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Lazy Prices

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ABSTRACT

Using the complete history of regular quarterly and annual filings by U.S. corporations, we show that changes to the language and construction of financial reports have strong implications for firms' future returns and operations. A portfolio that shorts "changers" and buys "nonchangers" earns up to 188 basis points per month in alpha (over 22% per year) in the future. Moreover, changes to 10-Ks predict future earnings, profitability, future news announcements, and even future firm-level bankruptcies. Unlike typical underreaction patterns, we find no announcement effect, suggesting that investors are inattentive to these simple changes across the universe of public firms.

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In a Grossman and Stiglitz (1976) world, agents are compensated for the marginal value of the information they collect, process, and impound into prices. Although this model is static, the dynamics of these underlying processes have changed drastically for investors over time. Information production and dissemination have seen a substantial decrease in cost over the past three decades. With this decrease in cost, the amount of information being produced has increased, making the search and processing problem more complex. If investors have not kept up with the magnitude and complexity of these changes, disclosed information may not be incorporated by even these Grossman-Stiglitz investors.

In this paper, we use the firms' annual statements to examine this tension. Prior literature documents that while at one time investors responded contemporaneously to financial statement releases that contained large changes, today, this announcement effect is less pronounced (Brown and Tucker (2011), Feldman et al. (2010)). This literature thus concludes that changes to 10-K documents have become less informative over time.[1] While we replicate this fact, that is, while we find no significant announcement effect associated with changes to regular filings, we show that this result misses a large and critically important component of these changes' impact on asset prices.

In particular, we find that the lack of announcement returns is *not* due to financial statements becoming less useful over time, but rather to investors missing these subtle but important signals from annual reports at the time of theirs release, perhaps due to the reports' increased complexity and length.[2] When we isolate changes to corporate reports using our approach, we find that document changes do impact stock prices in a large and significant way, but they do so with a lag: investors uncover the implications of the news contained in document changes only gradually over time, but eventually the news is fully impounded into stock prices and firm operations. Thus, in contrast to prior studies that argue that corporate documents are becoming less informative and hence less useful to investors in today's capital markets, our results suggest that 10-Ks contain rich information, but investors are initially missing a large part of their information. The findings in this paper thus point to an extreme, broad-based form of investor inattention to items that are foundational to the corporate reporting process, namely, quarterly and annual reports, which leads to large return predictability.

To motivate the increasing difficulty a Grossman-Stiglitz investor faces in the collection and processing of value-sensitive information, in Figure 1, we plot the

[1] Note that while Feldman et al. (2010) find a modest contemporaneous predictive effect of changes in sentiment in the MD&A section on stock returns, Brown and Tucker (2011) argue that announcement effects related to document changes have decreased over time, consistent with a decline in the informativeness of corporate filings.

[2] Also note that Loughran and McDonald (2017) point out that the average publicly traded firm's annual report is downloaded from the SEC's website by investors only 28.4 times immediately after 10-K filings; we suggest that most investors may not be carefully examining the filings to begin with. Of course, investors may be accessing this information from sources other than the SEC's website (Bloomberg, CapIQ, etc.).

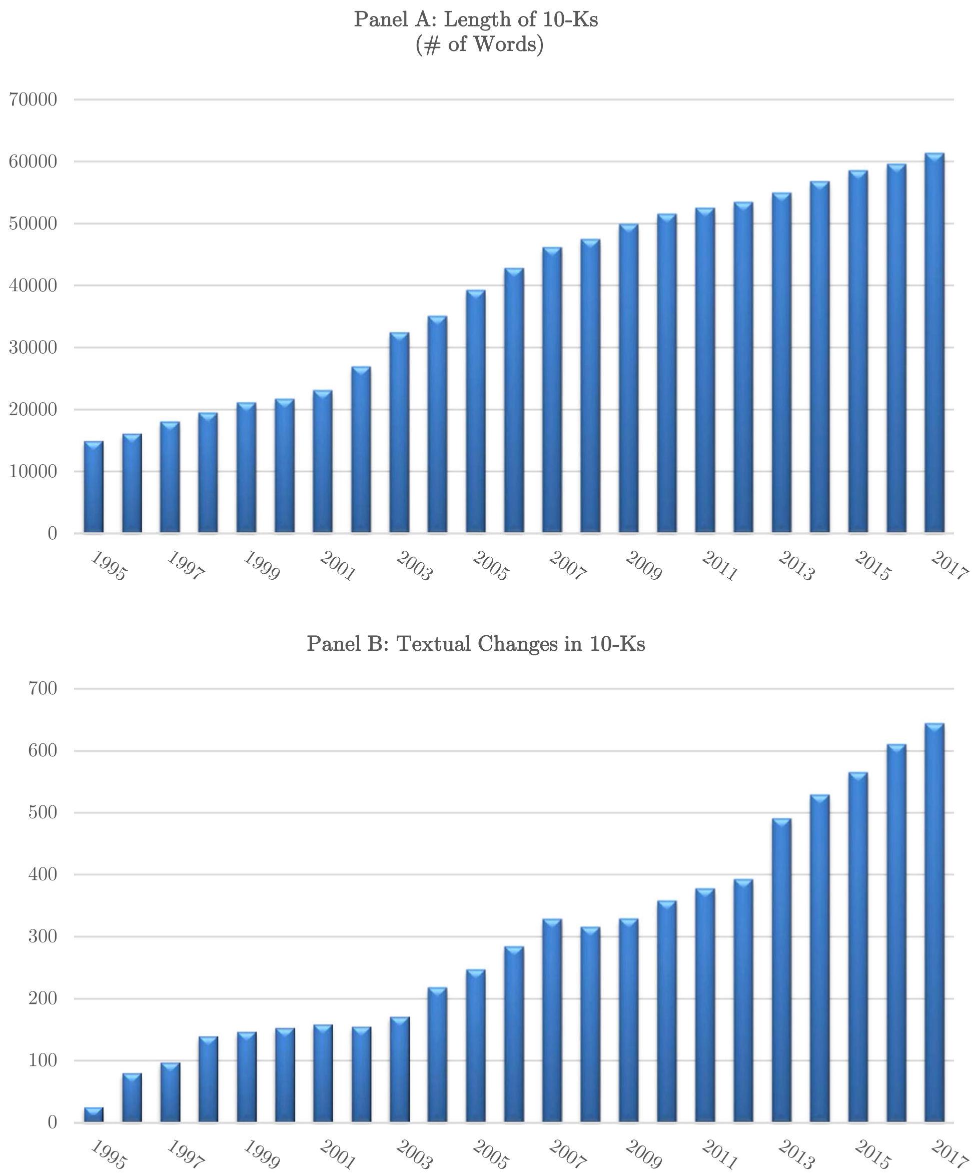


Figure 1. Length of 10-Ks and changes to 10-Ks over time. (Color figure can be viewed at wileyonlinelibrary.com)

simple average size of a firm's annual financial statement (10-K) as measured by the number of text words, that is, after stripping out tables, ASCII embedded information, jpeg files, etc. to focus solely on actual text, over our sample period. As can be seen in Panel A, the length of the average 10-K has grown dramatically over the last 20 years, with the present-day 10-K roughly size times as long as that in 1995.[3] Panel B shows that over the same period, the number of textual changes[4] has also grown substantially, increasing by over 12 times. Thus, not only are 10-Ks increasing in length (i.e., contain more text), but the number of changes is increasing year-over-year. We use this setting to explore how investors respond to these changes in information delivery and how this information eventually translates into stock prices and firm operations.

To illustrate our approach, consider the example of Baxter International Inc. Baxter is a bioscience and medical products firm headquartered in Deerfield, IL. The firm was founded in 1931, trades on the NYSE (ticker: BAX), and is a member of the S&P 500. The company's annual reports (10-Ks) historically had been similar over time, but something changed in 2009 when its year-over-year similarity score dropped.[5]

What caused Baxter's 2009 10-K to veer from the prior year in terms of the language used and information provided? Figure 2 shows some of the news headlines that flooded the media in the months following the release of the 2009 10-K on February 23, 2010. For instance, a *New York Times* article published on April 24, 2010, reported that the U.S. Food and Drug Administration (FDA) was clamping down on medical devices—in particular, on automated IV pumps used to deliver food and drugs. From the article: "*The biggest makers of infusion pumps include Baxter Healthcare of Deerfield*, *Ill.*; *Hospira of Lake Forest*, *Ill.*; *and CareFusion of San Diego.*" The article went on to quote an FDA's official commenting that the new, tighter regulations would slow down the FDA approval process for automated pumps. Then, on May 4 (just 10 days later), the *New York Times* reported that the FDA had imposed a large recall on Baxter, "Baxter International is *recalling* its *Colleague infusion pumps* from the American market under an agreement with federal regulators that sought to fix problems like battery failures and software errors."[6]

The stock returns of Baxter International moved substantially surrounding the *New York Times* articles. In the two-week period around the articles, Baxter's price fell by more than −20%. This is depicted in Figure 3, which also shows that the price remained depressed, not reverting over the subsequent six-month period. In contrast, we observe no significant reaction to Baxter's own disclosure of its 10-K on February 23, 2010, nearly two months before the news articles were published.

The question then is whether these two information releases were at all linked, that is, could something about the changes to Baxter's 10-K

[3] Li (2008) also documents this regularity.

[4] Here, the number of textual changes is defined simply as the number of instances in which a piece of text was removed, added, or modified as captured by Microsoft Word's "Compare Documents" function (Microsoft Word Tools menu, point to Track Changes, and click Compare Documents). This figure shows the average number of changes per firm per year.

[5] The similarity of Baxter's 2009 10-K dropped from a prior five-year average of 0.469 to 0.399. Similarity in this case is measured using the *Sim_MinEdit* measure (the smallest number of operations required to transform one document into the other), which is one of the four measures of document similarity we use throughout and discuss in further detail in Section II.

[6] The link to Baxter's 2009 full 10-K and accompanying exhibits, along with links to the full-length articles and excerpts, are included in Figure 2.

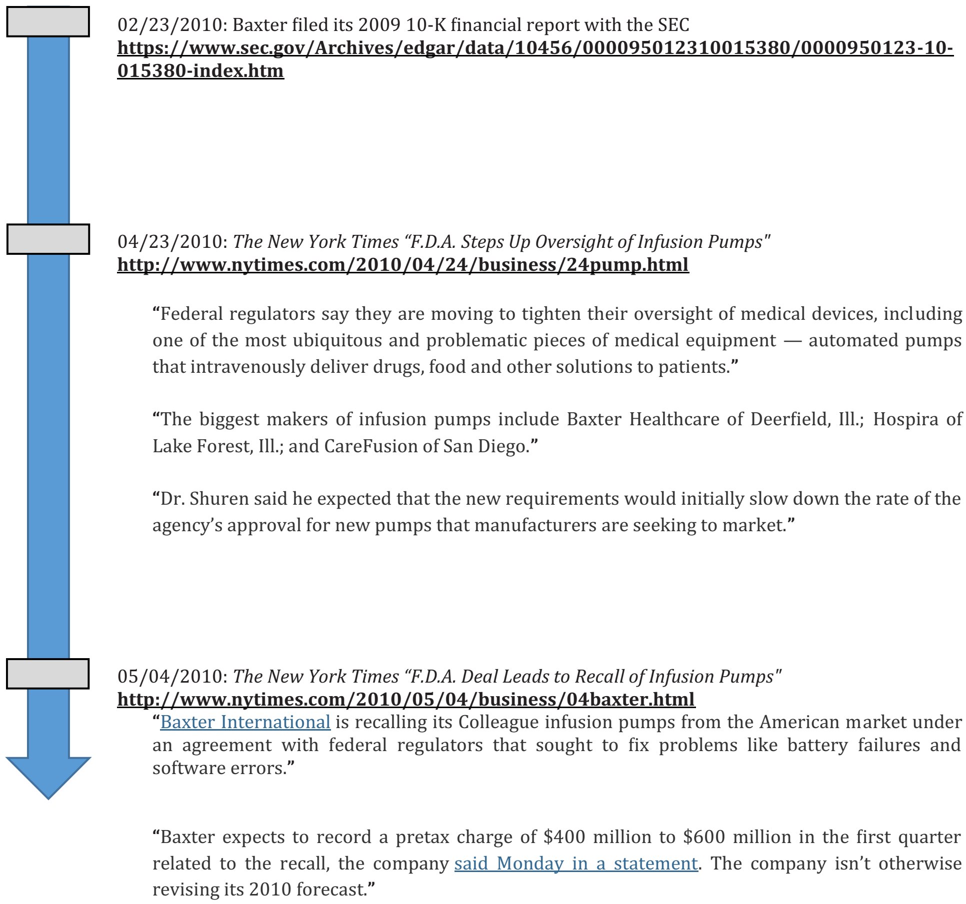


Figure 2. Main events and news articles regarding Baxter's recall of Colleague Pumps in 2010. (Color figure can be viewed at wileyonlinelibrary.com)

(reported two months before) have hinted at the portending news regarding the automated pump issue. Figure 4 provides some suggestive evidence in this direction by showing the incidence of keywords in Baxter's 10-Ks related to the FDA's clamp-down and the recall of Baxter's *Colleague Pump*. Figure 4 shows that Baxter's use of these words spiked in their 2010 report relative to previous years. In particular, Baxter's 2009 filing showed a 71% increase in mentions of "*FDA*," a 50% increase in "*Recall*," and a 182% increase in "*Colleague Pump*." Figure 5 presents more detailed, suggestive evidence on this point, by providing a number of parallel passages, from the 2009 versus 2008 versions of a passage that demonstrate Baxter's increased use of these terms.[7] For instance,

[7] See also Figure IA.1 in the Internet Appendix for additional passages related to the Baxter example. In addition, Figure IA.2 presents selected passages from successive 10-Ks from another

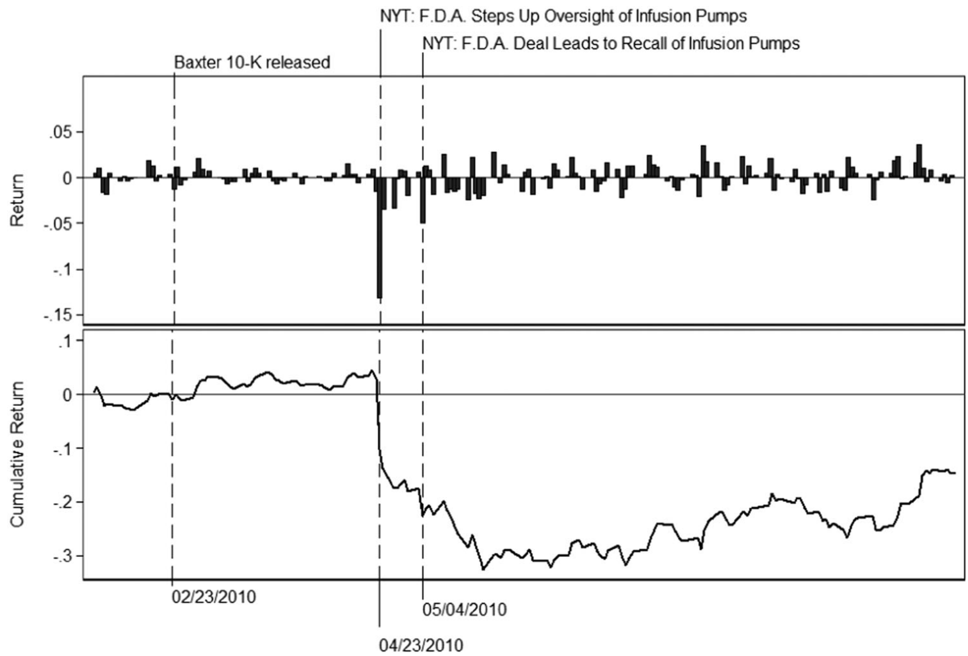


Figure 3. Baxter stock return. This figure reports the daily returns and the cumulative returns of Baxter International Inc. (NYSE: BAX) in the months following the release of Baxter's 2009 10-K report.

