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Cross-firm return predictability and accounting quality

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Abstract

We test the hypothesis that if poor accounting quality (AQ) is associated with poor investor understanding of firms' revenue and cost structures, then poor AQ stocks likely respond more slowly than good AQ stocks to new non-idiosyncratic information that affects both sets of firms. Consistent with this, results indicate that stock returns of good AQ firms significantly positively predict one-month-ahead stock returns to industry- and size-matched poor AQ firms. In testing a delayed-information-processing mechanism behind the cross-firm return predictability, we find that: (i) analyst earnings forecast revisions (FR) mimic the return patterns, as FR of good AQ firms significantly positively predict one-month-ahead FR of matched poor AQ firms; (ii) cross-firm return predictability is concentrated in months with substantial news arrival, including months with Federal Open Market Committee (FOMC) rate announcements, but not in no-news months; (iii) cross-firm return predictability is stronger when the good AQ predictor firms have a richer information environment than poor AQ firms as proxied by analyst following, institutional ownership, and the presence of a Big 4 auditor. Collectively, the results uncover a new relation between accounting quality and stock return dynamics.

KEYWORDS
accounting quality, analyst forecast, information processing, return predictability

JEL CLASSIFICATION
D83, G14, G17, M41

1 | INTRODUCTION

Understanding the dynamics of stock prices, and the role of accounting information therein, has been a central focus of much accounting research. A variety of price dynamics have been studied, and various attributes of accounting information have been examined, in the prior literature. In this paper we examine one pattern of price behavior, cross-firm return predictability, and whether it is related to one attribute of accounting information, accounting quality (AQ). By cross-firm return predictability we mean the ability of the returns of Firm A to consistently predict the returns of Firm B. By accounting quality (or financial statement quality), we mean conceptually the informativeness of financial statements for understanding the firm's economics and its revenue and cost structure, as such understanding forms the basis for predicting future cash flows. In particular, we examine whether the stock returns of good AQ firms predict one-month-ahead stock returns of poor AQ firms.

Consider two firms, P (poor AQ) and G (good AQ). When new value-relevant information arrives that affects both firms, the eventual updated price will reflect investors' consensus opinion about the future earnings or cash flow impact of this news. If updating the price does not occur instantaneously and involves a process of (i) investors forecasting the earnings impact for each firm, and (ii) aggregating investors' opinions about the earnings impact, then we hypothesize that AQ affects this updating process. Essentially, the idea is that understanding a firm's revenue and cost structures is likely relevant in order to forecast the earnings implication of new information, financial statements are likely a non-substitutable resource for understanding firms' revenue and cost structures, and poor understanding of firms' revenue and cost structures likely delays the completion of the updated forecast. In this example, financial statements are not the source of the new value-relevant information to be processed, in the sense that we are not examining stock price response to, for example, an earnings announcement. Rather, financial statements are a resource for understanding firms' underlying economics in order to process the earnings implications of industry or market-wide news (which we refer to as "common news"). If the hypothesis is empirically descriptive, its most direct implication is that good AQ firms' stock price will respond before poor AQ firms' stock price to new information, and the empirically testable implication is that the direction of good AQ firms' stock return is expected to predict the direction of poor AQ firms' stock return (i.e., we expect to observe positive return predictability).

Our research question is motivated primarily by two strands of literature. The first is the finance literature on cross-firm return predictability which shows return predictability from large to small firms (Hou, 2007; Lo & MacKinlay, 1990), and from firms with high to firms with low analyst following (Brennan, Jegadeesh, & Swaminathan, 1993), institutional ownership (Badrinath, Kale, & Noe, 1995), trading volume (Chordia & Swaminathan, 2000), and business homogeneity (Cohen & Lou, 2012). This evidence is largely interpreted in the literature as suggesting slow price adjustment to new, common information, where common information is non-firm-specific information that has value relevance across stocks. Left unexamined here is the role of accounting quality in interpreting the value implications of new information. In particular, if poor financial statement quality hinders investor understanding of firms' revenue and cost structure, and delays consensus in investor opinion about the earnings impact of the new information, we simply ask whether the returns of good AQ firms lead (or predict) the returns of poor AQ firms.

The second motivating literature for our study is the accounting literature examining the relation between AQ and different return patterns. One return pattern that has been examined is a stock return premium for poor accounting quality in the form of higher average future returns for poor AQ stocks relative to good AQ stocks. Here, Francis, LaFond, Olsson, and Schipper (2005) suggest there is a return premium for poor AQ stocks, but Core, Guay, and Verdi (2008) suggest there is no return premium. A return premium (which has been previously examined) is empirically distinct from delayed price adjustment (which we examine) since firm P may consistently respond to information after firm G but both firms may have the same long-run average returns. A second return pattern that has been studied is whether poor AQ firms have stronger return momentum or continuation, where momentum means that the return of a given stock predicts itself (rather than cross-firm predictability). Here, Francis, LaFond, Olsson, and Schipper (2007) examine whether poor AQ stocks have stronger post-earnings announcement drift, but the tests therein are somewhat indirect. Return momentum is empirically distinct from cross-firm predictability in that we examine the ability of firm G's returns to predict firm P's returns *after controlling for P's lagged return*. The next section contrasts the different return patterns in more detail, but to summarize, in this paper we are interested in a return pattern in the cross-section of AQ which has not been previously studied: cross-firm return predictability from good to poor AQ firms, rather than a return premium or return momentum.[1]

We proxy for accounting quality empirically using the AQ measure of Dechow and Dichev (2002), whereby large accrual variation unexplained by cash flow realizations represents poor AQ. We expect simply that a poor accrual to cash flow mapping likely detracts from investor understanding of, and consensus on, firms' revenue and cost structure, and therefore empirically indicates poor accounting quality. To examine the future return predictability of poor AQ stocks, we begin by pairing good and poor AQ stock portfolios as follows. Each year, the cross-section of stocks is sorted sequentially by industry, size, and AQ. Stocks in the low (high) AQ tercile represent the good (poor) AQ portfolio. Each good AQ portfolio is paired with a poor AQ portfolio that is industry- and size-matched, and we examine one-month-ahead return predictability from the good to the poor AQ portfolio.

In Fama and MacBeth's (1973) cross-sectional regressions of poor AQ stock returns on lagged returns of the matching good AQ portfolio, we document significant one-month-ahead return predictability from good to poor AQ stocks. The regressions control for firm size, book-to-market, short-term return reversal, return momentum, stock liquidity, and lagged industry returns. The return predictability from good to poor AQ stocks is not observed two and three months ahead, consistent with the information processing occurring within a month. Further, when we switch around the dependent variable from poor to good AQ stock returns, we observe that predictability does not flow in the reverse direction from poor to good AQ stock returns.

Evidence on the economic magnitude of the return predictability from good to poor AQ stocks, and on the ability of systematic risk factors to explain this predictability, comes from the time series factor model regressions of Fama and French (1993). At the end of each month, the cross-section of *good AQ* portfolios is sorted on the immediate past month return into winner and loser quintiles, where each quintile has good AQ portfolios from the different industry and size groups. We then *buy the poor AQ* matching portfolios of the good AQ winners and *sell the poor AQ* matching portfolios of the good AQ losers, and hold for one month. The idea is that the month $t+1$ return of poor AQ stocks follows the month t return of the matching good AQ stock. Controlling for exposure to the market, SMB, HML, momentum, and liquidity factors, the hedge portfolio yields an annualized alpha of 10%. Further, the alpha remains robust when the strategy is implemented in the largest tercile of stocks. Three points are particularly worthy of note: (i) The hedge portfolio is long and short in poor AQ stocks only. The hedge portfolio does not have good AQ stocks. This implies that *any difference in the long and short returns (or the return to the hedge portfolio) cannot be attributed to any potential systematic differences, risk or otherwise, between good AQ firms and poor AQ firms*; (ii) The robustness of the predictability in the largest stocks suggests that market microstructure biases (such as thin trading, for example) are unlikely to be an explanation; (iii) Since the regressions control for commonly suggested risk factors, the significant alpha suggests risk is unlikely to be an explanation for the cross-firm return predictability.

Three broad classes of explanations have been proposed for cross-firm return predictability: systematic risk differences; market microstructure biases; and differences in the speed with which common information is impounded into prices (or "information delay"). Since our evidence described above is inconsistent with the first two explanations, we pursue the information delay explanation in subsequent tests. Information delay could be due to information diffusion delays or information processing delays. Diffusion delay can be due to investor inattention or neglect, or participation constraints, that result from institutional frictions or investors' cognitive biases, for example (e.g., Hou, 2007; Hou & Moskowitz, 2005; Merton, 1987). Processing delay can result if investors have finite information processing capacity (Cohen & Lou, 2012). It is useful to note one advantage of the cross-firm return predictability setting in testing the relation between AQ and information processing delay. Implicit in cross-firm return predictability is that both stocks are responding to common or non-firm-specific information. As such, the characteristics of the information to be

[1] We discuss and contrast other related papers and literature (including the accounting literature on intra-industry information transfers) later in the paper.

processed are effectively held constant across stocks, allowing better identification of the effect of financial statement quality (AQ).

Intuitively, we expect that financial statements are used by investors to understand the firm's underlying economics and its revenue and cost structure, in order to form their priors about future cash flows. When new value-relevant information, whether common or firm-specific, arrives, investors have to update their priors. Many asset pricing models have investors aggregate and interpret information, beliefs, and opinions in developing their posteriors. This aggregation and interpretation process can take time, and continues until prices fully reflect all available information. Very simply, we hypothesize that when the quality of financial statements is poor, investors likely have poor priors and lack of consensus about priors, and it takes longer to update the stock price of poor AQ firms relative to good AQ firms.

A number of theoretical models provide structure on the intuition. Acemoglu, Chernozhukov, and Yildiz (2007) argue that "disagreement is the rule rather than the exception in practice,"[2] and develop a model of Bayesian learning in which two individuals with different priors have uncertainty about the interpretation of common signals. Acemoglu et al. (2007) show that: (i) Individuals never agree, even after observing the same infinite sequence of signals; (ii) Their opinions actually diverge, rather than converge, even after observing the same infinite sequence of signals. In other words, *learning does not generate consensus* in this setting. Translating this to our setting, *consensus on firms' revenue and cost structure is not guaranteed by learning, even though all investors observe the same set of financial statements.* From this result, intuition can subsequently lean on the dynamic rational expectations (DRE) model of Allen, Morris, and Shin (2006) and the dynamic differences of opinion (DDO) model of Banerjee, Kaniel, and Kremer (2009). Given an absence of convergence in beliefs and opinions among investors, and if stock price dynamics are described by a Keynesian beauty contest in which the pricing operator depends on average expectations about average expectations, Allen et al. (2006) and Banerjee et al. (2009) show that aggregation of information and of higher-order differences of opinion generate slow price adjustment. In contrast to the mechanism of the DRE and DDO models, the behavioral models of Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999) appeal to cognitive biases and bounded rationality in order to generate slow price adjustment.

To be clear, we do not test a specific theoretical model because those outlined above do not conform specifically to our setting (for example, those authors present no comparative statics related to accounting quality in their models).[3] Our contribution is to document a new empirical anomaly, and to suggest an opportunity for the development of richer asset pricing models that admit the sort of phenomena we document. In the remaining parts of the paper we explore whether cross-firm return predictability is consistent with delayed information processing.

