Economic Consequences of Hiring Wall Street Analysts as Investor Relations Officers

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December 20, 2017

Acknowledgements

We thank seminar participants at Concordia University, ESSEC Business School, the European Accounting Symposium for Young Scholars 2017, and Cass Business School CeFARR conference 2017 for valuable comments. We appreciate Nayana Reiter's clarifications related to data on corporate events. We thank Yetaotao Qiu, Mingyue Zhang, Sara Haddou, and Melanie Negreanu for excellent research assistance. This work was generously supported by Concordia University JMSB Supplementary Seed Funding SSHRC GRF S00386. Hope gratefully acknowledges funding from the Deloitte Professorship.

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Abstract

This paper examines economic consequences associated with the emerging practice of hiring financial analysts as investor relations officers (IRO). We posit that analysts-turned-IROs have a competitive advantage in communicating with investors, thereby lowering the effort expended by the investment community to process corporate disclosures. Using a unique manually-collected dataset on the employment history of IROs (compiled from LinkedIn, Capital IQ, RelationshipScience.com, and appointment press releases) and a difference-in-differences research design with matched control sample, we first show that 8-K disclosure readability improves after firms hire former analysts as IROs through reductions in length, complexity, and the proportion of uncertain financial terms. We also find some evidence that these companies are more likely to host analyst/investor days. Most importantly, we find increases in analyst following, institutional investors, and stock liquidity after hiring a former analyst as IRO. Overall, our findings suggest that firms benefit from hiring Wall Street analysts as IROs.

Investor relations; financial analysts; disclosure; information environment; institutional investors; stock liquidity

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1. Introduction

The investor relations (henceforth, IR) function is a bridge between the preparers of financial information and the users of this information, aiming to facilitate efficient and effective interaction between the firm and the investment community. Historically, the IR function has been viewed as a communications role (Korn Ferry Institute, 2015) and the investor relations officer (henceforth, IRO) has had background or training in communications and public relations (Brennan and Tamarowski, 2000). Recently, however, more companies turn to Wall Street to fill IR positions. For example, in a recent step toward a much-anticipated IPO, Spotify hired a former Wall Street veteran who had run the internet and media research groups at Barclays as Head of IR (Kafka, 2016). A National Investor Relations Institute (NIRI) survey found that 22% of the surveyed IROs working for Fortune 500 companies in 2014 are former sell-side or buy-side analysts, up from 10% in 2008 (Korn Ferry Institute, 2012, 2015). In September 2016, Brown, Call, Clement, and Sharp (2017) surveyed 610 IROs of U.S. listed companies; almost 30% reported having prior experience in investment banking or sell-side research.

The practical value and implications of shifting IROs' skill set from communications to financial acumen have stirred debate in the business media. For instance, a recent Wall Street Journal article suggests that while companies recruit former analysts as IROs to "talk to investors in their own language," these former analysts may "struggle with tactfully coaching fellow executives" (Stuart, 2016). In a similar vein, incumbent IROs interviewed by IR Magazine point out that companies hiring Wall Street analysts as IROs do not "take into account the full range of skills and experience an individual needs to work in investor relations" (Human, 2015). Given the important role played by IROs in communicating financial information to the investment community (Brown et al., 2017; Kirk and Vincent, 2014), and the fact that analysts are considered primary users of such information (Healy and Palepu, 2001; Schipper, 1991), we provide evidence to better understand the relation between IROs' prior experience as financial analysts and the effectiveness of the IR function.

We manually compile a unique dataset of employment history and biographical information for persons occupying the position of Head of IR from 2004 to 2016 in non-financial companies that are included in the S&P 500 market index. Our sample contains 452 unique *changes* in IROs, of which 118 cases involve hiring an IRO who used to be a financial analyst (hereafter, AIRO). We implement a difference-in-differences research design with a sample of treatment (AIRO = 1) and control (AIRO = 0) observations, matching (using Coarsened Exact Matching) on industry and firm size (firm characteristics), or on industry, IRO gender, university attended, and MBA degree (individual characteristics).

Hiring former analysts as IROs could change corporate disclosure in a way that is welcomed by the investment community. We hypothesize and find that the experience that AIROs have in reading countless corporate disclosures enables them to improve the disclosures their new employer makes. We test this by comparing the characteristics of 8-K filings on the criteria set out in the SEC's Plain English Disclosure Final Rules 421(b) and 421(d). We find that after hiring former analysts to head the IR function, 8-K filings become shorter, include fewer complex words, contain a smaller percentage of uncertain financial terms, and are overall more readable as measured by the Gunning Fog Index (Lehavy, Li, and Merkley, 2011; Li, 2008).

We then examine the effect of hiring a former analyst as IRO on the number of financial analysts following and institutional investors investing in the firms. Building and maintaining close relationships with financial analysts and institutional investors is a major focus of the IR function (Kirk and Vincent, 2014; NIRI, 2004). Prior research shows that analyst coverage and institutional ownership are increasing in corporate disclosure (Bushee and Noe, 2000; Diamond, 1985; Healy, Hutton, and Palepu, 1999; Merton, 1987), which is consistent with the notion that the effort analysts expend to analyze the firm is an important determinant of analyst coverage (Barth, Kasznik, and McNichols, 2001; O'Brien and Bhushan, 1990). An analyst has expertise in processing corporate disclosure and understands good-versus-bad disclosure practices from the perspective of investors. If a firm capitalizes on such expertise and deep understanding to reshape corporate disclosure and the way the firm's story is communicated, that is, by hiring a former analyst to head its IR function, the investment community would likely incur lower costs to process corporate disclosure. Thus, we expect firms to attract more interest from analysts and institutional investors after hiring a former financial analyst as IRO. Our findings are consistent with these expectations. In particular, we find a significant increase in analyst following and an increase in the number of institutional owners.

Next, we examine changes in liquidity following the recruitment of new IROs from Wall Street. Extant studies predict and find that stock liquidity is increasing in the quality of firm communication (Baiman and Verrecchia, 1996; Barry and Brown, 1984, 1985; Diamond and Verrecchia, 1991; Easley and O'Hara, 2004; Healy et al., 1999; Merton, 1987). Therefore, we expect an increase in stock liquidity following the recruitment of former analysts as IROs. Using Amihud's (2002) illiquidity ratio and bid-ask spreads as inverse measures of liquidity, we find evidence of increased liquidity. Inferences are unchanged after we control for the change in 8-K readability and in the number of analyst/investor days in the four quarters surrounding the IRO change, which suggests that it is not merely improved disclosure that leads to the effect we find for analysts-turned-IROs.

There are two limitations common to studies that examine the role that personal characteristics play on decisions or consequences at the firm level. One limitation is correlated omitted variables at the IRO level. If another personal characteristic is correlated with the person being employed as a financial analyst and also with her performance as IRO, not including this variable in our models could bias the effect we estimate. To address this potential endogeneity, we match treatment with control observations based on biographical details of the IRO (gender, university attended, and MBA degree). The results from matching on IRO characteristics are generally consistent with the ones from regressions run on the full sample or on the sample matched based on firm characteristics.