Word counts	2007 10-K	2008 10-K	2009 10-K
FDA	33	28	48
Recall	16	20	30
Colleague Pump	29	28	79

Figure 4. Important keywords. This table reports the count of keywords that are related to events related to the recall of Baxtrer's Colleague pumps in 2010.

one can see that Baxter changed the passage "It is possible that additional charges related to COLLEAGUE may be required in future periods" [2008] to "It is possible that *substantial* additional charges, *including significant asset impairments*, *related to COLLEAGUE may be required in future periods*" [2009]. Baxter also added the following to their 2009 10-K: "*The sales and marketing of our products and our relationships with healthcare providers are under increasing scrutiny by federal, state and foreign government agencies. The FDA, the OIG, the Department of Justice (DOJ) and the Federal Trade Commission have each increased their enforcement efforts . . .* "

company (Herbalife). The Internet Appendix is available in the online version of this article on *The Journal of Finance* website.

Example 1	
2008:	2009:
With respect to COLLEAGUE, the company remains in active dialogue with the FDA about various matters, including the company's remediation plan and reviews of the Company's facilities, processes and quality controls by the company's outside expert pursuant to the requirements of the company's Consent Decree. The outcome of these discussions with the FDA is uncertain and may impact the nature and timing of the company's actions and decisions with respect to the COLLEAGUE pump. The company's estimates of the costs related to these matters are based on the current remediation plan and information currently available. It is possible that additional charges related to COLLEAGUE may be required in future periods, based on new information, changes in estimates, and modifications to the current remediation plan as a result of ongoing dialogue with the FDA.	The company remains in active dialogue with the FDA regarding various matters with respect to the company's COLLEAGUE infusion pumps, including the company's remediation plan and reviews of the company's facilities, processes and quality controls by the company's outside expert pursuant to the requirements of the company's Consent Decree. The outcome of these discussions with the FDA is uncertain and may impact the nature and timing of the company's actions and decisions with respect to the COLLEAGUE pump. The company's estimates of the costs related to these matters are based on the current remediation plan and information currently available. It is possible that substantial additional charges, including significant asset impairments, related to COLLEAGUE may be required in future periods, based on new information, changes in estimates, and modifications to the current remediation plan.

Example 2	
2008:	2009:
In the third quarter of 2008, as a result of the company's decision to upgrade the global pump base to a standard software platform and other changes in the estimated costs to execute the remediation plan, the company recorded a charge of $72 million. This charge consisted of $46 million for cash costs and $26 million principally relating to asset impairments and inventory used in the remediation plan. The reserve for cash costs primarily consisted of costs associated with the deployment of the new software and additional repair and warranty costs. The following summarizes cash activity in the company's COLLEAGUE and SYNDEO infusion pump reserves through December 31, 2008.	In the third quarter of 2008, as a result of the company's decision to upgrade the global pump base to a standard software platform and other changes in the estimated costs to execute the remediation plan, the company recorded a charge of $72 million. This charge consisted of $46 million for cash costs and $26 million principally relating to asset impairments and inventory used in the remediation plan. The reserve for cash costs primarily consisted of costs associated with the deployment of the new software and additional repair and warranty costs. In 2009, the company recorded a charge of $27 million related to planned retirement costs associated with SYNDEO and additional costs related to the COLLEAGUE infusion pump. This charge consisted of $14 million for cash costs and $13 million related to asset impairments. The reserve for cash costs primarily related to customer accommodations and additional warranty costs. The charges were recorded in cost of sales in the company's consolidated statements of income, and were included in the Medication Delivery segment's pre-tax income. The following summarizes cash activity in the company's COLLEAGUE and SYNDEO infusion pump reserves through December 31, 2009.

Figure 5. Example passages and the changes made to them from Baxter's 10-Ks in 2008 and 2009. (Color figure can be viewed at wileyonlinelibrary.com)

Circling back, would being attentive to the changes in Baxter's 10-K have made a difference to investors in the company? Going back to Figure 3, the answer appears to be yes. Not only did the price of Baxter not move at all around the public filing of the 2009 10-K (February 23, 2010), but it did not move for the next two months—until the news report by the *New York Times* on April 23. Reading and reacting to these negative changes by shorting Baxter at any point in the two months leading up to the *New York Times* article would have allowed an investor to capture over 30% in returns in the month following the news release.

We demonstrate that this pattern of behavior, investor response, subsequent events, and return evolution are systematic across the entire cross-section of U.S. publicly traded firms from 1995 to 2014.

We first show that firms that change their reports experience significantly lower future stock returns. In particular, a portfolio that goes long "nonchangers" and short "changers" earns a statistically significant 34 to 58 basis points per month, up to 7% per year ($t = 3.59$), in value-weighted abnormal returns over the following year. These returns continue to accrue up to 18 months and do not reverse, implying that far from overreaction, these changes imply true, fundamental information for firms that get incorporated into asset prices only gradually in the months after the reporting change. As all publicly traded firms are mandated to file 10-Ks (and 10-Qs), the sample over which we show these abnormal returns is truly the universe of firms (not a small, illiquid, or otherwise selected subset).

We show that these findings cannot be explained by traditional risk factors, well-known predictors of future returns, unexpected earnings surprises, or news releases that coincide with the timing of these firm disclosures. Moreover, we find an economically and statistically zero announcement-day return (much like Baxter) in the full sample. This is in contrast to a gradual information diffusion type explanation that is consistent with the empirical pattern of many other regularities (e.g., post-earnings announcement drift, momentum, etc.), in which a large immediate response is followed by a much more modest but persistent drift in the same direction. Instead, the pattern we document is more consistent with investors simply failing to account for or be attentive to the systematic and rich information contained in simple changes to a firm's annual reports. Stock prices exhibit little to no reaction at the time of public filing by a firm even though there is a robust and systematic relationship (whereby changes predict future negative returns and negative real operational realizations), with the information impounded into prices only in the future.

Next, we explore the mechanism at work behind these return results. We show that firms' reporting changes are concentrated in the Management Discussion and Analysis (MD&A) section, the section of the report in which management has the most discretion and flexibility in terms of content. However, in terms of return-rich content, we find that while changes in MD&A section wording do predict large and significant abnormal returns, changes in the text of the Risk Factors section are even more informative for stock returns. For instance, the five-factor alpha on (Nonchangers – Changers) in the Risk Factors section is over 188 basis points per month ($t = 2.76$), or over 22% per year. Further, we find that changes in language referring to the executive (CEO and CFO) team or litigation and lawsuits are especially informative for future returns, as is the increased use of so-called "negative sentiment" words. For instance, changes focused on litigation and lawsuits underperform the nonchangers by over 71 basis points per month, or over 8.5% per year ($t = 3.29$).

We next turn to measures of real activity and show that changes to the 10-Ks predict future earnings, profitability, future news announcements, and even future firm-level bankruptcies. Moreover, much like return realizations, these appear to be largely unanticipated, as the real operational changes are not taken into account by analysts covering the firm—resulting in the 10-K changes significantly predicting future negative earnings surprises and negative cumulative abnormal returns (CARs) around these events.

Note that theory does not predict that changes must lead to negative returns. It may be just as plausible, ex ante, that firms make positive changes in their 10-K text that are ignored by investors and subsequently lead to positive realizations in returns and firm outcomes. Thus, the loading on unsigned text "changes" would be ambiguous. Two pieces of evidence speak to the strong observed negative relationship we document in the data with respect to returns and future outcomes. First, when we use natural language processing (NLP) textual signing of the underlying text of the changes, we note that 86% of changes consist of "negative" sentiment changes. When we separate out the 14% of changes that are "positive" changes, we do find that they predict significantly positive returns in the future. Second, and perhaps causing part of the disproportionate (86 to 14) ratio of negative (bad-news portending) changes, class-action lawsuits have been dominated by claims of the omission of negative news to existing shareholders (i.e., short-sellers have not had success suing firms for not properly disclosing material positive information in a timely fashion). This would asymmetrically increase the risk of failing to report negative information, leading to the asymmetric realizations of observed changes.

We perform a number of robustness checks across firm size, time, industry, firm events, etc. The effect that we document is not driven by any of these factors. In particular, the results are not driven by special firm events (e.g., M&A, SEO, or other large firm events that might necessitate changing of the 10-K) or certain industries, types, or characteristics of firms. In addition, the effect that we find does not appear to be a function of transaction costs or limits to arbitrage. The return results that we document have the following characteristics: they accrue over *months* following the release of the 10-K (so no high-frequency trading is needed); the portfolios have very modest turnover (around the infrequent reporting dates); the effects show up in value-weighted returns across the universe of all publicly traded firms (so are not concentrated in small firms); the average "changer" firm (to be shorted) is actually larger than the average long at \$3.5 billion market cap (vs. \$2.5 billion), and the average changer firm has relatively modest shorting fees—again actually less costly to short than the average stock in the long portfolio.

Our findings are also not driven solely by changes in the length of these documents. As mentioned above, while 10-Ks have observed a large increase in length over time, when we control for document length and document length changes, the impact of the changes we measure in the filings is a large and significant predictor of returns. In sum, controlling for these along with other characteristics and events (e.g., issuance, accruals, etc.), the act of substantively altering a firm's 10-K remains an economically large and statistically robust predictor of future returns and real firm operating changes.

Stepping back, these results, in a sense, require a differential "laziness" of investors with respect to a text compared to numerical financial statement entries. In particular, nearly every table in financial statements is shown with the current year's numbers along with a series of comparable reported numbers for past years. For instance, sales revenue of \$1.5 billion would mean little without the context of prior years' sales revenues. In contrast, investors do not make the same comparison of this year's text to last year's text. This simple comparison, as we show throughout the paper, contains rich information respect to a firm's future operations.

To parameterize and examine the actions of investors in more depth, we would ideally like to identify times when investors allocate more attention to a firm's 10-Ks, and in particular, to changes to 10-Ks. Although this has historically been difficult or impossible to measure, we attempt to do so using novel data from the Securities and Exchange Commission (SEC). Specifically, we filed a Freedom of Information Act (FOIA) request with the SEC to obtain data documenting: (i) every downloaded file from the SEC website's EDGAR (Electronic Data Gathering, Analysis, and Retrieval) downloadable service, (ii) the exact time-stamp indicating when the filing was downloaded, and (iii) the downloader's (partially masked for anonymity) IP address.[8] From this information, we construct a panel data set of 10-K downloading activity (which filings and when) for each investor over time. We use these data to identify 10-K releases (e.g., Apple in 2011) for which a large percentage of investors download not only the current year's 10-K but also the prior year's 10-K in at the same time. These investors plausibly have a higher likelihood of wanting to compare the two—given their joint downloading—than the majority of investors are simply downloading this year's 10-K filing alone. We find that when more investors are potentially comparing 10-Ks and "paying attention" to changes (i.e., by downloading both this year's and last year's 10-K), this attenuates the key return predictability effects we document in this paper, consistent with inattention being a mechanism behind our documented findings.[9] Finally, we investigate the nature of this inattention and show that investors have an easier time digesting qualitative changes when they are explicitly drawn to these changes through comparative statements included in the text (e.g., with statements such as "relative to prior year EBITDA" or "compared to last year"). In this sense, our paper documents new, granular evidence on the origins and characteristics of investor inattention by pinpointing which specific phrases and language patterns can help investors improve their ability to process textual information.

The remainder of the paper is organized as follows. Section I provides a brief background and literature review. Section II describes the data we use and explores the construction of firms' annual and quarterly reports. Section III examines the impact of these choices, and Section IV explores the mechanism driving our results in more detail. Section V concludes.

I. Background and Related Literature

Our paper contributes to several growing literatures, including but not limited to: (i) the broad topic of underreaction in stock prices and the impact of

[8] Note that these data are now publicly available on an ongoing basis.

[9] Note, however, that in these situations in which investors are presumably being more attentive (by simultaneously downloading and comparing year-over-year documents), we find that the *short-run* announcement effects are *more* pronounced, likely because investors immediately detect the changes in the reports and quickly impound these changes into stock prices.

investor inattention, (ii) the use of textual analysis in finance and accounting, and (iii) the information content of firms' disclosure choices.

