Essays on Financial Communication in Earnings Conference Calls

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Abstract

Earnings conference calls are an important platform of financial communication. They provide researchers with unique opportunities to observe firm managers' and financial analysts' interactions and natural communication style in a daily-task environment. Relying on multidisciplinary theories and methods, this dissertation studies financial communication in conference calls from both the managers' and the sell-side analysts' perspectives. It consists of three self-contained studies. Chapter 2 focuses on managers' communication strategies in conference calls. It explores, in the small non-negative earnings surprises setting, whether non-manipulators design communication strategies to separate themselves from earnings manipulators, and whether manipulators pool through obfuscation. Chapters 3 and 4 focus on sell-side analysts' communication behaviour in conference calls. Chapter 3 examines how analysts' people skills affect their communication behaviour and relationships with firm management. Chapter 4 applies both qualitative and quantitative discourse analyses and investigates how analysts use linguistic politeness strategies to establish socially desirable identities in publicly accessible analyst-manager interactions. The three studies combined contribute to the accounting literature by furthering our understanding of managers' and analysts' financial communication incentives and behaviour from multiple perspectives.

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Declaration of Authenticity

I, the undersigned, declare that this dissertation is original and authentic, and is the result of my own work. Except where acknowledged and referenced, all statements and arguments are my own.

I also declare that Chapter 3 of this dissertation is based on a paper co-authored with William J. Mayew, a professor of accounting at the Fuqua School of Business at Duke University, and that Chapter 4 is based on a paper co-authored with Veronika Koller, a reader in discourse studies at the Linguistics and English Language department at Lancaster University and my Ph.D. co-supervisor. For these two chapters, I was responsible for developing the research ideas (with suggestions from the co-authors), designing and conducting the empirical analyses (with advice from the co-authors) and writing the chapters. The contributions of the co-authors have been limited to the reasonable level expected in a doctoral dissertation at a research university in the United Kingdom.

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Chapter 1. Introduction

This dissertation investigates various financial communication phenomena in the setting of earnings conference calls. Conference calls have become an increasingly important channel of corporate voluntary disclosure since the 1990s (Bushee et al., 2003). Survey evidence shows that the majority (more than 90%) of U.S. public firms host quarterly earnings conference calls (NIRI, 2014). A typical conference call consists of two sections: the presentation section and the question-and-answer section (hereinafter, the Q&A section). During the presentation section, senior managers give presentations on firm strategies, past performance and forward-looking guidance. During the Q&A section, the audience (e.g. sell-side financial analysts) ask questions regarding managers' presentation, challenge managers' interpretation of company performance and seek information that managers might be unwilling to disclose (Hollander et al., 2010).

There are three main motivations for the investigation on financial communication through conference calls. First, these calls reflect the important role of the spoken component of corporate voluntary disclosure in financial markets. It has long been established that conference calls provide useful information to various groups of market participants. For example, Bowen et al. (2002) report that calls increase the amount of information available to analysts and their earnings forecast accuracy, as well as decrease forecast dispersion. Brown et al. (2004) document that calls lead to long-term reductions in information asymmetry among equity investors. Their results suggest that firms that hold conference calls more frequently have lower cost of capital. Kimbrough (2005) investigates whether conference calls accelerate analysts' and investors' responses to the future implications of current earnings announcements. He reports that the initiation of conference calls reduces both analysts' and investors' underreaction to currently announced earnings.

Second, conference calls allow researchers to observe managers' natural disclosure behaviour directly. Traditional written financial documents such as annual reports are prepared in advance and carefully scripted. Conference calls, on the other hand, consist of verbal communication between managers and the audience. While the presentation section of these calls is typically scripted in advance (Larker and Zakolyukina, 2012), the Q&A section consists of ad hoc interactions between managers and the audience and hence is more immediate, interactive and intense in nature than written disclosure (Merkl-Davis and Brennan, 2007; Lee, 2016). These characteristics of earnings conference calls provide managers with an opportunity to disclose information in a less-constrained fashion (Matsumoto et al., 2011). Therefore, conference calls provide researchers with a unique opportunity to observe managers natural disclosure and linguistic style.

Research shows that managers' linguistic disclosure style in conference calls is informative to investors. For example, Larcker and Zakolyukina (2012) develop a linguistic-based model based on CEO's and CFO's word use to predict financial restatement. They report that the model's predictive power is at least equivalent to models based on accounting and financial variables. Lee (2016) studies the consequences of managers adhering to predetermined scripts in the Q&A section. He explores the textual similarity between the presentation and Q&A sections and documents that a high level of similarity is associated with negative abnormal returns and analyst recommendation downgrades. Bushee et al. (2018) examine the linguistic complexity in earnings conference calls. They develop a novel approach to empirically decompose managers' linguistic complexity into the information and obfuscation components by using analysts' linguistic complexity as the benchmark. They document that the obfuscation (information) component is positively (negatively) associated with the firm's information asymmetry.

Third, as financial analysts can ask questions and directly interact with managers during the Q&A section, earnings conference calls provide a unique setting to study analysts' behaviour, incentives and relationships with firm management. Financial analysts are essential information intermediaries in the financial market and the main participants of conference calls. While there are numerous studies examining analysts' incentives and behaviour, early research provides limited insights due to the lack of access to analysts' behaviour in a daily-task environment (Bradshaw, 2011). The emergence of publicly accessible conference calls therefore provides fruitful avenues for researchers to observe analyst-manager interactions and examine analysts' behaviour more directly.

Both regulators and researchers have expressed concerns that, in order to access firm-specific information, analysts have incentives to maintain close relationships with firm management which results in optimistic bias towards the firm (e.g. Francis and Philbrick, 1993; Richards, 2002; Francis et al., 2004; Chen and Matsumoto, 2006; Westphal and Clement, 2008). Conference calls provide a unique setting to study analyst-manager relationships and interactions because managers have the discretion to choose which analysts to ask questions and typically pick analysts with friendly questions to set a favourable tone for the call (Mayew, 2008; Cen et al., 2019). The literature documents that sell-side analysts who are chosen to participate in these calls are more favourable and have better relationships with firm management (Mayew, 2008), have superior access to firm-specific information (Mayew et al., 2013), and have better career outcomes (Cen et al., 2019). Studies on analysts' language during these calls show that analysts praise managers during calls and that analysts who use more favourable language have better access to firm-specific information (Milian and Smith, 2017; Milian et al., 2017).

This dissertation consists of three related yet self-contained studies that aim to contribute to the financial communication literature from both the managers' and the sell-side analysts' perspectives. Chapter 2 investigates managers' conference call disclosure strategies when firms report small non-negative earnings surprises. Prior research documents that investors view small non-negative earnings surprises as a red flag for managerial opportunism and penalize all firms with such results even in the absence of hard evidence of earnings manipulation (Keung et al., 2010). This chapter extends the research on this pooling equilibrium by investigating managers' responses during the corresponding conference call. Results show that, compared with earnings manipulators, non-manipulators engage in credible disclosure and provide more negative forward-looking discussions and obfuscate less. Findings also show that manipulators intentionally pool by increasing obfuscation when they report small non-negative earnings surprises. Finally, the results suggest that the capital market responses to non-manipulators' and manipulators' conference call are statistically equivalent. Investors underreact to non-manipulators' calls initially and correct such an underreaction throughout the next quarter. The evidence suggests that, when opportunistic disclosers' pooling effect is strong, the informativeness of credible disclosers' conference calls can be compromised.

Chapter 3 focuses on the behaviour of sell-side analysts in conference calls. This chapter examines the effects of people skills on analysts' relationships with firm management and their informational outputs. People skills represent individuals' ability get along with, to communicate effectively with, and to foster trusting relationships with others (Morand, 2001, p.21). The nature of analysts' work requires good people skills to foster close relationships with firm management. Relying on research in psychology, sociology and economics, this chapter reasons that analysts from more individualistic, more trusting and lower power distance ethnic backgrounds have better people skills. Accordingly, an empirical proxy for people skills is developed using the first principal component of these three ethnic cultural traits. This empirical proxy is validated through analysts' linguistic behaviour during earnings conference calls. Empirical results show that analysts with better people skills have a higher probability of participating in conference calls and ask earlier questions. Mediation analysis suggests that analysts with better people skills benefit from good management relationships and possess superior firm-specific information. This chapter is the first to show the effects of people skills in the analyst labour market.

Chapter 4 also focuses on sell-side analysts. This chapter employs both qualitative and quantitative discourse analyses and examines how analysts use politeness in language to construct socially desirable identities during conference calls. Sell-side analysts have two conflicting identities. On the one hand, as their primary responsibility is for investor clients, they are "competent professionals" to investors. On the other hand, as they have incentives to seek good relationships with managers, they are "dependants of companies" who may bias their informational outputs towards management. As conference calls are publicly accessible in the U.S., analysts are expected to use politeness in language to present socially desirable identities. Discourse analysis shows that analysts use various politeness strategies to promote and balance the two identities depending on the context of conference calls. During calls with firms reporting extreme earnings increase, analysts use politeness to weaken the strength of their questions and promote their identity as dependants of companies. During calls with firms reporting extreme earnings decrease, however, the need to sustain their identity as competent professionals dominates their politeness behaviour. My study contributes to the literature by showing the importance of politeness in financial communication and illustrating how analysts use politeness in language to actively engage in identity construction in publicly-observable analyst-manager interactions.

A unique feature of this dissertation is its interdisciplinarity. Financial communication is a dynamic and multifaceted process that involves different groups of market participants. Both the content of conference call information and the way the information is communicated (i.e. the linguistic characteristics of managers and analysts) are informative. Apart from accounting researchers, researchers in other disciplines such as linguistics and computational science have studied various financial communication phenomena. Theories and empirical methods from areas outside of accounting, including psychology and linguistics, are useful for analysing and interpreting these phenomena. By bridging theories and methods from various disciplines, the studies in this dissertation aim to contribute to our knowledge on financial communication from multiple perspectives.

The remainder of my dissertation is organised as follows. Chapter 2 investigates the conference call communication strategies of earnings manipulators and non-manipulators when they report small non-negative earnings surprises. Chapter 3 studies how sell-side analysts' people skills affect their relationships with firm management and informational outputs. Chapter 4 examines how analysts use linguistic politeness strategies to establish socially desirable professional identities during conference calls. Chapter 5 concludes and makes suggestions for future research.

Chapter 2. Small Non-negative Earnings Surprises and Conference Call Communication

2.1. Introduction

Managers have incentives to avoid missing earnings benchmarks and may inflate reported earnings to achieve zero or positive earnings surprises (e.g. Burgstahler and Dichev, 1997; Brown, 2001; Matsumoto, 2002; Burgstahler and Eames, 2006; Brown and Pinello, 2007). Early evidence shows that firms with zero or positive earnings surprises enjoy higher market valuation (e.g. Bartov et al., 2002; Brown and Caylor, 2005; Bhojraj et al., 2009). Consequently, opportunistic managers may inflate reported earnings, leading to a discontinuity in the distribution of earnings surprises (Burgstahler and Dichev, 1997). Many studies show that the number of firms with small negative earnings surprises is significantly higher than the number of firms with small non-negative earnings surprises (e.g. Degeorge et al., 1999; Bhojraj et al., 2009; Gilliam et al., 2015).

Even sophisticated market participants such as analysts are not always able to determine whether earnings that meet or beat analysts' expectations are the result of genuine operating strength or accounting manipulation (de Jong et al., 2014). That is, investors have limited ability to (perfectly) distinguish between manipulators and non-manipulators. Consequently, starting from the 2000s, investors view small non-negative earnings surprises as a red flag for low accounting quality and managerial opportunism, and penalize all firms with such results accordingly based on rational expectations, even in the absence of hard evidence of earnings manipulation (Akerlof, 1970; Keung et al., 2010). Firms that meet analysts' expectations without the need for manipulation (hereinafter, non-manipulators) therefore become collateral damage and face a costly pooling equilibrium. This chapter investigates managers' responses to this pooling equilibrium during the corresponding earnings conference call and examine how market participants react to managers' communication strategies.

Manipulators and non-manipulators face different communication incentives in conference calls. Manipulators are expected to engage in opportunistic disclosures because they face incentives to delay incorporation of bad news into stock prices and thus preserve the pooling equilibrium. They are expected to withhold bad news to inflate investors' perceptions of the firm (e.g. Kothari et al., 2009; Beyer and Dye, 2012; Kim and Zhang, 2016; Bao et al., 2019). They can attempt to mimic non-manipulators' communication style to mislead investors. This mimicking strategy complements their earnings management behaviour as both are designed to delay revelation of bad news. Additionally, they have strong obfuscating incentives during the call to circumvent analysts' questions about bad news and hence delay its revelation (Bushee et al., 2018).

In contrast, non-manipulators are motivated to adopt credible communication policies to signal the strength of their underlying performance and avoid market underreaction to their earnings results. As credible disclosers, they are expected to engage in transparent disclosures and reveal bad news quickly for reputation and litigation concerns (e.g. Skinner, 1994; Rogers and Stocken, 2005; Miller and Bahnson, 2002; Beyer and Dye, 2012). Moreover, because they are cognizant of manipulators' incentives to mimic, non-manipulators are motivated to adopt signalling strategies that are costly for manipulators to imitate. An important difference between non-manipulators and manipulators is that results for the latter are expected to be less sustainable due to weaker underlying performance, coupled with reversal of income-increasing earnings management in future periods (e.g. DeFond and Park, 2001; Dechow et al., 2012; Chen et al., 2017).[1] Thus, if non-manipulators design a communication strategy to convey forward-looking information in a credible and timely manner, such a strategy is costly for manipulators to mimic.

Precisely how manipulators' and non-manipulators' communication strategies play out in practice, and how market participants respond to these strategies, are the empirical questions on which this chapter seeks evidence. The communication strategies of these two groups of firms are predicted to differ in two ways. First, negative forward-looking discussion is expected to be a separating strategy adopted by non-manipulators. This strategy signals non-manipulators' commitment to credible disclosures and is costly for manipulators to mimic. Second, it is predicted that obfuscation is used an intentional pooling strategy of manipulators to delay revelation of bad news.[2]

The conference call setting is used to study non-manipulators' and manipulators' communication strategies for the following reasons. First, conference call disclosure is more likely to manifest intentional disclosure choices because it is more spontaneous and less scripted than other financial documents, which contain substantial boilerplate texts that tend not to vary over time (Larcker and Zakolyukina, 2012; Lee, 2016; Bushee et al., 2018). Second, conference calls are important disclosure events that are directly associated with earnings announcements and convey economically material information

[1] Alternatively, the signalling viewpoint argues that only high-quality firms manipulate earnings because they have the underlying performance strength to absorb reversals in future periods (e.g. Beaver and Engel, 1996; Louis and Robinson, 2005; Fang and Fu, 2018). Thus, income-increasing earnings management can be a signal of fundamental strength. However, there is evidence against the signalling argument (e.g. Teoh et al., 1998; Bergstresser and Philippon, 2006). Specifically, recent evidence shows that firms that meet or beat earnings benchmarks through accrual-based earning management have inferior future performance (Chen et al., 2017).

[2] I do not study how manipulators mimic non-manipulators' communication style. Non-manipulators may exhibit linguistic characteristics of truthful communication that are unconscious in nature, such as the use of pronouns, lexical diversity and concrete language (e.g. ter Doest et al., 2002; Humpherys et al., 2011; Larcker and Zakolyukina, 2012; Elliott et al., 2015; Burgoon et al., 2016). These characteristics represent unconscious behaviour and do not reflect non-manipulators' intentional attempt to separate. As manipulators can strategically mimic these characteristics as cheap talk, there should be no systematic difference in these features between non-manipulators and manipulators in equilibrium.

to market participants (e.g. Brown et al., 2004; Frankel et al., 2010; Hollander et al., 2010). Importantly, managers are willing to devote time and efforts to discuss meeting and beating market expectations during these calls (Graham et al., 2005; Frankel et al., 2010). Third, conference calls are a powerful setting to examine managers' obfuscating behaviour (Larcker and Zakolyukina, 2012; Bushee et al., 2018).

Tests utilize a sample of conference call transcripts for 1,779 U.S. non-financial firm-quarters during the period 2010 to 2015 with quarterly earnings per share surprises in the zero-to-one cent range. Non-manipulators and manipulators are classified using an aggregate earnings manipulation indicator that combines three accounting-based earnings manipulation proxies: discretionary accruals (Kothari et al., 2005), non-GAAP manipulation (Doyle et al., 2013) and classification shifting (Fan et al., 2010). As predicted, results show that non-manipulators provide a higher proportion of negatively toned forward-looking discussion than manipulators in both the presentation and Q&A sections of conference calls. Results also show that non-manipulators have a lower obfuscation component of management linguistic complexity than manipulators in the Q&A. Findings are robust to controlling for firm characteristics and performance, and other conference call characteristics including speech length and the use of positive and negative words. Additional tests using seasonally adjusted changes in communication strategies suggest that manipulators intentionally increase obfuscating behaviour to pool when they report small non-negative earnings surprises. However, there is no conclusive evidence that non-manipulators intentionally increase negative forward-looking discussion or decrease obfuscation. It appears that non-manipulators exhibit consistency in their communication policy rather than intentionally changing their behaviour in an attempt to separate themselves from manipulators.

Next, I assess the capital market consequences of non-manipulators' and manipulators' communication strategies. Results show no statistically significant difference between the market reaction to conference calls or communication strategies for the two firm types. Results suggest that non-manipulators are unable to credibly signal the absence of earnings manipulation and that manipulators successfully obfuscate on the earnings announcement date. The findings are consistent with prior evidence that market participants cannot fully distinguish between non-manipulators and manipulators in the small non-negative earnings surprise category (Keung et al., 2010; de Jong et al., 2014). Given that non-manipulators exhibit strong obfuscating behaviour and can mimic manipulators' communication style to preserve the pooling equilibrium, it is not surprising that investors cannot understand non-manipulators' signals. Further analysis reveals that non-manipulators experience higher market returns than manipulators starting from the second month after the conference call and in particular around the conference call of the subsequent quarter. These findings are consistent with market participants underreacting to non-manipulators' initial earnings announcements and then gradually learning about firm type over the subsequent quarter.

The study contributes to prior research on several dimensions. First, it contributes to the literature on earnings benchmark beating. Prior research typically focuses on the factors that motivate managers to opportunistically meet and beat earnings benchmarks and how investors react to this opportunistic behaviour (e.g. Burgstahler and Dichev, 1997; Brown, 2001; Matsumoto, 2002; Brown and Pinello, 2007; Keung et al., 2010). Keung et al. (2010) document that investors view zero or small positive earnings surprises as a red flag and penalize both non-manipulators and manipulators even in the absence of hard evidence of earnings manipulation, indicating a communication friction. This leads to the question of whether non-manipulators intentionally design communication strategies to signal the truthfulness of performance but fail to do so due to strong pooling effects; or if they do not seek to intentionally separate at all. Focusing on this communication friction, I show that although non-manipulators engage in credible and transparent disclosure, there is no conclusive evidence that they proactively separate. Consequently, they cannot successfully signal the truthfulness of earnings results or differentiate themselves from manipulators on the earnings announcement date.

Second, I extend the literature on managers' behaviour during conference calls. Many prior studies on conference calls focus on how managers use language to deceive or obfuscate (e.g. Hobson et al., 2012; Larcker and Zakolyukina, 2012; Allee and DeAngelis, 2015). I explicitly examine whether and how firms with high-quality earnings adopt communication strategies to clarify the truthfulness of their results when they face strong pooling effects from opportunistic managers. I present evidence that high earnings-quality firms adopt credible and transparent communication strategies. Moreover, it appears that they do so as a consistent communication style, instead of designing communication strategies to intentionally separate when they report small non-negative earnings surprises.

I also contribute to the literature on the capital market effects of conference call communication. Prior studies document that conference calls provide information beyond earnings releases (e.g. Frankel et al., 1999; Kimbrough, 2005; Matsumoto et al., 2011) and that specific communication strategies can also be incrementally informative (e.g. Davis et al., 2015; Lee, 2016; Frankel et al., 2018). Building on this view, this study investigates the informativeness of conference call communication where opportunistic disclosers have strong pooling incentives to delay market reactions to earnings news. The results show that in such cases, opportunistic disclosers are successful at pooling, while credible disclosers' transparent communication strategies are associated with investor underreaction. Consequently, the informativeness of credible disclosers' conference calls is compromised. My findings extend the understanding of how communication incentives and strategies can affect the information content of earnings news (e.g. Bushee et al., 2003; Brochet et al., 2019).

The remainder of this chapter is organised as follows. Section 2.2 explains hypotheses development. Section 2.3 describes empirical research design. Section 2.4 provides sample selection process and descriptive statistics. Section 2.5 presents and discusses empirical results for the hypotheses. Section 2.6 performs market reaction tests. Section 2.7 summarises and concludes this chapter.

2.2. Hypotheses development

It has long been established that opportunistic managers can inflate reported earnings to meet or beat earnings benchmarks (e.g. Burgstahler and Dichev, 1997; Brown, 2001; Matsumoto, 2002). As investors have limited ability to unravel such opportunistic behaviour, they penalize all firms that report small non-negative earnings surprises even in the absence of hard evidence of earnings manipulation. Consequently, non-manipulators become collateral damage and face a costly pooling problem. To protect their reputation and prevent their stocks from being under-priced, non-manipulators have incentives to credibly convey transparent information in a timely manner to signal the truthfulness of their earnings performance to market participants.

Forward-looking discussion (hereinafter, FLD) is a major element of conference calls. The informativeness of FLD has been documented in various corporate disclosures (e.g. Bryan, 1997; Clarkson et al., 1999; Muslu et al., 2015). In the conference call setting, Matsumoto et al. (2011) find that managers provide more forward-looking discussion in the presentation when firm performance is poor, indicating that managers attempt to focus on the future instead of discussing the poor performance in the past. Theoretically, it is unclear how the quantity of FLD in conference calls may be different for non-manipulators and manipulators. Non-manipulators might discuss the future more to convince investors that their performance is sustainable. However, manipulators might also provide FLD as a mechanism for diverting attention away from artificially inflated past performance (Clatworthy and Jones, 2006; Matsumoto et al., 2011).

Recent research examines the tone of FLD. Li (2010) reports that firms with better performance, lower accruals, lower market-to-book ratio, less return volatility, more readable MD&As, and a longer history have more positive FLD in their MD&A. He also finds that, on average, firms with better future performance have more positive FLD. However, it is important to note that, although the disclosure tone can be informative and the positive association between tone and firm performance is an empirical regularity (e.g. Feldman et al., 2010; Price et al., 2012; Henry and Leone, 2016; Brochet et al., 2019), tone is driven by both the truthful representation of economic fundamentals and opportunistic disclosure incentives (Huang et al., 2014). Thus, the positive association between future performance and FLD tone may not hold when opportunistic disclosers have strong incentives to withhold bad news about the future. Consistent with this notion, Schleicher and Walker (2010) hypothesise that FLD tone can be used as an impression management tool to conceal negative outlook. They document that firms with impending performance declines strategically bias FLD tone to hide bad news.

Research suggests that optimistic future news can be less credible than negative future news (e.g. Hutton et al., 2003; Mercer, 2004; Baginski et al., 2016). Moreover, many studies show that credible disclosers release bad news quickly and provide transparent and timely disclosures cautiously in order to maintain reputation and disclosure credibility among investors, and mitigate litigation concerns (e.g. Skinner, 1994; Miller and Bahnson, 2002; Rogers and Stocken, 2005; Rogers et al., 2011; Beyer and Dye, 2012). Thus, non-manipulators are expected to be forthcoming about negative future prospects.

Importantly, if non-manipulators are forthcoming about bad news and accordingly adopt a communication strategy designed to provide credible FLD, such a strategy is costly for manipulators to mimic. In the small non-negative earnings surprise setting, since manipulators opportunistically overstate earnings to achieve reported earnings results, their performance can reverse in the future and be less sustainable than that of non-manipulators (e.g. DeFond and Park, 2001; Dechow et al., 2012; Chen et al., 2017). Prior research shows that opportunistic managers withhold bad news to boost stock prices and personal wealth (e.g. Kothari et al., 2009; Beyer and Dye, 2012; Kim and Zhang, 2016; Bao et al., 2019). Thus, manipulators are expected to withhold bad news about the future to inflate investors' perceptions of firm performance.

Based on the theory and evidence discussed above, I hypothesise that:

H1. Non-manipulators provide a higher proportion of negative forward-looking discussion than manipulators in conference calls.

It is well established in the literature that firms with poor performance and opportunistic incentives provide less transparent disclosures to reduce disclosure informativeness and increase information processing costs, so that bad news is not reflected in stock prices or conveyed with a delay (e.g. Bloomfield, 2002; Li, 2008; Lo et al., 2017; Bushee et al., 2018). Consistent with the obfuscation hypothesis, Li (2008) reports that 10-Ks of firms with lower earnings are harder to read and longer, and that firms with easier-to-read 10-Ks have more persistent positive earnings. He interprets the results as evidence that firms with poor earnings performance attempt to obfuscate bad news by reducing annual report readability. More recently, Lo et al. (2017) show that firms that beat the prior year's earnings through earnings management have less readable MD&As, suggesting a link between earnings manipulation and obfuscation. Meanwhile, Bushee et al. (2018) show that firms with higher obfuscating behaviour in conference calls have greater information asymmetry following earnings announcements, consistent with firms reducing the informativeness of disclosures through obfuscation.

Opportunistic managers have strong incentives to obfuscate in conference calls, so that they can prevent analysts' questions on bad news and hence delay the revelation of such information (Bushee et al., 2018). In the small non-negative earnings surprise setting, manipulators have strong obfuscating incentives because their earnings performance is artificial and potentially unsustainable. They need to reduce disclosure transparency and informativeness, so that investors cannot see through earnings manipulation behaviour or identify weak firm fundamentals. As a result, manipulators are expected to use obfuscation in conference calls as an intentional pooling strategy.

Non-manipulators, on the other hand, have less obfuscating incentive. Since non-manipulators are credible disclosers who have genuinely achieved their reported earnings results, they are expected to provide more transparent disclosure than manipulators and have less incentive to prevent the disclosure of bad news. I therefore hypothesise that:

H2. Non-manipulators exhibit less obfuscating behaviour than manipulators in conference calls.

2.3. Research design

2.3.1. Small non-negative earnings surprises

This study focuses on non-manipulators' and manipulators' different conference call communication strategies in the small non-negative earnings surprises setting.[3] In this setting, there are likely to be firms that have achieved earnings expectations through earnings manipulation and also firms whose benchmark beating is the results of fundamental economic performance (i.e. no earnings manipulation). Many prior studies use consensus analyst forecast as the earnings benchmark because anecdotal evidence suggests that managers consider analyst consensus an important benchmark to meet or exceed (e.g. Degeorge et al., 1999; Brown and Caylor, 2005; Doyle et al., 2006; Brown et al., 2009; Keung et al., 2010). Following this line of literature, quarterly earnings surprise is measured as firms' actual earnings per share (hereinafter, EPS) minus the latest median consensus EPS forecast prior to the corresponding earnings announcement (Keung et al., 2010).[4] A small non-negative earnings surprise firm-quarter is defined as one with quarterly earnings surprises between 0 and 1¢ (inclusive).

2.3.2. Non-manipulators/manipulators classification

In this study, manipulators are firms that report [0, 1¢] earnings surprises by inflating earnings. Non-manipulators are firms that achieve [0, 1¢] earnings surprises through fundamental economic performance and do not engage in earnings manipulation.

[3] I do not study expectation management because it is beyond the scope of this study. While expectation management has been studied in the literature of earnings benchmark beating (e.g. Bartov et al., 2002; Burgstahler and Eames, 2006), it is a separate issue from earnings manipulation. The earnings manipulation issue is that, conditional on what firms may have done in the past, they still need to manipulate earnings to achieve earnings benchmarks. Thus, this study takes expectation management as given because the research question focuses on how firms behave, condition on expectations.
[4] Results are robust to using the mean consensus EPS forecast as the benchmark. Results are also robust to using firms' pro forma EPS instead of I/B/E/S actual EPS (Bentley et al., 2018).

As firms can manipulate earnings using different accounting methods, the non-manipulators/manipulators classification scheme combines three accounting-based earnings manipulation proxies: discretionary accruals, non-GAAP manipulation and classification shifting.[5]

Discretionary accruals are a widely-used proxy for earnings management. Performance-matched discretionary accruals are estimated following Kothari et al. (2005).[6] They show that previous commonly-used discretionary accruals estimation methods (e.g. the modified-Jones model) are biased towards rejecting the null hypothesis of no earnings manipulation when manipulation incentives are related to performance. Following their method, abnormal accruals is first estimated with the following cross-sectional regression model:

$$Total\ Accruals_{i,q} = \alpha_0 + \alpha_1(1/ASSETS_{i,q-1}) + \alpha_2 \Delta SALES_{i,q} + \alpha_3 PPE_{i,q} + \varepsilon_{i,q} \tag{2.1}$$

where, for firm i in quarter q, $Total\ Accruals$ is the difference between income before extraordinary items and net cash flow from operating activities, scaled by opening total assets. $1/ASSETS_{i,q-1}$ is the inverse of opening total assets. $\Delta SALES_{i,q}$ is the one-period change in sales, scaled by opening total assets. $PPE_{i,q}$ is gross property, plant and equipment, scaled by opening total assets.

[5] Some argue that academic researchers do not have superior ability in detecting earnings manipulation over market participants, such as analysts, auditors and short sellers (Ball, 2013). Thus, if researchers claim that they can classify manipulators and non-manipulators, market participants should also be able to do so. However, it is important to note that not all the information that this study uses is available to investors on the earnings announcement date. In some cases, when some of the data are available, they are likely unaudited. Consequently, market participants may not be able to distinguish between manipulators and non-manipulators on the earnings announcement date. This is also one of the reasons why non-manipulators have incentives to separate themselves during conference calls. Moreover, to mitigate the concern that this study cannot effectively classify manipulators and non-manipulators using the three accounting-based proxies, robustness tests incorporate restatements, which is an ex post measure, into the classification scheme in robustness tests. For details, please see Section 2.5.4.

[6] While Kothari et al. (2005) develop the estimation method using annual data, it can also be applied to quarterly data (e.g. Ramanna and Roychowdhury, 2010).

Performance-matched discretionary accruals are then calculated by adjusting abnormal accruals estimated using Eq. (2.1) with the average abnormal accruals of a portfolio matched to industry and past operating performance. In each quarter, for each two-digit SIC-defined industry, four portfolios are created by sorting the data into quartiles of ROA in the same quarter of the previous year. Performance-matched discretionary accruals of a specific firm-quarter is the abnormal accruals of that firm minus the average abnormal accruals of the matched portfolio. A firm is considered as inflating accruals if it has positive performance-matched discretionary accruals.[7]

The second earnings manipulation proxy is non-GAAP manipulation. Both regulators and researchers have expressed concerns that managers may opportunistically use non-GAAP earnings to inflate investors' perceptions of firm performance (e.g. Heflin and Hsu, 2008; Kolev et al., 2008; Frankel et al., 2011; Doyle et al., 2013). Specifically, Doyle et al. (2013) provide evidence that managers opportunistically use non-GAAP earnings to meet or beat analyst forecasts. Non-GAAP manipulation is measured following Doyle et al. (2013). A firm is considered to be involved in non-GAAP manipulation if it has non-GAAP EPS greater than GAAP EPS. GAAP EPS is defined as Compustat EPS before extraordinary items and discontinued operations. Non-GAAP EPS is defined as I/B/E/S actual EPS.

The third earnings manipulation proxy is classification shifting. Classification shifting involves opportunistic managers classifying negative recurring items as special items and positive non-recurring items as core earnings to inflate core profitability (McVay, 2006; Fan et al., 2010). Quarterly classification shifting is measured following

[7] Results are robust to estimating discretionary accruals using Dechow et al.'s (1995) modified Jones model and Larcker and Richardson's (2004) modified Jones model with book-to-market ratio and cash flows.

Fan et al. (2010). Expected core earnings for firm i in quarter q is estimated using the following model within each industry-year-quarter excluding firm i:

$$CE_q = \alpha_0 + \alpha_1 CE_{q-4} + \alpha_2 CE_{q-1} + \alpha_3 ATO_q + \alpha_4 ACCRUALS_{q-4} + \alpha_5 ACCRUALS_{q-1} + \alpha_6 \Delta SALES_q + \alpha_7 NEG\_\Delta SALES_q + \alpha_8 RETURNS_{q-1} + \alpha_9 RETURNS_q + \varepsilon_{i,q} \tag{2.2}$$

where CE is core earnings, defined as sales minus cost of goods sold and SG&A expenses. ATO is asset turnover. $ACCRUALS$ is net income before extraordinary items minus cash from operations. $\Delta SALES$ is percentage change in sales. $NEG\_\Delta SALES$ equals $\Delta SALES$ if $\Delta SALES$ is negative, and 0 otherwise. $RETURNS$ is three-month market-adjusted returns. Expected core earnings for firm i in quarter q are measured using the estimated coefficients in Eq. (2.2) multiplied by the actual values of the variables for firm i. Unexpected core earnings are then calculated as the difference between reported and expected core earnings. Since classifying core expenses as non-recurring items inflates core earnings, firms are identified as engaging in classification shifting if their unexpected core earnings are positive (Athanasakou et al., 2011).

The classification of manipulators/non-manipulators is based on three conditions that suggest earnings inflation: positive performance-matched discretionary accruals; non-GAAP earnings higher than GAAP earnings; and positive unexpected core earnings. Small non-negative earnings surprise firms that meet at least two of the three conditions in the reporting quarter are classified as manipulators in that quarter. Small non-negative earnings surprise firms that meet none of the three conditions in the reporting and the previous four quarters are classified as non-manipulators in the reporting quarter.

It is important to note that the classification scheme is designed to minimize the possibility of mis-classification and to empirically distinguish between non-manipulators and manipulators as accurately as possible. Therefore, observations that appear ambiguous in terms of earnings manipulation are not classified as either non-manipulators or manipulators, and hence excluded from the sample of this study. More specifically, to ensure I can accurately classify non-manipulators, I require non-manipulators to not engage in earnings manipulation consistently for a sufficient amount of time. Thus, firms that meet none of the three conditions in the reporting quarter, but met one or more of them in the previous four quarters, are not classified as non-manipulators in the reporting quarter. Additionally, firms that meet only one of the three conditions in the reporting quarter are not classified as either non-manipulators or manipulators.

2.3.3. Measures of conference call communication strategies

A typical conference call comprises two sections: the management presentation section and the Q&A section. In order to measure the communication strategies of interest in the management presentation and Q&A sections separately, a Python script is used to parse the two sections. The script then extracts words spoken by managers in the presentation and Q&A sections, and words spoken by analysts in the Q&A section.

2.3.3.1. Negative FLD

To measure the proportion of negative forward-looking disclosure (FLD), FLD sentences first need to be identified in management speech in the presentation section and the Q&A section. The procedure starts by tokenizing management speeches into sentences using the Python NLTK program. The identification of FLD sentences combines techniques from the accounting literature (Matsumoto et al., 2011; Muslu et al., 2014) and computational linguistics (Bird et al., 2009). Python NLTK provides functions to classify forward-looking and non-forward-looking sentences. However, forward-looking identification using NLTK contains measurement error because it is not specifically designed for financial reporting language. For example, the words ‘expect’ and ‘anticipate’ are routinely used to deliver management guidance and forecasts, but NLTK does not classify sentences containing these words as forward-looking in some instances. Therefore, this study follows Muslu et al. (2014) and Matsumoto et al. (2011) to develop wordlists to identify FLD in conference calls. Matsumoto et al. (2011) provide a wordlist to identify FLD in conference calls; Muslu et al. (2014) provide a more comprehensive FLD identification scheme based on 10-K filings. Since written documents are different from oral communication, the wordlist in this study combines and modifies the identification schemes in these two studies into a comprehensive FLD identification scheme specifically for conference calls. The classification scheme classifies a sentence as forward-looking if it: (1) contains words/phrases that indicate future time periods (e.g. “future”, “next quarter”, “next year”, etc.); (2) contains verbs or their conjugations that indicate future expectations, plans or actions (e.g. “anticipate”, “aim”, etc.); (3) contains a reference to a year after the year of the call; (4) contains other words/phrases that are typically used in management guidance (e.g. “guidance”, “projection”, etc.); or (5) is classified as forward-looking by Python NLTK. Further details are provided in Appendix 2.1.

