Audit Quality and Short-Side Mispricing

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Abstract: Auditors may affect short-side mispricing—where price-based information and corporate monitoring is limited due to market frictions—because under a risk-based audit, auditors seek to limit overstated performance and help enforce timely recognition of losses. We find that Big 4 (specialist) auditors are associated with a reduction in annual short-side accounting anomaly returns of 1.5 (0.9) percentage points. Inferences are robust to using a difference-in-differences design that exploits shocks to audit quality and to using entropy balancing. Consistent with auditors influencing anomaly returns specifically through the audit of annual financial statements, we do not find an association between high-quality auditors and finance anomaly returns. In cross-sectional analyses, we find that high-quality auditors are (are not) associated with a reduction in short-side accounting anomaly returns in subsamples where market frictions are high (low). Finally, evidence suggests that high-quality auditing helps analysts incorporate accounting anomaly information. Overall, our evidence suggests that high-quality auditors reduce short-side mispricing by improving the timeliness and credibility of financial reporting.

Key Words: Auditing; Accounting information; Mispricing; Cross-sectional return predictability; Market efficiency; Timely loss recognition

JEL Codes: G00, G14, M41, M42

1. Introduction

We examine whether audit quality affects short-side mispricing. While auditors play a critical role in attesting to the representational faithfulness of their clients' financial statements, the link between audit quality and short-side mispricing is not obvious. First, when market frictions are relatively large, as is the case for short selling, mispricing may continue in the presence of high audit quality because sophisticated investors cannot trade on information such that information is more slowly incorporated into prices. Second, the mispricing literature has found hundreds of anomalies, but more recent research finds that market reforms, highly informed investors, and large amounts of arbitrage capital have improved market efficiency such that accounting numbers may be less timely and relevant to equity market participants (Ball and Shivakumar 2008; Chordia et al. 2008, 2011; Chordia et al. 2014; Green et al. 2011; Green et al. 2017; McLean and Pontiff 2016; Rösch et al. 2017). Third, it is possible that any mispricing that remains is primarily from non-financial reporting information, on which the auditor does not opine.

Prior literature suggests two mechanisms through which auditors could affect short-side mispricing. First, short-side mispricing could result from aggressive financial reporting that overstates revenue or income. However, auditors experience significant litigation and reputation risk when revenue or income is overstated (e.g., Weber, Willenborg, and Zhang 2008; Skinner and Srinivasan 2012; Swanquist and Whited 2015). Under a risk-based audit, auditors focus on areas that would result in mitigating such overstatements because the risk of material misstatement is generally higher in these instances.[1] For example, auditors specifically consider

[1] Detection risk is the risk that the auditor's procedures do not identify material misstatements. Auditors perform substantive procedures to lower detection risk in response to higher risk of material misstatement in order to achieve an appropriate audit risk (i.e., risk of concluding that the financial misstatements are fairly presented when they are not).

risks of material misstatement due to incentives to meet performance targets from compensation contracts, analysts, and rating agencies (AS 2110).

Second, under a risk-based audit, auditors generally are most concerned about *unreported* income-decreasing accounting entries and *reported* income-increasing entries. Because of these asymmetric assurance incentives, auditors help monitor and enforce the timely reporting of losses (Francis and Krishnan 1999; Jackson and Liu 2010; Krishnan 2005; Nicoletti 2018). When financial reports recognize bad news on a timely basis, they preempt the slow incorporation of negative information represented by the short side of anomaly signals.

Our empirical strategy begins with 22 anomalies from Green, Hand, and Zhang (2017) that relate to year *t* annual financial statement information. The logic for selecting these anomalies is that the auditor for year *t* audits year *t* annual financial statement information. Thus, the auditor can have a direct effect on these anomalies. Using these 22 accounting anomalies, we create a net anomaly variable (*NET*) similar to Engelberg et al. (2018). This measure captures the difference between the number of long and short positions a stock belongs to based on individual anomaly variables sorted into quintiles within a given year. We then focus on the returns to anomalies, and specifically on returns to net measures that prescribe selling stocks short as these are instances where auditors have strong incentives to exert effort that avoids overstatements of income and improves the timely reporting of losses, both of which avoid overpricing and speed the incorporation of bad news information into prices.

Using 40,632 firm-year observations from 2005 to 2019,[2] we find that anomaly variables are associated with annual returns over this period, but that anomaly returns exist primarily in the

[2] We start the sample in 2005 because of the significant changes to auditing and financial reporting quality caused by the passage of The Sarbanes-Oxley Act of 2002 (SOX). SOX fundamentally changed auditing in many ways. For example, SOX created the Public Company Accounting Oversight Board (PCAOB) to regulate public-company audits. As part of regulating public-company audits, the PCAOB started inspecting audit firms in 2004. Also starting

short side, not in the long side consistent with market participants encountering stronger frictions when trading on short-side information.[3] Using an indicator for a Big 4 auditor or an industry specialist auditor (measured at the city level) as a proxy for a high-quality auditor, we find that high-quality auditors are associated with reduced short-side anomaly returns in both univariate and multiple regression analyses, which is consistent with high-quality auditors affecting financial statement information in a way that increases pricing efficiency where stocks are potentially over-valued or slow to incorporate negative information. Economically, annual short-side returns are reduced by 1.5 (0.9) percentage points when the auditor is a Big 4 (specialist).

Next, we perform tests that address concerns that results are due to correlated-omitted variables. First, we utilize a difference-in-differences design that exploits the staggered timing of initial PCAOB inspections, which represent shocks to audit quality (Gramling et al. 2011; DeFond and Lennox 2017; Fung et al. 2017; Gipper et al. 2020).[4] We find evidence of reduced short-side anomaly returns following initial PCAOB inspections of triennially inspected audit firms, which is consistent with improved audit quality reducing mispricing. However, we do not find evidence of reduced short-side anomaly returns following initial PCAOB inspection of triennially inspected audit firms where the PCAOB identified quality control issues at the audit firm and the audit firm did not timely remediate these issues. This suggests that instances where

in 2004, SOX required auditors of large public companies to opine on the effectiveness of internal controls. This requirement led to a significant increase in audit fees and the disclosure of many material weaknesses in internal control over financial reporting in 2004.

[3] This finding is consistent with prior research that finds that the short side of anomaly returns are stronger than the long side and that the returns to anomalies have declined in more recent periods (Chordia, Subrahmanyam, and Tong 2014; Stambaugh, Yu, and Yuan 2012; Chu, Hirshleifer, and Ma 2020).

[4] We focus on triennially inspected audit firms, as opposed to annually inspected audit firms, to take advantage of the staggered timing of initial PCAOB inspections for triennially inspected audit firms. Triennially inspected audit firms are smaller (i.e., they audit 100 or fewer issuers) than annually inspected audit firms. The decision of when to inspect audit firms for the first time is plausibly exogenous to the client, and the PCAOB inspects all audit firms in our sample. Given triennially inspected audit firms audit smaller public companies, this examination helps to alleviate concerns that our treatment variable is simply capturing company size.

PCAOB inspections did not improve an audit firm's quality are not associated with a reduction in short-side anomalies, as expected. Thus, for a correlated-omitted variable to explain our results, it would have to be correlated with the staggered timing of PCAOB inspections that plausibly improved audit firms' audit quality.

Second, we utilize an entropy balancing approach on our primary sample to mitigate concerns that inferences are due to differences in observables, and inferences remain. Third, we perform tests aimed at confirming our results are due to an auditor's effect on financial reporting, as opposed to an alternative explanation such as market frictions caused by information asymmetry. Auditor quality should reduce short-side anomaly returns when the anomaly signal is based on accounting reports (accounting anomalies), but should have no effect on the short side of anomaly returns that are based on non-accounting information (finance anomalies). However, market frictions caused by information asymmetry should affect short-side accounting and finance anomaly returns. We use size, analyst following, and bid-ask spreads as proxies for these market frictions. Empirically, we find that our proxies for low information asymmetry are associated with reduced short-side accounting anomaly returns, and that the effect of high-quality auditors remains when controlling for these proxies. Additionally, while we find that proxies for low information asymmetry are associated with reduced short-side finance anomaly returns, we find no effect of high-quality auditors on short-side finance anomaly returns. These results further suggest that our variables of interest capture auditor quality and that high-quality auditing reduces overstatements and helps enforce the timely recognition of losses.

We next consider that the effect of high-quality auditors on short-side returns should be more pronounced when other arbitrage costs are high. When arbitrage costs are high, arbitrageurs are more constrained in their ability to correct overpricing thereby limiting the information in market prices, which provides more opportunity for a high-quality auditor to reduce overpricing through financial reporting (Jones and Lamont 2002; Saffi and Sigurdsson 2011; Beber and Pagano 2013; Boehmer and Wu 2013). High arbitrage costs also often coincide with when information asymmetry between managers and investors is high. When information asymmetry between managers and investors is high, managers' opportunities and incentives for overstating performance and delaying the recognition of losses are strongest (Fang, Huang, and Karpoff 2016; Massa, Zhang, and Zhang 2015). Thus, we next examine cross-sectional cuts based on differences in arbitrage costs with a particular focus on information asymmetry. First, we split the sample based on median size (i.e., market value of equity) because smaller firms have higher transaction costs (Stoll and Whaley 1983; Lesmond, Ogden, and Trzcinka 1999), and we find that (1) anomaly returns are more pronounced in small firms and (2) high-quality auditors are associated with reduced short-side anomaly returns for small but not large firms. Second, we consider analyst following. Analysts follow firms with greater information availability and contribute to the amount of information available for a firm (Beyer, Cohen, Lys, and Walther 2010; Bozanic and Thevenot 2015; Brown, Call, Clement, and Sharp 2015). We find that high-quality auditors are associated with reduced short-side anomaly returns only in the subsample of firm-years with below median analyst following. Third, we consider bid-ask spreads and find that our primary results are only present in the subsample of firm-years with above median bid-ask spreads. All of these results are consistent with high-quality auditors improving price efficiency where arbitrage costs related to information asymmetry are largest.

Finally, we consider whether high-quality auditors assist analysts in incorporating accounting anomaly signals into their return forecasts. Engelberg et al. (2020, 2) find that analysts' return forecasts "predict returns in the opposite direction as forecasted by anomaly variables." They conclude that analysts through their target prices may contribute to mispricing. Similarly, prior research finds that analysts' target prices tend to be too optimistic and are noisy expectations of realized returns (Dechow and You 2020). Empirically, we find that analyst return forecasts for firms in accounting anomalies, particularly on the short side, are lower for firms with high-quality versus low-quality auditors. This suggests that high-quality auditing assists analysts in correctly processing accounting anomaly-related information and that the effect of high-quality auditing is strongest for the short side of anomaly information.