The second limitation is due to the fact that we do not observe a random assignment of IROs to companies. It is possible that the AIRO is recruited or self-selects into the job due to unobserved firm characteristics and the same firm characteristics also explain the changes we observe in the economic consequences examined. If this is the case, “endogenous IRO-firm matching” could bias the results (Bertrand and Schoar, 2003). Having an AIRO in place rather than a “regular” IRO strengthens the probability that the company actually reaches the desired economic consequences. As Custódio and Metzger (2014) point out, this view of endogenous IRO-firm matching is not necessarily inconsistent with a causal interpretation of the results if firms recruit AIROs with the expectation that they are able to generate the economic consequences.

Another possibility, however, is that due to certain characteristics the firm would still reach the economic consequences, regardless of who is in the IRO position. Under this view of the endogenous IRO-firm matching, some firm characteristics determine the choice of AIRO, but the AIRO is irrelevant to obtaining the economic consequences that are determined entirely by the pre-existing firm characteristics. Therefore, the economic consequences observed are not due to the AIRO's influence, but rather to other firm-level variables that also determine the "matching" between the firm and the AIRO. We address this possibility by investigating the *determinants* of hiring an AIRO rather than a regular IRO, conditional on a turnover in the IRO position. We then include the determinants as additional control variables in the consequences regressions. Doing so accounts for the effect of the firm characteristics that led to the matching between the IRO and the firm on analyst coverage and stock liquidity. The effect of the AIRO observed after including the determinant variables as controls can be cautiously interpreted as the personal influence of the IRO.

This study contributes to a small but growing stream of literature that examines the roles of the IR function (Brennan and Tamarowski, 2000; Bushee and Miller, 2012; Karolyi and Liao, 2017; Kirk and Vincent, 2014) and the IR process (Brown et al., 2017). To the best of our knowledge, ours is the first study that examines the role of personal characteristics of IROs. We add to this literature by documenting improvement in the information environment following the recruitment of former analysts who have first-hand experience and profound understanding of how the investment community uses and assesses financial information as IROs. Increased interest in the company and higher stock liquidity could lead to an increased stock price and easier financing and are, therefore, desirable from a firm's perspective. Our results should be useful to managers seeking to improve communications with investors.

We also contribute to the emerging literature on financial analysts' career outcomes. Existing studies in this area focus on the dark side (e.g., conflict of interests generated from "revolving-doors") of analysts' career progressions from financial intermediaries to senior management or board membership in corporations (Cohen, Frazzini, and Malloy, 2012;

Cornaggia, Cornaggia, and Xia, 2016; Horton, Serafeim, and Wu, 2017; Jiang, Wang, and Wang, 2017; Kempf, 2017; Lourie, 2015). For example, Lourie (2015) documents biases in equity analysts' summary forecasts in the year before they move into job positions in firms they covered, including positions in the IR function. We examine what happens *after* the career move and do not limit ourselves to the analysts who go through the "revolving door," thus portraying a more complete picture of this practice. We show that former analysts with experience in reading and analyzing complex corporate disclosure and who understand what the investment community needs from firms, bring significant benefits to their new employers.

Broadly, our study is related to the literature that investigates the effect that individuals have on firm decisions and firm-related outcomes (e.g., Bamber, Jiang, and Wang, 2010; Bertrand and Schoar, 2003). More recently, the literature has moved toward analyzing how various personal or biographical characteristics shape the effect that individuals have on firm decisions and firm-related outcomes, usually with a focus on chief executive officers or chief financial officers (e.g., Hoitash, Hoitash, and Kurt, 2016; Sunder, Sunder, and Zhang, 2017). Our focus on the IRO, the spokesperson of the company, extends this stream of literature.

Our paper also adds to the literature on the capital-market consequences of corporate disclosure and communication. While economic theory predicts that disclosure should reduce information asymmetry, thereby leading to various positive outcomes (Diamond and Verrecchia, 1991; Easley and O'Hara, 2004), as pointed out by Brennan and Tamarowski (2000) and Karolyi and Liao (2017), only some disclosures are adequately assessed by the investment community, hindering the speed of price discovery and full realization of the benefits of disclosure. By documenting the benefits of hiring IROs who "talk to investors in their own language," our results have implications for studies investigating the economic consequences of corporate disclosure.

2. Background and Hypotheses Development

2.1 The investor relations function

The role of IR is to manage the communications between insiders (i.e., management and board of directors) and outsiders (i.e., current and potential investors, financial analysts, media, and other stakeholders) (Brennan and Tamarowski, 2000; Kirk and Vincent, 2014). Brown et al. (2017) point out that “this important responsibility places IROs at the center of many disclosure-related activities, including conference calls, press releases, and other informal interactions with the investment community” and in position to manage the expectations of the investment community and control their access to top management. IROs prepare senior management for public calls and investor meetings, manage earnings-conference calls, and prepare and assist with company disclosures such as press releases and management discussion and analysis (Brown et al., 2017). IROs also act as a feedback loop by bringing back to management the views of analysts and investors about the company and helping managers understand what the investment community is thinking (IR Magazine, 2015, 2017).

Prior literature shows that improving communication with investors of small-cap companies by hiring an IR firm results in higher institutional investor ownership, analyst following, media coverage, and market-to-book ratio (Bushee and Miller 2012; see also Karoly and Liao 2017). Such actions are meant to strengthen the visibility of the firm, which in turn may have stock-market benefits. For example, the findings in Lehavy and Sloan (2008) suggest that visibility has the potential to affect firm valuation even more than fundamentals, providing support for Merton's (1987) theory that greater firm visibility widens investor recognition, broadens the investor base, and, thus, lowers the cost of capital.

When interviewed, specialists from IR firms suggest that since U.S. public companies tend to already have a relatively high level of public disclosure, the role of IR is to build and enhance management's credibility through direct contact with investors and information intermediaries and to further increase the quality of public disclosure (Bushee and Miller, 2012). IR could still create benefits even in large firms with a rich information environment. For example, Kirk and Vincent (2014) find that companies that employed a NIRI-certified IR professional were better able to navigate the disclosure requirements following Regulation Fair Disclosure. Furthermore, firms with professionalized in-house IR are more likely to organize events that facilitate interactions with capital-market participants such as conferences and analyst/investor days (Kirk and Markov, 2016).

Some prior studies point to the dark side of IR. For example, there is evidence that suggests that IR orchestrate conference calls such that analysts favorable to the company get to ask more questions, allowing the company to control the information flow to the market (Cohen, Lou, and Malloy, 2017) and that, through their connections with reporters and business journalists, IR firms increase the media coverage of good news and decrease the coverage of bad news for their clients, which results in transient positive abnormal returns (Solomon, 2012). These findings are consistent with Hong and Huang (2005) who show that investment in IR may be motivated by insiders' need for increased liquidity of their block of shares rather than improved share valuation.

Brennan and Tamarowski (2000) emphasize that the role of IR goes beyond simply disclosing information to investors and analysts; IROs also help increase the credibility of the firm's investment and product strategy. For example, besides organizing conference calls and analyst/investor days (Kirk and Markov, 2016), part of the role of IR is to attract the type of investors that the company desires. Harrison (2010) cites an IR professional as saying that IR is "targeting information to make sure [they] are hitting the right shareholders." A recent Nasdaq-commissioned survey finds that about half of the IRO respondents have been increasing their direct targeting efforts in the last three years (IR Magazine, 2016).

This stream of literature suggests that a professionalized IR function has the potential to benefit public companies in several ways. We investigate whether there are advantages to employing former financial analysts as IROs.

