Semantic progression in firm disclosure: The role of accounting conservatism

SEMANTIC PROGRESSION IN FIRM DISCLOSURE:

THE ROLE OF ACCOUNTING CONSERVATISM

BY

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ACCEPTANCE

This dissertation was prepared under the direction of the *Youngseok Moon*'s Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Business Administration in the J. Mack Robinson College of Business of Georgia State University.

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ABSTRACT

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This study examines whether and how accounting conservatism influences managerial discretion over semantic progression in the Management's Discussion and Analysis (MD&A) portion of 10-K filings. I utilize natural language processing techniques to capture circuitousness, a semantic progression measure that reflects whether the text in a document is "going in circles." I find a significant negative association between conservatism and circuitousness. In the cross-sectional analysis, I find that the negative relationship is pronounced among firms with higher long-term debt and those operating in more competitive product markets. Additionally, I find that the timeliness of news recognition is less asymmetric among firms with more circuitous reports. Collectively, the results highlight the governance role of accounting conservatism, promoting transparent and reliable financial reporting.

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I. INTRODUCTION

The Financial Accounting Standards Board (FASB) emphasizes *understandability* as one of the qualitative characteristics of financial information in the conceptual framework. *Understandability*, according to FASB (2018), "enables users to comprehend the information and therefore make it useful for making decisions." However, various forces can act as potential impediments in achieving this critical goal. As suppliers of financial reports, managers possess both the ability and incentives to significantly influence financial disclosures, potentially diminishing their clarity. Prior research indicates managers may intentionally hide adverse information through less readable reports (Li 2008; Brown and Tucker 2011; Guay, Samuels, and Taylor 2016;Bonsall, Leone, Miller, and Rennekamp 2017; Dyer, Lang, and Stice Lawrence 2017; Cohen, Malloy, and Nguyen 2020; Blankespoor, deHaan, and Marinovic 2020).[1] Consequently, readability plays a crucial role in ensuring that financial information is accessible and understandable to users, which is a fundamental requirement for informed decision-making.

However, limited research has explored the linguistic structure of qualitative disclosure as a potential factor influencing document readability (Allee and DeAngelis 2015; Guest and Yan 2023). The structure of a document plays a pivotal role in shaping readers' comprehension, as the presentation affects the extent to which readers can understand the content, and readers have limited cognitive capacity (Britton, Glynn, Meyer, and Penland 1982; Foltz, Kintsch, and Landauer 1998). Within this context, semantic progression, defined as how texts progress within a document, is a critical element guiding readers through its content. Hence, understanding financial information relies not only on word choice but also significantly on

[1] Although one could argue that managers may omit unfavorable information, I argue that litigation and reputation costs may prevent managers from omitting such information (Skinner 1994).

the organization and flow of text within financial reports.

This study examines whether conditional accounting conservatism (hereafter, "conservatism") impacts the semantic progression of financial reports. Managers may have incentives to favorably bias the information they provide. However, conservatism serves as a governance mechanism that reduces managerial opportunism, thereby enhancing the information environment (LaFond and Watts 2008; D'Augusta and DeAngelis 2020). Specifically, conservatism can discipline other information sources, such as qualitative disclosure. As information users can assess "softer" sources of information by utilizing accounting information as a benchmark, conservatism leaves little room for managers to strategically increase disclosure processing costs by making financial reports less readable. Hence, I hypothesize that conservatism is negatively associated with managers' use of circuitous language in the financial reports.

I utilize natural language processing techniques to capture the concept of semantic progression through "circuitousness," measuring the extent to which a document presents information in a roundabout manner (Toubia, Berger, and Eliashberg 2021; Guest and Yan 2023). A higher level of circuitousness indicates that a text meanders among unrelated topics, requiring greater cognitive effort to process.[2] Next, I investigate the relationship between conservatism and circuitousness in the Management's Discussion and Analysis (MD&A) section of 10-K reports between 1997 and 2019. I focus on the MD&A portion of 10-K filings, as it provides a broad overview of the company's operations, and thus offers management sufficient opportunities to increase disclosure processing costs (Li 2008, 2010; D'Augusta and DeAngelis 2020).[3] I utilize the machine learning-based conservatism from Bertomeu, Cheynel,

[2] I find that the relationship between information asymmetry and circuitousness is positive across different proxies of circuitousness, suggesting that obfuscating financial reports (MD&A) via circuitous language has an economically significant influence on increasing information asymmetry (in Table 4).

[3] The SEC (2003) specifically emphasize that companies "should avoid unnecessary duplicative disclosure that can tend to overwhelm readers…" and "should be presented in clear and understandable language… to provide

Liao, and Milone (2024), a proxy that applies the state-of-the-art neural network approach to the Khan and Watts (2009) model.

Consistent with my hypothesis, I find a negative association between conservatism and circuitousness. More specifically, I find that increasing conservatism from the bottom to the top decile is associated with a 0.166 (0.088) standard deviation decrease in circuitousness at the sentence level (250-word level). Overall, the results suggest that conservatism can play a governance role by reducing managers' incentives to use circuitous language in MD&A, highlighting the role of conservatism in enhancing transparency and facilitating informativeness in financial disclosures.

In the cross-sectional analysis, I expect that the negative relationship between conservatism and circuitousness is stronger for firms issuing long-term debt and operating within the competitive product market. First, prior literature suggests that debtholders demand conservatism for efficient contracting and monitoring purposes. For example, conservatism helps provide a reference point for debtholders in making their lending decisions. Second, prior literature suggests that higher product market competition influences conservatism to improve a firm's competitive advantage over its competitors. When a firm makes financial reporting decisions, it considers the potential impact on its competitive standing within the market: discouraging potential competitors from entering the market or existing competitors from overproducing. Consistent with expectations, I find a stronger negative correlation between conservatism and circuitousness for firms issuing long-term debt and those facing high product market competition.

I perform various supplement analyses to bolster my main findings. First, I assess the sensitivity of the results using alternative measures of conservatism used in prior research (e.g.,

clearer and better organized presentations of MD&A…"

Khan and Watts 2009) and find consistent results. Next, since prior literature considers conservatism to be stable over time (; Khan and Watts 2009; Callen, Segal, and Hope 2010), I re-run the main test using lagged conservatism and the three-year average decile rank of conservatism to mitigate concerns that unobservable year-specific events may drive the main results (García Lara et al. 2016; D'Augusta and DeAngelis 2020). The results are qualitatively similar to the main findings, suggesting that they are not driven by unobservable factors that simultaneously affect circuitousness and conservatism. Additionally, I replicate Basu's (1997) model of asymmetric timeliness and find that the timeliness of news recognition is less asymmetric among firms that use circuitousness to obfuscate adverse information. These supplemental analyses provide additional support for the hypothesis that higher levels of conservatism reduce managers' incentives to increase disclosure processing costs, reinforcing the role of conservatism in promoting transparent and informative financial disclosures.

This study contributes to existing literature in several ways. First, it extends the literature by focusing on the structural aspects of financial reports. Limited research has explored the linguistic structure of qualitative disclosure (Loughran and McDonald 2016; Bochkay, Brown, Leone, and Tucker 2023). Allee and DeAngelis (2015) are the first to examine whether tone words are spread across qualitative disclosure. Motivated by Toubia et al. (2021), Guest and Yan (2023) provide evidence of how semantic progression matters in financial reports. Utilizing natural language processing techniques, this study adds to this stream of literature by focusing on whether managers are incentivized to alter the structure of financial reports and what factors constrain such behavior. In addition, this study focuses on the interplay between hard information and soft disclosure, emphasizing whether and how hard information disciplines and shapes the credibility and reliability of soft information (Ball 2001; Ball and Shivakumar 2008; LaFond and Watts 2008; Ball, Jayaraman, and Shivakumar 2012; Kim and Nikolaev 2024). Building upon D'Augusta and DeAngelis (2020), this study find evidence that conservatism can serve as a governance role by constraining managers' tendency to increase the processing cost of unfavorable information through linguistic complexity.

Third, I contribute to the growing literature on managers' influence on investors' disclosure processing costs. Managers are likely to consider the disclosure quantity, timing, format, and features that can affect investors' disclosure processing costs. Prior research investigates the relationship between disclosure processing costs and the amount of disclosure (Basu, Pierce, and Stephan 2019; Blankespoor 2019; Abramova, Core, and Sutherland 2020), the types of disclosure (Guay et al. 2016; Chen, Hepfer, Quinn, and Wilson 2018; Park, Schrand, and Zhou 2023), and the strategic choices of disclosure narratives (Li 2008; You and Zhang 2009; Miller 2010; Lehavy, Li, and Merkley 2011; Lawrence 2013; Loughran and McDonald 2014; D'Augusta and DeAngelis 2020;). By investigating how managers' choices in the MD&A section of 10-K reports can affect investors' processing costs, this study sheds light on the relationship between the structural aspects of qualitative disclosure and the costs associated with disclosure processing.

II. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Qualitative Disclosure and Semantic Progression

"Hard" information is generally characterized as objective, verifiable, quantitative, standardized, and less manipulative, indicating that it is easily collected, processed, and transmitted to its users (Dye and Sridhar 2004; Bertomeu and Marinovic 2016; Liberti and Peterson 2019). That is, hard information is "difficult to disagree" (Ijiri 1975). Accounting numbers from a firm's balance sheets and income statements are examples of hard information. Therefore, there is less room for disagreement regarding the interpretation of sales and net income numbers (Liberti and Peterson 2019).

In contrast, "soft" information can "easily be pushed in one direction or another" (Ijiri, 1975). It can be subjective, less verifiable, and more open to managerial discretion (Dye and Sridhar 2004; Bertomeu and Marinovic 2016; Liberti and Peterson 2019). Qualitative disclosures, including narratives provided in corporate reports, typically serve as sources for communicating soft information. For example, the textual components of mandatory filings are considered as soft information.[4]

Since financial reports include not only hard but also soft information that can be useful for information users, recent scholars have shown interest in soft information (Li 2008; You and Zhang 2009; Loughran and McDonald 2011, 2014; Huang, Teoh, and Zhang 2014; Guay et al. 2016; Bushee, Gow, and Taylor 2018; D'Augusta and DeAngelis 2020). Prior studies have examined various sources of soft information, including the whole 10-K filings (Li 2008; You and Zhang 2009; Miller 2010; Loughran and McDonald 2011, 2014; Lehavy et al. 2011; Lawrence 2013; Guay et al. 2016;), the MD&A portion of the 10-Ks (Li 2008, 2010; Feldman, Govindaraj, Livnat, and Segal 2010; Brown and Tucker 2011; D'Augusta and DeAngelis 2020;), and earnings conference calls (Allee and DeAngelis 2015; Bushee et al. 2018).

Prior literature has explored the interplay between hard and soft information, emphasizing the confirmatory role of hard information on soft information (Ball 2001; Ball and Shivakumar 2008; Ball et al. 2012). Ball (2001) argues that the primary role of financial reporting is to supply credible information for efficient contracting with the firm. In addition, reliable information supply can enhance the quality of non-accounting disclosures, thereby disciplining managers' truthful disclosure of unverifiable information. Prior analytical studies have developed a model in which hard, verifiable information and soft disclosure are complements (Gigler and Hemmer 1998; Bertomeu and Marinovic 2016). Prior literature has provided evidence supporting the argument that hard, verifiable information disciplines and

[4] Although the classification of information into hard and soft is defined in a distinctive way, information is "neither absolutely hard nor absolutely soft" (Dye and Sridhar 2004).

enhances the credibility of softer information (LaFond and Watts 2008; Baginski, Demers, Wang, and Yu 2016; D'Augusta and DeAngelis 2020). In addition, recent study by Kim and Nikolaev (2024) suggest that the interaction between accounting information and narrative disclosures are more informative in predicting a firm's future than either type of information alone.