Negative FLD is captured using two methods: a sentence-based approach and a word-based approach. Under the sentence-based approach, negative FLD (denoted as $FLDneg\_sentence$) is the percentage of negative FLD sentences relative to the total number of FLD sentences. Negative FLD sentences are defined as sentences that include at least one negative or negated positive word, and no positive or negated negative words. Under the word-based approach, the proxy for negative FLD (denoted as $FLDneg\_word$) is the percentage of negative and negated positive words relative to the total number of words of FLD. Loughran and McDonald's (2011) wordlist is used to identify negative and negated positive words. Both $FLDneg\_sentence$ and $FLDneg\_word$ are measured separately for the presentation and Q&A sections.[8]

I use both the sentence-based and the word-based measures for two reasons. First, they can both contain measurement error. Prior accounting and finance studies typically use the word-based approach (e.g. Frankel et al., 2010; Loughran and McDonald, 2011; Mayew et al., 2015). However, if a sentence contains several negative words, these words will contribute to a higher level of negativity under the word-based approach, although it is likely that they describe the same economic event. Thus, the sentence-based measure is complementary to the word-based measure by considering this potential bias of the word-based measure. Nonetheless, the sentence-based measure may also contain measurement error. Since management speech is tokenized into sentences using automated techniques, measurement error can be induced due to inaccurate sentence splits. Second, the two measures reflect different aspects of how managers provide negative FLD. The word-based measure may better reflect the intensity of negative words used in FLD as a whole. However, sentences as textual units provide context better than words to help investors understand the topic of interest. The sentence-based measure better captures the amount of negative news in FLD at the sentence level.

[8] I choose Loughran and McDonald's (2011) wordlist because it contains a comprehensive set of negative words. Other wordlist used in accounting and finance research such as Henry's (2006, 2008) wordlist do not include such a comprehensive list of negative words. Using Loughran and McDonald's (2011) wordlist, I can therefore measure negative FLD more accurately and comprehensively.

2.3.3.2. Obfuscation

Obfuscation is measured by estimating the obfuscation component of management linguistic complexity following Bushee et al. (2018).[9] Bushee et al. (2018) show that theoretically there are two latent components of management linguistic complexity: obfuscation and information. For example, if analysts ask complex questions, managers are more likely to provide complex answers, which reflects disclosure informativeness instead of obfuscation.

Bushee et al. (2018) develop and validate an empirical method to separate the obfuscation and information components of management linguistic complexity. Linguistic complexity is measured by the Gunning (1952) Fog index. A high Fog index indicates high linguistic complexity. The assumption of their method is that analysts have no obfuscating incentives. Thus, analysts' linguistic complexity in the Q&A section can serve as a benchmark level of linguistic complexity in the absence of obfuscation. The obfuscation component of management linguistic complexity (denoted as $Obfu$) is estimated using the following regression:

$$Fog(Manager)_{i,q} = \alpha_0 + \alpha_1 Fog(Analyst)_{i,q} + \sum Business\ Complexity\ Proxies + \varepsilon_{i,q} \tag{2.3}$$

where the estimated value of ε (i.e. the residual) is $Obfu$. Business complexity proxy variables are firm size, leverage, book-to-market ratio, stock returns, acquisitions, capital

[9] Early research tends to assume that good news is easy to read, and that obfuscation is conceptually equivalent to language complexity (Li, 2008). However, theory and evidence highlight that disclosure language can be complex for reasons other than obfuscation, such as the complexity of underlying operations and litigation concerns (Bloomfield, 2008; Guay et al., 2016).

intensity, capital expenditures, R&D, debt and equity issuance, cash flow volatility, goodwill impairments and restructuring charges. $Obfu$ is estimated separately for the presentation and Q&A sections with management Fog index computed separately for each section.

A higher value of $Obfu$ corresponds to a higher level of obfuscation. It is important to note that because the obfuscation component of linguistic complexity is regression residuals, its mean is zero by construction. $Obfu$ = 0 does not suggest that obfuscation is zero (Bushee et al., 2018).

2.3.4. Empirical model

To test whether there are differences between non-manipulators' and manipulators' communication strategies, I estimate the following model:

$$\begin{aligned}
&Communication\ Strategy_{i,q}^{k} \\
&\qquad = \alpha_0 + \alpha_1 NM_dummy_{i,q} + \alpha_2 Size_{i,q} + \alpha_3 Growth_{i,q} + \alpha_4 ROA_{i,q} \\
&\qquad + \alpha_5 EarnVol_{i,q} + \alpha_6 Ret_{i,q} + \alpha_7 RetVol_{i,q} + \alpha_8 Leverage_{i,q} \\
&\qquad + \alpha_9 MTB_{i,q} + \alpha_{10} Analyst_{i,q} + \alpha_{11} Age_{i,q} \\
&\qquad + \sum \alpha_j Conference\ Call\ Control_{i,q} + \sum Firm\ FE \\
&\qquad + \sum YearQuarter\ FE + \varepsilon_{i,q}
\end{aligned} \tag{2.4}$$

The unit of observation is a firm-quarter. Subscripts i and q indicate firms and quarters, respectively. The dependent variable is conference call communication strategy, where the superscript k represents: $FLDneg\_sentence$, $FLDneg\_word$, or $Obfu$. The explanatory variable of interest is NM_dummy, which takes the value of one if a firm is a non-manipulator in a [0, 1¢] earnings surprises quarter, and zero if it is a manipulator. I expect a positive association between $FLDneg\_sentence$ and NM_dummy, a positive association between $FLDneg\_word$ and NM_dummy, and a negative association between $Obfu$ and NM_dummy.

I include additional firm-specific variables to control for factors likely to be associated with conference call communication and earnings manipulation. All variables are defined in Appendix 2.2. I first control for firm size ($Size$) because it influences many aspects of a firm's operations, business and information environment (Li, 2008; Brochet et al., 2019). I include the following contemporaneous quarterly firm performance variables to capture the effects of current performance on conference call communication: sales growth ($Growth$), ROA ratio ($ROA_{i,q}$) and earnings volatility ($EarnVol$) (Li, 2008; Davis et al., 2015). I also control for leverage ($Leverage$) and market-to-book ratio (MTB) to proxy for the firm's growth potential, complexity and uncertainty (Li, 2008; Brochet et al., 2019). I include analyst coverage ($Analyst$) to control for differences in firms' information environment driven by the demand side (Brochet et al., 2019). I control for firm age (Age) because older firms may face less information asymmetry and hence provide more transparent disclosure (Li, 2008). Additionally, I control for firm stock market performance using quarterly stock returns (Ret) and return volatility ($RetVol$) (Li, 2008; Davis et al., 2015; Lee, 2016). I also include conference call-level variables, i.e. the total word count and the percentage of positive/negative/uncertain words, to proxy for the amount of information released and the overall sentiment of the call (Brochet et al., 2019). Additionally, when $FLDneg\_sentence$ or $FLDneg\_word$ ($Obfu$) is the dependent variable, latent components of management linguistic complexity (the length of FLD) are (is) included as additional controls.

Firm fixed effects are included to account for unobservable firm characteristics that affect communication style. Year-quarter fixed effects are included to control for time-specific determinants of communication strategies. Standard errors are clustered by firm because of likely serial correlation in dependent and independent variables (Petersen, 2009).

2.4. Sample selection and descriptive statistics

Table 2.1 Panel A describes the sample selection process. Data are drawn from multiple sources. Quarterly conference call transcripts are sourced from Thomson Reuters Eikon. I obtain accounting data from Compustat, returns data from CRSP, and analyst data from I/B/E/S. The sample period is from January 2010 to December 2015.[10] Sample construction starts by matching firm-quarter observations for non-financial U.S. firms with available data on Compustat to conference call transcripts in English with managers speaking in both the presentation and Q&A sections and analysts speaking in the Q&A section. This leads to 25,071 transcripts. Requiring data from CRSP and I/B/E/S reduces the sample to 21,112 conference calls. After excluding observations outside the [0, 1¢] quarterly earnings surprises bin, 3,037 observations remain, of which 358 firm-quarter observations are in the non-manipulator sub-sample, and 1,421 in the manipulator sub-sample. The final sample therefore comprises 1,779 quarterly conference call transcripts from 684 U.S. non-financial firms.[11] Panel B of Table 2.1 reports the sample

[10] The sample only includes the post-crisis period from 2010 to 2015 to avoid potential confounding effects of the financial crisis.

[11] The decrease from 3,037 to 1,779 observations results from 1,258 observations being ambiguous to be classified as a non-manipulator and manipulator. For details, please see Section 2.3.2. Moreover, to gauge the accuracy of non-manipulator and manipulator classification, a comparison with the prior literature in terms of the proportion of non-manipulator/manipulator is made. Given that this study aggregates various earnings manipulation methods in the classification, there is no prior study that is directly comparable. Nonetheless, Koh et al. (2008) estimates that approximately 50% of firms with small positive earnings surprises engage in accrual-based earnings manipulation, consistent with my classification outputs.

distribution by year. Later years of the sample contain more observations than earlier years because the number of firms using conference calls increases over time.

[Insert Table 2.1 here]

Table 2.2 presents descriptive statistics and univariate test results. Panel A lists descriptive statistics for communication strategy variables. H1 considers whether non-manipulators provide a higher proportion of negative FLD than manipulators. Thus, univariate tests compare both the total amount of FLD and the proportion of negative FLD of non-manipulators and manipulators.[12] The amount of FLD in the presentation (Q&A) section is the percentage of FLD sentences relative to the total number of sentences of management speech in the presentation (Q&A) section. On average, 25.3% (20.7%) of non-manipulators' presentation (Q&A) is classified as FLD. As for manipulators, only 22.2% (18.2%) of their presentation (Q&A) is FLD. The differences are statistically significant.

[Insert Table 2.2 here]

In terms of the sentenced-based negative FLD proxy, a higher value of $FLDneg\_sentence$ corresponds to more negative sentences in FLD. In the presentation section, results reveal that non-manipulators have a statistically significantly higher proportion of negative sentences within FLD (mean = 13.6%, median = 11.2%) than manipulators (mean = 12.4%, median = 11.1%). In the Q&A section, non-manipulators (mean = 9.8%, median = 8.3%) also provide a higher proportion of negative FLD sentences than manipulators (mean = 9.7%, median = 7.9%), but only the difference

[12] The amount of FLD is not a main variable of interest because its relation with earnings manipulation is theoretically ambiguous.

between the medians is statistically significant. These results provide some support for H1.[13]

In terms of word-based negative FLD, a higher value of $FLDneg\_word$ corresponds to more negative FLD. In the presentation section, non-manipulators' FLD is more negative (mean = 0.84%, median = 0.72%) than that of manipulators (mean = 0.78%, median = 0.68%). Both the mean and median are statistically significantly different. In the Q&A section, non-manipulators (mean = 0.56%, median = 0.49%) also provide more negative FLD than manipulators (mean = 0.56%, median = 0.48%), but the differences between means and medians are not statistically significant. These results provide some support for H1.

H2 predicts that non-manipulators exhibit a lower level of obfuscation than manipulators. A higher value of $Obfu$ corresponds to a higher level of obfuscation. Non-manipulators' average obfuscation is 0.05 in the presentation and -0.07 in the Q&A, whereas manipulators' average obfuscation is 0.51 in the presentation and 0.14 in the Q&A. The differences between non-manipulators and manipulators are statistically significant in both the presentation and Q&A sections, consistent with H2. Moreover, both groups of firms exhibit a lower level of obfuscation in the Q&A section, indicating that management's ability to obfuscate may be limited due to interactions with analysts.

Panel B of Table 2.2 lists descriptive statistics for firm characteristics and performance. Non-manipulators are on average statistically smaller ($Size$ = 6.85 vs 7.99), have higher sales growth ($Growth$ = 0.25 vs 0.04), higher ROA (ROA = 0.02 vs 0.01),

[13] Note that under the sentence-based approach, $FLDneg\_sentence$ is scaled by the number of FLD sentences. This could potentially be problematic because the number of FLD sentences differs across manipulators and non-manipulators. In the extreme, 100% $FLDneg\_sentence$ for both manipulators and non-manipulators indicates both groups present the same proportion of negative FLD. However, the raw number of negative FLD content will be higher for non-manipulators because they provide more FLD in the first place. Thus, the sentence-based measure of negative FLD biases against my prediction and may yield low power tests.

lower earnings volatility ($EarnVol$ = 2.04 vs 2.88), higher return volatility ($RetVol$ = 0.04 vs 0.03), lower leverage ($Leverage$ = 0.18 vs 0.26), higher market-to-book ratio (MTB = 1.51 vs 1.34) and higher analyst coverage ($Analyst$ = 0.34 vs 0.31), and are younger (Age = 2.57 vs 2.96). Collectively, results suggest that non-manipulators are firms with stronger fundamental performance, higher growth potential and better information environment, consistent with theory.

Univariate findings in Table 2.2 are broadly consistent with H1 and H2. Overall, non-manipulators have not only a higher amount of FLD, but also a higher proportion of negative sentences and words within FLD than manipulators. In addition, non-manipulators exhibit a lower level of obfuscating behaviour than manipulators.

Table 2.3 presents correlations among NM_dummy, communication strategy variables and other control variables. Spearman (Pearson) correlations appear above (below) the diagonal. Both $FLD(Present)$ and $FLD(Q\&A)$ are significantly and positively correlated with NM_dummy, confirming that non-manipulators provide more forward-looking statements in conference calls. $FLDneg\_sentence$ in the presentation section is positively correlated with NM_dummy, consistent with the univariate test result in Table 2.2 Panel A. $FLDneg\_word$ in both the presentation and Q&A is positively correlated with NM_dummy, suggesting that non-manipulators use more negative words in conference calls. Moreover, $Obfu$ in both the presentation and Q&A is negatively correlated with NM_dummy, suggesting that manipulators exhibit a higher level of obfuscation than non-manipulators in conference calls.

[Insert Table 2.3 here]

2.5. Analysis

2.5.1. Differences in negative FLD between non-manipulators and manipulators

Table 2.4 presents results from the OLS estimation of Eq. (2.4) with $FLDneg\_sentence$ as the dependent variable to test H1. The coefficient on NM_dummy is expected to be positive. Columns (1) – (2) present results for the presentation section of conference calls. In column (1), the model fits well with an adjusted R^2 of 32%. The coefficient on NM_dummy is positive (7.373) and statistically different from zero at the 10% level (t-stat = 1.67), which provides weak evidence that non-manipulators provide a higher proportion of negative sentences in FLD than manipulators. In column (2), conference call linguistic features (i.e. call sentiment, call length and latent components of management linguistic complexity) are included as control variables. The coefficient on NM_dummy remains positive (8.099) and statistically significant (t-stat = 1.91). This suggests that, all else being equal, non-manipulators provide 8% more negative FLD sentences than manipulators in the presentation section.

[Insert Table 2.4 here]

Columns (3) – (4) report results for the Q&A section. In column (3), the coefficient on NM_dummy is positive (6.816) and statistically significant (t-stat = 1.70), indicating that non-manipulators exhibit a higher proportion of negative sentences in FLD than manipulators in the Q&A section. In column (4), after controlling for additional conference call linguistic characteristics, the coefficient on NM_dummy is positive (7.179) with increased statistical significance (t-stat = 2.09). These results suggest that, on average, non-manipulators have 7% more negative FLD sentences than manipulators in the Q&A section.[14]

Other firm characteristics and performance variables exhibit statistically significant associations with $FLDneg\_sentence$. In the presentation section, larger firms, firms with sales decreases and firm with lower quarterly stock returns provide more negative FLD, on average. In the Q&A section, smaller firms, more levered firms and older firms use more negative sentences in FLD. The associations between $FLDneg\_sentence$ and $Size$ in the presentation and Q&A sections have opposite signs. In the presentation section, larger firms give more negative FLD, consistent with prior evidence that large firms are subject to more strict scrutiny and higher political costs, and hence issue more cautious FLD (Watts and Zimmerman, 1986; Li, 2010). In the Q&A section, the negative association between firm size and negative FLD could be driven by analysts' questions: as smaller firms do not provide as many negative FLD as larger firms in the presentation, analysts may ask smaller firms to provide more details on this topic.

Table 2.5 presents the results from the estimation of Eq. (2.4) with $FLDneg\_word$ as the dependent variable. The coefficient on NM_dummy is expected to be positive and statistically significant. The first two columns present results for the presentation section. In column (1), the coefficient on NM_dummy is positive (0.094) and statistically different from zero at the 5% level (t-stat = 2.21), indicating that non-manipulators use more negative words in FLD than manipulators. Column (2) includes extra conference call linguistic features as control variables. The coefficient on NM_dummy remains positive (0.103) and statistically significant (t-stat = 2.39).

[14] As discussed in the univariate analysis results, non-manipulators have an overall higher amount of FLD in management speeches and a higher proportion of negative sentences in FLD than manipulators. Multivariate analysis results (untabulated) also show that non-manipulators have a higher proportion of FLD in management speeches than manipulators after controlling for firm characteristics, performance and other call linguistic features.

Columns (3) – (4) report results for the Q&A section. In column (3), the coefficient on NM_dummy is positive (0.339) and statistically significant (t-stat = 6.30). In column (4), after controlling for additional call linguistic characteristics, the coefficient on NM_dummy remains positive (0.356) with increased statistical significance (t-stat = 6.75).

[Insert Table 2.5 here]

Other firm characteristics and performance variables exhibit statistically significant associations with $FLDneg\_word$. In the presentation section, larger firms, firms with higher earnings volatility and longer presentation section provide more negative FLD, on average. In the Q&A section, firms with less volatile stock returns, higher leverage, longer Q&A section and more informative calls provide more negative FLD. The negative association between $FLDneg\_word$ and call length is consistent with the prior finding that managers tend to hold longer calls when they have more negative news to discuss (Matsumoto et al., 2011).

Taken together the results in Tables 2.4 and 2.5, it appears that non-manipulators are more willing to disclose negative news about the future than manipulators, consistent with H1.[15]

[15] The main tests examine negatively toned FLD because the focus is on whether non-manipulators tend to provide credible FLD and release bad news more quickly than manipulators. I also explore the difference in positive FLD between non-manipulators and manipulators (results untabulated). The findings are that non-manipulators' amount of positive FLD is either statistically equivalent to or less than that of manipulators. This is consistent with the prediction that non-manipulators commit to credible and cautious disclosures, while manipulators attempt to inflate investors' perceptions of firm outlook.

2.5.2. Differences in obfuscation between non-manipulators and manipulators

H2 predicts that non-manipulators exhibit a lower level of obfuscating behaviour than manipulators. Table 2.6 presents the results from the OLS estimation of Eq. (2.4) with $Obfu$ as the dependent variable. The coefficient on NM_dummy is expected to be negative and statistically significant. Columns (1) – (2) provide results for the presentation section. In column (1), the coefficient on NM_dummy is negative (-0.668) but not statistically significant (t-stat = -0.29). In column (2), after controlling for additional linguistic features, the coefficient on NM_dummy remains negative (-0.525) and insignificant (t-stat = -0.23). Results are consistent with Bushee et al. (2018), who also find that, in a firm fixed effects model, within-firm variation in obfuscation in the presentation section is limited because of scripting.[16] Columns (3) – (4) provide results for the Q&A section. In column (3), the coefficient on NM_dummy is negative (-0.935) and statistically different from zero at the 5% level (t-stat = -1.92), suggesting that non-manipulators display less obfuscation than manipulators. Column (4) further controls for additional conference call linguistic features. The coefficient on NM_dummy is still negative (-0.971) and marginally significant (t-stat = -1.87).

[Insert Table 2.6 here]

Given that $Obfu$ is constructed from regression residuals, it is unintuitive to interpret economic significance directly from the raw results in Table 2.6. To calibrate economic effects, the rank of $Obfu$ is used. The $Obfu$ measure is ranked into percentiles from 0 to 99, where a higher rank indicates more severe obfuscating behaviour. The average percentile ranks of $Obfu(Present)$ and $Obfu(Q\&A)$ of non-manipulators are 46 and 47, respectively. The average ranks of $Obfu(Present)$ and $Obfu(Q\&A)$ of

[16] Scripting refers to the disclosure behaviour that managers adhere to predetermined scripts in their conference call speeches (Lee, 2016).

manipulators are 52 and 51, respectively. Univariate tests show that the difference between the average ranks of non-manipulators and manipulators is statistically significant in both the presentation (p-value = 0.02) and Q&A (p-value = 0.07). The rank of $Obfu$ is then used as the dependent variable to re-estimate the regressions in Table 2.6. In the presentation section, regression results (untabulated) show that the coefficient on NM_dummy is negative but not statistically significant. In the Q&A section, the coefficient on NM_dummy is –26 and statistically significant (t-stat = -1.85). This suggests that non-manipulators rank lower than manipulators by 26 in terms of obfuscation in the Q&A section, all else being equal.

Other firm characteristics also exhibit significant associations with $Obfu$. Firms with lower ROA and younger firms have a higher level of obfuscation in the presentation section. Firms with lower analyst following have higher obfuscation in both the presentation and Q&A, consistent with prior evidence that firms with higher disclosure quality have more analyst following (e.g. Bushman et al., 2004). Moreover, firms that use more positive words exhibit higher obfuscation in both the presentation and Q&A, consistent with prior evidence that positive tone can be used as an opportunistic disclosure tool (e.g. Huang et al., 2013; Rogers et al., 2011).

Collectively, results in Table 2.6 provide some support for H2 that manipulators exhibit a higher level of obfuscation than non-manipulators, although the difference is only statistically and economically meaningful in the Q&A section. Moreover, the difference only reveals marginal statistical significance.

2.5.3. Changes in communication strategies

The results thus far indicate that non-manipulators and manipulators use different communication strategies in conference calls. However, it is empirically unclear if non-manipulators and manipulators are intentionally designing their communication strategies to achieve their distinct communication goals when they report small non-negative earnings surprises. One might argue that the differences in communication strategies are driven by firms' general communication style or unobservable fundamentals, instead of disclosure incentives resulting from small non-negative earnings surprises. To address such potential concerns over endogeneity associated with omitted variables, I analyse the changes in non-manipulators' and manipulators' communication strategies to further assess whether non-manipulators (manipulators) adjust their communication strategies to proactively separate (pool) when they report small non-negative earnings surprises.

Change analysis is conducted by comparing seasonally adjusted changes in non-manipulators' and manipulators' communication strategies. I estimate the following model to perform change analysis:

$$\begin{aligned} \Delta Communication\ Strategy^{k}_{i,q} &= \alpha_0 + \alpha_1 NM\_dummy_{i,q} + \alpha_2 \Delta Size_{i,q} + \alpha_3 \Delta Growth_{i,q} + \alpha_4 \Delta ROA_{i,q} \\ &+ \alpha_5 \Delta EarnVol_{i,q} + \alpha_6 \Delta Ret_{i,q} + \alpha_7 \Delta RetVol_{i,q} + \alpha_8 \Delta Leverage_{i,q} \\ &+ \alpha_9 \Delta MTB_{i,q} + \alpha_{10} \Delta Analyst_{i,q} + \alpha_{11} \Delta Age_{i,q} \\ &+ \sum \alpha_j \Delta Conference\ Call\ Control_{i,q} + \sum YearQuarter\ FE + \varepsilon_{i,q} \end{aligned} \tag{2.5}$$

The dependent variable is the seasonally adjusted change in conference call communication strategy: $\Delta FLDneg\_sentence$, $\Delta FLDneg\_word$ or $\Delta Obfu$, and equals the difference between the communication strategy of the current quarter and that of the same quarter of the previous year.

To construct the change analysis sample, the same quarter of the previous year is required not to be a [0, 1¢] earnings surprises quarter for both current-quarter non-manipulators and manipulators. Thus, whether firms proactively change communication strategies when they report small non-negative earnings surprises can be examined. In addition, manipulators are also required to engage in earnings manipulation in the same quarter of the previous year to be included in the change analysis sample.[17] In this way, I can ensure the change analysis results are driven by the communication incentives resulted from moving into a small non-negative earnings surprise quarter.

H1 posits that non-manipulators commit to credible disclosure during conference calls and provide more negative FLD than manipulators. If non-manipulators adjust their communication strategies to proactively separate, then I expect them to increase the proportion of negative FLD when they move into a small non-negative earnings surprise quarter. Stated another way, $\Delta FLDneg\_sentence$ and $\Delta FLDneg\_word$ are expected to be positive for non-manipulators. As for manipulators, as they have opportunistic incentives to withhold negative information, I expect them to have less negative FLD when moving into a small non-negative earnings surprise quarter (i.e. have negative $\Delta FLDneg\_sentence$ and $\Delta FLDneg\_word$). I therefore expect α_1 in Eq. (2.5) to be positive when the dependent variable is $\Delta FLDneg\_sentence$ or $\Delta FLDneg\_word$.

H2 predicts that as manipulators are opportunistic disclosers who aim to delay the revelation of bad news, they exhibit more obfuscating behaviour than non-manipulators. If manipulators adjust their communication strategies to proactively pool when they

[17] This requirement only applies to manipulators because non-manipulators by design do not engage in earnings manipulation in the reporting and the previous four quarters.

move into a small non-negative earnings surprise quarter, then I expect them to intentionally increase the level of obfuscation. That is, $\Delta Obfu$ for manipulators is expected to be positive. I also expect non-manipulators' $\Delta Obfu$ to be close to 0 because they have achieved the reported earnings genuinely and presumably have no significant extra incentives for obfuscation. As a result, I expect α_1 in Eq. (2.5) to be negative when the dependent variable is $\Delta Obfu$.

Table 2.7 provides results for change analysis. Panel A presents univariate analysis results. For changes in the overall amount of FLD in management speeches (ΔFLD), on average, non-manipulators increase the proportion of FLD (mean ΔFLD in presentation = 1.801% and in Q&A = 1.721%), while manipulators decrease it (mean ΔFLD in presentation = -0.774% and in Q&A = -0.625%). The differences are statistically significant. In terms of changes in negative FLD, non-manipulators increase the proportion of negative sentences in FLD (mean $\Delta FLDneg\_sentence$ in presentation = 0.837% and in Q&A = 0.478%), whereas manipulators show a decrease (mean $\Delta FLDneg\_sentence$ in presentation = -1.126% and in Q&A = -0.822%). The differences between non-manipulators' and manipulators' changes are statistically significant. In terms of $\Delta FLDneg\_word$, non-manipulators increase the average proportion of negative words in FLD (mean $\Delta FLDneg\_word$ in presentation = 0.031% and in Q&A = 0.075%), whereas manipulators show a small increase in the presentation (0.001%) and a small decrease in the Q&A (-0.001%). The differences between non-manipulators' and manipulators' $\Delta FLDneg\_word$ are not statistically significant in either the presentation or Q&A section. Collectively, univariate analysis results provide no consistent evidence regarding whether non-manipulators intentionally adjust their FLD to be more negative as a separating strategy in a small non-negative earnings surprises quarter.

[Insert Table 2.7 here]

H2 posits that manipulators intentionally use obfuscation as a pooling strategy. Consistent with H2, results show that manipulators increase obfuscation in both the presentation (mean $\Delta Obfu$ = 0.618) and Q&A (mean $\Delta Obfu$ = 0.379) sections. As for non-manipulators, while they exhibit a slight increase in obfuscation in the mean (mean $\Delta Obfu$ in presentation = 0.176 and in Q&A = 0.004), median changes are negative and indicate a decrease in obfuscation (median $\Delta Obfu$ in presentation = -0.010 and in Q&A = -0.019). Univariate tests show that the differences between manipulators' and non-manipulators' $\Delta Obfu$ are statistically significant for both the presentation and Q&A sections. Results are consistent with manipulators intentionally increasing obfuscation in conference calls when reporting small non-negative earnings surprises.

Table 2.7 Panel B presents multivariate analysis results on estimating Eq. (2.5). NM_dummy is the explanatory variable of interest. Columns (1) – (2) report estimations for $\Delta FLDneg\_sentence$ in the presentation and Q&A sections, respectively. The coefficient on NM_dummy is positive and statistically significant in both columns, suggesting that the difference between non-manipulators' and manipulators' $\Delta FLDneg\_sentence$ is statistically significant after controlling for firm performance and characteristics changes. Columns (3) – (4) report estimations for $\Delta FLDneg\_word$ in the presentation and Q&A sections, respectively. The coefficient on NM_dummy is not statistically significant in either column, consistent with the univariate test results.

To summarise, there is mixed evidence for H1 regarding whether non-manipulators adjust their FLD to be more negative as an intentional separating strategy. While results show that they increase the proportion of negative FLD sentences when they report small non-negative earnings surprises, there is no significant difference between non-manipulators' and manipulators' changes in negative words in FLD.

Columns (5) – (6) report estimations for $\Delta Obfu$ in the presentation and Q&A sections, respectively. In column (5), the coefficient on NM_dummy is negative but not statistically significant. In column (6), the coefficient on NM_dummy is negative and statistically significant, indicating that the difference between non-manipulators' and manipulators' $\Delta Obfu$ is significant in the Q&A after controlling for firm performance and characteristics.

Collectively, there is supporting evidence that manipulators use obfuscation as an intentional pooling strategy. They increase obfuscation when they report small non-negative earnings surprises, indicating that they are driven by opportunistic disclosure incentives and do not mimic non-manipulators' credible communication strategy.

2.5.4. Robustness tests

2.5.4.1. Alternative non-manipulator/manipulator classifications

As the results of this study depend on the extent to which non-manipulators and manipulators can be accurately classified, several robustness checks are conducted with various alternative non-manipulator/manipulator classifications to confirm the main results in Tables 2.4 – 2.7. First, the classification scheme described in Section 2.3.2 is modified in four ways: (1) replacing the condition positive discretionary accruals with discretionary accruals higher than the median of all Compustat firms; (2) replacing the condition non-GAAP earnings higher than GAAP earnings with non-GAAP earnings converting negative GAAP earnings surprises to positive non-GAAP earnings surprises; (3) replacing the condition positive unexpected core earnings with unexpected core earnings higher than the median of all Compustat firms; and (4) requiring non-manipulators to meet none of the conditions in both the reporting and the previous eight quarters. Results (untabulated) are consistent with those reported in Tables 2.4 – 2.7.

Next, I modify the non-manipulator/manipulator classification scheme in Section 2.3.2 to include ex post restatements as an extra earnings manipulation criterion to replicate the main results. I measure restatements using the financial fraud data from Audit Analytics. An alternative non-manipulator dummy, NM_Res, is defined. NM_Res takes the value of one if a firm has $NM\_dummy = 1$ and does not engage in financial fraud for the reporting and the previous four quarters; and zero if a firm has $NM\_dummy = 0$ or committed financial fraud for the reporting quarter.

Table 2.8 presents the results on re-estimating regressions in Tables 2.4 – 2.6 using NM_Res as the test variable. Columns (1) – (2) report the estimation for $FLDneg\_sentence$ in the presentation and the Q&A, respectively. In both columns, the economic and statistical significance of the coefficient on NM_Res are comparable to the results in Table 2.4. Columns (3) – (4) report the estimation for $FLDneg\_word$ in the presentation and the Q&A, respectively. In both columns, the economic and statistical significance of the coefficient on NM_Res are comparable to the results in Table 2.5. Columns (5) – (6) list the estimations for $Obfu$. Results are consistent with those in Table 2.6. Additionally, I also re-estimate the change analysis results in Table 2.7 using NM_Res as the test variable instead of NM_dummy. Results (untabulated) are consistent with those in Table 2.7.

[Insert Table 2.8 here]

A limitation of NM_Res is that it measures restatements using financial fraud, which represents the most severe type of restatements and the most extreme case of poor accounting quality, limiting the ability to generalize the results to less extreme restatements (Hribar et al., 2014). To mitigate such a concern, I further expand the definition of restatements to include both financial fraud and accounting issues to take account of less severe restatements. Data on restatements related to accounting issues are obtained from Audit Analytics. Results estimated using the non-manipulator/manipulator classification with this expanded definition of restatements (untabulated) are consistent with those reported in Tables 2.4 – 2.7, with statistically more significant results for the estimation for $Obfu$ in the Q&A section in Table 2.6.

2.5.4.2. Alternative obfuscation measures

The main analysis uses the raw regression residuals of Eq. (2.3) as the empirical proxy for obfuscation (i.e. $Obfu$). This implies a level of precision in the measurement of obfuscation, which is likely not justified. The measure is likely to contain measurement error since it is estimated using regression residuals. Therefore, two less granular obfuscation proxies are considered to assess the robustness of the results. First, the percentile ranking of $Obfu$ is used as the dependent variable. Second, a dummy variable is created. It takes the value of 1 if a firm-quarter observation has $Obfu \geq 0$; and 0 if a firm-quarter observation has $Obfu < 0$. The regressions in Table 2.6 are re-estimated by using both the percentile ranked variable (OLS regressions) and the dummy variable (logistic regressions) as the dependent variable. The results (untabulated) are consistent with those in Table 2.6.

2.5.4.3. Entropy balancing for the non-manipulator and manipulator sub-samples

The non-manipulator and manipulator sub-samples have unbalanced sample sizes in the main analysis. Moreover, as shown by the descriptive statistics in Table 2.2 Panel

B, observations in the two sub-samples exhibit different characteristics. Thus, a potential concern is that differences in non-manipulators' and manipulators' communication strategies might be driven by confounding factors. To mitigate such a concern, this sub-section conducts robustness analysis that applies entropy balancing (Hainmueller, 2012) to assemble a manipulator sub-sample that exhibits covariate balance with the non-manipulator sub-sample.

Entropy balancing weights control sample units to achieve covariate balance and exactly matches the covariate moments for the treatment and control groups, adjusting to inequalities in the variable distributions between the two groups (Hainmueller, 2012; Zhao and Percival, 2017). It achieves covariate balance between the treatment and control groups along the first, second and third moments of the control variable distributions, and does not require researchers to make subjective design choices that affect the composition of the control group (Hainmueller, 2012). It is a newly-developed matching technique that has recently been introduced and used in the accounting literature (Wilde, 2017; McMullin and Schonberger, 2018). It is more flexible than nearest-neighbour techniques (e.g. propensity score matching) because while propensity score adjustments typically lead to low levels of covariate balance in practice, entropy balancing tackles this problem by using a reweighting scheme where covariate balance is directly built into the weight function that is used to adjust the control sample units (Hainmueller, 2012; Hainmueller and Xu, 2013).

Specifically, I attempt to apply propensity score matching (PSM) but fail to achieve covariate balance along some dimensions. I therefore do not use PSM in the robustness checks because differences in covariates represent poor matching quality and lead to biased tests (Shipman et al., 2017). Using entropy balancing, my non-manipulator and manipulator sub-samples achieve covariate balance based on the reweighting scheme without design choices that affect the composition of the manipulator sub-sample and, hence, the results of the analysis. I use the non-manipulator and entropy-balanced manipulator sub-samples to perform the robustness checks. Results (untabulated) are consistent with those in Tables 2.4 – 2.7.

2.6. Market reaction tests

Having established that manipulators design communication strategies to intentionally preserve the pooling equilibrium, the study next investigates how listeners of conference calls, i.e. investors, respond by examining stock returns to conference calls and specific communication strategies. If non-manipulators are successful at signalling the absence of earnings manipulation, investors should react more positively to their calls and/or communication strategies. If manipulators are successful at pooling, there should be no significant difference between the market reactions across the two groups of firms.

Empirically, it is unclear if market participants can distinguish between non-manipulators and manipulators. On the one hand, prior evidence suggests that market participants cannot fully separate non-manipulators and manipulators and discount earnings results of all firms with small non-negative earnings surprises (Keung et al., 2010). As my results suggest that manipulators exhibit strong obfuscating behaviour, it is possible that investors cannot observe the differences between these two groups of firms. On the other hand, investors might be able to distinguish between non-manipulators and manipulators because there is some evidence that non-manipulators attempt to differentiate themselves by engaging in credible disclosure during conference calls. If investors can to some extent process the information contained in non-manipulators' credible disclosure, then they may be able to separate non-manipulators from manipulators.

