Changing the channel: The relation between information complexity and disclosure channel richness

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The final copy of this thesis has been examined by the signatories, and we find that both the content and the form meet acceptable presentation standards of scholarly work in the above mentioned discipline.

ABSTRACT

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Thesis directed by Professor Jonathan L. Rogers and Professor Sarah L.C. Zechman

I examine the role of information complexity in disclosure channel choice and its implications for market participants. Organizational communication theory suggests that because managers prefer efficient communication, they match underlying information complexity to internal communication channel richness (e.g. interaction, language variety and cues). Although external disclosures diverge from internal firm communication in important ways, I find evidence consistent with predictions from the management theory in the external quarterly reporting setting. Specifically, I find information complexity is associated with the allocation of information across the earnings announcement press release and conference call. The positive relation between complexity and richness is mitigated when managers have weakened preferences for (or ability to facilitate) communication efficiency. Moreover, placing complex information in lean channels is associated with slower price formation. The results are consistent with managers, on average, choosing disclosure channel to reduce the cost of processing their disclosures.

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1. Introduction

Managers choose from several channels when disclosing firm information to outside parties. Examples include SEC filings, press releases, social media posts, press interviews, conference calls, investor conferences, and analyst/investor days. Moreover, the number of channels available has increased over time and these channels vary on dimensions such as written versus oral language, the variety of language used, and the opportunity for interaction with investors and analysts. Despite the increase in channels available and the differences across channels, our understanding of how managers make disclosure channel decisions is limited. I investigate the role of ex ante information complexity in the disclosure channel decision and whether channel choice has implications for the market's response to firm information.[1]

I draw from the "media richness" literature from the management field (e.g., Daft and Lengel, 1986) to provide insight into the disclosure channel choice. Managers use internal channels such as memos, e-mails and telephone calls to communicate with employees. These channels vary in richness, which is defined by the number cues provided (e.g. natural language, tone of voice, body language), the diversity of language choices supported, and whether the channel provides an opportunity for interaction. Daft and Lengel (1986) suggest that managers match information complexity to channel richness when communicating with other employees within the firm: rich channels facilitate efficient communication of complex topics, while less rich (lean) channels are suitable for straightforward information.

Although the external disclosure decision diverges from internal communication choice along several dimensions, I argue predictions from the media richness literature are applicable to external disclosure channel choice. A key assumption underlying the management theory is that

[1] "Ex ante" information complexity refers to the complexity of the underlying information being communicated, before the manager makes any decisions about how to disclose the information externally.

managers and employees are time constrained, and thus prefer information to be processed *as accurately and quickly as possible* (efficient internal communication). Prior research has shown that managers face many considerations when communicating externally including career concerns, legal risk and market forces. However, managers also likely seek to reduce market uncertainty and avoid costly clarifying or follow-up disclosure (i.e. Graham, Harvey and Rajgopal, 2005). Therefore, I expect the average manager to prefer *efficient external communication* and minimize time costs associated with the accurate transmission of their message.

If this preference dominates other pressures faced by managers making external disclosure decisions (on average), information complexity will be positively associated with disclosure channel richness. For example, managers will disclose straightforward information (e.g., EPS, financial metrics) in lean channels such as press releases and complex information (e.g., forward-looking, strategic topics) in rich channels such as conference calls or investor meetings. Moreover, the positive relation between complexity and richness will be diminished when other incentives or frictions are sufficiently strong. Examples of mitigating factors include high proprietary costs, litigation risk, upcoming equity issuance, bad news and high levels of algorithmic trading.

Finally, if matching complexity to channel richness improves communication efficiency, there will be implications for how market participants process *complex information*. While conveying complex information in rich channels minimizes time costs associated with both sending and receiving the accurate message, conveying straightforward information in lean channels is more likely to reduce time costs to the sender than to the recipient in the external disclosure setting (as equity investors are likely able to extract this information from any channel). Therefore, I predict that prices impound information more efficiently when managers place complex information in rich channels than when they place complex information in lean channels.

The predictions will not hold if media richness theory's key assumption is violated and managers do not exhibit a first order preference for efficient communication. For example, managers may be indifferent about minimizing time costs, providing investors process disclosures accurately. Legal, career or regulatory considerations may also consistently dominate any preference for efficient external communication for the average manager. Even if managers do prefer timely transmission of their message, the efficient markets hypothesis suggests information will be immediately incorporated into price regardless of format (Fama, 1970). Finally, algorithms and humans face different processing costs (Allee, DeAngelis and Moon, 2018). As investors are increasingly using algorithms to trade on firm news and efficiently incorporate news into prices (O'Hara, 2015; Rogers, Skinner and Zechman, 2017), managers may choose channels that reduce the processing costs of algorithmic traders over those of live human investors.

I first test these predictions by examining the allocation of information across the quarterly earnings press release and conference call. These disclosures generally occur within the same 24-hour window and convey firm economic performance for the same period yet vary in richness. The call provides several cues (e.g. natural language, verbal cues) and offers managers the opportunity to interact with analysts. Moreover, spoken words generally contain more diverse language than written documents contain (Chafe and Tannen, 1987). The conference call is therefore a relatively rich channel. The earnings announcement contains formal language and offers neither verbal cues nor an opportunity for interaction, and is thus relatively lean. I proxy for information complexity in two ways, using (1) firm-level measures, since complex firms have more complex information to communicate (Bushee, Gow, and Taylor, 2018) and (2) message-level measures (e.g. word counts created using complex and straightforward topic word lists).

Results from several analyses support the prediction that ex ante information complexity is positively associated with channel richness. First, topic modeling analysis suggests that topics communicated in the conference call are relatively complex compared to those communicated in the corresponding press release. Second, regression analysis indicates that more of complex firms' quarterly disclosures are released in the prepared portion of the call than in the press release. Furthermore, within-firm analysis suggests managers disclose more quarterly information in the call relative to the press release when their overall message is complex.

While my primary setting holds timing, dissemination and decision to disclose reasonably constant, I am limited to two channels. Moreover, unobservable disclosure characteristics may endogenously influence channel choice for reasons other than (but correlated with) complexity. Therefore, I also examine Tax Cuts and Jobs Act ("TCJA") disclosures. This tax reform materially and simultaneously affected most firms that pay corporate taxes; however, the effect of the TCJA on multinational firms was considerably more complex than the effect on domestic firms (EY, 2018; Tax Foundation, 2017). I predict and find in small-sample analysis that multinational firms are more likely to discuss the TCJA in rich channels relative to otherwise similar domestic firms, further supporting the finding that information complexity is associated with channel richness.

I return to the quarterly reporting setting to examine variation in the complexity-richness match. Managers face a variety of considerations when releasing financial disclosures that are not of concern when communicating internally. Therefore, I predict that the positive relation between complexity and richness will be mitigated when these other pressures or frictions weaken the preference for or ability to facilitate efficient communication. For example, I predict and find that managers facing high proprietary costs, upcoming equity issuance and managing older firms will be less likely to match complexity to richness. Within-firm analysis suggests that firm-quarters in which managers report bad news, perceive high litigation risk and face high levels of algorithmic trading also exhibit weakened complexity-richness matching.

I next investigate the implications of complexity-richness matching for market participants. When managers disclose complex information in lean channels, their firms experience a smaller market response around the earnings announcement (measured by the absolute value of three-day returns and the intraperiod timeliness metric) relative to an entropy balanced control sample disclosing similarly complex information in rich channels. This suggests complexity-richness matching improves the efficiency with which information is incorporated into price.

By drawing from the media richness literature, I provide new evidence of how ex ante information characteristics (e.g. complexity) play a role in channel choice. Moreover, this study is the first to provide evidence that channel choice has implications for the efficiency of price formation. Research that examines disclosures in a single channel should consider whether the channel is appropriate for the information of interest to the researcher, while studies examining disclosures across multiple channels should consider whether they may be capturing different information in channels of varying richness. Finally, my results can inform managers' disclosure channel decisions and help investors navigate firm disclosures across different channels.

While this study provides insights into how information characteristics play a role in channel decisions in the absence of strategic motives, other research related to this study examines strategic uses of disclosure channels. Through these studies, we learn that litigation risk, proprietary costs and bad news incentives push managers to consider channel characteristics such as private versus public communication, salience and timing in making channel decisions (e.g., Bamber and Cheon, 1998; Davis and Tama-Sweet, 2012; Myers Scholz and Sharp, 2013; Crowley, 2016). Moreover, these studies are useful in motivating cross-sectional analysis as they highlight frictions that may weaken the complexity-richness relation.

This study also extends the literature examining the costs of processing firms' financial disclosures. Prior research indicates that managers can affect processing costs using language complexity (Li, 2008; Bushee, et al., 2018), within-document emphasis (Bowen, Davis and Matsumoto, 2005; Elliott, 2006), and disclosure timing (deHaan, Shevlin and Thornock, 2015). I find that disclosure channel is another such tool and find evidence consistent with managers, on average, choosing channels to reduce the costs of processing their disclosures.

Finally, my evidence improves our understanding of why managers communicate certain topics in conference calls. Prior research uses calls as a measure of voluntary disclosure (Tasker, 1998; Kimbrough and Louis, 2011) and finds that quarterly calls are informative (Frankel, Johnson and Skinner, 1999; Lansford, Lee and Tucker, 2009; Matsumoto, Pronk and Roelofsen, 2011). While these studies suggest that conference calls contain forward-looking and non-financial information (Matsumoto et al., 2011; Kimbrough and Louis, 2011), management forecasts (Lansford et al., 2009), and operational topics (Gomez, Lee, Heflin and Wang, 2018), this study is among the first to provide evidence around (i) *why* firms communicate complex topics in the call over other channels, (ii) circumstances that drive managers to deviate from this strategy and (iii) the implications of this choice for the efficiency of price formation.

2. Background and Hypothesis Development

2.1 The Disclosure Channel Decision

Managers choose from a variety of channels (e.g. SEC filings, social media posts, conference calls, analyst/investor days) when issuing financial disclosures.[2] These channels vary in important ways including written versus verbal communication, audio versus visual cues, language used and opportunity for interaction. Despite the increase in and diversity of channels available, we know little about how managers make disclosure channel decisions.

One key obstacle faced by prior research is the lack of analytical predictions to motivate our understanding of how managers make channel decisions.[3] Markets are often assumed to be efficient (Fama, 1970), implying firms' financial information will be incorporated into price immediately regardless of format. However, if investors are inherently constrained in their ability to process information (Simon, 1955; Bloomfield, 2002) and "search costs" vary across channels (Stigler, 1961; Bloomfield, 2002), choosing an appropriate disclosure channel should facilitate more efficient processing of firm information (Hirshleifer and Teoh, 2003). Prior research finds managers use language complexity (Li, 2008; Bushee, et al., 2018), emphasis (Bowen, et al., 2005; Elliott, 2006), and timing (deHaan, et al., 2015) to affect processing costs. I conjecture that disclosure channel is an alternative tool managers have available to achieve this end.[4]

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[2] Other terms used to describe disclosure channels include "outlet," "venue," "medium" and "vehicle" (Mayew, 2012). Managers have already decided to disclose the information in question prior to choosing channel. Therefore, unless the channel is part of the disclosure requirement (i.e. information that must be disclosed in a 10-K), both voluntary and mandatory disclosures are relevant in this setting. Moreover, I remain agnostic to the omission or truthfulness of information disclosed, as managers also make these choices prior to arriving at the channel decision.

[3] Contemporaneous analytical research suggests that channel may be one mechanism that managers can use to strategically communicate bad news to investors with varying sophistication levels (Crowley, 2018). However, the questions of how managers choose channel in the absence of bad news or between public channels accessible by all investors remain unanswered.

[4] These processing costs are most similar to the "acquisition costs" studied by Blankespoor, deHaan, Wertz and Zhu (2018). I assume that investors are aware of publicly available channels, and that they have sufficient accounting knowledge to "integrate" the information disclosed.

At least four empirical studies examining strategic disclosure behavior incorporate channel choice into their research design. For example, Bamber and Cheon (1998) examine how litigation risk and proprietary cost incentives influence the forthcomingness of managers' guidance disclosures and use public versus private channels a proxy thereof. Both Davis and Tama-Sweet (2012) and Crowley (2016) argue that managers behave strategically by shifting bad news disclosures to "less salient" SEC filings. Myers, et al. (2013) suggest the presence of outside monitors mitigates strategic channel use for restatement disclosures. While these studies are useful in suggesting how different aspects of channel can be used to obfuscate disclosures, it is unclear how these results generalize to disclosure choice absent these incentives. Moreover, it is also not clear how one might apply these results to channel choice beyond the channels and specific disclosures studied (Mayew, 2012). Finally, the question of how *information characteristics* play a role in channel choice remains unanswered. As summarized by Mayew (2012, p.839): "What we lack is a clear understanding of how managers choose a disclosure outlet when they want to make a particular disclosure. Given the vast menu of available options, investigating the choice of disclosure outlet seems to be a natural next step."

While my intent is to provide insights into how managers choose one channel over other channels available for a given disclosure, my analysis is also related to research that focuses on individual channels (e.g. conference calls). For example, related studies use conference calls as measures of voluntary disclosure (Tasker, 1998; Frankel, et al., 1999; Kimbrough and Louis, 2011) and study the informativeness of calls more generally (Frankel et al., 1999; Matsumoto et al., 2011; Mayew and Venkatachalam, 2012). Prior studies suggest that conference calls contain forward-looking and non-financial information both in earlier disclosure regimes when earnings calls were infrequent (Matsumoto et al., 2011) and in the M&A setting (Kimbrough and Louis, 2011). Gomez et al. (2018) provide more recent evidence of earnings call content and find that different topics are associated with price movement at the sentence level. However, *why* managers choose conference calls over other channels to communicate certain information and the implications for price formation are unexamined in the existing literature.

2.2 Media Richness Theory

The management field's media richness theory describes managers' internal communication channel decisions.[5] The firm is a complex system of human interactions, and the individuals involved are time, brain-power and processing-capability constrained (Simon, 1955; Cyert and March, 1963; Simon, 1979). Galbraith (1974) suggests the flow of information within an organization can be structured so that relevant information arrives to appropriate individuals as it is needed. Daft and Lengel (1986) extend this research by finding that the use of appropriate channels can improve the efficiency of the flow of information between constrained employees.

Managers evaluate communication channels' "richness" using cues, language variety, and opportunity for interaction. For example, a telephone call contains several cues (tone of voice, emotion and inflection, natural language), as well as greater language variety relative to the written word (Chafe and Tannen, 1987).[6] The opportunity for interaction allows the sender to understand and respond to recipients' misunderstandings, further improving efficiency of communication. In comparison, an internal memo also contains natural language, but offers neither additional cues, language variety nor opportunity for interaction. Using these criteria, communication channel richness is generally depicted on a continuum (Figure 1, Panel A).

[5] Media richness theory is a "theory" in the sense that it is a system of ideas used to explain a situation or justify an action (oxforddictionaries.com). The theory is not consistent with analytical modeling.

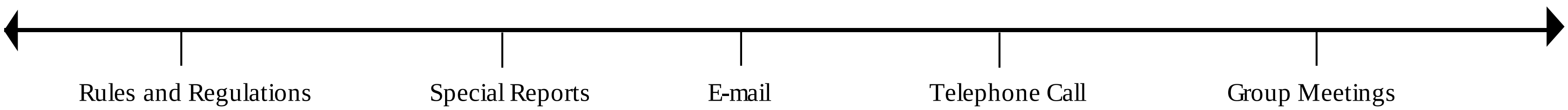
[6] Another approach to answering this question would be to draw on psychology and linguistics literature studying written versus spoken word. This literature examines differences in language and idea variety and how spoken versus written language is interpreted differently by recipients (Horowitz and Newman, 1964; Chafe and Tannen, 1987). However, studying this dimension in isolation is less comprehensive and does not generalize to all channel decisions.

Figure 1
Media Richness Examples

Panel A: Examples from Management Theory (Daft and Lengel, 1986; Webster and Trevino, 1995; Kahai and Cooper, 2003)

Lean channel (fewer cues, less language variety no interaction)
Suitable for communicating straightforward information.

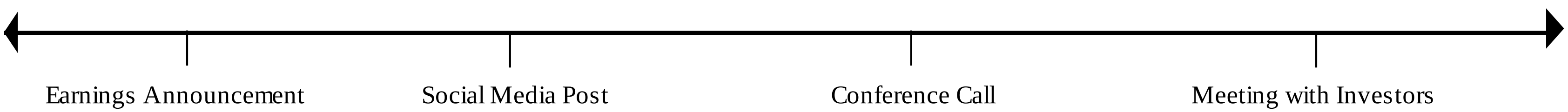
Rich channel (more cues, language variety, interaction)
Suitable for communicating complex information.



Panel B: Examples from External Reporting (my application of Media Richness Theory)

Lean channel (fewer cues, less language variety no interaction)
Suitable for communicating straightforward information.

Rich channel (more cues, language variety, interaction)
Suitable for communicating complex information.



Note: This figure compares channels of varying richness from both the management literature (internal firm disclosures) and my application of media richness theory (external financial disclosures).

Rich channel characteristics facilitate the efficient understanding of complex messages. Lean channels contain insufficient communication avenues to effectively communicate complex messages but are useful for quickly communicating well-understood messages or "standard data." Because all employees are time constrained, they prefer efficient communication and communicate complex information in rich channels and straightforward messages in lean channels accordingly (Daft and Lengel, 1986).[7]

2.3 Channel Richness and External Disclosures

Because prior research in accounting and finance offers little to motivate on-average predictions around disclosure channel choice, I examine whether management's media richness literature provides insights into the decision.[8] This approach allows for objective characteristics of both the underlying information communicated and disclosure channels available to predict (i) how managers choose to disclose information across different channels, (ii) when managers deviate from this strategy and (iii) the implications of this choice for market participants.

Although the external disclosure channel decision departs from internal communication channel choice in important ways (described in detail below), I argue predictions from the media richness literature are relevant to the external channel decision for several reasons. First, all parties involved in both internal and external channel decisions – managers, market participants, employees receiving internal communication – are similarly time and brain-power constrained (Hirshleifer and Teoh, 2003; Galbraith, 1974).

[7] I use information "complexity" to refer to information that is complicated or nuanced, and thus requires some level of explanation. The management theory generally uses the term "equivocality" meaning "ambiguity, the existence of multiple and conflicting interpretations about an organizational situation," or information requiring explanation (Daft and Lengel, 1986). While complex information is a subset of equivocal information, the predictions about "equivocal" information should hold for "complex" information examined in this study.

[8] A recent variant on media richness theory, media synchronicity theory, was developed in response to recent changes in communication such as the use of "emojis" and other features of social interaction (Dennis, Fuller and Valacich, 2008). Because these innovations in communication are not applicable to this accounting setting, I rely on media richness theory to guide my predictions.