Hence, stakeholders rely heavily on narratives to process the financial data in documents. Readability, defined as "the ability of individual investors and analysts to assimilate valuation-relevant information from a financial disclosure" (Loughran and McDonald 2014), is crucial in effectively conveying value-relevant information to investors. For example, the objectives of MD&A in the 10-K report are "to provide a narrative explanation of a company's financial statements… through the eyes of management" and "to provide information about the quality of, and the potential variability of, a company's earnings and cash flow." (SEC 2008).[5]

However, qualitative disclosures, such as MD&A and other textual components in financial reporting, are useful only when investors can process information cost-effectively. Bloomfield (2002) proposes the incomplete revelation hypothesis, suggesting that if information is difficult to extract from disclosures, it is less likely to be fully or efficiently incorporated into market prices. Managers may intentionally make reports less readable to hide adverse information and "make it harder for investors to uncover information" (Bloomfield 2002). By strategically increasing the processing cost of adverse information, managers can prevent complete revelation of market prices.

[5] Regulators also emphasize the importance of clear and understandable communications with investors. For example, the SEC developed A Plain English Handbook (1998) for all regulated entities to use plain English guidelines in their disclosures. Additionally, the SEC (2003) mandates the presentation of MD&A in "clear" and "understandable" language, thereby encouraging firms to provide investors with less complex and convoluted disclosures. However, researchers find evidence of an increasing trend of less readable reports (Li 2008; Brown and Tucker 2011; Guay et al. 2016; Dyer et al. 2017; Bonsall et al. 2017; Cohen et al. 2020).

Recent empirical studies generally find that readability is one of the factors affecting disclosure processing costs, as less readable reports are associated with lower earnings (Li 2008), investors' underreaction (You and Zhang 2009), increased short selling pressure (Li and Zhang 2015), and higher stock price crash risk (Kim et al. 2019). Li (2008) finds evidence that firms with lower earnings provide complex annual reports, consistent with the view that managers have incentives to obfuscate information. Individual, small investors tend to invest more in firms with more readable filings, as clear and concise disclosure reduces small investors' informational disadvantages (Miller 2010; Lawrence 2013). Lehavy et al. (2011) and Loughran and McDonald (2014) find that less readable filings are associated with more (less) analyst dispersion (forecast accuracy). Drake, Roulstone, and Thornock (2016) find that investors seek old EDGAR filings when financial reporting is complex, indicating a preference for less complex information.

However, readability also reflects the underlying business complexity (Bloomfield 2008).[6] Complex transactions may require firms to use complex language, which differs from the managerial obfuscation hypothesis that managers strategically obfuscate information. For example, firms with multiple divisions or complex business models may produce complex financial reports to accurately explain the nature of their businesses (Loughran and McDonald 2014, 2016). Bushee et al. (2018) decompose readability into two components: information and obfuscation. They find that the obfuscation component is positively associated with information asymmetry, indicating that obfuscation may reduce the informativeness of disclosure.

In addition, prior literature often focuses on word choices to measure readability and overlooks its structure (Guest and Yan 2023). The structure of a document plays a critical role

[6] Since complex transactions are very likely to require specialized knowledge to process, multi-faceted transactions are likely to have high integration costs (Blankespoor et al. 2020).

in shaping readers' comprehension. First, the representation of information influences the extent to which readers can grasp the content. Second, readers have limited cognitive capacity. To optimize comprehension, the structural design of a document should be mindful of not overtaxing this limited cognitive capacity (Foltz et al. 1998; Britton et al. 1982).

Proxies such as the Fog Index, which considers average sentence length and complex words (words with three or more syllables), are commonly used but fail to capture the structural aspects of the document. Guest and Yan (2023) address this limitation by examining how information presentation matters in a financial context. Using a progression complexity measure, they find that circuitousness is negatively (positively) associated with positive earnings persistence (absolute analyst forecast errors), indicating that managers tend to strategically increase disclosure processing costs by making financial reports circuitous.[7]

In summary, recent research demonstrates a growing interest in soft information in financial reports and emphasizes the importance of readability for effective communication. While evidence supports the notion that managers may obfuscate information via syntax, further research is needed to fully establish the relationship between hard and soft information. Motivated by these studies, I investigate the relationship between hard and soft information, focusing on accounting conservatism and the structural aspect of disclosure.

Accounting Conservatism

According to FASB (1980), conservatism is defined as "a prudent reaction to uncertainty … if two estimates of amounts … are about equally likely, conservatism dictates using the less optimistic estimate." Researchers suggest that conservatism is a "stronger verifiability requirement" for recognizing good news than bad news (Basu 1997; Watts 2003a).

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[7] Circuitousness reflects whether the text wanders through distinct themes (Toubia et al. 2021; Guest and Yan 2023).

According to this definition, earnings reflect bad news more quickly than they do good news.[8] Prior literature has extensively studied conservatism based on this definition, focusing on its effects on capital market participants and the factors influencing its level (Basu 1997; Beatty, Weber, and Yu 2008; LaFond and Watts 2008; Zhang 2008; Kim, Li, Pan, and Zuo 2013).

Prior literature highlights the role of various stakeholders, including debtholders, shareholders, auditors, and regulators, in shaping the demand for conservatism (Watts 2003a, 2003b; Zhong and Li 2016). First, debtholders demand conservatism primarily as a mechanism to mitigate agency conflicts between insiders and outside stakeholders who maximize their welfare (Jensen and Meckling 1976; Watts 2003a). Managers have incentives to potentially transfer wealth from debtholders to shareholders, but timely loss recognition enables debtholders to respond to covenant violations and enforce protective rights promptly. If covenants are violated, debtholders can gain control rights from managers and protect their interests in a timely manner. Also, conservatism ensures lower bound measures of accounting numbers, enabling lenders to incorporate the lower bound in their lending decisions.

Therefore, prior empirical literature examines whether conservatism is related to debt contracting (Beatty et al. 2008; Nikolaev 2010). When public debt is a more important source of financing, the demand for conservatism is greater than when private debt is (Ball, Kothari, and Robin 2000). Conservatism also reduces the cost of debt (Ahmed, Billings, Morton, and Stanford-Harris 2002; Zhang 2008). Tan (2013) finds that conservatism increases after covenant violations, and the effect is stronger when creditors have greater bargaining power, when a firm's operation is more uncertain, and when a Chief Restructuring Officer is in place.

[8] More precisely, researchers have distinguished two distinct types of accounting conservatism: unconditional conservatism and conditional conservatism (Beaver and Ryan 2005). Conservatism can be unconditional, or news-independent. Understating assets by immediate expensing is one of the examples of unconditional conservatism. Conditional conservatism is news-dependent and refers to an accounting principle that negative news is recognized more quickly and more thoroughly than positive news.

Second, shareholders demand conservatism to reduce information asymmetry and mitigate agency conflicts with managers. For example, managers are more likely to have information about future cash flows from a newly developed product than shareholders. Executive compensation contracts are used to mitigate the agency problem and reduce the information asymmetry between managers and shareholders. Conservatism provides a signal to shareholders to investigate losses by recognizing bad news in a timelier manner. In addition, by providing verifiability, conservatism reduces the likelihood that managers exert to overstate earnings linked to their compensation, preventing managers from investing in negative net present value projects (Ball and Shivakumar 2005).

LaFond and Watts (2008) investigate whether information asymmetry between insiders and outside investors generates changes in accounting conservatism and find that greater information asymmetry increases conservatism. Consistent with the notion that conservatism facilitates efficient contracting between managers and shareholders, LaFond and Roychowdhury (2008) find a negative relationship between conservatism and managerial ownership, indicating that shareholders demand conservatism. Similarly, Ramalingegowda and Yu (2012) investigate which shareholders demand conservatism. They find that institutional investors demand conservatism since they are likely to monitor managers. In addition, hedge fund activists demand conservatism, suggesting that conservatism is a crucial mechanism for shareholders to increase monitoring effectiveness (Cheng, Huang, and Li 2015). In sum, shareholders demand conservatism as a governance tool that facilitates efficient contracting (Ball 2001; Watts 2003a).

Third, auditors demand conservatism due to information asymmetry and potential litigation risks. Watts (1993) suggests that litigation costs can be a source of conservatism since auditors are conditionally liable for financial reporting. Since overstatement of earnings has a higher likelihood of litigation risk than understatement of earnings (Kellogg 1984), auditors have an incentive to demand conservatism. Also, Basu (1997) finds that conservatism increases during periods of greater exposure to legal liability, indicating that auditors demand conservatism.

Overall, multiple stakeholders–debtholders, shareholders, and auditors–demand accounting conservatism for various reasons. In addition, prior literature finds evidence that conservatism is stable over time since it is a policy variable (Khan and Watts 2009; Callen et al. 2010), suggesting that the primary factor driving conservatism implementation is the demand for conservatism by these stakeholders.

Importantly, conservatism serves as a key governance mechanism by constraining managerial opportunism (Watts 2003a ; Kothari, Ramanna, and Skinner 2010). Managers, who possess superior information about the firm's operations compared to other stakeholders, may have incentives to favorably bias the information they provide.[9] However, conservatism serves as a governance mechanism that reduces managerial opportunism, thereby mitigating various agency problems (Watts 2003a, 2003b; Ball and Shivakumar 2005; García Lara et al. 2007; LaFond and Watts 2008; LaFond and Roychowdhury 2008). For example, shareholders and debtholders advocate for more conservatism to counteract managers' opportunistic behavior (Ahmed and Duellman 2007; Chung and Wynn 2008; Hui, Matsunaga, and Morse 2009; García Lara et al. 2009, 2011, 2014, 2016). In addition, accounting conservatism can reduce financing and borrowing costs, consistent with the notion that conservatism can serve as a governance mechanism (Zhang 2008; Kim et al. 2013).

Furthermore, LaFond and Watts (2008) argue that conservatism, by providing the best possible and verifiable "hard" information, can generate credible information from "soft"

[9] Since financial statements are the primary source from which outside stakeholders obtain firms' information, financial reporting influences information asymmetry between insiders and outside stakeholders.

sources such as qualitative disclosure. For instance, more conservative firms will report negative news sooner rather than later, making it costly for managers to strategically hide adverse information. Recent evidence by D'Augusta and DeAngelis (2020) suggests that conservatism serves a governance role by disciplining qualitative information. Specifically, they find a negative relationship between conservatism and upward tone management, the first direct evidence that conservatism reduces the manipulation of qualitative disclosure. Their findings highlight the importance of conservatism in maintaining the credibility of qualitative disclosure. In sum, stakeholders view conservatism as a key mechanism that "constrains management's opportunistic behavior and mitigates agency problems arising from information asymmetry." (Kim et al. 2013).

Hypothesis Development

Previous literature has emphasized the role of accounting information in confirming and disciplining other information provided by managers (Gigler and Hemmer 1998; Ball 2001, 2013; Ball and Shivakumar 2008). Under this argument, the presence of reliable and verifiable accounting information can improve the credibility of unverifiable "soft" information, implying that financial reporting and disclosure are complements (Ball et al. 2012; Ball 2013). Recent evidence by Kim and Nikolaev (2024) extends this view by demonstrating that narrative disclosures contextualize accounting numbers, thereby enhancing their informativeness. While previous research has primarily focused on the confirmatory role of accounting information, limited research has focused on the disciplinary effect of accounting information on qualitative disclosure (D'Augusta and DeAngelis 2020).

Managers often possess superior information about the firm's operation and have incentives to delay the market reaction of unfavorable news. Consistent with incomplete revelation hypothesis, managers may strategically increase the complexity of firm's qualitative disclosure to obscure unfavorable news, increasing disclosure processing costs for investors. In other words, Managers have incentives to favorably bias information, through manipulating tone or providing complex financial disclosures (Li 2008; Li and Zhang 2015; Kim et al. 2019; D'Augusta and DeAngelis 2020). In addition, Guest and Yan (2023) provide evidence that managers tend to use circuitous language to hide bad news.

However, conservatism can serve as a mechanism to constrain managers' opportunistic behavior.[10] Specifically, conservatism can discipline other information sources. LaFond and Watts (2008) suggest that conservatism, by providing the best possible and verifiable "hard" information, can generate credible information from "soft" sources of information. Consistent with this view, prior literature finds evidence that conservatism can serve as a governance mechanism on other disclosure channels (Hui et al. 2009; Kim et al. 2013; García Lara et al. 2014). Recent study by D'Augusta and DeAngelis (2020) finds that conservatism constrains managers' upward tone management in MD&A.