2.2 Financial analysts' career outcomes

A number of papers examine financial analysts' career paths inside the brokerage-firm industry as it relates to characteristics of their output (Bradley, Gokkaya, and Liu, 2017; Hong and Kubik, 2003), major events such as mergers and acquisitions for the companies they cover (Wu and Zang, 2009), or their apparent connections to the management of the companies they cover (Cen, Chen, Dasgupta, and Ragunathan, 2017).

Another relatively recent stream of literature investigates career outcomes in the context of the revolving-door phenomenon characterized by a person seeking employment in a company that she was monitoring in her immediately prior position.[1] The revolving-door literature generally focuses on possible biases exhibited by revolving-door employees toward their future

[1] The revolving-door phenomenon has been examined in a range of settings, including for federal public employees hired into the lobbying industry (Blanes i Vidal, Draca, and Fons-Rosen, 2012), political appointments from the private sector and corporate appointments of former government officials (Luechinger and Moser, 2014), moving from a regulatory agency such as the SEC to positions in regulated firms (DeHaan, Kedia, Koh, and Rajgopal, 2015; Shive and Forster, 2017), auditors becoming CFOs (Geiger, Lennox, and North, 2008; Geiger, North, and O'Connell, 2015; Menon and Williams, 2004), credit-rating analysts hired by the companies they previously rated (Cornaggia, Cornaggia, and Xia, 2016), and banking analysts hired by banks they covered (Horton et al., 2017).

employers. Cohen et al. (2012) find that analysts who are appointed to boards of directors are overly and unrealistically optimistic about the prospects of their future employers. Similarly, Lourie (2015) finds that in their last year as analysts, revolving-door analysts issue more optimistic forecasts, target prices, and recommendations for their future employers compared to other analysts and become more pessimistic about other firms' prospects. These results are consistent with Hong and Kubik (2003) who find that more optimistic analysts fare better in their career, regardless of the accuracy of their forecasts, and suggest that analysts use their position to curry favors with the companies they seek employment in.

2.3 Endogenous IRO-firm matching: Determinants of hiring a former analyst as IRO

The main role of IROs is to effectively communicate "the story" of the company to the investment community. Starting from this notion and using survey and interview-based insights from the professional (e.g., IR Magazine, 2015, 2017) and academic literature (Brown et al., 2017) on the challenges that the IR function faces and what senior management expects from IR, we consider several firm-level characteristics that could potentially drive the firm to appoint a former analyst as IRO.

More innovative firms potentially have a harder time communicating their story to the investment community. For example, Internet-based business models can be more difficult to fit into well-established industry patterns and are therefore harder to grasp (Fan, 2016). Poor firm performance could also be a reason for a firm to hire a former analyst as IROs who could better explain, for example, the reasons for the poor performance or its transitory nature. Similarly, firms that are more prone to litigation may want a reassuring and familiar voice communicating to their shareholders and potential investors.

Further, firms that are on a growing trend or have high growth opportunities would presumably need the support of the investment community to reach the envisioned growth. This means that these firms would need to keep the investment community engaged and paying attention to "their story." However, we expect that very young firms are less likely to hire a former analyst as IRO. Surveyed IROs mention that their role is often restricted in young firms because the founder or CEO is more likely to spend significant time engaging with the investment community (IR Magazine, 2013). At the other end of the spectrum, older and larger firms that are well-established might be more interested in ensuring the succession for the roles of chief financial officer or chief executive officer and might be more inclined to use the IRO position as a stepping stone for inside personnel, rather than hiring outsiders.

2.4 Corporate disclosure

The investment community, regulators, as well as academic researchers frequently raise concerns about the ever-increasing effort exerted by investors, even sophisticated ones, to struggle through the highly technical and complex financial reporting and disclosure (CFA Institute, 2015; Deaves, Dine, and Horton, 2006; Lehavy et al., 2011; SEC, 2006, 2008). IROs, often nicknamed "Chief Disclosure Officers," play a key role in setting the disclosure policy of the firm (Brennan and Tamarowski, 2000; Kirk and Vincent, 2014; NIRI, 2005, 2011).

Disclosure theory predicts that analyst coverage and institutional interest are increasing in corporate disclosure (Diamond, 1985; Diamond and Verrecchia, 1991; Merton, 1987). Consistent with these theoretical predictions, prior studies find a positive relation between improvements in corporate disclosure and analyst and institutional investor following (Bushee and Noe, 2000; Healy et al., 1999; Lang and Lundholm, 1996, among others). This evidence is consistent with the effort analysts and institutional investors expend to analyze the firm being an important determinant of analyst coverage and institutional interest (Barth et al., 2001; O'Brien and Bhushan, 1990).

SEC Plain English Final Rules 421 (b) and 421 (d) require registrants to (1) present information in clear and concise sections, paragraphs, and sentences, (2) avoid vague boilerplate explanations, and (3) avoid legal terminology.[2] Based on these aspects and on the importance that the analyst community places on the quality of corporate disclosures (Lang and Lundholm, 1993), we hypothesize that AIROs improve the quality of corporate disclosures to help the investment community better grasp the story of the company.

A recent stream of research investigates the various corporate disclosure channels that firms use to disclose information to capital-market participants (Mayew, 2012 provides a review). The disclosure channels we refer to above (i.e., press releases and SEC filings) do not involve face-to-face interaction between management and investors. Other channels involve the interaction between management and investors such as earnings-announcement presentations and conference calls (Matsumoto, Pronk, and Roelofsen, 2011), presentations at broker-hosted conferences (Green, Jame, Markov, and Subasi, 2014), and analyst/investor days (Kirk and Markov, 2016).

Of these disclosure events, we expect analysts-turned-IROs to favor analyst/investor days based on their prior experience as financial analysts. Our expectation is based on the assumption that most S&P 500 companies organize quarterly conference calls and on the discussion provided by Kirk and Markov (2016) that suggests that the more rigid nature of broker-hosted conferences might leave analysts less satisfied with that opportunity to interact with management. Kirk and Markov (2016) point out that analyst/investor days are hosted and paid for by the firms

[2] https://www.sec.gov/rules/final/33-7497.txt

and are, therefore, flexible in terms of format, timing, duration, and organization. During analyst/investor days, guests interact informally with, on average, 10–14 firm representatives, including top- and mid-level managers (Kirk and Markov, 2016) which provides ample opportunities for analysts and investors to gather additional information on firm strategy, operations, and performance.[3] As a former analyst, the AIRO likely has a better understanding of how such events help companies to communicate with the investment community. Additionally, Kirk and Markov (2016) find that the firm's IR function plays a significant role in organizing and coordinating analyst/investor days. Therefore, we expect AIROs to engage their new company in such corporate disclosure events.

To summarize, given their prior position as direct consumers of corporate disclosures, we expect analysts-turned-IROs to work on improving their employer's disclosure either in terms of how the context is exposed or in terms of the channels used for disclosure and communication. We formalize this expectation in the following hypothesis (in alternative form):

H1: Firms experience an improvement in corporate disclosure after hiring a former financial analyst as investor relations officer.

It is not clear, however, whether AIROs would be able to improve corporate disclosure more than other IROs. For example, a career IRO would presumably have had varied experience dealing with a wide spectrum of analyst and investor preferences; other IROs may have had more formal training in public communication. While the AIRO draws from her personal experience as analyst, a regular IRO may draw from a broad experience of responding to investor and analyst's needs.