The magnitude and nature of our return predictability results add new evidence and much-needed granularity to existing stock price underreaction and inattention studies. As described in Tetlock's (2014) review article, several papers document that underreaction is strongest when investors fail to pay attention to informative content. For example, Tetlock (2011) constructs measures of "stale" news stories and demonstrates that investors overreact to stale information and underreact to novel information. Da, Engelberg, and Gao (2011) use Google search activity to pinpoint retail investor attention, while Ben-Raphael, Da, and Israelson (2017) measure institutional attention using Bloomberg search activity. The latter shows that stock price drift is most pronounced for stocks with the least amount of institutional attention. Another novel measure of attention is by Engelberg, Sasseville, and Williams (2012), who show that spikes in TV ratings (presumably driven by retail investors) during the Jim Cramer "Mad Money" show are linked to an overreaction in stock prices for the companies recommended during the show. By contrast, in this paper, we document an acute form of investor inattention that impacts a large cross-section of firms, is centered on the most important corporate disclosures that firms make, and leads to large return predictability. Further, we use novel data from the SEC's log files to demonstrate that variation in attention to these same items (annual report) leads to variation in these return predictability patterns. Finally, we dig into the nature of this inattention and show that investors have an easier time digesting qualitative changes (i.e., changes in text, as opposed to numbers) when they are explicitly drawn to these changes through comparative statements included in the text; when such comparisons are not included, investors simply do not identify meaningful changes to these documents. Our evidence implies that it is not merely the difference between quantitative and qualitative information that matters for investors (as in Engelberg (2008)), but also the way in which qualitative information is constructed and presented.[10] Our paper thus helps micro-found some of the more general evidence on inattention and underreaction in stock prices by clarifying what it is exactly that investors fail to recognize.

In attempting to identify textual changes at the document level, our paper also contributes to the large and fast-growing field of textual analysis. As a result of increased computing power and advances in the field of NLP, many recent papers have tried to employ automated forms of textual analysis to address important questions in finance and accounting; Loughran and McDonald (2016) provide a helpful survey of some of these papers. Most relevant to our study are the articles that analyze the link between textual information in firm disclosures (such as the 10-Ks and 10-Qs that feature in

[10] Note that we also explicitly show (see Tables V, VI, and Table IA.IX in the Internet Appendix) that our document similarity measure is distinct from previously used textual measures that focus on sentiment and/or negative words (such as those in Tetlock, Saar-Tsechansky, and Macskassy (2008) or Loughran and McDonald (2011)).

our analysis) and firm behavior and performance.[11] For example, Li (2008) employs a form of textual analysis and finds that the annual reports of firms with lower earnings (as well as those with positive but less persistent earnings) are harder to interpret. Li (2010) also finds that firms' tone in forward-looking statements in the MD&A section can be used to predict future earnings surprises. Meanwhile, Nelson and Pritchard (2007) explore the use of cautionary language designed to invoke the safe harbor provision under the Private Securities Litigation Reform Act of 1995 and find that firms that are subject to an increases in litigation risk change their cautionary language to a larger degree relative to the previous year, but fail to remove the previous cautionary language after a decrease in litigation risk. In addition, Feldman et al. (2010) find that a positive tone in the MD&A section is associated with modestly higher contemporaneous and future returns and that an increasingly negative tone is associated with lower contemporaneous returns.[12] In our paper, we show that the document similarity measure we employ predicts future returns even after controlling for any impact of disclosure sentiment.

Finally, a handful of additional papers explore other aspects of firm-level annual reports, in studying the impact of different types of corporate disclosure. For instance, Lee (2012) finds less earnings-related information is incorporated into a firm's stock price during the three days following 10-Q filing for firms with longer or less readable 10-Qs. Meanwhile, Dyer, Lang, and Stice-Lawrence (2017) show that 10-Ks have become longer and more complex and examine some of the reasons behind these trends. Perhaps closest to our paper is Brown and Tucker (2011), who focus on year-over-year changes in the text of the MD&A section and find that changes in this section are related to future operating changes (e.g., accounting-based performance measures, as well as liquidity measures). They also find that contemporaneous returns around 10-K filing dates are increasing in changes to the MD&A. Importantly, Brown and Tucker (2011) report that "While MD&A disclosures have become longer over time, they have become more like what investors saw in the previous year . . . Moreover, we find that the price responses to MD&A modifications have weakened over time . . . suggesting a decline in MD&A usefulness." What we show in this paper, in contrast, is that changes in 10-Ks are actually remarkably useful for investors, as they predict large negative returns in the future. So, while we confirm their findings from recent years that announcement effects associated with document changes are close to zero,[13] we show that this is *not* because

[11] Note that before the advent of advanced computing techniques, several papers focused on hand-coded analysis of disclosure content, for example, in the MD&A section of annual reports (see Bryan (1997), Rogers and Grant (1997)). Other papers used survey rankings in order to quantify the level of disclosure (see Clarkson, Kao, and Richardson (1999), Barron, Kile, and O'Keefe (1999)). See Cole and Jones (2005) and Feldman et al. (2010) for a survey of earlier evidence.

[12] See also Muslu et al. (2015), Li (2011), Loughran and McDonald (2016), and Das (2014) for a survey of various textual analysis approaches.

[13] Note that while our results here pertain to the entire 10-K, we have confirmed that the announcement effects associated with changes to the various subsections (including the MD&A) are also statistically indistinguishable from zero.

the document changes have become less useful. Rather, it is because investors are missing the subtle but important signals concentrated in annual reports at the time of their release, perhaps due to their increased complexity and length. Isolating changes using our approach, we find that these have powerful predictability for future asset prices. Thus, far from becoming less informative as past literature suggests, our results indicate that 10-Ks and 10-Qs continue to have a large and significant role to play through the present day. Yet the rich information in these documents—and the changes to the information conveyed—appears to be largely missed by investors. Price revelation, therefore, occurs only gradually over time, with both asset prices and real activity reacting slowly over the next 6 to 12 months after the document changes.

II. Data and Summary Statistics

We draw from a variety of data sources to construct the sample used in this paper. We begin by downloading all complete 10-K, 10-K405, 10-KSB, and 10-Q filings from the SEC's EDGAR website[14] from 1995 to 2014. All complete 10-K and 10-Q filings are in HTML text format and contain an aggregation of all information that is submitted with each firm's file, such as exhibits, graphics, XBRL files, PDF files, and Excel files. Similar to Loughran and McDonald (2011), we focus our analysis on the textual content of the document. We extract only the main 10-K and 10-Q texts in each document and remove all tables (if their numeric character content is greater than 15%), HTML tags, XBRL tables, exhibits, ASCII-encoded PDFs, graphics, XLS, and other binary files.[15]

We use monthly stock returns from the Center for Research in Security Prices (CRSP) and firms' book value of equity and earnings per share from Compustat. We also obtain analyst data from the Institutional Brokers Estimate System (I/B/E/S), and sentiment category identifiers from Loughran and McDonald's (2011) Master Dictionary.

We capture quarter-on-quarter similarities between 10-Q and 10-K filings using four similarity measures taken from the literature in linguistics, textual similarity, and NLP: (i) cosine similarity, (ii) Jaccard similarity, (iii) minimum edit distance, and (iv) simple similarity. We describe each measure, and its respective calculation, below.

The first measure is referred to as the cosine similarity. This measure, which has also been used in the finance literature by Hanley and Hoberg (2010), is computed between two documents—D_1 and D_2—as follows. Let D_{S1} and D_{S2} be the set of terms occurring in D_1 and D_2, respectively. Define T as the union of D_{S1} and D_{S2}, and let t_i be the i^{th} element of T. Define the term frequency vectors of D_1 and D_2 as

$$D_1^{TF} = \left[nD_1\left(t_1\right), nD_1\left(t_2\right), \ldots, nD_1 t_N\right] \text{ and } D_2^{TF} = \left[nD_2\left(t_1\right), nD_2\left(t_2\right), \ldots, nD_2 t_N\right],$$

[14] https://www.sec.gov/edgar/.

[15] Bill McDonald provides a detailed description on how to strip 10-K/Qs down to text files: http://sraf.nd.edu/data/stage-one-10-x-parse-data/ .

where $nD_k(t_i)$ is the number of occurrences of the term t_i in D_k. The cosine similarity between two documents is then defined as

$$Sim\_Cosine = \frac{D_1^{TF} \cdot D_2^{TF}}{||D_1^{TF}|| \times ||D_2^{TF}||},$$

where the dot product, $\cdot$, is the scalar product and the norm, $\|\ \|$, is the Euclidean norm. For a textual and numerical example, consider the following three short texts:

- D_A: We expect demand to increase.
- D_B: We expect worldwide demand to increase.
- D_C: We expect weakness in sales.

It is easy to see that D_A is very similar to D_B and that D_A is more similar to D_B than it is to D_C. The cosine similarity of D_A and D_B is computed as follows: the union $T(D_A, D_B)$ is

$$T\,(D_A, D_B) = \left[\text{we, expect, worldwide, demand, to, increase}\right],$$

and term frequency vectors of D_A and D_B are

$$D_A^{TF} = \left[1,\ 1,\ 0,\ 1,\ 1,\ 1\right] \text{ and } D_B^{TF} = \left[1,\ 1,\ 1,\ 1,\ 1,\ 1\right],$$

and hence cosine similarity score of D_A and D_B is

$$Sim\_Cosine\,(D_A, D_B) = \frac{(1 \times 1 + 1 \times 1 + 0 \times 1 + 1 \times 1 + 1 \times 1 + 1 \times 1)}{\left(\sqrt{1^2 + 1^2 + 1^2 + 1^2 + 1^2}\right) \times \left(\sqrt{1^2 + 1^2 + 1^2 + 1^2 + 1^2 + 1^2}\right)} = 0.91.$$

Similarly, the cosine similarity of D_A and D_C is computed as follows: the union $T(D_A, D_C)$ of D_A and D_C is

$$T\,(D_A, D_C) = \left[\text{we, expect, demand, to, increase, weakness, in, sales}\right],$$

and the term frequency vectors of D_A and D_C are

$$D_A^{TF} = \left[1,\ 1,\ 1,\ 1,\ 1,\ 0,\ 0,\ 0\right] \text{ and } D_C^{TF} = \left[1,\ 1,\ 0,\ 0,\ 0,\ 1,\ 1,\ 1\right],$$

in which case, the cosine similarity score of D_A and D_C is

$$Sim\_Cosine\,(D_A, D_C) = \frac{(1 \times 1 + 1 \times 1 + 1 \times 0 + 1 \times 0 + 1 \times 0 + 0 \times 1 + 0 \times 1 + 0 \times 1)}{\left(\sqrt{1^2 + 1^2 + 1^2 + 1^2 + 1^2}\right) \times \left(\sqrt{1^2 + 1^2 + 1^2 + 1^2 + 1^2}\right)} = 0.40.$$

Clearly, D_A is more similar to D_B than to D_C and the cosine similarity measures capture this difference in similarity.

Out second similarity measure, the Jaccard similarity measure, uses the same term frequency vectors/sets as the cosine similarity measure and is defined as

$$Sim\_Jaccard = \frac{\left|D_1^{TF} \cap D_2^{TF}\right|}{\left|D_1^{TF} \cup D_2^{TF}\right|}.$$

In other words, the Jaccard similarity measure is computed as the size of the intersection divided by the size of the union of the two term frequency sets. Note that the Jaccard measure is binary (each word is counted only once in a given set) while the Cosine similarity measure includes frequency (includes counts of each word). Using the same D_A, D_B, and D_C as above, the Jaccard similarities are

$$Sim\_Jaccard\,(D_A, D_B) = \frac{|\{\text{we, expect, demand, to, increase}\}|}{|\{\text{we, expect, worldwide, demand, to, increase}\}|} = \frac{5}{6} = 0.83.$$

$$Sim\_Jaccard\,(D_A, D_C) = \frac{|\{\text{we, expect}\}|}{\left|\{\text{we, expect, demand, to, increase, weakness, in, sales}\}\right|} = \frac{2}{8} = 0.25.$$

The third similarity measure we employ, *Sim_MinEdit*, is computed by counting the smallest number of operations required to transform one document into the other. Again using D_A, D_B, and D_C as above, transforming D_A to D_B only requires adding the word "worldwide," while transforming D_A to D_C requires deleting the three words "demand," "to," and "increase," and adding the three words "weakness," "in," and "sales."

Finally, our fourth similarity measure, *Sim_Simple*, uses a simple side-by-side comparison method. Specifically, we use the function "Track Changes" in Microsoft Word or the function "diff" in the Unix/Linux terminal to compare the old document D_1 with the new document D_2. We first identify the changes, additions, and deletions while comparing the old document with the new document. To do so, we count the number of words in those changes, additions, and deletions and normalize the total count by the average size of the old document D_1 and the new document D_2 :

$$c = \left[\text{additions} + \text{deletions} + \text{changes}\right] / \left[(Size\ D_1 + Size\ D_2)/2\right].$$

To obtain a similarity measure that has values between [0, 1], where one means that the two documents are identical, as with the prior three similarity measures we then normalize by scaling c to compute *Sim_Simple* as:

$$Sim\_Simple = [c_{\max} - c]\,/c_{\max}.$$

Note that each annual 10-K report contains 15 schedules, and each quarterly 10-Q report contains 10 schedules. The common schedules for both 10-K and

	Form 10-K
Item 1	Business
Item 1A	Risk Factors
Item 2	Properties
Item 3	Legal Proceedings
Item 4	Mine Safety Disclosures
Item 5	Market for Registrant's Common Equity, Related Stockholder Matters and Issuer Purchases of Equity Securities
Item 6	Selected Financial Data
Item 7	Management's Discussion and Analysis of Financial Condition and Results of Operations
Item 7A	Quantitative and Qualitative Disclosures About Market Risk
Item 8	Financial Statements and Supplementary Data
Item 9	Changes in and Disagreements With Accountants on Accounting and Financial Disclosure
Item 9A	Controls and Procedures
Item 9B	Other Information
Item 10	Directors, Executive Officers and Corporate Governance
Item 11	Executive Compensation
Item 12	Security Ownership of Certain Beneficial Owners and Management and Related Stockholder Matters
Item 13	Certain Relationships and Related Transactions, and Director Independence
Item 14	Principal Accounting Fees and Services

	Form 10-Q
Item 1	Financial Statements
Item 2	Management's Discussion and Analysis of Financial Condition and Results of Operations
Item 3	Quantitative and Qualitative Disclosures About Market Risk
Item 4	Controls and Procedures
Item 21	Legal Proceedings
Item 21A	Risk Factors
Item 22	Unregistered Sales of Equity Securities and Use of Proceeds
Item 23	Defaults Upon Senior Securities
Item 24	Mine Safety Disclosures
Item 25	Other Information

Figure 6. Section definitions in 10-Ks and 10-Qs.