In addition, conservatism can encourage managers to discuss bad news or limit managers to emphasize good news. Intuitively, as information users can assess "softer" sources of information by utilizing accounting information as a benchmark, conservatism leaves little room for managers to strategically increase disclosure processing costs by making financial reports less readable. For instance, more conservative firms will report negative news sooner than later. This will expose managers' opportunism (e.g., burying bad news in between other news) faster as investors now have a better understanding of the bad news. As a result, managers have little room to strategically hide adverse information in a qualitative form because investors can assess qualitative disclosure using accounting information. Similarly,

[10] Prior literature suggests that the primary factor driving conservatism implementation is the demand for conservatism by various stakeholders (Khan and Watts 2009; Callen et al. 2010). Therefore, I treat conservatism as a stable, policy variable.

"strong verifiability requirements" for good news limit managers from promoting good news. In essence, conservatism provide verifiable "hard" information that can act as a benchmark in assessing "soft" disclosures, thereby limiting managers from strategically altering the structure of financial reports.

Based on these arguments, I formulate my hypothesis as follows:

Hypothesis: Conservatism is negatively associated with semantic progression.

III. RESEARCH DESIGN

Measure of Conservatism

The main proxy for conservatism is Machine-learning Conservatism (*MLC)* measure developed by Bertomeu et al. (2024).[11] Khan and Watts (2009) propose a conservatism proxy using firm characteristics, including size, market-to-book, and leverage. Bertomeu et al. (2024) apply a state-of-the-art neural network to estimate conservatism, which does not assume a linear functional form in the estimation process.

It is important to note that generated-regressor proxies are usually susceptible to several issues, such as model misspecification and sampling errors, as researchers generate such proxies with a linear relationship assumption that is not observable (Basu and Byzalov 2024; Chen, Hribar, and Melessa 2022). However, Bertomeu et al. (2024) suggest that machine learning-generated conservatism measures are relatively robust to specification errors, lead to fewer incidences of insignificant results, and improve the measurement of accounting proxies as the machine learning method does not presume specific functional forms.

Prior literature finds that the Khan and Watts (2009) model mitigates endogeneity concerns to a certain extent as their measure is based on a linear combination of size, leverage,

[11] I thank Bertomeu et al. (2024) for sharing their data online.

and market-to-book ratio, despite the criticisms of validity behind conservatism proxies based on the Basu approach (Ettredge, Huang, and Zhang 2012; García Lara et al. 2016).[12] By adding five additional variables that might be related to conservatism, Bertomeu et al. (2024) find that a machine learning approach produces a better proxy for conservatism compared to linear models with three features, eight features, and machine learning models with three features.[13]

Measure of semantic progression

Following Guest and Yan (2023), I pre-process all 10-Ks and extract MD&As from the annual reports. I start with the Loughran and McDonald (2021) cleaned 10-X files[14] and tokenize the texts using the Python natural language toolkit, NLTK. Next, I split each document into non-overlapping information chunks, which can be either sentence-level or 250-word-level.[15] I keep words in the same sentence within the same chunk to avoid breaking them up. As a result, the average size of a 250-word (sentence) chunk is 261 (27) words, indicating that some chunks contain slightly more than 250 words. Third, chunks are represented in high-dimensional space using word embeddings, ensuring that each chunk is mapped into this space using the pre-trained GloVe model of a 300-dimensional vector (Pennington, Socher, and Manning 2014). As a result, each chunk is represented as a point in a high-dimensional space.

Next, I compute the main proxy for semantic progression: *CIRCUIT*, a measure from Toubia et al. (2021), which applies natural language processing and machine-learning techniques to represent texts in a high-dimensional semantic space. *CIRCUIT* is defined as the ratio of the excess distance traveled—calculated as the difference between the actual distance

[12] By construction, the proxy of Khan and Watts (2009) changes when the three measures used in the model change over time. The proxy can effectively capture the variation in conservatism at the firm-level (Ettredge et al. 2012).
[13] These variables include volatility, net operating accruals, cash flow from operations, investment cycle, and firm age.
[14] The resulting files can be found here: https://sraf.nd.edu/sec-edgar-data/.
[15] Toubia et al. (2021) document that although their main specifications target 250-word as chunk size, the results are qualitatively the same using 125-word and 375-word as chunk size. Guest and Yan (2023) also find the results are similar using 125-word and 375-word instead of 250-word as chunk size.

a document travels from chunk to chunk and the shortest possible path—to the shortest possible path.

$$CIRCUIT = \frac{\sum_{t=1}^{T-1} distance(t,t+1) - Length\ of\ the\ shortest\ path}{Length\ of\ the\ shortest\ path} \quad (1)$$

Higher *CIRCUIT* values indicate that the document does not follow the optimal path, as *CIRCUIT* is, by definition, always greater than or equal to 0 (0 if the document is taking the optimal path). Hence, if the MD&A content is highly circuitous, it implies that the content is circling and not taking the most straightforward path to explain the company's financial statements. For instance, if a firm's MD&A discusses the past, the future, and the present and then circles back to the past and the future instead of the past, the present, and the future sequence, the document would be more difficult to understand. Toubia et al. (2021) further provide evidence that the correlation between machine-learning-based circuitousness and human perception is 75 percent, indicating that their automated measure reasonably correlates with human judgments.

For illustrative purposes, I provide an example of circuitousness based on actual MD&A in Appendix B.[16] First, I present the actual sequence of MD&A to calculate the level of circuitousness, followed by alternative, hypothetical sequences. This example is based on the MD&A section of the Brown-Forman Corporation's annual report for the fiscal year 2017. The sequence begins with an explanation of net sales, followed by gross profit, advertising expenses, cash flow, and liquidity. It is important to note that the first three chunks follow the sequence typically observed in general income statements, whereas Cash Flow and Liquidity are more closely related to cash flow statements.

The actual sequence of Brown-Forman Corporation's MD&A has a circuitousness

[16] A detailed example using the actual MD&A section in the 10-K of Brown-Forman Corporation for fiscal year 2017 can be found in Appendix B.

value of 0.05, indicating that the current route that the MD&A takes is close to the shortest possible path. However, if the sequence of the MD&A changes in hypothetical scenarios (from 1 to 3), the level of circuitousness increases significantly as the hypothetical paths do not follow an efficient route. For example, in hypothetical sequence 1, where chunk 4 is placed between chunks 1 and 2, the level of circuitousness increases to 0.25. If chunks 5 and 4 are inserted between chunks 1 and 2, and chunks 2 and 3, respectively, the circuitousness value increases to 0.36 in hypothetical sequence 3. Overall, this example demonstrates that circuitousness effectively captures the indirect route a text can take, illustrating the potential impact of varying sequences on the readability and efficiency of financial disclosure.

Other variables

I control for firms' financial information, including *Size, Tobin's Q, ROA, Leverage, Growth, Acquisition, RD, Capex, Financing, σ CFO, Restructuring, Loss, Specitems, IOR, Num_Analysts, Segment_Bus, Segment_Geo,* and *NDCons*. *Size* is defined as the natural logarithm of market capitalization at the beginning of the year. *Tobin's Q* is defined as the natural logarithm of the ratio of the sum of the market value of equity and the book value of the total debt to the sum of the book value of equity and the book value of the total debt. *ROA* is the ratio of net income over total assets. *Leverage* is the ratio of total liability to assets at book values. *Growth* is the change in sales scaled by total sales. *Acquisition* is the total acquisitions scaled by total assets at the beginning of the year. *RD* is defined as total research and development expenses scaled by sales. *Capex* is the capital expenditure scaled by total assets. *Financing* is the ratio of stock and debt issuances to total assets. *σ CFO* is defined as the standard deviation of cash flows from operations scaled by total assets over a 5-year window. *Restructuring* is an indicator variable equal to one if a firm had a restructuring charge and zero otherwise. *Loss* is an indicator variable equal to one if net income is negative and zero otherwise. *Specitems* is special items scaled by the market value of equity. *IOR* is the ratio of the total shares of institutional ownership to the total shares outstanding. *Num_Analysts* is defined as the natural logarithm of the number of analysts covering the firm. *Segment_Bus* is the number of business segments, and *Segment_Geo* is the number of geographical segments. Following Lawrence, Sloan, and Sun (2013), I use *NDCons*, defined as an indicator variable equal to one if the beginning book-to-market ratio is higher than one and zero otherwise, to control non-discretionary conservatism. All continuous variables are winsorized at the top and bottom 1 percent.

Sample selection

I construct the sample using EDGAR, CRSP, Compustat, I/B/E/S, and Thomson Reuters 13F data. To construct the sample used in this study, I first begin by downloading MD&A data from the 10-K files from 1997 to 2019. I start with 107,611 observations with financial data from Compustat and CRSP and merge with 80,261 MD&As from 10-Ks during the sample period, dropping MD&As with fewer than 300 words. After matching CRSP, Compustat, Audit Analytics, I/B/E/S, and Thomson Reuters 13F data, the sample used in this study consists of 42,764 firm-year observations. Table 1 shows the sample selection process.

Table 2 reports the descriptive statistics for the variables used in this study. The average of *Circuit_sent* (*Circuit_250w*) in the study is 0.51 (0.20), with a standard deviation of 0.09 (0.07). *MLC* has a mean of 0.01, with a standard deviation of 0.02. The mean of *Size* is 6.18, comparable to 5.35 of the Compustat universe. The mean of *Tobin's Q* is 2.24, comparable to the 2.02 of the Compustat universe. The mean of *Leverage* (*Loss*) is approximately 25 percent (35 percent), comparable to 32 percent (39 percent) of the Compustat universe. The average sales growth (*Growth*), *RD*, and *Capex* of the sample are 0.15, 0.27, and 0.05, respectively. The average sales growth (*Growth*), *RD*, and *Capex* of the Compustat universe are 0.13, 0.29, and 0.04, respectively. Overall, the sample in this study is comparable to the Compustat universe.

Figures 1 and 2 illustrate the trends of readability measures in the MD&A sections of 10-K reports. Prior literature suggests that the Fog index and the length of MD&A, on average, have both increased over time (Brown and Tucker 2011; Li 2008). I find similar results in that the MD&A Fog index and length have both increased over time. In contrast, I find that the levels of circuitousness at both the sentence and 250-word level, on average, remain relatively stable over time, possibly indicating that circuitousness captures different aspects of the qualitative disclosures that traditional readability measures do not capture.[17]

Table 3 shows the Pearson and Spearman correlations for all the variables in the sample. Both Pearson and Spearman correlations between *CIRCUIT* and *MLC* are negative and significant, indicating preliminary evidence of a negative relationship between obfuscation and conservatism.

Model specification

To test the effect of conservatism on circuitousness, I consider the following model:

$$\begin{aligned} CIRCUIT_{i,t} = {} & \alpha_0 + \alpha_1 MLC_{i,t} + \alpha_2 NDCons_{i,t} + \alpha_3 Size_{i,t} + \beta_4 Q_{i,t} + \alpha_5 ROA_{i,t} \\ & + \alpha_6 Leverage_{i,t} + \alpha_7 Growth_{i,t} + \alpha_8 Acquisition_{i,t} + \alpha_9 RD_{i,t} + \alpha_{10} Capex_{i,t} \\ & + \alpha_{11} Financing_{i,t} + \alpha_{12}\, \sigma\, CFO_{i,t} + \alpha_{13} Restructuring_{i,t} + \alpha_{14} Loss_{i,t} \\ & + \alpha_{15} Specitems_{i,t} + \alpha_{16} IOR_{i,t} + \alpha_{17} Num\_Analysts_{i,t} + \alpha_{18} Segment\_Bus_{i,t} \\ & + \alpha_{19} Segment\_Geo_{i,t} + \varepsilon. \end{aligned} \tag{2}$$

where i is firm index, and t is year index. The dependent variable $CIRCUIT_{i,t}$ contains two types: sentence-level ($Circuit\_sent_{i,t}$) and 250-word chunk-level ($Circuit\_250w_{i,t}$). Control variables include *Size, Tobin's Q, ROA, Leverage, Growth, Acquisition, RD, Capex, Financing, σ CFO, Restructuring, Loss, Specitems, IOR, Num_Analysts, Segment_Bus, Segment_Geo,* and *NDCons.* All continuous variables are standardized with a mean of zero and standard deviation of one for ease of interpretation. I also include year-fixed effects and industry-fixed effects

[17] Guest and Yan (2023) find similar results using 10-K reports: a stable trend of circuitousness in the 10-K reports over time.

based on Fama-French 48 classification on the regression. Under my hypothesis that conservatism disciplines obfuscation, I expect a significantly negative α_1.