We contribute to the auditing literature that has examined whether auditors affect stock prices. This literature finds evidence that suggests that high-quality auditing affects market reactions to earnings announcements and the amount of firm-specific information incorporated in stock prices (Teoh and Wong 1993; Gul, Kim, and Qiu 2010). We contribute to this literature by providing evidence that auditors play a role in mitigating mispricing on the short side, particularly when arbitrage costs are high. We also contribute to the auditing literature by computing an actual value of a high-quality audit. While it is practically impossible to determine the market value of audits on average, our point estimates suggest that an average firm-year with accounting information that results in a short-side anomaly has a 0.9 to 1.5 percentage point higher annual return when engaging a high-quality versus low-quality auditor. This reduction in short-side anomaly returns equates to a difference of $49 to $83 million for the mean firm market capitalization of $5.54 billion. We also contribute to the auditing literature on the efficacy of the PCAOB (e.g., Krishnan et al. 2017), as our results suggest that auditors help mitigate short-side mispricing by improving audit quality in response to PCAOB inspections.

We also contribute in two specific ways to prior research on market efficiency and anomalies by studying the role of a uniquely incentivized institution – auditing. Prior work finds that financial reporting quality affects mispricing (Bernard and Thomas 1990; Amir, Kama, and Levi 2015; Engelberg, McLean, and Pontiff 2018; Du and Jiang 2020). Additional work finds that improved information quality reduces anomaly returns (Ferguson and Matolcsy 2004; Drake et al. 2009; Chan et al. 2009; Engelberg et al. 2018). First, we find evidence that suggests that high-quality auditing reduces short-side accounting anomaly returns but does not reduce short-side finance anomaly returns. By comparison, our evidence suggests that proxies for low information asymmetry (i.e., high information quality) are negatively associated with both short-side accounting and finance anomaly returns. Second, we also find no evidence of long-side accounting anomalies during our sample period and no evidence that high-quality auditing affects long-side accounting anomalies. Thus, we contribute to the capital market literature by providing evidence that is consistent with auditors assisting in market efficiency in situations where accounting information is relevant to short-side mispricing, particularly where other market participants are limited due to high arbitrage costs. In other words, high-quality auditing appears to help level the *accounting* information set across investors when trading frictions limit learning from trading activity, but auditing does not seem to matter in the absence of trading frictions or in situations unrelated to accounting.

Finally, we contribute to the analyst literature, particularly as it relates to analysts processing anomaly-related information (Engelberg et al. 2020). Our evidence suggests that high-quality auditors can help analysts process accounting-related anomaly information by improving the timeliness and credibility of financial reporting.

2. Related literature and hypothesis development

2.1 Related literature

In this section, we discuss a small number of the most relevant papers from the large literatures in three topic areas: market anomalies, accounting usefulness, and auditing.

2.1.1 Market anomalies

A large literature finds evidence that market prices deviate from models of expected returns, i.e., anomalous returns. Novy-Marx and Velikov (2016) study the returns to anomalies with a focus on transaction costs. They find that some anomaly returns survive adjustments for transaction costs but transaction costs always reduce the returns to would-be arbitrageurs. Other related research finds that market frictions deter costly arbitrage (Dow and Gorton 1994; Shleifer and Vishny 1997). However, more recent research finds that markets have become more efficient as arbitrage costs have declined and anomaly return research has been published (Chordia et al. 2008, 2011; Chordia et al. 2014; Green et al. 2017; McLean and Pontiff 2016).

Most relevant to our research, Stambaugh, Yu, and Yuan (2012) find that the short side of anomalies have the most anomalous returns and that these returns are likely the result of mispricing as they are correlated with investor sentiment. The short side of anomalies means the stocks that an anomaly variable predicts as having the lowest future returns and the long side means the stocks that an anomaly variable predicts as having the highest future returns. To exploit these predicted returns most papers form portfolios that assume an investor buys stocks in the long side and sells (through short selling) stocks in the short side. The motivation and results in Stambaugh et al. (2012) are that it is more costly or not always possible for arbitrageurs to take short positions in stocks and therefore stocks are more often overpriced than underpriced (Miller 1977). This is important because prior research finds that when short selling is unconstrained, market prices are more efficient (Jones and Lamont 2002; Saffi and Sigurdsson 2011; Beber and Pagano 2013; Boehmer and Wu 2013). Additionally, when short selling is restricted, managers' financing, investing, and reporting decisions receive less scrutiny leading to more earnings management (Fang, Huang, and Karpoff 2016; Grullon, Michenaud, and Weston 2015; Massa, Zhang, and Zhang 2015).

2.1.2 Accounting usefulness

Lee (2001) discusses the role of accounting in informationally-efficient markets. In particular, Lee (2001) discusses that accounting information could help markets become more efficient as other forces cause prices to fluctuate around the informationally-efficient price. Among other findings, prior research finds evidence that accounting information provides information to market participants (Ball and Brown 1968), that investors search for more accounting information when the existing information set is less rich (Drake, Roulstone, and Thornock 2016), and that accounting information can improve managers' investment decisions (Chen, Hope, Li, and Wang 2011; Shroff, Verdi, and Yu 2014). However, prior research also finds that market prices anticipate much of the information in earnings and that earnings information provides only a small amount of the total information in stock returns (Beaver, Lambert, and Morse 1980; Kothari and Sloan 1992; Ball and Shivakumar 2008). As market prices become more efficient by incorporating a more complete information set, the informational role of accounting becomes even more questionable and some research points to the deteriorating usefulness of accounting (Lev 2018).

Seminal research in accounting has examined whether and concluded that accounting numbers are useful to equity market participants (e.g., Ball and Brown 1968; Ball and Brown 2014). However, market reforms, highly-informed investors, and large amounts of arbitrage capital have improved market efficiency such that accounting numbers may be less timely and relevant (Ball and Shivakumar 2008; Chordia et al. 2008, 2011; Chordia et al. 2014; Green, Hand, and Soliman 2011; Green et al. 2017; McLean and Pontiff 2016; Rösch, Subrahmanyam, and Van Dijk 2017). Yet, research suggests that market frictions remain. In particular, apparent anomalous patterns in returns "anomalies" continue to persist where arbitrage is most costly – where short selling is required and where trading costs and information asymmetry are high (Novy-Marx and Velikov 2016; Stambaugh and Yuan 2017).

2.1.3 Audit quality

Reputation and litigation incentives motivate auditors to provide high-quality audits (DeAngelo 1981; Palmrose 1988). For example, auditors experience market share losses upon revelation of low-quality auditing that damages auditor reputation or increases auditor litigation risk (Weber et al. 2008; Skinner and Srinivasan 2012; Swanquist and Whited 2015).[5] Auditors can also experience losses due to regulatory findings, and as such, are motivated by the threat of regulatory intervention (DeFond and Zhang 2014; Boone, Khurana, and Raman 2015).[6]

One way that auditors manage the risk of loss due to reputation, litigation, and regulatory risk is by utilizing the audit risk model.[7] Audit risk is the risk that the auditor concludes that there are no material misstatements in the financial statements when there really are (AS 1101). Auditors use the concept of audit risk to plan a risk-based audit (e.g., AS 2101; AS 2105; AS 2110; AS 2301). Under a risk-based audit, the auditor responds to the risk of material

[5] Reputation and litigation effects are extremely difficult to separate (Ball 2009). There is also evidence that high-quality auditors are associated with lower rates of accounting fraud and that auditors respond to lawsuits by improving audit quality (Lennox and Pittman 2010; Lennox and Li 2014). These studies are consistent with auditors seeking to avoid reputation damage and litigation risk.
[6] Regulatory intervention could affect both reputation and litigation risk.
[7] Auditors also manage the risk of loss due to reputation, litigation, and regulatory risk by having a strong system of quality controls (QC 20; QC 30; QC 40). These types of controls enable audit firms to maintain independence, manage personnel, engage appropriate clients, etc.

misstatement (e.g., managerial incentives to overstate income, subjectivity within an estimate, competition within an industry, or weak internal controls) by altering audit procedures to reduce audit risk to an acceptably low level (AS 1101). After performing sufficient, appropriate audit procedures, auditors opine with reasonable assurance that the financial statements are fairly presented in accordance with a financial reporting framework (GAAP in the U.S.). The concept of fair presentation is equivalent to the concept of faithful representation, meaning that a high-quality audit would enhance “the relevance and reliability of accounting information to financial statement users by focusing on economic substance” (DeFond, Lennox, and Zhang 2018).

2.2 Hypotheses development

Managerial incentives to meet performance benchmarks are generally asymmetric. For example, managers generally have incentives to inflate not deflate income to meet earnings targets (Kerstein and Rai 2007; Caramanis and Lennox 2008; Dichev et al. 2013). Managers also have incentives to withhold and delay the reporting of bad news (Kothari, Shu, and Wysocki 2009). Additionally, significant stock drops due to overstating income or revenue often trigger litigation, which auditors want to avoid.

At the same time, arbitrageurs’ ability to exploit mispricing is asymmetric. Arbitrageurs with negative information on a stock have to borrow shares to sell and then must later repurchase the shares. The frictions to short selling make stock prices less efficient regarding information about overpricing (Miller 1977; Saffi and Sigurdsson 2011; Beber and Pagano 2013). Specifically, short-selling anomalies represent instances where asset prices are over-valued, because, for example, accounting information is overstated (i.e., biased) or does not timely reflect bad news.

Due to reputation and litigation risk and the use of the audit risk model, auditors should affect financial reporting quality in two ways that are relevant to short-side mispricing. First, auditors specifically consider areas where management has incentives to overstate performance. For example, AS 2110 requires auditors to consider risks of material misstatement due to contractual commitments, compensation arrangements, measures used by rating agencies and analysts, and measures used internally to monitor performance. Thus, auditors exert more effort in areas that have a higher risk of material misstatement, with the aim to identify where management may have overstated performance through biased accounting information. Second, auditors generally gain more assurance on the completeness of income-decreasing accounting entries and the occurrence of income-increasing accounting entries (Francis and Krishnan 1999; Jackson and Liu 2010). Thus, auditors help enforce the asymmetric timely recognition of losses (Krishnan 2005; Nicoletti 2018), which preempts the slow incorporation of bad news indicative of short-side mispricing.