If information processing frictions delay stock price revisions for poor AQ firms, they likely similarly delay revisions of stock price inputs, such as future earnings expectations, for such firms. In other words, if investors are affected by information processing frictions, then information intermediaries in the stock market are likely similarly affected. We test this by examining whether equity analyst earnings forecast revisions (FR) exhibit similar predictability patterns from good to poor AQ stocks. In Fama-MacBeth regressions of poor AQ firms' FR on lagged FR of the matching good AQ firms, we document significant one-month-ahead FR predictability. The regressions control for lagged FR of the poor AQ firm, industry FR, and firm and stock characteristics. Finally, switching around the dependent variable from poor to good AQ firms' FR indicates there is no reverse predictability from poor to good AQ firms.

If the delayed-information-processing hypothesis is empirically descriptive, we expect stronger stock return predictability from good to poor AQ firms in months when there is more information arriving in the market compared to months when there is less information arriving. We use two proxies for news months: months in the extreme quartiles

[2] Acemoglu et al. (2007) note that "Just to mention a few instances, there is typically considerable disagreement even among economists working on a certain topic. For example, economists routinely disagree about the role of monetary policy, the impact of subsidies on investment or the magnitude of the returns to schooling." In accounting, such disagreement among scholars is commonly observed in a variety of literatures, and disagreement appears to be the norm rather than the exception.

[3] Verrecchia (1980) develops a model of delayed price adjustment when the quality of the new signal or information is poor, holding constant the quality of the pre-existing information set. In this paper, in contrast, we hold constant across stocks the quality of the new signal since it is a common signal. Rather, we effectively vary the quality of the pre-existing information set in the form of accounting quality.

of monthly market returns; and months with Federal Open Market Committee (FOMC) rate announcements. The first proxies for any news that moves the markets, and the second proxy allows us to test a specific item of news. FOMC rate announcements affect consumption and investment and therefore firms' future earnings. Results indicate significant return predictability from good to poor AQ stocks in months with extreme market returns, but not in months with moderate market returns. There is also stronger return predictability in months with FOMC rate announcements compared to no-announcement months.

As another test of the delayed information processing explanation, we expect stronger (weaker) return predictability when the information environment of the predictor, the good AQ firms, is richer (poorer) than that of poor AQ firms. The prediction is tested using three proxies for firms' information environment: analyst following, institutional ownership, and the presence of a Big 4 auditor. We find stronger return predictability from good AQ firms with high analyst following to poor AQ firms with low analyst following. Similarly, we find stronger return predictability from good AQ firms with high institutional ownership to poor AQ firms with low institutional ownership, and from good AQ firms with high quality auditor to poor AQ firms with low quality auditor.

Next, as an alternative measure of accounting quality we use the FOG index (El-Haj, Rayson, Walker, Young, & Simaki, 2019; Li, 2008) which is an index of the readability of qualitative information in annual financial statements. Qualitative information likely provides context and facilitates interpretation of numerical data, and low quality qualitative information is less likely to enhance investors' priors or to generate consensus in these priors. The Securities and Exchange Commission (SEC) provides guidelines for, and encourages the use of, plain English in disclosures and financial reports, suggesting readability affects investors' information processing costs. We find significant return predictability from good to poor AQ firms, but not reverse predictability, consistent with the main tests. This result is consistent with information processing frictions affecting the speed with which information is impounded in stock prices.

We conduct a battery of robustness tests described in detail in Section 6. In particular, the return predictability we document is not due to differences in general business volatility (cash flow, earnings, or stock return volatility) between good and poor AQ firms, nor is it due to differences in earnings announcement dates between good and poor AQ firms.

Finally, we examine whether poor AQ hinders investor understanding of firms' fundamentals and delays information processing internationally. Using a sample of 32 countries, we find that stock return predictability and analyst forecast revision predictability are observed internationally. This is an important out-of-sample test.

We contribute to the literature in a number of ways. First, given the absence of theory that predicts cross-firm predictability related to accounting quality, any future theory is likely to be more robust if it has a richer and more diverse set of empirical facts to confront. The literature advances through accumulation of documented empirical facts. Our contribution is to document a new set of facts and results that are incremental to prior results (more on this below). Second, we contribute to the literature on accounting quality by documenting results using AQ and FOG. Given the lack of consensus on earnings quality metrics (Dechow, Ge, & Schrand, 2010), it seems useful for the literature to establish a collection of results regarding which metrics work under which circumstances. This objective need not be addressed only through studies that directly horserace different metrics in certain scenarios. Rather, the objective can also be advanced through papers such as ours in which horseracing metrics is not the intended objective. Third, relative to Cohen and Lou (2012), we document an incremental accounting effect in cross-firm predictability. This incremental effect is of the magnitude of 78.4 basis points alpha monthly ($t = 3.09$). Further, we present new results on predictability in news versus no-news months, which goes to the heart of the hypothesis that cross-predictability is due to delays in processing news.

Our results have a number of new implications. First, from the perspective of firms, it seems useful to understand that the quality of their accounting can affect the speed with which investors and analysts process news. The Cohen and Lou result is not actionable by firms since the number of business segments is a very long-run choice. Our result, in contrast, is actionable if firms can alter accrual variability (AQ) and the readability of their financial statements (FOG index). Second, for academic studies, research on analysts (such as studies on analyst forecast revisions) might be enhanced by incorporating the knowledge that accounting quality affects the speed with which they update forecasts.

In addition, it seems useful when conducting event studies to understand that poor AQ firms react more slowly. In this case, researchers might want to use a longer event window. Third, for investors, our results present a new trading strategy.

It is worth emphasizing that our contribution is *not* to provide a new meta-conclusion such as "accounting information or quality affects stock returns," "there is cross-firm predictability in stock returns," "investors face information processing frictions," or "stock prices exhibit delayed adjustment to new information." Clearly, such meta-conclusions are already available in the literature. Rather, our contribution is to provide new evidence of previously undocumented empirical patterns relating stock returns and AQ. As Kuhn (1962) notes, continuously providing new empirical evidence, not new meta-conclusions, is part of the standard method and purpose of science.

One caveat is that accounting quality is an unobservable construct and research in this area faces the limitation of requiring observable proxies. If a reader accepts AQ and FOG as plausible proxies for accounting quality, our results provide evidence on the hypothesis we posit.

The rest of this paper proceeds as follows. Section 2 describes prior literature, and Section 3 describes the data and estimation of accounting quality. Section 4 describes the tests of return predictability, including cross-sectional and time series tests. Section 5 describes analyst forecast revision predictability tests, return predictability tests in news versus no-news months, and return predictability tests as the firm information environment varies. Section 6 describes a battery of robustness tests. Section 7 describes the tests of return predictability and analyst forecast revision predictability using international data and extended sample period. Section 8 concludes. Data definitions are presented in the Appendix.

2 | BACKGROUND

There is voluminous prior research in each of the areas of accounting quality, patterns of price behavior, analyst forecasts, and related topics. The prior research has varying degrees of separation from our work, and we have reviewed papers most directly related to ours in the previous section. We review briefly, but not exhaustively, some additional related research below, and any omission is inadvertent. The bottom line in terms of contrasting with the prior literature is that there is no prior evidence relating AQ to cross-firm stock return predictability or cross-firm analyst forecast revision predictability, making these results novel and direct evidence on the impact of accounting quality on stock return dynamics.

In traditional asset pricing theory with frictionless capital markets, stock prices impound new information instantaneously and completely. A number of theoretical and empirical papers explore the impact of frictions such as incomplete information (Merton, 1987), differential information across securities (Barry & Brown, 1984; Bawa, Brown, & Klein, 1979), asymmetric information across investors (Barth, Cahan, Chen, & Venter, 2017; Easley, Hvidkjaer, & O'Hara, 2002), slow information diffusion (Hong, Lim, & Stein, 2000), differences in higher-order investor beliefs due to differential private information (Allen et al., 2006) or differential opinions (Banerjee et al., 2009), investors' cognitive biases and bounded rationality (conservatism in Barberis et al., 1998; biased self-attribution in Daniel et al., 1998; newswatchers in Hong & Stein, 1999), and delayed information processing due to limited information processing capacity or resources (Callen, Khan, & Lu, 2013; Cohen & Lou, 2012; Hou & Moskowitz, 2005). The evidence suggests these frictions are important for understanding asset price dynamics and, in particular, slow price adjustment to information.

Lead-lag effects in returns have been documented across firms of different size (Hou, 2007; Lo & MacKinlay, 1990), degrees of analyst following (Brennan et al., 1993), institutional ownership (Badrinath et al., 1995), trading volume (Chordia & Swaminathan, 2000), and business diversity (Cohen & Lou, 2012). Much of the evidence is interpreted as consistent with slow price adjustment. In Section 6.3 we show that our results are incremental to these previously documented effects.

Callen et al. (2013) ("CKL") examine the relation between AQ and stock price delay, and whether the interaction of poor AQ and delay results in a stock return premium. This paper differs in a number of ways: (i) CKL examine the association between AQ and a model-implied measure of stock price delay in order to show that poor AQ is associated with greater delay. In contrast, we test the most direct implication of variation in price delay which is that if stock P is more delayed than stock G then the returns of G should predict the return of P. This surprisingly simple and direct implication has not previously been tested. (ii) CKL test predictability associated with market-wide news, but there are many different types of news that could be associated with cross-firm predictability. Ours is therefore a more general test of this hypothesis. (iii) CKL have no evidence on delays in analyst forecast revision that mirror delays in stock price adjustment, and this result is important because it speaks to underlying mechanisms behind slow price adjustment. (iv) Our tests obviate the need for a model-implied measure of stock price delay as used in CKL. Reducing model dependence in testing similarly reduces model dependence of the inferences (or improves generalizability).

There is also a literature that explores cross-sectional determinants of own price momentum or drift, such as information uncertainty and accounting quality. For example, Francis et al. (2007) explore the role of accounting quality in explaining post-earnings announcement drift; Shivakumar (2006) shows that unexpected cash flows more positively predict future price drift than accruals; Gleason and Lee (2003) explore determinants of price drift following analyst forecast revisions; Amir, Kama, and Levi (2015) explore how earnings component persistence affects price drifts; Zhang (2006) explores the role of information uncertainty in own price momentum; and Clement, Lee, and Yong (2019) show that the presence of sophisticated investors is associated with small price drift. Our tests show cross-firm predictability *incremental to* own-price momentum, since we examine predictability from good AQ to poor AQ stocks controlling for the lagged return of the poor AQ stock.

In addition, there is a literature on intra-industry information transfers whereby an idiosyncratic price-relevant event at firm A affects the stock price of firm B in the same industry. Examples of events at firm A include an earnings announcement, report of monthly revenue figures for a retailer, an accounting restatement, a bankruptcy filing, or a dividend initiation (e.g., Firth, 1996; Foster, 1981; Gleason, Jenkins, & Johnson, 2008; Lang & Stulz, 1992; Olsen & Dietrich, 1985). This literature hypothesizes that an event at firm A causes investors to expect a similar event at firm B in the same industry, thereby leading to an impact on firm B's stock when there is an event at firm A. In other words, observing an event at firm A causes investors to revise their beliefs about the likelihood of the same event occurring at firm B, thereby leading to a price impact on firm B's stock. Some ways our research differs include: (i) we show a differentially delayed response to common news rather than to an information event at one firm; (ii) we relate cross-firm stock return predictability to a firm characteristic, AQ, rather than to an information event at one firm; and (iii) we show consistent or regular, rather than episodic or event-dependent, predictability from good to poor AQ firms. Ultimately there is no prior paper in the intra-industry information transfer (or other) literature that documents the patterns of stock return and analyst forecast revision predictability from good to poor AQ firms as in this paper. Our main emphasis in not that we arrive at different broad conclusions from the intra-industry information transfer literature but rather that our results are different and novel. In this sense we view our work as complementing that important literature.