IV. RESULTS

Validation test

Prior literature suggests that readability in financial reports is a significant factor through which managers influence investors' information processing (Cohen, Malloy, and Nguyen 2020). The incomplete revelation hypothesis posits that information is less likely to be incorporated into market prices if it is "harder for investors to uncover" (Bloomfield 2002). In other words, managers may intentionally provide investors with less readable reports to delay market reactions. When managers expect negative earnings growth, they are more likely to present information in a circuitous manner, which makes it harder for investors to uncover the true financial health of the company. Hence, more circuitous financial reports can affect market prices by increasing information asymmetry, as investors might require more time and effort to understand the information, leading to delays in their decision-making (Bloomfield 2002; Bushee, Gow, and Taylor 2018).

Alternatively, circuitousness in financial reports may not be related to information asymmetry. First, given that mandatory financial documents such as 10-K filings comprise both quantitative data and qualitative narratives, the impact of structural design on information asymmetry may not be substantial. Second, consistent with Bloomfield (2008), complex structure may be expected in cases where complex transactions are common, thereby not necessarily viewed as a negative signal by investors. Shifts in narratives may help investors to understand firms' underlying performance as seemingly unrelated points may be related, allowing investors to connect different points.

To validate whether managers tend to use circuitous language to hide adverse information, I replicate Bushee, Gow, and Taylor's (2018) main test, examining the relationship between circuitousness and information asymmetry. Table 4 presents the validation results. Columns (1) through (4) report the regression results between circuitousness (*Circuit_Sent*) and information asymmetry (*Illiquid%*), controlling for industry- and year-fixed effects in columns (2) and (4). The coefficients of *Circuit_Sent* in column (1) and (2) are 0.023 and 0.020, positive and significant, respectively, suggesting a positive relationship between circuitousness and information asymmetry. Specifically, the coefficients indicate that, moving from the bottom to the top decile, *Circuit_Sent* is associated with a 0.020 increase in Illiquidity.[18] In addition, the coefficients in columns (3) and (4) indicate that, moving from the bottom to the top decile, *Circuit_250w* is associated with a 0.019 increase in *Illiquidity*. Overall, the results imply that the structural component of disclosure is an important factor affecting information asymmetry.

Conservatism and semantic progression – hypothesis testing

Table 5 reports the regression results of testing my hypothesis. Columns (1) and (2) in Panel A report the regression results between the machine learning-based conservatism proxy (*MLC* and *MLC_Decile*) and the circuitousness in MD&A at the sentence level (*Circuit_Sent*). The coefficients of *MLC* and *MLC_Decile* in columns (1) and (2) are -0.038 and -0.166, both negative and significant at the 1 percent level, respectively, indicating a negative association between conservatism and circuitousness. Specifically, the coefficient in column (2) suggests that increasing machine-learning based conservatism from bottom to top decile is associated with a 0.166 standard deviation decrease in *Circuit_Sent*.[19]

Columns (1) and (2) in panel B display the regression results between the machine-learning based conservatism proxy (*MLC* and *MLC_Decile*) and the circuitousness in MD&A

[18] Based on the median value (0.0069) and 52nd values (0.0084), *Circuit_Sent* from the bottom to the top decile leads to a 21 percent increase in *Illiquidity*, indicating the results are economically significant.
[19] In economic terms, the coefficient in column (1) suggests that a one-standard-deviation increase in machine-learning based conservatism is associated with a 0.038 standard deviation decrease in *Circuit_Sent*.

at 250 word-level (*Circuit_250w*). Consistent with the previous findings, the coefficients in both columns (1) and (2) are negative and significant (-0.020 and -0.088, respectively). In other words, the coefficient in column (2) suggests that increasing machine-learning based conservatism from the bottom to the top decile is associated with a 0.088 standard deviation decrease in *Circuit_250w*. Consistent with the hypothesis that managers have incentives to use circuitous language to obfuscate information and that conservatism plays a governance role by reducing such incentives, the results suggest that conservatism constrains such behavior in the MD&A sections of 10-K reports.[20]

I also find evidence that *Size*, *Leverage*, *Restructuring*, *Loss*, and *Segment_Bus* (*Capex* and *Specitems*) are positively (negatively) associated with circuitousness across all columns. Overall, consistent with my hypothesis, all coefficients of *MLC* (*MLC_Decile*) are negative and significant, suggesting that conservatism has an economically significant influence on managers' use of circuitous language in MD&A.

Cross-sectional analysis – Debtholders' demand for conservatism

Prior literature on conservatism suggests that debtholders demand conservatism for efficient contracting and monitoring (Ball et al. 2000; Beatty et al. 2008; Khan and Watts 2009; Nikolaev 2010; Watts 2003a). Conservatism serves as a mechanism for establishing lower bounds for accounting numbers, providing lenders with a reference point to consider in their lending decisions (Khan and Watts 2009). This suggests a higher level of conservatism for more levered firms. Therefore, I examine whether the association between circuitousness and conservatism is stronger for firms with higher debt.

To test this prediction, I focus on long-term debt issuance, since short-term debt can

[20] The results are qualitatively similar if circuitousness is measured at a 125-word chunk or a 375-word chunk (untabulated).

alleviate agency costs from information asymmetry, lowering the demand for conservatism (Khurana and Wang 2015). I partition firm-year observations based on long-term debt issuance, the top (bottom) quartile to the high (low) long-term debt issuance subsample. Table 6 reports the regression results of the cross-sectional analysis using long-term debt issuance. The coefficients of *MLC* and *MLC_decile* for firms with higher long-term debt issuance are negative and significant in columns (2), (4), (6), and (8), while the coefficients of *MLC* and *MLC_decile* for firms with lower long-term debt issuance are insignificant in columns (1), (3), (5), and (7). In addition, the differences in the coefficients of *MLC* and *MLC_decile* between the two subsamples are significant in all cases, indicating that the negative relationship between circuitousness and conservatism is stronger for firms with higher long-term debt issuance.[21]

Cross-sectional analysis – proprietary costs

Prior theories suggest that proprietary costs drive firms' disclosure choices (Clinch and Verrecchia 1997; Dye 1986, 2001; Verrecchia 1983, 1990, 2001). Clinch and Verrecchia (1997) argue that when a firm makes financial reporting decisions, it considers the potential impact on its competitive standing within the market. For example, firms may recognize losses sooner rather than later to discourage potential competitors from entering a competitive market, or to discourage existing competitors from overproducing. Consistent with this view, Dhaliwal, Huang, Khurana, and Pereira (2014) find a positive relationship between conservatism and product market competition, suggesting that conservatism is greater when firms are facing higher product market competition. Therefore, I examine whether the association between circuitousness and conservatism is stronger for firms in highly competitive markets.

To test this prediction, I first utilize data provided by Hoberg and Phillips (2010,

[21] The results are qualitatively similar if I use *Leverage* or the long-term debt that matures in three, four, and five years, instead of long-term debt issuance.

2016)[22] [23], the Text-based Network Industry Classifications (TNIC) similarity score from 10-K, and the Herfindahl–Hirschman index (HHI). Then, I partition the total observations based on the TNIC similarity score and HHI, firm-year observations that are in the top (bottom) quartile to high (low) competition subsample.

Table 7 reports the results. Panel A reports the regression results of the analysis using the TNIC similarity score. The coefficients of *MLC* and *MLC_decile* for firms facing high product market competition are negative and significant in columns (2), (4), (6), and (8), while the coefficients of *MLC* for firms facing low product market competition are marginally significant or insignificant in columns (1), (3), (5), and (7). In addition, the differences in the coefficients of *MLC* and *MLC_decile* between two subsamples are significant for all columns, indicating that the negative relationship between circuitousness and conservatism is stronger for firms facing higher product market competition.

Panel B reports the regression results of the analysis using HHI. The coefficients of *MLC* and *MLC_decile* for firms facing high product market competition are negative and significant in columns (2), (4), (6), and (8), whereas the coefficients of *MLC* for firms facing low product market competition are insignificant in columns (1), (3), (5), and (7). In addition, the differences in the coefficients of *MLC* and *MLC_decile* between the two subsamples are significant in all cases, indicating that the negative relationship between circuitousness and conservatism is stronger for firms facing higher product market competition. Collectively, the findings suggest that the negative association between circuitousness and conservatism is stronger for firms facing high product market competition, indicating that conservatism's governance role is strengthened in competitive markets.

[22] I thank Hoberg and Phillips (2010; 2016) for sharing their data online.
[23] http://hobergphillips.tuck.dartmouth.edu/industryclass.htm

V. SUPPLEMENT ANALYSIS

To address the potential endogeneity concerns that empirical research often has, I perform various robustness checks to dispel those concerns.

Alternative Measures of Conservatism

First, Bertomeu et al. (2024) also perform by-year estimation (*MLCy*) in the models and find that both machine learning conservatism proxies (*MLC* and *MLCy*) with more economic features and yearly estimation better explain the differential timeliness. Specifically, they document that these two benchmarks better capture the properties of conservatism: conservatism should be persistent and should increase after misstatement detection. Second, I measure conservatism using a frequently-used proxy, the conservatism score proposed by Khan and Watts (2009). They estimate the level of conservatism by interacting the Basu (1997) model with size, market-to-book, and leverage. However, to match *MLC*, I follow Bertomeu et al. (2024) and add volatility, net operating accruals, cash flow from operations, investment cycle, and firm age to the model to calculate *LC* and *LCy* (by-year estimation). Therefore, I repeat the analysis using different proxies of conservatism and find the results consistent with the main findings.

Table 8 reports the regression results of the alternative conservatism measures, *MLCy*, *LC*, and *LCy*. Consistent with the prediction, the coefficients of *MLCy* in columns (1) and (3) in panel A are -0.044 and -0.018, respectively, negative and significant, suggesting a negative relationship between *MLCy* and *CIRCUIT*. Panels B and C present the results using frequently-used conservatism proxies from the Khan and Watts (2009) approach. The coefficients of *LC* in Panel B columns (1) and (3) are negative and significant, -0.057 and -0.045, respectively, consistent with the main findings. Similarly, the coefficients of *LCy* in Panel C columns (1) and (3) are negative and significant, -0.031 and -0.027, respectively. Overall, the results provide consistent evidence that increasing conservatism reduces managers' opportunistic behavior through circuitousness.

Lagged Conservatism

Prior literature suggests that conservatism is stable and changes slowly over time (Khan and Watts 2009; Callen et al. 2010).[24] Therefore, using previous values of conservatism helps alleviate some concerns about unobservable year-specific events (D'Augusta and DeAngelis 2020; García Lara et al. 2016).[25] I repeat the analysis using the past year's *MLC* and the three-year average decile ranks of *MLC* to measure conservatism.

Table 9 presents the results. The coefficients of MLC_{t-1} in Panel A are negative and significant across the two measures of *CIRCUIT*, consistent with the main findings. Specifically, the results are qualitatively similar to the main findings, implying that conservatism is indeed stable over time. In addition, the coefficients of the three-year average decile rank of *MLC* in Panel B are also negative and significant at the 1 percent level, consistent with the main findings. Together, these results suggest that unobservable factors that decrease circuitousness may not be associated with variations in conservatism, consistent with the view that conservatism prevents managers' opportunism.

Basu (1997) model

I replicate the Basu (1997) model by incorporating the three-way interaction among stock returns, an indicator variable of negative stock returns, and *CIRCUIT*. I estimate the regression model below:

$$NI_{i,t} = \gamma_0 + \gamma_1 Neg_{i,t} + \gamma_2 Ret_{i,t} + \gamma_3 Neg \times Ret_{i,t} + \gamma_4 CIRCUIT_{i,t} + \gamma_5 Neg \times CIRCUIT_{i,t} + \gamma_6 Ret \times CIRCUIT_{i,t} + \gamma_7 Neg \times Ret \times CIRCUIT_{i,t} + \varepsilon. \quad (3)$$

[24] Figure 3 illustrates the trend of *MLC*, suggesting that conservatism is indeed stable over time.
[25] As noted by D'Augusta and DeAngelis (2020) and García Lara et al. (2016), past conservatism is likely to be associated with current conservatism, but not with contemporaneous events that affect disclosure characteristics.

where *NI* is net income scaled by the market value of equity. *Neg* is an indicator variable equal to one if *Ret* is negative, and zero otherwise. *Ret* is the 12-month buy-and-hold return during the fiscal year. Since this test examines whether the timeliness of news recognition is less asymmetric among firms hiding adverse information, I expect the coefficient γ_7 to be negative and significant. Table 10 presents the results: the negative and significant coefficient γ_7 indicates that this is the case for *Circuit_Sent*.