Second, both information communicated in external disclosures and information communicated internally vary in complexity. “Information complexity” refers to whether the underlying economic information itself (e.g. the topic communicated) is complicated or requires explanation, *prior to any disclosure choices being made*. For example, topics range from arguably straightforward (quarterly EPS) to more complex (M&A activity or restructuring strategy).[9]

Third, external disclosure channels also vary in richness. SEC filings and press releases are relatively lean channels, whereas managers also have richer channels available such as conference calls and investor meetings. Prior empirical and experimental research indicates that vocal cues (Hobson, Mayew and Venkatachalam, 2011; Mayew and Venkatachalam, 2012), visual cues (Blankespoor, Hendricks and Miller, 2017; Cade, Koonce and Mendoza, 2018) and interaction (Cade, 2018; Matsumoto, et al., 2011) provide incremental information to market participants. Moreover, visual cues and opportunities for interaction are distinguishing features of investor conferences and analyst/investor days (Bushee, Jung and Miller, 2011; Kirk and Markov, 2016).

Prior research also suggests that managers are motivated to effectively communicate their financial information when disclosing externally (i.e. Ajinkya and Gift, 1984; Tasker, 1998; Riedl and Srinivasan, 2010; Kimbrough and Louis, 2011).[10] However, for media richness theory to hold in this setting, managers must prefer efficient external communication (i.e. timely transmission of accurate information). I conjecture that managers prefer efficient communication for two reasons. First, managers prefer reduced market uncertainty (i.e. Graham, et al., 2005; Billings, Jennings and Lev, 2015). If information is inefficiently incorporated into price, the uncertainty is at least

[9] While ex ante information complexity is generally correlated with the complexity of its disclosure, managers sometimes send complex signals to communicate straightforward information (Li, 2008; Bushee, et al., 2018). The complexity of the underlying information itself (not the signal) is the type of complexity that I examine.
[10] Other studies, including Schrand and Walther, 2000 and Davis and Tama-Sweet, 2012 argue that managers disclose opportunistically when faced with incentives that are strong enough to motivate the behavior (for example, when performance is bad). See cross-sectional tests where I examine differences in incentives (tests of H2).

temporarily unresolved and may increase (Rogers, Skinner and Van Buskirk, 2009). Second, issuing disclosures is costly to the manager in terms of time and resources (Stigler, 1961; Verrecchia, 1990; Beyer et al., 2010). Therefore, managers likely wish to avoid clarifying or follow-up disclosures in the event information is inefficiently processed upon its first release. If managers prefer efficient communication, they will use rich external channels to communicate complex information and lean channels to communicate uncomplicated information.[11]

H1: Information complexity is positively associated with disclosure channel richness.

As the external disclosure decision departs from internal channel choice in important ways, I may not find evidence to support this prediction. For example, the key assumption underlying the media richness literature (managers prefer efficient communication) may not hold in the external disclosure setting. Managers may be indifferent to the speed of information processing, if information is processed *accurately*. Even if managers prefer communication efficiency, firms may have channel policies and managers may be unable to freely choose channel. Given the high costs of all external disclosures, channels may not vary in cost to the manager.

Moreover, if markets are efficient, information should be incorporated into price immediately regardless of the channel used. Relatedly, algorithmic traders increasingly trade on firm news and in turn, improve price efficiency (O'Hara, 2015; Rogers, et al., 2017). As algorithms and humans face different processing costs (Allee, et al., 2018), managers may choose channels to reduce costs to algorithmic traders. If algorithms process lean channels more efficiently, managers

[11] If complexity-richness matching facilitates efficient communication, it is unsurprising that this practice is manifested in disclosure "norms," practitioner best practices or corporate disclosure policies (e.g. https://www.niri.org/ NIRI/media/NIRI/sampledocs/0615_NIRI_IRU_FullBook_LR.pdf). As these conventions are likely developed from manager/investor preferences, this phenomenon is consistent with my predictions. This further underscores the importance of understanding deviations from the matching strategy (H2).

may shift information to lean channels. Alternatively, if algorithms process channels equally well, there could be no relation between complexity and richness.

Finally, managers face additional pressures when communicating externally which may weaken the desire or ability to improve communication efficiency. For example, managers facing upcoming equity issuance will have incentives to "hype the stock" (Lang and Lundholm, 2000).[12] Managers may also be required to disclose information they would prefer to withhold such as bad news (Kothari, Shu and Wysocki, 2009; Davis and Tama-Sweet, 2012; Crowley, 2016) and proprietary information (Verrecchia, 1983; Bamber and Cheon, 1998). Moreover, some managers may be unable to reduce processing costs by matching information complexity to channel richness. Managers of older firms may have longstanding policies in place or be inflexible in their disclosure decisions. Managers of firms with substantial algorithmic trading may choose channel to reduce processing costs of the algorithmic traders over those of active human investors.

If these pressure and dynamics consistently dominate the preference for efficient communication, I will not find the positive relation between complexity and richness predicted by H1. However, it is possible the extent to which these pressures influence channel choice varies by firm and over time. Therefore, I predict that when managers are in situations that weaken the incentive for or ability to facilitate efficient communication, they are less likely to match complexity to richness.

H2: The positive relation between information complexity and disclosure channel richness is mitigated when other incentives are sufficiently strong.

Finally, matching information complexity to channel richness has implications for how market participants process *complex information*. Media richness theory suggests managers match

[12] If the firm's underlying economic information helps managers to "hype the stock," this situation may strengthen the complexity-richness relation. See section 4 for details.

message complexity to channel richness specifically because it should allow investors to process firm disclosures more efficiently. One key difference between internal and external communication is that message recipients in the external disclosure setting (market participants) are assumed to pay attention to all public disclosures. For this reason, placing uncomplicated information in lean channels is unlikely to substantially reduce time costs to market participants and straightforward information should be processed efficiently from any channel. However, to the extent (i) conveying *complex information* in rich channels reduces the cost of processing firm disclosures and (ii) lower processing costs result in more efficient market response to firm news (Hirshleifer and Teoh, 2003), the third prediction follows directly:

> *H3: Market participants process complex information in rich channels more efficiently than complex information in lean channels.*

It is possible that managers attempt to reduce processing costs by matching complexity to richness but are unsuccessful (in which case, I will not find market results). To the extent markets are efficient, investors will fully process publicly available information regardless of disclosure format. Moreover, if algorithms play a larger role in price formation than humans play, attempts to reduce humans' processing costs will be ineffective at improving communication efficiency.

3. Sample, Key Variables and Descriptive Statistics

3.1. Sample Selection

The final sample used in my study contains 20,174 firm-quarters. Table 1 provides sample selection details, which are described in detail below.

Table 1
Sample Reconciliation

	Firm-Quarters	Pct/Total
2007-2016 Compustat ∩ CRSP ∩ IBES	151,477	100%
Less:		
Stock price < $5	(23,575)	16%
Insufficient data for other key controls	(80,302)	53%
No earnings announcement 8-K	(8,839)	6%
Sample for call collection	38,761	26%
Less:		
No CQ FD coverage	(2,760)	7%
No transcript available on CQ FD	(15,827)	41%
Final Sample	20,174	52%

Note: This table contains sample selection details. I begin with the intersection of Compustat, CRSP and IBES from 2007-2016. I then require consistent data in CRSP, I/B/E/S and Compustat from the sample period (which results in the greatest sample attrition). Sample firms are significantly older, larger and better performing than the broader Compustat population. I also require that the earnings announcement is identifiable in an SEC form 8-K filing, and the full conference call transcript is available on Factiva's CQ FD database with identifiable prepared remarks and Q&A section. While CQ FD covers the majority of firms, they report only an "Event Brief" for several firm-quarters. Although the final sample contains only 52% of the 38,761 firm-quarters available to collect, 93% of those firms are represented in the final sample. Moreover, *ROA* and *FirmAge* of sample firm-quarters are not statistically different from other firm-quarters without full transcripts available on CQ FD. Firm-quarters in my final sample are smaller and have a smaller analyst following, although differences are economically small (*MVE* = 7.80 v. 8.01, p-value < 0.001; *AnalystFollow* = 2.30 v. 2.38 p-value < 0.001).

I begin with the intersection of Compustat, CRSP and IBES firm-quarters from 2007 through 2016.[13] I then require stock price greater than $5 and sufficient data for the entire sample

[13] My sample begins in 2007, as SEC filings' headers and html coding are inconsistent and thus difficult to parse in earlier years (Loughran and McDonald, 2016). It ends in 2016 as this was the last year for which four quarters of data were available when I began this study. While the financial crisis is included in my study, time fixed effects should account for any crisis effects in channel choice. Moreover, my results are robust to excluding these years.

period.[14] I require the earnings announcement to be filed in an 8-K and identify earnings announcements by searching for Item 2.02 8-Ks with filed or conformed dates within two days of the Compustat earnings report date. Finally, I require the full conference call transcript to be available for download from Factiva's CQ FD database and that the transcript has identifiable prepared and Q&A sections (see section 3.2.1 for partitioning procedures).[15] This results in a final sample of 20,174 firm-quarters.

3.2 Key Variables

3.2.1 Complexity Measures

I first proxy for information complexity with firm-level measures, since complex firms have more complex information to disclose (Bushee, et al., 2018). *NumSegments* is the log of one plus the number of segments reported in Compustat.[16] *NumLocations* is the log of one plus the number of unique subsidiary locations reported in Exhibit 21 of the most recent 10-K.[17] *Intangibles* is intangible assets scaled by total assets (Barth, Kasznik and McNichols, 2001). *StdROA* is the standard deviation of net income scaled by total assets over the previous 16 quarters. This measure is a reasonably comprehensive proxy for the complexity associated with variable performance, as it includes variation in both operating income and special items. Finally, because these four

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[14] While this step limits hand collection to firms with enough data for within-firm analysis, it also introduces survivorship bias into the results and lessens generalizability. Sample firms are significantly older, larger and better performing than the broader Compustat population (untabulated).

[15] While CQ FD covers the majority of firms, they report only an "Event Brief" for several firm-quarters. Although the final sample contains only 52% of the 38,761 *firm-quarters* available to collect, 93% of those *firms* are represented in the final sample. Moreover, *ROA* and *FirmAge* of sample firm-quarters are not statistically different from other firm-quarters. Firm-quarters in my final sample are smaller and have a smaller analyst following, although differences are economically small (*MVE* = 7.80 v. 8.01, p-value < 0.001; *AnalystFollow* = 2.30 v. 2.38 p-value < 0.001).

[16] To ensure accurate measurement of ASC 280 operating segments, I compare 10-K segment disclosures to Compustat for a random selection of sample firms. Segments reported in the 10-K match Compustat "operating segments" if reported. If not reported, 10-K segments most often correspond to Compustat "business segments." Geographic segments in Compustat did not match 10-K segments for any firms examined. Therefore, *NumSegments* = Compustat operating segments if populated and Compsutat business segments otherwise.

[17] Dyreng, Hoopes, Langetieg and Wilde, 2018 find that firms strategically omit tax haven countries from their Exhibit 21. This behavior should add noise to the measure and bias coefficients toward zero.

measures represent different aspects of firm complexity, I use principal components analysis to extract the underlying complexity element of the four measures. Two factors load with eigenvalues > 1; however, because the first factor has the largest eigenvalue (1.56) and the four variables load positively on the factor as expected, I follow Rogers and Stocken (2005) and retain the first factor for use in the analysis (*ComplexFirmFactor*).

I proxy for message-level complexity with discussion of complex and straightforward topics. To begin, I isolate the press release attachment in the earnings announcement 8-K and remove images, tables, and pdfs. I then download transcripts and partition those into the prepared and Q&A sections. I split the documents into prepared and Q&A portions using various forms of "Question and Answer" ("Q&A," "Questions and Answers," etc.). I use the prepared portion of the call to calculate message-level complexity, as managers allocate content to this portion ex ante and analysts are more likely to direct topics discussed in the Q&A portion of the call.[18]

I assume firm strategy and future-oriented discussion are relatively complex topics: I measure the overall complexity of the firm's quarterly disclosures by counting words from strategy and forward-looking word lists in both the earnings announcement and the prepared portion of the earnings call, and scaling that total by total words across both documents (*StrategyWords* and *FwdLookingWords*).[19] Word lists are provided in Appendix B. I choose shorter lists where possible

[18] As managers exercise discretion in the information released in their answers to analyst questions (Lee, 2015; Mayew, 2008), it is possible excluding the Q&A portion of the call ignores allocation of information to the rich channel. In untabulated analysis, I include the text from managers' answers to analyst questions in (i) the numerator and denominator of the *PctCall* variable and (ii) the calculation of word counts used to create independent variables in Table 4. Nine of the ten coefficients on complexity variables in Tables 3 and 4 continue to load as expected. Interestingly, the coefficient on *StrategyWords* becomes negative and significant. Without further examination into the questions asked by analysts, it is unclear what is driving this finding (e.g. managers avoiding answering questions about strategic topics, analysts not asking about strategic topics, etc.) As analyst behavior is outside the scope of this study, I leave this question to future research. Nonetheless, this untabulated result suggests that excluding Q&A does not materially influence the inferences from my findings.

[19] Alternative approaches such as term-document weighting or word proximity measures, while potentially more nuanced, can introduce noise to the analysis. While a word count or a "bag-of-words" approach is relatively coarse, resulting variables are easy to interpret and less susceptible to error (Loughran and McDonald, 2016). Relatedly, I choose to use raw word counts over counting sentences including words from word lists, as sentences can be

to eliminate noise in the measures from potentially irrelevant words (Loughran and McDonald, 2016). I build the strategy word list from the results of topic modeling analysis presented in Appendix 1A of Ronda-Pupo and Guerras-Martin (2012).[20] I obtain the forward-looking word list from Bozanic, Roulstone and Van Buskirk (2018). Results are robust to using similar word lists following both Matsumoto, et al. (2011) and Marshall and Skinner (2018).

I next measure the discussion of straightforward topics (*AccountingWords* and *EarningsWords*), by counting financial statement and earnings words from both the press release and the prepared portion of the earnings call, and scaling that by total words across both documents. I create the financial statement word list from reading balance sheets and income statements of a random selection of sample firms (excluding industry-specific line items). I use the earnings word list from Marshall and Skinner (2018). With the exception of revenue and expense words (included in *AccountingWords*), this list is also consistent with Bozanic et al. (2018). Finally, I use principal components analysis to construct a factor capturing the common complexity element of each of the word count variables. Again, although two factors load with eigenvalues > 1, I use the factor with the largest eigenvalue (1.64) and on which complex topic counts load positively and the straightforward topic counts load negatively (*ComplexMsgFactor*).

While message-level measures allow for within-firm variation, the complicated nature of text analysis results in relatively noisy variables. A second weakness of these measures is that the classification of word lists as "complex" and "straightforward," was a subjective process (see section 3.3 for discussion of how Q&A helps validate these assumptions). Conversely, firm-level

challenging to parse (especially in SEC filings), and may add additional noise to measures (Loughran and McDonald, 2016). Results are qualitatively and generally quantitatively robust to using sentences.

[20] The *Strategic Management Journal* study surveys academic strategic management papers over the last several decades. I create the word list using representative words from their topics; however, the results are robust to including all words from their Appendix 1A.

measures are easier to interpret, more objective and are used in prior research; but provide only cross-sectional variation in complexity. For these reasons, I use both measures to test H1.

3.2.2 Channel Richness Measure

I use *PctCall* to capture the allocation of financial information to the rich channel. *PctCall* is equal to the number of words in the prepared portion of the earnings call divided by the total number of words in the earnings announcement and the prepared portion of the call.[21]

3.2.3 Market Test Measures

To measure deviation from expected complexity-channel matching policy, I calculate the residual from a regression of *PctCall* on all firm-level and message-level complexity variables, control variables and year-quarter and fiscal quarter fixed effects (adjusted R^2 = 0.166). As H3 concerns the specific mismatch or deviation in which complex information is disclosed in lean channels, my key independent variable is *UnexpectedEA*. I set this indicator variable equal to one if the firm-quarter is in the bottom decile of *Abn_Call*: negative residuals are associated with less disclosure in the call than expected given observed complexity. I measure market response using the absolute value of three-day returns around the earnings announcement (*AbsRet3D*) and an intraperiod timeliness metric (*IPT*, discussed in detail in section 4.3.2).

3.3 Descriptive Statistics

Table 2, Panel A includes descriptive statistics for sample firm-quarters. 57% of prepared quarterly reporting words take place in the earnings call. Moreover, 2.7% of total words across the earnings announcement and the prepared portion of the call are strategy words, 1.7% are forward-

[21] One concern with *PctCall* is both changes to the numerator or changes to the overall quarterly disclosure affect the measure. In untabulated analysis, I have confirmed that complexity variables are positively associated with the number of words in the call and negatively associated with the number of words in the press release (separately). See section 4.1.4 for additional procedures performed to address this concern.

looking words, 3.2% are financial statement words, and 1.1% are earnings words.[22] Surprisingly, 2.0% of the Q&A words are strategy words, 1.9% are forward-looking words, 1.0% are financial statement words and only 0.2% are earnings words. This evidence is consistent with the conjecture that financial statements and earnings are relatively straightforward topics that are less likely to require explanation (and therefore less likely to warrant questions from analysts during the call).

Table 2, Panel B presents firm-quarter descriptive statistics partitioned on whether *PctCall* is less than or greater than the sample median. As expected, higher values of *PctCall* are associated with more complex messages. Interestingly, Q&A length is statistically equivalent across the two sub-samples, suggesting managers allocate the same amount of time to questions, regardless of the relative length of the prepared portion of the call. Furthermore, while there are statistically significant differences in key controls across the two groups (controls described in section 4), most are economically small. Regardless, I use controls in all specifications and firm fixed effects to identify within-firm changes where appropriate. However, it is unlikely I have fully controlled for differences in these firms and results should be interpreted accordingly.

[22] I remove tables from the earnings announcements to ensure the financial statements themselves are not included in the word counts artificially inflating the number of financial statement words in that channel.

Table 2
Descriptive Statistics

Panel A: Full Sample

	N	Mean	SD	P25	P50	P75
Complexity:						
NumSegments	20,174	1.155	0.594	0.693	1.386	1.609
NumLocations	20,174	2.122	1.045	1.099	2.079	2.944
Intangibles	20,174	0.181	0.195	0.017	0.112	0.295
StdROA	20,161	0.014	0.016	0.004	0.008	0.016
ComplexFirmFactor	20,161	0.000	1.249	-0.887	-0.006	0.894
StrategyWords	20,174	0.027	0.008	0.021	0.026	0.032
FwdLookingWords	20,174	0.017	0.006	0.013	0.017	0.021
AccountingWords	20,174	0.032	0.010	0.026	0.032	0.039
EarningsWords	20,174	0.011	0.005	0.008	0.011	0.014
ComplexMsgFactor	20,174	0.000	1.276	-0.804	0.074	0.901
Channel Decision:						
PctCall	20,174	0.567	0.142	0.477	0.573	0.662
Abn_Call	20,157	0.000	0.131	-0.082	0.003	0.085
Market Participant Response:						
AbsRet3D	20,094	0.050	0.047	0.015	0.035	0.070
IPT	20,171	14.33	33.54	8.258	14.34	20.14

Note: Panel A contains descriptive statistics for all key independent, dependent and control variables. Panel B contains descriptive statistics partitioned on whether the percent of the total discussion in the prepared portion of the earnings call is above or below the sample median (i.e. high discussion in earnings announcement v. high discussion in prepared portion of call). T-test differences from zero identified by *** p<0.01, ** p<0.05, * p<0.1. All complexity variables are significantly different across the two groups in the predicted direction and all continuous variables are winsorized at 1% and 99%. See Appendix A for variable definitions, and Appendix B for corresponding word lists where relevant.