[3] A Wall Street Journal article points to how, in March 2015, following a string of conversations between investors and Procter & Gamble's CEO, A.G. Lafley, an analyst covering the firm came to believe that Mr. Lafley would step down sooner than expected. Four months later the firm made such an announcement (Ng and Troianovski, 2015).

2.5 Analyst and investor following

Building and maintaining close relationships with analysts and institutional investors is a major focus of the IR function. For example, of the 604 IROs that Brown et al. (2017) surveyed, 90% and 83%, respectively, consider that interacting with institutional investors and sell-side analysts is a very important part of their job. We expect firms hiring former analysts to head the IR function to experience an increase in analyst following and institutional investor interest thanks to the inside information that the analyst-turned-IRO brings about how analysts and investors make decisions.

Having worked in the investment community, an analyst has first-hand experience in reading, processing, and analyzing corporate disclosures; hence she has a better appreciation of good-versus-bad disclosure practices from the perspective of investors. She also has a deep understanding of the usages of disclosure channels and financial language. Consequently, an AIRO is likely to have an edge over other IROs when it comes to "talking to investors in their own language." As a result, analysts and institutional investors are likely to incur lower costs in extracting decision-useful information from disclosures made by (or influenced by) analysts-turned-IROs.[4] Thus, we expect firms to experience an increase in analyst following and institutional investor ownership after hiring an IRO from Wall Street.

While improvements in disclosure could be one way through which the AIRO enhances IR, other parts of an IROs job are also likely to contribute to attracting additional interest from analysts and investors. Surveys find that IROs prepare top management for conferences and meetings with the investment industry (IR Magazine, 2017). Beyond what managers

[4] We acknowledge that opportunistic CEOs may use the expertise of analysts-turned-IROs to hide bad news. This possibility, however, would bias against our findings.

communicate verbally, body language and other non-verbal cues could inform analysts and investors (Mayew and Venkatachalam, 2012). Their prior experience gives AIROs intimate knowledge about the insights and conclusions analysts and investors can draw from how management communicates, verbally or non-verbally. As a result, for the better or worse, they are in a position to coach managers better on how to present—and represent—the company. Hence, based on the above discussion, we hypothesize that (in the alternative form):

H2: Firms experience an increase in analyst following and institutional investor ownership after hiring a former financial analyst as investor relations officer.

However, differences between working in the financial services industry versus the corporate world may pose a challenge for AIROs. For example, some IROs believe that long-term experience of working in a company before being appointed as Head of IR allows for a different relationship with top management and that analysts may lack the coaching and communication skills required for working effectively with management (Goldberger, 2017; Human, 2015; Stuart, 2016). Such internal frictions could potentially dent the story and message the company wants to communicate externally and create doubt for investors following the company.

2.6 Stock-market consequences

Our last hypothesis relates to stock liquidity. Disclosure theory predicts that liquidity decreases in corporate disclosure (Barry and Brown 1984, 1985; Merton 1987; Diamond and Verrecchia 1991; Easley and O’Hara 2004). Consistent with these predictions, Welker (1995) finds that higher quality disclosure is associated with lower bid-ask spreads and Healy et al.

(1999) document that firms with sustained increases in disclosure ratings experience decreases in bid-ask spreads (see also Leuz and Verrecchia 2000).

Financial analysts tend to specialize by industry and therefore develop deep industry knowledge (Brown, Call, Clement, and Sharp, 2015) that could be useful for corporate employers.[5] Based on the competitive advantage that analysts-turned-IROs potentially have over regular IROs in terms of understanding the industry, and their role in communicating publicly and privately with investors and capital market participants, we hypothesize that:

H3: Firms experience an increase in stock liquidity after hiring a former financial analyst as investor relations officer.

However, we may not find support for these hypothesized benefits for several reasons. While analysts are often regarded as information intermediaries between the firm and investors, an alternative view is that they are information providers (Bhushan, 1989). Diamond (1985) models a substitution effect between corporate disclosure and the activities of financial analysts, suggesting that making more informative disclosures directly available to investors reduced the benefits to analysts' private information production. Consistent with this alternative view, Lobo, Song, and Stanford (2012) find that analyst coverage decreases when firms provide high-quality financial reporting, and Lehavy et al. (2011) report that analyst following is greater for firms with less readable 10-K filings. Diamond and Verrecchia (1991) show that when information asymmetry between a firm and investors is large, reducing such asymmetry results in higher liquidity and higher demand from institutional investors initially but subsequent reduction in information asymmetry accentuates exit from market making, leading to lower demand from

[5] A recent IR Magazine article points out that "investment bankers and sell-side analysts […] bring tremendous industry insight" to an IRO position (Goldberger, 2017).

institutional investors and lower liquidity. It is thus possible that hiring a former analyst as IRO leads to less favorable economic consequences.

3. Data and Research Design

3.1 Data collection

Using Compustat North America, we compile a list of non-financial companies included in the S&P 500 market index and perform the data collection in two steps. For these firms, we compile a list of individuals who have occupied the Head of IR position by collecting data from (1) the current investor relations contact on the company's IR website, (2) the list of participants in conference calls held by the company, (3) the contact details on the firm's earnings press releases, and (4) the predecessor and successor names in Head of IR appointment press releases, where available, and (5) S&P Capital IQ (i.e., persons that occupied the job functions of "Head of Investor Relations", "Investor Relations Professional"). Besides the name of the person, we also collect the dates of their employment as IROs using information from LinkedIn, Capital IQ, RelationshipScience.com, and appointment press releases.[6] Importantly, where possible we corroborate this information with the dates of conference calls where the person participated as IRO or with the dates of press releases where the person was the IR contact.[7]

We note two additional details related to data collection. First, we can only identify the person holding the highest-ranking function in the IR team.[8] Survey evidence shows that in 84%

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[6] LinkedIn has over 450 million registered members worldwide who publicly post their profiles (https://press.linkedin.com/about-linkedin). Other recent studies that use LinkedIn either as the main or a supplementary data source include Cornaggia, Cornaggia, and Israelson (2017), Cornaggia, Cornaggia, and Xia (2016), Fracassi, Petry, and Tate (2016), and Jiang et al. (2017).

[7] We infer employment dates from the person's presence as IRO in the company's conference calls or on corporate press releases when employment dates are not available from the other sources mentioned above.

[8] For example, if the company has both a vice-president of IR and a director of IR, we retain only the vice-president's name; if the company hires a director of IR and a manager of IR without having a vice-president of IR, we retain only the director's name.

of companies, the Head of IR is the primary contact with the investment community (Karolyi and Liao, 2017), thus providing support for examining IROs.[9] Second, in some cases the Chief Financial Officer is also the Head of IR, either to ensure the transition until a new IRO is hired to replace the outgoing one or on a permanent basis. We eliminate these cases since they are not relevant to our research question.[10] The outcome of this first step is a historical list of IROs per company and their employment dates as IRO.

In the second step of the data-collection process, we search the IRO's name on LinkedIn with the goal of identifying and collecting information on the IRO's previous job positions (i.e., position, dates of employment, and employer) and demographics (i.e., age, gender, and education).[11] We complement the information obtained from LinkedIn with information from appointment press releases that often list the appointee's prior job positions, age, and education and from corporate websites that sometimes contain summary biographies of top-level management employees.[12] We eliminate the cases where the Head of IR was previously in a low-ranking position in the same IR team. Such cases would add noise to our tests since we cannot know if and to what extent these persons influenced the activity and performance of the IR function from the low-ranking position. The resulting dataset is an expanded panel with observations at the firm-IRO-job level.