3 | DATA

Accounting data is extracted from Compustat, stock return data is from CRSP, analyst data from IBES, and institutional ownership data from Thompson. We begin with an initial sample of CRSP and Compustat data from 1962 to 2012. Data requirements in calculating variables of interest reduce the sample period as described below. Due to data availability, tests using analyst (institutional ownership) data are estimated over the post-1983 (post-1979) period. Detailed variable definitions are presented in the Appendix.

TABLE 1 Industry distribution

	Industry	Frequency	Percent	Cumulative frequency	Cumulative percent
1	Consumer NonDurables	38,413	10.6	38,413	10.6
2	Consumer Durables	16,124	4.45	54,537	15.05
3	Manufacturing	85,244	23.52	139,781	38.56
4	Oil, Gas, and Coal Extraction and Products	16,451	4.54	156,232	43.1
5	Chemicals and Allied Products	18,263	5.04	174,495	48.14
6	Business Equipment	59,902	16.53	234,397	64.67
7	Telephone and Television Transmission	7,769	2.14	242,166	66.81
8	Utilities (deleted)	0	0	0	0
9	Wholesale, Retail, and Some Services	49,438	13.64	291,604	80.45
10	Healthcare, Medical Equipment, and Drugs	27,432	7.57	319,036	88.02
11	Financials (deleted)	0	0	0	0
12	Other	43,432	11.98	362,468	100

Notes: This table presents the number and relative frequency of firm-months in the sample, by industry, from 1969 to 2012. Industry definitions are from Fama and French. The frequencies are of good and poor AQ firm-months only.

We delete firms with negative book equity, and trim the extreme one percentiles of accounting variables in order to mitigate the influence of outliers. We further delete stocks with stock price less than $5 at the beginning of the return prediction year in order to mitigate the influence of market microstructure effects.[4]

3.1 | Estimating accounting quality

Non-cash earnings, or accruals, are the signature output of the accounting system. Accruals can lead or lag the underlying cash flow, and therefore represent *estimates* of the amount earned. For example, credit sales are an estimate of collectible future cash, and the accrued revenue leads the underlying cash in this case. Prepaid expenses, on the other hand, lead the associated accrual, since the accrual expense on the income statement is recognized only when the service is consumed in the future. Accruals are therefore subject to managerial estimation errors and bias.

We measure accounting quality as the reliability with which accruals map to cash flows (Dechow & Dichev, 2002; McNichols, 2002). In particular, AQ is measured as the standard deviation, over the most recent five years, of the residuals from the following model:

$$Accruals_t = \alpha_1 + \alpha_2 CFO_{t-1} + \alpha_3 CFO_t + \alpha_4 CFO_{t+1} + \alpha_5 \Delta Sales_t + \alpha_6 PPE_t + \varepsilon_t, \tag{1}$$

where t indexes the year, *Accruals* is non-cash earnings, *CFO* is operating cash flows, $\Delta Sales$ is the change in sales, and *PPE* is property, plant, and equipment. All variables are scaled by lagged total assets. The model is estimated cross-sectionally for each industry-year with at least 20 observations. Since AQ_t requires future information in the form of CFO_{t+1} in model (1), all tests use AQ_{t-1} in order to avoid look-ahead bias. Large values of *AQ* represent poor accounting quality, and hence we use the terms "poor" and "good" accounting quality in the paper in order to keep the exposition clear.

Table 1 presents the industry distribution of the final sample of good and poor AQ firms (firms in the middle AQ tercile are not in the sample). We delete utilities and financials because accruals are not meaningful for these

[4] In untabulated tests, the main result is robust without these filters.

TABLE 2 Descriptive statistics

Variable	*N*	Mean	Std Dev	Q1	Median	Q3
Panel A: Good AQ sample						
AQ	190,206	0.015	0.008	0.009	0.014	0.019
Ret	190,206	0.013	0.116	−0.048	0.007	0.067
Size	190,206	12.941	2.052	11.400	12.823	14.279
B/M	184,952	−0.580	0.749	−1.041	−0.548	−0.066
Turn	184,254	0.088	0.110	0.023	0.048	0.110
Inst holding	148,612	0.500	0.269	0.292	0.506	0.707
FR	64,742	−0.001	0.008	−0.001	0.000	0.001
Analyst following	140,811	9.071	10.099	1.000	6.000	14.000
FOG	98,938	17.737	2.839	17.693	18.218	18.678
Big4	134,382	0.721	0.449	0.000	1.000	1.000
Panel B: Poor AQ sample						
AQ	191,035	0.058	0.030	0.037	0.051	0.072
Ret	191,035	0.011	0.134	−0.061	0.004	0.075
Size	191,035	12.627	1.856	11.283	12.566	13.875
B/M	191,035	−0.758	0.826	−1.230	−0.698	−0.194
Turn	184,535	0.123	0.159	0.031	0.067	0.153
Inst holding	147,930	0.489	0.290	0.244	0.485	0.715
FR	64,742	−0.001	0.010	−0.002	0.000	0.001
Analyst following	140,811	8.462	9.362	1.000	6.000	13.000
FOG	103,404	21.258	1.677	20.274	20.866	21.722
Big4	136,831	0.689	0.463	0.000	1.000	1.000

Notes: This table presents descriptive statistics separately for the sample of all firm-months with good and poor AQ, where *AQ* is accounting quality. The sample covers 1969-2012 for all variables except analyst-related variables which are available from 1984, institutional ownership which is available from 1980, and FOG which is available from 1996 to 2010. Detailed variable definitions are presented in the Appendix.

industries (for example, they have no inventories). Table 2 provides descriptive statistics for the good and poor AQ firms separately. The sample for the returns-based tests starts from 1969 due to data requirements in calculating *AQ*. The mean of *AQ* is 0.015 and 0.058 for the good and poor AQ firms, respectively, and its distribution is consistent with the prior literature (Callen et al., 2013). Table 3 shows means of monthly cross-sectional correlations in order to reduce the influence of time effects.

3.2 | Matching good and poor AQ portfolios

We create matched pairs of good and poor AQ stock portfolios as follows. At the end of each April (by when almost all firms have released their annual financial statements), we sort firms sequentially into Fama-French 12 industry groups, then size terciles, and then AQ terciles. We refer to the bottom (top) AQ tercile as the good (poor) AQ portfolio, and delete utilities and financials which are more regulated industries. Each good AQ portfolio is paired with the industry- and size-matched poor AQ portfolio. Therefore there are 30 such good and poor AQ portfolios (one each in the 10 industry × 3 size groupings).

TABLE 3 Correlations

	AQ	*RET*	*Size*	*B/M*	*Turn*	*FR*	*FOG*	*Analyst following*	*Inst holding*	*Big4*
AQ		**−0.013**	**−0.280**	**−0.101**	**0.216**	**−0.049**	**0.049**	**−0.216**	**−0.161**	**−0.083**
RET	**−0.026**		−0.002	**0.013**	**−0.018**	**0.153**	0.000	0.006	−0.001	−0.001
Size	**−0.287**	**0.025**		**−0.361**	**0.041**	**0.093**	**0.028**	**0.723**	**0.461**	**0.171**
B/M	**−0.066**	0.003	**−0.384**		**−0.156**	**−0.085**	**−0.020**	**−0.202**	**−0.050**	**−0.008**
Turn	**0.224**	**−0.024**	**0.119**	**−0.160**		**−0.021**	**0.060**	**0.222**	**0.227**	**0.046**
FR	**−0.024**	**0.185**	**0.063**	**−0.074**	**−0.015**		**−0.015**	**0.064**	**0.021**	**0.014**
FOG	**0.064**	−0.002	**0.011**	**−0.020**	**0.084**	−0.006		**0.052**	**0.059**	**0.012**
Analyst following	**−0.289**	**0.024**	**0.696**	**−0.227**	**0.309**	**0.048**	**0.048**		**0.361**	**0.126**
Inst holding	**−0.132**	**0.016**	**0.463**	**−0.059**	**0.355**	0.004	**0.043**	**0.403**		**0.164**
Big4	**−0.082**	**0.006**	**0.172**	**−0.013**	**0.072**	**0.010**	**0.008**	**0.149**	**0.151**	

Notes: This table presents a Pearson (top) and Spearman (bottom) correlation matrix of variables used in the study. *AQ* is accounting quality. The table reports means of monthly cross-sectional correlations, and the time-series mean and standard error are used for statistical inference to control for time effects. Bold indicates *two-tailed p*-value < 0.05. Detailed variable definitions are presented in the Appendix.

4 | STOCK RETURN PREDICTABILITY FROM GOOD TO POOR AQ FIRMS

This section describes tests examining one-month-ahead return predictability from good AQ stock portfolios to their poor AQ matching portfolio. Section 4.1 describes cross-sectional characteristics-based return predictability tests, while Section 4.2 describes time series factor-model return attribution tests.

4.1 | Cross-sectional stock return predictability

The basic hypothesis is that if common (non-firm-specific) information flows more slowly into poor AQ stocks than good AQ stocks, we expect return predictability from good to poor AQ stocks.[5] We estimate monthly firm-level cross-sectional regressions:

$$\mathrm{PAQret}_t = \beta_1 + \beta_2\mathrm{GAQret}_{t-1} + \beta_3\mathrm{PAQret}_{t-1} + \beta_4\mathrm{Indret}_{t-1} + \beta_5\mathrm{Size} + \beta_6 B/M + \beta_7\mathrm{Mom} + \beta_8\mathrm{Turn} + e_t \qquad (2)$$

The dependent variable is the poor AQ portfolio stock return, *PAQret*, and 't' indexes the month. The main independent variable of interest is the lagged return of its matched good AQ portfolio, *GAQret*. The regression controls for one-month lagged poor AQ return and industry return (*Indret*), as well as size, book-to-market, return momentum (*Mom*), and stock turnover (*Turn*) of the poor AQ portfolio. *AQ*, *Size*, *B/M*, *Mom*, and *Turn* are all measured at the end of April each year, and the return prediction runs from May through the following April. Each cross-sectional regression has observations on 30 portfolios.

Panel A of Table 4 shows Fama and MacBeth (1973) coefficients and t-statistics from estimation of equation (2), with standard errors adjusted for autocorrelation up to 12 lags. Panel A reports four columns of results corresponding to four specifications with different dependent variables as indicated in each column header. In the first and second columns, the dependent variable is *PAQret*. As the columns show, lagged *GAQret* loads significantly positively

[5] Our hypothesis is that stocks react to arriving macro news in the same direction on average, as supported by the empirical regularity that stocks generally have positive betas. We also verify that, in our regression sample, less than 0.5% of stocks have negative market betas.