Table 2 (Continued)
Descriptive Statistics

Panel A: Full Sample, Continued

	N	Mean	SD	P25	P50	P75
Other Variables:						
AbsSurp	20,174	0.005	0.017	0.000	0.001	0.003
AnalystFollow	20,174	2.302	0.611	1.792	2.303	2.773
ATscore	9,294	0.000	1.437	-0.829	0.093	0.953
AvgTurnover	20,174	0.002	0.001	0.001	0.002	0.002
BadNewsSurp	20,174	0.332	0.471	0.000	0.000	1.000
CallNextDay	20,175	0.262	0.439	0.000	0.000	1.000
Contemp10K10Q	20,175	0.206	0.404	0.000	0.000	0.000
Dispersion	20,174	0.036	0.050	0.010	0.020	0.040
EquityIssue	20,174	0.068	0.252	0.000	0.000	0.000
ERC	20,174	0.125	0.173	0.017	0.070	0.177
FirmAge	20,174	3.234	0.547	2.833	3.135	3.714
HistFCError	20,174	0.000	0.003	0.000	0.001	0.001
InstOwn	20,174	0.481	0.384	0.000	0.611	0.817
MTB	20,174	3.301	4.455	1.335	2.094	3.452
MVE	20,174	7.800	1.507	6.716	7.621	8.724
NewsCoverage	20,174	1.494	1.601	0.000	1.099	2.303
OldFirm	20,174	0.243	0.429	0.000	0.000	0.000
PctLitigiousWords	20,174	0.340	0.280	0.147	0.256	0.445
PctNegativeWords	20,174	0.983	0.497	0.622	0.890	1.253
RedactedFiling	20,170	0.072	0.259	0.000	0.000	0.000
ROA	20,174	0.012	0.021	0.003	0.011	0.021
StdRet	20,174	0.022	0.013	0.013	0.018	0.026
Surprise	20,174	0.000	0.018	-0.001	0.000	0.002
WordsCall	20,174	2025	783	1467	1932	2474
WordsEA	20,174	1604	882	997	1406	1998
WordsQA	20,174	2910	1224	2015	2877	3748
StrategyWordsQA	20,174	0.020	0.007	0.015	0.020	0.024
FwdLookingWordsQA	20,174	0.019	0.005	0.015	0.018	0.022
AccountingWordsQA	20,174	0.010	0.005	0.006	0.009	0.012
EarningsWordsQA	20,174	0.002	0.002	0.000	0.001	0.002

Table 2 (Continued)
Descriptive Statistics

Panel B: Low v. High Discussion in Call

	High EA Disc. (PctCall < P50)		*High Call Disc. (PctCall > P50)*		**Difference**
	Mean	**SD**	**Mean**	**SD**	**(Mean)**
Complexity:					
NumSegments	1.146	0.641	1.165	0.543	0.019 **
NumLocations	2.063	1.057	2.181	1.030	0.118 ***
Intangibles	0.167	0.192	0.196	0.197	0.029 ***
StdROA	0.013	0.016	0.015	0.017	0.002 ***
ComplexFirmFactor	-0.089	1.310	0.089	1.179	0.177 ***
StrategyWords	0.026	0.008	0.027	0.008	0.001 ***
FwdLookingWords	0.016	0.005	0.018	0.006	0.002 ***
AccountingWords	0.034	0.010	0.031	0.009	-0.003 ***
EarningsWords	0.013	0.005	0.010	0.005	-0.002 ***
ComplexMsgFactor	-0.322	1.297	0.322	1.169	0.644 ***
Channel Decision:					
PctCall	0.455	0.092	0.680	0.079	0.225 ***
Abn_Call	-0.092	0.094	0.092	0.087	0.183 ***
Market Participant Response:					
AbsRet3D	0.047	0.046	0.053	0.048	0.006 ***
IPT	14.09	33.48	14.57	33.60	0.472

Table 2 (Continued)
Descriptive Statistics

Panel B: Low v. High Discussion in Call, Continued

	High EA Disc. (PctCall < P50)		*High Call Disc. (PctCall > P50)*		**Difference (Mean)**
	Mean	**SD**	**Mean**	**SD**	
Other Variables:					
AbsSurp	0.005	0.019	0.004	0.014	-0.001 ***
AnalystFollow	2.276	0.608	2.329	0.612	0.053 ***
ATscore	-0.030	1.420	0.031	1.455	0.061 **
AvgTurnover	0.002	0.001	0.002	0.001	0.000 ***
BadNewsSurp	0.348	0.476	0.316	0.465	-0.032 ***
CallNextDay	0.297	0.457	0.226	0.418	-0.071 ***
Contemp10K10Q	0.202	0.401	0.210	0.407	0.008
Dispersion	0.038	0.051	0.034	0.048	-0.004 ***
EquityIssue	0.070	0.255	0.066	0.248	-0.004
ERC	0.109	0.160	0.141	0.184	0.032 ***
FirmAge	3.236	0.548	3.231	0.546	-0.005
HistFCError	0.000	0.003	0.001	0.003	0.000 ***
InstOwn	0.462	0.379	0.500	0.388	0.037 ***
MTB	3.226	4.604	3.376	4.301	0.150
MVE	7.829	1.527	7.771	1.488	-0.058 ***
NewsCoverage	1.490	1.641	1.497	1.559	0.007
OldFirm	0.247	0.431	0.239	0.426	-0.009
PctLitigiousWords	0.366	0.274	0.314	0.283	-0.052 ***
PctNegativeWords	0.010	0.005	0.010	0.005	0.000 ***
RedactedFiling	0.070	0.255	0.075	0.263	0.005
ROA	0.011	0.020	0.014	0.022	0.003 ***
StdRet	0.021	0.013	0.022	0.013	0.001 ***
Surprise	0.000	0.020	0.000	0.015	0.000
WordsCall	1720	649	2330	787	610 ***
WordsEA	2101	919	1107	467	-994 ***
WordsQA	2899	1252	2921	1195	22
StrategyWordsQA	0.020	0.007	0.020	0.007	0.000
FwdLookingWordsQA	0.019	0.005	0.019	0.005	0.000
AccountingWordsQA	0.010	0.005	0.009	0.005	0.000 ***
EarningsWordsQA	0.002	0.002	0.002	0.002	0.000 ***

4. Research Design and Results

4.1. Tests of H1: Complexity and Disclosure Channel

4.1.1 Topic Modeling Analysis

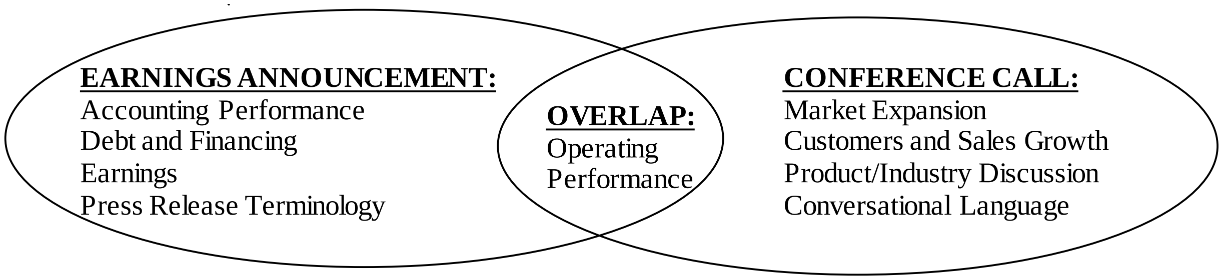
I first perform a topic modeling analysis to provide initial text-based evidence that information complexity is positively associated with channel richness (H1). I create three text files for each firm quarter. The first contains the words used in both the earnings announcement and in the prepared portion of the call, the second contains remaining words from the earnings announcement, and the third contains remaining words from the prepared portion of the call. I perform Latent Dirichlet Allocation (LDA) analysis on each of group, which generates 20 representative words from each of 12 topics for earnings announcements and earnings calls and 6 topics for overlap words.[23]

To summarize the LDA output, I subjectively group topics into representative subjects (Figure 2, Panel A). Figure 2, Panel B contains word clouds created using wordle.net: all representative words are included, with greater prominence objectively assigned to words that occur more frequently in the topic modeling output. The LDA analysis provides preliminary evidence to corroborate predictions made in H1: the earnings call (rich channel) contains discussion of complex topics such as market growth and expectations, while the press release (lean channel) covers more straightforward topics such as net income and EPS.

[23] 18% of total words are used in both the earnings announcement and the conference call which approximately corresponds to the representative topics: 6/(12+12+6) = 0.2. This evidence also suggests managers, on average, are reporting a substantial amount of information uniquely in the call and earnings announcement.

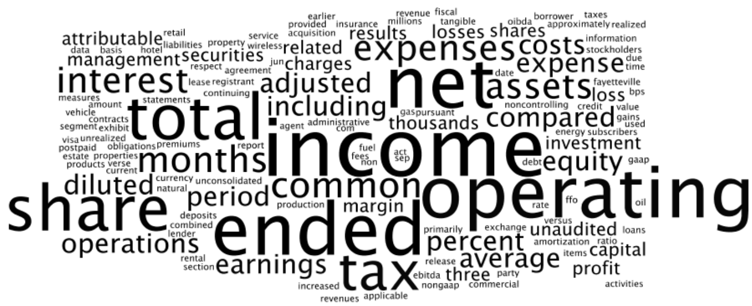
Figure 2
Content of Earnings Announcements, Conference Calls, and Overlap

Panel A: Venn Diagram



Panel B: Representative Words

EARNINGS ANNOUNCEMENT:



OVERLAP:

CONFERENCE CALL:

Note: To create this figure, I performed topic modeling analysis (specifically, Latent Dirichlet Allocation or "LDA") on the text from earnings announcements, the prepared portion of the conference call and overlapping words. The analysis generates 20 representative words from each of 12 topics for announcements/calls and 6 topics for the overlapping texts (as these texts are much shorter). Panel A includes my subjective classification of the topics generated by the LDA analysis. To the extent topics overlapped, I grouped them together under a common label. The wordles in Panel B were created objectively using wordle.net and the 240 (or 120) representative words generated by the LDA analysis.

4.1.2 Firm-Level Complexity

I next regress *PctCall* on firm-level complexity variables, controlling for firm characteristics: the log of market value of equity to capture firm size (*MVE*), market-to-book ratio to capture growth (*MTB*), log of one plus the number of years of data in Compustat to measure firm age (*FirmAge*) and return on assets as a proxy for quarterly performance (*ROA*). I follow prior research and control for information environment: *AnalystFollow* is equal to the log of one plus the number of analysts following the firm, *HistFCError* is equal to the average analyst forecast error (scaled by price) from previous 16 quarters, and *NewsCoverage* is equal to the log of one plus the number of Dow Jones press releases issued during the prior 12 months. I control for the firm's investor base with *InstOwn* equal to the percent of shares owned by institutions and *AvgTurnover* equal to average monthly volume divided by average shares outstanding for the prior 12 months (Bushee, et al., 2003). To measure earnings informativeness, I calculate *ERC* as the earnings response coefficient on quarterly earnings for previous 16 quarters. Finally, I control for the amount of news in the quarterly earnings reports with the absolute value of that quarter's earnings surprise (*AbsSurp*) and the total number of words in both documents (*LogWords*).

The OLS regressions for the firm-level complexity analysis are presented in Table 3.[24]

[24] I choose not to use bounded tobit regressions due to the difficulties associated with calculating and interpreting goodness of fit. However, the results in Tables 3-5 are robust to using tobit regressions.

Table 3
H1: Firm-level Complexity and Disclosure Channel

		DEPVAR = *PctCall*				
Complexity Measure =		*NumSegments*	*NumLocations*	*Intangibles*	*StdROA*	*ComplexFirmFactor*
	Pred	(1)	(2)	(3)	(4)	(5)
Complexity	(+)	0.015**	0.011***	0.064***	0.630***	0.013***
		(2.383)	(3.138)	(3.604)	(3.872)	(4.255)
MVE		-0.006	-0.006	-0.004	-0.003	-0.007*
		(-1.600)	(-1.566)	(-0.936)	(-0.693)	(-1.868)
MTB		0.001	0.001	0.001	0.000	0.001
		(0.925)	(1.090)	(0.787)	(0.381)	(0.868)
FirmAge		0.011	0.011	0.013**	0.015**	0.009
		(1.531)	(1.555)	(1.977)	(2.155)	(1.358)
AnalystFollow		0.022***	0.018**	0.017**	0.018**	0.021***
		(2.948)	(2.510)	(2.246)	(2.493)	(2.851)
ROA		0.117	0.118	0.111	0.157	0.111
		(0.874)	(0.881)	(0.836)	(1.196)	(0.829)
InstOwn		0.001	-0.000	-0.000	0.002	-0.001
		(0.076)	(-0.033)	(-0.032)	(0.236)	(-0.104)
ERC		0.051***	0.050***	0.040**	0.055***	0.043**
		(2.906)	(2.844)	(2.227)	(3.104)	(2.442)
HistFCError		2.323***	2.324***	2.250***	2.392***	2.338***
		(3.006)	(2.998)	(2.843)	(3.084)	(3.030)
NewsCoverage		0.000	0.000	-0.000	-0.000	-0.000
		(0.085)	(0.016)	(-0.101)	(-0.154)	(-0.045)
AvgTurnover		1.507	1.839	2.916	0.299	1.970
		(0.582)	(0.714)	(1.126)	(0.116)	(0.770)
AbsSurp		-0.148	-0.152	-0.096	-0.201*	-0.132
		(-1.297)	(-1.326)	(-0.821)	(-1.737)	(-1.173)
LogWords		-0.070***	-0.072***	-0.072***	-0.069***	-0.073***
		(-6.928)	(-7.173)	(-7.155)	(-6.813)	(-7.226)
Year-Qtr FE		Y	Y	Y	Y	Y
Fiscal Qtr FE		Y	Y	Y	Y	Y
Observations		20,170	20,170	20,170	20,157	20,157
Adj R-Squared		0.0622	0.0642	0.0659	0.0630	0.0699

Note 1: This table contains results of tests of H1, which predicts that more complex disclosures are allocated to rich channels. The dependent variable is *PctCall* which is equal to the number of words in the prepared portion of the earnings call, divided by words in the earnings announcement plus words in the prepared portion of the conference call. Consistent with expectations, complex firms (measured by number of segments, number of subsidiary locations, intangible assets, standard deviation of ROA and a PCA firm complexity factor) allocate more information to the conference call relative to the earnings announcement.

Note 2: All specifications are OLS regressions (results robust to using bounded Tobit), t-stats in parentheses. Coefficients different from zero identified by *** p<0.01, ** p<0.05, * p<0.1 (two-tailed) and standard errors clustered at the firm level. Variable definitions in Appendix A.

I include year-quarter and fiscal quarter fixed effects to account for time trends and seasonality in the data and cluster standard errors at the firm level.[25] Consistent with expectations, all four complexity measures and the first complexity factor are positively associated with *PctCall*, suggesting complex firms allocate more of their quarterly disclosures to rich channels. A one standard deviation increase in the factor score is associated with a 1.6% increase in the percent of quarterly discussion in the call (54 words for the median firm).

4.1.3 Message-Level Complexity

OLS regressions for the message-level analysis are presented in Table 4. The model is consistent with Table 3, with (i) message-level in place of firm-level complexity variables and (ii) the inclusion of firm fixed effects to isolate within-firm changes in topic complexity. As expected, the allocation of information to the rich channel is positively associated with message complexity. A one standard deviation increase in forward-looking word percentage is associated with a 3.3% increase in the percent of the total disclosure occurring in the prepared portion of the call (111 words for the median firm) consistent with prior research suggesting that calls contain forward-looking statements and guidance (Lansford, Lee and Tucker, 2009; Matsumoto et al., 2011; Kimbrough and Louis, 2011). A one standard deviation increase in the complexity factor is associated with a 5.0% increase in discussion in the call or 166 words for the median firm.

[25] I cluster standard errors at the firm level throughout the analysis to account for within firm serial correlation (Petersen, 2009). Although year by calendar quarter and fiscal quarter fixed effects should control for a significant portion of time effects in the data, if firms are not equally affected by common shocks, residuals of different firms in the same quarter may still be correlated (Conley, Goncalves and Hansen, 2018). Two-way clustering requires that both (i) the minimum number of clusters to approach infinity (or be otherwise large), and (ii) different firms from different years are uncorrelated, which is a restrictive assumption if observations are serially and cross-sectionally correlated (Conley et al., 2018). Finally, Coney et al., 2018 suggest the most conservative approach for panel data is to use Fama-MacBeth sample splitting procedures with few large N groups. The key results in Tables 3 and 4 are robust to clustering by firm and year, by firm and calendar quarter and Fama-MacBeth regressions (by year). Although the coefficients on *UnexpectedEA* in IPT regressions throughout the various standard error specifications, the *UnexpectedEA* coefficient becomes marginally significant when clustering by firm and year and in Fama-MacBeth regressions. Overall, the standard errors do not appear to be understated due to this research design choice.

Table 4
H1: Message-level Complexity and Disclosure Channel

				DEPVAR = *PctCall*		
Complex/Straightforward =		*StrategyWords*	*FwdLookingWords*	*AccountingWords*	*EarningsWords*	*ComplexMsgFactor*
	Pred	(1)	(2)	(3)	(4)	(5)
ComplexMsg	(+)	2.588***	5.951***			0.039***
		(8.923)	(14.111)			(20.872)
StraightforwardMsg	(-)			-3.689***	-8.162***	
				(-14.434)	(-17.306)	
MVE		0.005	0.006	0.005	0.007	0.006
		(1.041)	(1.379)	(1.041)	(1.504)	(1.313)
MTB		-0.000	-0.000	-0.001	-0.000	-0.001
		(-0.911)	(-0.791)	(-1.566)	(-0.961)	(-1.268)
FirmAge		-0.075***	-0.053**	-0.060**	-0.075***	-0.056**
		(-2.833)	(-2.061)	(-2.320)	(-2.900)	(-2.208)
AnalystFollow		0.012**	0.008	0.010*	0.005	0.004
		(2.071)	(1.411)	(1.738)	(0.899)	(0.674)
ROA		-0.013	-0.002	-0.082	0.007	-0.052
		(-0.217)	(-0.028)	(-1.319)	(0.114)	(-0.821)
InstOwn		-0.009	-0.008	-0.006	-0.009	-0.005
		(-0.893)	(-0.853)	(-0.584)	(-0.890)	(-0.532)
ERC		0.008	0.010	0.010	0.013	0.013
		(0.880)	(1.197)	(1.134)	(1.510)	(1.534)
HistFCError		-0.076	0.189	0.046	0.171	0.179
		(-0.129)	(0.346)	(0.079)	(0.308)	(0.339)
NewsCoverage		0.000	-0.000	0.000	0.000	-0.000
		(0.075)	(-0.223)	(0.244)	(0.082)	(-0.002)
AvgTurnover		-0.551	-1.821	-0.786	-1.680	-1.843
		(-0.281)	(-0.937)	(-0.404)	(-0.879)	(-0.986)
AbsSurp		-0.026	-0.010	-0.027	-0.029	-0.023
		(-0.300)	(-0.114)	(-0.290)	(-0.313)	(-0.239)
LogWords		-0.017	-0.004	-0.017	-0.029**	-0.018
		(-1.380)	(-0.304)	(-1.444)	(-2.442)	(-1.537)
Firm FE		Y	Y	Y	Y	Y
Year-Qtr FE		Y	Y	Y	Y	Y
Fiscal Qtr FE		Y	Y	Y	Y	Y
Observations		20,170	20,170	20,170	20,170	20,170
Adj R-Squared		0.593	0.605	0.607	0.611	0.626

Note 1: This table contains message-level results of tests of H1, which predicts that more complex disclosures are disclosed in rich channels. The dependent variable is *PctCall* which is equal to the number of words in the prepared portion of the earnings call, divided by words in the earnings announcement plus words in the prepared portion of the conference call. Consistent with expectations, complex messages are associated with increased conference call length relative to the earnings announcement in a given quarter and straightforward messages are negatively associated with conference call length relative to the earnings announcement. Finally, a factor constructed using PCA (increasing in complex words and decreasing in straightforward words) is positively associated with words in the prepared portion of the call.