Because an audit by a high- versus low-quality auditor is more likely to result in high-quality financial reporting as reflected by less upwardly biased and more timely negative information, we expect that firms in short-side anomalies that are audited by high-quality auditors have lower short-side returns compared to similar firms that are audited by low-quality auditors. Stated differently, we expect the financial statement information of firms in short-side anomalies to be more informative (less biased and more timely) when audited by a high-quality auditor, allowing for less mispricing. Thus, we state our primary hypothesis in the alternative as follows:

> **A high-quality auditor reduces short-side anomaly returns compared to a low-quality auditor.**

The null hypothesis includes the possibility that more informative accounting information would not affect short-side anomaly returns because accounting information is not useful. For example, the financial statements could lack information value because accounting standards are not written to reflect economic substance or because private information is disclosed via channels other than the financial statements such that the financial statements provide no incremental informational value.

3. Research design

3.1 Anomaly measure

Our anomaly measure is created using 22 anomalies from Green et al. (2017) that relate to year *t* annual financial statement information. We select these anomaly measures because auditors are likely to directly affect these anomalies through the audit of a firm's annual financial statements (see Appendix A for detail on the 22 anomalies).[8] Anomaly measures are sorted by year into quintiles, with the extreme quintiles defined as the long and short sides of the anomaly strategy. We follow Engelberg et al. (2018) in constructing a net anomaly variable (*NET*), which is the difference between the number of long-side and short-side anomaly portfolios that an observation belongs to. To examine differences in long- versus short-side portfolios, we use the decomposed version of the net variable, which is simply the number of long-side anomaly portfolios (*LONG*) that an observation belongs to or the number of short-side anomaly portfolios (*SHORT*) that an observation belongs to, multiplied by negative one.

3.2 Measuring high-quality auditors

The literature concludes that Big 4 auditors and industry specialist auditors provide better audit quality than non-Big 4 auditors and non-industry specialist auditors, respectively (DeFond and Zhang 2014). Theory suggests that Big 4 auditors provide better audit quality because larger

[8] We do not include quarterly anomalies, even if they are related to the financial statements, because auditors do not audit 10-Qs.

auditors have greater reputational capital, deeper pockets to satisfy litigation claims, and presumably more competence. Industry specialist auditors provide better audit quality because they develop deep knowledge of the industry in which they specialize and develop a reputation for providing high-quality audits within that industry (Reichelt and Wang 2010). Thus, we use indicators for whether or not a firm-year is audited by a Big 4 auditor or by an industry specialist auditor as proxies for a high-quality audit. Specifically, *BIG4* is set to one when a firm-year is audited by Deloitte, Ernst & Young, KPMG, or PricewaterhouseCoopers. *SPECIALIST* is set to one for a given city-industry-year when the auditor has the largest two-digit SIC market share based on audit fees and when this market share is more than 10 percentage points larger than the second largest auditor within the same city-industry-year (Reichelt and Wang 2010).

3.3 Empirical design

To examine whether a high-quality auditor reduces anomaly returns, we estimate the following model using ordinary least squares regressions:

$$RET_{it+1} = \beta_0 + \beta_1 NET_{it} + \beta_2 NET*HIGH\_QUALITY\_AUDITOR_{it} + \beta_3 HIGH\_QUALITY\_AUDITOR_{it} + CONTROLS + Year\ fixed\ effects + Audit\ office\ fixed\ effects + u \quad (1)$$

where *RET* represents annual returns for firm *i* measured over the twelve-month period beginning with the fifth month after year *t* (i.e., after the accounting information is most likely available to market participants). *NET* is our primary anomaly variable as described in Section 3.1. *NET* is measured using annual anomaly variables as of fiscal year-end *t*. *HIGH_QUALITY_AUDITOR* represents one of our two measures of high-quality auditors: Big 4 and specialist auditors. These variables, denoted *BIG4* and *SPECIALIST*, are indicator variables that take on a value of one if firm *i* is audited by a Big 4 or specialist auditor, respectively, in year *t*, and zero otherwise. We include control variables that have been documented to affect anomaly returns. Specifically, we control for variables that are the current standard in the asset pricing literature (Fama and French 2015): firm size (*LN_MVE*), operating profitability (*OPERPROF*), asset growth (*AGR*), and book-to-market (*BM*) because these variables have been shown to explain a large number of anomalies (Chen and Zhang 2010; Fama and French 2016). We include cross-sectional characteristics rather than time series factors because recent research finds that characteristics are controls for risk exposure and better capture the cross-section of returns than factors (Bessembinder, Cooper, and Zhang 2019; Kelly, Pruitt, and Su 2019; Kozak, Nagel, and Santosh 2020; Raponi, Robotti, and Zaffaroni 2020).[9] The model includes *Year fixed effects* to control for time-specific trends in anomaly returns, and *Audit office fixed effects* because audit quality is a function of the audit office (Francis and Yu 2009) and returns could be correlated within an audit office.[10] Detailed variable definitions are provided in Appendix B.

To specifically examine our primary hypothesis, we further decompose the *NET* variable into its long and short components. To estimate the effect of high-quality auditors on the long- and short-side anomaly portfolio returns separately, we estimate the following equation using ordinary least squares regressions:

$$RET_{it} = \beta_0 + \beta_1 LONG_{it} + \beta_2 SHORT_{it} + \beta_3 LONG*HIGH\_QUALITY\_AUDITOR_{it} + \beta_4 SHORT*HIGH\_QUALITY\_AUDITOR_{it} + \beta_5 HIGH\_QUALITY\_AUDITOR_{it} + CONTROLS + Year\ fixed\ effects + Audit\ office\ fixed\ effects + u \qquad (2)$$

with variables defined as described above in equation (1), and *LONG* and *SHORT* replacing the *NET* anomaly variable. In equation (2), *LONG* and *SHORT* represent the number of long-side anomaly portfolios or the number of short-side anomaly portfolios that an observation belongs to as of fiscal year-end *t*, respectively. Our primary hypothesis predicts a negative coefficient on

[9] In untabulated tests, we find similar results when using portfolios formed by sorting on the net measure and *BIG4* or *SPECIALIST* and controlling for the Fama-French three time series factors.
[10] We create audit office fixed effects by MSA.

our main interaction variable of interest, *SHORT*HIGH_QUALITY_AUDITOR*. In subsequent analyses, we employ various specifications of equation (2) to help address challenges related to casual identification.

4. Sample selection and data

The sample period begins in 2005 due to the significant changes to the audit profession in the early 2000s.[11] We restrict the sample to non-financial US firms with common stock listed on the NYSE, AMEX, or NASDAQ (Green et al. 2017). We obtain 44,119 firm-years at the intersection of Compustat, CRSP, and Audit Analytics with annual return data for the period 2005 through 2019. We lose 1,394 firm-years when we drop observations missing data necessary to calculate control variables. We then cut 2,093 observations that are missing auditor office information. Our sample selection process yields a sample of 40,632 firm-year observations for regressions that use *BIG4* as a proxy for audit quality. The sample drops to 31,203 for our analyses that use *SPECIALIST* as a proxy for audit quality due to additional data requirements in constructing the variable. Table 1 describes our sample selection process.

[Insert Table 1]

Table 2 presents descriptive statistics for the main variables in our analyses. All continuous variables are winsorized by year at the 1st and 99th percentiles. Within our sample, the *NET* anomaly variable has a mean value of -0.040, and values of -4 and 4 at the 10th and 90th percentiles, respectively. Within the main sample, 71.4 percent of the observations are audited by a Big 4 auditor, and within the specialist sample, 38.5 percent of the observations are audited by a

[11] The Sarbanes-Oxley Act of 2002 (SOX) initiated a wave of significant changes related to improving the reliability of financial reporting. Many of these changes affected the audit profession. For example, beginning in 2004, SOX required auditors to opine on the design and operating effectiveness of internal controls over financial reporting of large clients (i.e., accelerated filers). This new internal controls opinion significantly changed the way in which auditors execute audits. Additionally, SOX created the PCAOB to regulate public company auditing. The PCAOB began inspecting audit firms in 2004.

specialist auditor. Additionally, the correlation between *BIG4* (*SPECIALIST*) and *LN_MVE* is 0.55 (0.27) (untabulated). Thus, using *SPECIALIST* as an alternative proxy to *BIG4* helps to alleviate concerns related to uncontrolled for size effects when using *BIG4* to capture audit quality.

[Insert Table 2]

5. Test results

5.1 Univariate analysis

Table 3 reports initial univariate results based on annual sorts of the *NET* anomaly variable. The *NET* variable is ranked into quintiles where the highest (lowest) extreme is classified as the *NET* anomaly long (short) quintile. Consistent with expectations from anomaly research, short net portfolios (i.e., anomaly sells) have significantly lower returns than long net portfolios (i.e., anomaly buys). This provides preliminary evidence that anomaly returns exist in our sample. Additionally, returns are significantly larger for firm-years with Big 4 auditors across the three lowest quintile ranks of *NET*, and significantly larger for firm-years with specialist auditors in the two lowest quintile ranks of *NET*. The results in the short quintile of *NET* are consistent with H1. Specifically, these results provide evidence that high-quality auditors are associated with reduced short-side anomaly returns, suggesting that high-quality auditors can help improve market efficiency.

[Insert Table 3]

5.2 Primary analysis

Table 4 reports the primary results of estimating equations (1) and (2). We begin by examining the baseline model of the association between the net anomaly variable (*NET*) and annual returns (*RET*) in column (1) and the association between the long-side (*LONG*) and short-side (*SHORT*) variables and annual returns in column (2).[12] In column (1), the coefficient on *NET* is positive and significant, suggesting that our identified anomaly variables are associated with annual returns during our sample period. Moreover, in column (2), the coefficient on *LONG* (*SHORT*) is insignificant (positive and significant), and the coefficient on *SHORT* is statistically larger than the coefficient on *LONG* (p-value < 0.01, untabulated), suggesting that the anomaly returns are driven by the anomaly sells.[13]

[Insert Table 4]

Next, we include interactions between the high-quality auditor proxies and *NET, LONG*, and *SHORT* to examine whether high-quality auditors reduce anomaly returns. Columns (3) and (5) present the results using the interaction with the *BIG4* and *SPECIALIST* indicator variables with *NET*. The coefficient on the main effect for *NET* continues to be positive and significant, but the interaction between *NET* and *BIG4* (*SPECIALIST*) is negative and significant suggesting that Big 4 (specialist) auditors reduce anomaly returns. Columns (4) and (6) present the results of our tests of H1. In these columns, the coefficients on the main effect are positive and significant only on the short side (*SHORT*). The coefficient on the long-side interaction variable is insignificant in both the Big 4 and specialist specifications *(LONG*BIG4* and *LONG*SPECIALIST*), but the interaction variable of interest is negative and significant for both high-quality auditor proxies (*SHORT*BIG4* and *SHORT*SPECIALIST*).