TABLE 4 Cross-sectional return predictability

Panel A: Cross-sectional regressions

	$PAQret_t$	$PAQret_t$	$PAQret_t$ – $Indret_t$	$PAQret_t$ – $GAQret_t$
Intercept	0.822***	−0.213	−1.099	−1.415*
	(3.17)	(−0.28)	(−1.15)	(−1.90)
$GAQret_{t-1}$	8.349***	5.821***	6.569***	5.553**
	(5.52)	(3.31)	(2.72)	(2.31)
$PAQret_{t-1}$		−3.363**	−3.001	−2.808
		(−2.22)	(−1.49)	(−1.51)
$Indret_{t-1}$		17.480***	21.607***	1.699
		(4.39)	(3.51)	(0.41)
Size		0.106*	0.142*	0.114**
		(1.83)	(1.78)	(1.98)
B/M		0.719***	0.705***	0.678***
		(3.43)	(2.65)	(3.03)
Mom		1.583***	1.605**	1.295**
		(3.40)	(2.52)	(2.36)
Turn		1.353	−1.542	1.145
		(0.46)	(−0.42)	(0.40)
Adj. R^2	0.05	0.24	0.20	0.12

Panel B: Reverse return predictability

	$GAQret_t$
$PAQret_{t-1}$	−0.252
	(−0.18)
CONTROLS	YES
Adj. R^2	0.25

Panel C: Return predictability horizon

	2-month	3-month
	$PAQret_t$	$PAQret_t$
$GAQret_{t-2}$	1.114	
	(0.60)	
$GAQret_{t-3}$		1.463
		(1.02)
CONTROLS	YES	YES
Adj. R^2	0.23	0.22

Panel D: Weekly return predictability

	Week 1	Week 2	Week 3	Week 4
	$PAQret_t$	$PAQret_t$	$PAQret_t$	$PAQret_t$
$GAQret_{t\text{-}1}$	3.092***	0.968	1.528*	0.096
	(3.54)	(1.04)	(1.91)	(0.12)
CONTROLS	YES	YES	YES	YES
Adj. R^2	0.23	0.20	0.19	0.19

Notes: The table reports Fama-MacBeth coefficients, and *t*-statistics in parentheses, from monthly cross-sectional regressions of the dependent variables given in the column headers on the independent variables listed, from 1969 to 2012. *AQ* is accounting quality; *PAQret* is the monthly return of the poor AQ portfolio; *GAQret* is the monthly return of the matching good AQ portfolio; *Indret* is the monthly industry return; *Size* is log market value of equity; *B/M* is log book-to-market ratio; *Mom* is return momentum; *Turn* is stock turnover. *AQ*, *Size*, *B/M*, *Mom*, and *Turn* are measured annually at the end of April. In Panels B, C and D, Controls include all controls listed in Panel A. Detailed variable definitions are presented in the Appendix. Standard errors are adjusted for autocorrelation up to 12 lags. ***, **, and * indicate *two-tailed p*-values less than 0.01, 0.05, and 0.10, respectively.

(p-value < 0.01) consistent with common information flowing into poor AQ stocks with a delay relative to good AQ stocks. The coefficient of lagged *GAQret* in the second column is 5.821 (p-value < 0.01), indicating that a one standard deviation increase in *GAQret* leads to a 68-basis-point increase in *PAQret* the following month. In the second column, one-month-lagged *PAQret* loads significantly negatively, consistent with short-term return reversal (Jegadeesh, 1990). Lagged industry return loads significantly positively (Moskowitz & Grinblatt, 1999), as do *B/M* and *Mom*, while stock turnover loads significantly negatively.

The third column of Table 4, Panel A, shows results when the dependent variable is *PAQret* adjusted for contemporaneous industry returns, to ensure that predictability from good to poor AQ stocks is not due simply to industry momentum. As the column shows, lagged *GAQret* continues to load significantly positively (p-value < 0.01), which is inconsistent with the predictive power of lagged *GAQret* in the first column being driven by industry momentum. The fourth column of Panel A shows results when the dependent variable is *PAQret* adjusted for the contemporaneous return of its good AQ match, in order to address two potential concerns. First, it could be that *PAQret* and *GAQret* are contemporaneously correlated and that the predictive power of lagged *GAQret* is due to this contemporaneous correlation combined with return continuation of *GAQret*. Second, it could be that lagged *GAQret* is a finer measure of the portion of lagged industry returns relevant to the matched poor AQ firm, since the good and poor AQ portfolios are matched pairs and likely better peers for valuation purposes, and as such, industry momentum again explains the predictive power of lagged *GAQret*. As the fourth column of results shows, lagged *GAQret* continues to load significantly positively (p-value < 0.05), consistent with delayed information processing for poor AQ firms.

We explore three extensions of the tests in Panel A. Panel B of Table 4 explores whether there is reverse return predictability from poor AQ to good AQ stocks. The dependent variable in Panel B is *GAQret*, and the main independent variable of interest is lagged *PAQret*. As Panel B shows, lagged *PAQret* does not predict *GAQret*, further mitigating concern that the main result earlier in Panel A might be due to general industry momentum or some unidentified correlation structure not stemming from delayed information processing. Panel C of Table 4 examines the predictability horizon, and reports two columns of results corresponding to two specifications in which the monthly independent variables are lagged two and three months, respectively. In the first column two-month-lagged *GAQret*, and in the second column three-month-lagged *GAQret*, do not load significantly. This suggests information processing delays due to poor AQ do not extend beyond one month. Finally, in Panel D we test the timing of return predictability in each week of the month ahead. Strong predictability appears in the first week, and largely dissipates after the third week, suggesting information processing delays are not very long-lived.

4.2 | Time series stock return attribution tests

In this section we provide evidence on the economic magnitude of abnormal returns from a trading strategy based on return predictability from good to poor AQ firms. At the end of each month, we sort the 30 good AQ portfolios into quintiles based on their immediate-past-month returns in order to identify recent winners (top quintile portfolios) and losers (bottom quintile portfolios). For each good AQ winner (loser) we buy (sell) the matching poor AQ portfolio and hold the hedge portfolio for one month. If poor AQ is associated with delayed information processing and return predictability flows from good to poor AQ firms, we expect the hedge portfolio to yield significantly positive alphas.

Panel A of Table 5 reports alphas and factor loadings from Fama and French (1993) calendar-time regressions of the hedge portfolio on risk factors. We report results for the long leg (L), short leg (S), and the hedge portfolio (L – S), separately. The first three rows report the average raw return, which is 90 basis points per month (p-value < 0.01) for the hedge portfolio. The second set of three rows report the Fama and French (1993) model alpha. The third set of three rows adds the Carhart (1997) momentum factor UMD, while the fourth set of three rows further adds the Pástor and Stambaugh (2003) liquidity factor LIQ. In all models, the hedge portfolio alpha is significant (p-value < 0.01) and the five-factor alpha is 10% annualized on average. The alphas come from the long leg in all models, mitigating concerns about short sale constraints potentially affecting the strategy. Panel B of Table 5 repeats the calendar-time

TABLE 5 Time series return attribution

		Return	Alpha	Mkt-RF	SMB	HML	UMD	LIQ	Adj. R^2
Panel A: All stocks									
Univariate	L	1.518***							
		(5.00)							
	S	0.619**							
		(1.98)							
	L – S	0.899***							
		(4.35)							
3-Factor	L		0.926***	98.304***	93.824***	25.657***			0.79
			(6.50)	(30.20)	(20.21)	(5.17)			
	S		(0.02)	119.042***	61.286***	30.267***			0.79
			(−0.16)	(35.93)	(12.97)	(6.00)			
	L – S		0.949***	−20.738***	32.538***	−4.611			0.06
			(4.66)	(−4.46)	(4.91)	(−0.65)			
4–Factor	L		0.947***	97.822***	93.713***	24.901***	−2.368		0.79
			(6.51)	(29.46)	(20.16)	(4.91)	(−0.74)		
	S		0.13	115.723***	60.522***	25.069***	−16.290***		0.80
			(0.87)	(35.13)	(13.13)	(4.99)	(−5.13)		
	L – S		0.822***	−17.902***	33.191***	−0.168	13.922***		0.08
			(3.99)	(−3.81)	(5.05)	(−0.02)	(3.07)		
5-Factor	L		0.952***	97.799***	93.695***	24.937***	−2.392	−0.887	0.79
			(6.48)	(29.41)	(20.14)	(4.91)	(−0.75)	(−0.22)	
	S		0.12	115.731***	60.528***	25.056***	−16.281***	0.31	0.80
			(0.85)	(35.08)	(13.11)	(4.98)	(−5.12)	(0.08)	
	L – S		0.828***	−17.932***	33.167***	−0.119	13.889***	−1.197	0.08
			(3.98)	(−3.81)	(5.04)	(−0.02)	(3.06)	(−0.21)	
Panel B: Large stocks									
		Return	Alpha	Mkt-RF	SMB	HML	UMD	LIQ	Adj. R^2
Univariate	L	1.421***							
		(4.74)							
	S	0.45							
		(1.43)							
	L – S	0.969**							
		(4.18)							
3-Factor	L		0.805***	102.921***	32.217***	5.26			0.73
			(5.03)	(27.77)	(6.03)	(0.93)			
	S		−0.208	110.841***	32.665***	6.40			0.75
			(−1.27)	(29.37)	(6.00)	(1.11)			
	L – S		1.012***	−7.92	−0.448	−1.145			0.00
			(4.27)	(−1.44)	(−0.06)	(−0.14)			

(Continues)

TABLE 5 (Continued)

Panel B: Large stocks		Return	Alpha	Mkt-RF	SMB	HML	UMD	LIQ	Adj. R^2
4-Factor	L		0.868***	101.675***	32.049***	2.83	−6.854*		0.73
			(5.34)	(27.13)	(6.02)	(0.49)	(−1.96)		
	S		−0.034	107.414***	32.201***	−0.268	−18.853***		0.76
			(−0.21)	(29.04)	(6.12)	(−0.05)	(−5.46)		
	L − S		0.902***	−5.739	−0.153	3.101	11.999**		0.01
			(3.75)	(−1.04)	(−0.02)	(0.36)	(2.32)		
5-Factor	L		0.835***	101.740***	32.367***	2.61	−6.591*	5.30	0.73
			(5.07)	(27.17)	(6.07)	(0.45)	(−1.88)	(1.25)	
	S		−0.066	107.476***	32.509***	−0.484	−18.599***	5.117	0.76
			(−0.41)	(29.07)	(6.18)	(−0.09)	(−5.38)	(1.22)	
	L − S		0.901***	−5.736	−0.142	3.093	12.008**	0.181	0.01
			(3.70)	(−1.03)	(−0.02)	(0.36)	(2.32)	(0.03)	

Notes: The table reports alphas, factor loadings, and *t*-statistics in parentheses, from Fama and French (1993) calendar-time regressions of monthly returns to a poor AQ hedge portfolio on returns to the factors listed. Panel A presents results for the full sample, while Panel B presents results for the largest stocks (top size tercile) only. The regressions require at least 10 stocks in the portfolio every month. L is Long, S is short, and L – S is the hedge portfolio. Mkt-Rf is the market excess return; SMB and HML are the Fama and French (1993) size and book-to-market factors; UMD is the Carhart (1997) momentum factor; LIQ is the Pástor and Stambaugh (2003) liquidity factor. Industry- and size-adjusted matched pairs of good and poor AQ portfolios are created at the end of every April. At the end of every month, we rank good AQ portfolios into winner and loser quintiles based on immediate-past-month returns. The poor AQ hedge portfolio is formed by buying (selling) poor AQ portfolios matching the good AQ winners (losers), and holding for one month. Detailed variable definitions are presented in the Appendix. ***, **, and * indicate *two-tailed p*-values less than 0.01, 0.05, and 0.10, respectively. The alpha is reported in percentage points.

regressions for hedge portfolios formed from stocks in the largest size tercile only, where market microstructure frictions, transactions costs, and poor investor recognition concerns are likely lowest. As Panel B shows, the alphas remain robust. Finally, in untabulated tests, we skip one day after the end of each month before forming the hedge portfolio in order to allow time for an asset manager to implement the strategy, and find significant five-factor alphas of 9.2% annualized (p-value $<$ 0.01). Collectively, these results reinforce the cross-sectional tests of return predictability from good to poor AQ stocks in Table 4.

5 | EXPLORING THE DELAYED INFORMATION PROCESSING HYPOTHESIS

In this section we present evidence on the hypothesized mechanism behind return cross-predictability from good to poor AQ firms. Section 5.1 examines analyst forecast revision predictability, while Section 5.2 examines return predictability in news periods versus no-news months. Section 5.3 examines the relation between return predictability and the firm information environment.