VI. CONCLUSION

Managers often attempt to hide information by making disclosures more difficult for investors to process. However, conservatism can serve as a constraint on such behavior since conservatism reveals the underlying information that managers wish to hide. Conservatism plays a governance role by providing hard, verifiable accounting information that can confirm and discipline soft sources of disclosure. Thus, I examine whether accounting conservatism constrains managers' incentives to alter the structure of MD&A in 10-K filings. Using natural language processing, I analyze the textual components in the MD&A section and construct a measure of semantic progression, circuitousness, a proxy reflecting the structural aspect of disclosure. Consistent with the hypothesis, I find that conservatism is negatively associated with circuitousness. My findings are robust to alternative measures of conservatism and lagged conservatism. I also document that the timeliness of news recognition is less asymmetric among firms hiding adverse information. Taken together, my results provide evidence of conservatism's role in reducing managers' incentives to use circuitousness to obfuscate information.

My study suggests that managers strategically alter the structure of financial reports by intentionally increasing investors' disclosure processing costs. However, it also highlights the governance role of conservatism in constraining managers' obfuscation of information in qualitative disclosures. The findings of this study are of interest to information users, preparers, and regulators. Understanding how managers hide information by providing less readable reports allows investors to assess the value of qualitative disclosures more effectively. Furthermore, this study contributes to the ongoing debate in prior literature regarding the benefits of conservatism. That is, whether it adds noise or helps form better information environments. My paper adds to the latter in that conservatism can serve as a mechanism to reduce managers' incentives to engage in opportunistic behaviors, thus enhancing the formation of more informative and reliable information environments.

Future research could extend this study in the following ways. First, while this study focuses on the MD&A sections of 10-K reports, it is important to note that managers primarily use these reports as a means of one-way communication to supply financial information. The negative relationship between circuitousness and conservatism may differ when considering cases involving two-way interactions. Therefore, future research could explore how the relationship between obfuscation and conservatism varies in contexts with interactive communication channels. Second, the MD&A sections of 10-K reports can be considered quasi-mandatory – mandatory components that just meet the minimal standards and discretionary components beyond the minimum. It is essential to acknowledge that the impact of conservatism on qualitative disclosures may not be easily generalized to other sources of voluntary disclosure, such as earnings conference calls, press releases, and social media. Future studies could investigate the influence of conservatism on these voluntary sources to gain a more comprehensive understanding. Third, other external or internal governance mechanisms may also influence the quality and content of qualitative disclosures. Further research is needed to explore the interplay between hard and soft information and how different governance mechanisms interact to shape the nature of qualitative disclosure.

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Figure 1: Trends of Circuitousness in the MD&A (*Circuit_Sent* and *Circuit_250w*)

Notes: This figure plots the time trends of the circuitousness measures in MD&A in this study. *CIRCUIT _Sent* (*CIRCUIT_250w*) is defined as the ratio of the actual distance a document travels consecutively from chunk to chunk to the shortest possible path minus one at the sentence level (at the 250-word level).

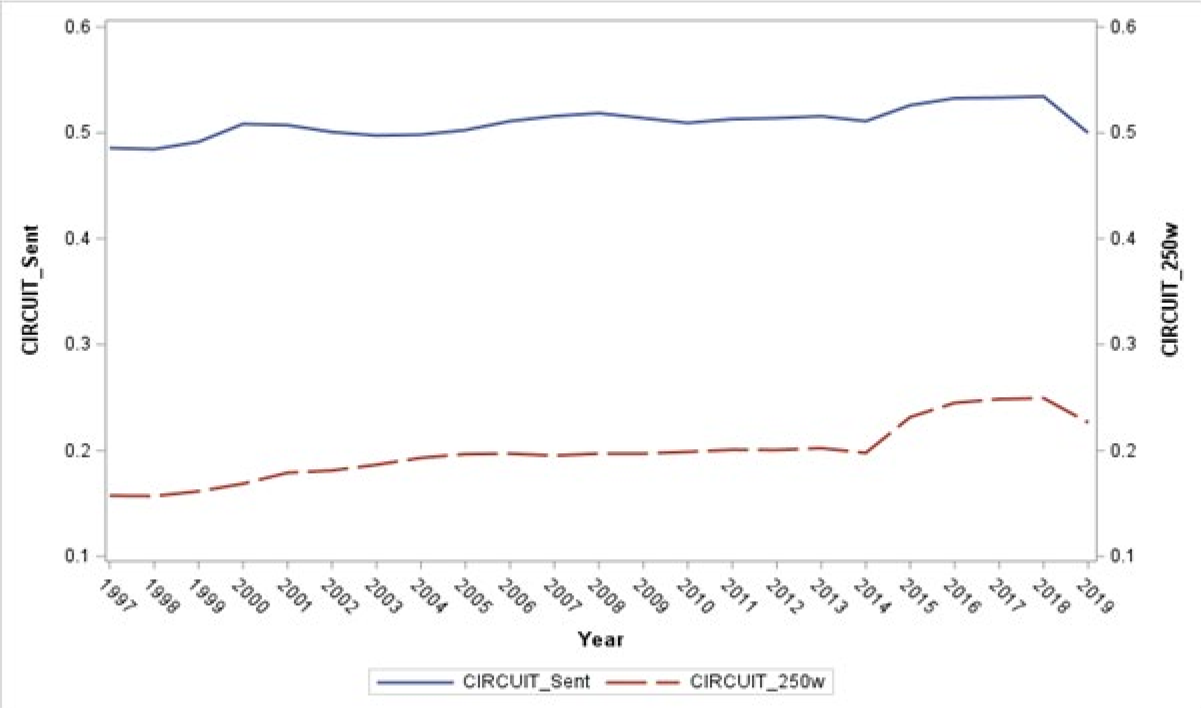

Figure 2: Trends of traditional readability measures in the MD&A (*Number of Words* and *Fog Index*)

Notes: This figure plots the time trends of the traditional readability measures in MD&A in this study. *Number of Words* is defined as the number of words in the MD&A section of 10-K reports in thousands. *Fog Index* is defined as the sum of the average words per sentence and the percentage of complex words (words with three syllables or more), multiplied by 0.4.

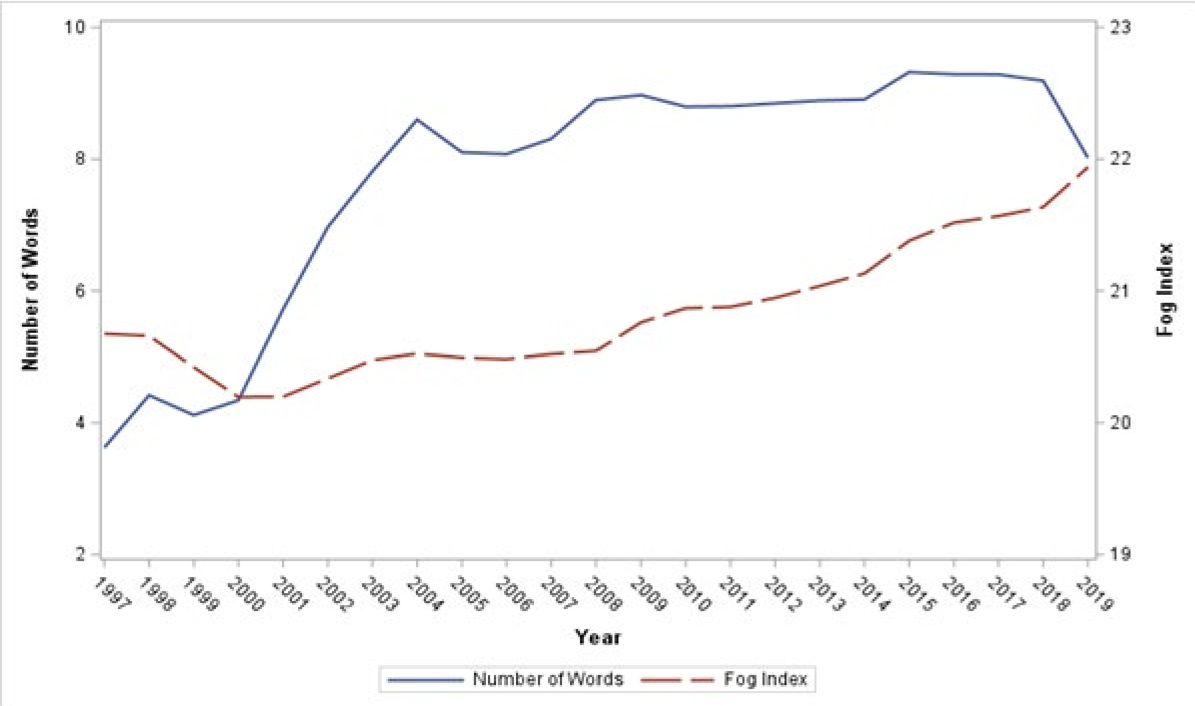

Figure 3: Trend of machine learning conservatism (*MLC*)

Notes: This figure plots the time trend of the machine-learning-based conservatism measure in this study. *MLC*, a measure from Bertomeu et al. (2024), applies a state-of-the-art neural network approach to estimate conservatism. Starting from Khan and Watts (2009) incorporating size, market-to-book, and leverage to calculate conservatism, Bertomeu et al. (2024) add five additional variables that are potentially related to conservatism in Khan and Watts (2009): volatility, net operating accruals, cash flow from operations, investment cycle, and firm age.

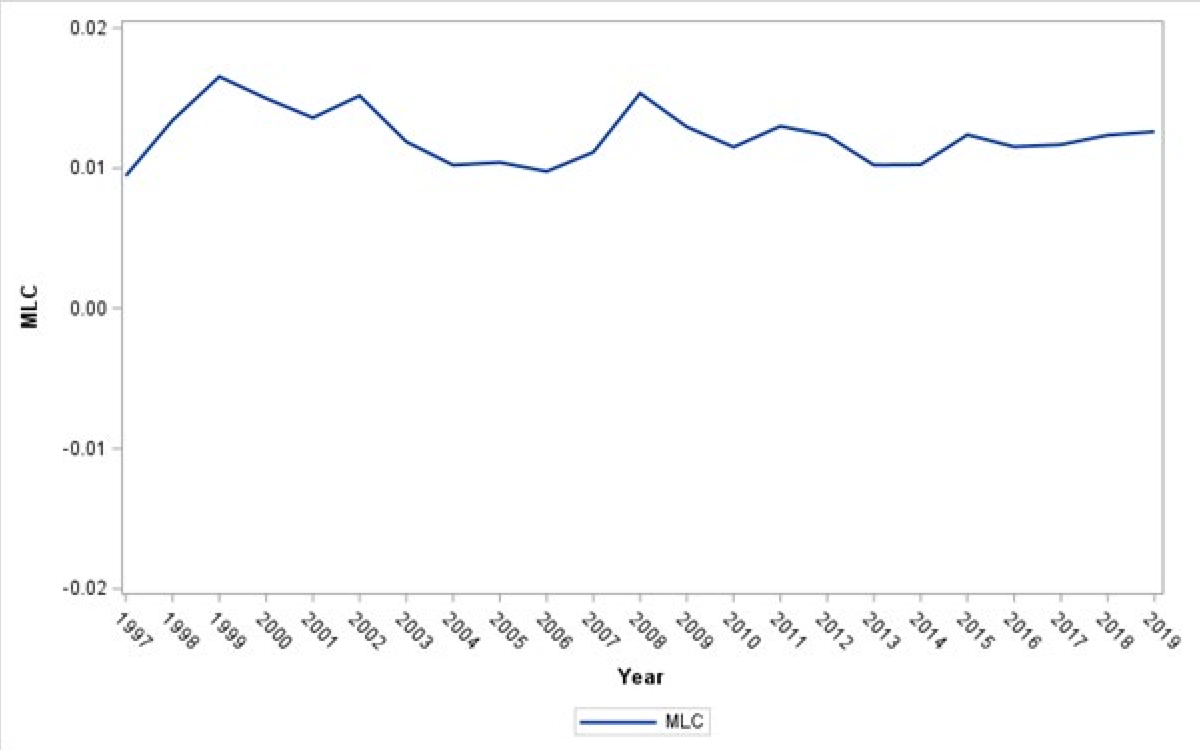

Table 1: Sample Selection

	Firm-years
Firm-years from universe of Compustat (with total assets)	
(fiscal years 1997 - 2019)	107,661
Observations with missing control variables	
(from Compustat and CRSP)	(5,122)
Observations with missing MD&A circuitousness data	
(from EDGAR)	(22,278)
Observations with missing analyst and institutional ownership information	
(from I/B/E/S and Thomson Reuter Ownership database)	(7,420)
Observations with missing values for variables necessary to calculate conservatism	(30,077)
Total Observations	42,764

Table 2: Descriptive Statistics

This table presents descriptive statistics for the variables in this study. The sample is constructed from Compustat, CRSP, Thompson Reuters, and I/B/E/S. The sample has 42,764 firm-year observations and covers firms from 1997 to 2019. All variables are winsorized at the 1st and 99th percentiles.