Collectively, columns (4) and (6) show that both the relation between anomaly strategies and returns and the impact of high-quality auditors are driven by the short side of the anomaly portfolio. From an economic perspective, the coefficient on *SHORT*BIG4*

[12] When *BIG4* is used as a high-quality auditor proxy, the main effect is not included because it is subsumed by the audit office fixed effects (i.e., *BIG4* is collinear with the audit office fixed effects).
[13] By construction, the values for *SHORT* are all less than zero. Thus, a positive coefficient on *SHORT* means that the firm-years within the short-side anomalies earn negative (positive) returns when taking a long (short) position.

(*SHORT*SPECIALIST*) corresponds to a 1.5 (0.9) percentage point reduction in the return for the short-side anomaly, which represents 68 (60) percent of the average short-side anomaly return when the auditor is not a Big 4 (specialist). Overall, and consistent with the predictions of H1, the results suggest that high-quality auditors reduce short-side anomaly returns. This is consistent with high-quality auditors, and, therefore, high-quality accounting, improving market efficiency where arbitrage is costly.

5.3 Tests of identification

It is possible that our results are due to correlated-omitted variables. For example, employing a Big 4 auditor is correlated with firm size. For this reason, we control for firm size (*LN_MVE*) and use industry specialist as an alternative proxy for auditor quality in our primary specification.[14] Next, we perform several additional analyses aimed at examining whether our primary results are due to audit quality.

5.3.1 PCAOB initial inspections – a shock to audit quality

First, we utilize a difference-in-differences regression that exploits staggered initial PCAOB inspections. Since 2004, the PCAOB has inspected audit firms to "drive improvement in the quality of audit services."[15] Prior research finds evidence of improved audit quality following PCAOB inspections (Gramling et al. 2011; DeFond and Lennox 2017; Fung et al. 2017; Gipper et al. 2020). Therefore, if high-quality auditing plays a unique role in reducing mispricing, we expect to find reduced short-side anomaly returns following the initial PCAOB inspection of a firm's auditor. We estimate the following regression using a generalized difference-in-differences design to examine the effect of PCAOB inspections on anomaly returns (Fung et al. 2017 and Shroff 2020 use similar designs):

[14] The results in Table 4 are also robust to interacting *NET*, *LONG*, and *SHORT* with *LN_MVE* (untabulated).
[15] Per https://pcaobus.org/oversight/inspections (accessed on February 10, 2021).

$$RET_{it} = \beta_0 + \beta_1 LONG_{it} + \beta_2 SHORT_{it} + \beta_3 LONG*INSPECT_{it} + \beta_4 SHORT*INSPECT_{it} + \beta_5 INSPECT_{it} + CONTROLS + Year\ fixed\ effects + Audit\ office\ fixed\ effects + u \tag{3}$$

INSPECT is an indicator variable equal to one if firm *i*'s auditor has been inspected by the PCAOB, and zero otherwise.[16] Thus, *INSPECT* captures an increase in audit quality that is due to a PCAOB inspection. If high-quality audits reduce short-side anomaly returns, then we expect to find a negative coefficient on our main interaction variable of interest, *SHORT*INSPECT*.

For this analysis, we focus on a subsample of firms audited by triennially inspected audit firms as opposed to annually inspected audit firms to exploit the variation in the timing of initial inspections that exists for triennially inspected audit firms.[17] This subsample also helps to alleviate endogeneity concerns inherent in using Big 4 auditors as a proxy for high audit quality by focusing on a subset of firms audited by non-Big 4 auditors. The downside of using this subsample is that it has a relatively low number of observations, which limits the statistical power of the tests. Table 5, Panel A, presents the distribution of initial PCAOB inspections among triennially inspected auditors in our sample.[18]

[Insert Table 5]

We require each firm in the sample to have at least one observation in the pre- and post-inspection period. As such, we begin our sample in 2004 so that we can include initial

[16] We utilize the end of PCAOB fieldwork date as the date to determine whether an audit firm has been inspected because this is when the audit firm will know all the findings from the inspection and can act on these findings. Therefore, if a firm's year-end is after their auditor's initial PCAOB inspection fieldwork date, then *INSPECT* would be set to 1 for that firm-year. For example, if the PCAOB initially inspected an audit firm between April 18, 2006 and April 27, 2006, then firm-years with year-ends after April 27, 2006 that are audited by this audit firm would have *INSPECT* = 1.
[17] The PCAOB inspects the largest audit firms annually. For example, the Big 4 were inspected initially in 2004 and have been inspected every year since.
[18] The majority of initial inspections occur prior to 2012. Results are robust to dropping observations that engage an auditor that underwent an initial inspection in 2013 and later.

inspections in 2005.[19] We limit our sample to a three-year period before and after each initial inspection. This process results in a total sample of 1,161 firm-year observations representing 135 unique auditors.

Table 5, Panel B, column (1), presents the results of estimating equation (3). Consistent with expectations, our main interaction variable of interest, *SHORT*INSPECT*, is negative and significant, suggesting that the improvement in audit quality from PCAOB inspections is associated with reduced short-side anomaly returns.

We perform two additional analyses to support our inferences. First, to validate the parallel trends assumption, we re-estimate equation (3) and include pre-inspection year indicator variables. $INSPECT_{-2}$ and $INSPECT_{-1}$ are equal to one for two years and one year prior to each firm's auditor's initial inspection, respectively. The results presented in column (2) support the parallel trends assumption, as the coefficients on the interactions between $SHORT*INSPECT_{-2}$ and $SHORT*INSPECT_{-1}$ are insignificant. The coefficient on our interaction variable of interest, *SHORT*INSPECT*, remains negative and significant.

Second, as a falsification test, we include an indicator variable, *INSPECT_PART2*, that takes on a value of one if firm *i*'s auditor has been inspected by the PCAOB and the PCAOB publicly releases Part II of the initial inspection report, and zero otherwise.[20] A PCAOB inspection consists of two parts. First, the PCAOB inspects a non-random sample of audits, and the PCAOB notes any related deficiencies within Part I of the related inspection report. Second, the PCAOB inspects the audit firm's system of quality controls. The PCAOB notes any quality

[19] Results do not hold if we begin our sample in 2005 to align with our primary analyses; however, doing so eliminates 41 of 135 initial inspections and 292 of 1,161 observations, significantly reducing the power of the tests.
[20] We construct *INSPECT_PART2* just like *INSPECT*, except that *INSPECT_PART2* is only set to 1 if Part II of the initial inspection report is publicly disclosed. In this specification, *INSPECT* is equal to zero when *INSPECT_PART2* is equal to one.

control issues within Part II of the related inspection report, but this portion of the report is redacted such that the general public cannot see any Part II issues that the PCAOB identified. However, if an audit firm fails to remediate the quality control criticisms within 12 months of the inspection, the PCAOB publicly discloses Part II of the report (PCAOB 2006). Thus, these situations arguably represent instances where an audit firm has not taken steps to improve audit quality. As such, we do not expect to find a significant change in anomaly returns following initial PCAOB inspections that resulted in public Part II disclosures. In other words, we expect to find an insignificant coefficient on *SHORT*INSPECT_PART2*. Column (3) presents the results of the falsification test. Consistent with expectations, we find no evidence of an effect of PCAOB inspections on short-side anomaly returns when a firm's auditor fails to remediate quality control issues. However, we continue to find a negative and significant coefficient on *SHORT*INSPECT*.

Taken together, these results support our proposed mechanism of PCAOB inspections influencing short-side anomaly returns, specifically through the improvement in audit quality realized by audit firms following initial inspection. For a correlated-omitted variable to explain our results, it would have to be correlated with the staggered timing of PCAOB inspections that plausibly improved audit firms' audit quality.

5.3.2 Entropy balancing

Next, we utilize an entropy balancing approach. We acknowledge that clients are not randomly assigned across auditors, and that auditor choice may be related to client-specific characteristics, which could endogenously affect anomaly returns. For example, the previous literature has questioned whether an indicator for a Big 4 auditor captures client characteristics, especially client size (Lawrence, Minutti-Meza, and Zhang 2011; Minutti-Meza 2013). However, others conclude that this concern does not overturn the literature that concludes that Big 4 auditors provide high-quality audits (DeFond, Erkens, and Zhang 2016).

Entropy balancing helps alleviate concerns related to functional form misspecification by balancing on observables. We balance observations based on the first three moments of all control variables. Table 6 presents the results of estimating equation (2) using the balanced sample. Consistent with our main results, the coefficients on the interaction variables of interest, *SHORT*BIG4* and *SHORT*SPECIALIST*, in columns (1) and (2), respectively, are negative and significant suggesting that high-quality auditors reduce anomaly returns, specifically on the short side. Overall, our main results are robust to entropy balancing.

[Insert Table 6]

5.3.3 Accounting mechanism versus information asymmetry

Next, we consider three proxies for information asymmetry to further demonstrate that our results are due to an auditor's effect on financial reporting (i.e., through reducing overstatements and enforcing timely recognition of losses). We first re-estimate equation (2) and control for interactions between our *LONG* and *SHORT* anomaly variables and three information asymmetry measures: *SIZE* is an indicator variable equal to one for observations above the median market value of equity, and zero otherwise; *HIGH_ANALYST* is an indicator variable equal to one for observations above the median value for analyst following, and zero otherwise; and *LOW_BASPREAD* is an indicator variable equal to one for observations below the median value for bid-ask spreads, and zero otherwise.

Table 7, Panel A, presents the results when including the additional control variables. The coefficients on *SHORT*BIG4* and *SHORT*SPECIALIST* remain negative and significant in columns (1) and (2), respectively. Additionally, the interactions between *SHORT* and *SIZE* in columns (1) and (2) and between *SHORT* and *HIGH_ANALYST* in column (2) are negative and significant.[21] This evidence suggests that (1) audit quality uniquely affects short-side mispricing and (2) information asymmetry also affects short-side mispricing.

