 3, Panel B. Panel B examines whether more human involvement, as proxied by higher management fees, mitigates quantitative funds' lower returns around standard changes. *High Fee Fund* is an indicator variable that equals one if the percentage of management fee charged by a fund is among the top 30% of funds and zero otherwise. *High Fee Fund* is held constant for each fund during each of the event period. The control variables in Panel B include *Age*, *FundAssets*, *ExpRatio*, *Load*, *Turnover*, *FundFlow*, *FlowVol*, *Size*, *Momentum*, *Book-to-Market*, plus *High Fee Fund* interacted with each of these variables. All 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: Variation in Quant Cutoff

	Y = ***Fund Return*** **(%)**				
	(1)	(2)	(3)	(4)	(5)
	90^{th} Percentile	80^{th} Percentile	70^{th} Percentile	60^{th} Percentile	50^{th} Percentile
Post × *Quant*	-0.28***	-0.17***	-0.17***	-0.14***	-0.12***
	(-3.70)	(-3.16)	(-3.61)	(-3.08)	(-2.89)
Controls	Yes	Yes	Yes	Yes	Yes
Year × *Month* FE	Yes	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.88	0.88	0.88	0.89	0.89
Observations	32,036	40,234	47,680	58,203	66,891

Panel B: Management Fee and Return

	Y = ***Fund Return*** **(%)**			
	(1)	(2)	(3)	(1) – (3)
	Pension	**NCI**	**Lease**	**Combined**
Post × *Quant*	-0.29**	-0.78***	-0.19***	-0.40***
	(-2.15)	(-4.47)	(-3.24)	(-4.98)
Post × *Quant* × *High Fee Fund*	0.41*	1.26***	0.07	0.48***
	(1.67)	(3.11)	(0.44)	(2.69)
Controls + Controls × *High Fee Fund*	Yes	Yes	Yes	Yes
Year × *Month* FE	Yes	Yes	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes
R-squared	0.75	0.90	0.86	0.88
Observations	11,191	10,297	10,548	32,036