Note 2: All specifications are OLS regressions (results robust to using bounded Tobit), t-stats in parentheses. Coefficients different from zero identified by *** p<0.01, ** p<0.05, * p<0.1 (two-tailed) and standard errors clustered at the firm level. All variables are defined in Appendix A and corresponding word lists are presented in Appendix B where relevant.

4.1.4 Complexity-Richness Match Robustness Tests

2017 Tax Cuts and Jobs Act Disclosures

There are several benefits to using the allocation of information across the earnings call/press release to examine channel choice. First, this setting holds timing, dissemination and the decision to disclose reasonably constant: most firms issue an earnings announcement and host a conference call each quarter and within the same 24-hour period. Managers have flexibility in the disclosures made in these channels and the two channels vary considerably in richness. The setting also allows for large sample analysis. However, because managers use both channels each quarter, they are forced to place information in each (even if they only have complex information to communicate). In addition, managers realistically have a menu of disclosure channels available and these tests only consider two. Finally, it is possible managers match information to channel for reasons other than (but correlated with) information complexity.

To address these concerns, I examine the channel choice for 2017 Tax Cuts and Jobs Act ("TCJA") disclosures. The TCJA was signed into law on December 22, 2017 and had a plausibly material impact on all firms paying corporate taxes simultaneously. Importantly, the act drastically changed and increased complexity around the taxation of foreign income (EY, 2018; Avi-Yonah, 2018). Therefore, multinational firms should be more likely to discuss TCJA effects in rich channels relative to domestic firms.

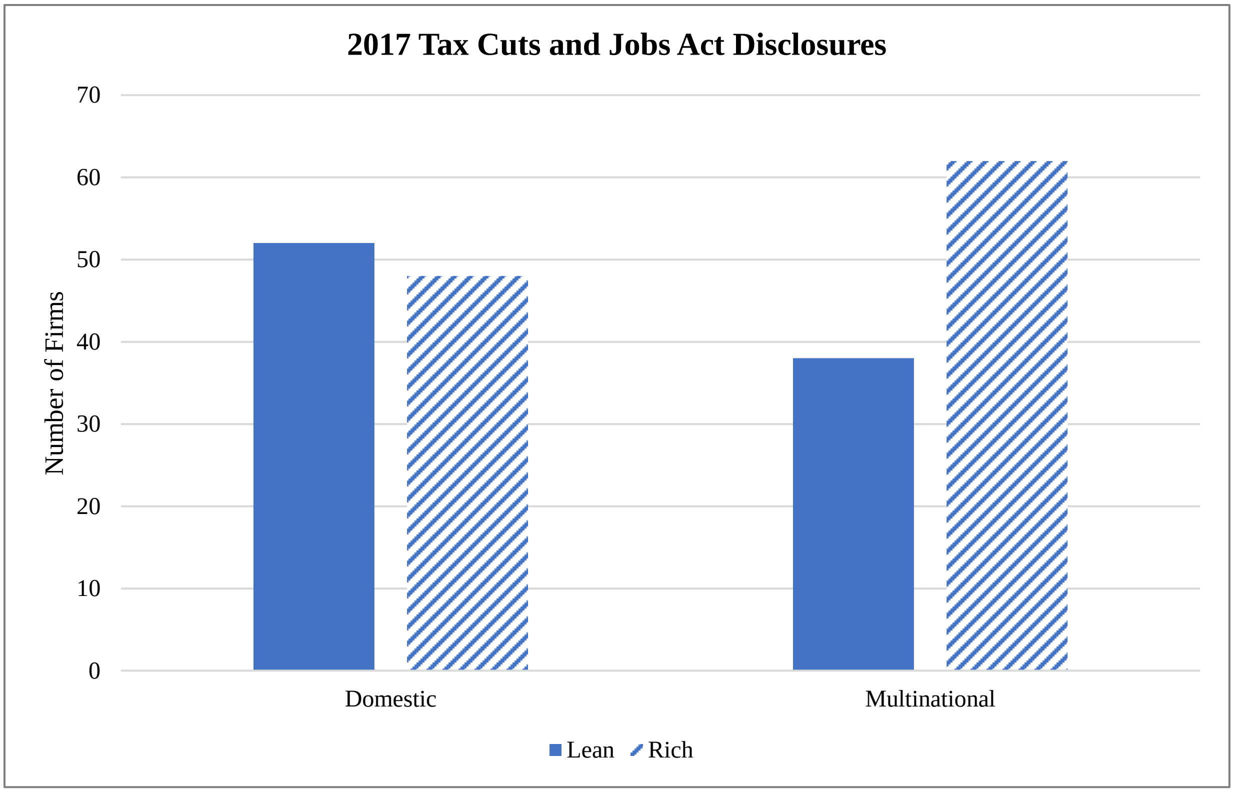
To test this prediction, I match multinational firms to domestic firms using size, change in ETR and industry, and examine communication across all publicly available channels for mention of the TCJA. Specifically, I download 10-Ks filed between June 30, 2017 and June 30, 2018. I classify firms with stock price > $5 as multinational or domestic following the existing tax literature: if the firm reports a subsidiary in different country, I consider that firm multinational

(Dyreng et al., 2018). I next calculate the GAAP effective tax rate change from the first calendar quarter of 2017 to the first calendar quarter of 2018 to proxy for the materiality of TCJA effects. Finally, I match each multinational firm to the domestic firm closest in size from the same Fama-French 12 industry category and ETR revision decile. This approach results in 484 matched pairs.

Next, I randomly select 100 matched pairs and attempt to search all public disclosures made by those 200 firms between December 15, 2017 and June 30, 2018 for mention of the TCJA. Specifically, I search 10-Ks, 10-Qs, 8-Ks, press releases posted on the corporate website, conference call transcripts and transcripts from investor conferences and analyst/investor days, using computer-assisted techniques as appropriate. I consider SEC filings and press releases to be "lean channels" and transcripts from calls and investor meetings to be "rich channels."

While all firms mention the TCJA in a 10-Q or 10-K, multinational firms are more likely to also discuss the TCJA in a rich channel relative to domestic firms (see Figure 3: 62 multinational firms disclosing in rich channels versus 48 domestic firms, p-value = 0.046). Furthermore, the chi-square statistic for testing for the equivalence of the distribution of rich/lean channels across domestic and multinational firms is 3.956 (p-value = 0.047), further underscoring the positive association between information complexity and channel richness.

Figure 3
H1: Information Complexity and Disclosure Channel



	Domestic	Percent Domestic	Multinational	Percent Multinational	Difference	
SEC Filing	42	42%	27	27%	15%	**
EA/Press Release	10	10%	11	11%	-1%	
Lean Channels	52	52%	38	38%	14%	**
Conference Call	38	38%	43	43%	-5%	
Investor Meeting	10	10%	19	19%	-9%	*
Rich Channels	48	48%	62	62%	-14%	**

Note 1: This figure contains additional tests of H1 using Tax Cuts and Jobs Act ("TCJA") disclosures. Because the 2017 TCJA had more complex effects on multinational firms than domestic firms, I expect multinational firms to discuss the TCJA in richer channels relative to domestic firms. I match domestic firms to multinational firms and read publicly available disclosures for a random sample of 100 pairs (200 firms). Figure 3 tabulates the results from this search. Specifically, the table includes the richest channel used for each of the 200 firms (all firms disclose TCJA in 10-Qs and 10-Ks as required). As expected, multinational firms are more likely to discuss TCJA effects in rich channels where domestic firms are more likely to only discuss the TCJA in lean channels.

Note 2: Results of t-tests for differences in means across domestic and multinational firms are reported with differences less or greater than zero identified by *** p<0.01, ** p<0.05, * p<0.1.

Sophisticated Investor Demand

Although the results in Table 4 provide better identification by capturing within-firm variation, it is possible that managers choose channel to ensure certain information reaches sophisticated investors (Crowley, 2016, 2018). If information provided to different audiences is uncorrelated with complexity, catering to audiences will introduce attenuation bias to the results. However, if sophisticated investors both follow rich channels and demand complex information, this behavior may introduce omitted variable bias into the analysis presented in Tables 3 and 4. While *InstOwn* and *AnalystFollow* help control for differences in audience across firm-quarters, I also reperform the analysis in specification (5) from Tables 3 and 4 individually on each sample quartile of *InstOwn* and *AnalystFollow*. If sophisticated investor or analyst demand affects the complexity-channel matching observed in Tables 3 and 4, the relation should be weaker (stronger) for firms with less (more) institutional ownership or smaller (larger) analyst following. The coefficients on complexity factors are significantly positive and consistent in magnitude across quartiles (apart from firm-level complexity in the top quartile of *InstOwn*). This suggests the results in Tables 3 and 4 are not entirely attributable to complexity-audience matching.

Disclosure Volume

If managers with complex information have more to disclose overall, the complexity-richness relation may be influenced by complex firms' need for more disclosure space (e.g. Tasker, 1998). I control for total news with *AbsSurp* and *LogWords* in Tables 3 and 4 to help mitigate this concern. The results are robust to (i) using the log of words in the prepared portion of the call as the dependent variable, (ii) controlling for length of the earnings announcement in place of total words, and (iii) excluding length controls altogether. If the amount of information influences the complexity-channel matching observed in Tables 3 and 4, the relation should be weaker (stronger) for firms with less (more) total information to disclose. The coefficients on both complexity factors are at least marginally significant, positive and relatively consistent in magnitude for all *AbsSurp* quartiles and all but the firm-level factor for the first quartile of *LogWords*. Overall, this evidence suggests that results in Tables 3 and 4 cannot be entirely attributed to disclosure space limitations.

4.2. Tests of H2: Managerial Incentives and Disclosure Channel

H2 predicts the relation between information complexity and channel richness will be mitigated when managers face frictions that weaken either the *preference for* or *ability to facilitate* communication efficiency. I use proxies for these circumstances providing both cross-sectional variation and within-firm variation.

First, I argue that managers of firms with high proprietary costs are less likely to prefer efficient disclosure processing. I identify firms with high proprietary costs (*RedactedFiling*) as those citing confidential treatment requests in that quarter's 10-Q or 10-K (Verrecchia and Weber, 2006). I also argue that firms issuing equity greater than 5% of total assets in the subsequent year have incentives to "hype the stock" that may alter the preference for efficient communication (*EquityIssue*, consistent with Tan, Wang, and Welker, 2011). I also expect older firms to face frictions in implementing the complexity-richness match. For example, these firms may have longstanding policies in place and be less likely to accommodate changes in information complexity with different channels accordingly (*OldFirm* = 1 if firm quarter in top quartile of *FirmAge*).[26] Because I expect to observe cross-sectional variation in *RedactedFiling*, *EquityIssue*,and *OldFirm*, I regress *PctCall* on these variables, interactions with the firm complexity factor (*ComplexFirm*) and controls from Table 3.

[26] To validate this assumption, I calculate the standard deviation of *PctCall* over the prior 8 quarters for firms with *OldFirm* =1 and *OldFirm* = 0 with sufficient quarterly data. Consistent with the conjecture older firms face frictions when making channel choices, the standard deviation of PctCall values is significantly less than that of firms in lower firm age quartiles (p-value = 0.0522).

I also argue managers of firms reporting bad news have weakened incentives to inform. To measure bad news, I calculate the number of negative words in the earnings announcement and the prepared portion of the call divided by the total number of words in both documents, multiplied by 100 for ease of interpretation (*PctNegativeWords*).[27] I also expect managers perceiving high litigation risk to face frictions in choosing channel: these managers' desire to avoid or accommodate legal scrutiny may drive them to deviate from the optimal channel-richness matching strategy. I calculate *PctLitigiousWords* following Loughran and McDonald, 2016 as their litigious word list is designed to capture "propensity for legal contest." Finally, because complexity-richness matching facilitates efficient information processing for human investors, I expect managers of firms with high levels of algorithmic trading to be less likely to match complexity to richness. I use *ATscore* to proxy for this friction, following Weller (2016) and Stephan (2018).[28] Because I expect to observe within-firm variation in these circumstances, I regress *PctCall* on *PctNegativeWords*, *PctLitigiousWords* and *ATscore*, interactions with message-level complexity factors, and controls from Table 4.

The cross-sectional results are presented in Table 5, Panel A and the within-firm results are presented in Table 5, Panel B.

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[27] While both Henry (2008) and Loughran and McDonald (2011) are commonly used negative financial disclosure word lists, I choose Henry's word list as it is shorter and unnecessary words likely introduce noise into word count measures. I chose to use negative words without subtracting or otherwise accounting for positive words, because managers may (a) use positive words as "window dressing" around negative news, or (b) negate positive words to communicate negative messages (Loughran and McDonald, 2016). Because negative words are rarely used when communicating a positive message, using negative words exclusively introduces less noise.

[28] *ATscore* is calculated using four algorithmic trading proxies from the SEC's MIDAS dataset (Weller, 2016). First, I calculate the average odd lot volume ratios, trade to order ratios, cancel to trade ratios and trade size for the quarter preceding the earnings announcement. Following Stephan (2018), I use the first principal component of those four variables (*ATscore*) to proxy for the level of algorithmic trading. Consistent with existing research, *ATscore* is positively associated with the odd lot volume ratio and cancel to trade ratios, and negatively correlated with trade to order ratios and trade size. Because the MIDAS dataset begins in 2013, I experience substantial sample attrition when I include this variable and the generalizability of this result should therefore be interpreted with caution.

Table 5
H2: Deviations from Complexity-Richness Matching

Panel A: Cross-sectional variation in frictions

		DEPVAR = *PctCall*		
	Pred	(1)	(2)	(3)
Channel Matching Frictions:				
*ComplexFirmFactor*RedactedFiling*	(-)	-0.011**		
		(-1.974)		
*ComplexFirmFactor*EquityIssue*	(-)		-0.014*	
			(-1.679)	
*ComplexFirmFactor*OldFirm*	(-)			-0.015**
				(-2.257)
Baseline Effects:				
ComplexFirmFactor	(+)	0.014***	0.013***	0.017***
		(4.363)	(3.947)	(4.713)
RedactedFiling		0.009		
		(1.096)		
EquityIssue			0.003	
			(0.342)	
OldFirm				0.011
				(1.299)
Controls Included		Y	Y	Y
Year-Qtr FE		Y	Y	Y
Fiscal Qtr FE		Y	Y	Y
Observations		20,157	19,225	20,157
Adj R-Squared		0.0706	0.0444	0.0719

Table 5 (Continued)
H2: Deviations from Complexity-Richness Matching

Panel B: Within-firm variation in frictions

		DEPVAR = *PctCall*		
	Pred	(1)	(2)	(3)
Channel Matching Frictions:				
*ComplexMsgFactor*PctNegativeWords*	(-)	-0.007***		
		(-3.111)		
*ComplexMsgFactor*PctLitigiousWords*	(-)		-0.016***	
			(-3.514)	
*ComplexMsgFactor*ATscore*	(-)			-0.003**
				(-2.518)
Baseline Effects:				
ComplexMsgFactor	(+)	0.045***	0.045***	0.038***
		(15.518)	(18.592)	(14.146)
PctNegativeWords		0.011***		
		(3.586)		
PctLitigiousWords			-0.062***	
			(-7.631)	
ATscore				0.003**
				(2.086)
Controls Included		Y	Y	Y
Firm FE		Y	Y	Y
Year-Qtr FE		Y	Y	Y
Fiscal Qtr FE		Y	Y	Y
Observations		20,170	20,170	9,292
Adj R-Squared		0.627	0.632	0.715

Note 1: This table contains results of tests of H2, which predicts that the relation in H1 is mitigated when the manager's desire for or ability to facilitate efficient processing of disclosure is weakened. In particular, this set of tests examines whether firm-level and message-level results presented in Tables 3 and 4 change when firms have strong enough incentives to deviate. Panel A contains incentives that are expected to deviate cross-sectionally, and Panel B contains incentives for which I expect to capture within-firm variation. Consistent with expectations, complex firms are less likely to disclose more in the call when managers face these frictions.

Note 2: All specifications are OLS regressions (results robust to using bounded Tobit), t-stats in parentheses. Coefficients different from zero identified by *** p<0.01, ** p<0.05, * p<0.1 (two-tailed) and standard errors clustered at the firm level. Controls include *MVE, MTB, FirmAge, AnalystFollow, ROA, InstOwn, ERC, HistFCError, NewsCoverage, AvgTurnover, AbsSurp* and *LogWords*. All variables are defined in Appendix A.

The evidence in Table 5 is consistent with H2: the presence of communication frictions mitigates the positive relation between complexity and richness. For example, moving from 0 to 1 in *RedactedFilings* (*EquityIssue*) almost completely (completely) offsets the positive relation between the complex firm factor and *PctCall*, whereas a 6.4% nominal increase in negative words is required to eliminate the complex message relation. Overall, these tests provide evidence suggesting the complexity-richness relation is mitigated when the key assumption is relaxed.

4.3. Tests of H3: Disclosure Channel Decision and Market Response

4.3.1 Short-window returns

H3 predicts that market participants process complex information in rich channels more efficiently than they process complex information in lean channels. I use *UnexpectedEA* to proxy for firms disclosing complex information in lean channels. This variable is equal to one if the firm quarter is in the first decile of *Abn_Call* (signed residual from regression of *PctCall* on complexity variables and controls) and 0 otherwise. I then take an entropy balancing approach to identifying control firms disclosing complex information in rich channels as predicted by the strategy. First, I restrict the pool of comparison firm quarters to those with residuals in the 5th and 6th decile of *Abn_Call*, as these sample firms are allocating their quarterly disclosures to the call as expected (e.g., residuals closest to zero). I then entropy balance on the predicted value of *PctCall* to ensure I am comparing "deviating" firms to "matching" firms with similar observed complexity. Finally, I also balance the comparison sample on circumstances associated with deviations (e.g. frictions identified in tests of H2, with the exception of *ATscore* to avoid sample attrition). The descriptive statistics are presented in Table 6.