We manually code whether each job position that a person has held is a financial analyst job in the financial services industry based on the job title or description and the employer

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[9] A company could have several members in the IR team but their identity is much harder to establish compared to the identity of the Head of IR since their names usually do not appear in conference calls or press releases.

[10] We also eliminate the few companies that do not have an in-house IR function.

[11] To fill in gaps in employment history, we also use Bloomberg, BoardEx, RelationshipScience.com, and magazine articles (e.g., Investor Relations Magazine) written about the IRO. These additional sources, however, generally help only to a small extent.

[12] In some cases, we can identify the previous employers or jobs a person has had but not the employment dates. This happens especially when the person does not have a LinkedIn profile and the appointment press release or the corporate website summary is not specific about employment dates. We nevertheless include these non-dated previous jobs in our dataset.

name.[13,14] We retain the firm observations with *changes* in IROs and use the manually coded data to distinguish between companies that hire an IRO with prior job experience as a financial analyst (AIRO = 1) and companies that hired an IRO without experience as a financial analyst (AIRO = 0).

3.2 Research design

Given the possibility of endogenous IRO-firm matching, we first examine the *determinants* of hiring a former analyst as IRO. We identify the fiscal quarter when the IRO change occurred as Q0 (i.e., the event quarter) and include as potential determinants firm variables computed over the four fiscal quarters prior to the change (Q−4 to Q−1). We estimate the following Probit regression model:

$$\begin{aligned} AIRO = \alpha_0 &+ \alpha_1 Analyst\ Coverage + \alpha_2 \#Institutional\ Investors \\ &+ \alpha_3 Bid\ Ask\ Spread\ + \alpha_4 Market\ Capitalization \\ &+ \alpha_5 Stock\ Return\ Volatility + \alpha_6 Market\ to\ Book + \alpha_7 Financing \\ &+ \alpha_8 R\&D + \alpha_9 Litigation\ Risk + \alpha_{10} Return\ on\ Assets + \alpha_{11} Loss \\ &+ \alpha_{12} Leverage + \alpha_{13} NASDAQ + \alpha_{14} Firm\ Age + Industry\ FE +\ \gamma \end{aligned} \tag{1}$$

The dependent variable is the indicator variable *AIRO* that takes the value 1 if the IRO hired in fiscal quarter Q0 was previously employed as a financial analyst and 0 otherwise. Since the main role of IROs is to communicate with stock-market participants, we include several

[13] There are positions as "Financial Analyst" in manufacturing firms, for example. These are not Wall Street analyst positions but positions in which the employee performs business analysis and forecasting and reports to top management.

[14] The IRO appointment press release often emphasizes the analyst experience of newly-minted IROs. For example, the appointment announcement of Kathleen A. Lally as Vice President – Investor Relations of Public Service Enterprise Group on January 3, 2007, highlights that "Lally comes to PSEG after spending two and a half years at the investment firm Angelo Gordon & Co., most recently as portfolio manager. Lally has extensive and diverse Wall Street experience on both the buy side as an investor and the sell side as an equity research analyst. Lally has worked on the buy side at JK Utility Advisory and Silcap, and has sell side experience at firms such as Salomon Brothers, Brown Brothers Harriman and Pershing" (https://www.pseg.com/info/media/newsreleases/2007/2007-01-03.jsp accessed on September 29, 2017).

variables that reflect the firm's visibility and information environment prior to the IRO change (i.e., averages over quarters Q−4 to Q−1). Specifically, we include the number of analysts covering the firm, the number of institutional shareholders, and market capitalization (all three variables are log-transformed). Bid-ask spreads, daily stock-return volatility, and an indicator variable that distinguishes whether the firm shares trade on NASDAQ as opposed to NYSE, capture the information asymmetry between investors and uncertainty about the firm.

Firms may choose the new IRO such that their abilities match the complexity and growth of the firm. The market-to-book ratio proxies for the firm's growth opportunities; firms that are on a growing trend have incentives to "do their best" to maximize their chances that the investment community will regard their strategy positively. The indicator variable *Financing* takes the value 1 if the firm has been able to attract stock market financing in the prior year to account for the firm's financing needs. This variable accounts for the prior ability of the firm to successfully "sell" their story to investors. Research and development expenditures (*R&D*) account for the idea that companies that are more complicated may choose to hire an AIRO to explain their activities to the investment community. The indicator variable *Litigation Risk* is based on the firm's SIC industry classification and identifies the firms that, due to their business activity, face high securities class action litigation risk. Following Ali and Kallapur (2001), firms in the following industries are considered of high litigation risk: 2833–2836 and 8731–8734 (pharmaceuticals and biotechnology), 3570–3577 and 7370–7374 (computers and programming), 3600–3674 (electronics), and 5200–5961 (retailing).

We test the role of several firm characteristics in the matching between the firm and IROs. Firms may choose an AIRO based on prior firm performance. We include the return on assets ratio (*Return on Assets*) and an indicator variable for whether the company has made losses in the prior four quarters (*Loss*). The firm may also choose the IRO based on its capital structure and life-cycle stage. Therefore, we include the log-transformation of firm age (*Firm Age*) and leverage ratio computed as total debt to assets (*Leverage*). The argument is that the firm chooses an AIRO at the optimal time in its business life cycle.

To account for any firm-IRO matching due to intrinsic industry characteristics, we include industry fixed effects based on the Fama-French 12 industry classification.[15] While *Litigation Risk* is also based on industry, the fixed effects are defined at a different level (Fama-French 12 industry classification versus four-digit SIC code) so we are able to include both in the model.

In order to analyze the *consequences* of hiring an AIRO, we estimate the following difference-in-differences research design using the sample firms that change to an AIRO and a matched control group of companies that hire a "regular" IRO, similar to the research design used by Bushee and Miller (2012) and Kirk and Vincent (2014). To match the firms that hire an AIRO with firms that hire a "regular" IRO, we implement Coarsened Exact Matching (CEM).[16,17] Since matching is done directly on covariates rather than the outcome of a first-stage model, CEM avoids the problems caused by first-stage model specification and functional

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15 We obtain the classification from Professor French's website athttp://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_12_ind_port.html.