10-Q reports are: Management's Discussion and Analysis of Financial Condition and Results of Operations, Risk Factors, Legal Proceedings, Quantitative and Qualitative Disclosure about Market Risks, Control and Procedures, and Other Information. These schedules (or "items") of 10-K and 10-Q reports are listed in Figure 6. We identify the textual content of each schedule by capturing regular expressions that contain the word "item" and the schedule name. Since schedule labels are very inconsistent across filings, we process all 10-K and 10-Q filings many times to capture the exceptions. First, we use regular expressions to capture the most common structure for schedule titles: lines that start with "Item" + "a number" + "title name." We then capture exceptions to the common rule, for example, lines with only "Item" +

Table I

Summary Statistics for Firms' 10-Ks and 10-Qs

Panel A reports summary statistics for 10-Ks and 10-Qs over the period 1995 to 2014. *Document Size* is the number of words in each document. *Sentiment of Change* is the number of negative words in *Change* normalized by the number of words in *Change*, where *Change* is additions, deletions, and other changes identified from the function "diff" in Unix/Linux or the function "Track Changes" in Microsoft Word. *Uncertainty of Change* and *Litigiousness of Change* are the number of words categorized as uncertainty and litigiousness, respectively, normalized by the size of *Change*. *Change CEO* and *Change CFO* are indicator variables equal to 1 if the 10-K or 10-Q mentions a change in CEO or CFO, respectively. Sentiment category identifiers (e.g., negative, uncertainty, litigious) come from Loughran and McDonald's (2011) Master Dictionary. Panel B reports the summary statistics of four different measures of document similarity. Panel C reports the correlations between the four similarity measures used in this paper. *Sim_Cosine* is the cosine similarity measure, *Sim_Jaccard* is the Jaccard similarity measure, *Sim_MinEdit* is the minimum edit distance similarity measure, and *Sim_Simple* is the simple side-by-side comparison. Details on how we compute the four similarity measures can be found in the Internet Appendix

Panel A: Summary Statistics of Document Charateristics

	Count	Mean	*SD*	1%	50%	99%
Document Size—10-K	86,965	44,508.81	36,479	7,573	35,787	180,388
Document Size—10-Q	258,271	15,805.9	20,542.78	1,327	10,674	97,521
Sentiment of Change	345,639	0.07736	0.0179074	0	0.000146	0.003503
Uncertainty of Change	345,639	0.0005234	0.0110212	0	0.0001286	0.0026464
Litigiousness of Change	345,639	0.0009594	0.016019	0	0.0000668	0.0051982
Change CEO	345,639	0.0556158	0.2291785	0	0	1
Change CFO	345,639	0.0242542	0.1538377	0	0	1

Panel B: Summary Statistics of Similarity Measures

	Count	Mean	*SD*	1%	50%	99%
Sim_Cosine	327,130	0.8721032	0.1910398	0.1367042	0.947125	0.9951641
Sim_Jaccard	327,130	0.3948525	0.190596	0.0364943	0.4108108	0.765858
Sim_MinEdit	327,130	0.3763384	0.1714118	0.0516403	0.3927964	0.7649283
Sim_Simple	327,130	0.1464663	0.0927251	0.0427717	0.1171773	0.4283921

Panel C: Correlation

	Sim_Cosine	*Sim_Jaccard*	*Sim_MinEdit*	*Sim_Simple*
Sim_Cosine	1.0000			
Sim_Jaccard	0.6049	1.0000		
Sim_MinEdit	0.5031	0.7921	1.0000	
Sim_Simple	0.2076	0.4815	0.5834	1.0000

"a number," lines with only "number" + "title names," etc., while also ensuring that each schedule is captured exactly once. We repeat this process many times and incorporate new exceptions each time.

Table I presents summary statistics for our final data set, which consists of all 10-Ks and 10-Qs downloaded from the SEC EDGAR websites from 1995 to 2014. In Panel A, *Document Size* is the number of words in each report, and *Size of Change* is the number of words that change relative to a prior report (in the case of a 10-K, the change is measured relative to the prior year's 10-K, and in the case of a 10-Q, the change is measured relative to the same quarter's 10-Q in the prior year). We find that the average 10-K contains 44,430 words, while the average 10-Q contains roughly one-third as many words (15,724).

For some of our tests of the mechanism, we also draw sentiment category identifiers and word lists (e.g., measures of negative words, uncertainty, litigiousness, etc.) from Loughran and McDonald's (2011) Master Dictionary.[16] In Panel A, *Sentiment of Change* is the number of negative words normalized by the size of the change, and *Uncertainty of Change* and *Litigiousness of Change* are the number of words categorized by "uncertainty" and "litigiousness," respectively, normalized by the size of the change. Finally, we parse 10-K/Q documents for mentions of CEO or CFO turnover and define *Change CEO* and *Change CFO* as indicator variables equal to 1 if the 10-K or 10-Q mentions a change in CEO or CFO, respectively. More specifically, we search for instances in which a word from the set {appoint, elect, hire, new, search} and a word from the set {CEO, CFO, Chief Executive Officer, Chief Financial Officer} appear within 10 words of each other. The table shows that CEO and CFO changes are mentioned in roughly 2% to 5% of the reports, on average.

Panel B of Table I presents the summary statistics for the four similarity measures. Each of the measures ranges from zero to one, but the ranges differ across the four measures. For example, the distribution of the *Sim_Cosine* measure is fairly narrow, with a mean of 0.87 and a standard deviation of 0.20, while the distribution of the *Sim_Simple* measure is centered at a much lower level, with a mean of 0.15 and a standard deviation of 0.10. Recall that higher values indicate a higher degree of document similarity across years between the 10-Ks (or 10-Qs), while lower values indicate more changes across documents. Also, note that we winsorize any outliers of these measures (at the 1st and 99th percentiles) before including them in our subsequent analyses.

Panel C of Table I reports the correlations between the measures. All four measures are strongly positively correlated with each other, although the correlation between *Sim_Simple* and *Sim_Cosine* is only 0.19, all of the other pairwise correlations between the four measures exceed 0.5.

III. The Implications of Changes in Reporting Behavior

In this section, we examine the implications of firms' decisions to change the language and construction of their SEC filings. In particular, we explore the nature of these changes and their implications for firms' future actions and outcomes.

We begin by analyzing the future stock returns associated with firms that change their reports substantially versus those that do not. First, we compute standard calendar-time portfolios. We then control for additional determinants of returns by employing Fama-MacBeth monthly cross-sectional regressions.

[16] These words are available at: https://sraf.nd.edu/textual-analysis/resources/.

A. Calendar-Time Portfolio Returns

For each of the four similarity measures described in the previous section, we compute quintiles each month based on the prior month's distribution of similarity scores across all stocks. For firms with a fiscal year-end in December, we use the following reports: for calendar quarter Q1, we use the release of a firm's 10-Q, which generally occurs in April or May; for calendar quarter Q2, we use another release of a firm's 10-Q, which generally occurs in July or August; for calendar quarter Q3, we use another release of a firm's 10-Q, which generally occurs in October or November; and for the year-end results we use the release of the full-year 10-K, which typically occurs in February of March.[17] Similarity scores are computed relative to the prior-year report that lines up in calendar time with the report in question (so, e.g., 2005 Q1 10-Qs are compared with 2004 Q1 10-Qs).[18] Stocks enter the portfolio in the month after the public release of one of their reports, which induces a lag in our portfolio construction. Note that in all of our tests, firms are held in the portfolio for three months. Portfolios are rebalanced monthly. The average monthly returns are reported in Table II.

Panel A of Table II presents equal-weighted calendar-time portfolio returns. Quintile 1 (Q1) corresponds to firms that have the least similarity between documents this year and last year, and hence, this portfolio consists of the "big changers." Quintile 5 (Q5) corresponds to firms that have the most similarity in their documents across years, and hence this portfolio represents the "little to no changers." Q5 to Q1 refers to the long-short (L/S) portfolio that goes long Q5 and short Q1 each month.

Panel A shows that the L/S portfolio earns a large and significant abnormal return ranging between 18 and 45 basis points per month. This result is unaffected by controlling for the three Fama-French factors (market, size, and value), or two additional momentum and liquidity factors. These results suggest that the return spreads we see between these portfolios are not driven by systematic loadings on commonly known risk factors. Notably, all four measures of similarity deliver this pattern, suggesting that our results are not driven by the particular way in which we compute year-over-year changes in the documents. This finding indicates that firms that make significant changes to their disclosures in a given year experience lower future returns. Firms that

[17] See Figure IA.IV in the Internet Appendix for a depiction of the average clustering of release dates, by month, for the 10-Ks and 10-Qs in our sample. Also note that for firms with "off-cycle" fiscal year-ends, we use their reports in an analogous way as presented here, but incorporate the different timing. For example, firms with a fiscal year-end in June typically release their annual 10-Ks in August and September, and for the other three calendar quarters we would analyze their 10-Qs instead.

[18] Note that due to seasonality in sales and operations (and the associated discussion of the seasonal patterns in the company filings), the most comparable report for a given 10-K is the prior-year 10-K (as opposed to the prior-quarter 10-Q), and the most comparable report for a given 10-Q is the prior-year 10-Q in that same quarter. As shown in Table IA.XIII in the Internet Appendix, when we restrict our sample to year-over-year changes in the text of 10-Ks (and hence remove all 10-Q changes), or when we limit attention to year-on-year changes in the text of 10-Qs (and hence remove all 10-K changes), our main portfolio result from Table II is similar.

Table II

Main Results—Calendar-Time Portfolio Returns

This table reports calendar-time portfolio returns. Portfolio returns are multiplied by 100. Sim_*Cosine* is the cosine similarity measure, *Sim_Jaccard* is the Jaccard similarity measure, *Sim_MinEdit* is the minimum edit distance similarity measure, and *Sim_Simple* is the simple side-by-side comparison. For each of the four similarity measures, we compute quintiles based on the prior year's distribution of similarity measures across all stocks. Stocks then enter the quintile portfolios in the month after the public release of one of their 10-K or 10-Q reports. Stocks are held in the portfolio for three months. We report excess returns (return minus risk-free rate), Fama-French three-factor alphas (market, size, and value), and five-factor alphas (market, size, value, momentum, and liquidity). Panel A reports equal-weighted portfolio returns, and Panel B reports value-weighted portfolio returns. t-Statistics are reported below the estimates. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively

Panel A: Equally Weighted

	Sim_Cosine						*Sim_Jaccard*					
	Q1	Q2	Q3	Q4	Q5	Q5 – Q1	Q1	Q2	Q3	Q4	Q5	Q5 – Q1
Excess return	0.63*	0.72*	0.72**	0.85**	0.92***	0.31***	0.59	0.67*	0.69*	0.82**	0.98***	0.38***
	(1.68)	(1.96)	(2.11)	(2.59)	(2.80)	(3.13)	(1.48)	(1.74)	(1.89)	(2.35)	(3.01)	(2.65)
Three-factor alpha	−0.15**	−0.08	−0.05	0.09	0.18***	0.34***	−0.16**	−0.10	−0.06	0.08	0.28***	0.44***
	(−2.19)	(−1.10)	(−0.72)	(1.21)	(2.66)	(4.45)	(−1.99)	(−1.22)	(−0.81)	(1.05)	(3.47)	(4.56)
Five-factor alpha	−0.12*	−0.05	−0.04	0.10	0.21***	0.32***	−0.14*	−0.07	−0.06	0.09	0.28***	0.42***
	(−1.75)	(−0.74)	(−0.53)	(1.29)	(3.28)	(4.21)	(−1.84)	(−0.93)	(−0.86)	(1.19)	(3.57)	(4.31)
	Sim_MinEdit						*Sim_Simple*					
	Q1	Q2	Q3	Q4	Q5	Q5 – Q1	Q1	Q2	Q3	Q4	Q5	Q5 – Q1
Excess return	0.61	0.66*	0.70*	0.86**	0.99***	0.36***	0.72*	0.79**	0.82**	0.90***	0.90***	0.18
	(1.60)	(1.78)	(1.94)	(2.58)	(3.36)	(2.69)	(1.87)	(2.12)	(2.34)	(2.73)	(3.04)	(1.20)
Three-factor alpha	−0.19**	−0.14*	−0.10	0.10	0.30***	0.48***	−0.08	−0.02	0.03	0.14**	0.20**	0.28***
	(−2.56)	(−1.91)	(−1.52)	(1.37)	(4.00)	(5.96)	(−1.09)	(−0.21)	(0.38)	(2.01)	(2.57)	(3.22)
Five-factor alpha	−0.15**	−0.11	−0.08	0.12*	0.30***	0.45***	−0.06	0.03	0.04	0.16**	0.21***	0.27***
	(−2.14)	(−1.59)	(−1.31)	(1.70)	(4.11)	(5.46)	(−0.89)	(0.37)	(0.63)	(2.30)	(2.68)	(3.01)

(*Continued*)