To empirically test market reactions to non-manipulators' and manipulators' conference calls and communication strategies, I specify the following OLS regression models:

$$\begin{aligned} CAR[0,+1] = \; & \alpha_0 + \alpha_1 NM\_dummy_{i,q} + \alpha_2 Size_{i,q} + \alpha_3 Growth_{i,q} + \alpha_4 ROA_{i,q} \\ & + \alpha_5 EarnVol_{i,q} + \alpha_6 Ret_{i,q} + \alpha_7 RetVol_{i,q} + \alpha_8 Leverage_{i,q} \\ & + \alpha_9 MTB_{i,q} + \alpha_{10} Analyst_{i,q} + \alpha_{11} Age_{i,q} + \sum Firm\ FE \\ & + \sum YearQuarter\ FE + \varepsilon_{i,q} \end{aligned} \tag{2.6}$$

$$\begin{aligned} CAR[0,+1] = \; & \alpha_0 + \alpha_1 Communication\ Strategy_{i,q}^{k} + \alpha_2 Size_{i,q} + \alpha_3 Growth_{i,q} \\ & + \alpha_4 ROA_{i,q} + \alpha_5 EarnVol_{i,q} + \alpha_6 Ret_{i,q} + \alpha_7 RetVol_{i,q} \\ & + \alpha_8 Leverage_{i,q} + \alpha_9 MTB_{i,q} + \alpha_{10} Analyst_{i,q} + \alpha_{11} Age_{i,q} \\ & + \sum \alpha_j Conference\ Call\ Control_{i,q} + \sum Firm\ FE \\ & + \sum YearQuarter\ FE + \varepsilon_{i,q} \end{aligned} \tag{2.7}$$

where $CAR[0,+1]$ is the empirical proxy for market reaction. It is measured as the value-weighted market-adjusted return for the two-day window [0, +1] surrounding the conference call date.

Eq. (2.6) tests whether investors react differently to non-manipulators' and manipulators' conference calls. $NM\_dummy_{i,q}$ is the test variable. If investors can distinguish between non-manipulators and manipulators due to conference calls, then they are expected to react to non-manipulators' conference calls more positively. In this case, α_1 is expected to be positive and statistically significant. On the other hand, if investors cannot separate the two firm types using information from conference calls, then α_1 is expected to be not statistically significant.

Eq. (2.7) tests whether investors react differently to non-manipulators' and manipulators' specific conference call communication strategies. The test variable, $Communication\, Strategy_{i,q}^{k}$, represents the following communication strategies: $FLDneg\_sentence$, $FLDneg\_word$, or $Obfu$. If investors can separate non-manipulators from manipulators because they understand the information in non-manipulators' credible communication strategy, then α_1 is expected to be positive when the test variable is $FLDneg\_sentence$ or $FLDneg\_word$. That is, investors react more positively to non-manipulators' separating communication strategy. However, if investors cannot process the information in non-manipulators' credible communication strategy, then α_1 is expected to be not statistically significant when the test variable is $FLDneg\_sentence$ or $FLDneg\_word$. As for when $Obfu$ is the test variable, if manipulators are successful at obfuscating, then investors will not be able to distinguish between non-manipulators and manipulators. In this case, α_1 is expected to be not statistically significant. On the other hand, if manipulators cannot obfuscate successfully, then α_1 is expected to be negative because investors are expected to react negatively to such an opportunistic communication strategy.

Table 2.9 presents results for the market reaction tests. Panel A reports univariate tests for the difference in $CAR[0,+1]$ between non-manipulators and manipulators. On average, non-manipulators' $CAR[0,+1]$ is 0.8%, while the comparable value for manipulators is 0.1%. The difference is statistically significant at the 1% level. Non-manipulators' median $CAR[0,+1]$ is 0.3%, while the comparable value for manipulators is 0%. The difference between medians is statistically significant at the 5% level. Overall, univariate tests show that non-manipulators have more positive returns around conference calls than manipulators.

[Insert Table 2.9 here]

Table 2.9 Panel B reports multivariate analysis results.[18] Column (1) estimates Eq. (2.6) to investigate if there are different market reactions to non-manipulators' and manipulators' conference calls after controlling for other factors. The coefficient on NM_dummy is positive (0.015), but not statistically significant (t-stat = 1.60). This suggests that after controlling for firm characteristics and performance, market reactions to conference calls of non-manipulators and manipulators are statistically equivalent. Thus, the more positive market reaction to non-manipulators' conference calls shown in univariate tests in Table 2.9 Panel A appears to be driven by other firm characteristics and economic fundamentals, but not the conference call disclosure *per se*.

Columns (2) – (7) estimate Eq. (2.7) to examine if there are different market reactions to specific conference call communication strategies. Columns (2) – (5) focus on non-manipulators' separating communication strategy, i.e. negative forward-looking discussion. In columns (2) – (5), the test variables are $FLDneg\_sentence(Present)$, $FLDneg\_sentence(Q\&A)$, $FLDneg\_word(Present)$, $FLDneg\_word(Q\&A)$, respectively. The coefficient on the test variable is not statistically significant in any of the columns, indicating that non-manipulators' separating communication strategy does not lead to more positive market reaction. That is, non-manipulators cannot successfully separate themselves from manipulators using credible communication in conference calls.

Columns (6) – (7) examine whether manipulators can successfully pool and use $Obfu(Present)$ and $Obfu(Q\&A)$ as the test variable, respectively. If manipulators can

[18] The results in Table 2.9 Panel B and Table 2.10 Panel B are robust to not controlling for firm fixed effects.

successfully pool, then the coefficient on the test variable is expected to be not statistically significant. On the other hand, if investors can see through manipulators' obfuscating behaviour, then the coefficient on the test variable is expected to be negative and statistically significant. Results show that the coefficients on $Obfu(Present)$ and $Obfu(Q\&A)$ are both not statistically significant, indicating that manipulators are successful at pooling on the conference call date using obfuscation.

To further understand if communication strategies have incremental effects over a firm being a non-manipulator or a manipulator, regressions are estimated using $CAR[0, +1]$ as the dependent variable and the interaction term of NM_dummy and each communication strategy as the main independent variable of interest. Results (untabulated) show that the coefficients on the interaction terms are not statistically significant, suggesting that investors do not react differently to non-manipulators with more negative FLD or manipulators with higher obfuscation.

Collectively, the results in Table 2.9 show that the market reactions to non-manipulators' and manipulators' conference calls and specific communication strategies are statistically equivalent. This indicates that non-manipulators cannot credibly signal the absence of earnings management and that manipulators are successful at preserving the pooling equilibrium at the earnings announcement date. To the extent that manipulators' obfuscation strategy is designed to fool the market, it is not surprising that investors cannot understand non-manipulators' signals during conference calls.[19]

[19] I also perform market reaction tests using the abnormal trading volume for the two-day window [0, +1] around the conference call date and Amihud's (2002) measure of illiquidity for the two-day window [0, +1] around the conference call date as the empirical proxies for market reaction. The abnormal trading volume is calculated as the percentile ranks of the average retail share volume for the two-day window [0, +1] surrounding the reporting quarter earnings conference call date scaled by the average retail share volume for the window [-54, -5] before the call (Israeli et al., 2019). Illiquidity is the percentile ranks of the average value of the Amihud (2002) measure of illiquidity for the two-day window [0, +1] surrounding the reporting quarter earnings. The Amihud (2002) measure of illiquidity is calculated as the absolute value of daily return scaled by the daily dollar volume (in millions) (Bushee et al., 2018). Results (untabulated)

If investors fail to understand non-manipulators' signals at the earnings announcement and underreact, they are expected to gradually learn about firm type and correct the underreaction afterwards. I therefore test for reversal in market reactions to non-manipulators after the current-quarter conference calls (e.g. Cox and Peterson, 1994; Benou, 2003; Savor, 2012). I test for reversal throughout the quarter after the conference call by estimating the following regression:

$$\begin{aligned} &After\ Call\ Return_{i,q}^{l} \\ &\quad = \alpha_0 + \alpha_1 NM\_dummy_{i,q} + \alpha_2 Size_{i,q} + \alpha_3 Growth_{i,q} + \alpha_4 ROA_{i,q} \\ &\quad + \alpha_5 EarnVol_{i,q} + \alpha_6 Ret_{i,q} + \alpha_7 RetVol_{i,q} + \alpha_8 Leverage_{i,q} \\ &\quad + \alpha_9 MTB_{i,q} + \alpha_{10} Analyst_{i,q} + \alpha_{11} Age_{i,q} + \sum Firm\ FE \\ &\quad + \sum YearQuarter\ FE + \varepsilon_{i,q} \end{aligned} \tag{2.8}$$

where $After\ Call\ Return_{i,q}^{l}$ is the value-weighted market-adjusted return for the one-month, two-month or three-month windows (i.e. $CAR[+2, +30]$, $CAR[+2, +60]$ or $CAR[+2, +90]$) after the current-quarter conference call date. The test variable in Eq. (2.8) is NM_dummy. If investors learn about firm type during the subsequent quarter and correct the previous underreaction, then α_1 is expected to be positive.

I also test for whether the reversal happens around the conference call of the subsequent quarter by estimating the following regression:

show that both abnormal trading volume and illiquidity are statistically equivalent for non-manipulators and manipulators, further supporting the findings in Table 2.9.

$$
\begin{aligned}
&NextCall\_CAR[0,+1] \\
&\quad = \alpha_0 + \alpha_1 NM\_dummy_{i,q} + \alpha_2 Size_{i,q+1} + \alpha_3 Growth_{i,q+1} \\
&\quad + \alpha_4 ROA_{i,q+1} + \alpha_5 EarnVol_{i,q+1} + \alpha_6 Ret_{i,q+1} + \alpha_7 RetVol_{i,q+1} \\
&\quad + \alpha_8 Leverage_{i,q+1} + \alpha_9 MTB_{i,q+1} + \alpha_{10} Analyst_{i,q+1} + \alpha_{11} Age_{i,q+1} \\
&\quad + \alpha_{12} NM\_dummy_{i,q+1} + \sum Firm\ FE + \sum YearQuarter\ FE + \varepsilon_{i,q+1}
\end{aligned}
\tag{2.9}
$$

where $NextCall\_CAR[0,+1]$ is the value-weighted market-adjusted return for the two-day window surrounding the conference call date of the subsequent quarter. The test variable in Eq. (2.9) is $NM\_dummy_{i,q}$. If investors learn about firm type and distinguish between current-quarter non-manipulators and manipulators around earnings announcement of the subsequent quarter, then α_1 is expected to be positive.

Table 2.10 presents the results on testing market reaction reversal. Panel A reports univariate analysis results. Non-manipulators have statistically significant higher $CAR[+2,+30]$, $CAR[+2,+60]$, $CAR[+2,+90]$ and $NextCall\_CAR[0,+1]$ than manipulators. This indicates that non-manipulators have significantly more positive returns than manipulators throughout the subsequent quarter after the current earnings announcement date, supporting the prediction that investors gradually learn about firm type and correct previous underreaction afterwards.

[Insert Table 2.10 here]

Table 2.10 Panel B reports multivariate regression results. Columns (1) – (3) estimate Eq. (2.8) with the dependent variables being $CAR[+2,+30]$, $CAR[+2,+60]$ and $CAR[+2,+90]$, respectively. If investors start to distinguish between non-manipulators and manipulators gradually, then the coefficient on NM_dummy is expected to be positive and statistically significant. In column (1), the coefficient on NM_dummy is positive (0.004) but not statistically significant. In both columns (2) – (3), the coefficient on NM_dummy is positive and marginally significant at the 10% level, indicating that non-manipulators have more positive $CAR[+2, +60]$ and $CAR[+2, +90]$ than manipulators, all else being equal. Column (4) estimates Eq. (2.9) with the dependent variable being $NextCall\_CAR[0, +1]$. The coefficient on NM_dummy is positive (0.008) and statistically significant at the 10% level. This suggests that investors react more positively to non-manipulators' subsequent-quarter conference calls.

Collectively, results in Table 2.10 indicate that non-manipulators experience incrementally more positive returns than manipulators starting from the second month after the current-quarter conference call and around the call of the subsequent quarter. The evidence supports the prediction that investors underreact to non-manipulators' current-quarter conference calls initially and gradually learn about firm type and correct prices afterwards.

2.7. Summary and conclusion

Prior research shows that investors penalize all firms with small non-negative earnings surprises, including those that genuinely achieve this performance (Keung et al., 2010). This leads to the question of whether non-manipulators intentionally attempt to separate by designing communication strategies that strongly signal the truthfulness of performance but fail, or if they do not proactively separate. This chapter uses the conference call setting to study whether and how non-manipulators use communication strategies to separate themselves from manipulators, and how manipulators attempt to pool through obfuscation. The results show that non-manipulators provide more negative forward-looking discussion than manipulators in both the presentation and the Q&A. The results also show that non-manipulators exhibit a lower level of obfuscation in the Q&A section than manipulators. By examining seasonally adjusted changes in communication strategies, the study finds that manipulators significantly increase the level of obfuscation when they report [0, 1¢] earnings surprises, suggesting that they intentionally adjust communication strategies to achieve the pooling equilibrium. As for non-manipulators, results suggest that they do not proactively change communication strategies to distinguish themselves from manipulators. Instead, their communication strategies appear to be relatively consistent over time.

Market reaction analysis shows that investors cannot distinguish between non-manipulators and manipulators based on conference call communication strategies. This indicates that non-manipulators cannot credibly signal the absence of earnings manipulation and manipulators are successful at pooling at the earnings announcement date. To the extent that manipulators engage in opportunistic communication strategies to fool the market, it is not surprising that investors cannot understand non-manipulators' signals during conference calls. Additionally, the results suggest that while market participants underreact to non-manipulators earnings announcements, they gradually learn about firm type and correct prices throughout the subsequent quarter.

The empirical results and interpretations of this study are limited to the extent to which the study can accurately classify non-manipulators and manipulators in the research design. In addition, this study cannot speak to the generalizability of the communication strategies outside of the conference call setting (e.g. 10-K, 10-Q and press releases). Moreover, while the results provide some evidence on the different communication strategies of non-manipulators and manipulators and their capital market consequences, regression results sometimes reveal marginal statistical significance.

The study adds to and brings together strands of literature that investigate earnings benchmark beating, the role of earnings manipulation in explaining corporate disclosures, and the textual content of disclosures and their capital market consequences. Collectively, the results speak to the pooling equilibrium in the small non-negative earnings surprises setting. Even though non-manipulators engage in transparent and credible communication, they fail to successfully distinguish themselves from manipulators at the earnings announcement date. Since firms that manipulate earnings have strong pooling incentives and tailor their conference call communication to proactively prevent the revelation of bad news, the informativeness of conference calls of firms with truthful earnings performance appears to be compromised.

Appendix 2.1. Classification of Forward-looking Discussion

The classification of forward-looking discussion combines three tools: Python NLKT (Natural Language Toolkit) program, forward-looking wordlist in Matsumoto et al. (2011) and forward-looking identification scheme in Muslu et al. (2014). The identification follows two steps:

1. NLTK is used to tokenize management speeches in conference calls into sentences. NLTK has an advantage in performing this task because it does not misclassify punctuations in numbers or abbreviations (e.g. “24.3” and “U.S.”) as sentence breaks. Many methods used in the prior literature, for example the Perl routine *Lingua::EN::Fathom* in Li (2008), suffer from such a misclassification problem.

2. A sentence is classified as forward-looking discussion if it meets at least one of the following criteria:

(1) It contains words/phrases that indicate future time periods: “future”, “next fiscal”, “next month”, “next period”, “next quarter”, “next year”, “next week”, “incoming fiscal”, “incoming month”, “incoming period”, “incoming quarter”, “incoming year”, “incoming week”, “coming fiscal”, “coming month”, “coming period”, “coming quarter”, “coming year”, “coming week”, “upcoming fiscal”, “upcoming month”, “upcoming period”, “upcoming quarter”, “upcoming year”, “upcoming week”, “subsequent fiscal”, “subsequent month”, “subsequent period”, “subsequent quarter”, “subsequent year”, “subsequent week”, “following fiscal”, “following month”, “following period”, “following quarter”, “following year”, “following week”.

(2) It contains words/phrases that indicate expectations, plans or actions for the future: “anticipate”, “aim”, “assume”, “commit”, “estimate”, “expect”, “forecast”,

“foresee”, “hope”, “intend”, “plan”, “seek” and “target”. For each verb, the following conjugations are included (“anticipate” is used as an example for brevity of explanation): “anticipates”, “anticipated”, “anticipating”, ““anticipation”, “anticipations”.

(3) It contains a reference to a year that comes after the year of the call (such as “2014” when call year is 2013). Any use of characters (“$”, “£”, “%”, “,”) in between or before or after the digits disqualifies the number from being tagged as year.

(4) It contains the following words/phrases: “guidance”, “projection”, “projections”, “outlook”, “going to”, “prospect”.

(5) It is classified as forward-looking by the Python NLTK program.

Appendix 2.2. Variable Definitions

Non-manipulator Dummy

Variables	Definitions
NM_dummy	An indicator variable that is equal to 1 if the firm is identified as a non-manipulator in a small non-negative earnings surprises fiscal quarter; and 0 if identified as a manipulator. Non-manipulator/manipulator classification is based on three conditions: positive performance-matched discretionary accruals (Kothari et al., 2005); non-GAAP earnings higher than GAAP earnings (Doyle et al., 2013); and positive unexpected core earnings (Fan et al., 2010). Firms that meet none of the three conditions in the reporting and the previous four quarters are classified as non-manipulators in the reporting quarter. Firms that meet at least two of the three conditions in the reporting quarter are classified as manipulators in that quarter.

Conference Call Communication Strategy Variables

Variables	Definitions
FLD	Forward-looking discussion measured at the sentence-level in management speeches, calculated as the number of forward-looking sentences scaled by the total number of sentences, times 100. The variable is calculated for the presentation and Q&A sections of a conference call separately.
$FLDneg\_sentence$	Negative forward-looking discussion measured at the sentence-level in management speeches, calculated as the number of negative forward-looking sentences scaled by the number of forward-looking sentences, times 100. A sentence is classified as negative if it contains at least one negative or negated positive word from the Loughran and McDonald's word lists. The variable is calculated for the presentation and Q&A sections of a conference call separately.
$FLDneg\_word$	Negative forward-looking discussion measured at the word-level in management speeches, calculated as the number of negative or negated positive words in forward-looking discussion scaled by the total number of words of forward-looking discussion, times 100. Negative and positive words are from the Loughran and McDonald's word lists. The variable is calculated for the presentation and Q&A sections of a conference call separately.
$Obfu$	Estimated latent obfuscation component of management linguistic complexity in conference calls, following Bushee et al. (2018). The variable is calculated for the presentation and Q&A sections of a conference call separately.
ΔFLD	Seasonally adjusted changes in the number of forward-looking sentences in management speeches. It is calculated FLD in the current quarter conference call minus FLD in the call of the same quarter of the previous year. The variable is calculated for the presentation and Q&A sections of a conference call separately.
$\Delta FLDneg\_sentence$	Seasonally adjusted changes in negative forward-looking discussion (sentence-level). It is calculated as $FLDneg\_sentence$ in the current quarter conference call minus $FLDneg\_sentence$ in the call of the same quarter of the previous year. The variable is calculated for the presentation and Q&A sections of a conference call separately.
$\Delta FLDneg\_word$	Seasonally adjusted changes in negative forward-looking discussion (word-level). It is calculated as $FLDneg\_word$ in the current quarter conference call minus $FLDneg\_word$ in the call of the same quarter of the previous year. The variable is calculated for the presentation and Q&A sections of a conference call separately.
$\Delta Obfu$	Seasonally adjusted changes in the estimated latent obfuscation component of management linguistic complexity in conference calls. It is calculated as $Obfu$ in the current quarter conference call minus $Obfu$ in the call of the same quarter of the previous year. The variable is calculated for the presentation and Q&A sections of a conference call separately.

Appendix 2.2 (Continued.)

Firm Characteristics and Performance Variables

Variables	Definitions
$Size$	The log of total assets (Compustat item: ATQ).
$Growth$	Sales growth, calculated as the change in total sales (Compustat item: SALEQ) relative to the same quarter last year, scaled by the total sales of the same quarter last year.
ROA	Return on assets ratio, calculated as earnings before extraordinary times (Compustat item: IBQ) scaled by total assets (Compustat item: ATQ).
$EarnVol$	Earnings volatility in the prior year, calculated as the log of the standard deviation of earnings (Compustat item: IBQ) during the prior four fiscal quarters.
Ret	The value-weighted market-adjusted stock return during the fiscal quarter.
$RetVol$	Stock return volatility in the prior year, calculated as the log of the standard deviation of the monthly stock returns in the prior year.
$Leverage$	Total debt (Compustat items: DLCQ + DLTTQ) scaled by the market value of assets (Compustat items: (PRCCQ * CSHOQ) + DLTTQ).
MTB	The log of the market-to-book ratio. The market-to-book ratio is calculated as the market value of equity (Compustat items: PRCCQ * CSHOQ) scaled by book value of equity (Compustat item: TEQQ).
Age	The log of the number of years since a firm's first appearance in the CRSP monthly stock return files.
$Analyst$	The log of the number of analysts issuing earnings forecasts for any horizon during the fiscal quarter, scaled by the log of total assets.

Conference Call Control Variables

Variables	Definitions
Pos	The percentage of positive and negated negative words in management speech. Negative and positive words are from the Loughran and McDonald's word lists. The variable is calculated for the presentation and Q&A sections of a conference call separately.
Neg	The percentage of negative and negated positive words in management speech. Negative and positive words are from the Loughran and McDonald's word lists. The variable is calculated for the presentation and Q&A sections of a conference call separately.
Unc	The percentage of uncertain words in management speech. Uncertain words are from the Loughran and McDonald's word lists. The variable is calculated for the presentation and Q&A sections of a conference call separately.
Len	The log of the total number of words of management speech. The variable is calculated for the presentation and Q&A sections of a conference call separately.
$Info$	Estimated latent information component of management linguistic complexity in conference calls, following Bushee et al. (2018). The variable is calculated for the presentation and Q&A sections of a conference call separately.

Market Reaction Variables

Variables	Definitions
$CAR[0,+1]$	The value-weighted market-adjusted return for the two-day window [0, +1] surrounding the reporting quarter earnings conference call date.
$CAR[+2,+30]$	The value-weighted market-adjusted return for the window [+2, +30] following the reporting quarter earnings conference call date.

Appendix 2.2 (Continued.)

$CAR[+2, +60]$	The value-weighted market-adjusted return for the window [+2, +60] following the reporting quarter earnings conference call date.
$CAR[+2, +90]$	The value-weighted market-adjusted return for the window [+2, +90] following the reporting quarter earnings conference call date.
$NextCall\_CAR[0, +1]$	The value-weighted market-adjusted return for the two-day window [0, +1] surrounding the subsequent quarter earnings conference call date.

This appendix presents variable definitions in Chapter 2.

Table 2.1. Sample

Panel A. sample selection process

		Number of Firm-quarters
Non-financial firm-quarters with available Compustat data between 2010-2015		37,823
After excluding firm-quarters with missing conference call data		28,010
After excluding firm-quarters with missing CRSP data		25,071
After excluding firm-quarters with missing IBES data		21,112
After excluding firm-quarters outside of [0, 1¢] bin		3,037
After excluding firm-quarters do not meet non-manipulator or manipulator criteria		1,779
Of which:	Non-manipulators	358
	Manipulators	1,421

Panel B. sample distribution by year

Year	Non-manipulators	Manipulators	Total
2010	58	176	234
2011	97	183	280
2012	49	208	257
2013	63	294	357
2014	52	280	332
2015	39	280	319
Total	358	1,421	1,779

This table presents sample selection and distribution. The sample is constructed from the intersection of Thomson Reuters Eikon, Compustat, I/B/E/S and CRSP. The sample spans the time period January 2010 to December 2015 and covers a total of 1,779 firm-quarter observations with [0, 1¢] earnings surprises. Panel A reports the process of sample selection. Panel B reports the distribution of the sample by year.

Table 2.2. Descriptive Statistics

Panel A. Communication Strategy Variables

	Non-manipulators (N = 358)					Manipulators (N = 1,421)					p-value for difference	
	Mean	sd	p1	Median	p99	Mean	sd	p1	Median	p99	Mean	Median
$FLD(Present)$ (%)	25.30	9.34	9.41	25.24	51.41	22.19	9.06	5.13	21.54	45.46	0.00^{***}	0.01^{***}
$FLD(Q\&A)$ (%)	20.66	7.87	7.26	19.42	46.21	18.24	7.59	5.42	17.09	39.29	0.00^{***}	0.01^{***}
$FLDneg\_sentence(Present)$ (%)	13.63	9.99	1.20	11.20	46.66	12.44	10.17	0.00	11.11	50.00	0.05^{**}	0.02^{**}
$FLDneg\_sentence(Q\&A)$ (%)	9.81	8.62	1.20	8.34	38.70	9.66	9.12	0.00	7.90	40.00	0.78	0.09^{*}
$FLDneg\_word(Present)$ (%)	0.84	0.50	0.00	0.72	2.55	0.78	0.56	0.00	0.68	2.68	0.09^{*}	0.02^{**}
$FLDneg\_word(Q\&A)$ (%)	0.56	0.42	0.00	0.49	2.32	0.56	0.44	0.00	0.48	2.25	0.79	0.37
$Obfu(Present)$	0.05	2.89	-4.64	-0.60	8.85	0.51	3.01	-4.34	-0.12	9.44	0.02^{**}	0.01^{**}
$Obfu(Q\&A)$	-0.07	1.54	-2.79	-0.16	4.75	0.14	1.58	-2.92	-0.09	4.75	0.05^{**}	0.07^{*}

Panel B. Firm-level Control Variables

	Non-manipulators (N = 358)					Manipulators (N = 1,421)					p-value for difference	
	Mean	sd	p1	Median	p99	Mean	sd	p1	Median	p99	Mean	Median
$Size$	6.85	1.55	3.30	6.88	10.45	7.99	1.64	4.85	7.96	11.81	0.00^{***}	0.01^{***}
$Growth$	0.25	0.39	-0.02	0.15	1.66	0.04	0.18	-0.46	0.03	0.58	0.00^{***}	0.01^{***}
ROA	0.02	0.05	-0.10	0.02	0.08	0.01	0.03	-0.10	0.01	0.05	0.00^{***}	0.01^{***}
$EarnVol$	2.04	1.27	0.23	1.82	5.48	2.88	1.56	0.35	2.66	6.98	0.00^{***}	0.01^{***}
Ret	1.02	0.08	0.84	1.05	1.13	1.02	0.07	0.84	1.02	1.12	0.90	0.23
$RetVol$	0.04	0.01	0.02	0.04	0.06	0.03	0.01	0.02	0.03	0.06	0.00^{***}	0.01^{***}
$Leverage$	0.18	0.20	0.00	0.10	0.97	0.26	0.18	0.00	0.23	0.85	0.00^{***}	0.01^{***}
MTB	1.51	0.63	0.46	1.38	3.07	1.34	0.65	0.39	1.22	3.69	0.00^{***}	0.01^{***}
$Analyst$	0.34	0.09	0.00	0.34	0.52	0.31	0.08	0.09	0.31	0.46	0.00^{***}	0.01^{***}
Age	2.57	0.91	0.00	2.77	4.47	2.96	0.89	0.69	3.00	4.49	0.00^{***}	0.01^{***}

This table presents descriptive statistics of variables for non-manipulators and manipulators, respectively. Panel A reports the descriptive statistics of communication strategy variables. Panel B reports the descriptive statistics of control variables. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively, for t-test of means and Wilcoxon test of medians. See Appendix 2.2 for variable definitions.

Table 2.3. Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1)NM_dummy	1.00	0.13***	0.15***	0.06***	0.04*	0.07***	0.28***	-0.06**	-0.04*	0.41***	0.22***	-0.26***	0.01	0.13***	-0.26***	0.13***	0.15***	-0.16***
(2)FLD(Present)	0.14***	1.00	0.32***	0.09***	0.07***	0.05**	0.02	0.00	-0.01	0.10***	0.07***	-0.01	-0.04	-0.01	-0.09***	0.06**	0.09***	0.03
(3)FLD(Q&A)	0.13***	0.31***	1.00	0.03	0.10***	0.00	0.05**	0.04	-0.01	0.05**	-0.02	-0.05**	-0.07***	0.00	-0.02	0.04*	0.06***	-0.01
(4)FLDneg_sentence (Present)	0.05**	0.01	0.02	1.00	0.06**	0.73***	0.23***	0.03	0.00	-0.06**	0.03	-0.04	-0.03	0.02	-0.03	0.02	0.00	0.02
(5)FLDneg_sentence (Q&A)	0.01	0.05**	0.10***	0.05*	1.00	0.12***	0.64***	-0.02	0.03	0.06**	-0.09***	0.00	0.04	0.00	0.01	0.00	0.00	0.04
(6)FLDneg_word (Present)	0.05**	0.00	-0.02	0.70***	0.12***	1.00	0.35***	0.01	0.00	-0.01	-0.03	0.01	0.02	0.02	-0.02	0.02	0.01	0.00
(7)FLDneg_word (Q&A)	0.27***	0.02	0.03	0.28***	0.55***	0.41***	1.00	-0.02	-0.02	0.09***	-0.04	-0.05**	0.05*	0.08***	-0.04	0.03	0.02	-0.03
(8)Obfu(Present)	-0.06**	-0.01	0.03	0.06**	-0.03	0.03	-0.02	1.00	0.37***	-0.08***	-0.01	-0.04*	-0.06**	-0.19***	-0.02	0.05**	-0.05**	-0.02
(9)Obfu(Q&A)	-0.05**	-0.01	-0.02	-0.01	0.03	0.00	-0.03	0.39***	1.00	-0.04	-0.05*	0.05*	-0.06**	-0.04	0.02	0.01	-0.04*	0.00
(10)Growth	0.30***	0.07***	0.01	-0.03	0.03	-0.01	0.05*	-0.03	0.00	1.00	0.20***	-0.19***	-0.02	0.09***	-0.25***	0.20***	0.17***	-0.18***
(11)ROA	0.11***	0.03	-0.03	0.01	-0.02	0.00	0.01	-0.03	-0.03	0.05**	1.00	0.03	0.04*	0.00	-0.46***	0.39***	0.04	0.15***
(12)EarnVol	-0.25***	-0.01	-0.04*	-0.03	0.01	0.02	-0.04	-0.06**	0.05*	-0.14***	0.00	1.00	0.06***	-0.10***	0.12***	0.06**	0.00	0.31***
(13)Ret	-0.02	-0.02	-0.09***	0.00	0.05*	0.06**	0.04	-0.03	-0.06**	-0.02	0.05**	0.09***	1.00	0.05**	0.00	-0.04	-0.05**	-0.01
(14)RetVol	0.15***	0.00	-0.03	0.02	0.00	0.02	0.08***	-0.19***	-0.06**	0.04	0.05**	-0.08***	0.03	1.00	0.09***	-0.22***	-0.07***	-0.12***
(15)Leverage	-0.17***	-0.07***	-0.02	-0.04	0.05**	-0.02	-0.02	-0.03	0.02	-0.13***	-0.22***	0.10***	-0.02	0.08***	1.00	-0.45***	-0.31***	-0.11***
(16)MTB	0.10***	0.06**	0.05**	0.02	0.01	0.03	0.05*	0.00	0.01	0.10***	0.12***	0.06**	-0.01	-0.20***	-0.37***	1.00	0.26***	0.01
(17)Analyst	0.15***	0.07***	0.07***	0.02	-0.02	0.01	0.02	-0.06**	-0.06**	0.11***	-0.08***	-0.01	-0.05**	-0.09***	-0.27***	0.26***	1.00	-0.20***
(18)Age	-0.17***	0.04	-0.01	-0.01	0.05**	0.00	-0.02	-0.05**	-0.01	-0.11***	0.07***	0.32***	0.01	-0.11***	-0.11***	-0.03	-0.17***	1.00

This table presents the correlations among earnings manipulation, call communication strategies and firm-level variables. Spearman (Pearson) correlations appear above (below) the diagonal. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix 2.2.