16 The Stata and SAS codes to implement CEM are available at https://gking.harvard.edu/cem.

17 Several studies discuss potential problems raised by propensity score matching (PSM) (Lennox, Francis, and Wang, 2012; Shipman, Swanquist, and Whited, 2017; Tucker, 2010). Specifically, PSM introduces a "random matching" problem (King et al., 2011). King et al. (2011) show that random matching occurs because the number of required matched controls is specified ex-ante (i.e., usually through a caliper distance), which forces the algorithm to find a match even when there is none. Additionally, PSM relies on the functional form of the first-stage propensity score model to discriminate between matching alternatives, which means that second-stage results could be sensitive to the choices researchers make in the first stage (Lennox et al., 2012; Tucker, 2010). Consequently, we follow DeFond, Erkens, and Zhang (2016) and apply CEM, a method designed to match on a coarsened range of covariates rather than on propensity score values (Iacus, King, and Porro, 2012).

form.[18] To test our hypotheses on the consequences of hiring AIROs, we run the following model on the sample of AIRO and non-AIRO matched observations.

$$\begin{aligned} Change\ in\ Y\ =\ & \beta_0 + \boldsymbol{\beta_1 AIRO} + \beta_2 Prior\ Change\ in\ Y + \beta_3 Analyst\ Coverage \\ & + \beta_4 \#Institutional\ Investors + \beta_5 Bid\ ask\ Spread \\ & + \beta_6 Market\ Capitalization + \beta_7 Stock\ Return\ Volatility \\ & + \beta_8 Market\ to\ Book + \beta_9 Financing + \beta_{10} R\&D + \beta_{11} Litigation\ Risk \\ & + \beta_{12} Return\ on\ Assets + \beta_{13} Loss + \beta_{14} Leverage + \beta_{15} NASDAQ \\ & + \beta_{16} Firm\ Age + Industry\ FE + \varepsilon \end{aligned} \qquad (2)$$

where *Y* refers to variables that proxy for the constructs hypothesized in H1–3. In all cases, the dependent variable is the *change* in the average value of *Y* over fiscal quarters Q+1 to Q+4 after the quarter when the IRO changed compared to the average value of *Y* over quarters Q−4 to Q−1 before the IRO change.

The main variable of interest is the indicator *AIRO*. Given our research design, the coefficient β_1 measures the incremental change in the dependent variable from before to after the change to AIRO relative to the change to a regular IRO. In other words, the difference-in-differences specification compares the company that hires an AIRO with itself in the pre-AIRO period (i.e., within firm) and with companies that hire a regular IRO, again before and after the change (i.e., across firms).

Specifically, to test H1 we proxy for corporate disclosures using the Gunning Fog readability index (Li, 2008), total word count, complex word count, and the proportion of uncertain words (Loughran and McDonald, 2011) in 8-K filings. To confirm H1, we expect a negative coefficient β_1 on *AIRO*, which would mean that 8-K filing readability increases after

[18] Since CEM does not use a single scalar to match, it takes into account higher moments of covariate distributions (King et al., 2011). Not imposing matching on first-stage propensity score values also means that the CEM algorithm establishes empirically the size of the matched control group which alleviates the random matching problem. Overall, CEM has been shown to dominate other common matching methods for causal inference in observational data (Iacus, King, and Porro, 2011).

changing to an AIRO (i.e., higher Gunning Fog index values reflect lower readability), the length is shorter, there are fewer complex words, and a lower proportion of uncertain terms.

To take into account the role that IROs can play in types of disclosure channels other than SEC filings, we employ two variables related to analyst/investor days (Kirk and Markov, 2016): (1) an indicator variable that takes the value 1 if the firm hosts analyst/investor days during a fiscal quarter (*Change Analyst/Investor Days*) and (2) the number of analyst/investor days *(Change #Analyst/Investor Days*). A positive coefficient β_1 would imply that the AIRO organizes more analyst/investor day events compared to the prior period before her appointment and compared to matched control firms that hired a regular IRO, confirming H1.

To test H2, we use the change in analyst coverage (*Change Analyst Coverage*) and number of institutional shareholders (*Change #Institutional Investors*) after-to-before the IRO change as proxies for interest from analysts and institutional investors (e.g., Bushee and Miller 2012). We expect positive β_1 coefficients in order to confirm H2.

To test H3, we use the Amihud (2002) stock illiquidity ratio (*Change Amihud Ratio*) and the bid-ask spread (*Change Bid-Ask Spread*). Confirming H3 rests on finding negative β_1 coefficients since a higher Amihud (2002) ratio or a higher bid-ask spread reflect lower liquidity (Amihud and Mendelson, 1986).

Following Bushee and Miller (2012), in each regression we include as control variable the change in the dependent variable *Y* over the four quarters prior to IRO change (i.e., *Prior Change in Y* equals to *Y* in Q−1 minus *Y* in Q−4) to control for underlying trends specific to *Y*. Additionally, we include all the independent variables from the determinants model in Equation (1) as control variables in Equation (2).[19] Including these controls alleviates the potential concern that the results reflect firm characteristics that led the company to choose an AIRO at the time of

[19] These variables are computed as average values over the four quarters prior to the change in IRO.

IRO turnover rather than the new IRO exerting her style and influence on the firm's information environment (i.e., matching versus influence). Detailed variable definitions and data sources are provided in Appendix A.

4. Results

4.1 Summary statistics

Given the sample restrictions discussed above, the fact that our research design requires one year of data prior to the IRO change, and considerations related to data availability, our sample spans the period 2004–2016.[20] We identify a full sample of 452 firm-quarters (corresponding to 268 unique firms) with changes in IROs, 118 of which are changes to an AIRO and 334 changes to a regular IRO.[21] Since our dependent variables are measured over the four quarters after the IRO change compared to the four quarters before, we retain only IROs with tenure of at least one year.[22] While the effective sample of AIROs appears to be relatively small, it nonetheless reflects the emerging nature of the practice of hiring IROs from Wall Street. Moreover, our sample size is comparable with studies examining the revolving-door phenomenon.[23]

[20] Earlier information about employment history is generally harder to find from public sources. Additionally, analyst/investor days are covered consistently in FactSet starting in 2003.

[21] We identify 680 IRO appointments starting in or after fiscal quarter Q1 2004 for non-financial firms in S&P 500 corresponding to 339 unique firms. We lose 53 observations (15 unique firms) where IRO employment history is not publicly available from our sources of data. The number of observations further drops when we eliminate internally-promoted IROs (97 observations), IROs that are appointed on an interim basis or are replaced within 12 months after appointment (25 observations) and observations missing accounting or finance data (53 observations).

[22] A minimum tenure requirement of one year also allows for the IRO to imprint her style on the way the IR department functions. Based on data availability and sample construction restrictions, the earliest IRO appointment in our sample is in June 2004 and the latest in September 2016.

[23] For example, without imposing restrictions on the population of companies or on the job that former analysts take, Lourie (2015) finds 299 financial analysts who were hired in companies they covered in the period 1999–2014. As an additional example, Cohen et al. (2012) examine 51 instances of equity analysts appointed as directors of companies they previously covered.

Panels A and B of Table 1 report the sample distribution by year and industry, respectively. Panel C presents descriptive biographical information about the IROs in our sample. In both sub-samples, males occupy 70% or more of the IRO positions, but the percentage is higher for AIROs. Most IROs in both sub-samples have an MBA, but more AIROs are MBA graduates. Regular IROs have a Master (non-MBA) as highest education level in a larger proportion compared to AIROs. Finally, AIROs are significantly more likely to have attended an Ivy League university.

Panel A of Table 2 reports descriptive statistics on firm characteristics over the four quarters prior to IRO changes. All continuous variables are winsorized at the 1st and 99th percentiles. Consistent with S&P 500 firms being the largest and most visible firms in the U.S. economy, the median company in the sample has 12.2 billion dollars in total market capitalization, ROA of 1.7%, with total debt representing 22.8% of total assets, has been incorporated for 39 years, has a market-to-book ratio of 2.861, is followed by 19 analysts, and has 409 institutional investors. About 28% of the sample observations are companies operating in litigation-prone industries, 83.7% have issued equity during the year, 8.7% are loss-making, and 24.1% are listed on NASDAQ.