[Insert Table 7]

To further support our interpretation of high-quality auditors reducing anomaly returns, specifically through the audit of annual financial statements, we examine finance-related anomaly returns. We do not expect high-quality auditors to have an effect on finance-related anomaly returns. We identify seven finance anomalies that are unlikely to be directly related to the mispricing of accounting information, which should arguably be uncorrelated with an auditor's influence on the annual financial statements (see Appendix C for details on these anomalies). Similar to the *NET* variable, we construct the finance anomaly portfolio by sorting the anomaly values by month into quintiles, and defining the extreme quintiles as the long (*FINANCE_LONG*) and short (*FINANCE_SHORT*) side of the anomaly strategy. We re-estimate equation (2) using the new anomaly variables and monthly returns.[22] We also interact the finance anomaly variables with size, analyst coverage, and bid-ask spreads to compare auditor effects and information asymmetry effects. We expect the short-side interactions with these proxies for information asymmetry to be negatively significant because their effects should not be limited to accounting anomaly returns. However, we expect that the short-side interactions with high-quality auditors will not be significant because auditors do not affect the information related to these anomalies.

[21] In Table 7, we include both *SIZE* and *LN_MVE,* which are both measures of size and are positively correlated (0.7989). Inferences are the same if we exclude the main effect of *SIZE* or if we exclude *LN_MVE* from the regression.
[22] We use monthly instead of annual returns because the finance anomalies are typically constructed based on monthly sorts.

Table 7, Panel B, presents the results of our tests examining finance anomaly returns. Similar to our results using anomalies that the auditor should affect, the finance anomaly returns exist only on the short side. Importantly, the coefficients on *FINANCE_SHORT*BIG4* and *FINANCE_SHORT*SPECIALIST* in columns (1) and (2) are insignificant, suggesting that high-quality auditors do not reduce finance anomaly returns on the short side. This insignificance stands in contrast to the coefficients on *FINANCE_SHORT*SIZE*, *FINANCE_SHORT*HIGH_ANALYST*, and *FINANCE_SHORT*LOW_BASPREAD*, which are negative and significant in both columns.

Overall, the evidence presented in Table 7 suggests that information asymmetry affects accounting and finance anomaly returns, whereas the effect of high-quality auditors appears to be limited to accounting-based anomaly returns, consistent with the mechanism proposed in the hypothesis section. This also helps mitigate concerns related to endogeneity, because the endogeneity concern (e.g., that our measures of high-quality auditors are picking up reduced market frictions or effects of auditor-client matching) would likely apply to both accounting and finance anomalies.

5.4 Additional analyses

5.4.1 Cross-sectional analyses

We next consider that the effect of high-quality auditors on short-side returns should be more pronounced when other arbitrage costs are high, because arbitrageurs are more constrained in their ability to correct overpricing and to monitor misreporting in these instances. High arbitrage costs also often coincide with when information asymmetry between managers and investors is high. This high information asymmetry increases an auditor’s incentives to monitor and constrain aggressive reporting decisions. While there are a number of possible arbitrage frictions, we are primarily interested in those that are related to information asymmetry because these are most directly related to risk of material misstatement (i.e., most directly related to an external audit). For that reason, we use three information-related arbitrage costs: market capitalization, analyst coverage, and bid-ask spreads (Hong, Lim, and Stein 2000; Goyenko, Holden, and Trzcinka 2009).

Table 8 reports results when splitting the sample based on median size (*MVE*), median analyst following (*NANALYST*), and median bid-ask spreads (*BASPREAD*). Panel A presents descriptive statistics by the median splits for high- and low-quality auditors. The descriptive statistics demonstrate that there is a lot of variation in the use of a high-quality auditor across the measures of information asymmetry.

In Panels B and C, we re-estimate equation (2) after splitting the sample based on the variables described above: size, analyst following, and bid-ask spreads. The results for Big 4 auditors in Panel B are consistent with the results for specialist auditors in Panel C. In columns (1) and (2), we find that anomaly returns are driven by the short side in small firms. Specifically, the coefficient on *SHORT* in column (1) is statistically different than the corresponding coefficient in column (2) (p-value < 0.01, untabulated) in Panel B and C. Similarly, in columns (3) through (6), we find that anomaly returns are driven by firms with low analyst following and high bid-ask spreads. The coefficient on *SHORT* in column (3) is statistically different than the corresponding coefficient in column (4) (p-value < 0.01, untabulated), and the coefficient on *SHORT* in column (6) is statistically different than the corresponding coefficient in column (5) (p-value < 0.01, untabulated), in Panel B and C. Importantly, the coefficients on *SHORT*BIG4* and *SHORT*SPECIALIST* in Panel B and C, respectively, are negative and significant only in the subsample of small firms (column (1)), firms with low analyst following (column (3)), and firms with high bid-ask spreads (column (6)). Taken together, the results presented in Table 8 provide evidence consistent with high-quality auditors reducing short-side anomalies where arbitrage costs related to information asymmetry are highest. This is important given that the use of high-quality auditors is less frequent in firms where the unique benefits of high-quality auditing may be the highest.

[Insert Table 8]

5.4.2 Analysts' return forecasts

Finally, we consider the effect of high-quality auditing on analysts' return forecasts. Engelberg et al. (2020) find that although anomaly portfolios are associated with stock returns, analysts' actionables fail to reflect the information found in such anomaly variables. The authors conclude that investors using the actionable information provided by analysts, which contradict anomaly variables, may further contribute to anomaly mispricing. Therefore, we next explore whether high-quality auditors improve financial statement information which then helps analysts provide better return forecasts.

Table 9, Panel A, reports univariate results for analysts' return forecasts across the annual sorts of the *NET* anomaly variable. *FORECAST* is calculated using the IBES Summary database. We use the mean 12-month price target from IBES to calculate the 12-month return forecast by subtracting the current price from the mean 12-month price target and dividing by the current price. Consistent with Engelberg et al. (2020), we find that return forecasts contradict the *NET* variable. Specifically, short net portfolios (anomaly sells) have significantly *higher* forecasted returns than long net portfolios (anomaly buys), and forecasted returns appear to decline from the short to the long quintiles, suggesting that analysts get return forecasts wrong with respect to anomaly signals. This pattern of return forecasts that is the mirror opposite of the anomaly portfolios exists in both the high- and low-quality auditor samples; however, the effect is weaker in magnitude in the presence of high-quality auditors. For example, the return forecast is 0.620 higher for anomaly sells than anomaly buys for firms using a non-Big 4 auditor, and only 0.242 higher for firms using a Big 4 auditor. Similarly, the return forecast is 0.415 higher for anomaly sells than anomaly buys for firms using a non-specialist auditor, and only 0.194 higher for firms using a specialist auditor.

Panel B of Table 9 presents the results of a multiple regression analysis. We re-estimate equation (2) with analysts' return forecast (*FORECAST*) as the dependent variable. The main effect on *SHORT* is negative and significant, suggesting that the contradiction between analysts' return forecasts and anomaly signals is driven by short-side anomaly portfolios. We find a positive and significant coefficient on our interaction variables of interest, *SHORT*BIG4* and *SHORT*SPECIALIST*, in columns (1) and (2), respectively. Consistent with the univariate analysis, these results suggest that the negative relation between anomaly portfolios and analysts' return forecasts is partially mitigated by high-quality auditors. Overall, our findings are consistent with high-quality auditing assisting analysts in incorporating accounting information into their actionable information.

[Insert Table 9]

6. Conclusion

We examine whether high-quality auditors reduce short-side anomaly returns. Auditors can affect short-side anomaly returns by limiting aggressive financial reporting and enforcing the timely recognition of losses. We focus on 22 anomalies that relate to year *t* annual financial statement information, because auditors can affect the reliability of the accounting numbers that are used to create these anomalies. Using 40,632 firm-year observations from 2005 to 2019, we find that short-side returns (i.e., anomaly sells) are stronger than long-side returns (i.e., anomaly buys). We also find that high-quality auditors (i.e., Big 4 or industry specialist auditors) are associated with reduced anomaly returns in both univariate and multiple regression analyses. In multiple regression analyses, short-side returns are reduced by 1.5 (0.9) percentage points when the auditor is a Big 4 (specialist), which represents 68 (60) percent of the average short-side anomaly return when the auditor is not a Big 4 (specialist).

We then perform several analyses that help mitigate concerns that our results are spurious. First, results are robust to using a difference-in-differences design that exploits staggered initial PCAOB inspections, which represent shocks to audit quality. Second, results are robust to utilizing an entropy-balancing approach, which balances the treatment and control observations based on observables. Third, we find that both high-quality auditors and proxies for low information asymmetry are associated with reduced short-side accounting anomaly returns. However, while we find that proxies for low information asymmetry are associated with reduced short-side finance anomaly returns, we find no effect of high-quality auditors on short-side finance anomaly returns. These results are consistent with our proposed mechanism (i.e., that high-quality auditing reduces overstatements and helps enforce the timely recognition of losses).

In additional analyses, we examine cross-sectional cuts based on median size, analyst following, and bid-ask spreads, which serve as proxies for differences in arbitrage costs based on information asymmetry. Across all three proxies, we find that high-quality auditors are associated with reduced short-side anomaly returns in subsamples where information asymmetry is high, but not in subsamples when information asymmetry is low. Finally, we examine whether high-quality auditing assists analysts by improving their return forecasts, which are contradictory to anomalies. We find evidence that suggests that high-quality auditing helps analysts better incorporate accounting anomaly signals into their forecasts.

We contribute to the auditing literature that links high-quality auditing to stock prices by providing evidence that auditors play a role in mitigating mispricing on the short side. We also contribute to the literature on market efficiency and anomalies. Overall, our evidence suggests that improving accounting information can lead to more efficient capital markets (Lee 2001), and that high-quality auditors play an important role in improving market efficiency. Finally, we contribute to the analyst literature by providing evidence that suggests that high-quality auditors enable analysts to better incorporate accounting anomaly signals.