Table 2.4. Earnings Manipulation and Negative Forward-looking Discussion (Sentence-level)

	Presentation		Q&A	
	(1)	(2)	(3)	(4)
	$FLDneg\_sentence$	$FLDneg\_sentence$	$FLDneg\_sentence$	$FLDneg\_sentence$
NM_dummy	7.373*	8.099*	6.816*	7.179**
	(1.67)	(1.91)	(1.70)	(2.09)
$Size$	5.433**	4.539**	-3.489*	-3.838*
	(2.44)	(2.07)	(-1.69)	(-1.94)
$Growth$	-3.221	-4.114*	2.372	1.490
	(-1.54)	(-1.93)	(0.99)	(0.65)
ROA	-9.647	-8.039	-10.978	-9.861
	(-0.65)	(-0.56)	(-0.96)	(-0.88)
$EarnVol$	-0.178	-0.245	0.171	0.193
	(-0.32)	(-0.45)	(0.40)	(0.46)
Ret	-8.898	-9.584*	5.856	6.767
	(-1.64)	(-1.76)	(0.90)	(1.07)
$RetVol$	9.602	33.871	-26.221	-30.093
	(0.13)	(0.45)	(-0.45)	(-0.50)
$Leverage$	-0.486	-2.870	3.831*	3.945*
	(-0.08)	(-0.50)	(1.78)	(1.78)
MTB	0.133	0.720	0.667	0.487
	(0.10)	(0.48)	(0.48)	(0.35)
$Analyst$	11.962	10.275	13.132	11.055
	(1.26)	(1.10)	(1.39)	(1.16)
Age	0.319	0.832	0.777**	0.843**
	(0.09)	(0.22)	(2.21)	(2.35)
$Pos(.)$		-1.284		1.227
		(-1.11)		(1.37)
$Neg(.)$		1.285		-0.747
		(0.81)		(-0.41)
$Unc(.)$		0.144		1.705
		(0.08)		(1.39)
$Len(.)$		2.406		0.598
		(1.33)		(0.50)
$Info(.)$		0.952		0.266
		(1.28)		(0.53)
$Obfu(.)$		0.120		0.014
		(0.79)		(0.05)
Firm FE	YES	YES	YES	YES
Yr-Qtr FE	YES	YES	YES	YES
N	1,779	1,779	1,779	1,779
Adjusted R^2	0.32	0.31	0.17	0.18

This table presents results from estimating the relation between earnings manipulation and sentence-level negative forward-looking discussion in conference calls when firms report quarterly earnings surprises between [0, 1¢] (i.e. Eq. (2.4)). Columns (1) and (2) list results for the presentation section of conference calls, in which $Pos(.)$, $Neg(.)$, $Unc(.)$, $Len(.)$, $Info(.)$, $Obfu(.)$ denote $Pos(Present)$, $Neg(Present)$, $Unc(Present)$, $Len(Present)$, $Info(Present)$, $Obfu(Present)$, respectively. Columns (3) and (4) list results for the Q&A section of conference calls, in which $Pos(.)$, $Neg(.)$, $Unc(.)$, $Len(.)$, $Info(.)$, $Obfu(.)$ denote $Pos(Q\&A)$, $Neg(Q\&A)$, $Unc(Q\&A)$, $Len(Q\&A)$, $Info(Q\&A)$, $Obfu(Q\&A)$, respectively. All variables are as defined in Appendix 2.2. t-statistics appear in parentheses and are based on standard errors clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 2.5. Earnings Manipulation and Negative Forward-looking Discussion (Word-level)

	Presentation		Q&A	
	(1)	(2)	(3)	(4)
	$FLDneg\_word$	$FLDneg\_word$	$FLDneg\_word$	$FLDneg\_word$
NM_dummy	0.094**	0.103**	0.339***	0.356***
	(2.21)	(2.39)	(6.30)	(6.75)
$Size$	0.310***	0.293***	-0.016	-0.024
	(3.05)	(2.83)	(-0.85)	(-1.29)
$Growth$	-0.065	-0.080	-0.063	-0.082
	(-1.07)	(-1.30)	(-0.89)	(-1.22)
ROA	-0.275	-0.129	-0.363	-0.210
	(-0.64)	(-0.30)	(-1.05)	(-0.67)
$EarnVol$	0.047*	0.046*	0.019	0.016
	(1.93)	(1.86)	(1.22)	(1.05)
Ret	0.494**	0.374	0.264	0.189
	(2.00)	(1.49)	(1.00)	(0.75)
$RetVol$	-2.619	-1.733	-7.184**	-6.941**
	(-0.87)	(-0.57)	(-2.06)	(-1.97)
$Leverage$	-0.056	-0.047	0.443*	0.417*
	(-0.57)	(-0.45)	(1.95)	(1.73)
MTB	0.011	0.016	0.035	0.034
	(0.40)	(0.58)	(1.32)	(1.19)
$Analyst$	0.037	0.033	-0.117	-0.162
	(0.18)	(0.15)	(-0.43)	(-0.58)
Age	-0.228	-0.233	0.013	0.014
	(-1.60)	(-1.62)	(0.64)	(0.69)
$Pos(.)$		-0.003		0.079
		(-0.11)		(1.56)
$Neg(.)$		-0.027		0.085
		(-0.58)		(1.08)
$Unc(.)$		-0.058		-0.036
		(-1.24)		(-0.89)
$Len(.)$		0.102**		0.088*
		(2.37)		(1.74)
$Info(.)$		-0.013		0.034*
		(-0.52)		(1.82)
$Obfu(.)$		0.007		-0.001
		(1.31)		(-0.12)
Firm FE	YES	YES	YES	YES
Yr-Qtr FE	YES	YES	YES	YES
N	1,779	1,779	1,779	1,779
Adjusted R^2	0.31	0.31	0.23	0.24

This table presents results from estimating the relation between earnings manipulation and word-level negative forward-looking discussion in conference calls when firms report quarterly earnings surprises between [0, 1¢] (i.e. Eq. (2.4)). Columns (1) and (2) list results for the presentation section of conference calls, in which $Pos(.)$, $Neg(.)$, $Unc(.)$, $Len(.)$, $Info(.)$, $Obfu(.)$ denote $Pos(Present)$, $Neg(Present)$, $Unc(Present)$, $Len(Present)$, $Info(Present)$, $Obfu(Present)$, respectively. Columns (3) and (4) list results for the Q&A section of conference calls, in which $Pos(.)$, $Neg(.)$, $Unc(.)$, $Len(.)$, $Info(.)$, $Obfu(.)$ denote $Pos(Q\&A)$, $Neg(Q\&A)$, $Unc(Q\&A)$, $Len(Q\&A)$, $Info(Q\&A)$, $Obfu(Q\&A)$, respectively. All variables are as defined in Appendix 2.2. t-statistics appear in parentheses and are based on standard errors clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 2.6. Earnings Manipulation and Obfuscation

	Presentation		Q&A	
	(1)	(2)	(3)	(4)
	$Obfu$	$Obfu$	$Obfu$	$Obfu$
NM_dummy	-0.668	-0.525	-0.935^{*}	-0.971^{*}
	(-0.29)	(-0.23)	(-1.92)	(-1.87)
$Size$	0.240	0.350	-0.200	-0.225
	(0.50)	(0.72)	(-0.93)	(-1.03)
$Growth$	0.648	0.581	0.394	0.390
	(1.14)	(1.05)	(1.31)	(1.33)
ROA	-3.806^{**}	-4.012^{***}	-0.265	-0.376
	(-2.51)	(-2.73)	(-0.32)	(-0.45)
$EarnVol$	-0.187^{*}	-0.163	-0.009	-0.007
	(-1.80)	(-1.60)	(-0.17)	(-0.14)
Ret	-0.672	-0.766	-1.030	-0.957
	(-0.53)	(-0.61)	(-1.44)	(-1.34)
$RetVol$	-12.834	-11.840	9.877	9.985
	(-0.84)	(-0.79)	(1.17)	(1.20)
$Leverage$	-0.840	-0.809	-0.125	-0.167
	(-0.57)	(-0.56)	(-0.15)	(-0.19)
MTB	-0.404	-0.445	-0.184	-0.190
	(-1.18)	(-1.30)	(-1.08)	(-1.12)
$Analyst$	-3.902^{**}	-4.383^{***}	-1.595^{**}	-2.083^{***}
	(-2.39)	(-2.71)	(-2.12)	(-2.76)
Age	-0.425^{***}	-0.434^{***}	-0.096	-0.097
	(-2.69)	(-2.80)	(-1.07)	(-1.09)
$Pos(.)$		0.367^{**}		0.442^{***}
		(2.02)		(4.26)
$Neg(.)$		-0.332		-0.017
		(-0.94)		(-0.08)
$Unc(.)$		0.141		0.022
		(0.36)		(0.13)
$Len(.)$		0.245		0.077
		(0.52)		(0.46)
$FLD(.)$		0.006		-0.001
		(1.38)		(-0.60)
Firm FE	YES	YES	YES	YES
Yr-Qtr FE	YES	YES	YES	YES
N	1,779	1,779	1,779	1,779
Adjusted R^2	0.53	0.53	0.51	0.51

This table presents results from estimating the relation between earnings manipulation and obfuscation in conference calls when firms report quarterly earnings surprises between [0, 1¢] (i.e. Eq. (2.4)). Columns (1) and (2) list results for the presentation section of conference calls, in which $Pos(.)$, $Neg(.)$, $Unc(.)$, $Len(.)$, $FLD(.)$ denote $Pos(Present)$, $Neg(Present)$, $Unc(Present)$, $Len(Present)$, $FLD(Present)$, respectively. Columns (3) and (4) list results for the Q&A section of conference calls, in which $Pos(.)$, $Neg(.)$, $Unc(.)$, $Len(.)$, $FLD(.)$ denote $Pos(Q\&A)$, $Neg(Q\&A)$, $Unc(Q\&A)$, $Len(Q\&A)$, $FLD(Q\&A)$, respectively. All variables are as defined in Appendix 2.2. *t*-statistics appear in parentheses and are based on standard errors clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 2.7. Earnings Manipulation and Communication Strategies: Change Analysis

Panel A. Univariate Analysis

	Mean		p-value for mean difference	Median		p-value for median difference
	Non-manipulator	Manipulator		Non-manipulator	Manipulator	
$\Delta FLD(Present)$	1.801	-0.744	0.000***	0.623	-0.561	0.000***
$\Delta FLD(Q\&A)$	1.721	-0.625	0.000***	1.102	0.275	0.000***
$\Delta FLDneg\_sentence(Present)$	0.837	-1.126	0.001***	0.048	-0.167	0.004***
$\Delta FLDneg\_sentence(Q\&A)$	0.478	-0.822	0.046**	0.102	-0.583	0.025**
$\Delta FLDneg\_word(Present)$	0.031	0.001	0.712	0.016	0.000	0.955
$\Delta FLDneg\_word(Q\&A)$	0.075	- 0.001	0.415	0.000	-0.012	0.504
$\Delta Obfu(Present)$	0.176	0.618	0.034**	-0.010	0.062	0.098*
$\Delta Obfu(Q\&A)$	0.004	0.379	0.001***	-0.019	0.312	0.001***

Panel B. Multivariate Analysis

	(1) $\Delta FLD\_sentence$ $(Present)$	(2) $\Delta FLD\_sentence$ $(Q\&A)$	(3) ΔFLD_word $(Present)$	(4) ΔFLD_word $(Q\&A)$	(5) $\Delta Obfu$ $(Present)$	(6) $\Delta Obfu$ $(Q\&A)$
NM_dummy	2.389***	2.068**	-0.044	0.108	-0.252	-0.333**
	(2.61)	(2.16)	(-0.51)	(0.96)	(-1.15)	(-2.54)
Control Variables	YES	YES	YES	YES	YES	YES
Yr-Qtr FE	YES	YES	YES	YES	YES	YES
N	1,127	1,127	1,127	1,127	1,127	1,127
Adjusted R^2	0.02	0.04	0.00	0.00	0.03	0.02

This table presents results of comparing the seasonally adjusted changes in communication strategies between non-manipulators and manipulators. Panel A presents univariate test results. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, for *t*-test of means and Wilcoxon test of medians. Panel B presents multivariate test results (i.e. Eq. (2.5)). See Appendix 2.2 for variable definitions. *t*-statistics appear in parentheses and are based on standard errors clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 2.8. Earnings Manipulation and Communication Strategies: Including Financial Fraud Restatements as An Additional Criterion in Non-manipulator/Manipulator Classification

	(1)	(2)	(3)	(4)	(5)	(6)
	$FLDneg\_sentence$ $(Present)$	$FLDneg\_sentence$ $(Q\&A)$	$FLDneg\_word$ $(Present)$	$FLDneg\_word$ $(Q\&A)$	$Obfu$ $(Present)$	$Obfu$ $(Q\&A)$
NM_Res	8.054*	7.182*	0.102**	0.356***	-0.370	-1.789**
	(1.90)	(1.88)	(2.36)	(6.76)	(-0.24)	(-2.06)
$Size$	4.667**	-3.972**	0.294***	-0.023	0.417	-0.231
	(2.13)	(-2.00)	(2.84)	(-1.27)	(0.86)	(-1.06)
$Growth$	-3.808*	1.672	-0.080	-0.081	0.596	0.419
	(-1.79)	(0.73)	(-1.31)	(-1.21)	(1.08)	(1.44)
ROA	-8.665	-10.511	-0.109	-0.199	-3.999***	-0.375
	(-0.61)	(-0.94)	(-0.25)	(-0.63)	(-2.71)	(-0.44)
$EarnVol$	-0.434	0.212	0.041*	0.014	-0.158	0.005
	(-0.84)	(0.50)	(1.67)	(0.93)	(-1.57)	(0.10)
Ret	-8.524	5.952	0.381	0.182	-0.622	-1.195*
	(-1.36)	(0.93)	(1.51)	(0.72)	(-0.50)	(-1.82)
$RetVol$	41.090	-26.608	-1.847	-6.960**	-9.533	12.322
	(0.54)	(-0.44)	(-0.60)	(-2.02)	(-0.62)	(1.54)
$Leverage$	-2.218	3.949*	-0.029	0.457*	-0.798	-0.100
	(-0.39)	(1.77)	(-0.28)	(1.89)	(-0.55)	(-0.12)
MTB	0.574	0.373	0.018	0.033	-0.429	-0.197
	(0.38)	(0.27)	(0.64)	(1.15)	(-1.25)	(-1.15)
$Analyst$	9.340	11.628	0.051	-0.094	-4.279***	-1.911***
	(1.00)	(1.21)	(0.23)	(-0.33)	(-2.66)	(-2.61)
Age	0.646	0.868**	-0.266*	0.017	-0.430***	-0.151
	(0.17)	(2.42)	(-1.76)	(0.83)	(-2.75)	(-0.30)
Linguistics Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Yr-Qtr FE	YES	YES	YES	YES	YES	YES
N	1,763	1,763	1,763	1,763	1,763	1,763
Adjusted R^2	0.31	0.18	0.29	0.23	0.53	0.50

This table presents robustness test results from estimating the relation between earnings manipulation and conference call communication strategies with including financial fraud restatements as an additional criterion in the non-manipulator/manipulator classification. The test variable, NM_Res, equals 1 if a firm: (1) has NM_dummy = 1 in a quarter; *and* (2) does not have restatements (financial fraud) in the same quarter and the previous four quarters. NM_Res equals 0 if a firm has: (1) NM_dummy = 0 in a quarter; *or* (2) restatements (financial fraud) in the same quarter. In columns (1) and (3), linguistics controls include $Pos(Present)$, $Neg(Present)$, $Unc(Present)$, $Len(Present)$, $Info(Present)$, $Obfu(Present)$. In columns (2) and (4), linguistics controls include $Pos(Q\&A)$, $Neg(Q\&A)$, $Unc(Q\&A)$, $Len(Q\&A)$, $Info(Q\&A)$, $Obfu(Q\&A)$. In column (5), linguistics controls include $Pos(Present)$, $Neg(Present)$, $Unc(Present)$, $Len(Present)$, $FLD(Present)$. In column (6), linguistics controls include $Pos(Q\&A)$, $Neg(Q\&A)$, $Unc(Q\&A)$, $Len(Q\&A)$, $FLD(Q\&A)$. All variables are as defined in Appendix 2.2. t-statistics appear in parentheses and are based on standard errors clustered by firm. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 2.9. Earnings Manipulation and Cumulative Abnormal Returns around Conference Calls

Panel A. Univariate tests

	Mean		p-value for mean difference	Median		p-value for median difference
	Non-manipulator	Manipulator		Non-manipulator	Manipulator	
$CAR[0,+1]$	0.008	0.001	0.006***	0.003	-0.000	0.021**

Panel B. Multivariate tests

	(1) CAR $[0,+1]$	(2) CAR $[0,+1]$	(3) CAR $[0,+1]$	(4) CAR $[0,+1]$	(5) CAR $[0,+1]$	(6) CAR $[0,+1]$	(7) CAR $[0,+1]$
NM_dummy	0.015						
	(1.60)						
$FLDneg\_sentence$ $(Present)$		0.000					
		(0.75)					
$FLDneg\_sentence$ $(Q\&A)$			0.000				
			(0.69)				
$FLDneg\_word$ $(Present)$				0.001			
				(0.39)			
$FLDneg\_word$ $(Q\&A)$					-0.002		
					(-0.75)		
$Obfu(Present)$						-0.000	
						(-0.26)	
$Obfu(Q\&A)$							-0.001
							(-1.33)
Control Variables	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES
Yr-Qtr FE	YES	YES	YES	YES	YES	YES	YES
N	1,779	1,779	1,779	1,779	1,779	1,779	1,779
Adjusted R^2	0.51	0.52	0.52	0.51	0.52	0.51	0.52

This table presents results on the difference in market reactions to non-manipulators' and manipulators' conference calls and communication strategies. Market reaction, $CAR[0,+1]$, is the cumulative abnormal returns for the two-day window [0, +1] around the conference call date. Panel A presents univariate analysis results. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, for *t*-test of means and Wilcoxon test of medians. Panel B presents multivariate analysis results (i.e. Eq. (2.6) in column (1) and Eq. (2.7) in columns (2) – (7)). All variables are as defined in Appendix 2.2. *t*-statistics appear in parentheses and are based on standard errors clustered by firm. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

Table 2.10. Earnings Manipulation and Future Cumulative Abnormal Returns

Panel A. Univariate tests

	Mean		p-value for mean difference	Median		p-value for median difference
	Non-manipulator	Manipulator		Non-manipulator	Manipulator	
$CAR[+2,+30]$	0.016	0.009	0.035**	0.030	0.007	0.043**
$CAR[+2,+60]$	0.051	0.003	0.000***	0.051	0.005	0.000***
$CAR[+2,+90]$	0.077	0.011	0.000***	0.089	0.014	0.000***
$NextCall\_CAR[0,+1]$	0.006	0.001	0.026**	0.002	0.000	0.086*

Panel B. Multivariate tests

	(1)	(2)	(3)	(4)
	CAR $[+2,+30]$	CAR $[+2,+60]$	CAR $[+2,+90]$	$NextCall\_CAR$ $[0,+1]$
NM_dummy	0.004	0.045*	0.050*	0.008*
	(0.39)	(1.90)	(1.94)	(1.93)
Control Variables	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Yr-Qtr FE	YES	YES	YES	YES
N	1,779	1,779	1,779	1,779
Adjusted R^2	0.22	0.38	0.35	0.20

This table presents results on the difference in market reactions subsequent to non-manipulators' and manipulators' conference calls (i.e. Eq. (2.8)), and on the difference in market reactions to non-manipulators' and manipulators' conference calls of the subsequent quarter results (i.e. Eq. (2.9)). Market reactions subsequent to conference calls are proxied by $CAR[+2,+30]$, $CAR[+2,+60]$ and $CAR[+2,+90]$. Market reactions to conference calls of the subsequent quarter is proxied by $NextCall\_CAR[0,+1]$. Panel A presents univariate analysis results. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively, for *t*-test of means and Wilcoxon test of medians. Panel B presents multivariate analysis results. All variables are as defined in Appendix 2.2. *t*-statistics appear in parentheses and are based on standard errors clustered by firm. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively.

Chapter 3. People Skills and Analyst Outcomes

"*My first year as Chief Risk Officer was an enlightening experience, because the biggest challenge of the job turned out to be communication. And as you become more senior, you realize that everything comes down to the soft skills.*"

— Keishi Hotsuki (2017), Chief Risk Officer of Morgan Stanley

3.1. Introduction

This chapter focuses on the role of people skills in the sell-side analyst labour market. People skills represent one's ability to get along with, to communicate effectively with, and to develop and maintain trusting relationships with others (Morand, 2001, p.21).[20] This chapter specifically investigates whether analysts with better people skills possess and benefit from better management relationships. The study is motivated by research showing the importance of people skills in daily social interactions, as well as in the labour market. It has long been established in psychology and sociolinguistics research that people skills are an essential factor in shaping social interactions, interpersonal relationships and workplace performance (e.g. Gardner, 1983; Sternberg, 1984; Gist et al., 1991; Goleman, 1996; Morand, 2001; Lievens and Sackett, 2012).

Over the past four decades, people skills have become increasingly vital in the labour market because, unlike technical and computing skills, people skills cannot be substituted by machines (Borghans et al., 2014; Deming, 2017). In the U.S., the

[20] The term "people skills" is often used loosely and as an umbrella term that covers various skills, such as communication skills and teamwork skills. Moreover, the terms "people skills", "social skills", "socioemotional skills" "interpersonal skills" and "emotional intelligence" are sometimes used interchangeably. This study uses the term "people skills" and follows the definition by Morand (2001, p.21).

Secretary's Commission on Achieving Necessary Skills (SCANS) report (1991) identifies interpersonal skills as one of five main competencies that are needed for success in the world of work. A number of recent studies in economics identify people skills as an important determinant of labour market outcomes, such as teamwork productivity, occupational choices and wages (Borghans et al., 2008, 2014; Deming, 2017; Deming and Kahn, 2018). Practitioners and the financial press also recognize people skills as one of the most fundamental qualities in business and financial professions (e.g. Hayes, 2013; Loten, 2017; Goldman Sachs, 2017; Morgan Stanley, 2017). Nevertheless, despite the importance of people skills, there is insufficient evidence on the effects of people skills in the financial market.

The nature of analysts' work requires people skills. Analysts seek to maintain a close relationship with managers to obtain superior access to firm-specific information (e.g. Lim, 2001; Chen and Matsumoto, 2006; Westphal and Clement, 2008; Mayew et al., 2013; Soltes, 2014; Brown et al., 2015). The analyst-management relationship is a type of interpersonal relationship that consists of interactions between the two parties. It is therefore predicted that analysts with good people skills can get along with and handle interaction and communication with managers effectively, leading to a close analyst-management relationship.

The limited evidence on the effects of analysts' people skills results partly from the difficulty in operationalizing the construct. I therefore begin by proposing and validating an empirical proxy for people skills, guided by psychology, economics and sociolinguistics research. This empirical measure is the first principal component of three ethnic cultural traits: individualism, trust and power distance. Analysts' people skills are measured based on their inherited ethnic cultural traits, which are transmitted across generations and significantly influence how individuals behave in interpersonal relationships in both personal and professional settings (e.g. Triandis, 1994; Bisin and Verdier, 2000; Hofstede, 2001; Guiso et al., 2006; Nguyen et al., 2017). Moreover, research shows that people skills are developed early in life and that early childhood experience has a persistent long-term impact on adult outcomes (e.g. Flinn and Ward, 2004; Flinn et al., 2005; Cunha and Heckman, 2007; Deming, 2009; Howie et al., 2010; Chetty et al., 2011).

Research in cross-cultural psychology suggests that individuals with more individualistic, more trusting, and lower power distance cultural backgrounds have better people skills. Individuals from a high individualistic culture are more confident and more charismatic in social interactions, and are more skilled in initiating social relationships than those from a low individualistic culture (e.g. Ellis, 1991; den Hartog et al., 1999; Triandis, 2001). Individuals with a more trusting cultural background are more friendly, reliable and honest, and better at interpersonal reciprocity and workplace cooperation (e.g. Rotter, 1971; Kramer, 1999; Stolle et al., 2008; Williams and Bargh, 2008). Individuals from lower power distance cultures exhibit greater proactivity in social interactions and are better at establishing personal relationships (e.g. Tyler et al., 2000; Sagie and Aycan, 2003; Hsiung and Tsai, 2017). Therefore, it is expected that analysts from more individualistic, more trusting, and lower power distance cultures are better at establishing and maintaining both professional and personal relationships with managers.

Relying on the recently developed epidemiological approach for ancestry identification, analyst ethnicity is identified based on their names that are obtained from quarterly earnings conference call transcripts and I/B/E/S. The empirical analysis is conducted using a sample of analysts following U.S. listed firms. A single country focus provides an identification strategy that separates the effects of people skills on analyst outcomes from potential confounding factors such as the legal and institutional environment of different countries.

My sample consists of 2,955 analysts and 31,980 U.S. firms' quarterly earnings conference call transcripts between 2011 – 2015. Individualism, trust and power distance scores for each ethnic group are calculated according to Hofstede (2001, 2011) culture index and the World Value Survey (Inglehart et al*.,* 2014). The first principal component of an analyst's ethnic individualism, trust and power distance culture scores is the operational measure for people skills that I use in the empirical analysis.

A concern with the research design is that the study does not directly observe an analyst's people skills but rather infers it based on the analyst's ethnic cultural background. To mitigate this concern, the operational measure for people skills is validated using analysts' linguistic behaviour during conference calls because how analysts interact with managers provides direct evidence on their people skills. Computational linguistic methods are utilized on conference call transcripts to extract analysts' linguistic features that are conceptually linked to people skills. Following psychology and sociolinguistics research, the validation tests focus on analysts' ingratiation behaviour during conference calls.

Ingratiation is the attempt by an individual to form a positive impression and increase liking in the eyes of others in social interactions (Liden and Mitchell, 1988; Vonk, 2002). Therefore, ingratiation can reflect a person's people skills. Research shows that analysts have incentives to compliment managers in conference calls (Milian and Smith, 2017; Milian et al., 2017), which is evidence of analysts' ingratiation behaviour in interactions with firm management. Psychology research shows that a moderate level of ingratiation is the most effective at producing positive interpersonal relation outcomes. A high level may arouse suspicions of the ingratiator's ulterior motives and, hence, backfire, while a low level may go unnoticed (e.g. Jones, 1964; Jones and Wortman, 1973; Gordon, 1996; Brodsky and Cannon, 2006). Thus, a U-shaped relation between analysts' people skills and ingratiation behaviour during conference calls is predicted. Analysts with poor people skills are expected to exhibit a high level of ingratiation, while those with good people skills exhibit a moderate level. Analysts with medium people skills are expected to exhibit a lower level of ingratiation than those with good people skills. Supportive evidence is reported for those predictions.

The study then proceeds to examine the effects of people skills on analyst outcomes. I predict that analysts with better people skills can establish closer relationships with managers because they can handle interpersonal interaction and communication more effectively. Conference calls provide a powerful social setting to observe analyst-management relationships. Academic research and anecdotal evidence suggest that managers screen conference call participants and prioritize some participants over the others, and that analysts with better management relationships have a higher probability of both participating in calls and, conditional on participating, asking earlier questions in the Q&A section (e.g. Mayew, 2008; NIRI, 2014; Cen et al., 2019). Therefore, my analysis uses conference call participation and the order of questions as the empirical proxies of analyst-manager relationships. Results show that analysts with better people skills have a higher probability of participating in conference calls and ask earlier questions, consistent with these analysts having closer relationships with firm management.

Finally, I investigate whether analysts with better people skills benefit from their advanced management relationships by testing whether they possess superior firm-specific information. Results show that analysts with better people skills issue more accurate earnings forecasts. Mediation analysis shows that their possession of superior private information partly stems from their close relationships with firm management. I also find that analysts' people skills are not associated with All-Star status or re-employment after brokerage closures, indicating that although analysts with better people skills enjoy informational benefits from better relationships with firm management, the effects are not significant enough to generate better career outcomes.

This study contributes to the literature in two ways. First, it contributes to the emerging literature on the importance of people skills in the labour market. Recent developments in economics research show that people skills influence labour market outcomes such as productivity, occupational choices and wages (Borghans et al., 2008, 2014; Deming, 2017; Deming and Kahn, 2018). However, the impact of people skills on specific financial market participants has not been studied in the prior literature. Financial analysts are essential market participants because they serve as important information intermediaries between firms and investors. Adding to the literature on the value of people skills, this study sheds light on why and how such skills matter in the financial analyst labour market.

Second, the study adds to the literature on financial analysts. While analysts play an important role in financial markets, regulators have long been concerned about analysts' conflicts of interest (e.g. Richards, 2002; SEC, 2010), including analyst incentives to foster close management relationships in order to access firm-specific private information (e.g. Lim, 2001; Chen and Matsumoto, 2006; Ljungqvist et al., 2006;

Westphal and Clement, 2008; Mayew et al., 2019). Thus, understanding the factors that underpin the development of analyst-management relationships is essential for both investors and regulators. Prior literature shows that, in addition to economic incentives, gender (Kumar, 2010) and certain cultural traits (Bhagwat and Liu, 2018) can influence analyst outcomes. In this study, I provide evidence that analysts with better people skills have better management relationships and benefit from superior private information. My work extends the existing literature by documenting the first evidence of the impacts of people skills on analyst outcomes.

My results also have implications for practitioners. While childhood experience heavily influences skills development, workplace-based programs can also facilitate skills improvements (Kautz et al., 2017). People skills are becoming more and more fundamental in financial markets because they cannot be replaced by automation. Recently, both investment banking professionals and the financial press have drawn attention to the development of people skills for employees and business school students (e.g. Hayes, 2013; Loten, 2017; Goldman Sachs, 2017; Morgan Stanley, 2017). Consistent with this trend, the results speak to the value of people skills in the financial profession.

The remainder of this chapter is organised as follows. Section 3.2 explains the prior literature and hypotheses development. Section 3.3 describes research design, including developing empirical construct of people skills. Section 3.4 provides descriptive statistics of the sample and results on validating the empirical construct of people skills. Section 3.5 presents empirical results on the hypotheses. Section 3.6 assesses the implications of people skills on analysts' access to firm-specific information. Section 3.7 concludes this chapter.

3.2. Prior Literature and Hypotheses development

I examine the effects of people skills on sell-side analysts' outcomes. The importance of people skills in social interactions and interpersonal relationships has long been recognized in psychology research (e.g. Gardner, 1983; Sternberg, 1984; Gist et al., 1991; Goleman, 1996; Morand, 2001; Lievens and Sackett, 2012). The value of people skills has been examined in various professions. Duffy et al. (2004) examine the role of people skills in the medical profession. They report that doctors' people skills are important in fostering doctor-patient relationships, shaping diagnoses and initiating therapies. Anderson et al. (2009) investigate whether people skills affect therapeutic outcomes. They show that therapists' ability to respond to challenging interpersonal situations has a significant influence over therapist-patient interactions and clinical outcomes.

A number of recent economics studies examine the influence of people skills on labour market outcomes. Borghans et al. (2014) report a rapid increase in the importance of people skills in the labour market from the late 1970s to the early 1990s. They show that people skills are important determinants of labour-market outcomes, such as occupational choices and wages, and that the increasing demand for people skills explains gender and racial wage gaps to some extent. Deming (2017) investigates the increasing importance of social skills in the U.S. labour market. He reports that between 1980 and 2012, there were large increases in both social skill-intensive occupations and the wages for these occupations in the U.S. He also finds that the labour market return on social skill-intensive occupations is significantly greater than on other occupations, especially in the 2000s. Deming and Kahn (2018) use social-skill requirements in job advertisements to investigate whether variations in the demand for social skills can explain labour market outcomes and firm performance. They find that the level of people skills required by a job can positively predict occupational wages and that the demand for people skills can positively predict firm performance.

Despite the importance of people skills in social interactions generally and specifically in the labour market, there is insufficient evidence on the role of people skills in the financial market. Apart from professional expertise and technical abilities, analysts' professional tasks also require people skills because they need to establish and maintain good management relationships to obtain firm-specific information. Analysts with good people skills are expected to be effective in establishing and maintaining relationships with managers in both professional and personal settings. Conversely, analysts with poorer people skills face greater interpersonal and communication barriers with managers than those with better people skills.

While analyst-management relationships are unobservable in the cross-section, conference calls as a public disclosure event provide a powerful setting to empirically gauge such relationships. As a public disclosure event, researchers can observe which analysts among those following the firm are selected to publicly engage with firm management. Managers have discretion to choose which analysts participate in the calls (Mayew, 2008; Mayew et al., 2013). The probability of participating in conference calls reflects the strength of an analyst's relationship with firm management (Mayew, 2008; Cen et al., 2019). I therefore hypothesise that:

H1. Analysts with better people skills are more likely to participate in conference calls.

Conference call participation is driven jointly by managers selecting analysts with stronger relationships to participate and analysts actively seeking participation. Therefore, while call participation can indicate analysts who have a relationship with firm management, it is possible that participating analysts make more effort to participate and do not necessarily have a strong relationship with management *per se*. To mitigate this potential threat to the construct validity of call participation, I also use the order in which analysts ask questions in the Q&A section to proxy for management relationships. Conditional on having already make the effort to participate in conference calls, the order in which analysts ask questions reflects their management relationships. Early conference call questioning reflects stronger management relationships because prior research and anecdotal evidence reveal that managers are likely to pick analysts with "friendly" questions as early participants (Cen et al., 2019). I therefore hypothesise that:

H2. Analysts with better people skills ask earlier questions in the Q&A section of conference calls.

3.3. Research design

3.3.1. Empirical models

To investigate how analysts' people skills affect their conference call participation as predicted by H1, I use Mayew's (2008) specification as the baseline model for conference call participation. The following logistic regression model is specified to test H1 with analysts indexed as a, firms as i, and quarters as q:

$$
\begin{aligned}
\Pr\ (Participate_{a,i,q})& \\
= {}& \alpha_0 + \alpha_1 PeopleSkills_a + \alpha_2 Sbuy_{a,i,q} + \alpha_3 Buy_{a,i,q} + \alpha_4 Sell_{a,i,q} \\
&+ \alpha_5 Ssell_{a,i,q} + \alpha_6 QAmin_{a,i,q} + \alpha_7 NumAnalyst_{a,i,q} + \alpha_8 Allstar_{a,i,q} \\
&+ \alpha_9 PriorAcc_{a,i,q} + \alpha_{10} FirmExp_{a,i,q} + \alpha_{11} GenExp_{a,i,q} + \alpha_{12} Inds_{a,i,q} \\
&+ \alpha_{13} ForFreq_{a,i,q} + \alpha_{14} BrokerSize_{a,i,q} + \alpha_{15} Companies_{a,i,q} \\
&+ \alpha_{16} CCuser_{a,i,q} + \alpha_{17} PriorParticipate_{a,i,q} + \alpha_{18} RecHorizon_{a,i,q} \\
&+ \alpha_{19} MAS_a + \alpha_{20} UAI_a + \alpha_{21} LTOWVS_a + \alpha_{22} IVR_a + \varepsilon_{a,i,q}
\end{aligned} \tag{3.1}
$$

The dependent variable $Participate_{a,i,q}$ is an indicator variable that captures conference call participation at the analyst-firm-quarter level. It equals 1 if analyst a participates in the call of firm i in the quarter q; and 0 otherwise. For analysts who participate in conference calls, their full names are extracted from the transcripts. The last name and first name initial of all analysts in I/B/E/S are also obtained. Analysts' conference call participation is identified by merging analysts' names from I/B/E/S and those extracted from call transcripts. The test variable is $PeopleSkills_a$, the measure of analysts' people skills. H1 posits that analysts with better people skills have a higher probability of participating in conference calls. If H1 holds, then the coefficient α_1 is expected to be positive.

Eq. (3.1) controls for analyst characteristics that are known to affect conference call participation probability. All variables are defined in Appendix 3.1. Analyst characteristics include recommendation levels ($Sbuy$, Buy, $Sell$ and $Ssell$) and All-Star status ($AllStar$) because managers prefer analysts with more favourable recommendations and prestigious analysts (Mayew, 2008). The model also controls for the following proxies for analyst characteristics (ibid.): forecast accuracy and frequency ($PriorAcc$ and $ForFreq$), firm-specific and general experiences ($FirmExp$ and $GenExp$), number of industries and firms following ($Inds$ and $Companies$), and broker size ($BrokerSize$). These variables are constructed using data from I/B/E/S. For these variables, following standard procedure in the analyst literature, I calculate analyst peer-adjusted variables, which remove the need to control for firm-level characteristics and time fixed effects in regressions when working with a sample on all analysts that are actively following the sample firm (e.g. Clement and Tse, 2005; Mayew, 2008; Kumar, 2010; Clement and Law, 2014; He et al., 2019). These analyst characteristics variables are peer-adjusted using the following equation:[21]

$$Characteristic_{a,i,q} = \frac{Characteristic\_raw_{a,i,q} - \min\left(Characteristic\_raw_{i,q}\right)}{\max\left(Characteristic\_raw_{i,q}\right) - \min\left(Characteristic\_raw_{i,q}\right)} \tag{3.2}$$

By construction, all peer-adjusted analyst characteristics variables range from 0 – 1.

I also control for whether an analyst is a frequent conference call participant using the following proxies: the number of other conference calls that the analyst participates in during the same quarter ($CCuser$) and whether the analyst has participated in the firm's past conference calls ($PriorParticipate$). Moreover, I control for an analyst' recommendation horizon ($RecHorizon$) to proxy for the analyst's interest in the firm. It is also important to control for conference call characteristics that might influence the probability of participation. I include control variables for Q&A length ($QAmin$) and the

[21] Calculating analyst prior earnings forecast accuracy using this equation implies that larger values capture less accurate analysts. Following Mayew (2008), to allow conference call participation probability to increase with analyst forecast accuracy, prior forecast accuracy is calculated as: $PriorAcc_{a,i,q} = (\max(FE\_raw_{i,q}) - FE\_raw_{a,i,q}) / (\max(FE\_raw_{i,q}) - \min(FE\_raw_{i,q}))$, where FE denotes absolute forecast error.

number of participating analysts ($NumAnalyst$). Additionally, to control for cultural traits that might affect analyst behaviour and hence their relationships with firm management, Eq. (3.1) includes culture variables that are not used to construct the people skills variable: masculinity (MAS), uncertainty avoidance (UAI), long-term orientation ($LTOWVS$), and indulgence (IVR).

To test the relation between analysts' people skills and conference call question order as predicted by H2, the following OLS regression model is specified:

$$\begin{aligned} Order_{a,i,q} = {} & \alpha_0 + \alpha_1 PeopleSkills_a + \alpha_2 Sbuy_{a,i,q} + \alpha_3 Buy_{a,i,q} + \alpha_4 Sell_{a,i,q} \\ & + \alpha_5 Ssell_{a,i,q} + \alpha_6 Allstar_{a,i,q} + \alpha_7 PriorAcc_{a,i,q} + \alpha_8 FirmExp_{a,i,q} \\ & + \alpha_9 GenExp_{a,i,q} + \alpha_{10} Inds_{a,i,q} + \alpha_{11} ForFreq_{a,i,q} \\ & + \alpha_{12} BrokerSize_{a,i,q} + \alpha_{13} Companies_{a,i,q} + \alpha_{14} CCuser_{a,i,q} \\ & + \alpha_{15} PriorParticipate_{a,i,q} + \alpha_{16} RecHorizon_{a,i,q} + \alpha_{17} MAS_a \\ & + \alpha_{18} UAI_a + \alpha_{19} LTOWVS_a + \alpha_{20} IVR_a + \Sigma Firm\ FE + \Sigma YrQtr\ FE \\ & + \varepsilon_{a,i,q} \end{aligned} \tag{3.3}$$

The dependent variable $Order_{a,i,t}$ captures the order in which participating analysts ask questions in the Q&A section of a conference call. $Order$ equals 1 if the analyst is the first to ask question(s) in the Q&A section; 2 if the second; etc. A low value of $Order$ corresponds to earlier questions. H2 posits that analysts with better people skills ask earlier questions in the Q&A section. Thus, if H2 holds, α_1 is expected to be negative.

Eq. (3.3) is estimated with the sub-sample of analysts who participate in conference calls. Therefore, it is not necessary to control for Q&A length ($QAmin$) and the number of participating analysts ($NumAnalyst$) because these call characteristics only affect the probability of participating in a call, but not the order of questions within a call. Moreover, as Eq. (3.3) is not estimated with all analyst-firm-quarter observations in the full sample, I include firm and year-quarter fixed effects to control for unobservable firm- and year-quarter-related factors that affects analysts participating in conference calls.