Variable	N	Mean	Std Dev	25th Pctile	Median	75th Pctile
Circuit_Sent	42,764	0.51	0.09	0.46	0.51	0.57
Circuit_250w	42,764	0.20	0.07	0.16	0.20	0.25
MLC	42,764	0.01	0.02	0.00	0.01	0.02
LC	42,764	-0.01	0.09	-0.06	-0.01	0.05
NDCons	42,764	0.13	0.33	0.00	0.00	0.00
SIZE	42,764	6.18	1.90	4.80	6.17	7.51
Q	42,764	2.24	1.54	1.04	1.84	3.22
ROA	42,764	-0.04	0.30	-0.05	0.03	0.07
Leverage	42,764	0.25	0.31	0.01	0.19	0.38
Growth	42,764	0.15	0.47	-0.03	0.07	0.21
Acquisition	42,764	0.03	0.09	0.00	0.00	0.02
RD	42,764	0.27	1.72	0.00	0.00	0.09
Capex	42,764	0.05	0.06	0.02	0.03	0.07
Financing	42,764	0.36	0.72	0.08	0.17	0.38
σ CFO	42,764	0.08	0.13	0.03	0.05	0.09
Restructuring	42,764	0.30	0.46	0.00	0.00	1.00
Loss	42,764	0.35	0.48	0.00	0.00	1.00
SpecItems	42,764	-0.02	0.10	-0.01	0.00	0.00
IOR	42,764	0.58	0.31	0.32	0.64	0.85
# Analysts	42,764	1.57	0.96	0.69	1.61	2.30
Segment_Bus	42,764	2.43	2.00	1.00	1.00	4.00
Segment_Geo	42,764	2.55	2.32	1.00	2.00	4.00
Fog Index	42,764	20.83	1.40	19.86	20.75	21.71
Num_Words	42,764	8.04	4.21	5.05	7.56	10.44

Table 3: Pearson and Spearman correlation

This table presents the correlation matrix among the variables used in this study. Pearson (Spearman) correlations appear above (below) the diagonal. Coefficients that are significant at the 10% level are in bold. The sample is 42,764 observations from 1997 to 2019.

	Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
(1)	***Circuit_Sent***		**0.54**	**-0.1**	**-0.1**	**-0**	**0.18**	**-0**	**0.06**	**0.08**	0.00	**0.05**	**-0.1**	**0.01**	**-0.1**	**-0.08**	**0.12**	**-0**	**-0**	**0.16**	**0.16**	**0.07**	**0.07**	**-0.1**	**0.44**
(2)	***Circuit_250w***	**0.50**		**-0.1**	**-0.1**	**-0.1**	**0.18**	**-0**	**0.01**	**0.08**	**-0**	-0.01	0.01	**-0**	**-0**	**-0.04**	**0.11**	0.01	**-0**	**0.18**	**0.14**	**0.04**	**0.02**	**0.11**	**0.5**
(3)	***MLC***	**-0.11**	**-0.07**		**0.60**	**0.30**	**-0.40**	**-0.43**	**-0.01**	**0.18**	**-0.11**	**-0.07**	**-0.04**	**-0.11**	**0.01**	**-0.01**	**-0.03**	**0.08**	**-0.11**	**-0.25**	**-0.38**	**0.05**	**-0.09**	**-0.05**	**-0.1**
(4)	***LC***	**-0.12**	**-0.10**	**0.71**		**0.28**	**-0.57**	**-0.39**	0.00	**0.03**	**-0.17**	**-0.07**	**-0.08**	**-0.14**	**-0.06**	**-0.04**	**-0.04**	**0.06**	**-0.13**	**-0.31**	**-0.54**	**0.06**	**-0.08**	**-0.12**	**-0.2**
(5)	***NDCons***	**-0.05**	**-0.05**	**0.26**	**0.27**		**-0.30**	**-0.23**	**-0.06**	**-0.05**	**-0.11**	**-0.08**	**-0.03**	**-0.08**	**-0.05**	**-0.03**	0.00	**0.16**	**-0.19**	**-0.18**	**-0.27**	**0.01**	**-0.05**	**-0.05**	**-0.1**
(6)	***SIZE***	**0.21**	**0.20**	**-0.44**	**-0.58**	**-0.29**		**0.11**	**0.26**	**0.13**	**0.04**	**0.09**	**-0.06**	**0.09**	**-0.16**	**-0.23**	**0.19**	**-0.35**	**0.09**	**0.64**	**0.78**	**0.13**	**0.18**	**0.13**	**0.37**
(7)	***Q***	**-0.04**	**-0.03**	**-0.48**	**-0.40**	**-0.24**	**0.10**		**-0.06**	**-0.55**	**0.11**	**-0.06**	**0.13**	**-0.06**	**0.10**	**0.20**	**-0.09**	**0.01**	**0.13**	**0.02**	**0.12**	**-0.15**	**0.05**	**0.03**	**-0.08**
(8)	***ROA***	**0.05**	**-0.01**	**-0.18**	**-0.12**	**-0.20**	**0.38**	**0.18**		0.00	**-0.02**	**0.07**	**-0.27**	**0.09**	**-0.25**	**-0.40**	**-0.01**	**-0.50**	**0.22**	**0.23**	**0.15**	**0.09**	**0.09**	**-0.10**	**0.03**
(9)	***Leverage***	**0.10**	**0.09**	**0.17**	**0.03**	**-0.02**	**0.23**	**-0.79**	**-0.06**		**0.10**	**0.21**	**-0.03**	**0.13**	**0.22**	**-0.04**	**0.03**	**0.01**	**-0.05**	**0.07**	**0.10**	**0.04**	**-0.07**	**0.08**	**0.12**
(10)	***Growth***	0.01	**-0.03**	**-0.22**	**-0.23**	**-0.17**	**0.11**	**0.16**	**0.20**	**0.03**		**0.15**	**0.03**	**0.15**	**0.13**	**0.10***	**-0.12**	0.00	**0.05**	**-0.04**	**0.06**	**-0.04**	**-0.05**	**0.04**	**-0.03**
(11)	***Acquisition***	**0.12**	**0.03**	**-0.14**	**-0.14**	**-0.10**	**0.26**	**-0.05**	**0.14**	**0.18**	**0.18**		**-0.04**	**0.01**	**0.07**	**-0.06**	**0.01**	**-0.08**	0.01	**0.09**	**0.08**	**0.07**	**0.04**	**0.02**	**0.03**
(12)	***RD***	**-0.07**	**-0.05**	**-0.16**	**-0.18**	**-0.11**	**-0.10**	**0.43**	**-0.26**	**-0.32**	**0.04**	**-0.07**		**-0.07**	**0.13**	**0.21**	**-0.04**	**0.19**	**0.01**	**-0.07**	**-0.01**	**-0.09**	**-0.08**	**0.11**	**-0.03**
(13)	***Capex***	**0.01**	-0.01	**-0.16**	**-0.14**	**-0.11**	**0.15**	**-0.09**	**0.18**	**0.18**	**0.17**	**-0.01**	**-0.27**		**0.02**	**-0.07**	**-0.16**	**-0.10**	**0.06**	**0.02**	**0.13**	**-0.03**	**-0.09**	**-0.06**	**-0.05**
(14)	***Financing***	**-0.05**	**-0.04**	**0.01**	**-0.03**	**-0.04**	**-0.31**	**0.09**	**-0.23**	**0.06**	**0.13**	**0.02**	**0.20**	**-0.02**		**0.41**	**-0.08**	**0.18**	0.01	**-0.23**	**-0.15**	**-0.08**	**-0.09**	**0.04**	**-0.07**
(15)	***σ CFO***	**-0.14**	**-0.10**	**0.04**	**0.04**	**0.04**	**-0.43**	**0.25**	**-0.23**	**-0.27**	**0.02**	**-0.22**	**0.29**	**-0.13**	**0.32**		**-0.08**	**0.23**	**0.01**	**-0.25**	**-0.18**	**-0.12**	**-0.10**	**0.04**	**-0.10**
(16)	***Restructuring***	**0.12**	**0.11**	**-0.01**	**-0.05**	0.00	**0.19**	**-0.08**	**-0.09**	**0.08**	**-0.18**	**0.11**	**0.10**	**-0.14**	**-0.09**	**-0.10**		**0.06**	**-0.14**	**0.23**	**0.16**	**0.09**	**0.23**	**0.07**	**0.25**
(17)	***Loss***	**-0.05**	0.00	**0.08**	**0.06**	**0.16**	**-0.36**	**-0.02**	**-0.82**	**-0.05**	**-0.16**	**-0.17**	**0.30**	**-0.17**	**0.26**	**0.31**	**0.07**		**-0.26**	**-0.25**	**-0.21**	**-0.11**	**-0.06**	**0.13**	0.00
(18)	***SpecItems***	**-0.09**	**-0.08**	**-0.04**	**-0.03**	**-0.08**	**-0.04**	**0.18**	**0.29**	**-0.14**	**0.14**	**-0.12**	**-0.02**	**0.09**	**-0.01**	**0.05**	**-0.40**	**-0.26**		**0.02**	**0.06**	**-0.03**	**-0.01**	**-0.02**	**-0.06**
(19)	***IOR***	**0.18**	**0.19**	**-0.27**	**-0.33**	**-0.17**	**0.65**	**0.02**	**0.25**	**0.14**	**0.03**	**0.22**	**-0.08**	**0.06**	**-0.30**	**-0.33**	**0.23**	**-0.25**	**-0.10**		**0.62**	**0.07**	**0.16**	**0.11**	**0.29**
(20)	***# Analysts***	**0.17**	**0.15**	**-0.45**	**-0.57**	**-0.25**	**0.78**	**0.10**	**0.22**	**0.17**	**0.13**	**0.22**	**-0.01**	**0.16**	**-0.20**	**-0.30**	**0.15**	**-0.20**	**-0.06**	**0.61**		**0.04**	**0.14**	**0.12**	**0.31**
(21)	***Segment_Bus***	**0.08**	**0.05**	**0.08**	**0.09**	**0.02**	**0.10**	**-0.13**	**0.06**	**0.10**	**-0.03**	**0.13**	**-0.10**	0.01	**-0.12**	**-0.13**	**0.07**	**-0.10**	**-0.06**	**0.05**	0.00		**0.10***	0.00	**0.12**
(22)	***Segment_Geo***	**0.08**	**0.01**	**-0.09**	**-0.08**	**-0.05**	**0.17**	**0.08**	**0.07**	**-0.05**	**-0.03**	**0.14**	**0.26**	**-0.09**	**-0.09**	**-0.07**	**0.24**	**-0.05**	**-0.11**	**0.14**	**0.12**	**0.09**		**-0.10**	**0.12**
(23)	***Fog Index***	**-0.11**	**0.12**	**-0.07**	**-0.13**	**-0.05**	**0.13**	**0.03**	**-0.14**	**0.05**	**0.02**	**0.05**	**0.10**	**-0.09**	**0.06**	**-0.03**	**0.08**	**0.12**	**-0.07**	**0.12**	**0.13**	0.00	**-0.09**		**0.20**
(24)	***Num_Words***	**0.41**	**0.49**	**-0.13**	**-0.20**	**-0.08**	**0.41**	**-0.07**	**-0.04**	**0.18**	**-0.04**	**0.14**	**0.01**	**-0.04**	**-0.10**	**-0.19**	**0.27**	0.00	**-0.18**	**0.33**	**0.34**	**0.10**	**0.13**	**0.23**	

Table 4: Circuitousness and Information Asymmetry

This table reports the relationship between information asymmetry (measured as *Illiquid %*) and circuitousness (measured *as Circuit_Sent* and *Circuit_250w*). Columns (2) and (4) present the regression results with industry and year-fixed effects. All independent variables are ranked into deciles and scaled to range from 0 to 1 for ease of interpretation. ***, **, and * represent statistical significance at 1%, 5%, and 10%. The standard errors, clustered by firm, are reported in parentheses.