5.1 | Analyst forecast revision predictability

If return predictability from good to poor AQ stocks is due to investors' information processing delays affecting poor AQ stocks, we expect similar information processing delays to affect information intermediaries in the equity market.

In particular, if the implications of common earnings-relevant news take longer to process for poor AQ firms than for good AQ firms, we expect analyst earnings forecast revisions (FR) for good AQ firms to predict one-month-ahead FR for poor AQ firms. As in Cohen and Lou (2012), the following model is estimated monthly in the cross-section:

$$\text{PAQFR}_t = \gamma_1 + \gamma_2\text{GAQFR}_{t-1} + \gamma_3\text{PAQFR}_{t-1} + \gamma_4\text{IndFR}_{t-1} + \gamma_5\text{Size} + \gamma_6 B/M + \gamma_7\text{Mom} + \gamma_8\text{Turn} + u_t \quad (3)$$

PAQFR is the one-month change in the consensus forecast of annual earnings for the poor AQ portfolio, while the main independent variable of interest, lagged *GAQFR*, is the change in the consensus forecast of annual earnings for the matched good AQ portfolio. *IndFR* is the average forecast revision for all firms in the industry.

Panel A of Table 6 reports Fama-MacBeth coefficients and *t*-statistics from estimation of equation (3), with standard errors adjusted for autocorrelation up to 12 lags. Panel A reports results for four specifications. The first specification regresses *PAQFR* on an intercept and *GAQFR* only, and, as the first column shows, *GAQFR* loads significantly positively (p-value < 0.10). The second specification is as in equation (3) and the second column of results shows lagged *GAQFR* loads significantly positively (p-value < 0.05), consistent with delayed information processing for poor AQ firms. To ensure this result is not due simply to industry momentum in FR, the dependent variable in the third specification in Panel A is *PAQFR* adjusted for contemporaneous *IndFR*. As the third column of results shows, lagged *GAQFR* continues to have significant predictive power (p-value < 0.05). Finally, the dependent variable *PAQFR* is adjusted for the contemporaneous *GAQFR* in the fourth column to control for contemporaneous news. The positive predictability remains significant.

Panel B of Table 6 examines whether there is reverse FR predictability from poor to good AQ firms. If the results in Panel A are due to general industry momentum in FR, we would expect to observe reverse predictability as well. The dependent variable in Panel B is *GAQFR*, and the table shows that lagged *PAQFR* has no predictive power, indicating an absence of reverse predictability.

Collectively the results in Panels A and B of Table 6 are consistent with poor AQ being associated with delayed processing of price-relevant information.

5.2 | Return predictability in news versus no-news months

If information processing delays explain return predictability from good to poor AQ firms, we expect predictability is stronger in months when more price-relevant information arrives in the market than in other months. The empirical strategy is to estimate the return predictability regression in equation (2) in news months and no-news months separately. We use two proxies for news arrival: the magnitude of market returns;[6] and rate announcements by the FOMC.

Using the first proxy we sort the time series of monthly market returns into quartiles based on returns, and consider the top and bottom quartiles as news months. The middle two quartiles are considered no-news months. Table 7 reports Fama and MacBeth (1973) coefficients and *t*-statistics from monthly cross-sectional estimation of equation (2). The table reports two columns of results, for news and no-news months, respectively. As Panel A shows, lagged *GAQret* loads significantly in news months (p-value < 0.01), but not in no-news months.

Using the second proxy we sort months into those with and without an FOMC rate announcement. The data are collected from the Federal Reserve and are available from 1990.[7] There are 80 months with rate announcements. As Panel B shows, there is stronger return predictability from *GAQret* following news months than no-news months.

[6] The constraint in testing the effect of industry news is empirical. The problem is that any given month may have industry-specific news for some industries only, and therefore any given month has too few observations for the cross-sectional regressions. For example, if a given month is classified as having news for three industries, this month would have only nine observations (3 industries × 3 size terciles × 1 AQ) available for the cross-sectional regression, which is insufficient.

[7] https://www.federalreserve.gov/monetarypolicy/openmarket.htm

TABLE 6 Analyst forecast revision predictability

Panel A: FR predictability				
	$PAQFR_t$	$PAQFR_t$	$PAQFR_t - IndFR_t$	$PAQFR_t - GAQFR_t$
Intercept	−0.086***	−0.697***	−0.636***	−0.451**
	(−4.79)	(−3.83)	(−3.35)	(−2.01)
$GAQFR_{t-1}$	9.281*	10.931**	13.235***	13.071**
	(1.90)	(2.41)	(2.97)	(2.52)
$PAQFR_{t-1}$		−6.485**	−6.065	−8.388*
		(−2.01)	(−1.37)	(−1.81)
$IndFR_{t-1}$		14.939**	11.576	−3.3020
		(2.07)	(1.10)	(−0.59)
Size		0.037***	0.038***	0.030**
		(3.12)	(2.99)	(2.18)
B/M		−0.073*	−0.07	−0.011
		(−1.74)	(−1.56)	(−0.21)
Mom		0.115	0.155	0.1030
		(1.41)	(1.66)	(1.25)
Turn		0.016	−0.00	−0.161
		(0.13)	(−0.00)	(−0.61)
Adj. R^2	0.07	0.29	0.29	0.217

Panel B: FR reverse predictability	
	$GAQFR_t$
$PAQFR_{t-1}$	0.979
	(0.33)
CONTROLS	YES
Adj. R^2	0.28

Notes: The table reports Fama-MacBeth coefficients, and *t*-statistics in parentheses, from monthly cross-sectional regressions of the dependent variables given in the column headers on the independent variables listed, from 1984 to 2012. *FR* is the revision in analysts' annual earnings forecast; *AQ* is accounting quality; *PAQFR* is the monthly FR of poor AQ portfolios; *GAQFR* is the monthly FR of the matching good AQ portfolios; *IndFR* is the monthly industry FR; *Size* is log market value of equity; *B/M* is log book-to-market ratio; *Mom* is return momentum; *Turn* is stock turnover. *AQ*, *Size*, *B/M*, *Mom*, and *Turn* are measured annually at the end of April. In Panel B, Controls include all controls listed in Panel A. Detailed variable definitions are presented in the Appendix. Standard errors are adjusted for autocorrelation up to 12 lags. ***, **, and * indicate *two-tailed p*-values less than 0.01, 0.05, and 0.10, respectively.

Overall, the results of both tests are consistent with a role for information processing frictions in return predictability from good to poor AQ firms.

5.3 | Predictability and firm information environment

In this section we further examine the information processing frictions hypothesis by testing how return predictability varies with the information environment of the predictor (good AQ) firms and the predicted (poor AQ) firms. The basic idea is that firms' information environment can potentially accentuate or mitigate the effects of poor accounting

TABLE 7 Return predictability in news versus no-news months

Panel A: Market returns as a proxy for news		
	***News* Months**	***No-news* Months**
	$PAQret_t$	$PAQret_t$
$GAQret_{t-1}$	7.244***	4.364
	(3.29)	(1.61)
CONTROLS	YES	YES
Adj. R^2	0.26	0.23
Panel B: FOMC rate announcements as a proxy for news		
	***News* Months**	***No-news* Months**
	$PAQret_t$	$PAQret_t$
$GAQret_{t-1}$	11.954***	4.755*
	(3.17)	(1.82)
CONTROLS	YES	YES
Adj. R^2	0.26	0.23

Notes: The table reports Fama-MacBeth coefficients, and *t*-statistics in parentheses, from monthly cross-sectional regressions of the dependent variables given in the column headers on the independent variables listed. *AQ* is accounting quality; *PAQret* is the monthly return of the poor AQ portfolio; *GAQret* is the monthly return of the matching good AQ portfolio. In Panel A, news (no-news) months are those in the top *and* bottom (middle two) quartiles of monthly market returns. In Panel B, news (no-news) months are those with (without) an FOMC rate announcement. Controls include all controls listed in Panel A of Table 4. Detailed variable definitions are presented in the Appendix. Standard errors are adjusted for autocorrelation up to 12 lags. ***, **, and * indicate *two-tailed p*-values less than 0.01, 0.05, and 0.10, respectively.

quality, if AQ is picking up information effects in the return predictability results. We therefore expect stronger return predictability from good AQ firms with a rich information environment (concordant effects) to poor AQ firms with a poor information environment (concordant effects), compared to the predictability from good AQ firms with a poor information environment (discordant effects) to poor AQ firms with a rich information environment (discordant effects). We use three proxies for the firm's information environment: analyst following, institutional ownership, and the presence of a Big 4 auditor. Analysts process, produce, and publicly disseminate information, and also add to firm visibility which can lead to additional information demand and production from other sources, collectively adding to the available information set. Institutional investors likely add to the information set through their own information production and trading activities, while Big 4 auditors are likely associated with higher quality audits and therefore more reliable information. We orthogonalize each of these variables with respect to the other two in the tests in order to capture incremental effects.

Panel A of Table 8 shows four columns of results. In the first column, good AQ firms with high analyst following are used to calculate *GAQret*, and poor AQ firms with low analyst following are used to calculate *PAQret*. In the second column, good AQ firms with low analyst following are used to calculate *GAQret*, and poor AQ firms with high analyst following are used to calculate *PAQret*. The table reports Fama-MacBeth coefficients and *t*-statistics from estimation of equation (2), with standard errors adjusted for autocorrelation up to 12 lags. The coefficient of lagged *GAQret* only is reported. In the first column of results, lagged *GAQret* significantly positively predicts *PAQret* (p-value < 0.05), but lagged *GAQret* does not load in the second column of results. This suggests the return predictability from good to poor AQ firms is stronger (weaker) when good AQ firms have a richer (poorer) information environment than poor AQ firms. The third and fourth columns show that predictability from good to poor AQ firms is also significant when they both have poor information environment, but not when they both have good information environment, consistent with the intuition that the information environment ameliorates the effect of poor accounting quality.