3.3.2. Sample

Individual analyst data is obtained from the following two sources: I/B/E/S detailed recommendation files and U.S. firms' quarterly earnings conference call transcripts. The sample period is 2011 – 2015. Conference call transcripts are downloaded from Thomson Reuters Eikon. Table 3.1 presents the sample construction process. The initial sample contains 54,644 transcripts. I then limit the sample to U.S. firms and excludes cross-listed foreign firms. This mitigates endogeneity concerns that the results might be driven by unobserved country and institutional characteristics. After excluding transcripts of cross-listed foreign firms, 40,418 transcripts remain.

[Insert Table 3.1 here]

A critical issue in the empirical design is that analysts' conference call participation is driven jointly by managers' discretionary choices and analysts seeking participation. As the hypotheses assume managers choose analysts with good relationships to participate in the call, it is essential to rule out the competing explanation that analysts differentially seek conference call participation. Analysts who are not actively following a firm presumably have little incentive to seek conference call participation, I therefore follow Mayew's (2008) sample construction choices and exclude analysts who may not be actively following a firm. The details are listed in Table 3.1. I require each analyst-firm-quarter observation to have an outstanding stock recommendation and an outstanding earnings forecast issued during the year preceding the fiscal quarter end date to ensure that the analyst is actively covering the firm. Sample construction also requires each analyst to have all analyst characteristics variables in Eq. (3.1) and Eq. (3.3) measurable. These sample screening choices lead to a final sample of 31,980 conference call transcripts and 239,153 analyst-firm-quarter observations.

3.3.3. Conceptual measurement of people skills

I use information on analysts' ethnic cultural traits to measure their people skills. It has long been established that ethnic cultural background affects personality, interpersonal behaviour and social relationships (e.g. Triandis et al., 1988; Triandis, 1994; Dawar et al., 1996; Diener et al., 2003; Hofstede and McCrae, 2004). More recently, the accounting and finance literature has provided evidence that cultural traits affect how individuals behave in social interactions and perform professional tasks in the financial market. Brochet et al. (2019) find that managers from ethnic groups with higher levels of individualism use more optimistic language and more self-references and make fewer apologies during earnings conference calls. Bhagwat and Liu (2018) report that analysts from a more trusting ethnic background react faster to management guidance than less trusting analysts.

As previously defined, people skills represent individuals' ability to get along with, communicate effectively with, and develop trusting relationships with others (Morand, 2001, p.21). Following this definition and research in psychology and economics, I argue that analysts whose ethnicity is associated with *more individualistic*, *more trusting*, and *lower power distance* culture have *better people skills*. It is well documented that these ethnic cultural traits shape how people behave in interpersonal relationships.

Individualism reflects a society's attitude towards the self and the emphasis on self-fulfilment (Hofstede, 2001). Cultures that are high in individualism encourage and reward individual initiative, while those low in individualism tend to subjugate individuals to the group (Dawar et al., 1996). People from a high individualistic culture are skilled in initiating social interactions, while those from a low individualistic culture are more reserved (Triandis, 2001). Moreover, individuals from a high individualistic culture are more confident, more active, more charismatic and more likely to emphasize the bright side of things in social interactions than those from a low individualistic culture (e.g. Ellis, 1991; den Hartog et al., 1999; Sims et al. 2015). Accordingly, analysts from a high individualistic culture are expected to be effective at establishing and maintaining relationships with management.

Trust represents the expectancy that words, promises and statements of others can be relied upon (Rotter, 1971). It embodies cultural meanings, social relations and individual personality (Fine and Holyfield, 1996; Doney et al., 1998). Trust is essential for establishing and maintaining interpersonal relationships in both professional and personal settings (Fukuyama, 1995; McAllister, 1995; Kramer, 1999). Trust can be viewed as "interpersonal warmth" in social interactions (Williams and Bargh, 2008, p. 606). Individuals with a more trusting cultural background are more friendly, reliable and honest. They are better at sincerity and relationship building, interpersonal reciprocity and workplace cooperation (e.g. Kramer, 1999; Stolle et al., 2008; Williams and Bargh, 2008). Thus, analysts from a more trusting culture are expected to be better at building relationships with managers.

Power distance is related to the power distribution in society. Low power distance culture values equality and equal communication, while high power distance culture emphasizes hierarchy and inequality as the basis of society (Hofstede, 2001). Power distance therefore reflects individuals' beliefs about equality, power and authority and is an important factor in shaping interpersonal behaviour and relationships (Kirkman et al., 2009; Tyler et al., 2000). Low power distance culture encourages open discussions and equal communication (Tyler et al., 2000; Hofstede, 2001). All else equal, individuals from a low power distance culture are more proactive at initiating communication and better at maintaining personal relationships on both professional and informal occasions (e.g. Newman and Nollen, 1996; Begley et al., 2002; Sagie and Aycan, 2003; Botero and Van Dyne, 2009; Hsiung and Tsai, 2017). Analysts from a low power distance culture are therefore expected to be good at establishing both professional and personal relationships with managers.

Having established that more individualistic, more trusting and lower power distance cultures contribute to better people skills, it is also important to clarify the assumptions underlying the proposed empirical proxy. There are two main assumptions. First, an individual's people skills are largely developed early in life and the effects are persistent over time. Childhood is crucial in skill development because it lays the foundation for later years (Kautz et al., 2017). The family plays a crucial role in shaping behaviour and abilities through parental inputs and the choice of child environments (Black et al., 2005; Cunha et al., 2006; Cunha and Heckman, 2007; 2008). Economics research provides consistent evidence that early childhood experiences have long-run impacts on adult outcomes (e.g. Garces et al., 2002; Case et al., 2005; Deming, 2009; Chetty et al., 2011). Specifically, childhood is a key stage when people skills are developed (Flinn and Ward, 2004; Flinn et al., 2005; Howie et al., 2010; King and Bjorklund, 2010).[22] People skills are learned early in life and affect adult outcomes such as occupations and earnings (Deming, 2017). Recent research finds strong correlations between socioemotional skills of children and adult outcomes including employment, work competence, earnings, and criminal activities (Masten et al., 2010; Harrist et al., 2014; Jones et al., 2015). There is also evidence that youths' interpersonal style and skills significantly affects their occupational choices and job performance in adulthood (Borghans et al., 2008; Lievens and Sackett, 2012).

Second, the effects of ethnic cultural traits endure over time. This is supported by both analytical and empirical evidence. Culture consists of the "customary beliefs and values that ethnic, religious, and social groups transmit fairly unchanged from generation to generation" (Guiso et al., 2006, p. 23). Bisin and Verdier (2000) develop a model to study why ethnic and religious traits can be resilient for generations. They show that the intergenerational transmission of ethnic and religious traits is facilitated by family socialization and marital segregation decisions, and that the dynamics of the distribution of ethnic and religious traits in a population converge to a heterogeneous limit distribution in which ethnic and religious minorities can never be assimilated. Empirically, many recent studies investigate the effects of ethnic cultural traits in financial markets. For example, Bhagwat and Liu (2018) report that the trust culture of different ethnic groups affects sell-side analysts' information processing and forecast

[22] For example, Howie et al. (2010) find that children of different ethnicities participate in activities outside of school hours at different levels, leading to differences in people skills development, because those activities improve children's social skills. Burchinal et al. (2000) show that children of colour are more likely to attend low-quality child care, which is related to poor development of social skills.

accuracy. In a corporate finance setting, Nguyen et al. (2017) find that the CEO's cultural heritage affects firm performance under competitive pressure.

It is nevertheless important to note that skill development can be a dynamic process and that people skills can also be learned during other stages in life. The proposed empirical construct does not capture the time-varying component of people skills. Therefore, Section 3.4 of this chapter provides evidence on construct validity and shows that as predicted the measure captures analyst people skills on average.

3.3.4. Operational measurement of people skills

The empirical measure of analysts' people skills is the first principal component of the following three ethnic cultural traits: individualism, trust and power distance. To capture analysts' ethnicity, I follow recent developments in the literature and map analysts' names into the geographic regions that are likely to represent their country of ancestry (e.g. Pool et al., 2015; Bhagwat and Liu, 2018; Brochet et al., 2019; Lourie et al., 2018; Merkley et al., 2019). This method is superior to using a sample of international analysts (i.e. a cross-country sample) because it isolates the effects of personal traits on analyst outcomes from other confounding institutional factors such as the economic, legal and political environment of different countries.

More specifically, ethnicity associated with analysts' names is measured using the recently developed epidemiological approach for ancestry identification by computer science research (Fernández, 2011; Liu, 2016; Merkley et al., 2019). Following prior literature (Pool et al., 2015; Adhikari and Agrawal, 2016; Lourie et al., 2018), I utilise the name-ethnicity classification algorithm developed by Ambekar et al. (2009). This classifier is trained using name-ethnicity pairs data extracted from Wikipedia and uses hidden Markov models and decision trees to predict the ethnicity of any given name. Using this classifier, analysts' names are mapped into one of the following ethnic groups: African, British, East Asian, East European, French, German, Hispanic, Indian, Italian, Japanese, Jewish, Muslim and Nordic.

As ancestry has continuous cultural and behavioural effects that can be transmitted from generation to generation (Bisin and Verdier, 2000; Guiso et al., 2006; Nguyen et al., 2017), I assume that analysts from the same ethnic group share similar individualism, trust and power distance values. To empirically measure the cultural values of analysts with a given ethnicity, I follow prior research and rely on Hofstede cultural index and the World Value Survey (e.g. Bhagwat and Liu, 2018; Brochet et al., 2019). Using Hofstede (2001, 2011) cultural index, the individualism (power distance) score for each ethnic group is calculated as the average individualism (power distance) score of countries/regions belonging to that ethnic group. The trust score for a given ethnicity is measured by the responses to the trust-related question in the 2016 World Value Survey (Inglehart et al., 2014): "Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people?" The mean value from the responses for each ethnic group is used as the trust score.

Appendix 3.2 lists countries/regions included in each ethnic group for the calculation of the culture scores. I require all countries/regions included to have data on all culture variables for the empirical analysis. Note that although the name-ethnicity classifier by Ambekar et al. (2009) assigns names into 13 ethnic groups, there are only 10 ethnic groups in my sample. The reason is that the French and Italian ethnic groups have missing trust culture data and the Jewish ethnic group has missing indulgence and trust culture data. Due to the data unavailability, those 3 ethnic groups are excluded from the sample.

I then perform principal component analysis and compute the people skills variable as the first principal component of an analyst's individualism, trust and power distance scores. Table 3.2 presents the details. Panel A lists the principal components from the principal component analysis. Component 1 has the eigenvalue of 2.77 and explains 0.92 of the total variance. Component 2 (3) has the eigenvalue of 0.16 (0.06) and explains only 0.06 (0.02) of the total variance. Panel B reports component loadings. Component 1 has statistically and economically significant correlations with all three of the culture variables (i.e. individualism, power distance and trust) as predicted by theory, whereas the rest of the components do not. Based on these principal component analysis results, only one meaningful principal component (i.e. the first principal component) emerges. Therefore, I use this first principal component to proxy for analyst people skills (denoted as $PeopleSkills$).

[Insert Table 3.2 here]

Table 3.2 Panel C lists the value of $PeopleSkills$ and the distribution of sample observations by ethnicity. 60% (65%) of sample analysts (analyst-firm-quarter observations) cluster in the British ethnic group. This is consistent with non-Hispanic White ethnic group making up more than 60% of the U.S. population between 2010 and 2015 (U.S. Census Bureau, 2015).

3.4. Descriptive statistics and validity of $PeopleSkills$

3.4.1. Correlation matrix and descriptive statistics

Table 3.3 presents the correlations among $PeopleSkills$, analyst-management relationship variables, and analyst characteristics variables. Spearman (Pearson) correlations appear above (below) the diagonal. Both the Spearman and Pearson correlations between $PeopleSkills$ and $Participate$ are positive (0.02 and 0.02, respectively) and statistically significant at the 1% level, consistent with H1 that analysts with better people skills are more likely to participate in conference calls. Both the Spearman and Pearson correlations between $PeopleSkills$ and $Order$ are negative (-0.01 and -0.02, respectively) and statistically significant at the 1% level. This is consistent with H2 that analysts with better people skills ask earlier questions in conference calls.

[Insert Table 3.3 here]

In terms of other analysts' characteristics, $FirmExp$ is positively correlated with $PeopleSkills$, indicating that analysts with better people skills follow firms for longer. This might be because those analysts can more effectively sustain relationships with the firm. $GenExp$ is also positively correlated with $PeopleSkills$, suggesting that analysts with better people skills have longer experience in the profession. $Inds$, $ForFreq$ and $Companies$ are all positively correlated with $PeopleSkills$. That is, analysts with better people skills tend to cover more industries and firms, and issue earnings forecasts more frequently.

Table 3.4 presents the means of analyst-management relationship variables and analyst characteristics variables according to people skills, as well as univariate analysis results. The mean of $Participate$ is 0.32 for low people skills analysts and 0.35 for high people skills analysts, respectively. The difference is statistically significant at the 1% level. The mean of $Order$ is 5.18 for low people skills analysts and 5.02 for high people skills analysts, respectively, and the difference is statistically significant at the 1% level. These results support that analysts with better people skills are more likely to participate in conference calls and ask earlier questions in the Q&A section.

[Insert Table 3.4 here]

In terms of other analyst characteristics, the mean of $FirmExp$ is 0.41 for low people skills analysts and 0.44 for high people skills analysts, respectively, and the difference is statistically significant at the 1% level. The mean of $GenExp$ is 0.40 for low people skills analysts and 0.44 for high people skills analysts, respectively, and the difference is significant at the 1% level. The mean of $Inds$ is 0.34 for low people skills analysts and 0.37 for high people skills analysts, respectively, and the difference is significant at the 1% level. These results suggest that analysts with high people skills have higher firm-specific and general experiences and follow more industries. Moreover, the mean of $CCuser$ is 4.18 for low people skills analysts and 4.78 for high people skills analysts, respectively, and the difference is statistically significant at the 1% level. This indicates that analysts with better people skills are more frequent conference call participants, consistent with the prediction of H1.

3.4.2. Validity of $\boldsymbol{PeopleSkills}$

A concern is that the empirical measure cannot directly capture an analyst's people skills, but rather infers it based on the analyst's ethnic cultural traits. It is possible, for example, that the analyst has later life experience that significantly alters their people skills. To address such a concern, this sub-section provides evidence on the validity of $PeopleSkills$ as the empirical proxy of people skills. Conference calls provide a unique setting for researchers to observe analysts' language in social interactions. If $PeopleSkills$ can sufficiently capture analysts' people skills, it should exhibit significant relations with analyst linguistic features that reflect such qualities. Following psychology and sociolinguistics research, the validity of $PeopleSkills$ is assessed using analysts' ingratiation behaviour during conference calls.

Ingratiation refers to the attempt in social interactions by an individual to form a favourable impression and increase liking in the eyes of others (Liden and Mitchell, 1988; Vonk, 2002). It can take the form of complimentary, flattery, conformity and providing favour (Jones, 1964; Tedeschi and Melburg, 1984; Ellis et al., 2002). Prior accounting research finds that analysts have incentives to use favourable language towards management (e.g. praise, complimentary and positive tone) during conference calls to establish management relationships (Milian and Smith, 2017; Milian et al., 2017). This suggests that ingratiation is a common method that analysts use to achieve close management relationships.

Psychology and organizational behaviour research provide ample evidence that, when successfully implemented, ingratiation can positively affect interpersonal relationships (e.g. Vonk, 2002; Varma et al., 2006; Harvey et al., 2007; Seiter, 2007). Importantly, psychology researchers have attempted to decide how much ingratiation can effectively increase the likeability of the ingratiator and elicit positive interpersonal outcomes. A high level of ingratiation can backfire as it may come across as insincere, self-serving, and manipulative, while a low level of ingratiation is likely to be unnoticeable. This is known as the ingratiator's dilemma (Jones, 1964; Vonk, 2007).

Ingratiation attempts can only be successful when the target deems it to be sincere (Appelbaum and Hughes, 1998). When the target is more powerful than the ingratiator, the ingratiator's likeability would increase between the low and moderate level of ingratiation but decrease with a high level of ingratiation (e.g. Jones, 1964; Jones and Wortman, 1973; Gordon, 1996; Brodsky and Cannon, 2006). A moderate level is less likely to evoke suspicions of the ingratiator's ulterior motives, while still ensuring the message is visible (Brodsky and Cannon, 2006).

I therefore predict a U-shaped relation between analysts' people skills and ingratiation behaviour during conference calls. Analysts with poor people skills are expected to exhibit a high level of ingratiation during conference calls because while they may intend to establish close management relationships, the lack of people skills leads to over-use of ingratiation. On the other hand, analysts with good people skills are expected to exhibit a moderate level of ingratiation. They are also expected to exhibit a higher level of ingratiation than those with medium people skills because they have better people skills.

To empirically test the validity of the empirical construct of people skills by assessing its association with analysts' ingratiation behaviour during conference calls, I estimate the following regression:

$$
\begin{aligned}
&Ingratiation_{a,i,q} \\
&\quad = \alpha_0 + \alpha_1 PeopleSkills_a + \alpha_2 PeopleSkills_a^2 + \alpha_3 Sbuy_{a,i,q} \\
&\quad + \alpha_4 Buy_{a,i,q} + \alpha_5 Sell_{a,i,q} + \alpha_6 Ssell_{a,i,q} + \alpha_7 Allstar_{a,i,q} \\
&\quad + \alpha_8 PriorAcc_{a,i,q} + \alpha_9 FirmExp_{a,i,q} + \alpha_{10} GenExp_{a,i,q} + \alpha_{11} Inds_{a,i,q} \\
&\quad + \alpha_{12} ForFreq_{a,i,q} + \alpha_{13} BrokerSize_{a,i,q} + \alpha_{14} Companies_{a,i,q} \\
&\quad + \alpha_{15} CCuser_{a,i,q} + \alpha_{16} PriorParticipate_{a,i,q} + \alpha_{17} RecHorizon_{a,i,q} \\
&\quad + \alpha_{18} MAS_a + \alpha_{19} UAI_a + \alpha_{20} LTOWVS_a + \alpha_{21} IVR_a + \Sigma Firm\ FE \\
&\quad + \Sigma YrQtr\ FE + \varepsilon_{a,i,q}
\end{aligned}
\tag{3.4}
$$

where $Ingratiation_{a,i,q}$ denotes the ingratiation behaviour of analyst a in the conference call of firm i in quarter q. It is calculated as the number of ingratiation words scaled by the total number of words by that analyst. To count the number of ingratiation words, I develop an ingratiation dictionary by extensive reading of conference calls transcripts and following psychology research (e.g. Ellis et al., 2002; Vonk, 2002; Seiter, 2007) and prior literature on analysts' complimentary behaviour during conference calls (Milian and Smith, 2017). The dictionary contains six categories of ingratiation words: (1) praises (e.g. "*great quarter*", "*nice quarter*"), (2) greetings (e.g. "*hello*", "*hi*"), (3) congratulations (e.g. "*congratulations*", "*congratulate*"), (4) thanks (e.g. "*thank*", "*gratitude*"), (5) laughter (e.g. "*laughter*", "*joke*")[23], and (6) the word "*please*". The details of the dictionary are explained in Appendix 3.3.

The theory predicts a U-shaped relation between analysts' people skills and ingratiation. Analysts with poor people skills are expected to exhibit a high level of

[23] In conference call transcripts, laughter is noted when analysts and/or managers laugh.

ingratiation, whereas those with good people skills are expected to exhibit a moderate level. Analysts with medium people skills are expected to exhibit a lower level of ingratiation than those with good people skills. According to this prediction, the coefficient α_1 in Eq. (3.4) is expected to be negative, while the coefficient α_2 is expected to be positive. The magnitude of α_1 is expected to be larger than α_2.

The mean value of $Ingratiation$ is 4.52%. The minimum and maximum values are 0% and 10.27%, respectively. The median is 4.31%. Figure 1 presents the scatterplot of the mean value of $Ingratiation$ according to the value of $PeopleSkills$ to illustrate their relation. As predicted, ethnic groups with poor people skills have the highest mean values of $Ingratiation$. Ethnic groups with medium people skills have low values of $Ingratiation$. Ethnic groups with high people skills exhibit a moderate level of $Ingratiation$.

To formally test the predicted U-shaped relation, Table 3.5 presents the results on estimating Eq. (3.4). To mitigate the effects of extreme values on regression estimates, $Ingratiation$ is winsorized at the 1% and 99% levels for estimating Eq. (3.4).[24] In column (1), $PeopleSkills$ and $PeopleSkills^2$ are regressed on $Ingratiation$ without any control variables. The coefficient on $PeopleSkills$ is -0.116 and statistically significant at the 1% level. The coefficient on $PeopleSkills^2$ is 0.010 and statistically significant at the 1% level. Column (2) estimates the relation after controlling for analyst characteristics variables. The coefficient on $PeopleSkills$ is -0.116 and statistically significant at the 1% level. The coefficient on $PeopleSkills^2$ is 0.010 and statistically significant at the 1% level. Column (3) estimates the relation after controlling for analyst characteristics and cultural traits. The coefficient on $PeopleSkills$ is -0.549 and is

[24] Results are robust to no winsorization of $Ingratiation$.

statistically significant at the 1% level. The coefficient on $PeopleSkills^2$ is 0.053 and statistically significant at the 1% level.[25] These results are consistent with prediction.

[Insert Table 3.5 here]

To test the validity of the U-shaped relation, I assess whether there are sufficient observations above the implied turning point (i.e. the point at which the curve attains its minimum). Based on the coefficient estimates for α_1 and α_2 in column (3), the implied turning point is when $PeopleSkills$ equals $-\frac{-0.549}{2*0.053} = 5.179$. Among the 80,160 observations used to estimate the regression, 25,519 observations have the value of $PeopleSkills$ above 5.179. That is, 31.84% of the sample observations are above the implied turning point, exceeding the benchmark of 10%. Therefore, the U-shaped relation is valid.

Collectively, the results support the prediction that analysts' people skills have a U-shaped relation with ingratiation behaviour in conference calls. Taken together, the evidence supports the validity of $PeopleSkills$ as an empirical proxy of analysts' people skills.

[25] The Adjusted R^2 of regressions in Table 3.5 is 0.05 in column (1) and 0.06 in columns (2) and (3). The low Adjusted R^2 is consistent with results reported by the prior literature on predicting analysts' linguistic behaviour during conference calls. For example, Milian et al. (2017) use analyst characteristics to predict analysts' positive tone, negative tone and praising during conference calls, and report Adjusted R^2 around 0.01.

3.5. Empirical results

3.5.1. People skills and management relationships

To assess H1 formally in multivariate analysis, estimation of Eq. (3.1) is presented in Table 3.6. H1 predicts that analysts with better people skills have a higher probability of participating in conference calls. If H1 holds, the coefficient on $PeopleSkills$ is expected to be positive.

Column (1) replicates the baseline model of conference call participation reported by Mayew (2008). Despite the different sample periods, my results are consistent with those by Mayew (2008). For example, analysts' favourable (unfavourable) recommendation increases (decreases) conference call participation probability. The only notable difference between my results and Mayew's (2008) is that the coefficient on $FirmExp$ in my regression is unexpectedly negative (-0.116) and significant at the 1% level, while Mayew (2008) reports a significant and positive coefficient estimate. My result suggests that analysts with relatively longer firm-specific experience have a lower probability of participating in conference calls. A possible reason is that analysts with sufficiently long experience following a firm have presumably already established relationships with firm management and can engage in private communication with managers (Soltes, 2014), therefore do not necessarily need to participate in a public disclosure event.

[Insert Table 3.6 here]

Column (2) estimates the relation between analysts' people skills and the probability of call participation without any control variables. The coefficient on $PeopleSkills$ is positive (0.018) and statistically significant at the 1% level. Column (3) estimates the relation between people skills and participation probability after controlling for the baseline model. The coefficient on $PeopleSkills$ remains positive (0.009) and statistically significant at the 1% level. Column (4) estimates the relation after controlling for the baseline model as well as analyst cultural traits. The coefficient on $PeopleSkills$ is positive (0.071) and remains statistically significant at the 1% level. These results support H1, which predicts a positive relation between analysts' people skills and the probability of conference call participation.

In terms of the economic significance, since $PeopleSkills$ is constructed using the first principal component of ethnicity-level individualism, trust and power distance culture scores, it is unintuitive to interpret directly from the coefficient estimates in Table 3.6. I therefore assess the marginal probability effects of ethnicity on the predicted probability of conference call participation because $PeopleSkills$ is measured at the ethnicity level. Analysts from ethnic groups with high $PeopleSkills$ are expected to have higher probability of participating in conference calls. I code ethnicities into a categorical variable and estimate the probability of participation for each ethnic group after controlling for individual analyst characteristics. The indicated participation probability for an analyst from the ethnic group with the lowest $PeopleSkills$ is 31%.[26] The implied probability of participation increases by 14 percentage points to 45% for an analyst from the ethnic group with the highest $PeopleSkills$, indicating a substantial economic increase in implied participation probability. Collectively, the results are consistent with H1, which predicts that analysts with better people skills are more likely to participate in conference calls.

[26] Predicted probabilities are calculated as $e^{(x'\hat{\beta})}/(1+e^{(x'\hat{\beta})})$, where $\hat{\beta}$ is the vector of fitted values from regression estimates for coefficients on ethnicities and x' is the vector of values equal to the sample mean for continuous control variables and 1 for dummy control variables.

Table 3.7 presents the results of estimating the relation between analysts' people skills and the order of questions in the Q&A section (i.e. Eq. (3.3)) to test H2. The analysis is performed using the sub-sample of analysts who participate in conference calls. If H2 holds, the estimated coefficient on $PeopleSkills$ is expected to be negative. Column (1) estimates the relation without controlling for other analysts' attributes. The coefficient on $PeopleSkills$ is -0.020 and statistically significant at the 1% level. Column (2) estimates the relation with controlling for analyst characteristics. The coefficient on $PeopleSkills$ is -0.024 and statistically significant at the 1% level. Column (3) estimates the relation with including additional ethnic cultural traits. The coefficient on $PeopleSkills$ is -0.037 and statistically significant at the 5% level. In terms of the economic significance, an increase in $PeopleSkills$ by 1 indicates asking 0.037 question earlier, all other things being equal. To put this in context, an analyst from the highest $PeopleSkills$ ethnic group asks 0.19 question earlier than an analyst from the lowest $PeopleSkills$ ethnic group on average, indicating marginal economic significance of the effects of people skills on the order of questions. Collectively, results in Table 3.7 suggest that analysts with better people skills ask earlier questions in conference calls, consistent with H2.

[Insert Table 3.7 here]

Other analyst characteristics variables also exhibit significant associations with $Order$ as suggested by the prior literature. For example, analysts with favourable (unfavourable) stock recommendations ask earlier (later) questions, consistent with analysts with favourable views have stronger relationships with firm management (Mayew, 2008). Star analysts ask earlier questions, indicating that managers prefer high-quality analysts (Mayew, 2008; Rennekamp et al., 2019). Moreover, analysts who have more general experience and follow more industries ask later questions. This might be because these analysts focus more on macro-level industry trends thereby diverting their attention from any particular firm (Mayew, 2008).

3.5.2. Robustness tests

3.5.2.1. Downsizing the British ethnic group

This sub-section summarises a series of robustness tests. I start by dealing with the unbalanced sample size. Table 3.2 Panel C shows that 60% (65%) of sample analysts (analyst-firm-quarter observations) are in the British ethnic group, leading to the concern that the results might be driven by its outnumbered size. To mitigate such a concern, robustness checks are performed by randomly choosing 6% of the observations from the British ethnic group so that each of the groups has similar density. After the random downsizing, the British group has 9,388 observations. Using the downsized sample, I re-estimate the regressions in Tables 3.5 – 3.7. Results are presented in Table 3.8.

[Insert Table 3.8 here]

Column (1) re-estimates results in Table 3.5 to assess the relation between analysts' people skills and ingratiation behaviour during conference calls (i.e. Eq. (3.4) to test the construct validity of $PeopleSkills$). The coefficient on $PeopleSkills$ ($PeopleSkills^2$) is -0.500 (0.048) and statistically significant at the 1% level. In terms of sign, magnitude, and statistical significance, the coefficients on $PeopleSkills$ and $PeopleSkills^2$ are consistent with the results in Table 3.5.[27] Column (2) re-estimates Eq.

[27] Note that the regressions in Table 3.8 columns (1) and (3) are estimated using the sub-sample of analysts that participate in conference calls. Therefore, the sample size is smaller than in column (2). In columns (1) and (3), the British ethnic group has 3,183 observations after the random downsizing.

(3.1) to examine the relation between analysts' people skills and conference call participation probability. The coefficient on $PeopleSkills$ is positive (0.082) and statistically significant at the 1% level, consistent with the results in Table 3.6. Column (3) re-estimates Eq. (3.3) to test H2 which posits that analysts with better people skills ask earlier questions during conference calls. The coefficient on $PeopleSkills$ is negative (-0.046) and statistically significant at the 1% level, supporting the results in Table 3.7.

Collectively, results in Table 3.8 show that the findings on the association between analysts' people skills and ingratiation behaviour and the association between people skills and management relationships are not driven by the outnumbered size of the British ethnic group.

3.5.2.2. Additional controls

Next, I re-estimate the main results by considering whether managers' ethnicity and analyst name fluency affect the relation between analysts' people skills and analyst-manager relationships. Prior economics studies show that commonalities in ethnic origins and cultural background promote interaction and communication (e.g. Lazear, 1999; Guiso et al. 2009; Fisman et al., 2017). Therefore, analysts who share a common ethnicity with members in the management team may have an advantage in establishing a superior management relationship. This is a particularly important factor because the $PeopleSkills$ measure is constructed based on analysts' ethnic cultural traits. To measure analyst-manager common ethnicity, the variable $SameEthnicity$ is constructed. It takes the value of 1 if the analyst shares common ethnicity with at least one manager in the conference call; and 0 if the analyst shares common ethnicity with no manager in the call.

In terms of analyst name fluency, psychology research shows that fluency increases cognitive operations and information processing (Hertwig et al., 2008; Oppenheimer, 2008). Easy-to-pronounce names (and their bearers) are judged more positively than difficult-to-pronounce names in social interactions (Laham et al., 2012). Finance research provides evidence that investors judge firms and stocks with more fluent names more positively than those with less fluent names (e.g. Green and Jame, 2013; Anderson and Larkin, 2019). According to this line of research, one may expect analyst name fluency to affect how they are perceived by managers and, hence, their management relationships. Therefore, I follow Green and Jame (2013) to construct the measure $Fluency$ to control for the potential effects of analyst name fluency. $Fluency$ is the aggregate fluency score of an analyst's last name based on three dimensions: $Length$, $Englishness$ and $Dictionary$. Details of these three dimensions are explained in Appendix 3.1. A higher value of $Fluency$ denotes that the analyst has a more fluent name.

In Table 3.9 Panel A, Eq. (3.1) is re-estimated by controlling for $SameEthnicity$ and $Fluency$. The dependent variable is the probability of conference call participation. Column (1) controls for $SameEthnicity$. The coefficient on $PeopleSkills$ is positive (0.067) and statistically significant at the 1% level. That is, in terms of sign, magnitude, and statistical significance, the coefficient on $PeopleSkills$ is consistent with the results in Table 3.6. The coefficient on $SameEthnicity$ is positive (0.046) and statistically significant at the 5% level. This suggests that analysts who share common ethnic backgrounds with managers are more likely to get conference call participation. Column (2) further adds in $Fluency$ as a control variable. The coefficient on $PeopleSkills$ remains positive (0.068) and statistically significant at the 1% level. The coefficient on $SameEthnicity$ remains positive (0.045) and significant at the 5% level. The coefficient on $Fluency$ is positive (0.010) and marginally significant at the 10% level. This indicates that analysts with more fluent names have a higher probability of participating in conference calls.

[Insert Table 3.9 here]

In Table 3.9 Panel B, Eq. (3.3) is re-estimated with controlling for $SameEthnicity$ and $Fluency$. The dependent variable is the order of questions in the Q&A section of conference calls. In column (1), after controlling for $SameEthnicity$, the coefficient on $PeopleSkills$ is negative (-0.043) and statistically significant at the 1% level. The coefficient on $SameEthnicity$ is positive (0.067), but not statistically significant. Column (2) further controls for $Fluency$. The coefficient on $PeopleSkills$ remains negative (-0.041) and statistically significant at the 1% level, consistent with the results in Table 3.7. The coefficient on $Fluency$ is positive (0.015), but not statistically significant, indicating that analyst name fluency does not significantly affect the order of questions. These results suggest that analysts with better people skills ask earlier questions during conference calls after controlling for same ethnicity with managers and name fluency.

Collectively, results in Table 3.9 further support the main findings that analysts with better people skills have closer relationships with firm management.

3.5.2.3. Heckman two-stage procedure for estimating the order of questions

My final robustness test considers the selection bias in estimating the order of analyst questions in Eq. (3.3). To estimate Eq. (3.3), the regressions in Table 3.7 are performed using the sub-sample of analysts who participate in conference calls. This sub-sample does not represent a random selection of analysts, leading to the concern that the selection bias may confound my results. To address this concern, I perform a robustness check that controls for potential self-selection bias (Heckman, 1979) to assess whether my results are sensitive to conditioning the sample on conference call participation.

The Heckman (1979) two-stage procedure uses the inverse Mills ratio to correct for the selection bias. Specifically, in the first stage, I re-estimate Eq. (3.1) using a probit model specification to estimate the inverse Mills ratio. The first-stage regression needs to be estimated using probit, which assumes a normal distributed error term (Lennox et al., 2011). In the second stage, I test the relation between analysts' people skills and conference call question order by re-estimating Eq. (3.3) with including the inverse Mills ratio as an additional control variable. Results (untabulated) are consistent with those in Table 3.7, suggesting the finding that analysts with better people skills ask earlier questions in conference calls is robust to controlling for the first-stage selection bias.

3.6. Implications: Do analysts benefit from better people skills?

Findings to this point have established that analysts with better people skills have closer relationships with firm management. An unsolved issue is whether analysts with better people skills benefit from their closer relationships with managers in the form of acquiring superior firm-specific information. Understanding the extent to which analysts benefit from better people skills is crucial for practitioners. If some analysts suffer from an information disadvantage due to their lack of people skills, people skills training may represent a valuable component of financial analysts' career development.

Empirically, one might expect analysts with better people skills to possess superior firm-specific information because of their closer relationships with managers.

There is evidence that analysts with better management relationships have access to superior private information and, hence, produce more accurate earnings forecasts (e.g. Mayew et al. 2013; Soltes, 2014; Brown et al., 2015). To investigate this issue, it would be ideal to measure the extent of private information exchange between different analysts and managers. Unfortunately, such events are unobservable. Therefore, I focus on whether analyst-management relationship (proxied by conference call participation) has mediation effects on the relation between analysts' people skills and forecast accuracy. The assumption is that analysts who possess more superior private information produce more accurate earnings forecasts. I perform mediation analysis using the following regressions:

$$\begin{aligned} ForAcc_{a,i,q} = \ & \alpha_0 + \alpha_1 PeopleSkills_a + \alpha_2 Sbuy_{a,i,q} + \alpha_3 Buy_{a,i,q} + \alpha_4 Sell_{a,i,q} \\ & + \alpha_5 Ssell_{a,i,q} + \alpha_6 Allstar_{a,i,q} + \alpha_7 PriorAcc_{a,i,q} + \alpha_8 FirmExp_{a,i,q} \\ & + \alpha_9 GenExp_{a,i,q} + \alpha_{10} Inds_{a,i,q} + \alpha_{11} ForFreq_{a,i,q} \\ & + \alpha_{12} BrokerSize_{a,i,q} + \alpha_{13} Companies_{a,i,q} + \alpha_{14} RecHorizon_{a,i,q} \\ & + \alpha_{15} MAS_a + \alpha_{16} UAI_a + \alpha_{17} LTOWVS_a + \alpha_{18} IVR_a + \Sigma Firm\ FE \\ & + \Sigma YrQtr\ FE + \varepsilon_{a,i,q} \end{aligned} \tag{3.5}$$

$$\begin{aligned} ForAcc_{a,i,q} = \ & \alpha_0 + \alpha_1 PeopleSkills_a + \alpha_2 Participate_{a,i,q} + \alpha_3 Sbuy_{a,i,q} \\ & + \alpha_4 Buy_{a,i,q} + \alpha_5 Sell_{a,i,q} + \alpha_6 Ssell_{a,i,q} + \alpha_7 Allstar_{a,i,q} \\ & + \alpha_8 PriorAcc_{a,i,q} + \alpha_9 FirmExp_{a,i,q} + \alpha_{10} GenExp_{a,i,q} + \alpha_{11} Inds_{a,i,q} \\ & + \alpha_{12} ForFreq_{a,i,q} + \alpha_{13} BrokerSize_{a,i,q} + \alpha_{14} Companies_{a,i,q} \\ & + \alpha_{15} RecHorizon_{a,i,q} + \alpha_{16} MAS_a + \alpha_{17} UAI_a + \alpha_{18} LTOWVS_a \\ & + \alpha_{19} IVR_a + \Sigma Firm\ FE + \Sigma YrQtr\ FE + \varepsilon_{a,i,q} \end{aligned}$$

(3.6)

where $ForAcc$ is defined as peer-adjusted forecast accuracy of an analyst's quarterly earnings forecast issues during the fiscal quarter after the current-quarter conference call. It is calculated as the largest after-call quarter absolute forecast error by an analyst following firm i minus the after-call quarter absolute forecast error for analyst a following firm i, with this difference scaled by the range in the after-call quarter absolute forecast error for all analysts following firm i. The earnings forecast is required to be issued after the call because conference call participation ($Participate$) is the empirical proxy for analyst-management relationships (Mayew et al., 2013). If superior private information stems from strong management relationships, access to superior private information should be measured after the conference call (i.e. after participation/non-participation happens).