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APPENDIX A

Anomaly Definitions

Anomaly Variable	Acronym	Author(s)	Date, Journal	Definition
Absolute accruals	*absacc*	Bandyopadhyay, Huang, and Wirjanto	2010, WP	Absolute value of acc
Working capital accruals	*acc*	Sloan	1996, TAR	Annual income before extraordinary items (ib) minus operating cash flows (oancf) divided by average total assets (at); if oancf is missing then set to change in act - change in che - change in lct + change in dlc + change in txp-dp
Cash flow to debt	*cashdebt*	Ou and Penman	1989, JAE	Earnings before depreciation and extraordinary items (ib+dp) divided by avg. total liabilities (lt)
Current ratio	*currat*	Ou and Penman	1989, JAE	Current assets / current liabilities
Depreciation / PP&E	*depr*	Holthausen and Larcker	1992, JAE	Depreciation divided by PP&E
Earnings to price	*ep*	Basu	1977, JF	Annual income before extraordinary items (ib) divided by end of fiscal year market cap
Gross profitability	*gma*	Novy-Marx	2013, JFE	Revenues (revt) minus cost of goods sold (cogs) divided by lagged total assets (at)
Operating profitability	*operprof*	Fama and French	2015, JFE	Revenue minus cost of goods sold - SG&A expense - interest expense divided by lagged common shareholders' equity
Organizational capital	*orgcap*	Eisfeldt and Papanikolaou	2013, JF	Capitalized SG&A expenses
Percent accruals	*pctacc*	Hafzalla, Lundholm, and Van Winkle	2011, TAR	Same as acc except that the numerator is divided by the absolute value of ib; if ib = 0 then ib set to 0.01 for denominator
Quick ratio	*quick*	Ou and Penman	1989, JAE	(current assets - inventory) / current liabilities
R&D to market capitalization	*rd_mve*	Guo, Lev, and Shi	2006, JBFA	R&D expense divided by end-of-fiscal-year market capitalization
R&D to sales	*rd_sale*	Guo, Lev, and Shi	2006, JBFA	R&D expense divided by sales (xrd/sale)
Real estate holdings	*realestate*	Tuzel	2010, RFS	Buildings and capitalized leases divided by gross PP&E
Return on invested capital	*roic*	Brown and Rowe	2007, WP	Annual earnings before interest and taxes (ebit) minus nonoperating income (nopi) divided by non-cash enterprise value (ceq+lt-che)
Sales to cash	*salecash*	Ou and Penman	1989, JAE	Annual sales divided by cash and cash equivalents
Sales to inventory	*saleinv*	Ou and Penman	1989, JAE	Annual sales divided by total inventory
Sales to receivables	*salerec*	Ou and Penman	1989, JAE	Annual sales divided by accounts receivable
Secured debt	*secured*	Valta	2016, JFQA	Total liability scaled secured debt
Sales to price	*SP*	Barbee, Mukherji, and Raines	1996, FAJ	Annual revenue (sale) divided by fiscal year-end market capitalization
Debt capacity/firm tangibility	*tang*	Almeida and Campello	2007, RFS	Cash holdings + 0.715 × receivables +0.547 × inventory + 0.535 × PPE/ total assets
Tax income to book income	*tb*	Lev and Nissim	2004, TAR	Tax income, calculated from current tax expense divided by maximum federal tax rate, divided by income before extraordinary items

APPENDIX B
Variable Definitions

RET	Annual returns for firm *i* over year t measured over the twelve-month period [*t*+5 months, *t*+17 months].
NET	The difference between the number of long and short anomaly portfolios a firm-year belongs to. Anomaly measures are sorted by year into quintiles, and are defined as long (short) portfolios if the anomaly measure falls into the highest (lowest) extreme quintile. See Appendix A for anomaly definitions.
LONG	The number of long-side anomaly portfolios a firm-year belongs to. See Appendix A for anomaly definitions.
SHORT	The number of short-side anomaly portfolios a firm-year belongs to, multiplied by -1. See Appendix A for anomaly definitions.
BIG4	An indicator that equals 1 for firm-years audited by a Big 4 auditor in year *t*, and 0 otherwise.
SPECIALIST	An indicator that equals 1 for firm-years audited by an industry specialist auditor in year *t*, and 0 otherwise. An auditor is considered an industry specialist when, for a given city-industry-year, the auditor has the largest two-digit SIC market share based on audit fees and when this market share is more than 10 percentage points larger than the second largest auditor within the same city-industry-year (Reichelt and Wang 2010).
LN_MVE	Natural log of fiscal year-end market capitalization.
OPERPROF	Revenue less cost of goods sold, SG&A expense, and interest expense, divided by lagged common shareholders' equity.
AGR	Annual percent change in total assets.
BM	Book value of equity divided by end of fiscal year-end market capitalization.
INSPECT	An indicator that equals 1 if firm *i*'s auditor has been inspected by the PCAOB, and 0 otherwise. *INSPECT* is also set to 0 when *INSPECT_PART2* is equal to 1.
INSPECT_PART2	An indicator that equals 1 if firm *i*'s auditor has been inspected by the PCAOB and the PCAOB publicly released Part 2 of the initial inspection report because the auditor failed to remediate quality control criticisms, and 0 otherwise.
NANALYST	Annual average of number of analyst forecasts for a firm for the twelve-month period [*t*+5 months, *t*+17 months]. Set to zero for firm-years missing analyst forecast data.
BASPREAD	Annual average of the daily bid-ask spread for a firm where the spread is defined as the daily highest ask price minus the daily lowest bid price divided by the average of the two.
SIZE	An indicator that equals 1 for firm-years above the median market value of equity, and 0 otherwise.
HIGH_ANALYST	An indicator that equals 1 for firm-years above the median value for analyst following, and 0 otherwise.
LOW_BASPREAD	An indicator that equals 1 for firm-years below the median value for bid-ask spreads, and 0 otherwise.
MONTHLY_RET	Monthly returns for firm *i*.

FINANCE_LONG	The number of long-side finance anomaly portfolios a firm-month belongs to. See Appendix C for finance anomaly definitions.
FINANCE_SHORT	The number of short-side finance anomaly portfolios a firm-month belongs to, multiplied by -1. See Appendix C for finance anomaly definitions.
FORECAST	12-month return forecast for firm i as of month t+5. Calculated by subtracting the current price from the mean 12-month price target and dividing by the current price.

APPENDIX C
Finance Anomaly Definitions

Anomaly Variable	**Acronym**	**Author(s)**	**Date, Journal**	**Definition**
Change in 6-month momentum	*chmom*	Gettleman and Marks	2006, WP	Cumulative returns from months *t-6* to *t-1* minus months *t-12* to *t-7*
Industry momentum	*indmom*	Moskowitz and Grinblatt	1999, JF	Equal weighted average industry 12-month returns
Maximum daily return	*maxret*	Bali, Cakici, and Whitelaw	2011, JFE	Maximum daily return from returns during calendar month *t-1*
12-month momentum	*mom12m*	Jegadeesh	1990, JF	11-month cumulative returns ending one month before month end
1-month momentum	*mom1m*	Jegadeesh and Titman	1993, JF	1-month cumulative return
36-month momentum	*mom36m*	Jegadeesh and Titman	1993, JF	Cumulative returns from months *t-36* to *t-13*
6-month momentum	*mom6m*	Jegadeesh and Titman	1993, JF	5-month cumulative returns ending one month before month end

Table 1. Sample Selection

Sample Construction	Firm-Years
Observations from fiscal years 2005-2019 with annual return data	44,119
Remove firm-years with missing data to estimate control variables	(1,394)
Remove firm-years with missing auditor office data for fixed effects	(2,093)
Big 4 Regression Sample	40,632
Remove firm-years with missing or insufficient specialist auditor data	(9,429)
Specialist Regression Sample	31,203

This table presents details of our sample selection process.

Table 2. Descriptive Statistics

	N	Mean	St. Dev	P10	P25	Median	P75	P90
Dependent Variable:								
RET	40,632	0.094	0.589	-0.532	-0.242	0.039	0.316	0.692
Anomaly Variables:								
NET	40,632	-0.040	3.252	-4.000	-2.000	0.000	2.000	4.000
LONG	40,632	3.926	2.090	1.000	2.000	4.000	5.000	7.000
SHORT	40,632	-3.966	2.662	-8.000	-5.000	-4.000	-2.000	-1.000
Audit Quality Variables:								
BIG4	40,632	0.714	0.452	0.000	0.000	1.000	1.000	1.000
SPECIALIST	31,203	0.385	0.487	0.000	0.000	0.000	1.000	1.000
Control Variables:								
LN_MVE	40,632	6.343	2.117	3.523	4.816	6.336	7.806	9.146
OPERPROF	40,632	0.745	1.470	-0.017	0.292	0.599	1.027	1.772
AGR	40,632	0.114	0.385	-0.180	-0.046	0.044	0.161	0.417
BM	40,632	0.547	0.619	0.092	0.230	0.429	0.718	1.123
Information Asymmetry Variables:								
NANALYST	40,632	6.679	7.166	0.000	1.000	4.333	10.000	17.375
BASPREAD	40,632	0.044	0.025	0.019	0.026	0.037	0.055	0.077

This table presents descriptive statistics for the main variables used in the analyses. The sample consists of 40,632 firm-year observations for the period 2005 to 2019. All variables are defined in Appendix B. Continuous variables have been winsorized at the 1st and 99th percentiles.

Table 3. Univariate Analysis

	BIG4=0	*BIG4*=1			*SPECIALIST*=0	*SPECIALIST*=1		
	Mean	Mean	Difference in Means	(t-stat.)	Mean	Mean	Difference in Means	(t-stat.)
1 (Short)	-0.062	0.080	0.143	9.093***	-0.007	0.079	0.086	4.775***
2	0.022	0.115	0.093	6.413***	0.083	0.110	0.028	1.866*
3	0.073	0.137	0.063	3.427***	0.119	0.124	0.004	0.238
4	0.109	0.129	0.019	1.498	0.118	0.131	0.013	1.057
5 (Long)	0.105	0.121	0.017	1.362	0.114	0.120	0.006	0.429
L-S	0.167	0.041			0.121	0.041		
t-stat.	9.373***	3.705***			8.786***	2.383**		

This table presents average returns (*RET*) by auditor quality for firm-years based on annual quintile sorts of the *NET* anomaly variable.