TABLE 8 Return predictability and firm information environment

Panel A: Analyst Following (AF)

	Good AQ with high AF to Poor AQ with low AF *$PAQret_t$*	Good AQ with low AF to Poor AQ with high AF *$PAQret_t$*	Good AQ with high AF to Poor AQ with high AF *$PAQret_t$*	Good AQ with low AF to Poor AQ with low AF *$PAQret_t$*
$GAQret_{t-1}$	6.503*	−1.138	−2.370	5.950**
	(1.82)	(−0.33)	(−0.66)	(2.04)
CONTROLS	YES	YES	YES	YES
Adj. R^2	0.19	0.25	0.28	0.18

Panel B: Institutional Ownership (IO)

	Good AQ with high IO to Poor AQ with low IO *$PAQret_t$*	Good AQ with low IO to Poor AQ with high IO *$PAQret_t$*	Good AQ with high IO to Poor AQ with high IO *$PAQret_t$*	Good AQ with low IO to Poor AQ with low IO *$PAQret_t$*
$GAQret_{t-1}$	8.395**	−0.493	0.348	6.234**
	(2.34)	(−0.13)	(0.08)	(2.07)
CONTROLS	YES	YES	YES	YES
Adj. R^2	0.21	0.23	0.27	0.18

Panel C: Big4 Auditors

	Good AQ with Big4 to Poor AQ with non-Big4 *$PAQret_t$*	Good AQ with non-Big4 to Poor AQ with Big4 *$PAQret_t$*	Good AQ with Big4 to Poor AQ with Big4 *$PAQret_t$*	Good AQ with non-Big4 to Poor AQ with non-Big4 *$PAQret_t$*
$GAQret_{t-1}$	8.950*	0.843	4.282	6.307**
	(1.76)	(0.09)	(1.14)	(1.97)
CONTROLS	YES	YES	YES	YES
Adj. R^2	0.17	0.27	0.25	0.20

Notes: The table reports Fama-MacBeth coefficients, and *t*-statistics in parentheses, from monthly cross-sectional regressions of $PAQret_t$ on the independent variables listed. *AQ* is accounting quality; *PAQret* is the monthly return of the poor AQ portfolio; *GAQret* is the monthly return of the matching good AQ portfolio; Controls include all controls listed in Panel A of Table 4. Panel A reports four columns of results. In the first (second) column of Panel A, firms in the good AQ portfolio with *high* (low) analyst following are used to calculate *GAQret*, while firms in the poor AQ portfolio with *low* (high) analyst following are used to calculate *PAQret*. In the third (fourth) column of Panel A, firms in the good AQ portfolio with *high* (low) analyst following are used to calculate *GAQret*, while firms in the poor AQ portfolio with *high* (low) analyst following are used to calculate *PAQret*. In the first (second) column of Panel B, firms in the good AQ portfolio with *high* (low) institutional ownership are used to calculate *GAQret*, while firms in the poor AQ portfolio with *low* (high) institutional ownership are used to calculate *PAQret*. In the third (fourth) column of Panel B, firms in the good AQ portfolio with *high* (low) institutional ownership are used to calculate *GAQret*, while firms in the poor AQ portfolio with *high* (low) institutional ownership are used to calculate *PAQret*. In the first (second) column of Panel C, firms in the good AQ portfolio with *high* (low) quality auditor are used to calculate GAQret, while firms in the poor AQ portfolio with *low* (high) quality auditor are used to calculate *PAQret*. In the third (fourth) column of Panel C, firms in the good AQ portfolio with *high* (low) quality auditor are used to calculate *GAQret*, while firms in the poor AQ portfolio with *high* (low) quality auditor are used to calculate *PAQret*. High (low) AF (or IO or Big4) is an indicator for above (below) the median residual when AF (or IO or Big4) is orthogonalized w.r.t. the other two variables. Detailed variable definitions are presented in the Appendix. Standard errors are adjusted for autocorrelation up to 12 lags. ***, **, and * indicate *two-tailed* *p*-values less than 0.01, 0.05, and 0.10, respectively.

Panel B of Table 8 repeats the test using institutional ownership, while Panel C repeats the test using the presence of a Big 4 auditor. The inferences are similar to those from Panel A.

The results in Table 8 suggest the firms' information environment can accentuate or mitigate the effects of poor accounting quality on return predictability, consistent with the information processing frictions hypothesis. Collectively, the results in this section are consistent with the hypothesis that poor accounting quality is associated with information processing delays that in turn lead to return predictability from good to poor AQ firms.

6 | OTHER TESTS

Sections 6.1–6.7 report results from a battery of robustness tests.

6.1 | Using FOG to measure accounting quality

As an alternative measure of accounting quality, we use the FOG index developed by Li (2008), which is a measure of the linguistic complexity of qualitative information in a firm's financial reports. The Li (2008) measure draws on the computational linguistics literature to measure text complexity based on the number of words per sentence and the number of syllables per word. The qualitative information in financial reports (for example, Management Discussion and Analysis) is helpful in contextualizing financial numbers and discerning future trends, and as such is likely relevant for stock prices. A high FOG index likely imposes greater information processing costs and hinders accurate understanding of the economics underlying the reported performance.

The SEC has long expressed concern for the lexical complexity of financial statements and has published plain English guidelines for corporate filings. In the preface to the SEC handbook,[8] Warren Buffett writes: "For more than forty years, I have studied the documents that public companies file. Too often, I've been unable to decipher just what is being said or, worse yet, had to conclude that nothing was being said. … Perhaps the most common problem (is) … stilted jargon and complex constructions." The handbook itself lists the "Common problems – long sentences, passive voice, weak verbs, superfluous words, legal and financial jargon, numerous defined terms, abstract words, unnecessary details, and unreadable design and layout." We therefore expect the FOG index to capture an aspect of accounting quality if it hinders accurate understanding of the underlying economics behind the reported financial statements.

Using FOG data from the website of Professor Feng Li,[9] we consider firms in the top (bottom) FOG tercile as poor (good) accounting quality firms. Table 9 shows results from return predictability tests using the FOG index. *GFIret* (*PFIret*) denotes returns of good (poor) FOG index firms. Only the coefficient of lagged *GFIret* is reported, for three specifications whose dependent variables are shown in the column headers. The dependent variables are *PFIret*, *PFIret – Indret*, and *PFIret – GFIret*, in the first, second, and third specifications, respectively. Lagged *GFIret* loads significantly positively (p-value < 0.05) in all three specifications, suggesting stock return predictability from good to poor accounting quality firms. Panel B examines reverse predictability from poor to good accounting quality firms, and lagged *PFIret* does not load significantly in Panel B, consistent with an absence of reverse predictability.

Collectively the results in this section reinforce the main results and are consistent with information processing delays leading to return predictability from good to poor accounting quality stocks.

[8] *A plain English handbook: How to create clear SEC disclosure documents*, SEC, August 1998, https://www.sec.gov/pdf/handbook.pdf, accessed March 13, 2015.

[9] http://webuser.bus.umich.edu/feng/

TABLE 9 Return predictability using the FOG index to measure accounting quality

Panel A: Return predictability using FOG			
	$PFIret_t$	$PFIret_t - Indret_t$	$PFIret_t - GFIret_t$
$GFIret_{t-1}$	3.647**	6.398**	5.721**
	(1.98)	(2.31)	(2.36)
CONTROLS	YES	YES	YES
Adj. R^2	0.22	0.20	0.11

Panel B: Reverse return predictability using FOG	
	$GFIret_t$
$PFIret_{t-1}$	1.751
	(0.78)
CONTROLS	YES
Adj. R^2	0.24

Notes: The table reports Fama-MacBeth coefficients, and *t*-statistics in parentheses, from monthly cross-sectional regressions of the dependent variables given in the column headers on the independent variables listed, from 1996 to 2010. FOG is an index of the linguistic complexity of financial statements, obtained from Professor Feng Li, and is used as a measure of accounting quality; *PFIret* is the monthly return of the poor FOG portfolio; *GFIret* is the monthly return of the matching good FOG portfolio; *Indret* is the monthly industry return; Controls include all controls listed in Panel A of Table 4. Detailed variable definitions are presented in the Appendix. Standard errors are adjusted for autocorrelation up to 12 lags. ***, **, and * indicate *two-tailed p*-values less than 0.01, 0.05, and 0.10, respectively.

6.2 | Return predictability using an alternative industry definition

In this section we use an alternative industry definition by matching firms on SIC code. The portfolio formation procedure is similar to that described earlier: at the end of each April we sort stocks sequentially by two-digit SIC industry, then size tercile, and then AQ tercile, with the requirement that each AQ tercile has at least three stocks. We then examine return predictability from good to poor AQ stock portfolios as in the main tests.

Panel A of Table 10 show the results from Fama and MacBeth's (1973) estimation of equation (2) using two-digit SIC and size matching. The panel reports three columns of results, corresponding to three regression specifications with different dependent variables as indicated in the column headers. In all specifications, lagged *GAQret* loads significantly positively, indicating significant return predictability from good to poor AQ stocks. Panel B examines reverse return predictability from poor to good AQ stocks. Lagged *PAQret* does not load significantly in Panel B, indicating no reverse predictability. Collectively, the results in Table 10 are consistent with the results presented earlier and with accounting quality being associated with delayed information processing.

6.3 | Controlling for analyst following, institutional holdings, the Cohen and Lou (2012) effect, and the Hameed, Morck, Shen, and Yeung (2015) effect

Table 11 shows robustness of the return predictability to additional controls. The table reports Fama and MacBeth (1973) coefficients and *t*-statistics from monthly cross-sectional regression of *PAQret* on the independent variables listed. The first regression specification controls for the number of analysts and institutional holdings, in addition to all control variables from Table 4. Neither the number of analysts nor institutional holdings loads significantly, while *GAQret* continues to significantly predict *PAQret*. This result reinforces the descriptive statistics in Table 2 which indicate that the good AQ and poor AQ samples (which are balanced on industry and size by construction) are also largely balanced on analyst following with means of 9 and 8.5, respectively. The results combine to suggest that our results

TABLE 10 Return predictability using SIC industry definition

Panel A: Return predictability with two-digit SIC and size matching			
	$PAQret_t$	*$PAQret_t$ – $Indret_t$*	*$PAQret_t$ – $GAQret_t$*
$GAQret_{t-1}$	1.857*	2.741*	5.839***
	(1.93)	(1.82)	(4.05)
CONTROLS	YES	YES	YES
Adj. R^2	0.05	0.05	0.04

Panel B: Reverse return predictability with two-digit SIC and size matching	
	$GAQret_t$
$PAQret_{t-1}$	0.309
	(0.34)
CONTROLS	YES
Adj. R^2	0.12

Notes: The table reports Fama-MacBeth coefficients, and *t*-statistics in parentheses, from monthly cross-sectional regressions of the dependent variables given in the column headers on the independent variables listed, from 1969 to 2012. *AQ* is accounting quality; *PAQret* is the monthly return of the poor AQ portfolio; *GAQret* is the monthly return of the matching good AQ portfolio; *Indret* is the monthly industry return; Controls include all controls in Panel A of Table 4. Each year, good (poor) AQ firms are those in the bottom (top) tercile of AQ. Each year poor AQ firms are matched to good AQ firms in the same two-digit SIC industry and size tercile. Detailed variable definitions are presented in the Appendix. Standard errors are adjusted for autocorrelation up to 12 lags. ***, **, and * indicate *two-tailed p*-values less than 0.01, 0.05, and 0.10, respectively.

are incremental to those in the prior literature documenting return predictability from high analyst following or institutional ownership firms to low analyst following or institutional ownership firms.

Cohen and Lou (2012) show that the returns to conglomerates (multiple segment firms) are predictable. In a simple test to distinguish their effect from ours, we exclude all multiple segment firms from the sample of poor AQ firms. The second specification in Table 11 shows that *GAQret* continues to significantly predict *PAQret*, indicating that the predictability documented here is distinct from that in Cohen and Lou (2012).

The third specification in Table 11 combines the first two specifications in order to control for the above effects concurrently. The dependent variable is *PAQret* for single segment firms only, and the controls include analyst following and institutional holdings. As the table shows, results remain robust.

To further distinguish our result from the Cohen and Lou (2012) effect and calibrate the magnitude of the incremental AQ effect, we re-estimate the tests in Table 5 Panel A after excluding returns to conglomerates from our trading strategy (recall that the Cohen and Lou trading strategy is implemented in conglomerates only). Table 12 shows the result. In particular, the hedge portfolio has a five-factor alpha of 78.4 basis points monthly ($t = 3.09$), which is an economically and statistically significant incremental effect (9.4% annualized alpha).

Finally, Hameed et al. (2015) examine the relation between "prominent" and "neglected" stocks and show that earnings forecast revisions of highly followed stocks predict the stock returns of neglected stocks. If AQ is simply capturing the Hameed et al. (2015) prominent and neglected stocks dichotomy, then controlling for the earnings forecast revision of good AQ stocks in the return predictability regression should (a) render the coefficient of good AQ stock returns insignificant in predicting poor AQ stock returns, and (b) the earnings forecast revision of good AQ stocks should significantly predict the stock returns of poor AQ stocks. Untabulated results show the opposite: good AQ stock returns, but not good AQ earnings forecast revisions, significantly predict poor AQ stock returns.