Table II—*Continued*

Panel B: Value Weighted

	Sim_Cosine						*Sim_Jaccard*					
	Q1	Q2	Q3	Q4	Q5	Q5 – Q1	Q1	Q2	Q3	Q4	Q5	Q5 – Q1
Excess return	0.43	0.47	0.55*	0.73**	0.78**	0.34**	0.23	0.32	0.48	0.61*	0.79**	0.56***
	(1.32)	(1.45)	(1.74)	(2.35)	(2.40)	(2.53)	(0.64)	(0.88)	(1.33)	(1.84)	(2.47)	(3.75)
Three-factor alpha	−0.15*	−0.15*	−0.04	0.10	0.20*	0.35***	−0.32***	−0.21	−0.09	0.07	0.23**	0.54***
	(−1.84)	(−1.79)	(−0.49)	(1.17)	(1.97)	(2.63)	(−2.97)	(−1.30)	(−0.73)	(0.60)	(2.01)	(4.08)
Five-factor alpha	−0.12	−0.19**	−0.06	0.12	0.23**	0.34**	−0.23**	−0.17	−0.07	0.13	0.23**	0.46***
	(−1.38)	(−2.13)	(−0.64)	(1.36)	(2.23)	(2.53)	(−2.20)	(−1.04)	(−0.59)	(1.18)	(2.11)	(3.44)
	Sim_MinEdit						*Sim_Simple*					
	Q1	Q2	Q3	Q4	Q5	Q5 – Q1	Q1	Q2	Q3	Q4	Q5	Q5 – Q1
Excess return	0.42	0.45	0.62*	0.76**	0.83***	0.39**	0.24	0.61*	0.77**	0.78**	0.74**	0.50***
	(1.25)	(1.38)	(1.88)	(2.42)	(2.92)	(2.31)	(0.69)	(1.88)	(2.45)	(2.53)	(2.48)	(2.69)
Three-factor alpha	−0.18**	−0.16*	−0.01	0.17*	0.28**	0.46***	−0.39***	0.02	0.18*	0.19*	0.19	0.58***
	(−2.29)	(−1.91)	(−0.14)	(1.74)	(2.49)	(3.06)	(−3.89)	(0.18)	(1.87)	(1.88)	(1.45)	(3.59)
Five-factor alpha	−0.17**	−0.14*	0.00	0.17*	0.21*	0.37**	−0.36***	0.05	0.18*	0.18*	0.15	0.51***
	(−2.02)	(−1.67)	(0.04)	(1.78)	(1.84)	(2.45)	(−3.49)	(0.66)	(1.78)	(1.71)	(1.15)	(3.14)

do *not* make changes are also associated with positive abnormal returns. Later in the paper, we explore the possible mechanisms behind this return result.

Panel B of Table II presents value-weighted portfolio returns, computed as in Panel A except that each stock in the portfolio is weighted by its (lagged) market capitalization. Panel B shows that the value-weighted portfolio returns are similar but somewhat larger in magnitude to the equal-weighted results, with the value-weighted L/S portfolio earning up to 58 basis points per month ($t = 3.59$) depending on the similarity measure employed. The portfolio return spread shows up on both sides, with "changers" (Q1) experiencing negative future returns and "nonchangers" (Q5) experiencing positive future returns. Importantly, Figure IA.3 in the Internet Appendix plots the annual time series of excess returns documented in Table II and shows that the number of positive excess return years is distributed quite evenly throughout the sample period, in line with the view that the abnormal returns documented in this paper are not concentrated in just a few quarters or years.[19]

We explore the evolution of both the long and the short legs of this portfolio using event-time returns in Figure 7. As can be seen from the event-time returns in Figure 6, any positive alpha on the Q5 long side (the "little to no changers") quickly reverts to zero, while the negative alpha persists and increases up to six months out—never reversing. Panel A of Figure 7 explores the longer term returns by computing the average CAR for each quintile portfolio sorted based on firms' similarity scores (here the *Sim_Jaccard* measure is used) from month one to six following portfolio formation. The panel shows that L/S returns accrue gradually over the course of the subsequent six months and do not reverse. Additionally, the long-term poor performance of Q1 (the "changers") is particularly strong and persistent in this figure.

Panel B of Figure 7 then takes an even more granular look at the L/S return effect by exploring the event-time announcement returns around the public release of these filings (from days $t-10$ to $t+10$). This panel shows that, like the example of Baxter International, Inc., there is no statistically or economically detectable effect around the announcement of these filings, but rather the return effect we document in this paper accrues gradually over the course of the following six months and does not revert. Taken as a whole, Figure 7 depicts that the information in a firm's decision to significantly change its reporting practices has a long-lasting impact on the firm value that does not accrue around the release of reports, but rather gradually through price revelation over time.

B. Characteristics of Quintile Portfolios

The finding that a significant portion of the return spread documented in Table II and Figure 7 comes from the short side raises questions about the

[19] To further confirm that our results are not driven by a few special years or quarters, we also exclude 2000, 2001, 2008, and 2009 from our portfolio tests. We find that the abnormal returns documented in Table II remain large and significant.

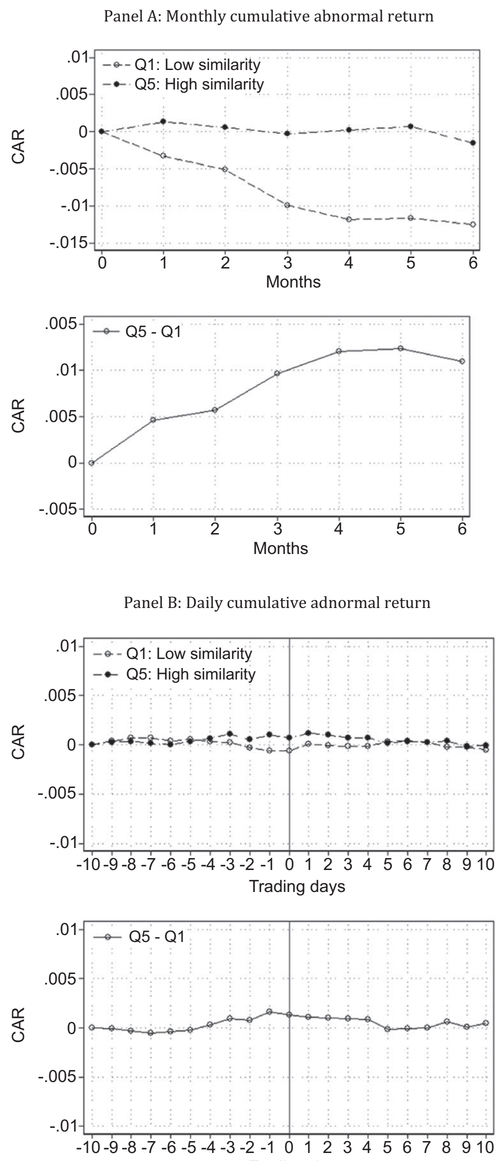


Figure 7. Event time returns. This figure plots weighted-average cumulative abnormal returns for the top (highest similarity) and bottom (lowest similarity) quintile portfolios. We compute quintiles based on the prior year's distribution of Jaccard similarity across all stocks. Abnormal returns are returns adjusted for market returns. Event dates are dates associated with public release of a 10-K or 10-Q. Panel A shows the weighted-average monthly cumulative abnormal returns for months one to six. Panel B shows the weighted-average daily cumulative abnormal returns for 10 days before to 10 days after the public release of a 10-K or 10-Q.

Table III
Characteristics of Quintile Portfolios

This table reports mean *Market Value of Equity* (determined at the end of the months in which the quintile cut-off points are determined, in $1,000 dollars), *Monthly Turnover*, *Shorting Fees*, and *Sentiment of Changes* of the five quintile portfolios.

	Q1	Q2	Q3	Q4	Q5
Market Value of Equity	3,507,587	3,219,430	2,829,955	2,504,717	2,464,603
Monthly Turnover	0.0663	0.0850	0.0804	0.0867	0.0706
Shorting Fees (bps)	71.6958	80.6361	92.0500	87.0690	73.5453
Sentiment of Changes	0.0016	0.0008	0.0006	0.0005	0.0004

composition and characteristics of both sides of the L/S portfolio. For example, it could be the case that the short side simply contains a set of smaller firms that are difficult (and expensive) to short. Or perhaps there is not a significant turnover of small or illiquid stocks to trade. Both of these possibilities might make the returns we document fall within simple limits of arbitrage. Table III presents the average size, turnover, shorting costs (in basis points), and sentiment (as defined in Table I) for all five quintile portfolios. As can be seen, there is little evidence that the short side contains an unusual set of firms on average; if anything, the firms in Q1 appear to be slightly larger and have lower average shorting costs. The only notable difference appears to be in the sentiment of the text of the firms' filings, a finding that we explore in more detail below. Moreover, given that turnover is so modest, value-weighted returns are a bit larger than equal-weighted returns, our sample comprises the entire universe of publicly traded firms (i.e., we do not restrict attention to a small set of firms or industries as every publicly traded firm is mandated to file 10-Ks and 10-Qs) and hence generate in large diversified portfolios for each quintile, and returns accrue only slowly over the following six months, we do not believe that limits to arbitrage contribute significantly to the return regularities observed.

C. Fama-MacBeth Regressions

We next run monthly Fama-MacBeth cross-sectional regressions of future individual firm-level stock returns on a host of known return predictors, plus our four similarity measures. As Table IV shows, each similarity measure is a positive and significant predictor of future stock returns, implying that those firms that make large changes to their reports experience lower future returns. This result continues to hold when we include a variety of additional return predictors: last month's (or last quarter's) standardized unexpected earnings surprise (*SUE*); *Size*, the log market value of equity; *log*(*BM*), the log book value of equity over market value of equity; *Ret*(−1,0), the previous month's return; and *Ret*(−12,−2), the cumulative stock return from month $t-12$ to month $t-2$. SUE is defined as the Compustat-based standardized unexpected earnings and is computed as in Livnat and Mendenhall (2006). The Compustat earnings

Table IV

Main Results—Fama-MacBeth Regressions

This table reports results of Fama-MacBeth cross-sectional regressions of individual firm-level stock returns on our four similarity measures and a number of known return predictors. Return, the dependent variable, is multiplied by 100. *Sim_Cosine* is the cosine similarity measure, *Sim_Jaccard* is the Jaccard similarity measure, *Sim_MinEdit* is the minimum edit distance similarity measure, and *Sim_Simple* is the simple side-by-side comparison. *Size* is log of market value of equity, *log*(*BM*) is log book value of equity over market value of equity, *Ret*(–1,0) is the previous month's return, and *Ret*(–12,–1) is the cumulative return from month –12 to month –1. *SUE* is the standardized unexpected earnings and computed as actual earnings per share minus average analyst forecast earnings per share, divided by the standard deviation of forecasts. *t*-Statistics are reported below the estimates. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively

	Ret											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Sim_Cosine	0.45***	0.31**	0.37**									
	(2.65)	(2.51)	(2.18)									
Sim_Jaccard				0.82***	0.66***	0.59***						
				(3.26)	(3.82)	(3.41)						
Sim_MinEdit							0.54**	0.41***	0.29**			
							(2.54)	(2.78)	(2.00)			
Sim_Simple										0.04**	0.03**	0.03**
										(2.10)	(2.25)	(2.11)
Size		0.00	0.00		0.01	0.01		0.01	0.01		0.01	0.00
		(0.11)	(0.05)		(0.25)	(0.11)		(0.26)	(0.10)		(0.24)	(0.05)
log(*BM*)		0.17*	0.16*		0.17*	0.16*		0.17*	0.16*		0.17*	0.16*
		(1.89)	(1.71)		(1.88)	(1.70)		(1.90)	(1.72)		(1.87)	(1.70)
Ret(–1,0)		−0.03***	−0.02***		−0.03***	−0.02***		−0.03***	−0.02***		−0.03***	−0.02***
		(−3.93)	(−3.68)		(−3.97)	(–3.70)		(−3.97)	(−3.69)		(−3.99)	(−3.71)
Ret(−12,−1)		0.64**	0.36		0.64**	0.36		0.64**	0.36		0.64**	0.37
		(2.34)	(1.25)		(2.34)	(1.25)		(2.34)	(1.24)		(2.35)	(1.29)
SUE			0.07***			0.07***			0.07***			0.07***
			(6.56)			(6.54)			(6.56)			(6.60)
Cons	0.58	0.58	0.67	0.64	0.46	0.69	0.76**	0.57	0.84	−0.02	−0.02	−0.01
	(1.45)	(0.67)	(0.57)	(1.64)	(0.52)	(0.58)	(1.98)	(0.64)	(0.71)	(−1.31)	(−1.02)	(−0.71)
R^2	0.00	0.04	0.05	0.00	0.04	0.05	0.00	0.04	0.05	0.00	0.04	0.05
N	713,451	713,451	496,084	713,451	713,451	496,084	713,451	713,451	496,084	713,680	713,680	495,931

surprise is based on the assumption that EPS follows a seasonal random walk, where the best expectation of the EPS in quarter t is the firm's reported EPS in the same quarter of the previous fiscal year. In terms of magnitude, the coefficient on *Sim_Simple* in column (12) (= 0.0292, $t = 2.11$), for example, implies that given a one-standard-deviation decrease in a stock's document similarity across years, returns are reduced by 36 basis points per month in the future.

IV. Mechanism

In this section, we explore the mechanism at work behind our key return results.

A. Explaining Changes in Reporting Behavior

We begin by regressing our similarity measures on several characteristics describing the documents in question. The goal of this exercise is to understand better what factors help explain changes in similarity for a given firm's document overtime.

We construct measures based on specific words, as well as sentiment-type measures based on available word dictionaries, in particular, using sentiment category identifiers and word lists (e.g., measures of negative words, uncertainty, litigiousness, etc.) from Loughran and McDonald's (2011) Master Dictionary. We construct *Sentiment of Change* as the number of negative words normalized by the size of the change; *Uncertainty of Change* and the *Litigiousness of Change* as the number of words categorized by "uncertainty" and "litigiousness," respectively, normalized by the size of the change; and *Change CEO* and *Change CFO* as indicator variables equal to 1 if the 10-K or 10-Q mentions a change in CEO or CFO, respectively.