Table 6
Descriptive Statistics: Market Tests

Panel A: Treat and Control Sample, Pre-Balancing

	UnexpectedEA = 0 (Abn_Call Dec. 5&6)				*UnexpectedEA = 1*				**Difference**
	N	**Mean**	**Variance**	**Skewness**	**N**	**Mean**	**Variance**	**Skewness**	**(Mean)**
Balance Variables:									
$\widehat{PctCall}$	4,032	0.567	0.003	-0.221	2,016	0.563	0.004	0.096	0.004 **
RedactedFiling	4,032	0.082	0.075	3.057	2,016	0.064	0.060	3.546	0.017 **
EquityIssue	4,032	0.070	0.065	3.372	2,016	0.083	0.076	3.015	-0.013 *
OldFirm	4,032	0.256	0.191	1.117	2,016	0.240	0.183	1.217	0.016
PctNegativeWords	4,032	0.989	0.250	1.111	2,016	0.952	0.258	1.014	0.037 ***
PctLitigiousWords	4,032	0.003	0.000	1.654	2,016	0.004	0.000	1.489	-0.001 ***
Other Key Variables:									
PctCall	4,032	0.570	0.004	-0.244	2,016	0.326	0.006	0.209	0.244 ***
Abn_Call	4,032	0.003	0.000	0.026	2,016	-0.237	0.003	-1.180	0.240 ***
AbsRet3D	4032	0.049	0.002	1.437	2,016	0.047	0.002	1.532	0.002 *
IPT	4032	15.41	1139	0.471	2,016	13.20	1078	-0.490	2.212 **

Panel B: Treat and Control Sample, Entropy Balanced

	UnexpectedEA = 0 (Abn_Call Dec. 5&6)				*UnexpectedEA = 1*				**Difference**
	N	**Mean**	**Variance**	**Skewness**	**N**	**Mean**	**Variance**	**Skewness**	**(Mean)**
Balance Variables:									
$\widehat{PctCall}$	2,016	0.563	0.004	0.096	2,016	0.563	0.004	0.096	0.000
RedactedFiling	2,016	0.065	0.060	3.545	2,016	0.064	0.060	3.546	0.000
EquityIssue	2,016	0.083	0.076	3.015	2,016	0.083	0.076	3.015	0.000
OldFirm	2,016	0.240	0.183	1.216	2,016	0.240	0.183	1.217	0.000
PctNegativeWords	2,016	0.952	0.258	1.014	2,016	0.952	0.258	1.014	0.000
PctLitigiousWords	2,016	0.004	0.000	1.489	2,016	0.004	0.000	1.489	0.000
Other Key Variables:									
PctCall	2,016	0.566	0.005	0.096	2,016	0.326	0.006	0.209	0.240 ***
Abn_Call	2,016	0.003	0.000	0.040	2,016	-0.237	0.003	-1.180	0.240 ***
AbsRet3D	2,016	0.048	0.002	1.460	2,016	0.047	0.002	1.532	0.001
IPT	2,016	15.43	1133	0.448	2,016	13.20	1078	-0.490	2.228 ***

Note 1: This table contains descriptive statistics for treatment and control variables used in H3, which predicts that market participants process disclosures more efficiently when managers place complex information in rich channels. Panel A contains variables used in entropy balancing and other key variables before the samples are balanced Panel B contains the treatment and control sample after balancing on the predicted value of *PctCall, RedactedFiling*, *EquityIssue*, *OldFirm*, *PctNegativeWords* and *PctLitigousWords*. The means, variances and skewness for these variables is no longer significantly different across treatment and control groups after balancing.

Note 2: All specifications are OLS regressions, t-stats in parentheses. Coefficients different from zero identified by *** p<0.01, ** p<0.05, * p<0.1 (two-tailed) and standard errors clustered at firm level. Variables definitions in Appendix A.

Entropy balancing across three moments results in treatment and control firms that appear identical in terms of predicted *PctCall, RedactedFiling, EquityIssue, OldFirm, PctNegativeWords* and *PctLitigiousWords*, but differ in matching strategy (and *Abn_Call*).

I first regress the absolute value of three-day returns on *UnexpectedEA*, a series of control variables, year-quarter fixed effects and fiscal quarter fixed effects. The controls capture variation in returns around the earnings announcement. *Surprise* is actual quarterly EPS minus analyst consensus immediately prior scaled by price, *AbsSurp* is the absolute value of *Surprise* and *BadNewsSurp* is an indicator variable equal to one if *Surprise* is less than zero. *Dispersion* is equal to the standard deviation of analysts' EPS forecasts immediately prior to the earnings announcement and *StdRet* is the standard deviation of returns over the 90-days prior to the announcement. I capture historical earnings informativeness with *ERC*, measured as the earnings response coefficient on quarterly earnings for previous 16 quarters. *CallNextDay* is an indicator = 1 if the transcript date is subsequent to the earnings announcement date, 0 otherwise. *Contemp10K10Q* is = 1 if the 10-K or 10-Q is filed on the same day as the earnings announcement, 0 otherwise (following Arif, Marshall, Schroeder and Yohn, 2018). All specifications are OLS regressions with standard errors clustered at the firm level.

Specifications (1) and (2) in Table 7 present initial tests of H3.

Table 7
H3: Disclosure Channel Decision and Market Response

		DEPVAR = *AbsRet3D*		DEPVAR = *IPT*	
	Pred.	(1)	(2)	(3)	(4)
Channel Decision:					
UnexpectedEA	(-)	-0.002	-0.003*	-2.310**	-2.293**
		(-1.255)	(-1.700)	(-2.475)	(-2.448)
Control Variables:					
Surprise			0.004		4.923
			(0.093)		(0.303)
AbsSurp			-0.051		1.843
			(-1.086)		(0.088)
Dispersion			0.027		-8.211
			(1.533)		(-0.816)
BadNewsSurp			0.001		0.404
			(1.068)		(0.392)
ERC			0.019***		4.307
			(4.591)		(1.330)
StdRet			1.206***		37.644
			(12.744)		(0.814)
CallNextDay			-0.006***		-1.056
			(-3.215)		(-0.956)
Contemp10K10Q			-0.001		-0.822
			(-0.825)		(-0.737)
Year-Qtr FE		Y	Y	Y	Y
Fiscal Qtr FE		Y	Y	Y	Y
Observations		6,027	6,027	6,048	6,048
Adj R-Squared		0.139	0.139	0.003	0.003

Note 1: This table contains results of tests of H3, which predicts that market participants process disclosures more efficiently when managers place complex information in rich channels. To test this prediction, I regress *AbsRet3D* and *IPT* on *UnexpectedEA,* which is an indicator = 1 if *Abn_Call* is in the lowest decile. *Abn_Call* is the residual from a regression of *PctCall* on firm-level complexity, message-level complexity and control variables. Consistent with expectations, disclosure strategies in which managers place more information than expected in the earnings announcement given observed complexity are associated with muted 3-day returns, although *UnexpectedEA* is only marginally associated with lower *IPT* values.

Note 2: All specifications are OLS regressions, t-stats in parentheses. Coefficients different from zero identified by *** p<0.01, ** p<0.05, * p<0.1 (two-tailed) and standard errors clustered at firm level. Variables definitions in Appendix A.

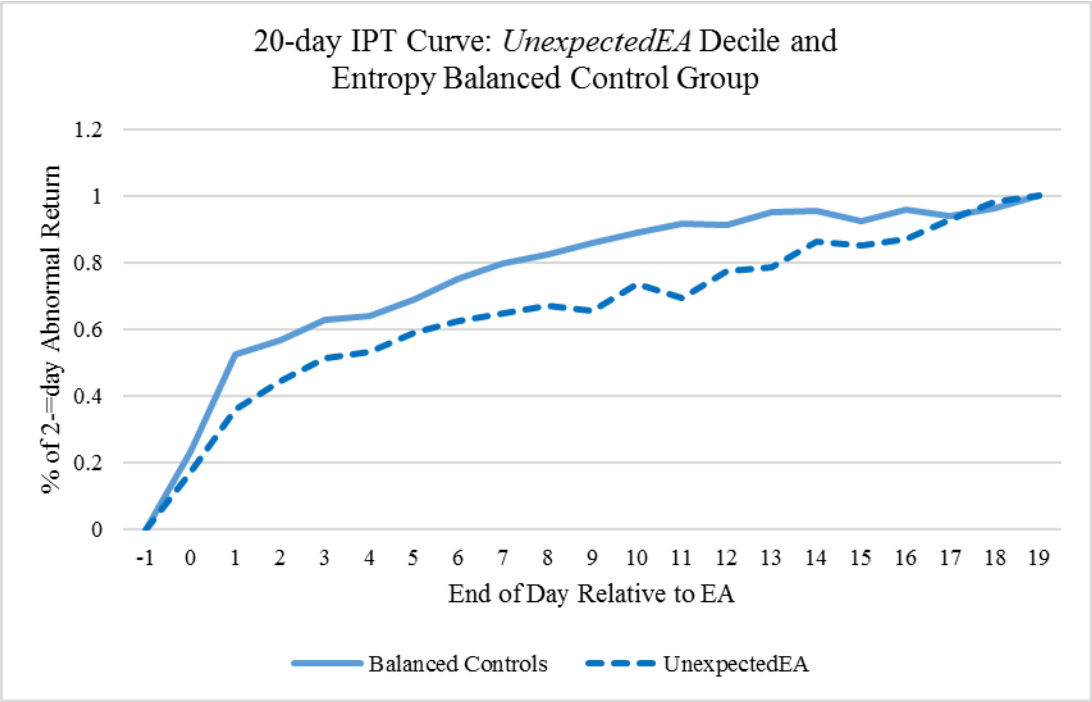
Although the entropy balanced treatment and control firm quarters do not appear to have significantly different *AbsRet3D* without controls; after adding earnings controls, *UnexpectedEA* becomes negatively associated with *AbsRet3D*. Moving from 0 to 1 in *UnexpectedEA* is associated with a 0.3% nominal decrease in the absolute value of returns in the three days around the earnings announcement (6% of total three-day returns for the median firm). The same situations that motivate deviations may also lead to slower incorporation of information into price. Although I entropy balance on the predicted value of *PctCall* and variables associated with deviations in tests of H2, the regression does not likely capture all reasons for deviating and cannot fully resolve this concern. Nonetheless, the evidence provides some evidence that deviations from the expected complexity-richness matching policy are associated with muted earnings announcement returns.

A second weakness of this analysis is that the magnitude of information in the quarterly reporting period could be correlated with both the allocation of information across channels and three-day returns. Moreover, the cues themselves may be informative (Matsumoto, et al., 2011; Hobson, Mayew and Venkatachalam, 2011; Mayew and Venkatachalam, 2012). To address these concerns, I perform an IPT analysis, which holds the total information communicated constant.

4.3.2 Intraperiod Timeliness (IPT) Analysis

I calculate *IPT* following prior research (Twedt, 2015; Butler, Kraft and Weiss, 2007) as buy-and-hold returns for each of 20 trading days starting with the earnings announcement date as day 0 up to the end of that day, scaled by the total return over the 20-day window. The *IPT* measure for each firm-quarter is the area under that curve and captures the speed with which news is incorporated into price, while holding the magnitude of news constant. I plot the values of *IPT* for firms in the bottom decile of *Abn_Call* (i.e. *UnexpectedEA*) and entropy balanced comparison firms in Figure 4.

Figure 4
H3: Disclosure Channel Decision and Market Response



	Abn_Call Decile 5	*UnexpectedEA*	Difference		P-Value from Permutation Simulation
IPT (0,19)	15.413	13.201	2.212	***	0.014

Note: This figure contains results of tests of H3, which predicts that market participants process disclosures more efficiently when managers place complex information in rich channels. To test this prediction, I plot the percentage of 20 trading day abnormal buy-and-hold returns earned each day from the day of the earnings announcement (day 0) to day 19 for firms in the first decile of *Abn_Call* (*UnexpectedEA*) and firms closest to predicted complexity-richness matching (median *Abn_Call* firm quarters). Consistent with predictions made in H3, when managers place more information in lean channels than expected given complexity, information is incorporated into price more slowly.

Consistent with expectations, when managers place complex information in lean channels, their disclosures are incorporated into price more slowly than when managers place complex information in rich channels. Moreover, the *IPT* values for these two groups of firms are statistically different using permutation simulations (implied p-value = 0.014), suggesting disclosure channel decision has implications for the incorporation of information into price.[29] Price informativeness for deviation firms catches up to matched firms on day 17.[30]

To further explore the difference in processing efficiency is attributable to complexity-richness matching, I regress individual firm-quarter values of *IPT* on *UnexpectedEA* and market control variables. The results are presented in Table 7, specifications (3) and (4). Again, I find *IPT* is negatively associated with *UnexpectedEA* using regression analysis (and including controls), further suggesting that disclosure channel choice plays a role in price formation.

4.3.3 Market Response Robustness Tests

To the extent firms either (a) host the earnings conference call the day after the earnings announcement or (b) release the 10-K or 10-Q on the day of the earnings announcement, the timing of these other disclosures may be associated with *AbsRet3D* and *IPT*. If these timing decisions are uncorrelated with deviation from the complexity-richness matching strategy, this should introduce attenuation bias in the results. However, if certain are less likely to deviate from the strategy and more likely to contemporaneously release 10-Qs, this could bias the analyses. Although I control for *CallNextDay* and *Contemp10K10Q* in the market analysis, I also reperform the analyses in Table 7 excluding firm-quarters with *CallNextDay* and *Contemp10K10Q* = 1. The market results hold after excluding these firms, with the exception of *AbsRet3D* when contemporary 10-K/10-Q firms are excluded (coefficient = -0.002, t-stat = -1.067) suggesting the findings reported in Table 7 are not entirely attributable to this disclosure behavior.

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[29] I follow prior research and use permutation analysis to test for significance in the difference in the *IPT* measure across the two groups. I randomly shuffle the firm-quarters across top and bottom quartiles 1000 times and examine the difference in *IPT* values across the shuffled groups. The difference in *IPT* is as extreme as it is in the observed groups in only 5 of 1000 shuffles (two tailed: |T|> T*), implying *IPT* is significantly different across the two groups.

[30]This result is consistent with complex information being incorporated into price more slowly overall than management forecast news. Twedt (2015) finds that price for firms with non-disseminated news takes 4 days to catch up to price response for firms with disseminated news.

5. Conclusion

Managers have many disclosure channels available to choose from when issuing financial disclosures, and these channels vary in important ways. Drawing from management's media richness literature, I predict that information complexity is positively associated with channel richness. Consistent with this prediction, I find evidence that information complexity is positively associated with channel richness, on average. I also find that relation is mitigated when managers face incentives that weaken the preference for or ability to facilitate efficient communication. Finally, I find that placing complex information in lean channels is associated with slower incorporation of information into price.

These findings contribute to the existing literature by showing how information characteristics may drive disclosure channel choice. Research that examines disclosures in a single channel should consider whether the channel is appropriate for the study, while research examining disclosures across multiple channels should consider whether they may be picking up different information in channels of varying richness. Moreover, these results are consistent with managers (on average) making disclosure channel decisions to reduce processing costs and improve the efficiency with which information is incorporated into price.

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Appendix A
Variable Definitions

Variable	*Definition*
Complexity:	
NumSegments	Log(1+number of reportable operating segments reported in Compustat). If no operating segments in Compustat, use business segments. See Section 3.2.1 for verification procedures performed around this measure.
NumLocations	Log(1+number of unique subsidiary locations reported in Exhibit 21 of the 10-K).
Intangibles	Intangible assets scaled by total assets.
StdROA	Standard deviation of *ROA* (net income divided by total assets) over previous 16 quarters (8 quarters required).
ComplexFirmFactor	First principal component constructed from four firm-level complexity variables (*NumSegments, NumLocations, Intangibles, StdROA*).
StrategyWords	Number of strategy words in earnings announcement plus strategy words in prepared portion of conference call, divided by total words in earnings announcement plus total words in prepared portion of conference call. Strategy words from Ronda-Pupo and Guerras-Martin, 2012. See Appendix B for word lists.
FwdLookingWords	Number of forward-looking words in earnings announcement plus forward-looking words in prepared portion of conference call, divided by total words in earnings announcement plus total words in prepared portion of conference call. Forward-looking words from Bozanic, Roulstone and Van Buskirk, 2018. See Appendix B for word lists.
AccountingWords	Number of financial statement words in earnings announcement plus financial statement words in prepared portion of conference call, divided by total words in earnings announcement plus total words in prepared portion of conference call. Identified financial statement words by reading a random sample of financial statements. See Appendix B for word lists.
EarningsWords	Number of earnings words in earnings announcement plus earnings words in prepared portion of conference call, divided by total words in earnings announcement plus total words in prepared portion of conference call. Earnings words from Marshall and Skinner, 2018. See Appendix B for word lists.
ComplexMsgFactor	First principal component constructed using four message-level complexity variables (*StrategyWords*, *FwdLookingWords*, *AccountingWords*, *EarningsWords*).
Channel Decision:	
PctCall	Number of words in prepared portion of conference call divided by number of words in prepared portion of conference call plus the number of words in the earnings announcement.

Appendix A (Continued)
Variable Definitions

Variable	*Definition*
Channel Decision, Continued:	
UnexpectedEA	Indicator variable = 1 if firm-quarter in bottom decile of *Abn_Call*, 0 otherwise: captures large negative deviations, suggesting less discussion in call than expected.
Abn_Call	Residual from regression of the *PctCall* on firm-level complexity variables, message-level complexity variables, controls and year and quarter fixed effects. More positive values represent abnormally high discussion in the prepared portion of the earnings call, more negative values represent abnormally high discussion in the earnings announcement.
Market Participant Response:	
AbsRet3D	Absolute value of 3-day market adjusted returns around the earnings announcement.
IPT	The area under the cumulative daily return curve over the 20-trading-day window beginning with the earnings announcement date. See Section 4.3.2 for further detail.
Other Variables:	
AbsSurp	Absolute value of *Surprise*, scaled by price.
AnalystFollow	Log(1+Number of analysts following firm).
ATscore	First principal component constructed from prior quarter's four algorithmic trading proxies (*OddLotVolumeRatio*, *TradeToOrderRatio*, *CancelToTradeRatio* and *TradeSize*) following Weller, 2016; Stephan, 2018.
AvgTurnover	Average monthly volume divided by average shares outstanding for twelve months prior to the earnings report date.
BadNewsSurp	Indicator variable = 1 if *Surprise* < 0, 0 otherwise.
CallNextDay	Indicator variable = 1 if date on conference call transcript is after the earnings announcement date, 0 otherwise.
Contemp10K10Q	Indicator variable = 1 if the 10-K or 10-Q was released on the same day as the earnings announcement, 0 otherwise.
Dispersion	Standard deviation of analyst EPS forecasts made immediately prior to earnings announcement date.
EquityIssue	Indicator variable = 1 if firm issues equity > 5% of assets in next year, 0 otherwise.
ERC	Earnings response coefficient on quarterly earnings for previous 16 quarters divided by 100 for ease of interpretation (requires minimum of 8 quarters).
FirmAge	Log(1+Number of years firm present in Compustat).
HistFCError	Average forecast error (EPS - outstanding analyst consensus forecast) over previous 16 quarters.
InstOwn	Percent of shares owned by institutional investors.