TABLE 11 Robustness tests controlling for analyst following, institutional holding, and the Cohen and Lou (2012) effect

	(1) $PAQret_t$	(2) $PAQret_t$	(3) $PAQret_t$
Intercept	−0.543	−0.059	−0.942
	(−0.42)	(−0.06)	(−0.61)
$GAQret_{t-1}$	5.884**	5.977***	6.657**
	(2.18)	(3.20)	(2.56)
$PAQret_{t-1}$	−2.432	−4.301***	−3.207
	(−1.25)	(−3.08)	(−1.65)
$Indret_{t-1}$	15.947***	16.172***	12.884**
	(3.44)	(3.35)	(1.98)
Size	0.139	0.067	0.126
	(1.09)	(0.97)	(0.79)
B/M	0.869***	0.455**	0.646*
	(3.09)	(1.99)	(1.82)
Mom	1.092*	0.820*	0.269
	(1.69)	(1.77)	(0.41)
Turn	−3.478	3.686	1.627
	(−1.29)	(1.15)	(0.49)
Analyst following	0.14		0.15
	(0.40)		(0.44)
Inst holding	0.43		0.08
	(0.38)		(0.07)
Adj. R^2	0.28	0.24	0.28

Notes: The table reports Fama-MacBeth coefficients, and *t*-statistics in parentheses, from monthly cross-sectional regressions of *PAQret* on the independent variables listed. *AQ* is accounting quality; *PAQret* is the monthly return of the poor AQ portfolio; *GAQret* is the monthly return of the matching good AQ portfolio; *Indret* is the monthly industry return; *Size* is log market value of equity; *B/M* is log book-to-market ratio; *Mom* is return momentum; *Turn* is stock turnover; *Analyst following* is the number of analyst following the firm; *Inst holding* is the institutional ownership. *AQ*, *Size*, *B/M*, *Mom*, *Turn*, *Analyst following*, and *Inst holding* are measured annually at the end of April. This table reports three specifications. The first specification controls for analyst following and the institutional holding in addition to the control variables reported in Table 4. The second specification controls for the Cohen and Lou (2012) effect by retaining only single segment firms in the poor AQ portfolio. The third specification combines the first two specifications to control for all effects concurrently. Detailed variable definitions are presented in the Appendix. Standard errors are adjusted for autocorrelation up to 12 lags. ***, **, and * indicate *two-tailed p*-values less than 0.01, 0.05, and 0.10, respectively.

6.4 | Accounting effect versus volatility effect

If the AQ measure is interpreted as the volatility of discretionary accruals, it might be of interest to examine whether the return predictability we document is an accounting effect or a general business volatility effect. To address this, we use three measures of volatility: operating cash flow volatility (*CFOVol*), earnings volatility (*EarnVol*), and stock return volatility (*RetVol*).

We begin by constructing portfolios of firms with high and low *CFOVol*, high and low *EarnVol*, and high and low *RetVol*. The portfolios are formed at the end of each April by sequentially sorting on industry, then size terciles, and

TABLE 12 The incremental alpha of AQ over the Cohen and Lou (2012) effect

		Return	Alpha	Mkt-RF	SMB	HML	UMD	LIQ	Adj. R^2
Univariate	L	1.428***							
		(4.35)							
	S	0.54							
		(1.57)							
	L − S	0.891***							
		(3.54)							
3 Factor	L		0.882***	95.784***	101.824***	18.814***			0.75
			(5.28)	(25.18)	(18.69)	(3.26)			
	S		(0.09)	120.162***	65.889***	30.627***			0.74
			(−0.50)	(29.95)	(11.47)	(5.04)			
	L − S		0.970***	−24.378***	35.935***	−11.813			0.06
			(3.91)	(−4.32)	(4.44)	(−1.38)			
4 Factor	L		0.881***	95.806***	101.825***	18.847***	0.109		0.75
			(5.16)	(24.67)	(18.67)	(3.21)	(0.03)		
	S		0.07	116.651***	65.731***	25.426***	−17.246***		0.75
			(0.38)	(29.10)	(11.68)	(4.19)	(−4.49)		
	L − S		0.814***	−20.845***	36.094***	−6.579	17.356***		0.08
			(3.25)	(−3.65)	(4.51)	(−0.76)	(3.17)		
5 Factor	L		0.879***	95.807***	101.825***	18.818***	0.124	0.44	0.75
			(5.09)	(24.64)	(18.65)	(3.19)	(0.03)	(0.09)	
	S		0.10	116.639***	65.741***	25.780***	−17.425***	−5.327	0.75
			(0.53)	(29.10)	(11.68)	(4.24)	(−4.53)	(−1.11)	
	L − S		0.784***	−20.831***	36.084***	−6.961	17.549***	5.767	0.08
			(3.09)	(−3.65)	(4.50)	(−0.80)	(3.20)	(0.84)	

Notes: The table shows results from re-estimating Table 5, Panel A, after excluding conglomerates. The table reports alphas, factor loadings, and *t*-statistics in parentheses, from Fama and French (1993) calendar-time regressions of monthly returns to a poor AQ hedge portfolio that excludes conglomerates on returns to the factors listed. The regressions require at least 10 stocks in the portfolio every month. L is Long, S is short, and L − S is the hedge portfolio. Mkt-Rf is the market excess return; SMB and HML are the Fama and French (1993) size and book-to-market factors; UMD is the Carhart (1997) momentum factor; LIQ is the Pástor and Stambaugh (2003) liquidity factor. Industry- and size-adjusted matched pairs of good and poor AQ portfolios are created at the end of every April. At the end of every month, we rank good AQ portfolios into winner and loser quintiles based on immediate-past-month returns. The poor AQ hedge portfolio is formed by buying (selling) poor AQ portfolios matching the good AQ winners (losers), and holding for one month. Detailed variable definitions are presented in the Appendix. ***, **, and * indicate *two-tailed p*-values less than 0.01, 0.05, and 0.10, respectively. The alpha is reported in percentage points.

then *CFOVol* (or *EarnVol*, or *RetVol*) terciles. The top *CFOVol* (or *EarnVol*, or *RetVol*) tercile is labeled *HighCFOVol* (or *HighEarnVol*, or *HighRetVol*), and the bottom *CFOVol* (or *EarnVol*, or *RetVol*) tercile is labeled *LowCFOVol* (or *LowEarnVol*, or *LowRetVol*). The middle tercile is deleted from the sample. *CFOVol* (*EarnVol*) is defined as the volatility of annual operating cash flows (earnings) over the last five years. *RetVol* is defined as the volatility of monthly returns over the last five years. Recall that poor (good) AQ firms have high (low) accrual volatility, and our main tests examine predictability from good to poor AQ firms. We conduct two sets of tests to address the question above.

First, we begin by replicating the main test in Table 4 with three additional controls: $LowCFOVolret_{t-1}$, $LowEarnVolret_{t-1}$, and $LowRetVolret_{t-1}$. We observe robust predictability from *GAQret* to *PAQret* (*GAQret* = 5.34, two-tailed p-value < 0.05). We then replicate Table 4 with six additional controls: $LowCFOVolret_{t-1}$, $LowEarnVolret_{t-1}$, $LowRetVolret_{t-1}$, $HighCFOVolret_{t}$, $HighEarnVolret_{t}$, and $HighRetVolret_{t}$. In other words, we control for low volatility measures that are contemporaneous with *GAQret* and high volatility measures that are contemporaneous with the dependent variable *PAQret*. The predictability from *GAQret* to *PAQret* remains robust (*GAQret* = 3.86, two-tailed p-value < 0.10).

Second, we replicate Table 4 after replacing the dependent variable *PAQret* with *HighCFOVolret* (or *HighEarnVolret*, or *HighRetVolret*). The regressions include all controls in Table 4 as well as *LowCFOVolret*, *LowEarnVolret*, and *LowRetVolret*. We do not observe return predictability from low to high volatility firms when the regressions control for *GAQret* and the other two low volatility metrics. For example, there is no return predictability from *LowCFOVolret* to *HighCFOVolret* when the regression controls for *GAQret*, *LowEarnVolret*, *LowRetVolret*, and all other controls.

Overall, the tests above suggest our main results reflect the effect of accounting quality rather than general business volatility.

6.5 | Is the predictability due to earnings announcement date differences?

A potential explanation for the predictability we document is that: (i) earnings announcements of poor AQ firms systematically lag earnings announcements of good AQ firms, and (ii) good AQ firms' earnings predict poor AQ firms' earnings but the market does not update the stock price of poor AQ firms until they announce their earnings. We address this question in two ways. First, we examine and find that poor AQ firms' earnings announcements *lead* good AQ firms' earnings announcements by a median of 1 day. Second, we exclude the three-day earnings announcement stock returns for both good and poor AQ firms and re-estimate Table 4. The predictability from *GAQret* to *PAQret* remains robust (*GAQret* = 4.28, two-tailed p-value < 0.05).

The results above suggest the return predictability we document is not explained by potential differences in earnings announcement dates.

6.6 | Calculating AQ using statement of cash flow data

Hribar and Collins (2002) suggest using Statement of Cash Flow (SCF) data to calculate accruals. This data is available from 1987. In untabulated tests, we calculate AQ using SCF data and find predictability from *GAQret* to *PAQret* remains robust (*GAQret* = 4.79, two-tailed p-value < 0.05).

6.7 | Concentration of earnings forecast revisions

Analysts are more likely to issue earnings forecast revisions before earnings announcement dates and many forecasts might be revised in early months of the year, from January to March. To examine whether our results are driven by these early months, we replicate Tables 4 and 6 after excluding observations in January/February or February/March. Results, untabulated, remain robust.

7 | OUT OF SAMPLE TESTS

We conduct two out-of-sample tests as described below.