Table V presents the results of panel regressions of document similarity (measured here using *Sim_Simple*)[20] on the above document characteristics, with firm and time fixed effects, and clustering at the firm level. The results show that less similarity (i.e., more changes) across documents is associated with more (negative) sentiment, higher uncertainty, more litigiousness, and more frequent mentions of CEO and CFO changes.[21] Each of these findings is highly statistically significant, and together they imply that the changes in reporting practices that we identify are associated with significant changes in the operations or prospects of the firm in question.

In Table VI, we explore the extent to which our return results are driven by aspects of the filings other than our specific measures of changes in document year-over-year similarity. For example, low sentiment, the length

[20] The results for the three other measures of similarity yield the same conclusions.

[21] This is consistent with Tetlock (2007) and Tetlock, Saar-Tsechansky, and Macskassy (2008), who show that investors pay special attention to negative words used in media reports. See Table IA.XII in the Internet Appendix for portfolio returns corresponding to double-sorts on similarity and (negative) sentiment.

Table V
Potential Mechanism

This table explores the potential mechanism behind our results. We regress our similarity measure on a host of characteristics describing the document in question. *Sim_Simple*, the dependent variable, is multiplied by 100. *Sentiment of Change* is the number of negative words in *Change* normalized by the number of words in *Change*, where *Change* is computed as the number of additions, deletions, and other changes identified from the function "diff" in Unix/Linux or the function "Track Changes" in Microsoft Word. *Uncertainty of Change* and *Litigiousness of Change* are the number of words categorized as uncertainty and litigiousness, respectively, normalized by the size of *Change*. *Change CEO* and *Change CFO* are indicator variables equal to 1 if the 10-K or 10-Q mentions a change in CEO or CFO, respectively. Sentiment category identifiers (e.g., negative, uncertainty, and litigious) come from Loughran and McDonald's (2011) Master Dictionary. All regressions include firm and month fixed effects. Standard errors are clustered at the firm level. *t*-Statistics are reported below the estimates. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

			Sim_Simple		
	(1)	(2)	(3)	(4)	(5)
Sentiment of Change	−2.49***				
	(−37.83)				
Uncertainty of Change		−3.57***			
		(−34.15)			
Litigiousness of Change			−0.12**		
			(−2.11)		
Change CEO				−0.01***	
				(−7.10)	
Change CFO					−0.01***
					(−5.75)
Cons	0.18***	0.19***	0.18***	0.18***	0.18***
	(28.52)	(17.40)	(17.25)	(17.31)	(17.29)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes	Yes
R^2	0.06	0.07	0.07	0.07	0.06
N	338,138	338,138	338,138	338,138	338,138

of the document, or changes in the length of the document might be more important predictors of returns or might drive out the forecasting power of our measure of (dis)similarity. We also construct the measure *Sentiment of Change is Positive* to focus on the sentiment of the changes we document, and to separate the positive and negative components of sentiment. The results show that even after controlling for the document-level characteristics above (in Fama-Macbeth monthly return predictability set up as in Table V), that similarity remains a large and significant predictor of future returns (t = 3.82). Decreases in sentiment alone do predict negative returns, as do increases in the length of the filings, but neither of these measures drives out the predictability of year-over-year changes in document similarity.[22]

[22] Note that in Table IA.II in the Internet Appendix, we also explore interactions between similarity and document-level characteristics such as sentiment. We find even stronger return pre-

Table VI

Fama-MacBeth Regressions, Controlling for Sentiment and Document Size

This table reports results of Fama-MacBeth cross-sectional regressions of individual firm-level stock returns on our *Sim_Jaccard* similarity measures and a number of known return predictors. *Return*, the dependent variable, is multiplied by 100. *Sim_Jaccard* is the Jaccard similarity measure. *Sentiment of Change is Positive* is the number of positive words in *Change*, normalized by the size of *Change*, where *Change* is additions, deletions, and other changes identified from the function "diff" in Unix/Linux or the function "Track Changes" in Microsoft Word. *Size* is log of market value of equity, *log*(*BM*) is log book value of equity over market value of equity, *Ret*(–1,0) is previous month's return, and *Ret*(–12,–1) is the cumulative return from month –12 to month –1. *Log*(*Document Size*) is the logarithm of the number of words in a document. Δ *Log*(*Document Size*) is the quarter-on-quarter change in *Log*(*Document Size*). *t*-Statistics are reported below the estimates. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

		Ret	
	(1)	(2)	(3)
Sim_Jaccard	0.57***	0.58***	0.58***
	(3.45)	(3.78)	(3.82)
Sentiment of Change is Positive	0.19***	0.21***	0.21***
	(3.85)	(4.21)	(4.33)
Log(*Document Size*)		0.01	0.03
		(0.65)	(1.40)
Δ *Log*(*Document Size*)			−0.41**
			(−2.30)
Size	0.00	0.00	−0.00
	(0.10)	(0.07)	(−0.01)
log(*BM*)	0.17	0.16	0.16
	(1.64)	(1.5858)	(1.5471)
Ret(−1,0)	−0.03***	−0.03***	−0.03***
	(−4.15)	(−4.19)	(−4.20)
Ret(−12, −1)	0.74***	0.74***	0.74***
	(2.71)	(2.70)	(2.69)
Cons	0.55	0.41	0.25
	(0.60)	(0.48)	(0.30)
R^2	0.0437	0.0445	0.0448
N	713,451	713,451	713,451

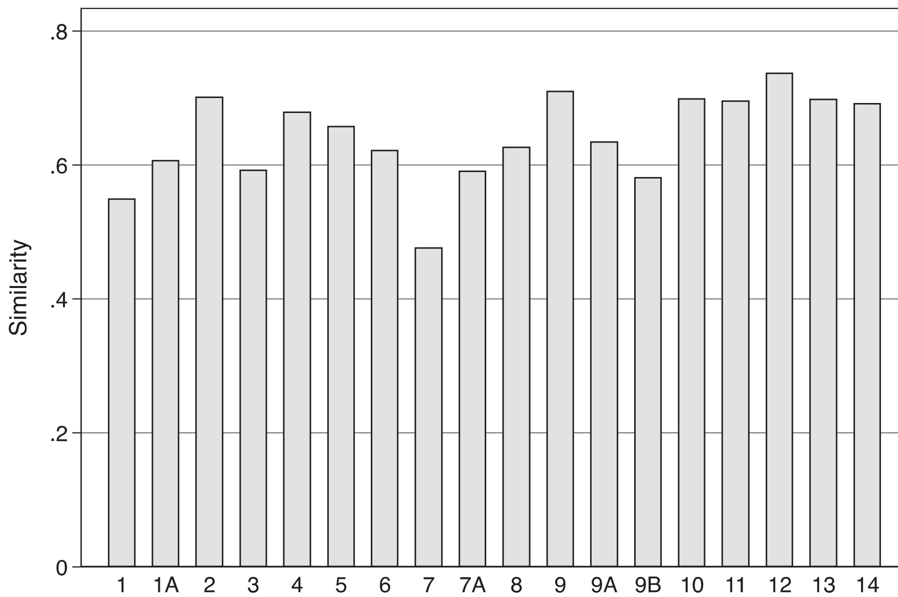
B. Isolating Key Sections of Reports

Next, we try to identify which sections of the quarterly and annual reports are associated with the largest decreases in year-over-year similarity for a given firm.

Figure 6 lists the standard sections that are present in firms' annual (10-K) and quarterly (10-Q) reports. Figure 8, Panel A, then plots the average similarity score for different items in firms' 10-Ks and shows that Item 7

dictability results. See also Table IA.IX in the Internet Appendix, which shows that tone/sentiment changes measured across the entire 10-K predict stock returns: negative tone changes predict neg-

Panel A: Change by Section – 10-K



Panel B: Change by Section – 10-Q

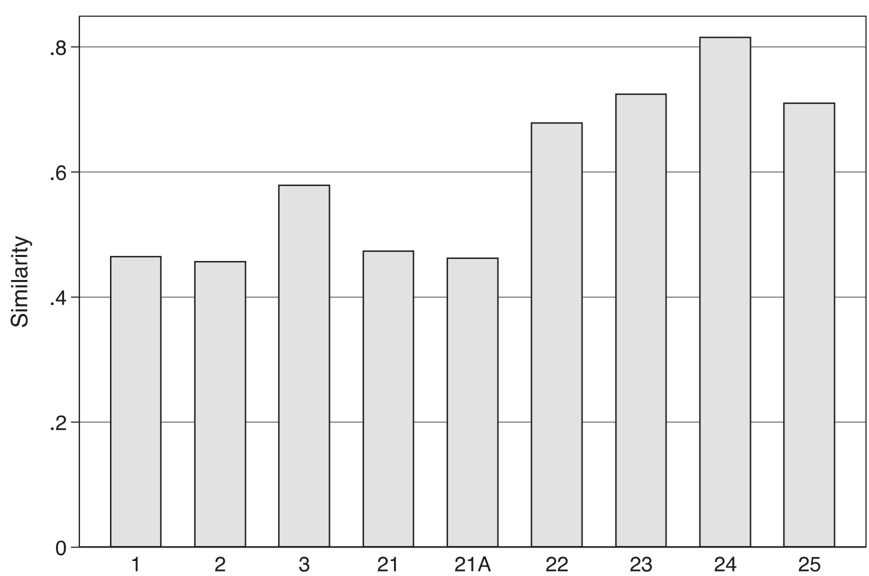


Figure 8. Change by section. Panel A shows the average Jaccard similarity for different sections of a firm's 10-K. Section definitions can be found in Figure 7. Panel B shows the average Jaccard similarity for different sections of a firm's 1Q-K.

(the MD&A section) displays a significantly lower average similarity over the other categories. Notably, this is the section of the 10-K in which management presumably has the most discretion over the content. Similarly, Figure 8, Panel B, reports the average similarity score for different items of firms' 10-Qs and again shows that the MD&A section (here Item 2) displays the lowest average similarity compared to the other items in the report (although several 10-Q items are closer in terms of year-over-year changes).

C. Return Predictability of Key Sections of Reports

We next take the item/section categories listed in Figure 6 and examine the return predictability associated with changes to each section. To do so, we construct similarity measures for each item of the 10-K using only the textual portion of the specific item. As before, for each of the four similarity measures, we compute quintiles based on the prior year's distribution of similarity scores across all stocks. Table VII reports evidence on which the key sections have the greatest return predictability and the corresponding calendar-time portfolio returns.

Table VII provides some interesting findings. However, there is variation in the consistency of the results across the different specifications in Panels A and B, and thus, we view these results as providing suggestive but not definitive evidence on where in the document the return results are most pronounced. For instance, Table VII indicates that changes in the MD&A section are associated with significant future return predictability, but the magnitude of this effect (ranging between 11 and 22 basis points per month) is often smaller than the effects associated with the Legal Proceedings section (Item 3 in the 10-K), the Quantitative and Qualitative Disclosures about Market Risk section (Item 7A), and particularly the Risk Factors section (Item 1A). Changes concentrated in the Risk Factors section, for example, yield L/S portfolio return alphas (Nonchangers minus Changers) of up to 188 basis points per month ($t = 2.76$), or over 22% in risk-adjusted abnormal returns per year in Panel A of Table VII. These results suggest that changes to some sections may be quite subtle and difficult for the market to detect, even though they may have large implications for future returns.

Given the potential structural break in reporting about risk-related items in the wake of Sarbanes-Oxley (see Li (2010)), we also rerun our analysis for the Risk Factors section in the post-Sarbanes-Oxley period (2003 to 2014). Table IA.I in the Internet Appendix shows that we continue to find large and significant return predictability associated with changes in the Risk Factors section in the more recent subperiod.

Finally, in Figure 9, we plot the value-weighted portfolio alphas by document section in a bar chart. This figure again highlights the large predictability of the Risk Factors section.

ative returns—and positive tone changes predict positive returns—but the return predictability of our document similarity measure is unaffected by the inclusion of these variables.

Table VII

Portfolio Sorts—By Document Section

This table reports calendar-time portfolio returns for the common sections of firms' 10-K and 10-Q financial reports: Management's Discussion and Analysis, Legal Proceedings, Quantitative and Qualitative Disclosures about Market Risk, Risk Factors, and Other Information. Portfolio returns are multiplied by 100. Similarity measures for each section are computed using only the textual portion in that section. For each of the four similarity measures, we compute quintiles based on the prior year's distribution of similarity measures across all stocks. Stocks then enter the quintile portfolio in the month after the public release of one of their 10-K or 10-Q reports. Firms are held in the portfolio for three months. We report Excess Returns (return minus risk free rate), Fama-French three-factor alphas (market, size, and value), and five-factor alphas (market, size, value, momentum, and liquidity) of the top minus bottom quintile portfolio (Q5 – Q1). Panel A reports equal-weighted portfolio returns, and Panel B reports value-weighted portfolio returns. t-Statistics are reported below the estimates. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

Panel A: Equally Weighted

	Sim_Cosine			*Sim_Jaccard*		
	Excess Return	Three-Factor Alpha	Five-Factor Alpha	Excess Return	Three-Factor Alpha	Five-Factor Alpha
Management's Discussion and Analysis	0.13	0.11*	0.12*	0.21**	0.22***	0.20***
	(1.57)	(1.66)	(1.68)	(2.51)	(3.15)	(2.81)
Legal Proceedings	0.36**	0.37***	0.33***	0.28	0.30**	0.25*
	(2.24)	(3.09)	(2.70)	(1.57)	(2.36)	(1.93)
Quant. and Qual. Disclosures about Market Risk	0.69***	0.68***	0.68***	0.20**	0.21***	0.19***
	(2.75)	(2.69)	(2.65)	(2.37)	(2.96)	(2.60)
Risk Factors	1.14	1.18	1.18	1.43**	1.44**	1.88***
	(1.61)	(1.63)	(1.64)	(2.13)	(2.45)	(2.76)
Other Information	0.20	0.27	0.36*	0.31*	0.37**	0.40**
	(1.08)	(1.47)	(1.92)	(1.78)	(2.19)	(2.30)

(*Continued*)