Appendix A (Continued)
Variable Definitions

Variable	*Definition*
Other Variables, Continued:	
MTB	Market value of equity divided by book value of equity.
MVE	Log of the market value of equity.
NewsCoverage	Log(1+Number of Dow Jones Press Releases) over year preceding earnings announcement date.
OldFirm	Indicator variable = 1 if firm in top quartile of *FirmAge*, 0 otherwise.
PctLitigiousWords	Number of litigious words in earnings announcement plus negative words in prepared portion of conference call, divided by total words in earnings announcement plus total words in the prepared portion of conference call, multiplied by 100. Litigious words are from Loughran and McDonald, 2011. The word list was designed to capture "propensity for legal contest." See Appendix B for representative words from list.
PctNegativeWords	Number of negative words in earnings announcement plus negative words in prepared portion of conference call, divided by total words, multiplied by 100. Negative words are from Henry, 2008. See Appendix B for word lists.
RedactedFiling	Indicator variable = 1 if firm uses "Confidential Treatment" language in quarter's 10-Q or 10-K, 0 otherwise.
ROA	Net income divided by total assets.
StdRet	Standard deviation of returns measured over 90 days prior to EA.
Surprise	Actual quarterly EPS reported on the earnings announcement date minus analyst consensus immediately prior, scaled by price.
WordsEA	Number of words in the earnings announcement.
WordsCall	Number of words in the prepared portion of the earnings call.
WordsQA	Number of words in the Q&A portion of the earnings call.
StrategyWordsQA	Number of strategy words in Q&A portion of conference call divided by total words in the Q&A portion of the conference call. Strategy words from Ronda-Pupo and Guerras-Martin, 2012. See Appendix B for word lists.
FwdLookingWordsQA	Number of guidance words in Q&A portion of conference call divided by total words in the Q&A portion of the conference call. Forward-looking words from Bozanic, Roulstone and Van Buskirk, 2018. See Appendix B for word lists.
AccountingWordsQA	Number of financial statement words in Q&A portion of conference call divided by total words in the Q&A portion of the conference call. Identified financial statement words by reading a random sample of financial statements. See Appendix B for word lists.
EarningsWordsQA	Number of earnings words in Q&A portion of the conference call divided by total words in the Q&A portion of the conference call. Earnings words from Marshall and Skinner, 2018. See Appendix B for word lists.

Note: All continuous variables are winsorized at 1% and 99%.

Appendix B
Word Lists

Topic	*Word list*
Strategy	'acquire', 'acquiring', 'acquisition', 'acquisitions', 'budget', 'budgeted', 'budgeting', 'capital', 'change', 'changed', 'changes', 'changing', 'competed', 'competing', 'competitive', 'competitor', 'competitors', 'competition', 'contract', 'contracted', 'contracting', 'contracts', 'discontinue', 'discontinued', 'discontinuing', 'disposal', 'dispose', 'disposed', 'disposing', 'disposition', 'employee', 'employees', 'growth', 'launch', 'launched', 'launching', 'lawsuit', 'litigation', 'market', 'markets', 'marketplace', 'merger', 'mergers', 'operation', 'operational', 'operations', 'product', 'production', 'products', 'release', 'released', 'releasing', 'sale', 'sector', 'sectors', 'selloff', 'settled', 'settlement', 'spend', 'spending', 'spinoff', 'strategic', 'strategies', 'strategy', 'tender', 'trend', 'trending', 'trends', 'venture'
Forward-Looking	'anticipate', 'anticipates', 'belief', 'beliefs', 'believe', 'believes', 'can', 'continue', 'continues', 'could', 'estimate', 'estimates', 'expect', 'expectation', 'expects', 'forecast', 'forecasts', 'forward', 'goal', 'goals', 'guidance', 'hope', 'hopes', 'intend', 'intends', 'intent', 'intention', 'intentions', 'may', 'might', 'objective', 'objectives', 'optimistic', 'ought', 'plan', 'plans', 'potential', 'predict', 'predicts', 'project', 'projection', 'projections', 'projects', 'schedule', 'scheduled', 'schedules', 'see', 'sees', 'shall', 'should', 'target', 'will'
Accounting	'amortization', 'asset', 'assets', 'balance sheet', 'cogs', 'costs', 'debt', 'depreciation', 'equity', 'expense', 'expenses', 'gain', 'goodwill', 'impairment', 'income', 'intangible', 'intangibles', 'inventories', 'inventory', 'liabilities', 'liability', 'loss', 'payable', 'payables', 'pp&e', 'property', 'r&d', 'receivable', 'receivables', 'revenue', 'revenues', 'sales', 'sg&a', 'tax', 'taxes'
Earnings	'earnings', 'eps', 'ebit', 'ebitda', 'deps', 'income', 'loss', 'profit'
Negative Sentiment	'below', 'challenge', 'challenged', 'challenges', 'challenging', 'decline', 'declined', 'declines', 'declining', 'decrease', 'decreased', 'decreases', 'decreasing', 'depressed', 'deteriorate', 'deteriorated', 'deteriorates', 'deteriorating', 'difficult', 'difficulty', 'disappoint', 'disappointed', 'disappointing', 'disappointment', 'disappoints', 'down', 'downturn', 'drop', 'dropped', 'dropping', 'drops', 'fail', 'failed', 'failing', 'fails', 'failure', 'fall', 'fallen', 'falling', 'falls', 'fell', 'hurdle', 'hurdles', 'least', 'less', 'low', 'lower', 'lowest', 'negative', 'negatively', 'negatives', 'obstacle', 'obstacles', 'penalties', 'penalty', 'poor', 'poorly', 'risk', 'risks', 'risky', 'shrink', 'shrinking', 'shrinks', 'shrunk', 'slump', 'slumped', 'slumping', 'slumps', 'smaller', 'smallest', 'threat', 'threaten', 'threatened', 'threatening', 'threats', 'uncertain', 'uncertainties', 'uncertainty', 'under', 'unfavorable', 'unsettled', 'weak', 'weaken', 'weakened', 'weakening', 'weakens', 'weakness', 'weaknesses', 'worse', 'worsen', 'worsening’
Litgious Sentiment	'absolve', 'acquit', 'adjudicate', 'allegations', 'appeal', 'attorney', 'bail', 'breach', 'claimant', 'collusion', 'contract', 'controvert', 'convict', 'countersuit', 'court', 'crime', 'decree', 'depose', , 'detainer', 'disaffirm', 'docket', 'encumbrances', 'exculpate', 'executor', 'forebears', 'grantor', 'incarcerate', 'indemnify', 'indict', 'infraction', 'interrogate', 'irrevocable', 'jurisdiction', 'jurors', 'jury', 'lawmaking', 'laws', 'lawsuit', 'legalize', 'legislate', 'legislator', 'libel', 'litigator', 'mistrial', 'nonterminable', 'nullify', 'perpetration', 'petitioned', 'petitioning', 'petitions', 'plaintiff', 'pleading', 'pleadings', 'pleads', 'postjudgment', 'prehearing', 'prejudice', 'pretrial', 'probation', 'promulgator''prosecution', 'punishable', 'quitclaim', 'recoupment', 'recourse', ''ruling', 'sentenced', 'sentencing', 'sequestrator', 'settlement', 'subpoena', 'subpoenaed', 'sue', 'tenantability', 'terminable', 'testify', 'tort', 'uncontracted', 'unencumber', 'unenforceable', 'unlawful', 'unremediated'

Note: This table contains the word lists used to create the message-level complexity measures used in Table 4 and the *PctNegativeWords* variable used in Table 5. The strategy word list is based on the results of topic modeling analysis presented in Appendix 1A of Ronda-Pupo and Guerras-Martin, 2012. Forward-looking statement word list is that used in Bozanic, Roulstone and Van Buskirk, 2018. To compile the financial statement word list, I examine balance sheets and income statements included in form 10-Ks from a random selection of sample firms (excluding industry-specific line items). Earnings words are from Marshall and Skinner, 2018, negative words are from Henry, 2008 and the above list contains representative words from Loughran and McDonald’s (2011) litigious word list.

Appendix C
Alternate Dependent Variables

One concern with the key dependent variable in this study, *PctCall*, is both changes to the numerator and changes to the denominator (overall quarterly disclosure) affect its value. This ambiguity around how changes to overall disclosure volume affect *PctCall* may raise questions about the relations documented in Tables 3 and 4. Therefore, in Table A1, I reperform tests of H1 with both (i) the number of words in the prepared portion of the call and (ii) the number of words in the earnings announcement press release as the dependent variable, without scaling by total words. The analysis shows that complexity variables are positively associated with the number of words in the call and negatively associated with the number of words in the press release, supporting my conjecture that the tests of H1 are not driven by unintended features of the *PctCall* fraction. See section 4.1.4 for additional procedures performed to address this concern.

Appendix C (Continued)
Alternate Dependent Variables
Table A1

Panel A: Firm-Level

		DEPVAR = *WordsCall*						DEPVAR = *WordsEA*				
Complexity Measure =		*NumSegments*	*NumLocations*	*Intangibles*	*StdROA*	*ComplexFirmFactor*		*NumSegments*	*NumLocations*	*Intangibles*	*StdROA*	*ComplexFirmFactor*
	Pred	(1)	(2)	(3)	(4)	(5)	Pred	(1)	(2)	(3)	(4)	(5)
Complexity	(+)	60.420**	43.733***	242.280***	2,543.441***	51.540***	(-)	-83.576***	-47.026***	-299.812***	-2,490.913***	-62.239***
		(2.526)	(3.415)	(3.602)	(4.221)	(4.411)		(-3.174)	(-3.262)	(-3.906)	(-3.633)	(-4.762)
MVE		-21.928	-21.264	-11.632	-7.811	-25.657*		39.497**	35.783**	25.336	21.716	42.255***
		(-1.462)	(-1.448)	(-0.788)	(-0.530)	(-1.731)		(2.490)	(2.262)	(1.606)	(1.378)	(2.668)
MTB		1.891	2.276	1.575	0.452	1.800		-3.294	-3.732	-2.914	-1.869	-3.142
		(0.782)	(0.950)	(0.645)	(0.194)	(0.731)		(-1.229)	(-1.424)	(-1.086)	(-0.722)	(-1.159)
FirmAge		19.097	19.341	30.071	35.173	13.857		-34.494	-38.164	-49.687*	-54.948*	-30.415
		(0.740)	(0.748)	(1.176)	(1.368)	(0.543)		(-1.199)	(-1.315)	(-1.740)	(-1.906)	(-1.070)
AnalystFollow		84.745***	71.358**	64.417**	71.375**	79.979***		-99.129***	-80.032**	-71.748**	-79.838**	-90.690***
		(2.965)	(2.515)	(2.251)	(2.505)	(2.853)		(-3.202)	(-2.573)	(-2.286)	(-2.546)	(-2.963)
ROA		730.651	733.801	707.136	892.892*	708.365		-598.708	-609.450	-573.092	-767.218	-574.789
		(1.508)	(1.513)	(1.479)	(1.885)	(1.465)		(-1.092)	(-1.114)	(-1.066)	(-1.420)	(-1.054)
InstOwn		5.560	1.416	1.750	11.522	-1.108		-14.814	-10.899	-10.356	-21.551	-7.238
		(0.159)	(0.041)	(0.050)	(0.330)	(-0.032)		(-0.377)	(-0.279)	(-0.262)	(-0.548)	(-0.185)
ERC		237.246***	231.875***	194.535***	251.685***	205.966***		-213.241***	-208.229***	-160.750**	-228.405***	-175.922**
		(3.348)	(3.292)	(2.699)	(3.541)	(2.902)		(-2.680)	(-2.623)	(-1.983)	(-2.865)	(-2.195)
HistFCError		8,175.220***	8,180.563***	7,890.632***	8,459.935***	8,233.939***		-5,268.320*	-5,224.233*	-4,892.562	-5,471.862*	-5,297.550*
		(2.981)	(2.966)	(2.805)	(3.079)	(3.001)		(-1.721)	(-1.697)	(-1.556)	(-1.784)	(-1.728)
NewsCoverage		8.120	7.359	6.160	5.453	6.718		-0.200	0.750	2.288	2.578	1.568
		(0.798)	(0.734)	(0.607)	(0.535)	(0.671)		(-0.018)	(0.069)	(0.207)	(0.232)	(0.145)
AvgTurnover		3,380.306	4,697.795	8,791.180	-1,540.776	5,204.110		-1,800.463	-3,739.435	-8,743.466	2,313.732	-4,306.305
		(0.363)	(0.503)	(0.935)	(-0.164)	(0.562)		(-0.180)	(-0.374)	(-0.868)	(0.230)	(-0.434)
AbsSurp		-379.591	-394.221	-180.713	-592.151	-314.268		603.636	609.246	352.740	804.995	528.434
		(-0.872)	(-0.898)	(-0.398)	(-1.334)	(-0.738)		(1.175)	(1.162)	(0.663)	(1.514)	(1.035)
LogWords		1,624.088***	1,615.988***	1,616.881***	1,629.065***	1,614.420***		1,879.354***	1,887.949***	1,888.218***	1,874.330***	1,891.055***
		(41.864)	(41.788)	(41.771)	(42.160)	(41.677)		(36.441)	(36.409)	(36.453)	(36.172)	(36.647)
Year-Qtr FE		Y	Y	Y	Y	Y		Y	Y	Y	Y	Y
Fiscal Qtr FE		Y	Y	Y	Y	Y		Y	Y	Y	Y	Y
Observations		20,170	20,170	20,170	20,157	20,157		20,170	20,170	20,170	20,157	20,157
Adj R-Squared		0.547	0.548	0.548	0.547	0.551		0.563	0.563	0.565	0.562	0.567

Note: This table contains results described herein, and takes the form of Tables 3 & 4 (described in section 4), using variables described in section 3. All specifications are OLS regressions, t-stats in parentheses. Coefficients different from zero identified by *** p<0.01, ** p<0.05, * p<0.1 (two-tailed) and standard errors clustered at the firm level.

Appendix C (Continued)
Alternate Dependent Variables
Table A1 (Continued)

Panel B: Message-Level

		DEPVAR = *WordsCall*						DEPVAR = *WordsEA*				
Complex/Straightforward =		*StrategyWords*	*FwdLookingWords*	*AccountingWords*	*EarningsWords*	*ComplexMsgFactor*		*StrategyWords*	*FwdLookingWords*	*AccountingWords*	*EarningsWords*	*ComplexMsgFactor*
	Pred	(1)	(2)	(3)	(4)	(5)	Pred	(1)	(2)	(3)	(4)	(5)
ComplexMsg	(+)	8,693.520***	23,285.529***			157.373***	(-)	-15,380.007***	-28,853.584***			-142.922***
		(7.083)	(14.008)			(20.763)		(-10.152)	(-14.678)			(-17.129)
StraightforwardMsg	(-)			-16,440.790***	-30,393.385***		(+)			12,558.293***	26,104.871***	
				(-15.970)	(-16.434)					(10.784)	(11.961)	
MVE		24.714	29.664*	24.054	32.666*	29.054*		-10.961	-18.818	-13.726	-20.751	-17.702
		(1.428)	(1.756)	(1.368)	(1.847)	(1.678)		(-0.535)	(-0.926)	(-0.637)	(-0.956)	(-0.830)
MTB		-1.938	-1.722	-3.091*	-2.017	-2.482		2.653	2.483	3.719**	2.889	3.306*
		(-1.101)	(-0.992)	(-1.824)	(-1.123)	(-1.454)		(1.494)	(1.390)	(2.074)	(1.595)	(1.866)
FirmAge		-253.235**	-167.764	-186.768*	-252.888**	-177.004*		304.737**	193.026	242.960**	294.474**	226.080*
		(-2.369)	(-1.625)	(-1.824)	(-2.442)	(-1.748)		(2.495)	(1.646)	(2.037)	(2.459)	(1.918)
AnalystFollow		37.488*	20.875	26.527	9.974	2.062		-17.357	2.004	-11.306	4.172	12.828
		(1.692)	(0.967)	(1.237)	(0.472)	(0.099)		(-0.651)	(0.077)	(-0.426)	(0.159)	(0.497)
ROA		-116.535	-76.101	-432.558*	-43.918	-277.068		-49.811	-111.758	169.118	-132.523	76.741
		(-0.531)	(-0.347)	(-1.892)	(-0.191)	(-1.211)		(-0.197)	(-0.440)	(0.636)	(-0.497)	(0.287)
InstOwn		-43.439	-39.740	-28.715	-42.207	-27.568		29.435	26.989	22.242	32.048	18.493
		(-1.124)	(-1.074)	(-0.751)	(-1.110)	(-0.746)		(0.684)	(0.658)	(0.513)	(0.749)	(0.440)
ERC		18.435	28.979	26.731	38.386	40.301		-42.708	-56.882	-51.149	-61.750	-64.369
		(0.494)	(0.781)	(0.733)	(1.032)	(1.100)		(-1.021)	(-1.354)	(-1.227)	(-1.475)	(-1.556)
HistFCError		-567.182	400.769	-161.575	308.746	377.013		1,099.503	-323.430	365.716	-36.709	-121.086
		(-0.259)	(0.199)	(-0.075)	(0.150)	(0.194)		(0.447)	(-0.145)	(0.149)	(-0.015)	(-0.053)
NewsCoverage		-0.376	-2.546	0.853	-0.391	-1.029		4.646	7.100	3.260	4.254	4.856
		(-0.054)	(-0.372)	(0.123)	(-0.057)	(-0.153)		(0.600)	(0.925)	(0.414)	(0.550)	(0.634)
AvgTurnover		-4,126.173	-8,992.803	-4,968.605	-8,263.518	-9,223.289		-1,081.829	5,281.340	192.939	3,043.325	4,087.883
		(-0.599)	(-1.325)	(-0.739)	(-1.228)	(-1.416)		(-0.133)	(0.650)	(0.024)	(0.370)	(0.510)
AbsSurp		-51.212	12.064	-58.464	-62.618	-37.552		72.224	-9.227	71.988	76.792	54.873
		(-0.138)	(0.032)	(-0.147)	(-0.160)	(-0.094)		(0.147)	(-0.019)	(0.139)	(0.150)	(0.106)
LogWords		1,856.236***	1,907.819***	1,854.219***	1,810.293***	1,851.813***		1,709.273***	1,646.426***	1,712.844***	1,750.572***	1,715.029***
		(38.871)	(41.307)	(39.693)	(38.383)	(40.515)		(29.376)	(29.499)	(28.691)	(29.350)	(29.459)
Firm FE		Y	Y	Y	Y	Y		Y	Y	Y	Y	Y
Year-Qtr FE		Y	Y	Y	Y	Y		Y	Y	Y	Y	Y
Fiscal Qtr FE		Y	Y	Y	Y	Y		Y	Y	Y	Y	Y
Observations		20,170	20,170	20,170	20,170	20,170		20,170	20,170	20,170	20,170	20,170
Adj R-Squared		0.788	0.795	0.799	0.797	0.807		0.806	0.811	0.806	0.806	0.814

Note: This table contains results described herein, and takes the form of Tables 3 & 4 (described in section 4), using variables described in section 3. All specifications are OLS regressions, t-stats in parentheses. Coefficients different from zero identified by *** p<0.01, ** p<0.05, * p<0.1 (two-tailed) and standard errors clustered at the firm level.

Appendix D
Including Answers in Call Measures

In my primary analysis, I use only the prepared portion of the conference call to calculate message-level variables, as well as *PctCall* (and by extension, *UnexpectedEA*). In this study, I seek to understand how managers allocate information to different channels ex ante. To the extent the analysts asking the questions are driving the nature of information released in the Q&A, the information content of the Q&A is outside the scope of this study. However, existing research has shown that managers exercise discretion in the information released in their answers to analyst questions (e.g., Lee, 2015; Mayew, 2008). Therefore, it is possible excluding the Q&A portion of the call in my primary analysis ignores allocation of information to the rich channel.