Panel B of Table 2 compares these firm characteristics prior to IRO changes between firms that subsequently change to AIROs and firms that change to regular IROs. Firms that subsequently hire AIROs are younger, smaller, and more prone to loss-making, consistent with firms that are in the earlier stages of their business life cycle. Firms that hire AIROs also receive relatively less attention from the buy-side and have higher bid-ask spreads and stock-return volatility. These differences in firm characteristics suggest that hiring AIRO is unlikely to be a random decision, but a strategic choice tailored to a firm's economic conditions and engagement with the investment community.

Table 3 reports the descriptive statistics on changes in corporate disclosure, analysts, institutional investors, and stock liquidity following IRO changes (panel A) and univariate statistics conditional on changing to AIROs or regular IROs (panel B). Compared to firms that change to regular IROs, 8-K filings issued by firms that change to AIROs become more readable, more concise, include fewer complex words, and contain a lower proportion of words that express uncertainty. Furthermore, firms in the AIRO subsample are more likely to host analyst/investor days or to host more such events, experience a greater increase in analyst following, and their stock becomes more liquid as indicated by the Amihud (2002) illiquidity ratio and the bid-ask spread. Overall, the univariate results in Table 3 are consistent with the appointment of AIROs leading to improvements in corporate disclosure practices, attracting more attention from financial analysts, and experiencing lower friction in stock trading as a sign of reduced information asymmetry between the firm and investors.

Testing the determinants of hiring an AIRO

Table 4 presents the results of a Probit model (model 1) and Linear Probability Model (model 2) that test the determinants of hiring an AIRO.[24] The independent variables are measured over the four fiscal quarters that precede the change in IRO. The coefficient on *Analyst Coverage* is positive and significant, which is consistent with the notion that firms hire AIROs as a response to increasing demand for better corporate disclosure from the investment community. The coefficient on *Market Capitalization* is negative and significant, while the coefficients on

[24] We use a Linear Probability Model (i.e., OLS) to mitigate the concern that including fixed effects in a Probit model could lead to biased estimated parameters (Greene, 2004).

Market-to-Book and *NASDAQ* are positive and significant. These results suggest that smaller firms, firms with higher growth opportunities as illustrated by higher market-to-book ratios, as well as firms listed on NASDAQ are more likely to hire AIROs. These results are consistent with the idea that firms that are smaller, more difficult to value, and on a growing trend are more likely to hire AIROs to facilitate their engagement with the capital market.

Testing Hypotheses 1–3

Panel A of Table 5 presents the results of estimating the effect of hiring an AIRO on the readability of the firm's 8-K filings. The dependent variable is the change in average Gunning Fog Index over four quarters after-to-before the change in IRO (*Change Gunning Fog Index*). The sample used for model (1) is the full sample of changes in IRO (452 observations). In model (2), the sample contains matched treatment (AIRO) and control (regular IRO) observations where the CEM matching is one-to-many based on firm characteristics, specifically industry and firm size measured using the natural logarithm of market capitalization. Matching on these variables yields a sample of 349 matched observations. Model (3) is also run on a matched sample; the matching is exact on variables related to the IRO (gender, MBA, and Ivy League education) and the industry of their new employers (401 matched observations). Matching on IRO characteristics accounts for the possibility of omitted control variables related to the IRO's personal characteristics and prior experience as a financial analyst.[25] The coefficients on *AIRO* are negative and significant across all three columns. As higher values of the Gunning Fog Index reflect lower disclosure readability, a negative change in the index reflects an improvement in disclosure readability.

Panel B presents the results of estimating the effect of hiring an AIRO on three other characteristics of 8-K filings: length, usage of complex words, and usage of uncertain financial terms as defined by Loughran and McDonalds (2011). We find that the coefficients on *AIRO* are negative and significant across all three model specifications, indicating that after hiring an AIRO and compared to similar firms and IROs, corporate disclosures become more concise and use fewer complex words. Since both total words and complex words contribute to the Gunning

[25] Even though matching on this set of personal characteristics increases our confidence that the main results are not driven by correlated omitted variables, we acknowledge that there is still a possibility that correlated but unobserved variables exist.

Fog index through a positive relation, these results provide insights into how AIROs help to improve 8-K readability. Additionally, we find a decrease in the proportion of uncertain financial terms used in 8-K filings after hiring an AIRO.[26]

We additionally conduct an *event study* around stock-market reactions to 8-K filings. In an untabulated test we find that the market reaction is significantly stronger for AIROs than for other IROs.[27] This finding supports the idea that the stock market views the hiring of an analyst-turned investor relations officer as positive news.

In Table 6, we test the change that AIROs bring for the firm's usage of analyst/investor days as private disclosure events where selected investors and analysts meet with the firm's management and visit the premises. We find some evidence indicating that firms are more likely to host analyst/investor days and that the frequency of such events increases after hiring an AIRO (i.e., the estimated coefficient is positive and significant in four of six models). This is consistent with the idea that prior experience as an audience member to disclosure events allows AIROs to shape their new employer's disclosure policy by orienting it toward events that they perceive as more useful and impactful for investors and analysts. Overall, the results in Tables 5 and 6 are consistent with our expectation formalized in H1 that firms experience an improvement in corporate disclosure after hiring a former financial analyst as IRO.

Table 7 presents the results of models that estimate the effect of hiring an AIRO on the change in number of analysts covering the firm (*Change Analyst Coverage*; Panel A) and the number of institutional shareholders (*Change #Institutional Investors*; Panel B). Consistent with

[26] Note that the model takes into account the general trend in the proportion of uncertain words prior to the change in IRO, thereby reducing the possibility that the coefficient on *AIRO* captures a practice that the firm began to implement prior to the arrival of the new IRO.
[27] Specifically, we run a differences-in-differences test where our variable of interest is the interaction term AIRO×POST. We average the market reactions across all 8-K filings within each firm-quarter. We similarly average the control variables by firm-quarter. We find a positive and statistically significant (at the 5% level using a two-sided test) estimated coefficient for AIRO×POST.

H2, in models (1)–(3) of both panels we find a significant increase in analyst following and institutional investors. Since our S&P 500-based sample firms are some of the most visible firms in the U.S., we do not merely interpret these results as implying that hiring AIROs increases the visibility of the firm, and thus attracts the attention from the investment community. Rather, the additional interest from financial analysts and investors also stems from improvements in disclosure practices, which reduces the effort and cost expended by the investment community to decipher corporate disclosures. In models (4)–(6) we test this reasoning by adding the change in 8-K filings readability as an additional control variable. The coefficients on *AIRO* remain positive and significant.[28] These results suggest that the improvements AIROs bring to *public* corporate disclosure are not the only driving forces for increased analyst following and institutional investor interest. IROs surveyed by Brown et al. (2017) reveal that private communication between IROs and investors is even more important than public filings for conveying the message of their company. Our findings suggest that the expertise that AIROs bring to their new position serves them to improve public disclosures but also to improve private communication with capital-market participants, which in turn attracts more interest from investors. The inferences are unaffected when we match on IRO characteristics (models 3 and 6), which gives us some confidence that it is their prior experience as financial analysts that plays a role rather than other personal characteristics.