If analysts with better people skills possess superior private information, the coefficient $\alpha_1$in Eq. (3.5) and the coefficient α_1 in Eq. (3.6) are expected to be positive. If these analysts obtain superior private information through their close relationships with managers, the coefficient α_2 in Eq. (3.6) is expected to be positive and the magnitude of coefficient $\alpha_1$in Eq. (3.5) is expected to be greater than that in Eq. (3.6).

Mediation analysis results are presented in Table 3.10. Panel A estimates stepwise by first examining the effects of people skills on forecast accuracy without controlling for conference call participation (i.e. Eq. (3.5)) in column (1). The coefficient on $PeopleSkills$ is positive (0.842) and statistically significant at the 1% level, indicating that analysts with better people skills issue more accurate earnings forecasts. Having established that analysts' people skills are positively associated with forecast accuracy, column (2) includes both $PeopleSkills$ and $Participate$ in the regression model to estimate Eq. (3.6). The coefficient on $Participate$ is positive (0.510) and statistically significant at the 5% level. The coefficient on $PeopleSkills$ remains positive (0.836) and statistically significant at the 1% level. The slight decrease in the magnitude of the coefficient on $PeopleSkills$ compared with column (1) (0.836 vs 0.842) suggests some mediating effects of $Participate$, consistent with prediction. Nonetheless, it is not perfect mediation since the coefficient on $PeopleSkills$ remains statistically different from zero.

[Insert Table 3.10 here]

To formally test whether the mediation effect of $Participate$ is statistically significant, the Sobel's (1982) test, Aroian's (1944) test, and Goodman's (1960) test are conducted (MacKinnon and Dwyer, 1993; MacKinnon et al., 1995). The intention of these tests is to assess whether the reduction in the effect of $PeopleSkills$ on $ForAcc$ is statistically significant after including the mediator (i.e. $Participate$) in the regression model. The test statistics are calculated using the coefficient and standard error for the association between $PeopleSkills$ and $Participate$ as well as those for the association between $Participate$ and $ForAcc$.[28] Results are presented in Table 3.10 Panel B. All three mediation tests yield a p-value below 0.05, indicating that the mediating effects of $Participate$ is statistically different from zero.

Collectively, the mediation analysis suggests that analysts with better people skills possess superior private information, which partly stems from their close relationships with firm management.

[28] The tests utilize the online test tool by Preacher (2001) at: http://quantpsy.org/sobel/sobel.htm.

Furthermore, I consider whether analysts with better people skills benefit from better career outcomes. Two types of career outcomes are considered, i.e. the probability of being rated as an All-Star analyst and the probability of being re-employed after brokerage house closures. Results (untabulated) show no statistically significant association between people skills and either career outcomes. This indicates that, although analysts with better people skills enjoy informational benefits, the effects are not sufficient enough to generate better career outcomes.

3.7. Conclusion

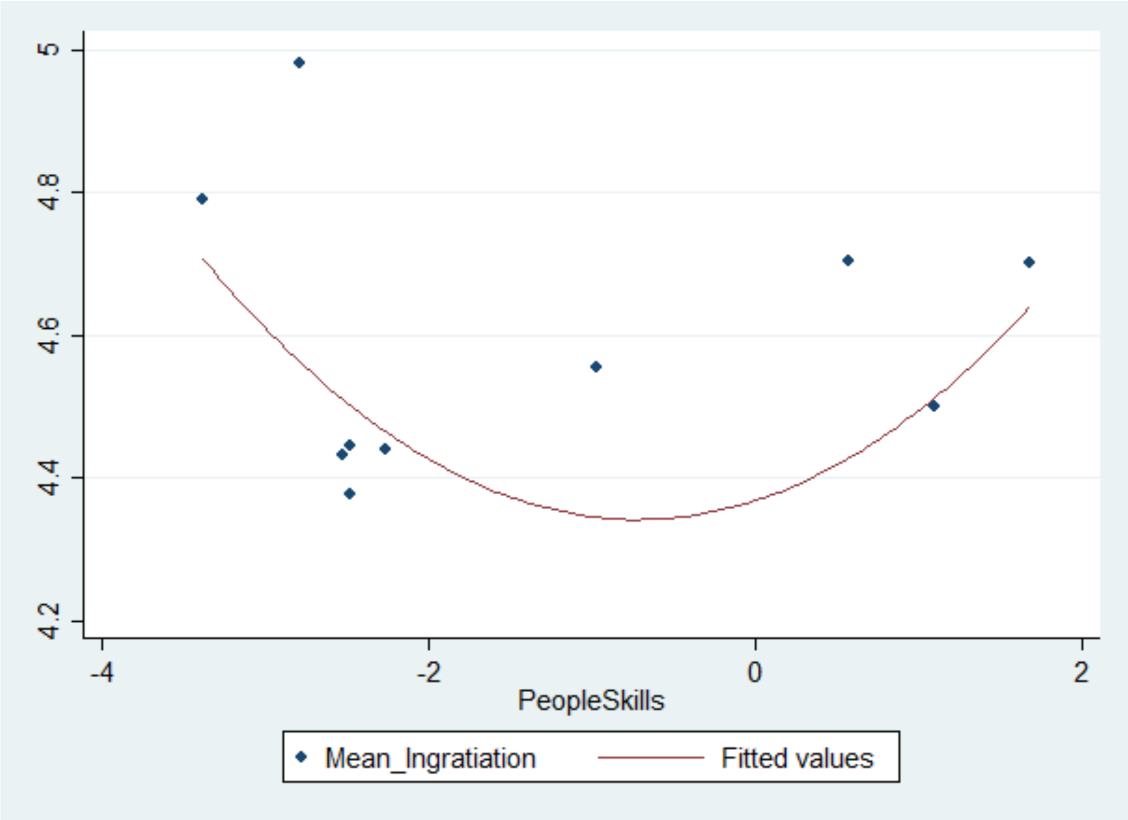
This chapter provides evidence on whether and how people skills affect sell-side analysts' outcomes. The investigation is motivated by the recent development in the economics literature that identifies the value of people skills in the labour market (e.g. Borghans et al., 2014; Deming, 2017; Deming and Kahn, 2018). Empirically assessing the effects of analysts' people skills is important because analysts' work requires them to maintain good management relationships. However, operationalizing people skills is difficult. I rely on psychology and sociolinguistics research to conceptualize and validate an operational proxy for the construct. Empirically, analysts' people skills are measured by combining three ethnic cultural traits: individualism, trust and power distance. The empirical proxy is validated by tests that link it to analysts' linguistic behaviour during conference calls.

Collectively, the results speak to the role of people skills in the analyst labour market. Using the earnings conference call setting to observe analysts-management relationships, results show that analysts with better people skills are more likely to participate in conference calls and ask earlier questions in the Q&A section. This supports the notion that analysts with better people skills are able to establish and maintain closer management relationships. The analysis then assesses whether analysts with better people skills benefit from their close management relationships and possess superior private information. Empirically, I model analyst forecast accuracy as a function of people skills and conference call participation and tests for the mediation effects of call participation. Mediation analysis suggests that analysts with better people skills possess superior private information, which is partly facilitated by their closer relationships with firm management.

The inferences are subject to the caveat that analysts' people skills are measured indirectly using their ethnic cultural traits. This assumes that on average analysts do not experience significant variations in people skills throughout their lifetime. The inferences are also limited by the extent to which the empirical proxies can accurately capture analyst-manager relationships, which is unobservable in nature. For example, analysts' conference call participation is affected by both management's preferences for friendly analysts and analysts' willingness to seek participation. The inferences are only as valid as the effectiveness of controlling for analysts' willingness to participate.

With these caveats in mind, the results add to the existing literature by providing the first evidence on the effects of people skills in the sell-side analyst labour market. In addition, given the recent growing attention on the value of people skills for financial professionals, the findings also have implications for practitioners.

FIGURE 1. Scatterplot of Mean Values of Ingratiation ($Mean\_Ingratiation$) by Analysts' People Skills ($PeopleSkills$)



This figure plots the relation between the mean value of $Ingratiation$ and $PeopleSkills$. All variables are defined in Appendix 3.1.

Appendix 3.1. Variable Definitions

People skills variable

Variables	Definitions
$PeopleSkills$	Analysts' people skills measured as the first principal component of an analyst's three ethnic cultural traits: individualism, trust and power distance.

Analyst-level variables

Variables	Definitions
$Participate$	Analyst participation on the conference call measured as 1 if the analyst asked a question during the call, and 0 otherwise.
$Order$	The order of which analysts ask questions in a conference call. It is measured as 1 if the analyst asks the first question, 2 if the second, etc.
$Ingratiation$	Analysts' ingratiation behaviour in a conference call measured as the total number of ingratiation words scaled by the total number of words by that analyst (expressed as a percentage).
$Sbuy$	Strong buy recommendation measured as 1 if I/B/E/S most recent outstanding stock recommendation prior to the conference call is a strong buy, and 0 otherwise.
Buy	Buy recommendation measured as 1 if I/B/E/S most recent outstanding stock recommendation prior to the conference call is a buy, and 0 otherwise.
$Hold$	Hold recommendation measured as 1 if I/B/E/S most recent outstanding stock recommendation prior to the conference call is a hold, and 0 otherwise.
$Sell$	Sell recommendation measured as 1 if I/B/E/S most recent outstanding stock recommendation prior to the conference call is a sell, and 0 otherwise.
$Ssell$	Strong sell recommendation measured as 1 if I/B/E/S most recent outstanding stock recommendation prior to the conference call is a strong sell, and 0 otherwise.
$AllStar$	All-star research analyst measured as 1 if the analyst made any of the Institutional Investor Research All-American teams at least once during the sample period, and 0 otherwise.

Appendix 3.1. (Continued)

$PriorAcc$	Prior earnings forecast accuracy, measured as the relative absolute forecast accuracy of the analyst's prior quarter earnings forecast. Relative absolute forecast accuracy is calculated as the largest prior quarter forecast error by an analyst following firm i in quarter t minus the prior quarter absolute forecast error for analyst a following firm i in quarter q, with this difference scaled by the range in the prior quarter absolute forecast error for all analysts following firm i in quarter q.
$FirmExp$	Firm experience measured as the relative time the analyst has covered the firm, where firm coverage is measured as the number of days between the conference call date and the analyst's first earnings forecast estimate date on I/B/E/S for the firm. Relative firm experience is calculated as the firm experience for analyst a following firm i in quarter q minus the smallest firm experience by any analyst following firm i in quarter q, with this difference scaled by the range in the firm experience for all analysts following firm i in quarter q.
$GenExp$	General experience measured as the relative time the analyst has been on I/B/E/S where time on I/B/E/S is measured as the number of days between the conference call date and the analyst's first earnings forecast estimate date on I/B/E/S for any firm. Relative general experience is calculated as the general experience for analyst a following firm i in quarter q minus the smallest general experience by any analyst following firm i in quarter q, with this difference scaled by the range in the general experience for all analysts following firm i in quarter q.
$Inds$	Industry coverage measured as the relative number of industries covered by the analyst over the most recently completed calendar year prior to the conference call date. Relative industry coverage is calculated as the industry coverage of analyst a following firm i in quarter q minus the smallest industry coverage by any analyst following firm i in quarter q, with this difference scaled by the range in industry coverage for all analysts following firm i in quarter q.
$ForFreq$	Forecast frequency measured as the relative number of quarterly earnings forecasts issued by the analyst for the firm over the most recently completed calendar year prior to the conference call date. Relative forecast frequency is calculated as the forecast frequency for analyst a following firm i in quarter q minus the lowest forecast frequency by any analyst following firm i in quarter q, with this difference scaled by the range in the forecast frequency for all analysts following firm i in quarter q.

Appendix 3.1. (Continued)

$BrokerSize$	Broker size measured as the relative number of analysts employed by the brokerage firm employing the analyst during the most recent calendar year prior to the conference call date. Relative broker size is calculated as the broker size for analyst a following firm i in quarter q minus the smallest broker size of any analyst following firm i in quarter q, with this difference scaled by the range in broker size for all analysts following firm i in quarter q.
$Companies$	Number of companies covered by the analyst during the most recently completed calendar year prior to the conference call date.
$CCuser$	For analyst a following firm i at fiscal quarter q, equals the total number of conference calls (excluding firm i) in which analyst a participated during the calendar quarter containing fiscal quarter for firm i.
$PriorParticipate$	Prior conference call participation measured as 1 if the analyst was identified as asking a question on any of the firm's prior conference calls in the sample, and 0 otherwise.
$RecHorizon$	Recommendation horizon measured as the number of days between the conference call date and the date of the analyst's most recent stock recommendation.
$SameEthnicity$	Analyst-management ethnicity match measured as 1 if the analyst has the same ethnicity with at least one manager in call; 0 if the analyst has same ethnicity with no manager in call.
$Fluency$	Analyst last name aggregate fluency score measured as the sum of the $Length$, $Englishness$ and $Dictionary$ scores, following Green and Jame (2013).
$Length$	Analyst last name length score. Analyst names fall into the top, middle and bottom tercile of length measured by number of letters are assigned a $Length$ score of 3, 2 and 1, respectively.
$Englishness$	Analyst last name Englishness score measured following Green and Jame (2013) and Travers and Olivier (1978). Analyst names fall into the bottom quintile of length-adjusted Englishness are assigned an $Englishness$ score of 0, and all others are assigned an Englishness score of 1.
$Dictionary$	Analyst last name fluency measured by ease of pronunciation following Green and Jame (2013). Analyst names pass Microsoft Word spell check in all lowercases are assigned a $Dictionary$ score of 1, and all others are assigned a $Dictionary$ score of 0.

Appendix 3.1. (Continued)

$ForAcc$	Forecast accuracy for the quarter after the conference call, measured as the relative absolute forecast accuracy of the analyst's quarterly earnings forecast for the quarter after the call. Relative absolute forecast accuracy is calculated as the largest after-call quarter forecast error by an analyst following firm i in quarter q minus the after-call quarter absolute forecast error for analyst a following firm i in quarter q, with this difference scaled by the range in the after-call quarter absolute forecast error for all analysts following firm i in quarter q.

Conference call-level variables

Variables	Definitions
$QAmin$	Length of the Q&A section of the conference call in minutes (where minutes are derived from total word count of transcript at 150 words per minute).
$NumAnalyst$	Number of sample analysts providing earnings forecasts and recommendations on I/B/E/S for the current quarter.

Ethnicity-level cultural variables

Variables	Definitions
MAS	Masculinity culture score in Hofstede cultural index.
UAI	Uncertainty avoidance culture score in Hofstede cultural index.
$LTOWVS$	Long- vs. short-term orientation culture score in Hofstede cultural index.
IVR	Indulgence vs. Restraint culture score in Hofstede cultural index.

This appendix presents variable definitions in Chapter 3.

Appendix 3.2. Ethnicity and Countries/Regions

Ethnicity	Countries / Regions
Greater European, British	U.S.A.; Great Britain; Australia; Canada; Ireland; New Zealand
Greater European, West European, Hispanic	Argentina; Brazil; Chile; Colombia; Costa Rica; Ecuador; El Salvador; Guatemala; Panama; Peru; Uruguay; Mexico; Venezuela; Spain; Portugal
Greater European, West European, Nordic	Belgium Netherland; Denmark; Finland; Norway; Sweden
Greater European, West European, Germanic	Germany; Switzerland German
Greater European, East European	Bulgaria; Croatia; Czech Rep; Estonia; Hungary; Poland; Romania; Russia; Slovak Rep; Slovenia
Greater African, Africans	Africa East; Africa West; Jamaica; Morocco
Greater African, Muslim	Arab countries; Turkey; Iran; Iraq
Asian, Greater East Asian, Japanese	Japan
Asian, Greater East Asian, East Asian	Taiwan; Thailand; Vietnam; Singapore; Philippines; South Korea; Malaysia; China; Hong Kong; Indonesia
Asian, Indian Sub-Continent	India

This appendix presents countries/regions included in each ethnic group for the calculation of culture scores.

Appendix 3.3. Ingratiation dictionary

To empirically measure analysts' ingratiation in conference calls, an ingratiation dictionary is developed through an extensive reading of conference calls transcripts and following prior literature on analysts' complimentary behaviour during the calls (Milian and Smith, 2017) and psychology research (e.g. Ellis et al., 2002; Vonk, 2002; Seiter, 2007). The dictionary contains six categories of words that captures different aspects of ingratiation:

1. Praises. Following Milian and Smith's (2017) method, the wordlist of praise phrases contains a positive adjective precedes a noun related to firm performance. The wordlist contains all potential pairing of 18 adjectives and 10 nouns. The adjectives are: "great", "good", "excellent", "nice", "fantastic", "remarkable", "incredible", "impressive", "tremendous", "solid", "outstanding", "terrific", "amazing", "phenomenal", "strong", "superb", "super" and "stellar". The nouns are: "quarter", "year", "fiscal year", "job", "work", "execution", "results", "print" and "number". The measure allows the noun "quarter" to be preceded by the words "first", "second", "third", or "fourth". Moreover, a praise phrase is not counted if one of the six negation words (i.e. "no", "not", "none", "neither", "never", or "nobody") occur within the three words preceding the phrase.

2. Greetings. This category contains the following words/phrases: "hello", "hi", "hey", "greeting", "greetings", "good day", "good morning", "good afternoon", "good evening", "good night", "how are you", "how have you been".

3. Congratulations. This category contains the following words: "congrat", "congrats", "congratulate", "congratulates", "congratulation", "congratulations".

4. Thanks. This category contains the following words: “thank”, “thanks”, “thankful”, “appreciate”, “appreciated”, “appreciation”, “cheers”, “appreciative”, “gratitude”, “grateful”.

5. Laughter. This category contains the following words: “laugh”, “laughter”, “laughing”, “joke”, “joking”, “kidding”.

6. The word “*please*”.

Table 3.1. Sample

Number of transcripts in English of Compustat firms between 2011-2015 from Thomson Reuters Eikon	54,644
Number of transcripts after excluding: Transcripts of non-U.S. firms	40,418
Number of transcripts after excluding: Transcripts with no I/B/E/S outstanding stock recommendation	39,040
Number of transcripts after excluding: Transcripts with no I/B/E/S analysts having current quarterly earnings forecast or earnings estimates outstanding for less than 365 days	38,271
Number of transcripts after excluding: Transcripts with no I/B/E/S analysts having data available to calculate analyst attributes	**31,980**
Number of analyst-firm-quarter observations in the final sample	**239,153**

This table presents the process of sample construction. The sample spans the time period January 2011 to December 2015 and covers a total of 31,980 quarterly earnings conference call transcripts and 239,153 analyst-firm-quarter observations.

Table 3.2. Construction of People Skills Variable: Principal Component Analysis

Panel A. Components

Component	Eigenvalue	Difference	Proportion	Cumulative
Component 1	2.77	2.61	0.92	0.92
Component 2	0.16	0.10	0.06	0.98
Component 3	0.06	.	0.02	1.00

Panel B. Component loadings

Variable	Component 1	Component 2	Component 3	Unexplained
Individualism	0.58	-0.60	0.55	0
Power distance	-0.59	0.17	0.79	0
Trust	0.57	0.78	0.26	0

Panel C. $PeopleSkills$ and sample distribution by ethnicity

Ethnicity	$PeopleSkills$ (Component 1)	Number of Analysts	%	Analyst-firm-quarter observations	%
Hispanic	-3.37	122	4.13	7,555	3.16
African	-2.78	70	2.37	4,826	2.02
East Asian	-2.51	233	7.88	13,982	5.85
Indian Sub-continent	-2.47	289	9.78	21,747	9.09
Muslim	-2.46	116	3.93	8,653	3.62
East European	-2.26	149	5.04	11,684	4.89
Japanese	-0.96	60	2.03	4,389	1.84
Germanic	0.58	87	2.94	6,329	2.65
British	1.09	1,762	59.63	156,462	65.42
Nordic	1.69	67	2.27	3,526	1.47
Total	.	2,955	100.00	239,153	100.00

This table presents the construction of the people skills variable (denoted as $PeopleSkills$), which is measured as the first principal component of the following three culture traits: individualism, power distance and trust. Panel A reports the components from principal component analysis. Panel B reports component loadings. Panel C reports $PeopleSkills$ and sample distribution by ethnicity. All variables are defined in Appendix 3.1.

Table 3.3. Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1)*PeopleSkills*	1.00	0.02***	-0.01***	-0.01***	0.00	0.01***	-0.01***	0.01***	-0.01***	0.05***	0.08***	0.02***	-0.01***	0.02***	-0.06***	0.04***	0.05***	0.00
(2)*Participate*	0.02***	1.00	0.01***	0.07***	0.06***	-0.09***	-0.04***	-0.03***	0.00	0.02***	-0.01***	0.00	0.07***	0.08***	0.09***	0.03***	0.39***	0.34***
(3)*Order*	-0.02***	0.01**	1.00	-0.05***	-0.07***	0.09***	0.05***	0.03***	0.02***	-0.10***	-0.02***	-0.06***	-0.03***	-0.07***	-0.07***	-0.08***	-0.05***	-0.06***
(4)*Sbuy*	-0.01***	0.07***	-0.05***	1.00	-0.33***	-0.46***	-0.11***	-0.05***	0.00	0.02***	0.00	0.01***	-0.04***	-0.03***	-0.03***	-0.03***	0.00***	0.05***
(5)*Buy*	0.00	0.06***	-0.07***	-0.33***	1.00	-0.57***	-0.14***	-0.06***	0.00***	0.01***	0.01***	-0.01***	-0.02***	0.05***	-0.05***	-0.01***	-0.02***	0.01***
(6)*Hold*	0.01***	-0.09***	0.09***	-0.46***	-0.57***	1.00	-0.19***	-0.09***	0.00	-0.03***	-0.01***	0.00	0.02***	-0.01***	0.02***	0.02***	0.02***	-0.04***
(7)*Sell*	-0.01***	-0.04***	0.04***	-0.11***	-0.14***	-0.19***	1.00	-0.02***	-0.01***	-0.02***	-0.01***	0.02***	0.07***	0.00	0.11***	0.03***	0.01***	-0.02***
(8)*Ssell*	0.01***	-0.03***	0.04***	-0.05***	-0.06***	-0.09***	-0.02***	1.00	0.00**	0.01***	0.01***	0.00***	0.01***	-0.02***	-0.03***	-0.01***	-0.01***	-0.02***
(9)*PriorAcc*	-0.01***	-0.01***	0.04***	-0.01***	0.01***	0.00**	-0.01***	0.00	1.00	0.00	0.00	-0.02***	0.00	-0.01***	-0.01***	-0.01***	0.00**	0.00
(10)*FirmExp*	0.05***	0.02***	-0.11***	0.03***	0.01***	-0.03***	-0.02***	0.01***	-0.01***	1.00	0.44***	0.05***	0.09***	0.12***	0.00*	0.14***	0.07***	0.13***
(11)*GenExp*	0.07***	-0.01***	-0.03***	0.00	0.01***	-0.01***	-0.01***	0.00*	-0.01***	0.42***	1.00	0.12***	0.13***	0.00	-0.04***	0.24***	0.10***	0.03***
(12)*Inds*	0.02***	0.00	-0.07***	0.01***	-0.01***	0.00***	0.02***	-0.01***	-0.02***	0.05***	0.12***	1.00	0.08***	0.02***	0.01***	0.42***	0.14***	0.01***
(13)*AllStar*	0.00	0.07***	-0.03***	-0.04***	-0.02***	0.02***	0.07***	0.01***	0.01***	0.09***	0.12***	0.07***	1.00	-0.04***	0.27***	0.18***	0.18***	0.07***
(14)*ForFreq*	0.02***	0.08***	-0.08***	-0.03***	0.05***	-0.02***	0.00	-0.02***	-0.02***	0.09***	-0.01***	0.01***	-0.04***	1.00	0.07***	0.06***	0.09***	0.12***
(15)*BrokerSize*	-0.06***	0.08***	-0.08***	-0.02***	-0.04***	0.02***	0.12***	-0.03***	-0.01***	0.00	-0.04***	0.01***	0.28***	0.07***	1.00	0.14***	0.15***	0.11***
(16)*Companies*	0.03***	0.02***	-0.09***	-0.03***	0.00**	0.01***	0.03***	-0.01***	-0.01***	0.14***	0.23***	0.43***	0.18***	0.05***	0.14***	1.00	0.32***	0.05***
(17)*CCuser*	0.05***	0.35***	-0.05***	-0.02***	-0.01***	0.02***	0.01***	-0.01***	-0.01***	0.06***	0.08***	0.14***	0.19***	0.08***	0.14***	0.33***	1.00	0.37***
(18)*PriorParticipate*	0.00	0.34***	-0.06***	0.05***	0.01***	-0.04***	-0.02***	-0.02***	-0.01***	0.12***	0.03***	0.01***	0.07***	0.12***	0.11***	0.04***	0.33***	1.00

This table presents the correlations among analysts' people skills, analyst-management relationship variables, and analyst characteristics variables. Spearman (Pearson) correlations appear above (below) the diagonal. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix 3.1.

Table 3.4. Descriptive Statistics: Mean Values of Variables

	$PeopleSkills$				
	Low (Hispanic, African, East Asian)	Medium (Indian Sub-continent, Muslim, East European, Japanese)	High (Germanic, British, Nordic)	Full sample	p-value for difference between Low and High
$Participate$	0.32	0.34	0.35	0.35	0.01^{***}
$Order$	5.18	5.14	5.02	5.06	0.01^{***}
$Sbuy$	0.23	0.21	0.21	0.21	0.01^{***}
Buy	0.30	0.29	0.29	0.29	0.44
$Hold$	0.42	0.44	0.44	0.44	0.01^{***}
$Sell$	0.04	0.05	0.05	0.05	0.01^{***}
$Ssell$	0.01	0.01	0.01	0.01	0.04^{**}
$PriorAcc$	0.63	0.63	0.63	0.63	0.09^{*}
$FirmExp$	0.41	0.39	0.44	0.43	0.01^{***}
$GenExp$	0.40	0.38	0.44	0.42	0.01^{***}
$Inds$	0.34	0.37	0.37	0.36	0.01^{***}
$AllStar$	0.10	0.12	0.11	0.11	0.01^{***}
$ForFreq$	0.37	0.39	0.40	0.39	0.01^{***}
$BrokerSize$	0.45	0.43	0.39	0.40	0.01^{***}
$Companies$	0.43	0.45	0.46	0.46	0.01^{***}
$CCuser$	4.18	4.48	4.78	4.65	0.01^{***}
$PriorParticipate$	0.72	0.74	0.73	0.73	0.01^{***}

This table presents the means of analyst-management relationship variables and analyst characteristics variables according to people skills. The last column presents the t-test statistic of the difference of the means between the highest people skills group and the lowest people skills group. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix 3.1.

Table 3.5. Analysts' People Skills and Ingratiation

	(1)	(2)	(3)
	$Ingratiation$	$Ingratiation$	$Ingratiation$
$PeopleSkills$	-0.116***	-0.116***	-0.549***
	(-4.94)	(-4.91)	(-7.01)
$PeopleSkills^2$	0.010***	0.010***	0.053***
	(5.07)	(5.11)	(6.95)
$Sbuy$		0.037*	0.033*
		(1.83)	(1.66)
Buy		-0.037**	-0.037**
		(-2.00)	(-1.99)
$Sell$		-0.014	-0.011
		(-0.32)	(-0.25)
$Ssell$		-0.181**	-0.170*
		(-2.03)	(-1.92)
$AllStar$		-0.054**	-0.056**
		(-2.12)	(-2.17)
$PriorAcc$		0.009	0.008
		(0.42)	(0.39)
$FirmExp$		-0.063**	-0.062**
		(-2.05)	(-2.01)
$GenExp$		-0.116***	-0.108***
		(-4.10)	(-3.83)
$Inds$		0.125***	0.118***
		(4.35)	(4.07)
$ForFreq$		-0.071***	-0.066***
		(-2.79)	(-2.59)
$BrokerSize$		-0.079***	-0.083***
		(-3.26)	(-3.41)
$Companies$		0.065**	0.056*
		(1.98)	(1.71)
$CCuser$		-0.012***	-0.011***
		(-4.95)	(-4.60)
$PriorParticipate$		-0.090***	-0.091***
		(-2.69)	(-2.72)
$RecHorizon$		0.000	0.000
		(0.44)	(0.50)
MAS			0.007***
			(4.26)
UAI			0.0015**
			(2.06)
$LTOWVS$			-0.004***
			(-2.87)
IVR			-0.019***
			(-5.55)
Firm FE	Yes	Yes	Yes
Year-Qtr FE	Yes	Yes	Yes
N	80,160	80,160	80,160
Adjusted R^2	0.05	0.06	0.06

Table 3.5. (Continued)

This table presents the results of validating the operational construct of analysts' people skills by assessing the relation between the construct and analysts' ingratiation behaviour during conference calls using OLS regressions (i.e. Eq. (3.4)). The dependent variable, $Ingratiation$, is measured as the total number of ingratiation words scaled by the total number of words by that analyst (expressed as a percentage). The test variable, $PeopleSkills$, is measured as the first principal component of an analyst's three ethnic cultural traits: individualism, trust and power distance. t-statistics appear in parentheses and are based on standard errors clustered by firm-call. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix 3.1.

Table 3.6. Analysts' People Skills and Conference Call Participation Probability

	(1)	(2)	(3)	(4)
	Pr $(Participate)$	Pr $(Participate)$	Pr $(Participate)$	Pr $(Participate)$
$PeopleSkills$		0.018***	0.009***	0.071***
		(6.81)	(3.05)	(10.08)
$Sbuy$	0.549***		0.549***	0.549***
	(42.49)		(42.49)	(42.47)
Buy	0.503***		0.504***	0.502***
	(41.59)		(41.63)	(41.45)
$Sell$	-0.317***		-0.317***	-0.316***
	(-11.53)		(-11.52)	(-11.49)
$Ssell$	-0.123**		-0.123**	-0.127***
	(-1.99)		(-2.00)	(-2.05)
$QAmin$	0.027***		0.027***	0.027***
	(40.42)		(40.42)	(40.38)
$NumAnalyst$	-0.021***		-0.021***	-0.021***
	(-47.02)		(-46.97)	(-47.01)
$AllStar$	0.135***		0.136***	0.149***
	(7.72)		(7.73)	(8.45)
$PriorAcc$	0.030*		0.030***	0.030**
	(1.95)		(1.98)	(1.98)
$FirmExp$	-0.116***		-0.117***	-0.117***
	(-6.48)		(-6.55)	(-6.52)
$GenExp$	-0.180***		-0.183***	-0.186***
	(-10.27)		(-10.42)	(-10.53)
$Inds$	-0.143***		-0.142***	-0.148***
	(-8.25)		(-8.21)	(-8.52)
$ForFreq$	0.169***		0.168***	0.165***
	(10.34)		(10.25)	(10.05)
$BrokerSize$	0.188***		0.191***	0.188***
	(11.88)		(12.05)	(11.84)
$Companies$	-0.810***		-0.811***	-0.803***
	(-37.90)		(-37.93)	(-37.52)
$CCuser$	0.173***		0.173***	0.173***
	(117.91)		(117.65)	(117.83)
$PriorParticipate$	1.786***		1.787***	1.789***
	(108.40)		(108.41)	(108.47)
$RecHorizon$	-0.001***		-0.001***	-0.001***
	(-19.62)		(-19.61)	(-19.54)
MAS				-0.011***
				(-16.22)
UAI				0.004***
				(7.84)
$LTOWVS$				0.003***
				(4.31)
IVR				-0.002**
				(-2.23)
N	239,153	239,153	239,153	239,153
Pseudo R^2	0.19	0.00	0.19	0.19

Table 3.6. (Continued)

This table presents results from estimating the relation between analysts' people skills and conference call participation probability using logistic regressions (i.e. Eq. (3.1)). The dependent variable is the probability of conference call participation. $Participate$ is measured as 1 if the analyst asked a question during the call, and 0 otherwise. The test variable, $PeopleSkills$, is measured as the first principal component of an analyst's three ethnic cultural traits: individualism, trust and power distance. t-statistics appear in parentheses and are based on standard errors clustered by firm-call. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix 3.1.

Table 3.7. Analysts' People Skills and Conference Call Question Order

	(1)	(2)	(3)
	$Order$	$Order$	$Order$
$PeopleSkills$	-0.020***	-0.024***	-0.037**
	(-2.62)	(-3.28)	(-2.07)
$Sbuy$		-0.749***	-0.751***
		(-23.79)	(-23.86)
Buy		-0.885***	-0.888***
		(-30.36)	(-30.46)
$Sell$		0.693***	0.690***
		(10.64)	(10.59)
$Ssell$		1.264***	1.255***
		(7.84)	(7.79)
$AllStar$		-1.065***	-1.069***
		(-26.25)	(-26.39)
$PriorAcc$		-0.041	-0.040
		(-1.32)	(-1.29)
$FirmExp$		-0.656***	-0.659***
		(-15.07)	(-15.13)
$GenExp$		0.298***	0.296***
		(7.38)	(7.33)
$Inds$		0.079**	0.086**
		(2.05)	(2.23)
$ForFreq$		0.022	0.021
		(0.59)	(0.57)
$BrokerSize$		-1.080***	-1.081***
		(-28.55)	(-28.57)
$Companies$		-0.284***	-0.281***
		(-6.17)	(-6.10)
$CCuser$		-0.048***	-0.048***
		(-14.18)	(-14.25)
$PriorParticipate$		-0.635***	-0.636***
		(-13.46)	(-13.50)
$RecHorizon$		0.000	0.000
		(0.70)	(0.68)
MAS			-0.003
			(-1.55)
UAI			-0.003***
			(-2.65)
$LTOWVS$			0.008***
			(4.95)
IVR			0.004*
			(1.91)
Firm FE	Yes	Yes	Yes
Year-Qtr FE	Yes	Yes	Yes
N	80,160	80,160	80,160
Adjusted R^2	0.26	0.30	0.30

Table 3.7. (Continued)

This table presents results from estimating the relation between analysts' people skills and conference call question order using OLS regressions (i.e. Eq. (3.3)). The dependent variable, $Order$, is the order of questions in conference calls. $Order$ is as 1 if the analyst asks the first question, 2 if the second, etc. The test variable, $PeopleSkills$, is measured as the first principal component of an analyst's three ethnic cultural traits: individualism, trust and power distance. t-statistics appear in parentheses and are based on standard errors clustered by firm-call. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix 3.1.