TABLE 13 Return predictability and analyst forecast revision: International evidence

Panel A: Country distribution				
Country name		**Freq**		**Percent**
Australia		777		2.86
Bermuda		55		0.2
Brazil		198		0.73
Switzerland		622		2.29
Chile		72		0.27
China		3,072		11.33
Cayman Islands		47		0.17
Germany		2,437		8.98
Spain		19		0.07
Finland		206		0.76
France		3,049		11.24
United Kingdom		2,898		10.68
Greece		84		0.31
Hong Kong		57		0.21
India		1,678		6.19
Israel		322		1.19
Italy		43		0.16
Japan		6,812		25.11
South Korea		1,834		6.76
Sri Lanka		35		0.13
Malaysia		290		1.07
Pakistan		67		0.25
Philippines		12		0.04
Poland		236		0.87
Saudi Arabia		19		0.007
Singapore		24		0.09
Sweden		861		3.17
Thailand		101		0.37
Turkey		101		0.37
Taiwan		809		2.98
Vietnam		115		0.42
South Africa		173		0.64
Panel B: Cross-sectional return predictability: Ex-US international sample				
	$PAQret_t$	$PAQret_t$	$PAQret_t - Indret_t$	$PAQret_t - GAQret_t$
Intercept	0.1210	1.0470	1.0090	0.4160
	(0.40)	(0.61)	(0.42)	(0.43)
$GAQret_{t-1}$	4.038***	2.704**	2.755*	7.852***
	(2.62)	(2.40)	(1.77)	(4.23)

(Continues)

TABLE 13 (Continued)

Panel B: Cross-sectional return predictability: Ex-US international sample				
	$PAQret_t$	$PAQret_t$	$PAQret_t - Indret_t$	$PAQret_t - GAQret_t$
$PAQret_{t-1}$		−2.3420	−4.551*	−4.597***
		(−1.32)	(−2.07)	(−3.92)
$Indret_{t-1}$		6.584**	7.860**	−0.1490
		(2.99)	(2.05)	(−0.09)
Size		0.0080	0.0020	0.0080
		(0.24)	(0.05)	(0.33)
B/M		0.1770	0.2280	0.0130
		(1.11)	(1.06)	(0.52)
Mom		0.1540	0.2490	0.1040
		(0.27)	(0.31)	(0.96)
Turn		41.9050	62.4620	8.2460
		(0.41)	(0.49)	(0.16)
Adj. R^2	0.04	0.203	0.155	0.044

Panel C: Analyst forecast revision predictability: Ex-US international sample			
	$PAQFR_t$	$PAQFR_t$	$PAQFR_t - IndFR_t$
Intercept	−0.376***	−0.117	0.286
	(−3.37)	(−0.06)	(0.11)
$GAQFR_{t-1}$	10.813	14.928**	29.991*
	(1.39)	(2.21)	(1.70)
$PAQFR_{t-1}$		−18.996*	−46.248**
		(−1.90)	(−2.05)
$IndFR_{t-1}$		−5.448	−14.9240
		(−1.09)	(−1.32)
Size		0.0220	0.0290
		(0.58)	(0.44)
B/M		0.065	−0.051
		(0.33)	(−0.21)
Mom		−0.3290	0.1390
		(−0.47)	(0.11)
Turn		−67.936**	−103.19
		(−2.18)	(−1.39)
Adj. R^2	0.230	0.551	0.457

Notes: This table presents country distribution (Panel A) and estimation results for cross-firm return predictability and analyst forecast revision predictability. Panel B and Panel C report Fama-MacBeth coefficients, and *t*-statistics in parentheses, from monthly cross-sectional regressions of the dependent variables given in the column headers on the independent variables listed, from 1994 to 2018. *AQ* is accounting quality; *PAQret* is the monthly return of the poor AQ portfolio; *GAQret* is the monthly return of the matching good AQ portfolio; *Indret* is the monthly industry return; *Size* is log market value of equity; *B/M* is log book-to-market ratio; *Mom* is return momentum; *Turn* is stock turnover; *FR* is the revision in analysts' annual earnings forecast; *PAQFR* is the monthly FR of poor AQ portfolios; *GAQFR* is the monthly FR of the matching good AQ portfolios. *AQ*, *Size*, *B/M*, *Mom*, and *Turn* are measured annually at the end of April. Detailed variable definitions are presented in the Appendix. Standard errors are adjusted for autocorrelation up to 12 lags. ***, **, and * indicate *two-tailed* *p*-values less than 0.01, 0.05, and 0.10, respectively.

TABLE 14 Return predictability and analyst forecast revision: Extended sample period

Panel A: Return predictability regressions				
	$PAQret_t$	$PAQret_t$	$PAQret_t$ – $Indret_t$	$PAQret_t$ – $GAQret_t$
$GAQret_{t-1}$	6.233***	4.714***	5.451***	7.468***
	(4.51)	(3.12)	(2.87)	(4.22)
CONTROLS	NO	YES	YES	YES
Adj. R^2	0.039	0.228	0.189	0.105
Panel B: FR predictability				
	$PAQFR_t$	$PAQFR_t$	$PAQFR_t - IndFR_t$	$PAQFR_t - GAQFR_t$
$GAQFR_{t-1}$	15.039***	10.321**	9.839**	10.321**
	(3.43)	(2.55)	(2.07)	(2.55)
CONTROLS	NO	YES	YES	YES
Adj. R^2	0.053	0.247	0.252	0.247

Notes: This table presents estimation results for cross-firm return predictability (Panel A) and analyst forecast revision predictability (Panel B) for the extended sample period, from 1969 to 2018. Panel A and Panel B report Fama-MacBeth coefficients, and *t*-statistics in parentheses, from monthly cross-sectional regressions of the dependent variables given in the column headers on the independent variables listed. *PAQret* is the monthly return of the poor AQ portfolio; *GAQret* is the monthly return of the matching good AQ portfolio; *FR* is the revision in analysts' annual earnings forecast; *PAQFR* is the monthly FR of poor AQ portfolios; *GAQFR* is the monthly FR of the matching good AQ portfolios. Controls include all controls listed in Table 4 Panel A (for Panel A) and Table 6 Panel A (for Panel B). Detailed variable definitions are presented in the Appendix. Standard errors are adjusted for autocorrelation up to 12 lags. ***, **, and * indicate *two-tailed p*-values less than 0.01, 0.05, and 0.10, respectively.

7.1 | International stocks

We extend our analysis to countries other than the United States in this subsection. There is prior empirical evidence that the lead-lag pattern of stock returns holds outside the US (e.g., Basu, Oomen, & Stremme, 2010; Goyal & Jegadeesh, 2018; Hung, 2008). While prior studies document a cross-*country* return predictability in the global setting (e.g., Albuquerque, Ramadorai, & Watugala, 2015; Rapach, Strauss, & Zhou, 2013), evidence on cross-*firm* return predictability is scant in an international setting. We expect our main findings could be generalized to other countries. Specifically, we examine the cross-firm return predictability and analyst forecast revision pattern conditional on AQ in an international sample.

Using the international data from Compustat Global, we obtain a sample of 32 countries (presented in Table 13, Panel A) to conduct the international test. As shown in Table 13, Panel B, we continue to find significant return predictability from good AQ stocks to poor AQ stocks with a one-month lag. The coefficient on the lagged *GAQret* in the second column with *PAQret* as the dependent variable is 2.704 with a *p*-value of 0.05. Panel C of Table 13 provides evidence supporting the information processing delay argument in the ex-US global setting using international analyst forecast data from IBES. It shows that analyst forecast revisions of poor AQ stocks mimic lagged good AQ stocks forecast revisions. Overall, we provide initial evidence that accounting quality affects the speed of non-idiosyncratic information incorporation not only in the US market but also globally.

7.2 | Extended sample period

We extend our tests of cross-firm return predictability and analyst forecast revisions to the latest sample period through 2018 and the results remain robust, as reported in Table 14.

8 | CONCLUSION

Financial statements summarize the financial implications of firms' myriad transactions, and are intended to inform investor expectations about future cash flows (Financial Accounting Standards Board, 1978). Financial statements necessarily include estimated amounts (such as various allowances), rather than amounts known with certainty. We refer to the informativeness of firms' financial statements for their revenue and cost structure and future cash flows as accounting quality, and examine whether AQ is associated with cross-firm return predictability. Given common (non-firm-specific) information that affects both poor and good AQ firms, we expect it takes longer to process the implications of this information for the poor AQ than for the good AQ firms if investors have limited information processing resources and capacity. If this is empirically descriptive, we expect the stock price revision of poor AQ firms to lag the stock price revision of comparable good AQ firms, and therefore expect return predictability from good to poor AQ firms.

We identify matched pairs of good and poor AQ firm portfolios by sorting firms sequentially each year into industries, then size terciles, and then AQ terciles. Each good AQ tercile portfolio is paired with its industry-size-matched poor AQ tercile portfolio. We then estimate monthly cross-sectional regressions of poor AQ stock returns on the one-month-lagged stock return of the matching good AQ portfolio, controlling for short-term return reversal, industry returns, size, book-to-market, return momentum, and stock turnover. Across a number of different specifications, results indicate robust return predictability from good to poor AQ stocks consistent with delayed information processing for poor AQ stocks.

Time series factor-model tests provide evidence on the economic magnitude of the return predictability. We form a hedge portfolio of long (short) poor AQ portfolios whose matching good AQ portfolios were recent one-month winners (losers). Fama and French (1993) calendar-time regressions indicate significant hedge portfolio five-factor alphas of about 10% annualized. The return predictability is robust when the hedge portfolio is formed only in the largest stocks. Market microstructure frictions, transactions costs, and poor investor recognition concerns are likely lowest among large stocks, and such are unlikely to explain the documented return predictability. The results appear more consistent with delayed information processing, which we explore further through a number of tests.

If the return predictability is due to delayed information processing by investors, then we expect equity market information intermediaries to be similarly affected by poor AQ. We therefore examine whether similar predictability is observed in analyst earnings forecast revisions. Consistent with the hypothesis, results indicate significant forecast revision predictability from good AQ firms to their poor AQ match, but no reverse predictability. Further, return predictability is concentrated in months with greater information arrival, compared to no-news months. Finally, we observe stronger return predictability from good to poor AQ stocks when the good AQ stocks have a relatively richer information environment as proxied by analyst following, institutional ownership, and the presence of a Big 4 auditor. Results are robust to different procedures for matching good and poor AQ stocks, and to alternative methods for estimating accounting quality. Collectively the results uncover a role for the quality of firms' accounting information in stock price dynamics.

One opportunity for future research is suggested by our time series return attribution test which indicates that the cross-firm return predictability is asymmetric and largely relates to a delayed processing of good news. This evidence is consistent with some prior literature. For example, McQueen, Pinegar, and Thorley (1996) find that the cross-autocorrelation from large stocks to small stocks is associated with a slow response by small stocks to good, but not to bad, common news. Peng, Johnstone, and Christodoulou (2020) predict and show that good news disclosure resolves more investor uncertainty than bad news disclosure. Research incorporating these asymmetric responses is one future opportunity.[10]

[10] We thank an anonymous referee for this suggestion.

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DATA AVAILABILITY STATEMENT

The data that support the findings are available through subscription to Wharton Research Data Services (WRDS). Accounting data is extracted from Compustat, stock return data is from CRSP, analyst data from IBES, and institutional ownership data from Thompson. Rate announcements by the Federal Open Market Committee (FOMC) are obtained via https://www.federalreserve.gov/monetarypolicy/openmarket.htm. The fog index is obtained from the website of Professor Feng Li: http://webuser.bus.umich.edu/feng/.

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APPENDIX

Variable definitions

Variable	Definition
AQ estimation variables	
Accruals	Accruals measured as the change in current assets (Compustat item ACT) minus the change in current liabilities (Compustat item LCT) minus the change in cash (Compustat item CHE) and plus the change in short debt (Compustat item DLC), scaled by beginning total assets
CFO	Cash flow from operations, measured as the difference between income before extraordinary items and accruals, scaled by beginning total assets
Δ*Sales*	Change in sales, scaled by beginning total assets
PPE	Gross property, plant, and equipment (Compustat item PPEGT), scaled by beginning total assets
AQ	Standard deviation over five years of residuals from the modified Dechow and Dichev (2002) model
Return regression variables	
PAQret	Monthly return of poor AQ portfolio
GAQret	Monthly return of good AQ portfolio
Indret	Monthly industry return excluding returns to poor AQ stocks
Size	Logarithm of market value of equity as at the end of each April
B/M	Logarithm of the ratio of book value of equity (CEQ) to market value of equity as at the end of each April
Mom	Return momentum, measured as cumulative return from month $t-2$ to $t-12$ at the end of each April
Turn	Stock turnover, measured as average of monthly trading volume divided by shares outstanding for each return year ended in April
Analyst following	The number of analysts that follow the firm for each return year ended in April
Inst holding	Institutional holding, measured as the percentage of shares held by institutional investors for each return year ended in April

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Variable	Definition
Forecast revision	
FR	Revision of analysts' forecast of annual earnings, measured as the one-month change in the consensus forecast, scaled by beginning stock price
PAQFR	FR for poor AQ portfolio
GAQFR	FR for good AQ portfolio
IndFR	Average forecast revision of all firms, excluding poor AQ firms, within industry