Table 4. High-Quality Auditors and Anomaly Returns

	Baseline		Big 4		Specialist	
	(1)	(2)	(3)	(4)	(5)	(6)
	RET	*RET*	*RET*	*RET*	*RET*	*RET*
NET	0.008***		0.014***		0.010***	
	(7.228)		(8.106)		(6.854)	
LONG		0.001		0.001		0.002
		(0.342)		(0.317)		(0.719)
SHORT		0.013***		0.022***		0.015***
		(8.894)		(9.275)		(7.736)
*NET*BIG4*			-0.010***			
			(-4.676)			
*NET*SPECIALIST*					-0.006**	
					(-2.452)	
*LONG*BIG4*				-0.002		
				(-0.491)		
*SHORT*BIG4*				-0.015***		
				(-5.002)		
*LONG*SPECIALIST*						0.001
						(0.253)
*SHORT*SPECIALIST*						-0.009***
						(-3.074)
SPECIALIST					0.008	-0.030*
					(1.124)	(-1.940)
LN_MVE	0.001	-0.003	0.001	-0.003	-0.001	-0.004*
	(0.480)	(-1.295)	(0.330)	(-1.231)	(-0.460)	(-1.698)
OPERPROF	0.000	0.001	0.001	0.001	0.003	0.003
	(0.191)	(0.332)	(0.283)	(0.397)	(0.914)	(0.946)
AGR	-0.041***	-0.037***	-0.041***	-0.037***	-0.038***	-0.035***
	(-5.257)	(-4.727)	(-5.303)	(-4.763)	(-4.479)	(-4.083)
BM	0.074***	0.070***	0.073***	0.069***	0.060***	0.057***
	(6.145)	(5.768)	(6.077)	(5.708)	(4.605)	(4.300)
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Audit Office Fixed Effects	YES	YES	YES	YES	YES	YES
Observations	40,632	40,632	40,632	40,632	31,203	31,203
R-squared	0.192	0.193	0.192	0.194	0.195	0.196
Adjusted R-squared	0.172	0.173	0.173	0.174	0.175	0.176

This table presents tests of the relation between high-quality audits and anomaly returns. Columns (1) and (2) report the results of estimating equations (1) and (2) without high-quality auditor proxies. Columns (3) and (4) report results using Big 4 auditors (*HIGH_QUALITY_AUDITOR = BIG4*), and columns (5) and (6) report results using specialist auditors (*HIGH_QUALITY_AUDITOR = SPECIALIST*). Robust *t*-statistics, based on standard errors clustered by firm, are presented in parentheses below the coefficients. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix B.

Table 5. PCAOB Inspections

Panel A. Initial Inspection Years

Initial Inspection Year	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**Total**
Inspected Auditors	41	67	7	0	6	2	4	0	1	0	2	2	1	2	135

Table 5 (continued)

Panel B. PCAOB Inspections and Anomaly Returns

	(1) *RET*	(2) *RET*	(3) *RET*
LONG	-0.019	-0.029	-0.020
	(-1.121)	(-0.457)	(-1.139)
SHORT	0.050***	0.106**	0.051***
	(3.671)	(1.992)	(3.706)
$INSPECT_{-2}$		-0.240	
		(-0.405)	
$INSPECT_{-1}$		-0.171	
		(-0.300)	
INSPECT	-0.267*	-0.455	-0.272**
	(-1.962)	(-0.811)	(-1.983)
INSPECT_PART2			-0.197
			(-0.286)
$LONG*INSPECT_{-2}$		0.006	
		(0.091)	
$SHORT*INSPECT_{-2}$		-0.081	
		(-1.417)	
$LONG*INSPECT_{-1}$		0.006	
		(0.097)	
$SHORT*INSPECT_{-1}$		-0.053	
		(-1.012)	
*LONG*INSPECT*	0.000	0.009	0.002
	(0.017)	(0.149)	(0.101)
*SHORT*INSPECT*	-0.032**	-0.088*	-0.032**
	(-2.199)	(-1.656)	(-2.192)
*LONG*INSPECT_PART2*			-0.024
			(-0.417)
*SHORT*INSPECT_PART2*			-0.021
			(-0.303)
LN_MVE	-0.041	-0.042	-0.042
	(-1.354)	(-1.389)	(-1.376)
OPERPROF	0.031	0.030	0.032
	(1.490)	(1.440)	(1.546)
AGR	-0.008	-0.012	-0.007
	(-0.169)	(-0.276)	(-0.149)
BM	0.233***	0.232***	0.233***
	(3.515)	(3.483)	(3.497)
Year Fixed Effects	YES	YES	YES
Audit Office Fixed Effects	YES	YES	YES
Observations	1,161	1,161	1,161
R-squared	0.320	0.324	0.320
Adjusted R-squared	0.194	0.195	0.192

This table presents tests of the effect of initial PCAOB inspections on anomaly returns. Panel A reports the distribution of initial inspections by year. Panel B, column (1) reports the results of estimating equation (3) using a sample of firm-years audited by triennially inspected audit firms. The variable *INSPECT* is equal to one if a firm's auditor has been inspected by the PCAOB. Column (2) includes pre-inspection year indicator variables. $INSPECT_{-2}$ and $INSPECT_{-1}$ are equal to one for two years and one year prior to each firm's auditor's initial inspection, respectively. Column (3) includes *INSPECT_PART2* which is equal to one if a firm's auditor has been inspected by the PCAOB and the PCAOB publicly disclosed Part II of the inspection report because the auditor failed to remediate quality control criticisms following inspection. In this analysis, our variable of interest, *INSPECT*, is only equal to one if a firm's auditor has been inspected by the PCAOB and the inspection did not result in a public disclosure of Part II of the inspection report (i.e., *INSPECT_PART2*=0). Robust t-statistics, based on standard errors clustered by firm, are presented in parentheses below the coefficients. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix B.

Table 6. Entropy Balancing

	(1)	(2)
	RET	*RET*
LONG	-0.003	0.001
	(-0.514)	(0.372)
SHORT	0.018***	0.011***
	(3.621)	(5.865)
*LONG*BIG4*	0.001	
	(0.257)	
*SHORT*BIG4*	-0.011**	
	(-2.016)	
*LONG*SPECIALIST*		0.000
		(0.141)
*SHORT*SPECIALIST*		-0.005*
		(-1.813)
SPECIALIST		-0.014
		(-1.008)
LN_MVE	-0.005	-0.005**
	(-1.482)	(-2.435)
OPERPROF	0.002	0.003
	(0.424)	(1.148)
AGR	-0.048***	-0.029***
	(-3.802)	(-3.121)
BM	0.039**	0.035***
	(2.385)	(2.772)
Year Fixed Effects	YES	YES
Audit Office Fixed Effects	YES	YES
Observations	40,632	31,203
R-squared	0.197	0.194
Adjusted R-squared	0.177	0.173

This table presents tests of the relation between high-quality audits and anomaly returns using our entropy balanced sample. We re-estimate equation (2) after performing entropy balancing. Column (1) (column (2)) presents the results after balancing Big 4 and non-Big 4 (specialist and non-specialist) observations based on the first three moments of all control variables. Robust *t*-statistics, based on standard errors clustered by firm, are presented in parentheses below the coefficients. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix B.

Table 7. Information Asymmetry Proxies and Finance Anomalies

Panel A. Information Asymmetry Controls

	(1) *RET*	(2) *RET*
LONG	-0.000	0.001
	(-0.102)	(0.303)
SHORT	0.023***	0.020***
	(8.978)	(7.610)
*LONG*BIG4*	-0.002	
	(-0.573)	
*SHORT*BIG4*	-0.009***	
	(-2.641)	
*LONG*SPECIALIST*		0.001
		(0.426)
*SHORT*SPECIALIST*		-0.006*
		(-1.895)
*LONG*SIZE*	0.005	0.002
	(1.269)	(0.430)
*SHORT*SIZE*	-0.007**	-0.010***
	(-2.285)	(-2.756)
*LONG*HIGH_ANALYST*	0.002	0.001
	(0.551)	(0.366)
*SHORT*HIGH_ANALYST*	-0.005	-0.007**
	(-1.528)	(-2.004)
*LONG*LOW_BASPREAD*	-0.004	-0.005
	(-1.548)	(-1.381)
*SHORT*LOW_BASPREAD*	-0.004	-0.003
	(-1.536)	(-1.136)
SPECIALIST		-0.018
		(-1.155)
SIZE	-0.053***	-0.053**
	(-2.651)	(-2.387)
ANALYST	-0.006	-0.013
	(-0.364)	(-0.721)
BASPREAD	0.087***	0.093***
	(5.571)	(5.145)
LN_MVE	-0.016***	-0.017***
	(-5.256)	(-5.125)
OPERPROF	0.002	0.003
	(0.651)	(1.171)
AGR	-0.037***	-0.035***
	(-4.691)	(-4.126)
BM	0.067***	0.053***
	(5.501)	(4.018)
Year Fixed Effects	YES	YES
Audit Office Fixed Effects	YES	YES
Observations	40,632	31,203
R-squared	0.198	0.201
Adjusted R-squared	0.178	0.181

Table 7 (continued)

Panel B. Finance Anomalies

	(1) *MONTHLY_RET*	(2) *MONTHLY_RET*
FINANCE_LONG	0.000	0.000
	(0.317)	(0.158)
FINANCE_SHORT	0.004***	0.004***
	(11.126)	(10.842)
*FINANCE_LONG*BIG4*	-0.000	
	(-0.033)	
*FINANCE_SHORT*BIG4*	-0.001	
	(-1.530)	
*FINANCE_LONG*SPECIALIST*		-0.001
		(-1.355)
*FINANCE_SHORT*SPECIALIST*		-0.001
		(-1.352)
*FINANCE_LONG*SIZE*	-0.001	-0.001
	(-1.108)	(-0.995)
*FINANCE_SHORT*SIZE*	-0.002***	-0.002***
	(-2.962)	(-2.881)
*FINANCE_LONG*HIGH_ANALYST*	-0.000	0.000
	(-0.510)	(0.386)
*FINANCE_SHORT*HIGH_ANALYST*	-0.002***	-0.002***
	(-3.628)	(-3.157)
*FINANCE_LONG*LOW_BASPREAD*	-0.000	-0.000
	(-0.421)	(-0.703)
*FINANCE_SHORT*LOW_BASPREAD*	-0.001**	-0.001**
	(-2.276)	(-2.465)
SPECIALIST		0.000
		(0.324)
SIZE	-0.000	-0.001
	(-0.102)	(-0.428)
HIGH_ANALYST	-0.003***	-0.004***
	(-3.032)	(-3.422)
LOW_BASPREAD	-0.001	-0.001
	(-0.765)	(-0.897)
LN_MVE	0.001***	0.001***
	(3.266)	(2.842)
OPERPROF	0.001***	0.001***
	(3.224)	(3.575)
AGR	-0.002***	-0.002**
	(-2.807)	(-2.413)
BM	0.004***	0.003***
	(6.160)	(4.455)
Month Fixed Effects	YES	YES

Audit Office Fixed Effects	YES	YES
Observations	464,082	356,167
R-squared	0.175	0.177
Adjusted R-squared	0.172	0.175

This table presents the results of our main analyses with added controls for information asymmetry proxies. In Panel A, we re-estimate equation (2) with added interactions for above-median size firms (*SIZE*), high analyst following (*HIGH_ANALYST*), and low bid-ask spreads (*LOW_BASPREAD*). In Panel B, we perform a falsification test of the relation between high-quality auditors and finance-related anomaly returns. We re-estimate equation (2) using the long and short sides of a finance-related net anomaly portfolio (*FINANCE_LONG* and *FINANCE_SHORT*, respectively) in place of our *LONG* and *SHORT* audit-related variables. We continue to include the additional interactions presented in Panel A. Column (1) reports results using Big 4 auditors (*HIGH_QUALITY_AUDITOR* = *BIG4*). Column (2) reports results using specialist auditors (*HIGH_QUALITY_AUDITOR* = *SPECIALIST*). Robust *t*-statistics, based on standard errors clustered by firm, are presented in parentheses below the coefficients. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix B.