Table VII—*Continued*

Panel A: Equally Weighted

	Sim_MinEdit			*Sim_Simple*		
	Excess Return	Three-Factor Alpha	Five-Factor Alpha	Excess Return	Three-Factor Alpha	Five-Factor Alpha
Management's Discussion and Analysis	0.18*	0.22***	0.19***	0.19***	0.19**	0.17**
	(1.95)	(3.16)	(2.67)	(2.67)	(2.54)	(2.32)
Legal Proceedings	0.22	0.25**	0.22*	0.13	0.16	0.12
	(1.27)	(2.30)	(1.93)	(0.82)	(1.41)	(1.10)
Quant. and Qual. Disclosures about Market Risk	0.16	0.23*	0.22*	0.13	0.11	0.07
	(1.18)	(1.74)	(1.67)	(0.16)	(0.13)	(0.08)
Risk Factors	1.02	1.85***	1.38**	1.25*	1.54**	1.77**
	(1.19)	(2.77)	(2.17)	(1.93)	(2.19)	(2.12)
Other Information	0.09	0.14	0.16	0.22	0.26**	0.22*
	(0.58)	(0.97)	(1.05)	(1.27)	(2.31)	(1.95)

(*Continued*)

Table VII—*Continued*

Panel B: Value Weighted

	Sim_Cosine			*Sim_Jaccard*		
	Excess Return	Three-Factor Alpha	Five-Factor Alpha	Excess Return	Three-Factor Alpha	Five-Factor Alpha
Management's Discussion and Analysis	0.27*	0.28*	0.22	0.47***	0.43***	0.33**
	(1.80)	(1.85)	(1.42)	(2.88)	(2.63)	(2.02)
Legal Proceedings	0.35*	0.32	0.32	0.18	0.10	0.05
	(1.66)	(1.53)	(1.47)	(0.81)	(0.46)	(0.21)
Quant. and Qual. Disclosures about Market Risk	0.39	0.44	0.45	0.47***	0.42***	0.38**
	(1.40)	(1.57)	(1.62)	(2.89)	(2.60)	(2.37)
Risk Factors	1.44*	1.50**	1.56**	1.18*	1.65***	1.56**
	(1.96)	(2.69)	(2.05)	(1.90)	(2.75)	(2.57)
Other Information	0.73**	0.75**	0.80**	0.54	0.49	0.43
	(2.13)	(2.21)	(2.30)	(1.56)	(1.42)	(1.20)
	Sim_MinEdit			*Sim_Simple*		
	Excess Return	Three-Factor Alpha	Five-Factor Alpha	Excess Return	Three-Factor Alpha	Five-Factor Alpha
Management's Discussion and Analysis	0.47***	0.44***	0.33*	0.38**	0.37**	0.25
	(2.67)	(2.64)	(1.97)	(2.06)	(2.12)	(1.42)
Legal Proceedings	0.14	0.05	0.07	0.30	0.24	0.27
	(0.61)	(0.25)	(0.30)	(1.26)	(1.0$)	(1.16)
Quant. and Qual. Disclosures about Market Risk	0.00	0.14	0.12	0.13	0.11	0.07
	(0.02)	(0.64)	(0.61)	(0.16)	(0.13)	(0.08)
Risk Factors	0.95	1.51**	1.05*	1.25	1.33	0.85
	(1.18)	(2.29)	(1.67)	(1.54)	(1.61)	(1.04)
Other Information	0.22	0.11	0.09	0.13	0.02	0.00
	(0.63)	(0.33)	(0.25)	(0.38)	(0.07)	(0.02)

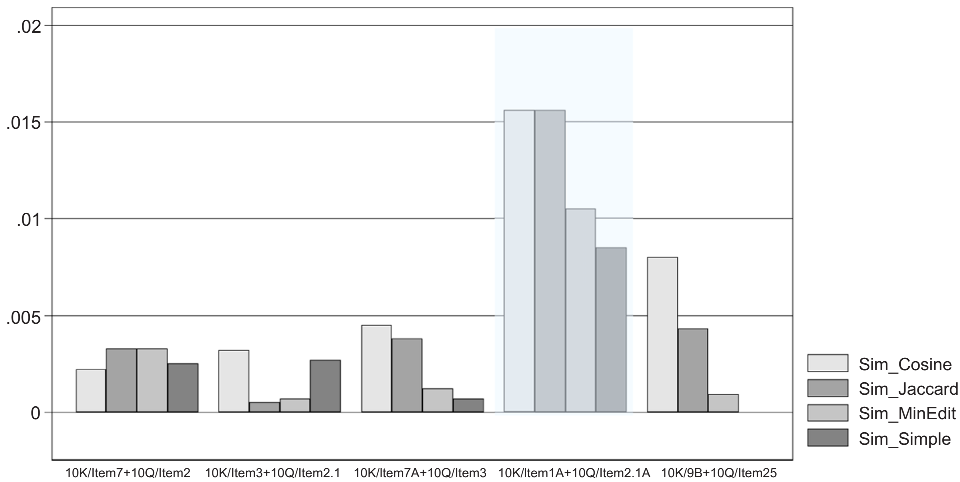


Figure 9. Five-factor alphas for portfolio sort, by important common sections for 10-Ks and 10-Qs. This figure shows the five-factor alphas (market, size, value, momentum, and liquidity) of the top (highest similarity) minus bottom (lowest similarity) quintile portfolio (Q5 – Q1) for the common sections of a firm's 10-K and 10-Q financial reports: Management's Discussion and Analysis, Legal Proceedings, Quantitative and Qualitative Disclosures about Market Risk, Risk Factors, and Other Information:
10-K/Item7 + 10-Q/Item2: Management's Discussion and Analysis of Financial Condition and Results of Operations
10-K/Item3 + 10-Q/Item2.1: Legal Proceedings
10-K/Item7A + 10-Q/Item3: Quantitative and Qualitative Disclosure about Market Risk
10-K/Item1A + 10-Q/Item2.1A: Risk Factors
10-K/Item9B + 10-Q/Item2.5: Other Information
Similarity measures for each section are computed using only the textual portion in that section. For each of the four similarity measures, we compute quintiles based on the prior year's distribution of similarity measures across all stocks. Stocks then enter the quintile portfolio in the month after the public release of one of their 10-K or 10-Q reports. Firms are held in the portfolio for three months.
(Color figure can be viewed at wileyonlinelibrary.com)

D. Interacting with Investor Attention

To explore our mechanism further, we next focus on cases in which investors *are* paying more attention to the filings. In these cases, the return effects we documented should be muted if our return predictability results are driven primarily by investor inattention. To identify variation in investor attention, we exploit a new database that captures investor behavior at a very granular level, namely, the SEC EDGAR traffic log download file. This database contains records of all downloads of corporate filings, matched to the IP addresses of the downloading agent/entity (see Chen et al. (2017), Loughran and McDonald (2017) for details). As in Loughran and McDonald (2017), we remove the impact of "robot requests," which consist of mass downloads by large institutional investors (often quantitative investment firms). To test the hypothesis that firms with more "attentive" investors see a more muted return predictability effect, we run Fama-MacBeth cross-sectional regressions of individual firm-level stock returns on our similarity measures plus interactions of these similarity measures with a measure of investor attention computed from the SEC log file. Specifically, we construct the variable *IPAccessMultipleYear*, as the number of unique IP addresses that access *both* the current 10-K/10-Q and the previous year's 10-K/10-Q for the same firm (normalized by the total number of unique IP addresses that access the current 10-K/10-Q). The idea behind this variable is that if investors are simultaneously downloading both this year's and last year's filings, it is more likely that they would pick up on the document changes driving our return results and as a result impound this information into prices more quickly upon the release of the current year's filing, resulting in lower future return predictability.

Table VIII shows that this pattern exists in the data. The interaction term on *IPAccessMultipleYear* $\times$ *Similarity* is consistently negative and is significant at the 5% level for two of the four similarity measures. For example, in column (8) of Table VIII, the coefficient on this interaction term is negative and significant ($= -0.010$, $t = -2.05$), implying that a one-standard-deviation increase in the number of unique IP addresses that check the changes in 10-Ks/10-Qs is associated with a decrease in the predictability of *Similarity* of -0.0136 (or 22%). We view these results as providing suggestive evidence that when investor attention to year-over-year corporate filings is greater, the return predictability results that we document in this paper are somewhat weaker.[23]

In Table IX, we dig even deeper into the nature of investor inattention by trying to pinpoint the precise manner in which markets fail to incorporate changes in qualitative as opposed to quantitative information. To do so, we attempt to isolate those firms that make comparative statements in the text of their annual and quarterly filings and compare them to firms that do not. For instance, we isolate the cases in which firms include phrases like "compared to last year (quarter)" or "relative to last year (quarter)" as well as references to the prior year (e.g., for a 2017 annual report, we isolate mentions such as "compared to 2016" or "relative to prior year"); a list of comparative phrases that we employ is provided in Panel B of Table IX. This procedure indicates that roughly one-third of the sample contains reports that make explicit comparative textual statements in their filings, while two-thirds of firms do not. We then divide the comparative sample into those firms that make explicit textual comparisons to specific accounting variables (e.g., "relative to prior year EBITDA") and those that do not.

[23] We also look at filing dates when investors are potentially distracted (as in Hirshleifer, Lim, and Teoh (2009)) by examining filing dates with over 100 earnings announcements on the same date (which we view as high distraction, low attention days), relative to filing dates with fewer than 100 earnings announcements. In Table IA.X in the Internet Appendix, we show that the return predictability associated with these high-distraction filing dates (the L/S portfolio spread is 47 basis points per month, $t = 2.75$) is indeed higher than the return predictability associated with low-distraction filing dates (the L/S portfolio spread is 30 basis points per month, $t = 1.43$). These results are again consistent with investor inattention being an important factor driving of our findings.

Table VIII
Interacting with Investor Attention

This table reports results of Fama-MacBeth cross-sectional regressions of individual firm-level stock returns on our similarity measures and interactions of the similarity measures with *IPAccessMultipleYear*. *Return*, the dependent variable, is multiplied by 100. *IPAccessMultipleYear* is a proxy for firms with investors who do check the changes in 10-Ks/10-Qs and is given as the number of unique IP addresses that access both the current 10-K/10-Q and previous year's 10-K/10-Q for the same firm normalized by the total number of unique IP addresses that access the current 10-K/10-Q. We download EDGAR traffic log file from the SEC and remove robot requests as in Loughran and McDonald (2017). *t*-Statistics are reported below the estimates. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

	Dependent Variable: Return							
	Sim_Cosine		*Sim_Jaccard*		*Sim_MinEdit*		*Sim_Simple*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Similarity	0.44**	0.42**	0.78***	0.84***	0.65***	0.73***	0.06**	0.06**
	(2.56)	(2.37)	(2.90)	(3.08)	(2.70)	(2.94)	(2.13)	(2.30)
IPAccessMultipleYear × *Similarity*		−0.27		−0.84**		−0.79*		−0.10**
		(−0.65)		(−2.08)		(−1.73)		(−2.05)
IPAccessMultipleYear		0.11		0.15		0.11		0.08**
		(0.31)		(0.86)		(0.50)		(2.05)
Cons	0.52	0.54	0.59	0.57	0.65	0.63	−0.04	−0.04*
	(1.16)	(1.20)	(1.36)	(1.31)	(1.50)	(1.44)	(−1.53)	(−1.70)
R^2	0.0006	0.0014	0.0016	0.0024	0.0017	0.0025	0.0019	0.0027
N	547,918	547,918	547,918	547,918	547,918	547,918	548,912	548,912

Table IX

Explicitly Comparative Statements

This table reports results of calendar-time portfolio value-weighted five-factor alphas (market, size, value, momentum, and liquidity) for samples of firms that explicitly make comparative statements in their annual and quarterly filings versus firms that do not. Portfolio returns are multiplied by 100. Firms that make explicit comparisons are taken to be those whose financial reports include phrases listed in Panel B. More specifically, we search for instances in which a word/phrase from Group A is within 10 words of a word/phrase from Group B. For each subsample, we compute quintiles based on the prior year's distribution of similarity scores across all stocks. Stocks then enter quintile portfolios in the month after the public release of one of their 10-K or 10-Q reports. Firms are held in quintile portfolios for three months. *t*-Statistics are reported below the estimates. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

Panel A: Alphas across Firms Making (Not Making) Explicit Comparison Statements in Year-over-Year Documents

Explicit Comparative Statements	Five-Factor Alpha, Jaccard Similarity					
	Q1	Q2	Q3	Q4	Q5	Q 5 – Q1
Yes	0.22	−0.24	−0.06	0.22	0.31	0.09
	(1.04)	(−0.84)	(−0.29)	(1.11)	(1.54)	(0.34)
	Q1	Q2	Q3	Q4	Q5	Q 5 – Q1
No	−0.36***	−0.07	−0.07	0.06	0.17	0.53***
	(−3.39)	(−0.57)	(−0.59)	(0.55)	(1.57)	(3.51)

Panel B: Example Phrases Captured in 10-Ks and 10-Qs

Group A	+	Group B
Sales		Last year
EBITDA		Prior year
ROA		Previous year
Operating income		Increase
Net income		Decrease
Earnings		Compared to
Dividends		Compared with
Revenue		

We find that our primary return predictability results are driven by the firms who do *not* make explicit textual comparisons to prior time periods in their filings. These results are consistent with the behavioral interpretation that firms that explicitly draw attention to prior years in their text and actively facilitate information processing on the part of investors are less likely to have changes in their reports go unnoticed by markets. Indeed, in Table IX, we find that our basic return predictability portfolio results from Table II concentrate among the firms those firms that do *not* make these kinds of explicit comparisons.

In addition, we find that the short-run announcement effect of document changes is significantly more pronounced for firms with investors who conduct multi-year downloads from the SEC server (see Table IA.VIII in the Internet Appendix). Recall that above, we show that the longer-term predictability results are weaker for these firms, but a natural implication of these findings is that the short-run announcement effects should be stronger. Thus, while we find no announcement effect overall in our sample associated with document changes, and no announcement effect for those firms for which investors are not downloading multi-year filings, we find a significant short-run announcement effect associated with document changes for those firms for which investors are conducting multi-year downloads. Since these firms' investor base is plausibly more attentive to year-over-year document changes (as proxied for by our multi-year SEC download measure), it is sensible that the immediate announcement effects associated with document changes would be more pronounced for these firms, as investors (and prices) quickly respond to these changes.