In Table A2, I include the text from managers' answers to analyst questions in (i) the numerator and denominator of the *PctCall* variable and (ii) the calculation of word counts used to create independent variables in Table 4. Nine of the ten coefficients on complexity variables in Tables 3 and 4 continue to load as expected. However, the coefficient on *StrategyWords* becomes negative and significant. Without further examination into the questions asked by analysts, it is unclear what is driving this result (e.g. managers avoiding answering questions about strategic topics, analysts not asking about strategic topics, etc.) As analyst behavior is outside the scope of this study, I leave this question to future research. Nonetheless, this result suggests that excluding the Q&A portion of the call does not materially influence my findings.

Appendix D (Continued)
Including Answers in Call Measures
Table A2

Panel A: Firm-Level

		DEPVAR = *PctCall*				
Complexity Measure =		*NumSegments*	*NumLocations*	*Intangibles*	*StdROA*	*ComplexFirmFactor*
	Pred	(1)	(2)	(3)	(4)	(5)
Complexity	(+)	0.013***	0.013***	0.062***	0.300***	0.013***
		(2.992)	(5.271)	(5.465)	(2.792)	(6.295)
MVE		-0.000	-0.001	0.002	0.002	-0.001
		(-0.041)	(-0.274)	(0.813)	(0.965)	(-0.563)
MTB		0.001*	0.001**	0.001*	0.001	0.001*
		(1.939)	(2.286)	(1.700)	(1.586)	(1.842)
FirmAge		-0.000	-0.001	0.002	0.003	-0.002
		(-0.006)	(-0.191)	(0.508)	(0.646)	(-0.395)
AnalystFollow		0.041***	0.038***	0.036***	0.038***	0.040***
		(8.070)	(7.726)	(7.249)	(7.516)	(8.162)
ROA		0.094	0.093	0.087	0.115	0.086
		(1.132)	(1.119)	(1.070)	(1.396)	(1.046)
InstOwn		0.013**	0.011*	0.012*	0.014**	0.011*
		(2.069)	(1.907)	(1.895)	(2.222)	(1.817)
ERC		0.036***	0.035***	0.025**	0.038***	0.028**
		(2.894)	(2.793)	(1.965)	(3.051)	(2.244)
HistFCError		1.508***	1.522***	1.443**	1.524***	1.525***
		(2.720)	(2.751)	(2.514)	(2.714)	(2.792)
NewsCoverage		-0.002	-0.002	-0.002	-0.002	-0.002
		(-0.869)	(-1.000)	(-1.150)	(-1.059)	(-1.087)
AvgTurnover		4.428**	4.670**	5.736***	4.019**	4.822***
		(2.385)	(2.570)	(3.094)	(2.165)	(2.666)
AbsSurp		-0.190**	-0.196**	-0.140	-0.213**	-0.178**
		(-2.112)	(-2.186)	(-1.519)	(-2.333)	(-1.998)
LogWords		-0.134***	-0.137***	-0.136***	-0.134***	-0.137***
		(-20.084)	(-20.677)	(-20.470)	(-19.905)	(-20.807)
Year-Qtr FE		Y	Y	Y	Y	Y
Fiscal Qtr FE		Y	Y	Y	Y	Y
Observations		20,170	20,170	20,170	20,157	20,157
Adj R-Squared		0.246	0.255	0.254	0.244	0.261

Note: This table contains results described herein, and takes the form of Tables 3 & 4 (described in section 4), using variables described in section 3. All specifications are OLS regressions, t-stats in parentheses. Coefficients different from zero identified by *** p<0.01, ** p<0.05, * p<0.1 (two-tailed) and standard errors clustered at the firm level.

Appendix D (Continued)
Including Answers in Call Measures
Table A2 (Continued)

Panel B: Message-Level

		DEPVAR = *PctCall*				
Complex/Straightforward =		*StrategyWords*	*FwdLookingWords*	*AccountingWords*	*EarningsWords*	*ComplexMsgFactor*
	Pred	(1)	(2)	(3)	(4)	(5)
ComplexMsg	(+)	-0.459*	0.955***			0.040***
		(-1.703)	(2.659)			(30.601)
StraightforwardMsg	(-)			-6.734***	-14.145***	
				(-29.526)	(-28.126)	
MVE		0.010***	0.010***	0.005	0.009***	0.007**
		(3.098)	(3.152)	(1.531)	(2.804)	(2.160)
MTB		-0.000	-0.000	-0.000	-0.000	-0.000
		(-0.211)	(-0.150)	(-1.456)	(-0.565)	(-1.281)
FirmAge		-0.047**	-0.045**	-0.030*	-0.052***	-0.035**
		(-2.474)	(-2.357)	(-1.728)	(-2.884)	(-2.029)
AnalystFollow		0.040***	0.041***	0.025***	0.022***	0.020***
		(9.621)	(9.701)	(6.233)	(5.493)	(5.061)
ROA		0.027	0.025	-0.081*	0.025	-0.031
		(0.623)	(0.595)	(-1.819)	(0.563)	(-0.678)
InstOwn		-0.008	-0.008	-0.002	-0.005	-0.004
		(-1.224)	(-1.192)	(-0.314)	(-0.811)	(-0.568)
ERC		0.006	0.006	0.006	0.010	0.008
		(0.988)	(1.012)	(1.023)	(1.646)	(1.444)
HistFCError		0.195	0.186	0.075	0.240	0.271
		(0.529)	(0.506)	(0.213)	(0.695)	(0.774)
NewsCoverage		0.001	0.001	0.001	0.000	0.001
		(0.406)	(0.375)	(0.736)	(0.399)	(0.495)
AvgTurnover		1.460	1.394	1.014	-0.090	0.140
		(1.064)	(1.019)	(0.822)	(-0.074)	(0.115)
AbsSurp		-0.024	-0.020	-0.034	-0.025	-0.031
		(-0.405)	(-0.347)	(-0.500)	(-0.407)	(-0.456)
LogWords		-0.104***	-0.104***	-0.070***	-0.087***	-0.070***
		(-12.350)	(-12.737)	(-8.882)	(-11.086)	(-8.769)
Firm FE		Y	Y	Y	Y	Y
Year-Qtr FE		Y	Y	Y	Y	Y
Fiscal Qtr FE		Y	Y	Y	Y	Y
Observations		20,170	20,170	20,170	20,170	20,170
Adj R-Squared		0.622	0.623	0.690	0.686	0.698

Note: This table contains results described herein, and takes the form of Tables 3 & 4 (described in section 4), using variables described in section 3. All specifications are OLS regressions, t-stats in parentheses. Coefficients different from zero identified by *** p<0.01, ** p<0.05, * p<0.1 (two-tailed) and standard errors clustered at the firm level.

Appendix E
Ruling Out Investor Demand

It is possible that managers choose channel to ensure certain information reaches sophisticated investors (Crowley, 2016, 2018). If true, this may introduce bias into my results. For example, if sophisticated investors both follow rich channels and demand complex information, this behavior could result in a positive correlation between information complexity and channel reason, without managers preferring efficient communication.

In Table A3, Panels A & B, I reperform the analysis in specifications (5) from Tables 3 and 4 (including *ComplexFirmFactor* and *ComplexMsgFactor*) individually on each sample quartile of *InstOwn* and *AnalystFollow*. If sophisticated investor or analyst demand affects the complexity-channel matching observed in Tables 3 and 4, the relation should be weaker (stronger) for firms with less (more) institutional ownership or smaller (larger) analyst following. The coefficients on complexity factors are significantly positive and relatively consistent in magnitude across quartiles (apart from firm-level complexity in the top quartile of *InstOwn*). This suggests the results in Tables 3 and 4 are not entirely attributable to complexity-audience matching.

Appendix E (Continued)
Ruling Out Investor Demand
Table A3

Panel A: Firm-Level

		DEPVAR = *PctCall*							
		Sample Quartiles of *InstOwn*				Sample Quartiles of *AnalystFollow*			
	Pred	*SQ1*	*SQ2*	*SQ3*	*SQ4*	*SQ1*	*SQ2*	*SQ3*	*SQ4*
ComplexFirmFactor	(+)	0.010*	0.022***	0.012**	0.000	0.015**	0.011**	0.014***	0.015**
		(1.761)	(3.555)	(2.368)	(0.089)	(2.195)	(2.153)	(2.750)	(2.562)
MVE		-0.009	-0.008	-0.003	-0.012*	-0.001	-0.014**	-0.017**	-0.012
		(-1.526)	(-1.079)	(-0.453)	(-1.891)	(-0.203)	(-2.306)	(-2.429)	(-1.529)
MTB		-0.000*	0.000	-0.000	0.000	0.000	0.000	-0.000**	-0.000
		(-1.877)	(0.177)	(-0.291)	(0.213)	(0.189)	(0.350)	(-2.034)	(-0.157)
FirmAge		0.013	0.009	-0.001	0.013	0.012	0.000	0.013	0.013
		(1.054)	(0.574)	(-0.094)	(1.138)	(0.906)	(0.015)	(1.134)	(1.018)
AnalystFollow		0.041***	-0.015	0.018	0.041***	0.032*	0.006	0.045	0.043
		(2.969)	(-1.031)	(1.364)	(3.408)	(1.676)	(0.225)	(1.377)	(1.449)
ROA		0.059	1.161***	0.226	0.239	0.147	0.102	0.191	0.882***
		(0.262)	(4.035)	(1.011)	(1.148)	(0.585)	(0.456)	(0.794)	(4.215)
ERC		0.081***	-0.047	0.040	0.061**	0.062	0.041	0.047*	0.039
		(2.839)	(-1.183)	(1.537)	(2.414)	(1.242)	(1.474)	(1.669)	(1.420)
HistFCError		1.783	1.066	3.880**	2.665*	0.756	3.443***	4.950***	0.879
		(1.376)	(0.597)	(2.264)	(1.942)	(0.477)	(2.750)	(3.034)	(0.609)
NewsCoverage		-0.001	0.006	-0.007	-0.003	0.002	-0.003	-0.004	-0.003
		(-0.327)	(1.252)	(-1.405)	(-0.853)	(0.346)	(-0.625)	(-0.764)	(-0.701)
AvgTurnover		-0.695	-1.530	3.207	-2.562	0.399	3.375	-3.696	2.940
		(-0.175)	(-0.254)	(0.710)	(-0.617)	(0.064)	(0.770)	(-0.878)	(0.673)
AbsSurp		-0.008	0.005	-0.015	-0.039**	0.010	-0.018	0.023	-0.053**
		(-0.455)	(0.177)	(-0.750)	(-1.985)	(0.591)	(-1.301)	(0.801)	(-2.575)
LogWords		-0.013	0.000	-0.034***	-0.034***	-0.026***	-0.009	-0.005	-0.020
		(-1.322)	(0.026)	(-3.703)	(-3.892)	(-2.951)	(-0.993)	(-0.550)	(-1.338)
Year-Qtr FE		Y	Y	Y	Y	Y	Y	Y	Y
Fiscal Qtr FE		Y	Y	Y	Y	Y	Y	Y	Y
Observations		6,054	3,470	4,915	4,786	4,920	5,319	4,294	4,692
Adj R-Squared		0.0610	0.0797	0.0351	0.0480	0.0410	0.0437	0.0491	0.0688

Note: This table contains results described herein, and takes the form of Tables 3 & 4 (described in section 4), using variables described in section 3. All specifications are OLS regressions, t-stats in parentheses. Coefficients different from zero identified by *** p<0.01, ** p<0.05, * p<0.1 (two-tailed) and standard errors clustered at the firm level.

Appendix E (Continued)
Ruling Out Investor Demand
Table A3 (Continued)

Panel B: Message-Level

		DEPVAR = *PctCall*							
		Sample Quartiles of *InstOwn*				Sample Quartiles of *AnalystFollow*			
	Pred	*SQ1*	*SQ2*	*SQ3*	*SQ4*	*SQ1*	*SQ2*	*SQ3*	*SQ4*
ComplexMsgFactor	(+)	0.043***	0.032***	0.037***	0.039***	0.035***	0.037***	0.042***	0.049***
		(12.012)	(7.503)	(10.111)	(10.454)	(9.615)	(10.701)	(12.023)	(12.417)
MVE		0.012	-0.001	0.006	0.007	-0.003	0.021**	0.010	0.006
		(1.509)	(-0.049)	(0.492)	(0.994)	(-0.271)	(2.556)	(1.228)	(0.711)
MTB		-0.000**	-0.000	-0.000***	-0.000	-0.000*	-0.000	-0.000*	0.000
		(-2.404)	(-0.251)	(-3.128)	(-0.550)	(-1.927)	(-0.950)	(-1.919)	(1.563)
FirmAge		-0.081	-0.020	-0.082	-0.108**	0.031	-0.159***	-0.028	-0.077
		(-1.452)	(-0.200)	(-1.240)	(-2.236)	(0.478)	(-3.269)	(-0.454)	(-1.137)
AnalystFollow		0.009	-0.007	-0.006	0.026**	0.013	-0.001	0.009	-0.011
		(0.929)	(-0.397)	(-0.493)	(2.224)	(1.059)	(-0.067)	(0.395)	(-0.507)
ROA		-0.006	0.054	-0.064	0.031	-0.042	0.119	-0.179	0.036
		(-0.052)	(0.350)	(-0.386)	(0.350)	(-0.333)	(1.025)	(-1.292)	(0.324)
ERC		0.018	-0.081***	0.022	0.035**	-0.006	-0.018	0.037**	0.014
		(0.884)	(-2.923)	(1.473)	(2.487)	(-0.193)	(-0.860)	(2.113)	(1.120)
HistFCError		-0.072	-0.288	1.738	-2.290*	-0.443	-0.711	0.335	1.472
		(-0.100)	(-0.187)	(1.309)	(-1.779)	(-0.512)	(-0.803)	(0.214)	(1.017)
NewsCoverage		-0.000	0.004	-0.003	0.002	-0.001	0.002	-0.000	0.003
		(-0.019)	(0.738)	(-0.865)	(0.477)	(-0.116)	(0.599)	(-0.123)	(0.796)
AvgTurnover		0.304	-4.746	-1.148	-3.998	2.808	-3.174	-1.118	-1.032
		(0.085)	(-0.829)	(-0.282)	(-1.246)	(0.608)	(-0.796)	(-0.241)	(-0.289)
AbsSurp		0.009	-0.013	-0.011	0.007	0.018	-0.011	-0.000	-0.002
		(1.326)	(-0.852)	(-0.755)	(0.577)	(1.402)	(-1.164)	(-0.005)	(-0.153)
LogWords		-0.010	-0.009	-0.036***	-0.018***	-0.009*	-0.011**	-0.020**	-0.037***
		(-1.639)	(-1.213)	(-5.639)	(-2.709)	(-1.836)	(-2.044)	(-2.471)	(-4.477)
Firm FE		Y	Y	Y	Y	Y	Y	Y	Y
Year-Qtr FE		Y	Y	Y	Y	Y	Y	Y	Y
Fiscal Qtr FE		Y	Y	Y	Y	Y	Y	Y	Y
Observations		6,054	3,470	4,915	4,786	4,920	5,319	4,294	4,692
Adj R-Squared		0.619	0.648	0.643	0.660	0.628	0.653	0.668	0.681

Note: This table contains results described herein, and takes the form of Tables 3 & 4 (described in section 4), using variables described in section 3. All specifications are OLS regressions, t-stats in parentheses. Coefficients different from zero identified by *** p<0.01, ** p<0.05, * p<0.1 (two-tailed) and standard errors clustered at the firm level.

Appendix F
Ruling Out Disclosure Volume

If (i) managers with complex information have more to disclose overall and (ii) the earnings announcement press release is insufficient for the managers to get their message across, the complexity-richness relation may be influenced by complex firms' need for more disclosure space (e.g. Tasker, 1998). I control for total news with *AbsSurp* and *LogWords* in Tables 3 and 4 to help mitigate this concern. If the amount of information influences the complexity-channel matching observed in Tables 3 and 4, the relation should be weaker (stronger) for firms with less (more) total information to disclose.

To rule out this effect, in Table A4, I reperform the analysis in specification (5) of Tables 3 and 4 on each sample of quartile of news controls (*AbsSurp* and *LogWords).* The coefficients on both complexity factors are at least marginally significant, positive and relatively consistent in magnitude for all *AbsSurp* quartiles and all but the firm-level factor for the first quartile of *LogWords*. Moreover, in Table A5 I show results are robust to (i) using the log of words in the prepared portion of the call as the dependent variable, (ii) controlling for length of the earnings announcement in place of total words, and (iii) excluding length controls altogether. Overall, this evidence suggests that results in Tables 3 and 4 cannot be entirely attributed to disclosure space limitations.

Appendix F (Continued)
Ruling Out Disclosure Volume
Table A4

Panel A: Firm-Level

		DEPVAR = *PctCall*							
		Sample Quartiles of *AbsSurp*				Sample Quartiles of *LogWords*			
	Pred	*SQ1*	*SQ2*	*SQ3*	*SQ4*	*SQ1*	*SQ2*	*SQ3*	*SQ4*
ComplexFirmFactor	(+)	0.017***	0.012***	0.009**	0.007	0.005	0.009*	0.013***	0.023***
		(4.396)	(3.058)	(2.267)	(1.641)	(0.984)	(1.837)	(3.154)	(4.850)
MVE		-0.011**	-0.006	-0.008*	-0.010**	-0.002	0.004	-0.007	-0.017***
		(-1.963)	(-1.191)	(-1.656)	(-2.174)	(-0.330)	(0.748)	(-1.423)	(-2.593)
MTB		-0.000*	-0.000	-0.000	0.000	-0.000	-0.000***	0.000	-0.000
		(-1.761)	(-0.476)	(-0.711)	(0.135)	(-0.296)	(-4.994)	(0.919)	(-1.537)
FirmAge		-0.000	0.001	0.010	0.025***	0.022	0.003	0.007	-0.009
		(-0.013)	(0.143)	(1.106)	(2.902)	(1.587)	(0.336)	(0.775)	(-0.873)
AnalystFollow		0.028***	0.020**	0.023**	0.022**	0.000	0.006	0.035***	0.045***
		(2.634)	(2.102)	(2.255)	(2.197)	(0.007)	(0.507)	(3.779)	(3.256)
ROA		0.394	0.285	0.278	0.217	-0.238	0.172	0.252	0.444**
		(1.552)	(1.448)	(1.379)	(1.568)	(-1.272)	(0.945)	(1.160)	(2.187)
InstOwn		0.016	0.013	-0.004	-0.001	-0.015	0.006	0.009	0.015
		(1.205)	(1.104)	(-0.350)	(-0.113)	(-0.897)	(0.436)	(0.705)	(0.981)
ERC		0.015	0.071***	0.067***	0.094***	0.035	0.036	0.058**	0.068**
		(0.671)	(3.608)	(2.987)	(3.292)	(1.369)	(1.500)	(2.528)	(2.041)
HistFCError		2.727**	3.814***	2.269*	1.388	3.656**	1.641	2.625**	1.532
		(2.259)	(3.072)	(1.923)	(1.615)	(2.199)	(1.258)	(2.444)	(1.303)
NewsCoverage		0.000	-0.000	-0.003	-0.005	0.000	-0.004	0.001	0.004
		(0.124)	(-0.101)	(-0.790)	(-1.372)	(0.010)	(-0.897)	(0.294)	(1.143)
AvgTurnover		5.006	3.681	1.820	-1.650	2.124	4.906	-1.585	-0.207
		(1.434)	(0.974)	(0.544)	(-0.550)	(0.422)	(1.313)	(-0.432)	(-0.053)
AbsSurp		-0.053	0.237	0.044	-0.013	-0.014	0.010	-0.005	-0.008
		(-0.185)	(0.867)	(0.318)	(-0.909)	(-0.545)	(0.567)	(-0.306)	(-0.633)
LogWords		-0.018**	-0.018**	-0.018**	-0.011	0.008	0.004	-0.011	-0.060***
		(-2.047)	(-2.332)	(-2.368)	(-1.577)	(0.801)	(0.442)	(-1.188)	(-6.759)
Year-Qtr FE		Y	Y	Y	Y	Y	Y	Y	Y
Fiscal Qtr FE		Y	Y	Y	Y	Y	Y	Y	Y
Observations		6,257	4,300	4,116	4,552	4,841	4,778	4,766	4,840
Adj R-Squared		0.0615	0.0435	0.0376	0.0335	0.0272	0.0277	0.0590	0.124

Note: This table contains results described herein, and takes the form of Tables 3 & 4 (described in section 4), using variables described in section 3. All specifications are OLS regressions, t-stats in parentheses. Coefficients different from zero identified by *** p<0.01, ** p<0.05, * p<0.1 (two-tailed) and standard errors clustered at the firm level.