Table 8. High-Quality Auditors and Information Asymmetry Splits

Panel A. Cross-Sectional Descriptive Statistics

	Size (*MVE*)			
	Below Median		Above Median	
	N	%	N	%
BIG4=1	9,871	49.2%	19,153	93.2%
BIG4=0	10,211	50.8%	1,397	6.8%
SPECIALIST=1	4,177	27.3%	7,833	49.2%
SPECIALIST=0	11,109	72.7%	8,084	50.8%

	Analyst Following (*NANALYST*)			
	Below Median		Above Median	
	N	%	N	%
BIG4=1	10,273	51.8%	18,751	90.2%
BIG4=0	9,560	48.2%	2,048	9.8%
SPECIALIST=1	4,336	29.2%	7,674	46.9%
SPECIALIST=0	10,525	70.8%	8,668	53.1%

	Bid-Ask Spreads (*BASPREAD*)			
	Below Median		Above Median	
	N	%	N	%
BIG4=1	17,124	84.5%	11,900	58.4%
BIG4=0	3,133	15.5%	8,475	41.6%
SPECIALIST=1	7,163	45.4%	4,847	31.4%
SPECIALIST=0	8,622	54.6%	10,571	68.6%

Table 8 (continued)

Panel B. Big 4 Auditors

	Dependent Variable = *RET*					
	(1)	(2)	(3)	(4)	(5)	(6)
	SIZE	*SIZE*	*NANALYST*	*NANALYST*	*BASPREAD*	*BASPREAD*
	Small	*Large*	*Low*	*High*	*Low*	*High*
LONG	0.000	-0.002	0.003	-0.001	-0.006*	0.003
	(0.135)	(-0.308)	(0.801)	(-0.242)	(-1.672)	(0.730)
SHORT	0.024***	0.008	0.024***	0.013**	0.006*	0.024***
	(8.833)	(1.039)	(8.700)	(2.292)	(1.748)	(7.850)
*LONG*BIG4*	-0.005	0.001	-0.007	-0.001	0.006	-0.003
	(-0.954)	(0.077)	(-1.530)	(-0.220)	(1.643)	(-0.582)
*SHORT*BIG4*	-0.010**	-0.006	-0.010***	-0.009	-0.005	-0.015***
	(-2.483)	(-0.731)	(-2.581)	(-1.482)	(-1.321)	(-3.835)
LN_MVE	-0.016***	-0.005**	-0.006	-0.010***	-0.012***	-0.020***
	(-2.682)	(-2.037)	(-1.412)	(-3.495)	(-6.218)	(-4.313)
OPERPROF	-0.001	0.002	-0.005	0.006**	0.002	-0.000
	(-0.128)	(0.728)	(-1.224)	(2.084)	(1.117)	(-0.101)
AGR	-0.039***	-0.027***	-0.044***	-0.037***	0.000	-0.038***
	(-3.509)	(-2.612)	(-3.710)	(-3.488)	(0.028)	(-3.581)
BM	0.072***	-0.022	0.095***	-0.023	-0.006	0.075***
	(5.289)	(-1.520)	(6.743)	(-1.240)	(-0.498)	(5.157)
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Audit Office Fixed Effects	YES	YES	YES	YES	YES	YES
Observations	20,082	20,550	19,833	20,799	20,257	20,375
R-squared	0.214	0.216	0.208	0.213	0.222	0.226
Adjusted R-squared	0.177	0.198	0.170	0.192	0.195	0.189

Table 8 (continued)

Panel C. Specialist Auditors

	Dependent Variable = *RET*					
	(1)	(2)	(3)	(4)	(5)	(6)
	SIZE	*SIZE*	*NANALYST*	*NANALYST*	*BASPREAD*	*BASPREAD*
	Small	*Large*	*Low*	*High*	*Low*	*High*
LONG	0.002	-0.002	-0.000	0.001	-0.001	0.004
	(0.648)	(-0.783)	(-0.022)	(0.334)	(-0.522)	(1.220)
SHORT	0.021***	0.001	0.022***	0.005*	0.002	0.017***
	(8.229)	(0.390)	(8.104)	(1.910)	(1.044)	(6.233)
*LONG*SPECIALIST*	-0.002	0.002	0.005	-0.004	0.001	0.001
	(-0.324)	(0.520)	(0.912)	(-1.058)	(0.328)	(0.200)
*SHORT*SPECIALIST*	-0.011**	0.000	-0.011**	-0.004	-0.002	-0.013***
	(-2.341)	(0.089)	(-2.294)	(-1.017)	(-0.595)	(-2.787)
SPECIALIST	-0.018	-0.005	-0.051*	0.008	-0.002	-0.052
	(-0.498)	(-0.305)	(-1.713)	(0.462)	(-0.112)	(-1.587)
LN_MVE	-0.016**	-0.006**	-0.006	-0.012***	-0.014***	-0.020***
	(-2.367)	(-2.022)	(-1.143)	(-3.439)	(-6.173)	(-3.920)
OPERPROF	0.001	0.003	-0.003	0.008**	0.004*	0.002
	(0.231)	(0.864)	(-0.689)	(2.313)	(1.827)	(0.362)
AGR	-0.038***	-0.024**	-0.038***	-0.039***	0.003	-0.035***
	(-3.069)	(-2.074)	(-2.964)	(-3.343)	(0.286)	(-3.070)
BM	0.060***	-0.017	0.081***	-0.024	-0.015	0.060***
	(3.836)	(-1.042)	(5.243)	(-1.051)	(-1.090)	(3.772)
Year Fixed Effects	YES	YES	YES	YES	YES	YES
Audit Office Fixed Effects	YES	YES	YES	YES	YES	YES
Observations	15,286	15,917	14,861	16,342	15,785	15,418
R-squared	0.216	0.218	0.210	0.219	0.220	0.231
Adjusted R-squared	0.177	0.198	0.169	0.198	0.193	0.193

This table presents the results of cross-sectional tests of the relation between high-quality auditors and anomaly returns based on information asymmetry. Panel A reports descriptive statistics for the cross-sectional splits based on median firm size, analyst following, and bid-ask spreads. Panel B reports the results using Big 4 auditors (*HIGH_QUALITY_AUDITOR* = *BIG4*), while Panel C reports the results using specialist auditors (*HIGH_QUALITY_AUDITOR* = *SPECIALIST*). We re-estimate equation (2) after splitting the sample on median size (*MVE*) in columns (1) and (2), median analyst (*NANALYST*) in columns (3) and (4), and median bid-ask spreads (*BASPREAD*) in columns (5) and (6). Robust *t*-statistics, based on standard errors clustered by firm, are presented in parentheses below the coefficients. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix B.

Table 9. Analysts' Return Forecasts

Panel A. Univariate Analysis

	BIG4=0	*BIG4*=1			*SPECIALIST*=0	*SPECIALIST*=1		
	Mean	Mean	Difference in Means	(t-stat.)	Mean	Mean	Difference in Means	(t-stat.)
1 (Short)	0.947	0.411	-0.536	-18.620***	0.639	0.378	-0.261	-9.451***
2	0.629	0.248	-0.381	-16.779***	0.366	0.240	-0.127	-6.598***
3	0.493	0.199	-0.294	-12.302***	0.295	0.197	-0.098	-4.823***
4	0.440	0.183	-0.256	-14.999***	0.264	0.188	-0.076	-5.035***
5 (Long)	0.327	0.169	-0.158	-9.439***	0.224	0.184	-0.041	-2.555**
L-S	-0.620	-0.242			-0.415	-0.194		
t-stat.	-17.350***	-17.980***			19.812***	-9.094***		

Table 9 (continued)

Panel B. Return Forecast Regression

	(1) *FORECAST*	(2) *FORECAST*
LONG	0.007	-0.001
	(1.059)	(-0.172)
SHORT	-0.088***	-0.065***
	(-12.806)	(-15.746)
*LONG*BIG4*	-0.012*	
	(-1.741)	
*SHORT*BIG4*	0.042***	
	(5.542)	
*LONG*SPECIALIST*		-0.001
		(-0.218)
*SHORT*SPECIALIST*		0.027***
		(4.446)
SPECIALIST		0.101***
		(3.562)
LN_MVE	-0.108***	-0.105***
	(-23.780)	(-20.386)
OPERPROF	-0.005	-0.008**
	(-1.475)	(-1.991)
AGR	0.002	0.001
	(0.115)	(0.086)
BM	-0.024	-0.034*
	(-1.517)	(-1.802)
Year Fixed Effects	YES	YES
Audit Office Fixed Effects	YES	YES
Observations	30,301	23,488
R-squared	0.257	0.254
Adjusted R-squared	0.239	0.234

This table presents tests of the relation between high-quality audits and analysts' return forecasts. Panel A presents average analyst return forecast (*FORECAST*) by auditor quality for firm-years based on annual quintile sorts of the *NET* anomaly variable. In Panel B we re-estimate equation (2) using analysts' return forecasts (*FORECAST*) in place of annual returns (*RET*) as the dependent variable. Column (1) reports results using Big 4 auditors (*HIGH_QUALITY_AUDITOR* = *BIG4*). Column (2) reports results using specialist auditors (*HIGH_QUALITY_AUDITOR* = *SPECIALIST*). Robust t-statistics, based on standard errors clustered by firm, are presented in parentheses below the coefficients. ***, **, and * represent statistical significance at the 1%, 5%, and 10% levels, respectively. All variables are defined in Appendix B.