	(1)	(2)	(3)	(4)
VARIABLES		*Illiquid %*		
Circuit_Sent	0.023***	0.020***		
	(0.005)	(0.005)		
Circuit_250w			0.019***	0.019***
			(0.004)	(0.004)
Size	-0.754***	-0.748***	-0.753***	-0.747***
	(0.007)	(0.007)	(0.007)	(0.007)
BM	0.109***	0.118***	0.109***	0.118***
	(0.007)	(0.007)	(0.007)	(0.007)
Leverage	-0.060***	-0.062***	-0.060***	-0.062***
	(0.005)	(0.006)	(0.005)	(0.006)
Acquisition	0.010***	0.006**	0.011***	0.007**
	(0.003)	(0.003)	(0.003)	(0.003)
Capex	0.028***	0.041***	0.028***	0.041***
	(0.005)	(0.005)	(0.005)	(0.005)
RD	0.027***	0.015**	0.027***	0.015**
	(0.005)	(0.007)	(0.005)	(0.007)
Financing	0.000	0.001	0.001	0.001
	(0.005)	(0.005)	(0.005)	(0.005)
σ CFO	-0.058***	-0.055***	-0.059***	-0.056***
	(0.005)	(0.005)	(0.005)	(0.005)
Goodwill	-0.007*	-0.007*	-0.006	-0.007*
	(0.004)	(0.004)	(0.004)	(0.004)
Restructuring	-0.001	-0.002	0.000	-0.002
	(0.003)	(0.004)	(0.003)	(0.004)
Loss	0.003	0.003	0.003	0.003
	(0.003)	(0.003)	(0.003)	(0.003)
SpecItem	-0.001*	-0.001**	-0.001*	-0.001*
	(0.000)	(0.000)	(0.000)	(0.000)
Word Count	-0.004	-0.001	-0.003	-0.001
	(0.005)	(0.005)	(0.005)	(0.005)
Fog	0.013***	0.008*	0.009**	0.004
	(0.005)	(0.005)	(0.005)	(0.005)
Constant	0.876***	0.871***	0.880***	0.873***
	(0.011)	(0.012)	(0.011)	(0.012)
Observations	54,177	54,177	54,177	54,177
Adj R-squared	0.577	0.581	0.577	0.581
Ind. FE	No	Yes	No	Yes
Year FE	No	Yes	No	Yes

Table 5: Panel A. Circuitousness at the sentence level and Machine learning conservatism

Panel A reports the relationship between machine learning conservatism (measured as *MLC* and *MLC_Decile*) and circuitousness (measured *as Circuit_Sent*). Columns (1) and (2) present the regression results with industry and year-fixed effects. All continuous variables are standardized with a mean of zero and standard deviation of one for ease of interpretation. ***, **, and * represent statistical significance at 1%, 5%, and 10%. The standard errors, clustered by firm, are reported in parentheses.

VARIABLES	(1) *Circuit_Sent*	(2) *Circuit_Sent*
MLC	-0.038*** (0.010)	
MLC_Decile		-0.166*** (0.040)
NDCons	0.020 (0.023)	0.015 (0.023)
Size	0.074*** (0.022)	0.072*** (0.022)
Q	0.006 (0.013)	0.001 (0.013)
ROA	0.004 (0.008)	0.004 (0.008)
Leverage	0.062*** (0.012)	0.058*** (0.012)
Growth	0.005 (0.005)	0.005 (0.005)
Acquisition	0.009 (0.006)	0.009 (0.006)
RD	-0.019*** (0.005)	-0.019*** (0.005)
Capex	-0.024** (0.012)	-0.026** (0.012)
Financing	-0.010 (0.021)	-0.008 (0.021)
σ CFO	-0.005 (0.008)	-0.005 (0.008)
Restructuring	0.103*** (0.018)	0.104*** (0.018)
Loss	0.036** (0.017)	0.036** (0.017)
Specitems	-0.011** (0.005)	-0.010** (0.005)
IOR	0.023 (0.014)	0.023 (0.014)
# Analysts	0.033* (0.018)	0.028 (0.018)
Segment_Bus	0.027*** (0.006)	0.028*** (0.006)
Segment_Geo	0.010** (0.005)	0.010** (0.005)
Constant	-0.135*** (0.024)	-0.044 (0.032)
Observations	42,764	42,764
Adj R-squared	0.068	0.068
Ind. FE	Yes	Yes
Year FE	Yes	Yes

Panel B. Circuitousness at the 250-words level and Machine learning conservatism

Panel B reports the relationship between machine learning conservatism (measured as *MLC* and *MLC_Decile*) and circuitousness (measured as *Circuit_250w*). Columns (1) and (2) present the regression results with industry and year-fixed effects. All continuous variables are standardized with a mean of zero and standard deviation of one for ease of interpretation. ***, **, and * represent statistical significance at 1%, 5%, and 10%. The standard errors, clustered by firm, are reported in parentheses.

VARIABLES	(1) *Circuit_250W*	(2) *Circuit_250W*
MLC	-0.020**	
	(0.010)	
MLC_Decile		-0.088**
		(0.036)
NDCons	-0.026	-0.029
	(0.021)	(0.021)
Size	0.067***	0.065***
	(0.020)	(0.020)
Q	0.023*	0.020
	(0.013)	(0.013)
ROA	-0.011	-0.011
	(0.008)	(0.008)
Leverage	0.061***	0.060***
	(0.012)	(0.012)
Growth	-0.002	-0.003
	(0.005)	(0.005)
Acquisition	-0.023***	-0.023***
	(0.005)	(0.005)
RD	-0.008	-0.008
	(0.006)	(0.006)
Capex	-0.012	-0.013
	(0.010)	(0.010)
Financing	-0.038***	-0.037***
	(0.013)	(0.013)
σ CFO	-0.003	-0.003
	(0.008)	(0.008)
Restructuring	0.058***	0.059***
	(0.017)	(0.017)
Loss	0.098***	0.098***
	(0.017)	(0.017)
Specitems	-0.010**	-0.010**
	(0.005)	(0.005)
IOR	0.037***	0.038***
	(0.012)	(0.012)
# Analysts	0.000	-0.003
	(0.016)	(0.016)
Segment_Bus	0.024***	0.025***
	(0.005)	(0.005)
Segment_Geo	-0.002	-0.002
	(0.005)	(0.005)
Constant	-0.090***	-0.042
	(0.021)	(0.028)
Observations	42,764	42,764
Adj R-squared	0.118	0.118
Ind. FE	Yes	Yes
Year FE	Yes	Yes

Table 6: Cross-sectional analysis – Debtholders' demand for conservatism

This table reports whether the relationship between machine learning conservatism (measured as *MLC* and *MLC_Decile*) and circuitousness (measured *as Circuit_Sent* and *Circuit_250W*) differs for firms with different levels of long-term debt issuance. All columns present the regression results with industry and year-fixed effects, subsampled based on long-term debt issuance. High (low) indicates that firm-year observations are in the top quartile of long-term debt issuance. All continuous variables are standardized with a mean of zero and standard deviation of one for ease of interpretation. ***, **, and * represent statistical significance at 1%, 5%, and 10%. The standard errors, clustered by firm, are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	*Circuit_Sent*	*Circuit_Sent*	*Circuit_Sent*	*Circuit_Sent*	*Circuit_250W*	*Circuit_250W*	*Circuit_250W*	*Circuit_250W*
MLC	-0.009	-0.084***			-0.010	-0.051*		
	(0.018)	(0.026)			(0.017)	(0.027)		
MLC_Decile			-0.093	-0.355***			-0.099	-0.235***
			(0.081)	(0.086)			(0.069)	(0.080)
Difference (Low - High)	0.075		0.257		0.041		0.136	
X^2	5.98**		5.30**		3.04*		2.87*	
Competition	Low	High	Low	High	Low	High	Low	High
Observations	5,321	5,304	5,321	5,304	5,321	5,304	5,321	5,304
Adj R-squared	0.080	0.078	0.081	0.080	0.133	0.134	0.134	0.134
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: Panel A. Cross-sectional analysis – proprietary costs: TNIC score

Panel A reports whether the relationship between machine learning conservatism (measured as *MLC* and *MLC_Decile*) and circuitousness (measured *as Circuit_Sent* and *Circuit_250W*) differs when firms face different levels of product market competition. All columns present the regression results with industry and year-fixed effects, subsampled based on TNIC score. High (low) competition indicates that firm-year observations are in the top (low) TNIC score quartile. All continuous variables are standardized with a mean of zero and standard deviation of one for ease of interpretation. ***, **, and * represent statistical significance at 1%, 5%, and 10%. The standard errors, clustered by firm, are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	*Circuit_Sent*	*Circuit_Sent*	*Circuit_Sent*	*Circuit_Sent*	*Circuit_250W*	*Circuit_250W*	*Circuit_250W*	*Circuit_250W*
MLC	-0.024	-0.059***			-0.001	-0.030**		
	(0.017)	(0.019)			(0.015)	-0.011		
MLC_Decile			-0.121*	-0.247***			-0.018	-0.138**
			(0.065)	(0.068)			(0.061)	(0.062)
Difference (Low - High)	0.035		0.126		0.029		0.120	
X^2	3.74*		4.15**		2.75*		4.03**	
Competition	Low	High	Low	High	Low	High	Low	High
Observations	10,259	9,618	10,259	9,618	10,259	9,618	10,259	9,618
Adj R-squared	0.073	0.060	0.073	0.061	0.137	0.107	0.137	0.107
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Panel B. Cross-sectional analysis – proprietary costs: HHI

Panel A reports whether the relationship between machine learning conservatism (measured as *MLC* and *MLC_Decile*) and circuitousness (measured *as Circuit_Sent* and *Circuit_250W*) differs when firms face different levels of product market competition. All columns present the regression results with industry and year-fixed effects, subsampled based on HHI. High (low) competition indicates that firm-year observations are in the top (low) HHI quartile. All continuous variables are standardized with a mean of zero and standard deviation of one for ease of interpretation. ***, **, and * represent statistical significance at 1%, 5%, and 10%. The standard errors, clustered by firm, are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	*Circuit_Sent*	*Circuit_Sent*	*Circuit_Sent*	*Circuit_Sent*	*Circuit_250W*	*Circuit_250W*	*Circuit_250W*	*Circuit_250W*
MLC	0.001	-0.077***			0.007	-0.053***		
	(0.016)	(0.020)			(0.016)	(0.020)		
MLC_Decile			-0.077	-0.255***			0.062	-0.169***
			(0.072)	(0.067)			(0.065)	(0.064)
Difference (Low - High)	0.078		0.178		0.060		0.231	
X^2	9.93***		8.10***		5.60**		6.54**	
Competition	Low	High	Low	High	Low	High	Low	High
Observations	10,086	9,430	10,086	9,430	10,144	9,450	10,144	9,450
Adj R-squared	0.089	0.078	0.089	0.079	0.142	0.123	0.142	0.123
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: Panel A. Alternative machine learning conservatism measure: MLCy

Panel A reports the relationship between alternative machine learning conservatism (measured as *MLCy* and *MLCy_Decile*) and circuitousness (measured as *Circuit_Sent* and *Circuit_250w*). Columns (1), (2), (3), and (4) present the regression results with industry and year-fixed effects. All continuous variables are standardized with a mean of zero and standard deviation of one for ease of interpretation. ***, **, and * represent statistical significance at 1%, 5%, and 10%. The standard errors, clustered by firm, are reported in parentheses.