Table 3.8. Robustness Tests: Downsized British Ethnic Group

	(1)	(2)	(3)
	$Ingratiation$	Pr ($Participate$)	$Order$
$PeopleSkills$	-0.500***	0.082***	-0.046**
	(-5.36)	(10.76)	(-2.06)
$PeopleSkills^2$	0.048***		
	(5.29)		
$Sbuy$	0.048	0.636***	-0.830***
	(1.29)	(30.82)	(-14.97)
Buy	-0.062*	0.583***	-0.928***
	(-1.93)	(30.01)	(-18.52)
$Sell$	-0.135**	-0.213***	0.619***
	(-2.02)	(-4.89)	(5.54)
$Ssell$	-0.054	-0.103	1.719***
	(-0.32)	(-1.03)	(5.92)
$AllStar$	0.040	0.167***	-0.801***
	(0.74)	(5.99)	(-10.67)
$PriorAcc$	0.048	-0.004	-0.068
	(1.27)	(-0.17)	(-1.29)
$FirmExp$	-0.012	-0.176***	-0.452***
	(-0.22)	(-6.15)	(-5.57)
$GenExp$	-0.224***	-0.263***	-0.231***
	(-4.31)	(-9.08)	(-3.04)
$Inds$	0.125**	-0.182***	0.421***
	(2.23)	(-6.45)	(6.01)
$ForFreq$	-0.075	0.167***	0.127*
	(-1.64)	(6.33)	(1.93)
$BrokerSize$	-0.115**	0.243***	-1.151***
	(-2.44)	(9.48)	(-16.38)
$Companies$	0.154***	-0.833***	-0.534***
	(2.61)	(-24.07)	(-6.43)
$CCuser$	-0.006	0.181***	-0.050***
	(-1.27)	(71.44)	(-8.26)
$PriorParticipate$	-0.006	1.806***	-0.601***
	(-0.11)	(68.34)	(-7.48)
$RecHorizon$	0.000	-0.001***	-0.000
	(0.23)	(-12.16)	(-0.70)
$QAmin$		0.027***	
		(26.48)	
$NumAnalyst$		-0.020***	
		(-30.15)	

Table 3.8. (Continued)

MAS	0.005**	-0.010***	-0.007***
	(2.38)	(-13.78)	(-3.35)
UAI	0.001	0.004***	-0.004***
	(0.70)	(7.38)	(-2.79)
$LTOWVS$	-0.003*	0.002***	0.011***
	(-1.78)	(3.04)	(5.82)
IVR	-0.017***	-0.001	0.005*
	(-4.21)	(-1.61)	(1.96)
Firm FE	YES	NO	YES
Year-Qtr FE	YES	NO	YES
N	30,196	30,196	92,079
Pseudo R^2	.	0.20	.
Adjusted R^2	0.08	.	0.34

This table presents results of robustness tests with downsized British Ethnic group. Column (1) presents the results on re-estimating Eq. (3.4). Column (2) presents the results on re-estimating Eq. (3.1). Column (3) presents the results on re-estimating Eq. (3.3). t-statistics appear in parentheses and are based on standard errors clustered by firm-call. $*$, $**$, and $***$ indicate significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix 3.1.

Table 3.9. Robustness Tests: Additional Control Variables

Panel A. Eq. (3.1) with controlling for manager ethnicity and analyst name fluency

	(1)	(2)
	Pr ($Participate$)	Pr ($Participate$)
$PeopleSkills$	0.067***	0.068***
	(8.98)	(9.08)
$SameEthnicity$	0.046**	0.045**
	(1.87)	(1.85)
$Fluency$		0.010*
		(1.85)
Controls	Yes	Yes
N	239,153	239,153
Pseudo R^2	0.19	0.19

Panel B. Eq. (3.3) with controlling for manager ethnicity and analyst name fluency

	(1)	(2)
	$Order$	$Order$
$PeopleSkills$	-0.043***	-0.041***
	(-2.31)	(-2.20)
$SameEthnicity$	0.067	0.066
	(1.15)	(1.13)
$Fluency$		0.015
		(1.12)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year-Qtr FE	Yes	Yes
N	80,160	80,160
Adjusted R^2	0.30	0.30

This table presents results of robustness tests with additional control variables. Panel A presents results from estimating the relation between analysts' people skills and conference call participation probability (i.e. Eq. (3.1)) with controlling for $SameEthnicity$ and $Fluency$. Panel B presents results from estimating the relation between analysts' people skills and conference call question order (i.e. Eq. (3.3)) with controlling for $SameEthnicity$ and $Fluency$. t-statistics appear in parentheses and are based on standard errors clustered by firm-call. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix 3.1.

Table 3.10. Analysts' People Skills and Forecast Accuracy: Mediation analysis

Panel A. Multivariate analysis

	(1)	(2)
	$ForAcc$	$ForAcc$
$PeopleSkills$	0.842***	0.836***
	(4.68)	(4.64)
$Participate$		0.510**
		(2.07)
Controls	Yes	Yes
Firm FE	Yes	Yes
Year-Qtr FE	Yes	Yes
N	123,179	123,179
Adjusted R^2	0.03	0.03

Panel B. Mediation test statistics

	Test statistics	p-value
Sobel test	2.02**	0.043
Aroian test	2.02**	0.044
Goodman test	2.03**	0.042

This table presents the results from estimating the relation between analysts' people skills and forecast error, as well as the mediating effects of analysts' management relationships (i.e. Eq. (3.5) and (3.6)). The dependent variable, $ForAcc$, is the relative absolute forecast accuracy of the analyst's quarterly earnings forecast issued within the quarter after the call date. The test variables are $PeopleSkills$ and $Participate$. $PeopleSkills$ is measured as the first principal component of an analyst's three ethnic cultural traits: individualism, trust and power distance. $Participate$ is measured as 1 if the analyst asked a question during the call, and 0 otherwise. Panel A presents the results on estimating Eq. (3.5) in column (1) and Eq. (3.6) in column (2). t-statistics appear in parentheses and are based on standard errors clustered by firm-call. Panel B presents mediation analysis test statistics. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. All variables are defined in Appendix 3.1.

Chapter 4. Analyst Discourse, Politeness Behaviour and Identities

4.1. Introduction

Sell-side financial analysts (hereinafter, analysts) play an essential role as information intermediaries in financial markets. They gather and process firm-specific information, produce earnings and revenues forecasts and stock recommendations, and serve as professional communication channels between managers and investors (Cheng et al., 2006; Lu et al., 2016). They contribute to society by assisting the conversion of intellectual capital into economic capital in financial markets (Fogarty and Rogers, 2005). As a professional group, analysts need to present socially desirable images to investors, managers and the media, in order to establish and maintain their professional standing. Professional identity represents not only the profession that individuals work in but also their beliefs, values and motives (Ibarra, 1999; Slay and Smith, 2011). This chapter investigates whether and how sell-side analysts construct and promote identities through their use of language to enact politeness in analyst-manager interactions during earnings conference calls.

Analysts have two identities, namely *"competent professionals"* and *"dependants of firms"*, due to their responsibilities and institutional incentives. Analysts' primary responsibility is to investor clients. In their relationship with investor clients, analysts are *"competent professionals"* because they are expected to be objective and play an external monitoring role to reduce agency costs (Jensen and Meckling, 1976; Healy and Palepu, 2001). Analysts therefore need to appear independent from managers to maintain credibility and reputation with investors (Brown et al., 2015). They have two main incentives to be accurate and neutral. First, reputation and career concerns motivate them to be accurate (Fang and Yasuda, 2009). Second, their reliance on institutional investors' performance ratings motivate them to provide accurate information because institutional investors prefer high-quality information (Cowen et al., 2006).

On the other hand, analysts are also *"dependants of firms"* because they have incentives to act favourably towards firms and management. Analysts may behave over-optimistically to maintain good management relationships and, hence, gain superior knowledge of firm-specific information (Mest and Plummer, 2003; Mayew et al., 2013). Moreover, they may show optimistic tendencies to generate investment banking work (Agrawal and Chen, 2008). Additionally, analysts may issue optimistic opinions to generate trading volume and increase the revenue of brokerage firms (Jackson, 2005).

Although analysts are essential participants in financial markets, they are subject to minimal rigorous regulation, leading to a high level of discretion over how they perform their professional tasks (Fogarty and Rogers, 2005). As a result, and despite decades of research, analysts' work remains hidden in a black box (Bradshaw, 2011), a mystery to the public. Consequently, there has been hardly any major challenge to analysts' professional identities.

The increasing use of earnings conference calls as a medium of financial communication can potentially disturb analysts' identities by exposing their workplace behaviour to public scrutiny. The question-and-answer (hereinafter, the Q&A) section of the conference call involves ad hoc analyst-manager interactions. Analysts can challenge managers' interpretation of firm performance, ask managers to confirm information, and require information that managers are unwilling or unable to disclose (Hollander et al., 2010). Due to the introduction of Regulation Fair Disclosure by the SEC in 2000, conference calls are required to be publicly accessible in the U.S, meaning that analysts not only negotiate their identities with managers but also perform to a public audience.

Investors and the media become the silent third parties in conference calls, observing and monitoring analyst behaviour.

From a social constructivist perspective, analysts' identities as competent professionals as well as dependants of firms can be seen as processes that are located in particular interactions in which these identities are negotiated, not least through discursive work (De Fina et al., 2006: 2). Ranging from professional interactions to informal everyday conversations, individuals use discourse to structure texts, establish identities and relationships, and represent events and entities (van Dijk, 1997: 2; Halliday and Matthiessen, 2004: 29-30). Prior research in financial communication finds that organisations and professional groups use discourse to construct identities and impressions (e.g. Craig and Amernic, 2004; Amernic and Craig, 2013; Clarke et al., 2009; Beelitz and Merkl-Davies, 2012). During conference calls, analysts can establish and promote their identities through the way they frame their questions to managers. If analysts behave in a manner that is inconsistent with the expectation of investors, the media or managers, their respective identities might be challenged, causing negative impacts on their credibility, reputation and career. Thus, analysts are expected to actively engage in identity construction during conference calls.

I examine how analysts construct and sustain identities through politeness in language. Politeness is constantly used in social interaction, including professional settings, to promote relationships and reduce confrontation (Brown and Levinson, 1987: 1; Thomas, 1995: 179; Leech, 2014: 9). Politeness is a critical aspect of analyst behaviour because it represents not only their existing relationships with managers but also the process by which analysts actively preserve and promote socially desirable identities through social interaction. For example, if analysts intend to promote their identity as dependants of firms, they can frequently enact politeness in language to mitigate their questions to managers, instead of using aggressive questioning strategies. On the other hand, if analysts attempt to emphasise their identity as competent professionals, they may avoid overly polite language and ask questions in a more direct manner (Salzedo et al. 2018). Collectively, through the strategic use of politeness in different situations, analysts aim to foster the impression that they are independent of firm management and yet sufficiently close to obtain firm-specific information (Fogarty and Rogers, 2005).

To investigate the politeness strategies that analysts use in conference calls, I perform quantitative and qualitative discourse analyses on a sample of conference call transcripts of 46 U.S. non-financial firms that report extreme earnings change. Results show that analysts adopt various politeness strategies and questioning styles to negotiate and enhance their different identities according to the performance of the firm. During calls of firms that report extreme earnings increases, analysts protect their identity as dependants of firms by asking questions in stages with frequent use of politeness strategies to justify questions. During calls of firms that report extreme earnings decreases, however, analysts prioritise their identity as competent professionals by using politeness to distance themselves from managers and asking questions in a more confrontational and less polite manner.

It is important to note that this study is different from a recent qualitative study by Abraham and Bamber (2017). Abraham and Bamber (2017) draw on sociology theories on surveillance and interaction ritual and use interview and observational data to examine analysts (dis)incentives to participate in conference calls in the U.K. Whereas, this study is different from theirs in three main aspects. First, we examine different research questions regarding analysts' conference call participation. Their focus is analysts' motivations to participate in calls, and document that analysts' decisions to participate is driven by self-promotion incentives and use participation to showcase their expertise. I focus on how analysts use language to sustain professional identities in a public disclosure event and emphasise the importance of linguistic politeness in financial communication. Second, we draw on different theories and employ different research methods. Abraham and Bamber (2017) rely on sociology theories and use observational and interview data to analyse analysts' motivations from a social and political perspective. In this study, I study analysts' use of language in conference calls using theories and close-reading discourse analysis methods from linguistics research. Third, they study conference calls in the U.K., while my data consists of calls of U.S. firms. The two countries have different institutional settings that might affect analysts' incentives and behaviour.

I make two contributions to the literature. First, I contribute to research in financial communication by highlighting the importance of politeness. Politeness behaviour is essential to social interaction and has been examined in various types of discourse (e.g. Pilegaard, 1997; Holmes, 2000; Harris, 2001; Jansen and Janssen, 2010). Given the complexity of analysts' identities, politeness is crucial in establishing and sustaining their identities and social relationships. I provide evidence on how analysts actively engage in identity construction using various politeness strategies during conference calls. To the best of my knowledge, this is the first study investigating analysts' politeness behaviour in financial communication. I suggest a new direction in financial communication research. Politeness is a fundamental element in financial communication because it can be used to construct, sustain and promote relationships among firms, analysts and various stakeholders. Future research may investigate linguistic politeness behaviour in not only analyst-manager interaction, but also the communication between firms and other parties.

Second, I contribute to a better understanding of analyst behaviour by shedding light on how they use language to present and enhance socially desirable identities. Given that analysts play an important role in wealth creation and distribution, the construction and maintenance of their identities are closely related to the stability of the financial and economic systems (Fogarty and Rogers, 2005). However, evidence on how analysts negotiate their identities through interaction with other parties in financial communication is currently limited. One reason for the limited evidence is the lack of opportunity for researchers to directly observe analysts' behaviour in a daily-task environment. Naturally occurring analyst-manager interactions constitute an important information input into analysts' decision-making processes (Bradshaw, 2011). Using the unique setting of earnings conference calls, I am able to observe and analyse analysts' natural linguistic behaviour in their interactions with firm management. This study thereby illuminates how analysts use language to construct and balance desirable professional identities in a real-life setting.

The remainder of this chapter is structured as follows. Section 4.2 introduces politeness theory. Section 4.3 explains the sample and the discourse analysis methods. Section 4.4 presents the results and interprets the findings. Section 4.5 concludes.

4.2. Politeness theory

Discourse refers to the linguistic elements of social life and social interaction, and represents the connections between language, society and power (Fairclough, 2003; van

Leeuwen, 2008: 6; Merkl-Davies and Koller, 2012). Discourse analysis investigates relations between the form and function of communication by studying the content and linguistic features of language in use (Renkema, 2004: 1; Gee, 2011: 8). Given the various facets of social interaction, linguists have developed a variety of theories and methods to study the different aspects of discourse. One of the most essential aspects of spoken interaction is politeness (Brown, 2001: 11620; Culpeper, 2011a: 1).

4.2.1. Definition and importance of politeness

Politeness is defined as the use of communicative strategies to reduce conflict and confrontation, and to establish, sustain and enhance social harmony (Leech, 1983: 82; Brown and Levinson, 1987: 1; Lakoff, 1989: 102; Thomas, 1995: 179; Leech, 2014: 9).[29] During the past thirty years, the interdisciplinary nature of politeness and its importance in social interaction have strengthened its prevalence in social science research (Culpeper, 2011a: 1). Politeness does more than depict external reality, it also contributes to constituting reality and negotiating social identities and relationships. As one of the pioneers in politeness research, Brown (2001: 11,620) states, "politeness in communication goes to the very heart of social life and interaction; indeed it is probably a precondition for human cooperation in general."

The definition of politeness is consistent with analysts' aims in analyst-manager interactions during conference calls. While analysts are expected to obtain information

[29] It is important to distinguish between politeness and impoliteness. Unlike politeness, impoliteness consists of the use of communicative strategies that violate obligations, anticipations or desires, and cause offense and negative emotional reactions, e.g. anger and hurt (Culpeper, 2015: 1). Typical examples of impoliteness include swearing, insults and threats (Culpeper, 2011b; Culpeper, 2015: 1). This chapter only investigates analysts' politeness behaviour and does not consider impoliteness.

from managers and behave in an objective manner, they are also expected to maintain good relationships and minimise conflicts with managers. Politeness serves an interpersonal function in social interaction (Brown and Levinson, 1987). During conference calls, analysts are expected to actively establish and sustain socially desirable identities through politeness behaviour in analyst-manager interactions.

4.2.2. Faced-based politeness theory

Numerous studies model politeness on a theoretical level (Culpeper, 2011a: 4; Kádár and Haugh, 2013: 13). A classic work that continues to function as a benchmark for current developments is Brown and Levinson's (1987) (hereinafter, B&L) face-based politeness theory. As arguably the most influential work in linguistic politeness research, this theory has an unprecedented status in both linguistics and other social science fields (Kádár and Haugh, 2013: 15). It consists of an extensive taxonomy of linguistic strategies of politeness, and provides explanations of individuals' intentions when a strategy is used. The theory conceptualises politeness through straightforward day-to-day linguistic behaviour (Werkhofer, 1992: 155; Kádár and Haugh, 2013: 15). The comprehensive and systematic nature of B&L's theory makes it an appropriate starting point to understand politeness in analyst discourse.

4.2.2.1. Face and face threatening acts

B&L's framework is based on Goffman's (1967: 5) concept of "face", which is defined as an image of the self that people present in social interaction as based on how they expect others to perceive them. In social interaction, we protect our own face to present an image of self that is consistent with our own expectations (Goffman, 1967: 5). We also protect others' face because such cooperative behaviour is useful in establishing an image of kindness and friendliness, which can be an important aspect of our identity (Culpeper, 2011a: 12). Additionally, we expect others to respect our own face and, hence, have expectations of how others will behave (Kádár and Haugh, 2013: 14).

B&L identify two aspects of face, namely negative and positive face. It is important to note that the terms 'negative' and 'positive' are technical terms with no evaluative meaning in B&L's framework. B&L (p. 62) define negative face as "the want of every competent adult member that his actions be unimpeded by others" (i.e. the desire to have freedom of action), and positive face as "the want of every member that his wants be desirable to at least some others" (i.e. the desire to be liked or admired).

However, face threatening acts (hereinafter, FTAs), which are actions that "run contrary to the face" of oneself or that of others (B&L: 65), are inevitable in social interaction (Jansen and Janssen, 2010). Based on the type of face that is threatened, FTAs are divided into positive and negative FTAs. In analyst-manager interaction, analysts can perform FTAs to managers' positive face by disagreeing with managers or expressing criticism.[30] Positive FTAs make managers appear less likable, competent or reputable, while FTAs that threaten managers' negative face include orders, requests, probing questions and suggestions. Negative FTAs hinder managers' freedom of action and territorial integrity by establishing expectations of certain behaviour on their part.

[30] Analyst-manager interactions are used as examples to explain the face-based politeness theory. In the context of this study, analysts (managers) are always the speaker (the hearer) in the interaction and the ones who perform FTAs. In actual Q&As of earnings conference calls, the roles of course switch back and forth between managers and analysts.

Importantly, FTAs towards managers also have an indirect impact on analysts' own face and identities. As individuals want to maintain their own face and expect that others will cooperate to protect their face, analysts are assumed to have expectations of managers' reaction to FTAs. That is, analysts can predict that managers expect them to avoid FTAs and are offended when FTAs are enacted. Given such predictions, analysts have to decide whether to perform FTAs or not. If they perform FTAs, then managers will be offended. Consequently, analysts' own positive face – being appreciated by managers - and their identity as dependants of firms will also be damaged. On the other hand, analysts' own negative face and their identity as competent professionals will be enhanced because they perform FTAs to obtain information from managers. Conversely, if analysts do not perform FTAs in the first place, they will avoid offending managers and, hence, protect managers' face. Thus, analysts' own positive face and identity as firm dependants will be protected because they have not threatened managers' face. By doing so, however, analysts will damage their own negative face and their identity as competent professionals because their freedom of seeking information is hindered.

4.2.2.2. Politeness strategies

As Culpeper and Hardaker (2018, p. 457) explain, there are many ways of being polite including indirectness, compliments, humour, self-deprecation, friendliness, deference and others. B&L (pp. 91-227) summarise various politeness strategies, each with specific linguistic features that mitigate face threats. While their categorisation is useful, it needs to be kept in mind that "it is speakers rather than utterances that are … polite" (Garcés-Conejos Blitvich, 2013, p. 3): the polite meaning does not reside in the phrases as such but in the context in which they are used. With that in mind, this study focuses on analysts' use of positive politeness and negative politeness strategies. Using positive politeness strategies mitigates face threats by maintaining managers' positive face and indicating that analysts understand managers' desires. When analysts use negative politeness strategies, on the other hand, they mitigate face threats by maintaining managers' negative face, i.e. their freedom of action.

Both positive and negative politeness strategies require analysts to give face to managers and counterbalance the expected face damage of FTAs (Culpeper, 2011a: 9). Positive and negative politeness strategies as summarised by B&L are listed and explained in Tables 4.1 and 4.2, respectively. These strategies are used to weaken the strength of FTAs, where the strength of an FTA is negatively associated with the degree of politeness (Kádár and Haugh, 2013: 15). It is important to note that using fewer politeness strategies (i.e. being less polite) does not equal being impolite. Indeed, politeness and impoliteness can be seen as two extremes with a neutral middle ground. For example, to correct a misunderstanding, one may take the polite approach and say 'I'm afraid I didn't make that quite clear' (a polite version with the speaker apologising and taking the onus on themselves); or may be impolite and say 'You are remarkably slow in understanding what I'm saying' (blaming the other and calling their competence into question); or may use a neutral formulation such as 'Actually, the point is that…'. In the context of conference calls, being less polite indicates that analysts put less effort into redressing the FTA, while still intending to save managers' face to some extent.

Positive politeness represents familiar and cooperative behaviour in social interaction (B&L: 129). Analysts can show positive politeness by expressing that they understand or share managers' wants and needs (B&L: 101). In addition, positive politeness strategies serve as "social accelerators" because, by using them, analysts imply that they wish to maintain a friendly and close relationship with managers (B&L: 103). As listed in Table 4.1, positive politeness strategies are categorised into three broad groups (B&L: 101-129). First, analysts may claim common ground with managers, by indicating that they and managers share values and aims. For example, analysts can achieve this by agreeing with managers. Second, analysts may attend to managers' positive face by conveying that they and managers are cooperatively involved in the activity at hand. Third, analysts can express positive politeness by directly satisfying some of managers' desires and, hence, showing they care about managers' face. An example of this strategy is to congratulate managers on good performance.

[Insert Table 4.1 here]

Negative politeness represents respect behaviour (B&L: 129). As shown in Table 4.2, negative politeness strategies can be classified into five broad mechanisms. First, analysts can be conventionally indirect by using sentences and phrases with contextually unambiguous meanings that are different from their literal meanings. For example, instead of saying 'Tell me about x' during conference calls, they could ask '*Can you* tell me about x?', which functions as an assertion that analysts require managers to disclose information, rather than a question about whether managers are able to do so. Such formulations can make requests efficiently, while simultaneously redressing managers' negative face by using so-called indirect speech acts with a conventional meaning. In the above example, the form is that of an interrogative ('Can you tell me about x?') but the function is that of a request.

[Insert Table 4.2 here]

Second, analysts may protect managers' negative face by formulating questions so as to acknowledge managers' desire to be unimpeded, especially when it comes to disclosing information that is unfavourable to the firm. A typical example is to use mitigating words, also known as hedging devices. For instance, the question '*Could* you give *a bit* of colour on what has changed?' is less direct and more polite than the blunt 'What has changed?' Third, analysts can indicate their intention of not coercing managers. This type of strategy is used when the FTA is about requiring certain actions of managers. For example, analysts can minimise the imposition by stating, for example, '*Perhaps* you can discuss this *a little bit*'. Fourth, analysts can express their awareness of managers' negative face and take it into consideration in deciding how to perform FTAs, e.g. apologising for performing the FTA. Fifth, analysts may attend to managers' negative face by going on record as incurring a debt (B&L: 209), e.g. 'Can you just explain that *for me* please?'

4.2.3. Criticisms of face-based politeness theory

While still an influential model of linguistic politeness, B&L's theory has attracted criticisms since its inception. First, B&L have been criticised for theorising face as 'a cognitive and individualistic construct that was possessed by a rational, rather than emotional, model person' (Garcés-Conejos Blitvich, 2013: 11). Previous research on financial analysts has demonstrated the role of emotion and cognitive process in analysts' behaviour (e.g. Mayew and Venkatachalam, 2013; Ho and Cheng, 2016).

Second, B&L discuss acts that threaten or redress face but fail to address acts that enhance face (Culpeper and Hardaker, 2018: 463) such as analysts praising firm performance or managers' decisions. To make up for that gap, Arundale (2010) proposes face-constituting theory as accounting for both separation and connection, threatening and constituting face as part of interpersonal, including professional, relationships.

Lastly, B&L's claim that their theory captures "universals in language usage" has been roundly refuted. B&L's notion of politeness, far from being universal, is in fact indebted to Western ideals of individualism (Culpeper and Hardaker, 2018: 462). Nonetheless, such a limitation of B&L's theory does not diminish the validity of the analysis in this study because the analysis is performed using U.S. firms' conference calls and the U.S. has an individualistic culture (Hofstede, 2001).

4.3. Discourse analysis: sample and methods

4.3.1. Sample

Following prior literature, the analysis of analyst politeness behaviour is based on a sample of U.S. non-financial firms with extreme earnings changes because the effects on financial communication behaviour are expected to be more detectable when firms experience extreme performance change (e.g. Courtis, 1998; Clatworthy and Jones, 2003; 2006). Change in earnings is measured by annual percentage change in net income (Compustat item: NI): $\{(NI_t - NI_{t-1}) / |NI_{t-1}|\} \times 100\%$.[31] I focus on year-end annual conference calls because the Q&A section of these calls are typically longer than Q1 – Q3 conference calls, therefore providing a richer setting to observe analysts' linguistic behaviour.

The sample selection process consists of the following steps. First, data on current and past annual net income of U.S. non-financial firms for the last fiscal year ended on or before 31 December 2014 were obtained from Compustat. After the calculation of

[31] Careful examination of the data is performed to ensure that the performance changes in the sample are not trivial (e.g. net income increases from $1 to $1,000).

annual percentage change in earnings, firms are ranked by the value of percentage earnings change. Then, conference call transcripts of firms that experience extreme earnings change for the fiscal year were downloaded from either Factiva or SeekingAlpha. For the increasing (decreasing) earnings sub-sample, starting from the firm with the largest earnings increase (decrease), transcripts were downloaded until 25 transcripts, which is a manageable sample size for discourse analysis, had been obtained.[32] Within each sub-sample, there are two transcripts that contain no Q&A section. Therefore, the final sample consists of 23 call transcripts of firms with the most extreme earnings increase and 23 of firms with the most extreme earnings decrease.

4.3.2. Discourse analysis methods

I proceed to discourse analysis after sample construction. I use both quantitative and qualitative methods to discourse analysis to obtain comprehensive evidence on analysts' politeness behaviour. In discourse analysis, the development of *a priori* hypotheses is not needed. Quantitative discourse analysis is useful in identifying the frequency and patterns of the linguistic devices of interest, and establishing associations between linguistic features and contextual factors (Lazaraton, 2002; Baker, 2006: 2; Connor-Linton and Amoroso, 2014). Qualitative discourse analysis lies within the interpretive or critical research tradition, focusing on how and why language is used in a particular context (Larazaton, 2002). It reinforces the results of quantitative analysis by providing more accurate and in-depth description of language use and establishing relationships between language and the broader contexts (Johnston, 2002: 69-70; Craig

[32] For the firms where no transcript has been obtained, it is presumed that they did not hold earnings conference call.

et al., 2013). Quantitative and qualitative approaches are complementary and form a cycle of research (Jick, 1979).

4.3.2.1. Quantitative discourse analysis

The coding procedure for quantitative analysis consists of four steps. First, both the presentation and the Q&A sections of conference call transcript and the firm's 10-K, which is accessed through EDGAR, are read. The purpose is to establish the context of firm performance and economic fundamentals because context is important in analysing politeness in situated interactions (Kádár and Haugh, 2013: 109).

Second, all analyst-manager interactions in the Q&A section are examined to determine whether analysts' questions constitute FTAs to managers. Following B&L's politeness framework, an analyst performs an FTA if an utterance, or a series of utterances together, is potentially considered by managers or analysts to compromise the positive and/or negative face wants of managers. [33] Table 4.3 summarises the circumstances under which utterance(s) by analysts are coded as a positive and/or negative FTA. As explained in Panel A, utterance(s) is (are) classified as a positive FTA if it is (they are) related to: (1) the firm's poor operational, financial, cash flows and/or stock market performance, poor future outlook or high risk; (2) the firm's legal problems; (3) the firm's unexpected or problematic executive turnovers; (4) the firm's better-performing competitors; and (5) investors lost confidence in the firm or the management team. Additionally, utterance(s) is (are) classified as a positive FTA if the analyst

[33] Utterances are the unit of analysis in discourse analysis. In the analysis in this chapter, an utterance is a sentence. I use the term 'utterance' because it is the correct terminology for discourse analysis.

challenges managers' interpretation of firm performance or future outlook, or indicates that the utterance(s) may offend managers.

[Insert Table 4.3 here]

As explained in Panel B, utterance(s) is (are) classified as a negative FTA according to the following criteria: (1) the analyst indicates that managers might be reluctant to react to the utterance(s) (i.e. reluctant to provide the information the analyst seeks); (2) managers indicate they are reluctant to react, but still provide the information the analyst seeks; (3) managers refuse to react; and (4) managers react to the utterance(s) without actually providing the information the analyst seeks.

Utterance(s) is (are) classified as a positive FTA when it (they) meets (meet) only the criteria of positive FTA; and negative FTA when only the criteria of negative FTA. If the criteria of both types of FTA are met, then it is classified as an FTA to managers' both positive and negative face. If the criteria of both types of FTA are not met, then it is classified as a non-FTA. After the classification of positive/negative FTAs, the name of the analyst who performs the FTA, the FTA texts, and the type of managers' face threatened were recorded. The total numbers of FTAs and non-FTAs in the call were also recorded.

Third, each FTA is then examined to identify positive and negative politeness strategies, following B&L's framework. As politeness strategies need to be understood in context, I do not restrict the search to certain pre-defined expressions or automate the coding process. Instead, for each politeness strategy identified, its type (i.e. positive or negative), linguistic marker (i.e. the word, phrase or sentence that is used to implement the politeness strategy), and the number of markers are manually recorded. Then, the total numbers of positive politeness strategy markers and negative politeness strategy markers for each call transcript are counted and recorded.

Fourth, given that the only coder was one of the authors and a coder's judgement may fluctuate among various occasions, intra-coder reliability is assessed (Chen and Krauss, 2004). Intra-coder reliability is measured using percentage agreement, which is the percentage of all coding decisions made by the coder on which the coder agrees on two coding occasions (Lombard et al., 2002). All transcripts are coded again after a lapse of three months with a resultant level of agreement of 87.21% for the entire sample on the use of politeness strategies. For the increasing earnings and decreasing earnings sub-samples, the agreement levels are 86.98% and 87.45%, respectively. Research suggests that an agreement level of 80% is acceptable (Lombard et al., 2002; Neuendorf, 2002: 145). Therefore, the reliability level of my study is adequate.

4.3.2.2. Qualitative discourse analysis

The study then embarks on qualitative discourse analysis. One purpose is to examine if the results of quantitative analysis can be upheld. Another purpose is to provide more in-depth analysis on how analysts structure FTAs and use politeness strategies under various circumstances and, hence, investigate how analysts use politeness in language to present socially desirable identities.

The analysis relies on turn-by-turn analysis of the cumulative linguistic realisations of analysts' politeness strategies. Defined as participants' contributions to a conversation, turns are a constitutive feature of spoken interaction. Commonly, conversation involves people taking turns and speaking one at a time (Sidnell, 2010). The analysis follows three steps. First, each transcript is read to investigate analysts' politeness behaviour in detail. The main foci are the structure of FTAs, how specific politeness strategies are used, and the directness of analysts' questioning style. Here, the concept of direct and indirect speech acts (Searle, 1969) is used: for the former, the form and function of an utterance converge, e.g. an interrogative is used to ask a question (e.g. "When did XY hand in her notice?"). In indirect speech acts, however, form and function diverge, e.g. an interrogative is used to make a request (e.g. "Can you give some colour on upfront costs?"). Indirect speech acts are an important linguistic resource for enacting negative politeness strategies.

Following the investigation into individual transcripts, typical examples of politeness and questioning strategies are recognised for increasing and decreasing earnings sub-samples, separately. The analysis then identifies how analysts promote one specific identity or balance their two identities through politeness in language. Finally, I compare analysts' politeness behaviour and identity construction across the two extreme earnings changes sub-samples.

4.4. Results and findings

4.4.1. Quantitative discourse analysis results

To obtain an overview of analysts' politeness behaviour, I begin by investigating the frequencies and patterns of FTAs and politeness strategies using quantitative discourse analysis. Table 4.4 lists the proportion of FTAs and the frequency of politeness strategies in both increasing and decreasing earnings sub-samples. The proportion of FTAs is first examined. The proportion of FTAs in a conference call is calculated as:

$$\frac{Frequency\ of\ FTAs}{Frequency\ of\ FTAs\ +\ Frequency\ of\ non-FTAs} \times 100$$

(4.1)

In the increasing earnings sub-sample, the average proportion of FTAs during a conference call is 41.1%. By contrast, in the decreasing earnings sub-sample, the average FTAs proportion is 65.54%. A t-test shows that the null hypothesis, i.e. that there is no difference between the mean values of proportions of FTAs for increasing earnings and decreasing earnings firms, should be rejected (p-value < 0.01). This indicates that analysts perform more FTAs during calls with firms reporting decreasing earnings than those reporting increasing earnings.

[Insert Table 4.4 here]

In terms of the frequency of politeness strategies, analysts on average use 8.34 politeness strategy markers, which contain 4.18 positive politeness and 4.16 negative politeness strategy markers, per FTA during calls with increasing earnings firms. In the decreasing earnings sub-sample, the mean value of politeness strategy markers per FTA is 5.75, with 2.59 positive politeness and 3.16 negative politeness strategy markers. According to t-tests, the null hypotheses that there is no difference between the mean values of (1) positive politeness strategy markers per FTA; (2) negative politeness strategy markers per FTA; and (3) positive and negative politeness strategy markers per FTA, for increasing and decreasing earnings firms, should all be rejected. Wilcoxon rank-sum tests reveal similar patterns in the differences between the median values of the proportion of FTAs and the number of politeness strategies. These results suggest that analysts use fewer politeness strategies during decreasing earnings firm calls than increasing earnings firm calls.

Results in Table 4.4 are consistent with theory and prior evidence in financial communication research. The primary goal of conference calls is to discuss firm performance. Managers' positive face is more easily threatened when performance is poor because analysts' questions on poor performance or challenges to managers' interpretations will make managers appear to be less competent and qualified. Moreover, managers' negative face is also more easily threatened when the firm experiences an extreme decrease in earnings because managers of poorly performing firms are likely to obfuscate information (e.g. Garcia Osma and Guillamón-Saorín, 2011; Merkl-Davies and Brennan, 2007; Patelli and Pedrini, 2014). Thus, analysts perform both positive and negative FTAs more often when firms experience an extreme decrease in earnings. Additionally, as managers may be reluctant to disclose information when firm performance is poor, analysts' identity as competent professionals is at stake because their aim for participating in earnings conference calls is to seek information. To sustain such an identity, analysts need to perform FTAs with efficiency, i.e. use fewer politeness strategies to mitigate FTAs. This indicates asking questions in a more confrontational manner.

Next, I compare analysts' use of positive and negative politeness strategies because these two types of politeness strategy are driven by different communication incentives. While positive politeness strategies indicate a friendly and close relationship between analysts and managers, negative politeness strategies help analysts distance themselves from managers. Table 4.5 compares the frequencies of positive and negative politeness strategies for the full sample, and for both the increasing and decreasing earnings sub-samples. In the decreasing earnings sub-sample, analysts on average use 2.59 positive politeness strategy markers and 3.16 negative politeness strategy markers per FTA. The difference between the means of positive and negative politeness strategy markers are statistically significant (p-values < 0.05). These results indicate that analysts use positive politeness strategies less frequently than negative politeness strategies during the calls of firms with extreme earnings decreases.[34]

[Insert Table 4.5 here]

As positive politeness strategies represent familiar and friendly behaviour, frequent use of such strategies can cultivate the impression that analysts are too close to managers and potentially biased towards them. As managers of poorly performing firms have incentives to obfuscate information, analysts need to emphasise their identity as competent professionals. The use of negative politeness enables analysts to clarify their distance to managers. To create the impression of independence and competence, analysts may therefore use negative politeness strategies more frequently than positive politeness strategies during conference calls with firms that report extreme earnings decreases. However, as evident in Table 4.5, results for the increasing earnings sub-sample and the full sample reveal no significant difference between the mean values of positive and negative politeness strategy markers per FTA. These results suggest that analysts only pay attention to avoiding positive politeness strategies when managers are likely to hinder information disclosure, so as not to endanger analysts' identity as competent professionals. Wilcoxon signed-rank tests provide similar results for medians of the use of positive and negative politeness strategies.