Appendix F (Continued)
Ruling Out Disclosure Volume
Table A4 (Continued)

Panel B: Message-Level

		DEPVAR = *PctCall*							
		Sample Quartiles of *InstOwn*				Sample Quartiles of *AnalystFollow*			
	Pred	*SQ1*	*SQ2*	*SQ3*	*SQ4*	*SQ1*	*SQ2*	*SQ3*	*SQ4*
ComplexMsgFactor	(+)	0.036***	0.038***	0.043***	0.039***	0.020***	0.030***	0.036***	0.042***
		(12.457)	(10.135)	(10.985)	(10.814)	(5.456)	(10.642)	(13.020)	(11.176)
MVE		0.010	-0.000	0.001	0.016**	-0.001	0.013**	-0.004	0.006
		(1.415)	(-0.002)	(0.146)	(2.080)	(-0.050)	(2.303)	(-0.650)	(0.627)
MTB		-0.000*	-0.000**	-0.000*	0.000	-0.000***	0.000***	-0.000*	-0.000
		(-1.800)	(-1.974)	(-1.862)	(0.639)	(-3.084)	(5.390)	(-1.867)	(-1.424)
FirmAge		-0.040	-0.063	-0.082*	-0.078	-0.144**	-0.072**	-0.019	-0.028
		(-0.945)	(-1.300)	(-1.751)	(-1.478)	(-2.445)	(-2.029)	(-0.496)	(-0.549)
AnalystFollow		0.014	0.009	0.007	0.005	0.007	0.006	0.008	-0.006
		(1.417)	(0.879)	(0.681)	(0.474)	(0.560)	(0.833)	(1.066)	(-0.497)
ROA		0.011	0.106	-0.108	-0.021	-0.074	0.081	0.081	-0.031
		(0.076)	(0.671)	(-0.748)	(-0.204)	(-0.589)	(0.839)	(1.001)	(-0.289)
InstOwn		-0.007	0.021	-0.019	0.005	0.006	-0.002	-0.012	-0.011
		(-0.556)	(1.132)	(-1.090)	(0.240)	(0.316)	(-0.196)	(-0.794)	(-0.666)
ERC		0.013	0.027	-0.012	0.027	0.001	-0.003	0.008	0.009
		(1.091)	(1.638)	(-0.592)	(0.941)	(0.030)	(-0.209)	(0.563)	(0.535)
HistFCError		-0.487	1.048	-1.250	0.437	-0.899	-0.518	0.583	0.704
		(-0.497)	(0.838)	(-1.273)	(0.493)	(-0.858)	(-0.741)	(0.669)	(0.705)
NewsCoverage		0.000	0.003	-0.002	0.000	0.000	-0.002	0.003	-0.004
		(0.085)	(0.881)	(-0.700)	(0.077)	(0.016)	(-0.984)	(1.235)	(-1.261)
AvgTurnover		-4.591	7.545*	-3.301	-6.373**	-3.064	-2.861	-2.738	-2.163
		(-1.348)	(1.727)	(-0.989)	(-2.070)	(-0.685)	(-0.949)	(-1.114)	(-0.611)
AbsSurp		-0.081	0.181	-0.026	-0.006	0.006	0.001	-0.002	-0.002
		(-0.527)	(0.802)	(-0.252)	(-0.731)	(0.581)	(0.068)	(-0.126)	(-0.166)
LogWords		-0.017***	-0.018**	-0.017***	-0.019***	0.005	-0.003	-0.009*	-0.025***
		(-2.748)	(-2.496)	(-2.725)	(-2.944)	(0.751)	(-0.558)	(-1.733)	(-4.491)
Firm FE		Y	Y	Y	Y	Y	Y	Y	Y
Year-Qtr FE		Y	Y	Y	Y	Y	Y	Y	Y
Fiscal Qtr FE		Y	Y	Y	Y	Y	Y	Y	Y
Observations		6,257	4,300	4,116	4,552	4,841	4,778	4,766	4,840
Adj R-Squared		0.676	0.627	0.639	0.583	0.662	0.785	0.782	0.750

Note: This table contains results described herein, and takes the form of Tables 3 & 4 (described in section 4), using variables described in section 3. All specifications are OLS regressions, t-stats in parentheses. Coefficients different from zero identified by *** p<0.01, ** p<0.05, * p<0.1 (two-tailed) and standard errors clustered at the firm level.

Appendix F (Continued)
Ruling Out Disclosure Volume
Table A5

		DEPVAR = *Log(WordsCall)*		DEPVAR = *PctCall*			
Complexity Measure =		*ComplexFirmFactor*	*ComplexMsgFactor*	*ComplexFirmFactor*	*ComplexMsgFactor*	*ComplexFirmFactor*	*ComplexMsgFactor*
	Pred	(1)	(2)	(3)	(4)	(5)	(6)
Complexity	(+)	0.029***	0.071***	0.010***	0.020***	0.012***	0.039***
		(4.521)	(18.661)	(5.372)	(14.694)	(3.742)	(20.681)
MVE		-0.016**	0.011	0.004*	0.008**	-0.011***	0.005
		(-2.032)	(1.176)	(1.805)	(2.485)	(-2.847)	(1.201)
MTB		0.001	-0.001	0.000	-0.001**	0.001	-0.000
		(1.138)	(-1.273)	(0.135)	(-2.418)	(1.055)	(-1.180)
FirmAge		0.017	-0.113**	0.000	-0.053***	0.011	-0.054**
		(1.281)	(-2.215)	(0.073)	(-3.128)	(1.539)	(-2.111)
AnalystFollow		0.039***	0.005	0.011**	0.006	0.020***	0.003
		(2.718)	(0.465)	(2.523)	(1.343)	(2.719)	(0.605)
ROA		0.264	-0.080	-0.333***	-0.164***	0.286**	-0.038
		(1.037)	(-0.683)	(-4.297)	(-3.863)	(2.061)	(-0.616)
InstOwn		-0.002	-0.009	-0.005	-0.001	0.001	-0.005
		(-0.136)	(-0.467)	(-0.943)	(-0.108)	(0.108)	(-0.566)
ERC		0.078**	0.017	0.024*	0.013*	0.043**	0.013
		(2.199)	(0.946)	(1.959)	(1.759)	(2.442)	(1.461)
HistFCError		4.037***	-0.506	0.936**	-0.325	2.388***	0.205
		(2.724)	(-0.477)	(2.117)	(-0.829)	(2.917)	(0.390)
NewsCoverage		-0.001	0.000	0.003*	0.002*	-0.002	-0.000
		(-0.162)	(0.117)	(1.887)	(1.908)	(-0.565)	(-0.131)
AvgTurnover		4.847	-5.045	2.029	0.441	1.653	-1.991
		(0.991)	(-1.502)	(1.148)	(0.330)	(0.643)	(-1.066)
AbsSurp		-0.247	-0.093	-0.033	0.030	-0.155	-0.028
		(-1.035)	(-0.446)	(-0.430)	(0.494)	(-1.340)	(-0.292)
LogWords		0.848***	0.949***				
		(43.864)	(41.907)				
Log(WordsEA)				-0.204***	-0.191***		
				(-68.262)	(-60.981)		
Firm FE		N	Y	N	Y	N	Y
Year-Qtr, Fiscal Qtr FE		Y	Y	Y	Y	Y	Y
Observations		20,157	20,170	20,157	20,170	20,157	20,170
Adj R-Squared		0.563	0.822	0.609	0.812	0.0422	0.625

Note: This table contains results described herein, and takes the form of Tables 3 & 4 (described in section 4), using variables described in section 3. All specifications are OLS regressions, t-stats in parentheses. Coefficients different from zero identified by *** p<0.01, ** p<0.05, * p<0.1 (two-tailed) and standard errors clustered at the firm level.

Appendix G
Alternative Word Lists

As discussed in Section 3, I assume firm strategy and future-oriented discussion are relatively complex topics. I then measure the overall complexity of the firm's quarterly disclosures by counting words from strategy and forward-looking word lists in both the earnings announcement and the prepared portion of the earnings call (*StrategyWords* and *FwdLookingWords*). I build the strategy word list from using representative words from the results of topic modeling analysis presented in Appendix 1A of Ronda-Pupo and Guerras-Martin (2012). The intent of this study was to survey strategic management literature over the years, and Appendix 1A summarizes the topics identified from their literature review. I obtain the forward-looking word list from Bozanic, Roulstone and Van Buskirk (2018).

In Table A6, I show results are robust to (i) using every word from the Ronda-Pupo and Guerras-Martin Appendix (not just selected representative words) to calculate *StrategyWords* and (ii) using forward-looking word lists from both Matsumoto, et al. (2011) and Marshall and Skinner (2018) to calculate *FwdLookingWords*. This suggests my inferences are not driven by word list choice.

Appendix G (Continued)
Alternative Word Lists
Table A6

		DEPVAR = *PctCall*		
ComplexMsg =		*StrategyWords*	*FwdLookingWords*	*FwdLookingWords*
Word List Used =		Full RG List	MPR List	MS List
	Pred	(1)	(2)	(3)
ComplexMsg	(+)	0.539***	5.906***	5.415***
		(2.838)	(10.987)	(13.993)
MVE		0.006	0.007	0.001
		(1.335)	(1.613)	(0.330)
MTB		-0.000	-0.000	-0.000
		(-0.864)	(-1.011)	(-0.980)
FirmAge		-0.073***	-0.064**	-0.053**
		(-2.764)	(-2.462)	(-2.044)
AnalystFollow		0.013**	0.011*	0.009
		(2.130)	(1.846)	(1.516)
ROA		0.011	-0.000	-0.041
		(0.180)	(-0.001)	(-0.670)
InstOwn		-0.010	-0.009	-0.007
		(-0.983)	(-0.946)	(-0.770)
ERC		0.008	0.008	0.010
		(0.929)	(0.930)	(1.097)
HistFCError		0.020	0.279	-0.030
		(0.034)	(0.491)	(-0.054)
NewsCoverage		0.000	0.000	0.000
		(0.058)	(0.242)	(0.159)
AvgTurnover		-0.880	-1.141	-0.942
		(-0.443)	(-0.571)	(-0.494)
AbsSurp		-0.025	-0.018	-0.008
		(-0.283)	(-0.207)	(-0.096)
LogWords		-0.017	-0.003	-0.010
		(-1.361)	(-0.218)	(-0.804)
Firm FE		Y	Y	Y
Year-Qtr FE		Y	Y	Y
Fiscal Qtr FE		Y	Y	Y
Observations		20,170	20,170	20,170
Adj R-Squared		0.587	0.600	0.603

Note: This table contains results described herein, and takes the form of Table 4 (described in section 4), using variables described in section 3. All specifications are OLS regressions, t-stats in parentheses. Coefficients different from zero identified by *** p<0.01, ** p<0.05, * p<0.1 (two-tailed) and standard errors clustered at the firm level.

Appendix H
Standard Errors

In reported tables, I cluster standard errors by firm. Although year by calendar quarter and fiscal quarter fixed effects should control for a significant portion of time effects in the data, if firms are not equally affected by common shocks, residuals of different firms in the same quarter may still be correlated (Conley, Goncalves and Hansen, 2018). Two-way clustering requires that both (i) the minimum number of clusters to approach infinity (or be otherwise large), and (ii) different firms from different years are uncorrelated, which is restrictive if observations are both serially and cross-sectionally correlated (Conley et al., 2018). Finally, Coney et al., 2018 suggest the most conservative approach for panel data is to use Fama-MacBeth sample splitting procedures with few large N groups.

The analysis using alternative standard error specifications is reported in Table A7. The key results in Tables 3 and 4 are robust to clustering by firm and year, by firm and calendar quarter and Fama-MacBeth regressions (by year). Although the coefficients on *UnexpectedEA* in IPT regressions remain significant throughout the various standard error specifications, the *UnexpectedEA* coefficient loses significance when clustering by firm and year and in Fama-MacBeth regressions. Overall, the standard errors do not appear to be understated.

Appendix H (Continued)
Standard Errors
Table A7

Panel A: Two-way cluster, Firm, Year

DEPVAR =		***PctCall***	***PctCall***	***AbsRet3D***	***IPT***
	Pred	(1)	(2)	(3)	(4)
ComplexFirmFactor	(+)	0.013***			
		(4.212)			
ComplexMsgFactor	(+)		0.039***		
			(22.018)		
UnexpectedEA	(-)			-0.003	-2.087**
				(-1.584)	(-1.962)
H1 Controls		Y	Y	N	N
H3 Controls		N	N	Y	Y
Firm FE		N	Y	N	N
Year-Qtr FE		Y	Y	Y	Y
Fiscal Qtr FE		Y	Y	Y	Y
Observations		20,157	20,170	6,027	6,048
Adj R-Squared		0.070	0.626	0.126	0.001

Panel B: Two-way cluster, Firm, Quarter

DEPVAR =		***PctCall***	***PctCall***	***AbsRet3D***	***IPT***
	Pred	(1)	(2)	(3)	(4)
ComplexFirmFactor	(+)	0.013***			
		(4.769)			
ComplexMsgFactor	(+)		0.039***		
			(24.583)		
UnexpectedEA	(-)			-0.003*	-2.087***
				(-1.865)	(-2.779)
H1 Controls		Y	Y	N	N
H3 Controls		N	N	Y	Y
Firm FE		N	Y	N	N
Year-Qtr FE		Y	Y	Y	Y
Fiscal Qtr FE		Y	Y	Y	Y
Observations		20,157	20,170	6,027	6,048
Adj R-Squared		0.070	0.626	0.126	0.001

Appendix H (Continued)
Standard Errors
Table A7 (Continued)

Panel C: Fama MacBeth Regressions

DEPVAR =		*PctCall*	*PctCall*	*AbsRet3D*	*IPT*
	Pred	(1)	(2)	(3)	(4)
ComplexFirmFactor	(+)	0.013***			
		(7.857)			
ComplexMsgFactor	(+)		0.031***		
			(27.894)		
UnexpectedEA	(-)			-0.002	-1.836*
				(-1.383)	(-1.719)
H1 Controls		Y	Y	N	N
H3 Controls		N	N	Y	Y
Firm FE		N	N	N	N
Year-Qtr FE		N	N	N	N
Fiscal Qtr FE		N	N	N	N
Observations		20,157	20,170	6,027	6,048
Adj R-Squared		0.059	0.119	0.099	0.001

Note: This table contains results described herein, and takes the form of Tables 3, 4 and 7 (described in section 4), using variables described in section 3. All specifications are OLS regressions, t-stats in parentheses. Coefficients different from zero identified by *** p<0.01, ** p<0.05, * p<0.1 (two-tailed) and standard errors clustered as described.

Appendix I
Other Disclosure Timing

It is possible that the timing of when managers release quarterly disclosures may be associated with both the allocation of information to the earnings announcement and the press release, as well as *AbsRet3D* and *IPT*. If these timing decisions are uncorrelated with deviation from the complexity-richness matching strategy, this should introduce attenuation bias in the results. However, if the same firms that deviate from the complexity-richness matching strategy are differentially likely to (i) contemporaneously release the 10-K or 10-Q or (ii) host their conference call on the day after the earnings press release, this could bias the coefficients.

Although I control for *CallNextDay* and *Contemp10K10Q* in the market analysis, I also reperform the analyses in Table 7 excluding firm-quarters with *CallNextDay* and *Contemp10K10Q* = 1 (Table A8). The market results hold after excluding these firms, with the exception of *AbsRet3D* when contemporary 10-K/10-Q firms are excluded (coefficient = -0.002, t-stat = -1.067). This finding suggests that the findings reported in Table 7 are not entirely attributable to the timing of other related quarterly disclosures.

Appendix I (Continued)
Other Disclosure Timing
Table A8

		DEPVAR = *AbsRet3D*		DEPVAR = *IPT*	
		Exclude if *CallNextDay* = 1	Exclude if *Contemp10K10Q* = 1	Exclude if *CallNextDay* = 1	Exclude if *Contemp10K10Q* = 1
	Pred.	(1)	(2)	(3)	(4)
Channel Decision:					
UnexpectedEA	(-)	-0.004**	-0.002	-3.013***	-1.970*
		(-2.364)	(-1.067)	(-2.745)	(-1.865)
Control Variables:					
Surprise		0.032	-0.003	3.492	2.822
		(0.423)	(-0.062)	(0.166)	(0.171)
AbsSurp		-0.005	-0.054	-17.288	-2.506
		(-0.069)	(-1.075)	(-0.649)	(-0.109)
Dispersion		0.012	0.032	-6.872	-11.249
		(0.708)	(1.451)	(-0.519)	(-0.913)
BadNewsSurp		0.002	0.003*	0.654	0.964
		(1.051)	(1.673)	(0.519)	(0.827)
ERC		0.015***	0.018***	4.699	2.652
		(3.138)	(4.226)	(1.352)	(0.752)
StdRet		1.218***	1.230***	23.861	80.296
		(10.845)	(11.087)	(0.397)	(1.515)
Contemp10K10Q		-0.001		-0.560	
		(-0.573)		(-0.433)	
CallNextDay			-0.006***		-0.834
			(-2.752)		(-0.681)
Year-Qtr FE		Y	Y	Y	Y
Fiscal Qtr FE		Y	Y	Y	Y
Observations		4,453	4,766	4,458	4,785
Adj R-Squared		0.134	0.130	0.009	0.001

Note: This table contains results described herein and takes the form of Table 7 (described in section 4), using variables described in section 3. All specifications are OLS regressions, t-stats in parentheses. Coefficients different from zero identified by *** p<0.01, ** p<0.05, * p<0.1 (two-tailed) and standard errors clustered at the firm level.