VARIABLES	(1) *Circuit_Sent*	(2) *Circuit_Sent*	(3) *Circuit_250W*	(4) *Circuit_250W*
MLCy	-0.044***		-0.018*	
	(0.011)		(0.010)	
MLCy_Decile		-0.242***		-0.155***
		(0.038)		(0.034)
Observations	42,764	42,764	42,764	42,764
Adj R-squared	0.068	0.070	0.118	0.119
Controls	Yes	Yes	Yes	Yes
Ind. FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Panel B. Alternative conservatism measure: LC

Panel B reports the relationship between alternative conservatism (measured as *LC* and *LC_Decile*) and circuitousness (measured as *Circuit_Sent* and *Circuit_250w*). Columns (1), (2), (3), and (4) present the regression results with industry and year-fixed effects. All continuous variables are standardized with a mean of zero and standard deviation of one for ease of interpretation. ***, **, and * represent statistical significance at 1%, 5%, and 10%. The standard errors, clustered by firm, are reported in parentheses.

VARIABLES	(1) *Circuit_Sent*	(2) *Circuit_Sent*	(3) *Circuit_250W*	(4) *Circuit_250W*
LC	-0.057***		-0.045***	
	(0.017)		(0.013)	
LC_Decile		-0.161***		-0.139***
		(0.056)		(0.049)
Observations	42,764	42,764	42,764	42,764
Adj R-squared	0.0683	0.068	0.119	0.119
Controls	Yes	Yes	Yes	Yes
Ind. FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Panel C. Alternative conservatism measure: LCy

Panel B reports the relationship between alternative conservatism (measured as *LCy* and *LCy_Decile*) and circuitousness (measured as *Circuit_Sent* and *Circuit_250w*). Columns (1), (2), (3), and (4) present the regression results with industry and year-fixed effects. All continuous variables are standardized with a mean of zero and standard deviation of one for ease of interpretation. ***, **, and * represent statistical significance at 1%, 5%, and 10%. The standard errors, clustered by firm, are reported in parentheses.

VARIABLES	(1) *Circuit_Sent*	(2) *Circuit_Sent*	(3) *Circuit_250W*	(4) *Circuit_250W*
LCy	-0.031***		-0.027**	
	(0.009)		(0.011)	
LCy_Decile		-0.081**		-0.059*
		(0.039)		(0.033)
Observations	42,764	42,764	42,764	42,764
Adj R-squared	0.067	0.067	0.118	0.118
Controls	Yes	Yes	Yes	Yes
Ind. FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Table 9: Panel A. Lagged machine learning conservatism

Panel A reports the relationship between lagged machine learning conservatism (measured as *MLC_lag*) and circuitousness (measured as *Circuit_Sent* and *Circuit_250w*). Columns (1) and (2) present the regression results with industry and year-fixed effects. All continuous variables are standardized with a mean of zero and standard deviation of one for ease of interpretation. ***, **, and * represent statistical significance at 1%, 5%, and 10%. The standard errors, clustered by firm, are reported in parentheses.

VARIABLES	(1) *Circuit_Sent*	(2) *Circuit_250W*
MLC_Lag	-0.046*** (0.011)	-0.017*** (0.006)
Observations	36,284	36,284
Adj R-squared	0.069	0.112
Controls	Yes	Yes
Ind. FE	Yes	Yes
Year FE	Yes	Yes

Panel B. Three-year average decile rank of machine learning conservatism

Panel A reports the relationship between lagged machine learning conservatism (measured as *MLC_Decile_3years*) and circuitousness (measured as *Circuit_Sent* and *Circuit_250w*). Columns (1) and (2) present the regression results with industry and year-fixed effects. All continuous variables are standardized with a mean of zero and standard deviation of one for ease of interpretation. ***, **, and * represent statistical significance at 1%, 5%, and 10%. The standard errors, clustered by firm, are reported in parentheses.

VARIABLES	(1) *Circuit_Sent*	(2) *Circuit_250W*
MLC_Decile_3years	-0.204*** (0.063)	-0.085*** (0.030)
Observations	30,974	30,974
Adj R-squared	0.072	0.107
Controls	Yes	Yes
Ind. FE	Yes	Yes
Year FE	Yes	Yes

Table 10: Basu (1997) model

This table reports the relationship between circuitousness (measured as *Circuit_Sent* and *Circuit_250w*) and conservatism, following Basu (1997). *Return* and *NEG* are the firm's annual stock return and an indicator variable equal to one if *Return* is negative and zero otherwise. All continuous variables are standardized with a mean of zero and standard deviation of one for ease of interpretation. ***, **, and * represent statistical significance at 1%, 5%, and 10%. The standard errors, clustered by firm and year, are reported in parentheses.

	(1)	(2)	(3)	(4)
	Basu (1997) Model			
VARIABLES	Ind. Var =	*Circuit_Sent*	Ind. Var =	*Circuit_250w*
NEG x Return	0.266***	0.315***	0.267***	0.239***
	(0.033)	(0.04)	(0.03)	(0.04)
NEG x Return x Circuitousness	-0.016*		0.027*	
	(0.009)		(0.01)	
NEG x Return x Circuit_Decile		-0.088**		0.049
		(0.04)		(0.04)
Constant	Yes	Yes	Yes	Yes
Control	Yes	Yes	Yes	Yes
Observations	46,628	46,628	46,628	46,628
Adj R-squared	0.063	0.063	0.064	0.063

Appendix A: Variable Definitions

Variable	Definition
Acquisition	The total acquisitions scaled by total assets at the beginning of the year.
Capex	The capital expenditure scaled by total assets.
CIRCUIT	The ratio of the excess distance traveled—calculated as the difference between the actual distance a document travels from chunk to chunk and the shortest possible path—to the shortest possible path.
Financing	The ratio of stock and debt issuances to total assets.
Growth	The change in sales scaled by total sales.
IOR	The ratio of the total shares of institutional ownership to the total shares outstanding.
Leverage	The ratio of total liability to assets at book values.
Loss	An indicator variable equal to one if net income is negative and zero otherwise.
MLC(y)	Neural network-based conservatism measure from Bertomeu et al. (2024). They use size, market-to-book, leverage, volatility, net operating accruals, cash flow from operations, investment cycle, and firm age to calculate *MLC(y)*.
NDCons	An indicator variable equal to one if the beginning book-to-market ratio is higher than one and zero otherwise.
Num_Analysts	The natural logarithm of the number of analysts covering the firm.
RD	The total research and development expenses scaled by sales.
Restructuring	An indicator variable equal to one if a firm had a restructuring charge and zero otherwise.
ROA	The ratio of net income over total assets.
Segment_Bus	The number of business segments.
Segment_Geo	The number of geographical segments.
Size	The natural logarithm of market capitalization at the beginning of the year.
Specitems	The special items scaled by the market value of equity.
Tobin's Q	The natural logarithm of the ratio of the sum of the market value of equity and the book value of the total debt to the sum of the book value of equity and the book value of the total debt.
σ CFO	The standard deviation of cash flows from operations scaled by total assets over a 5-year window.

Appendix B: Example of CIRCUITOUSNESS

In this appendix, I calculate CIRCUIT using an actual annual report: MD&A section in 10-K of Brown-Forman Corporation for the fiscal year 2017.[26] For illustration purposes, I present the actual sequence of the MD&A to calculate the level of circuitousness, followed by alternative, hypothetical sequences. The table below shows the calculated level of circuitousness.

Chunk 1: Net sales

> Net sales of $2,994 million decreased 3%, or $95 million, in fiscal 2017 compared to fiscal 2016. After adjusting reported results for (a) the net effect of acquisitions and divestitures, (b) the negative effect of foreign exchange, and (c) the estimated net decrease in distributor inventories, underlying net sales grew 3%. The negative effect of foreign exchange was driven primarily by the dollar's strengthening against the Mexican peso, euro, and British pound. The change in underlying net sales was driven almost equally by the positive impact of price/mix and volume growth. Volume growth was led by the Jack Daniel's family and the tequilas, partially offset by declines in Canadian Mist. Improved price/mix was driven by (a) higher average pricing on JDTW and the tequilas, and (b) a shift in sales out of lower-priced brands (most notably, Canadian Mist) to higher priced brands (most notably, Jack Daniel's family and Woodford Reserve; the gains were partially offset by declines in used barrel sales.

Chunk 2: Gross profit

> Gross profit of $2,021 million decreased $123 million, or 6%, in fiscal 2017 compared to fiscal 2016. Gross profit on an underlying basis improved 3% after adjusting reported gross profit for (a) the net effect of acquisitions and divestitures, (b) the negative effect of foreign exchange, and (c) the estimated net change in distributor inventories. The increase in underlying gross profit resulted from the same factors that contributed to the increase in underlying net sales partially offset by the same factors that drove higher underlying cost of sales. Gross margin decreased to 67.5% in fiscal 2017, down 190 basis points from 69.4% in fiscal 2016. The decrease in gross margin was primarily due to (a) the net effect of acquisitions and divestitures, (b) the negative effect of foreign exchange, and (c) an increase in underlying cost of sales.

Chunk 3: Advertising expenses

> Advertising expenses of $383 million decreased $34 million, or 8%, in fiscal 2017 compared to fiscal 2016. Underlying advertising expenses increased 2% after adjusting reported results for the net effect of acquisitions and divestitures and the benefit of foreign exchange. The increase in underlying advertising expense was driven by higher spending on (a) JDTW, due in part to the 150th anniversary of Jack Daniel's Distillery, (b) JD RTDs, partially due to new innovations, and (c) the launch of JDTF outside the United States. These increases were partially offset by lower spending for JDTF in the United States following the national introduction in late fiscal 2015 and for Finlandia Vodka.

Chunk 4: Cash flow

> Cash and cash equivalents declined $81 million in fiscal 2017, compared to a decline of $107

[26] The full report of Brown-Forman Corporation 10-K is available at https://www.sec.gov/Archives/edgar/data/14693/000001469316000160/bfb-2016430x10k.htm.

million in fiscal 2016. Cash provided by operations of $639 million was up $115 million from last year, largely reflecting the absence of a $125 million payment made during fiscal 2016 for estimated income taxes incurred on the sale of the Southern Comfort and Tuaca business. Cash used for investing activities was $422 million during fiscal 2017, an increase of $855 million over the $433 million in cash provided by investing activities during fiscal 2016. The increase of $855 million largely reflects the impact of the sale of the Southern Comfort and Tuaca business (for which we received cash of $543 million) in fiscal 2016 and the acquisition of BenRiach (for which we paid cash of $307 million) in fiscal 2017.

Chunk 5: Liquidity

We continue to manage liquidity conservatively to meet current obligations, fund capital expenditures, maintain dividends, and repurchase shares from time to time while reserving adequate debt capacity for acquisition opportunities. In addition to our cash and cash equivalent balances, we have access to several liquidity sources to supplement our cash flow from operations. One of those sources is our $800 million commercial paper program that we regularly use to fund our short-term credit needs and to maintain our access to the capital markets. During fiscal 2016, our commercial paper borrowings averaged $331 million, with an average maturity of 29 days and an average interest rate of 0.42%. During fiscal 2017, our commercial paper borrowings averaged $576 million, with an average maturity of 31 days and an average interest rate of 0.69%. Commercial paper outstanding was $269 million at April 30, 2016, and $208 million at April 30, 2017.

Sequence of chunks	**CIRCUITOUSNESS**
Actual sequence: Chunk 1 - 2 - 3 - 4 - 5	0.05
Hypothetical sequence 1: Chunk 1-4-2-3-5	0.25
Hypothetical sequence 2: Chunk 1-3-4-2-5	0.20
Hypothetical sequence 3: Chunk 1-5-2-4-3	0.36