Collectively, results from quantitative discourse analysis show that analysts use fewer politeness strategies during calls with decreasing earnings firm than increasing

[34] There is concern that analysts' linguistic behaviour may vary by industry. To resolve such a concern, t-tests, Wilcoxon rank-sum tests and Wilcoxon signed-rank tests are performed after firms are classified into sub-samples based on industries. Untabulated results show that there are no statistically significant differences of analysts' politeness behaviour between: (1) manufacturing and non-manufacturing firms; and (2) services and non-services firms.

earnings firm calls. Results also show that analysts use negative politeness strategies more frequently than positive politeness strategies during calls of firms with extreme earnings decreases. These results indicate that analysts adopt more confrontational questioning strategies and attempt to promote their identity as competent professionals when firms experience extremely poor performance.

4.4.2. Qualitative analysis

As discussed above, generally, the more politeness strategies analysts use to mitigate FTAs, the weaker FTAs become. To provide further insights, I perform qualitative discourse analysis to examine how analysts use various politeness and questioning strategies to promote and balance professional identities in different contexts. FTAs that concern the same topic from calls of increasing earnings firms and those of decreasing earnings firms are analysed and compared. Excerpts 1 and 2 show how analysts enact negative FTAs toward managers of increasing earnings and decreasing earnings firms, respectively. Both FTAs involve analysts seeking information on earnings and revenues.

[Earnings Conference Call Excerpt 1: Increasing earnings sub-sample]

Analyst 1: And just the one housekeeping thing. I don’t know, Tom,
whether you have any color on just your pro forma figures
for 2014 on revenue and EBITDA, and free cash flow, just
as we’re tuning up our models for going forward?

Manager 1: I don’t have anything at my fingertips to do that, but I can
try and give you some help. I think -- what I have done,
obviously, is give you Q4 same-station growth, and so you
can back into what those numbers were in previous years.
But I can try and give you some guidance on that, I just
don’t have the numbers here.

Analyst 1: Great. Okay. Thank you.

(Nexstar Broadcasting Group, Q4 2014 Earnings Call, 26 February 2015)

In Excerpt 1, an analyst performs a negative FTA to managers of an increasing earnings firm by asking for earnings, revenue and free cash flow information with various, mostly negative politeness strategies. The analyst repeatedly minimises the imposition on management through the use of ‘just’ (lines 1, 2 and 3; being negatively polite) and indirectly shows his reluctance by saying “I don’t know, Tom” (line 1; being negatively polite). He then moves on to attacking the manager’s negative face in “whether you have any color on just your pro forma figures for 2014 on revenue and EBITDA, and free cash flow” (lines 2-3). Although that utterance has the form of a declarative, it functions as a question (as also indicated by the question mark in the transcript), making it an indirect speech act and hence another negative politeness strategy. The analyst then explains that the reason he asks the question is to help with his forecasting models (lines 3-4, being positively polite). The manager answers the question by stating that he does not have the numbers (lines 5-10) and while this threatens the manager’s own positive face, he uses positive politeness towards the analyst by repeating his willingness to help. The analyst finishes the interaction by thanking the manager (line 11, being positively polite). This example illustrates how the analyst performs an identity as dependant of a firm with increasing earnings by minimising the FTAs performed.

[Earnings Conference Call Excerpt 2: Decreasing earnings sub-sample]

Analyst 2: Finally, the 18% to 22% exiting EBITDA margin target, at
a high-level what are the revenue expectations on an absolute

level that's consistent with that, so we get a sense of --?

Manager 2: Glenn, as we said in the remarks, these bookings will be in the high single digits. There is the lead in the -- the lag in the lead with the revenue in bookings; so at a constant-currency basis, the revenue growth would be lower single digits from a revenue standpoint.

Analyst 2: Great. Thanks a lot, guys.

(Monster Worldwide, Q4 2014 Earnings Call, 10 February 2015)

In Excerpt 2, the analyst performs a negative FTA towards managers of a decreasing earnings firm by seeking information on earnings and revenue targets. He starts by explaining this is his final question ("Finally", line 1; being negatively polite). He then enacts the FTA by directly asking a question about revenue expectations (lines 1-3). He attempts to provide reasons for the FTA by saying "so we get a sense of" (line 3, being positively polite), after which he gets interrupted by a manager. While the interruption itself could be seen as an attack on the analyst's negative face, the manager nevertheless starts his answer with a positive politeness marker, i.e. directly addressing the analyst (line 4). It should be noted that the manager's response does not provide the information that the analyst seeks, but the analyst ends the interaction by thanking the managers anyway (line 9, being positively polite). By comparing Excerpts 1 and 2, it is evident that the less frequent use of politeness strategies by analysts makes FTAs potentially stronger during the call with decreasing earnings firms than with increasing earnings firms.

Another noticeable pattern of analysts' politeness strategies with increasing earnings firms is that they ask questions in stages to justify and gradually enact FTAs. In contrast, during calls with decreasing earnings firms, many analysts appear to adopt a more direct questioning style, instead of paving the way for FTAs. Excerpts 3 and 4 below illustrate this pattern by showing analysts performing negative FTAs during calls of oil and gas firms in the increasing earnings and decreasing earnings sub-samples, respectively. The FTAs in both excerpts relate to cost control.

[Earnings Conference Call Excerpt 3: Increasing earnings sub-sample]

Analyst 3: Hopefully my second answer is a little quicker. Obviously,
there's a lot of debate over how quickly and what scale of
cost reduction the industry can expect in this lowered oil price
environment. If you could give us Devon's perspective, please,
in terms of what have you assumed in your capital budget by
way of cost reduction and ultimately what do you think it can
get to by year end as opposed to the average for the year?
I'll leave it there. Thank you.

(Devon Energy, Q4 2014 Earnings Call, 18 February 2015)

In Excerpt 3, the analyst performs a negative FTA to managers of an increasing earnings oil and gas firm by seeking information on cost reduction. The analyst starts by presumably trying to minimise the imposition on managers ("Hopefully my second answer is a little quicker", line 1; being negatively polite).[35] He then attempts to give reasons for his questions by linking them to an impersonal 'debate' ("Obviously, there's a lot of debate", lines 1-2; being positively and negatively polite), before gradually getting to the questions (lines 4-7). These are introduced with a conditional clause using a modal verb and the marker 'please' ("If you could give us Devon's perspective, please"), consistent with the analyst using a cluster of negative politeness strategies. Next, to avoid

[35] It is assumed that the analyst meant to say "hopefully, my second question will be a little quicker". Otherwise, the utterance would be an attack on manager's positive face.

putting too much pressure on managers, the analyst seeks to minimise the imposition by saying "I'll leave it there" (line 8, being negatively polite), and ends his turn by saying "Thank you" (line 8, being positively polite).

Here, it is clear to see a tension between the analyst's need to perform the FTA and undertake his work as a competent professional on the one hand, and the need to protect his identity as a dependant of the firm on the other. He performs the FTA in stages with various politeness strategies so that it becomes more polite and less strong. Additionally, he justifies the FTA by stating that there is a debate surrounding this issue. By doing so, the analyst distances himself from the FTA and preserves his identity as a dependant of the firm. On the other hand, the fact that he attempts to weaken the strength of the FTA indicates that he understands that managers may be reluctant to provide the information and that his own identity as a dependant of the firm might be impaired. Nevertheless, the analyst still performs the FTA to maintain his identity as a competent professional.

[Earnings Conference Call Excerpt 4: Decreasing earnings sub-sample]

Analyst 4: The last one for me: In terms of achieving those cost savings,
particularly on the G&A side, do you think there will be any
upfront costs associated with that, or are you just going to
be able to start to recognize the decreases over the next couple
of quarters, and will you be (multiple speakers) --?

(Swift Energy, Q4 2014 Earnings Call, 26 February 2015)

Excerpt 4 shows how an analyst performs a negative FTA to managers of an oil and gas firm with decreasing earnings by asking about cost savings. The analyst begins by minimising the imposition ("The last one for me", line 1; being negatively polite) and then directly identifies the topic of the FTA (lines 1-2), before stating his questions (lines 2-5). The FTA is mitigated only by asking about managers' thoughts rather than actual forecasts ("do you think there will be any upfront costs", lines 2-3; being negatively polite), thereby giving management more leeway to refute the answer later, should it turn out to be incorrect.

On balance, the questioning style of Analyst 4 is more confrontational than that of Analyst 3. Analyst 4 does not provide justification for the FTA but identifies the topic directly. Moreover, he uses fewer politeness strategies than Analyst 3. By comparing the politeness behaviour of Analysts 3 and 4, one can see a tension between analysts' need to sustain their different identities. During calls with increasing earnings firms, analysts appear to make great efforts to weaken FTAs and hence enhance their identity as dependants of firms. During calls with decreasing earnings firms, analysts' identity as competent professionals is at risk because managers may be reluctant to discuss the poor performance and future prospects. Thus, analysts adopt a more confrontational and less polite questioning style to pressure managers into talking, so that analysts can present themselves as competent professionals.

Nevertheless, some analysts also perform FTAs in stages and provide justification for FTAs during decreasing earnings firm calls. Under such circumstances, they adopt other strategies to maintain their identity as competent professionals. As illustrated in Excerpt 5, one strategy is to directly construct a public image as a competent professional.

[Earnings Conference Call Excerpt 5: Decreasing earnings sub-sample]

1 Analyst 5: Good morning. I would like to follow up on Jana's question.

I understand the difficulty of the situation, and your need for
limited comments, but nonetheless I think investors are certainly
very focused on how a search for replacing senior executives,
particularly now in light of the fact your COO has resigned, they
really would desire some more color as you're conducting both
a search for Board members, a search for executives presumably,
as well as undertaking this assessment of strategic alternatives.
How is the Board thinking about recruiting some high quality
talent, while there's a strategic alternatives analysis underway?
And related to that is your acting COO on the call today?

(Campus Crest Communities, Q4 2014 Earnings Call, 26 February 2015)

In Excerpt 5, the analyst performs FTAs both to managers' positive face (by mentioning the difficult situation the firm is in) and negative face (by demanding information managers are unwilling to disclose). The analyst performs the FTA in stages. She starts by saying "Good morning" (line 1, being positively polite), and then asserts her understanding of the situation and managers' needs (lines 2-3, being positively polite). The description of the firm's chaotic situation is possibly intended to justify the FTA, but nevertheless also constitutes an attack on managers' positive face. The analyst further justifies the FTA by ascribing it to their clients ("investors are certainly very focused on how a search for replacing senior executives … they really would desire some more color", lines 3-6). However, she also reinforces the (ascribed) FTA through intensifiers: "investors are certainly very focused", "they really would desire some more color". Finally, she targets managers' negative face by asking questions directly, although the first of them is about the firm's thoughts ("How is the board thinking about recruiting high-quality talent, while there's a strategic alternatives analysis underway?", lines 9-10; being negatively polite).

While Analyst 5 enacts the FTA in stages and justifies it, her questioning style still appears to be confrontational because she does not use many politeness strategies and, importantly, she explicitly establishes a public image for herself as acting on behalf of investors. As a result, she reinforces her identity as a competent professional and distances herself from the firm.

Additionally, as illustrated by Excerpt 6 below, where managers avoid disclosure of information, analysts sustain the identity as competent professionals by continuing to probe managers for answers.

[Earnings Conference Call Excerpt 6: Decreasing earnings sub-sample]

Analyst 6: What was the I guess surrounding Angel's resignation, who is running operations today? When did that happen? How do you go forward?

Manager 6: So Angel chose to resign to pursue opportunities in the Southwest near his family. We have been, that was an amicable and friendly resolution. And I can assure you I've been working day to day with our leasing and operations and facilities teams to deliver leasing results, and respond to tenant inquiries and tenant needs, and we've been doing that for a good while here. And I think it's evident in the results.

Analyst 6: When did that occur?

Manager 6: When did it occur? I don't know, I've been actively involved with things since the seven months I've been here, and [sic] team obviously has years of experience.

Analyst 6: When did Angel--?

Manager 6: As stated in the 8-K Angel formally gave his formal resignation on the 20th, and it is effective now.

(Campus Crest Communities, Q4 2014 Earnings Call, 26 February 2015)

In Excerpt 6, the analyst enacts an FTA towards managers' negative face (by seeking information that managers are reluctant to provide) as well as positive face (by mentioning the resignation of an executive). The analyst first identifies the topic of the FTA with a hesitancy marker ("What was the I guess surrounding Angel's resignation", line 1; being negatively polite), and then directly targets managers' negative face by asking three unmitigated questions in a row "who is running operations today? When did that happen? How do you go forward?" (lines 1-3). The manager's response, while including a positive politeness strategy ("I can assure you", line 6), does not provide the information that the analyst seeks. The analyst keeps putting pressure on managers by asking another unmitigated question ("When did that occur?", line 11). As the manager again fails to provide a satisfactory answer, the analyst attempts to rephrase the question by asking "When did Angel--?", before he is interrupted by the manager who provides information from the firm's 8-K.

The analyst-manager interaction in Excerpt 6 takes several turns because of the manager avoiding disclosing the requested information. The analyst prioritises his identity as a competent professional. Although the manager implies that he feels threatened by the FTA, the analyst keeps threatening the manager's face to obtain information and fulfil his responsibilities to investor clients.

In sum, qualitative discourse analysis provides more in-depth analysis of analysts' politeness behaviour. While both identities drive analysts' politeness behaviour to some extent, their importance varies according to firm performance. During calls with increasing earnings firms, analysts perform FTAs in stages with frequent use of politeness strategies to justify FTAs and weaken the strength of face threats to managers. During calls with decreasing earnings firms, analysts are willing to threaten managers' face and pressure them into talking, even though doing so might damage analysts' identity as dependants of firms. They ask questions in a less polite and more confrontational manner than during increasing earnings firm calls, suggesting that they intend to perform FTAs more efficiently.

4.4.3. Discussion

Three main findings emerge from the analyses above. First, analysts strategically use various politeness strategies during earnings conference calls to construct and enhance socially desirable identities. Both quantitative and qualitative analyses show that analysts enact politeness in language to construct different identities according to the circumstances. Second, analysts' use of politeness strategies varies with firm performance and managers' incentives to withhold information. Analysts make great efforts to redress FTAs during earnings conference calls with increasing earnings firms and perform FTAs more directly during decreasing earnings firm calls. Third, when necessary, analysts are willing to risk their identity as dependants of firms and prioritise the identity as competent professionals.

During earnings conference calls of firms that report decreasing earnings, analysts prioritise their identity as competent professionals. They perform FTAs to managers of decreasing earnings firms in a more confrontational manner with fewer politeness strategies, indicating they are willing to risk their identity as dependants of firms to maintain their identity as competent professionals. Nevertheless, the fact that analysts prioritise their identity as competent professionals when firm performance is poor does not mean that the identity as dependants of firms has no impact on analysts' language use. During calls of firms with increasing earnings, the identity as a competent professional is unlikely to be at risk because managers are expected to be relatively cooperative. Thus, analysts make great efforts to lessen the strength of FTAs and save managers' face, and to promote their identity of dependants of firms. These findings are consistent with Fogarty and Roger's (2005) statement that analysts aim to display a public image that they are independent from managers but still sufficiently close to gain information unavailable from other sources.

Collectively, there are two alternative interpretations for the findings of the present study. First, analysts may attempt to fulfil their responsibilities for investor clients by prioritising their identity of competent professionals in analyst-manager interaction where firm performance is poor. They sacrifice their identity as dependants of firms and perform FTAs to managers in a relatively confrontational and direct manner to pressure managers into disclosing information, keep a distance between themselves and managers, and stay impartial and rigorous. Such an interpretation of analysts' politeness behaviour is consistent with traditional agency theory, which suggests that analysts reduce agency costs by performing a monitoring role for shareholders (Jensen and Meckling, 1976; Healy and Palepu, 2001; Chen et al., 2016).

Second, analysts use politeness in language as an impression management tool to construct a public image that is consistent with investors' and the media's expectation, improve their credibility and, hence, sustain their identity as competent professionals. Analysts' intentions may merely be to construct a socially desirable image, instead of actually fulfilling their responsibilities as competent professionals. Therefore, during calls with decreasing earnings firms, analysts prioritise the competent professional identity so that they can portray themselves as neutral and impartial.

Brown et al.'s (2015) survey and interview evidence reveals analysts consider the enhancement of their credibility with investors as a more likely result of issuing unfavourable stock recommendations or earnings forecasts than losing the opportunity to participate in the Q&A section of earnings conference calls. This finding suggests that issuing unfavourable forecasts and stock recommendations, which are essentially positive FTAs to managers, promotes analysts' identity as competent professionals without severely damaging their identity as dependants of firms. Similarly, it suggests that performing FTAs to managers during earnings conference calls might not seriously undermine analysts' identity as dependants of firms. Thus, when firm performance is poor, analysts take the opportunity to construct and promote their identity as competent professionals to the public.

4.5. Conclusion

This chapter investigates how analysts use politeness in language to establish and maintain socially desirable identities in publicly accessible analyst-manager interaction. During earnings conference calls of firms with increasing earnings, analysts adopt more polite communicative strategies to maintain their relationships with managers. During calls of decreasing earnings firms, however, the need to sustain the competent professional identity appears to dominate analysts' politeness behaviour. These results are consistent with Fogarty and Rogers' (2005) statement that analysts aim to promote a social image that they are independent from managers, but close enough to obtain firm-specific information.

Analysts are a professional group that is closely related to the stability of financial markets. Investigating the language of analyst discourse (as demonstrated in this chapter) is important, because analysts have significant influence over the allocation and distribution of wealth within society and their discourse represents an essential aspect of their social life. Due to the implementation of Regulation Fair Disclosure and the increasing use of earnings conference calls, analyst behaviour is under greater scrutiny by investors and the media. As a result, analysts actively engage in identity construction to present a publicly desired image during these calls. Importantly, given that analysts' biased behaviour towards firms is widely documented, analysts can use discourse as a means of constructing identities that are consistent with investors' expectations.

As the first to explore how analysts use politeness to construct identities in naturally occurring social interaction, this study provides a glimpse into analysts' language use, politeness behaviour and identity construction. It would be useful for future research to examine and discriminate between the two alternative interpretations of the findings of this study. This may be achieved by using regression analysis and linking analysts' politeness behaviour to the properties of earnings forecasts. Moreover, the implication of analysts' politeness behaviour in analyst-manager interaction is worth studying. It would be interesting to investigate how investors perceive and benefit from analysts' politeness behaviour. Additionally, given the fundamental role of politeness in social interaction, future research may examine the politeness behaviour of various participants in financial communication, which this study could only hint at, e.g. managers, investors, and other stakeholders. This will enhance our understanding of how these participants use discourse to construct identities, legitimacy and reality.

Table 4.1. Positive Politeness Strategies as Summarised in B&L

Mechanism	Strategy	Example
Claim common ground	1. Notice, attend to hearer (his interests, wants, needs, goods)	That positioned you much better than your competitors. (China Ceramics Co. Ltd., Q4 and Fiscal Year-end 2014 Earnings Conference Call)
	2. Exaggerate (interest, approval, sympathy with hearer)	Your performance is absolutely sensational!*
	3. Intensify interest to hearer	I will be there in one second.*
	4. Use in-group identity markers	Are you guys expecting flat EBIT in that segment as well? (Gibraltar Industries, Inc., Q4 2014 Earnings Conference Call)
	5. Seek agreement	We did a great job, don't you think?*
	6. Avoid disagreement	Yes, I know. But you indicated earlier that there was a problem with ThinkGeek Solutions getting up and running in the third quarter. (Geeknet, Inc., Q4 2014 Earnings Conference Calls)
	7. Presuppose/raise/assert common ground	Just a quick follow-up, and I know you can't give color on the strategic review, so I'm not going to ask that. (Campus Crest Communities, Inc., Q4 2014 Earnings Conference Call)
	8. Joke	I'm very sad that San Francisco is not on the initial list. (laughter). (Container Store Group, Inc., Q4 and Fiscal Year 2014 Earnings Conference Call)
Convey that speaker and hearer are co-operators	9. Assert or presuppose speaker's knowledge of and concern for hearer's wants	And if you prefer to take it off-line, that is fine too. (TETRA Technologies, Inc., Q4 and Full Year 2014 Earnings Conference Call)
	10. Offer, promise	Come on, I'll buy you a drink.*
	11. Be optimistic	You won't mind if I borrow your book, right?*
	12. Include both speaker and hearer in the activity	So let's try to get our arms around what parts of the business are actually able to generate a profit for the firm. (Actions Semiconductor Co., Ltd., Q4 2014 Earnings Conference Call)
	13. Give (or ask for) reasons	Would you mind elaborating? I'm not familiar with what happened on Black Friday and Cyber Monday. (GeekNet, Inc., Q4 and Full Year 2014 Earnings Conference Call)
	14. Assume or assert reciprocity	I made the coffee yesterday, so it's your turn today.*
Fulfil hearer's want	15. Give gifts to hearer (goods, sympathy, understanding, cooperation)	Got it. Great. Thank you and congrats on all the progress. (MacroGenics, Inc., Q4 and Full Year 2014 Earnings Conference Call)

This table lists all positive politeness strategies as summarised by B&L. An example is provided for each strategy. The sources of the example for strategies 1, 4, 6, 7, 8, 9, 12, 13 and 15 are analysts' questions from earnings conference call transcripts. For the other strategies, which are not used in analysts' questions in sample transcripts, an example constructed using everyday situations is provided and marked by *.

Table 4.2. Negative Politeness Strategies as Summarised in B&L

Mechanism	Strategy	Example
Be indirect	1. Be conventionally indirect	Can you please explain how the re-organization of the corporate structure resulted in impairment charge to intangibles? (Actions Semiconductor Co., Ltd., Q4 2014 Earnings Conference Call)
Don't presume/assume	2. Question, hedge	So I am just wondering what has changed, if anything, with those programs in terms of size and timing? (Fuel System Solutions, Inc., Q4 and Year-end 2014 Earnings Conference Call)
Don't coerce hearer	3. Be pessimistic	And so Richard is not on the call currently? (Campus Crest Communities, Inc., Q4 2014 Earnings Conference Call)
	4. Minimise the imposition	Perhaps you can talk a little bit about the longer term dividend growth especially with 2017 in mind. (TerraForm Power, Inc., Q4 2014 Earnings Conference Call)
	5. Give deference	So please add that. (Container Store Group, Inc., Q4 and Fiscal Year 2014 Earnings Conference Call)
Communicate speaker's want to not impinge on hearer	6. Apologise	I'm sorry if I missed this. Did you talk about the EPS impact due to foreign-exchange? (Fuel System Solutions, Inc., Q4 and Year-end 2014 Earnings Conference Call)
	7. Impersonalise speaker and hearer	It looked like the equity on the consolidated joint venture impact was a great big negative in the quarter (Campus Crest Communities, Inc., Q4 2014 Earnings Conference Call).
	8. State the FTA as a general rule	The university requires students to be in residence for a set number of terms.*
	9. Nominalise	The report is due on Monday.*
Redress other wants of hearer's	10. Go on record as incurring a debt, or as not indebting hearer	I'd be extremely grateful if you could help me out.*

This table lists all negative politeness strategies as summarised by B&L. An example is provided for each strategy. The sources of the example for strategies 1, 2, 3, 4, 5, 6 and 7 are analysts' questions from earnings conference call transcripts. For the other strategies, which are not used in analysts' questions in sample transcripts, an example constructed using everyday situations is provided and marked by *.

Table 4.3. Classification Criteria of FTAs

Panel A. Positive FTAs

- Utterance(s) involve(s) firm's poor operational, financial and cash flows performance, poor stock market performance, poor future outlook or high risk;
- Utterance(s) involve(s) firm's legal problems;
- Utterance(s) involve(s) firm's unexpected or problematic executive turnovers;
- Utterance(s) involve(s) firm's better-performing competitors;
- Utterance(s) mention(s) that investors lost confidence in the firm or its management;
- Utterance(s) challenge(s) managers' interpretation of firm performance or future outlook;
- The analyst indicates that the utterance(s) might offend managers;

Panel B. Negative FTAs

- The analyst indicates that managers might be reluctant to react to the utterance (i.e. reluctant to provide the information the analyst seeks);
- Managers indicate that they are reluctant to react to the utterance, but decide to provide the information the analyst seeks;
- Managers refuse to react to the utterance;
- Managers to react to the utterance(s) without actually providing the information the analyst seeks.

This table presents the coding criteria for classifying analysts' utterance(s) as either an FTA or a non-FTA. Panel A and B list the circumstances under which analysts' utterance(s) are classified as an FTA to managers' positive and negative face, respectively. If (an) utterance(s) meet(s) the criteria in both panels, it is coded as an FTA to both managers' positive and negative face. If (an) utterance(s) meet(s) none of the criteria in both panels, it is coded as a non-FTA.

Table 4.4. Comparison of Politeness Behaviour for Increasing and Decreasing Earnings Sub-samples

	Increasing earnings sub-sample		*Decreasing earnings sub-sample*	
	Mean	Median	Mean	Median
Proportion of FTAs (%)	41.10^{***}	40.00^{***}	65.54	60.00
Positive politeness strategy markers per FTA	4.18^{***}	4.00^{***}	2.59	2.46
Negative politeness strategy markers per FTA	4.16^{**}	4.20^{**}	3.16	3.00
Positive and negative politeness strategy markers per FTA	8.34^{***}	7.67^{***}	5.75	5.40

This table lists and compares the frequency of analysts' politeness behaviour for increasing and decreasing earnings sub-samples. Significance levels of the difference between means are tested based on *t*-tests. For the proportion of FTAs, the null hypothesis is $H_0: Mean_{profitable} = Mean_{unprofitable}$, whilst the alternative hypothesis is $H_1: Mean_{profitable} < Mean_{unprofitable}$. For positive politeness strategy markers per FTA, negative politeness strategy markers per FTA, and positive and negative politeness strategy markers per FTA, the null hypothesis is $H_0: Mean_{profitable} = Mean_{unprofitable}$, whilst the alternative hypothesis is $H_1: Mean_{profitable} > Mean_{unprofitable}$. Significance levels of the difference between medians are tested based on the Z-statistics from Wilcoxon rank-sum tests. For the proportion of FTAs, the null hypothesis is $H_0: Median_{profitable} = Median_{unprofitable}$, whilst the alternative hypothesis is $H_1: Median_{profitable} < Median_{unprofitable}$. For positive politeness strategy markers per FTA, negative politeness strategy markers per FTA, and positive and negative politeness strategy markers per FTA, the null hypothesis is $H_0: Median_{profitable} = Median_{unprofitable}$, whilst the alternative hypothesis is $H_1: Median_{profitable} > Median_{unprofitable}$. *, **, and *** represent that the difference between mean or median is statistically significant at the 10%, 5% and 1% level, respectively.

Table 4.5. Comparison of the Number of Positive and Negative Politeness Strategies

	Positive politeness strategy markers per FTA		*Negative politeness strategy markers per FTA*	
	Mean	Median	Mean	Median
Decreasing earnings sub-sample	2.59**	2.46**	3.16	3.00
Increasing earnings sub-sample	4.18	4.00	4.16	4.20
Full sample	3.38	2.84	3.66	3.37

This table lists and compares analysts' use of positive and negative politeness strategies. Significance levels of the difference between means are tested based on t-tests. For the increasing earnings sub-sample, the decreasing earnings sub-sample and the full sample, the null hypothesis is $H_0: Mean_{positive\ politeness} = Mean_{negative\ politeness}$, whilst the alternative hypothesis is $H_1: Mean_{positive\ politeness} < Mean_{negative\ politeness}$. Significance levels of the difference between medians are tested based on the Z-statistics from Wilcoxon signed-rank tests. For the increasing earnings sub-sample, the decreasing earnings sub-sample and the full sample, the null hypothesis is $H_0: Median_{positive\ politeness} = Median_{negative\ politeness}$, whilst the alternative hypothesis is $H_1: Median_{positive\ politeness} < Median_{negative\ politeness}$. *, **, and *** represent that the difference between mean or median is statistically significant at the 10%, 5% and 1% level, respectively.

5. Conclusion

5.1. Summary

This dissertation studies financial communication from both the firm managers' and the sell-side analysts' perspectives in the setting of earnings conference calls. As an important financial communication channel, these calls provide researchers with a powerful setting to directly observe the natural behaviour of and the interactions between managers and analysts. As financial communication is a multifaceted business and social process, this dissertation draws upon theories and employs empirical methods from various disciplines, such as accounting, linguistics and psychology.

This dissertation consists of three related but self-contained studies, with each of them being an individual chapter. Chapter 2 focuses on managers' voluntary disclosure behaviour in conference calls when the firm reports small non-negative earnings surprise. As firms have incentives to inflate earnings to meet or beat market expectations, previous research finds that investors penalize all firms with small non-negative earnings surprises, even those that genuinely achieve such performance (Keung et al., 2010). This leads to the question of whether non-manipulators attempt to separate intentionally through truthful communication strategies but fail, or if they do not proactively separate. This chapter extends the research on this pooling equilibrium by investigating how earnings manipulators attempt to pool through obfuscation, and whether non-manipulators use credible communication strategies to separate themselves. Results show that non-manipulators are more forthcoming about negative future news and obfuscate less than manipulators, suggesting that they engage in credible conference call disclosure. Manipulators, on the other hand, intentionally pool by obfuscation. Moreover, the results show that investors underreact to non-manipulators' conference calls and correct such an underreaction throughout the following quarter, indicating that when opportunistic disclosers' pooling effect is strong, the informativeness of credible disclosers' conference calls is compromised.

Chapter 2 contributes to the accounting literature in three ways. First, it contributes to the literature on earnings benchmark meeting and beating. While prior research tends to focus on managers' incentives and market participant's reactions to opportunistic benchmark meeting and beating behaviour, this study focuses on how earnings manipulators and non-manipulators design conference call communication strategies to react to the pooling equilibrium in this setting. Second, this chapter adds to the literature on corporate voluntary disclosure in conference calls by examining whether and how high earnings-quality firms adopt specific communication strategies to clarify the truthfulness and credibility of their results when they face strong pooling effects from opportunistic managers. Third, it contributes to the literature on the capital market effects of conference calls. While prior studies generally report that conference calls provide useful information to investors, this chapter shows that informativeness of credible disclosers' conference calls can be compromised in certain circumstances.

Chapters 3 of this dissertation focuses on sell-side analysts as conference calls allow researchers to gauge analyst-manager relationships through analysts' conference call participation. Specifically, this chapter explores how analysts' people skills affect their relationships with firm management and informational outputs. People skills have become increasingly valuable in the labour market over the past decades because such skills cannot be substituted by machines. This chapter develops an empirical measure of analysts' people skills based on their ethnic cultural background. Consistent with theories and evidence from psychology and linguistics research, validation test shows that the empirical measure of people skills exhibits a U-shaped relation with analysts' ingratiating behaviour in conference calls.

The empirical results in Chapter 3 show that analysts with better people skills are more likely to participate in conference calls and ask earlier questions, indicating that these analysts have closer relationships with firm management than analysts with poorer people skills. To examine whether analysts can benefit from better people skills, mediation analysis results suggest that analysts with better people skills to some extent possess superior firm-specific information, which is partly facilitated by their closer relationships with firm management.

Chapter 3 has both contributions to the literature and implications for practitioners. It contributes to the emerging literature on the value of people skills in the labour market. Recent economics research documents that people skills have become more and more crucial in determining labour market outcomes such as wages and productivity. I focus on the specific impacts of people skills on sell-side analysts, who are important informational intermediaries in financial markets. I provide the first evidence that good people skills lead to stronger management relationships and access to superior firm-specific information for analysts. This chapter also contributes to the literature on analysts. Given analysts' biased incentives and conflicts of interest, it is essential for both regulators and investors to understand which factors underpin the development of analyst-management relationships. This chapter extends the prior literature by documenting how analysts' people skills affects their relationships with firm management. In terms of the practical implications, the financial press and investment banking professionals have recently advocated people skills development for business school students and financial industry employees. Echoing the practitioners' suggestions, the findings in this chapter shed lights on why and how people skills matter in financial markets.

Chapters 4 also focuses on sell-side analysts' conference call communication behaviour. Different from Chapter 3, this chapter examines analysts' linguistic politeness behaviour using theory from linguistics research and employs qualitative and quantitative discourse analysis methods. This chapter investigates how analysts use linguistic politeness in conference calls to establish socially desirable professional identities. They have two identities, i.e. competent professionals and dependants of firms. In their relationships with investor clients, analysts are competent professionals because they are expected to play an external monitoring role. In their relationships with managers, however, analysts are dependants of firms because they have incentives to build close and friendly relationships with managers. This chapter uses discourse analysis to study how analysts use politeness strategies to sustain and balance between the two identities in conference calls. During the conference calls of increasing earnings firms, analysts adopt more polite communication strategies to maintain friendly relationships with managers. During the calls of decreasing earnings firms, however, the need to maintain the competent professional identity dominates analysts' politeness behaviour. Collectively, results suggest that analysts aim to promote a socially desirable image that they are independent from managers, yet close enough to obtain information.

Chapter 4 contributes to financial communication research in two ways. First, it contributes to the literature by emphasising the importance of politeness in financial communication. While linguistics research shows that politeness is fundamental in social interactions and relationship construction, evidence on politeness in financial communication is largely missing from the existing literature. Politeness is a fundamental element in financial communication because it can be used to construct, sustain and promote relationships among firms, analysts and various stakeholders. Speaking to the value of politeness, I provide the first evidence on how analysts use politeness strategies in conference calls to sustain their professional identities in front of managers and investors. Second, this chapter furthers our understanding of analysts' behaviour by examining how they use language to establish and promote socially desirable identities in a daily-task environment. Given the essential role that analysts play in financial markets, it is important to understand how they construct professional identities because it is closely related to the stability of the financial system.

5.2. Limitations and suggestions for future research

The findings and conclusions from the studies in this dissertation are subject to several limitations, which yield opportunities for further research. First, in Chapter 2, the empirical results and inferences are limited to the extent to which earnings manipulators and non-manipulators can be accurately classified. To mitigate such a concern, the empirical research design incorporates various methods to classify non-manipulators and manipulators according to different criteria. Moreover, as Chapter 2 focuses on the post financial crisis period, the results might not be generalisable to the periods before or during the financial crisis, during which firms might manipulate earnings differently. Future research is encouraged to explore whether firms employ different communication strategies in conference calls during these time periods.

Second, in terms of Chapter 3, the main caveat is that analysts' people skills are measured based on ethnicity-level cultural traits. While such a measurement is justified by the theory and evidence that people skills are learned early in life and affected by ethnical culture background, as well as by the results of validation tests, the measure assumes that on average analysts do not experience significant variations in people skills as time passes. Due to the archival large-sample nature of this study, the time-varying component of people skills cannot be captured empirically. Thus, future research might use experimental or survey methods to further explore such a component of people skills and assess whether the level of analyst people skills vary significantly over time.

Third, as for Chapter 4, the discourse analysis method inherently attenuates the external validity of the results. As discourse analysis requires close reading and examination of the data, it is unrealistic to conduct analysis on a large sample. At the current stage, techniques in computational linguistics research are unable to automatically measure various politeness strategies because the analysis relies on the specific context of the social interactions (Kádár and Haugh, 2013: 109). Thus, it would be useful for future research in computational linguistics to develop methods to automatically assess linguistic politeness behaviour. Moreover, this chapter only explores analysts' politeness strategies in conference calls. Given the importance of politeness in social interactions in general, there are fruitful avenues for future research to evaluate the role of politeness in other financial communication settings.

Lastly, all three studies in this dissertation are conducted based on samples of earnings conference calls of U.S. public firms. Therefore, the generalisability of the findings to other countries with different languages, business practices, culture or legal systems is limited (El-Haj et al., 2019). Therefore, it is useful for future research to investigate conference call financial communication in other countries.

Despite the limitations, this dissertation contributes to accounting research by examining firm managers' and sell-side analysts' financial communication incentives and behaviour in earnings conference calls. Given the interdisciplinary nature of this work, it contributes to our knowledge on financial communication from various unique points of view.

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