E. Real Effects

To shed additional light on the factors that drive the return predictability results at the heart of our paper, we also examine the extent to which changes in document similarity predict a decline in future operating performance of the firms in question. In Table X, we provide evidence on the predictability of a firm's similarity score for future operating income, net income, and sales. All of the future accounting variables are measured two quarters ahead. Specifically, we define the following real measures of performance: *Oibdpq/L1atq* is operating income before depreciation (Oidbpq) divided by lagged total assets (L1atq), *Niq/L1atq* is net income (Niq) divided by lagged total assets (L1atq), and *Saleq/L1atq* is sales (Saleq) divided by lagged total assets (L1atq). All of these accounting variables are winsorized at the 1% level, and the regressions in this table include month, industry, and firm fixed effects. We also adjust standard errors for clustering at the monthly level.

Consistent with the idea that the return effects that we document in this paper are driven by real *future* declines in operating performance at the firms in question, Table X shows that all four similarity measures significantly predict these three measures of operating performance (profitability, operating profitability, and sales). For example, focusing on the *Sim_Jaccard* measure in the first row of Table X, we see that decreased similarity (i.e., more changes in the filings) is a significant predictor of lower future operating income, net income, and sales. These findings highlight the fact that the subtle changes in the filings that we identify in this paper are associated with fundamental changes in performance at these firms.

F. Other Sorts and Tests of the Mechanism

We run various additional tests that we tabulate in the Internet Appendix of this paper. For example, we run additional double-sorts of our portfolio tests, such as for samples of high and low levels of sentiment, uncertainty,

Table X

Real Effects

This table reports results of regressions of operating income, net income, and sales on a firm's lagged similarity measures. *Oibdpq/L1atq* is operating income before depreciation (Oidbpq) divided by lagged total assets (L1atq). *Niq/L1atq* is net income (Niq) divided by lagged total assets (L1atq). *Saleq/L1atq* is sales (Saleq) divided by lagged total assets (L1atq). Dependent variables are multiplied by 100. All variables in the table are winsorized at the 1% level. All regressions include month, industry, and firm fixed effects. Standard errors are adjusted for clustering at the monthly level. *t*-Statistics calculated using robust clustered standard errors are reported in parentheses. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively.

	Oibdpq/L1atq				*Niq/L1atq*				*Saleq/L1atq*			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Sim_Cosine	0.50*				0.48				0.01*			
	(1.96)				(1.44)				(1.95)			
Sim_Jaccard		0.68***				0.89***				0.01***		
		(10.68)				(10.48)				(7.83)		
Sim_MinEdit			0.65***				0.75***				0.02***	
			(12.48)				(10.89)				(14.48)	
Sim_Simple				0.51***				0.71***				0.01***
				(7.80)				(8.41)				(6.85)
Cons	−0.01***	−0.40***	−0.01***	−0.02***	−0.04***	−0.04***	−0.04***	−0.04***	0.21***	0.22***	0.22***	0.19***
	(−4.71)	(−3.05)	(−8.59)	(−6.33)	(−11.17)	(−24.07)	(−23.57)	(−12.76)	(27.33)	(51.47)	(53.73)	(27.67)
Month FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.0585	0.0116	0.2858	0.0558	0.0581	0.0549	0.2859	0.0588	0.0596	0.0563	0.287	0.2864
N	284,151	284,151	284,151	325,717	295,031	295,031	295,031	338,477	295,031	295,031	295,031	338,476

and litigiousness, where "low" and "high" are defined as less than and greater than the median, respectively. For each pair of low and high samples, we compute quintile portfolios similar to Table II. Table IA.II in the Internet Appendix shows that the return results documented earlier concentrate in the low sentiment, high uncertainty, and high litigiousness subsamples.[24] For instance, the L/S five-factor alpha for the Jaccard similarity measure is 71 basis points per month ($t = 3.29$) in the high litigiousness subsample, and 72 basis points per month ($t = 3.51$) in the high uncertainty subsample, or over 8% in terms of abnormal returns per year.

In Table IA.IV in the Internet Appendix, we drop all years associated with special events (e.g., M&As, joint ventures, divestitures, or strategic alliances) from the data. Such events would mechanically lead up to changes in firms' 10-Ks and 10-Qs, which could confound our results. We find that our results remain strong and statistically significant after dropping these special events from the sample.

We also examine whether document changes predict other types of changes for the firms in question, such as future news releases, changes in investor behavior, and notable events at these companies. In particular, in Table IA.VII in the Internet Appendix, we report the predictability of a firm's similarity score on a firm's future 8-K releases, short interest, earnings surprises (SUEs), and future bankruptcy events. We find suggestive evidence that decreases in year-over-year similarity predict increases in the number of future 8-Ks, increases in future short interest, negative future earnings surprises, and increases in the number of future bankruptcies. Collectively, these results suggest that document changes have some ability to forecast future (bad) news at the firms in question.

Next, we investigate the idea that textual similarity may be related to the life cycle of the firm. To measure a firm's life cycle, we follow Spence (1979), Kotler (1980), and Anthony and Ramesh (1992) and use (i) annual dividends as a percentage of income, (ii) percent sales growth, (iii) capital expenditures normalized by total assets, and (iv) firm age. We then run a regression of our Jaccard similarity measure on the lagged five-year average depreciation rate, sales growth, capital expenditures, and age. The regression is run over the entire sample from 1994 to 2014. The results are reported in Table IA.XI in the Internet Appendix. We find that the depreciation rate and firm age are negatively related to Jaccard similarity, while sales growth and capital expenditures are positively related to Jaccard similarity. These results suggest that firms increasingly modify their financial disclosures as they mature.[25]

[24] Table IA.III in the Internet Appendix also examines the impact of specific law firms that corporations employ to file their 10-Ks. The results provide suggestive evidence that in-house lawyers are associated with more year-over-year changes in filings.

[25] We also decompose the Jaccard similarity measure into expected and unexpected components based on the above predictors for a firm's life cycle. We find that the unexpected component of Jaccard similarity is slightly stronger, in terms of both magnitude and statistical significance, in predicting future stock returns.

Table XI

Robustness—Fama-MacBeth with More Controls

This table reports results of Fama-MacBeth cross-sectional regressions of individual firm-level monthly stock returns on our four similarity measures and a number of known return predictors. *Return*, the dependent variable, is multiplied by 100. *Size* is log of market value of equity, *log*(*BM*) is log book value of equity over market value of equity, *Ret*(–1,0) is previous month's return. *Ret*(–3,–1), *Ret*(–6,–1), *Ret*(–9,–1), *and Ret*(–12,–1) are the cumulative return from month −3 to month −1, month −6 to month −1, month −9 to month −1, and month −12 to month −1, respectively. *Invest* is capx/ppent. *GrossProfit* is (revt-cogs)/at. *FreeCashFlow* is (ni + dp − wcapch − capx)/at. *Accrual* is (Δact − chech − Δlct + Δdct + Δtxp − dp) scaled by average assets (at/2 + lag(at)/2). SUE is Compustat-based standardized unexpected earnings, computed as in Livnat and Mendenhall (2006). The Compustat earnings surprise is based on the assumption that EPS follows a seasonal random walk, where the best expectation of the EPS in quarter t is the firm's reported EPS in the same quarter of the previous fiscal year. t-Statistics are reported below the estimates. Statistical significance at the 1%, 5%, and 10% levels is indicated by ***, **, and *, respectively

	Ret			
	(1)	(2)	(3)	(4)
Sim_Cosine	0.38***			
	(3.19)			
Sim_Jaccard		0.55***		
		(4.20)		
Sim_MinEdit			0.35***	
			(3.06)	
Sim_Simple				3.18**
				(2.39)
Ret(−1,0)	−2.98***	−3.00***	−3.01***	−2.95***
	(−5.77)	(−5.81)	(−5.83)	(−5.58)
Ret(–3,–1)	0.00	−0.01	0.00	−0.05
	(−0.01)	(−0.01)	(−0.01)	(−0.11)
Ret(–6,–1)	(0.06)	(0.05)	−0.05	0.01
	(0.17)	(0.16)	(0.15)	(0.03)
Ret(–12,–1)	0.57**	0.57**	0.56**	0.59**
	(2.41)	(2.40)	(2.40)	−2.48
Size	0.00	0.01	0.01	−0.01
	(0.03)	(0.14)	(0.16)	(−0.19)
log(*BM*)	0.12**	0.13**	0.13**	0.12*
	(2.02)	(2.06)	(2.07)	(1.90)
Invest	−0.26	−0.24	−0.25	−0.23
	(−0.81)	(−0.75)	(−0.77)	(−0.69)
GrossProfit	0.33*	0.32*	0.32*	0.3
	(1.88)	(1.84)	(1.82)	(1.63)
Accrual	−0.98***	−0.98***	−0.98***	−1.07***
	(−4.16)	(−4.18)	(–4.17)	(−4.62)
FreeCashFlow	0.84**	0.80**	0.81**	0.86**
	(2.31)	(2.22)	(2.25)	(2.33)
SUE	0.11***	0.11***	0.11***	0.11***
	(5.53)	(5.55)	(5.57)	(4.88)
Cons	0.55	0.53	0.60	−2.06
	(0.71)	(0.68)	(0.78)	(−1.26)
R^2	0.0649	0.0651	0.0651	0.0674
N	630,081	630,081	630,081	569,180

G. Additional Robustness Checks

In our last set of analyses, we first perform robustness checks to ensure that our key findings are not simply repackaging a set of previously known return predictors. To do so, we rerun the Fama-MacBeth regressions from Table IV after including additional firm-level characteristics, such as accruals (to ensure that the accruals anomaly (see Sloan (1996)) is not driving our findings), investment, gross profitability, and free cash flow. Table XI indicates that none of these variables drives out the return predictability associated with changes to a firm's reporting practices (as captured by our similarity scores).[26]

Next, we directly examine the impact of industry concentration on the results we document. In particular, we test whether the results we document concentrate in any specific industry (or industries). For instance, if all "changers" were coming from a certain industry, and "nonchangers" from another, we would simply be longing and shorting different industries. To address this possibility, we run an industry-adjusted version of the calendar-time portfolios of Table II. Specifically, for each industry, we sort *that industry* into Q1 to Q5 based on changes in documents. We then aggregate each industry's Q1 to Q5 portfolios together into market-wide Q1 to Q5, now equivalently representing each industry by construction. Table IA.V in the Internet Appendix shows that the results remain strong and significant after making the industry adjustment, suggesting the main results we find are not linked to specific industries.

Finally, in Table IA.XIV in the Internet Appendix, we confirm that our results are not affected by including so-called "stop words" (see Loughran and McDonald (2011)) or by our particular filtering of the SEC filings. We remove stop words and use the cleaned 10-K/10-Q publicly available database provided by Loughran and McDonald (2011),[27] we find that our main portfolio results are even larger and more significant than those reported in Table II.

Taken together, our results indicate that subtle changes in firms' reporting behavior have substantial predictability for future returns in a manner that has not previously been documented in the literature.

V. Conclusion

In this paper, we show that the most comprehensive annual information releases that firms provide to markets—their mandated annual reports—have changed dramatically over time. In particular, these reports have become significantly longer and more complex. Although past literature finds that the announcement effect associated with these statements has been decreasing,

[26] To examine omitted variable biases—and their potential impacts on our estimation—in more depth, we follow Oster (2019) and Altonji, Elder, and Taber (2005) and evaluate the robustness to omitted variable bias by observing coefficient and R^2 movements after the inclusion of additional controls. The results, reported in Table IA.VI in the Internet Appendix, show that the predictability between changes in documents and future returns (*Similarity*) are unlikely to be significantly impacted by omitted variable concerns.

[27] See http://sraf.nd.edu/textual-analysis/resources/.

and thus concludes that they have become less informative over time, our evidence points to a different conclusion. We find that simple changes in reports are a powerful and robust indicator of future firm performance. Specifically, when firms break from their routine phrasing and content in their annual and quarterly reports, the change has important information content with respect to future firm outcomes.

However, investors are inattentive to the valuable information in these simple changes. A portfolio that shorts "changers" and buys "nonchangers" in annual and quarterly financial reports earns 30 to 50 basis points per month over the following year. The returns continue to accrue out to 18 months and do not reverse, which suggests that these return movements are not overreactions, but instead reflect true, fundamental changes to firms are gradually incorporated into asset prices only over the 12 to 18 months after the reporting change. Importantly, these return patterns hold for the entire universe of publicly traded firms (since public companies are mandated to file annual reports), large firms, as well as inexpensive to short firms, and they take place over months, and thus they are unlikely to be driven by limits to arbitrage. Moreover, unlike other traditional drift regularities (e.g., return momentum, industry momentum, Post Earnings Announcement Drift (PEAD)), these document changes are not accompanied by significant announcement returns, and hence are inconsistent with a standard underreaction story (as there is no initial reaction). Instead, they are consistent with a setting in which investors are inattentive to the rich information, which, as a result, impounded into prices only with a significant delay. Indeed, when we measure investors' propensity to "compare" this year's filings to those of prior years, and hence explicitly overcome the laziness/inattention mechanism that we propose in this paper, we find that the returns are significantly attenuated.

Technological advancements reducing the cost of information production and dissemination have made the job of a Grossman-Stiglitz investor more complex. Although technology could also aid in the collection and processing of this information, we show that simple changes in documents from one year to the next year contain powerful information that is seemingly being ignored by the capital markets. This insight likely applies more broadly to other forms of firm information. Documents such as bond covenants, lease arrangements, securities offering documents, and M&A prospectuses—that is, documents for which there are a regular cadence and repeated use—may be rich settings for further research. More broadly, yet, the implications of breaks from repeated behaviors in the corporate setting provide a critical yet understudied area in both corporate finance and asset pricing.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.
Replication code.