Finally, in Table 8, we present results of changes in liquidity following the recruitment of new IROs from Wall Street. In Panel A, we use Amihud's (2002) illiquidity ratio as an inverse measure of liquidity and find a negative and significant coefficient on *AIRO* in columns (1) through (3), which indicates an increase in stock liquidity for firms hiring AIROs relative to

[28] In untabulated analyses we also control for *Change #Analyst/Investor Days* in addition to *Change Gunning Fog Index* and inferences remain unchanged.

those hiring regular IROs. The results hold after we control for changes in the readability of 8-K filings in columns (4) through (6), suggesting that AIROs' effect on stock liquidity does not solely originate from improvement in corporate disclosure. In Panel B, we replace Amihud's (2002) illiquidity ratio with bid-ask spreads, and obtain similar, albeit weaker, results (i.e., significance in four of six columns).[29] Overall, results in Table 8 are consistent with H3 that firms experience an increase in stock liquidity after hiring a former financial analyst as IROs.[30]

Overall, the empirical findings suggest that hiring Wall Street analysts as IROs help the firms to establish better corporate disclosure practice, attract the attention from the investment community, and reduce frictions in the trading of the firms' stocks.[31]

5. Conclusion

In this paper, we investigate the economic consequences associated with the emerging practice of hiring financial analysts as investor relations officers (IRO). Our goal is to assess the role that prior experience as a financial analyst plays when the person is hired as IRO. To this end, we identify a sample of companies that changed their IROs. We manually collect information from various public sources such as *LinkedIn* and appointment press releases to identify the employment history of IROs and distinguish between IROs with or without prior

[29] Our S&P 500 indexed firms are among some of the most liquid firms on U.S. exchanges and bid-ask spreads are (lower-)bounded by tick size (e.g., $0.01 for NYSE), making it empirically difficult to document further improvement in bid-ask spreads.

[30] As explained, we use three approaches in the above analyses. As yet another (untabulated) test, we also consider characteristics of the *outgoing* IROs. We can identify 268 of the 452 outgoing IROs in our sample; 50 of these are AIROs. For the purpose of this sensitivity test, we assume that all outgoing IROs that we cannot identify are "regular" IROs (to avoid a too large drop in sample size). We then match on MBA degree, gender, Ivy League, industry, and type of outgoing IRO and repeat the tests. We find that all inferences remain intact.

[31] Our empirical analyses are based on the 118 analysts-turned-IROs. We have collected detailed information on what "type of analyst" the person was – sell-side, buy-side, or investment-banking analyst. The sample size becomes small when we estimate the regressions separately for these groups; however, we observe consistent and statistically significant findings for almost all outcome variables when using sell-side analysts only. The results are directionally consistent but statistically weaker when using only buy-side (or investment-banking) analysts. We do not want to draw strong conclusions based on these findings due to the small sample sizes.

analyst experience. We then compare the effect of changing to an IRO with analyst experience versus an IRO without analyst experience on variables that measure the firm’s disclosure, analyst following, institutional investors, and stock liquidity.

We find that there are benefits to hiring AIROs even for relatively large and visible S&P 500 companies. We argue that former financial analysts bring a heightened level of expertise to the IRO position. Since IROs’ main function is to facilitate the communication between management and the financial markets, the expertise gained as a financial analyst allows AIROs to better perform their jobs, with benefits for their employer. Specifically, the results indicate that changing to IROs with prior analyst experience is related to improvements in corporate disclosure readability, analyst coverage, number of institutional shareholders, and stock liquidity.

Recent anecdotes and surveys point to a trend of investor relations hiring individuals with financial expertise who can navigate the complex informational and regulatory environment. We find that expertise that goes beyond communication skills creates benefits by improving the information environment of the company. However, our article does not conclude that all firms should hire AIROs or that all financial analysts should pursue an IR career, as drawing such conclusions requires a full and complete cost-benefit analysis that is beyond the scope of this paper. Nonetheless, we believe our results have implications for both managers and investors, as well as for current or former financial analysts.

References

Ali, A., and Kallapur, S. (2001). Securities Price Consequences of the Private Securities Litigation Reform Act of 1995 and Related Events. *The Accounting Review*, *76*(3), 431–460.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets*, *5*(1), 31–56.

Amihud, Y., and Mendelson, H. (1986). Asset pricing and the bid-ask spread. *Journal of Financial Economics*, *17*(2), 223–249.

Baiman, S., and Verrecchia, R. E. (1996). The Relation among Capital Markets, Financial Disclosure, Production Efficiency, and Insider Trading. *Journal of Accounting Research*, *34*(1), 1–22.

Bamber, L. S., Jiang, J., and Wang, I. Y. (2010). What's my style? The influence of top managers on voluntary corporate financial disclosure. *Accounting Review*, *85*(4), 1131–1162.

Barry, C. B., and Brown, S. J. (1984). Differential information and the small firm effect. *Journal of Financial Economics*, *13*(2), 283–294.

Barry, C. B., and Brown, S. J. (1985). Differential Information and Security Market Equilibrium. *Journal of Financial and Quantitative Analysis*, *20*(4), 407–422.

Barth, M. E., Kasznik, R., and McNichols, M. F. (2001). Analyst Coverage and Intangible Assets. *Journal of Accounting Research*, *39*(1), 1–34.

Bertrand, M., and Schoar, A. (2003). Managing with Style: The Effect of Managers on Firm Policies. *The Quarterly Journal of Economics*, *118*(4), 1169–1208.

Bhushan, R. (1989). Firm Characteristics and Analyst Following. *Journal of Accounting and Economics*, *11*, 255–274.

Blanes i Vidal, J., Draca, M., and Fons-Rosen, C. (2012). Revolving Door Lobbyists. *American Economic Review*, *102*(7), 3731–3748.

Brennan, M. J., and Tamarowski, C. (2000). Investor Relations, Liquidity, and Stock Prices. *Journal of Applied Corporate Finance*, *12*(4), 26–37.

Brown, L. D., Call, A. C., Clement, M. B., and Sharp, N. Y. (2015). Inside the "Black Box" of sell-side financial analysts. *Journal of Accounting Research*, *53*(1), 1–47.

Brown, L. D., Call, A. C., Clement, M. B., and Sharp, N. Y. (2017). Managing the Narrative: Investor Relations Officers and Corporate Disclosure. *Working Paper*. Retrieved from https://ssrn.com/abstract=2934937

Bushee, B. J., and Miller, G. S. (2012). Investor relations, firm visibility, and investor following. *The Accounting Review*, *87*(3), 867–897.

Bushee, B. J., and Noe, C. F. (2000). Corporate Disclosure Practices, Institutional Investors, and Stock Return Volatility. *Journal of Accounting Research*, *38*(Supplement), 171–202.

Cen, L., Chen, J., Dasgupta, S., and Ragunathan, V. (2017). It's Showtime! Conference Call Participation and Analysts' Career Outcomes. *Working Paper*.

CFA Institute. (2015). *Addressing Financial Reporting Complexity: Investor Perspectives - Separate Private Company Accounting and Beyond*. Retrieved from http://www.cfapubs.org/doi/pdf/10.2469/ccb.v2015.n1.1

Cohen, L., Frazzini, A., and Malloy, C. J. (2012). Hiring Cheerleaders: Board Appointments of "Independent" Directors. *Management Science*, *58*(6), 1039–1058.

Cohen, L., Lou, D., and Malloy, C. (2017). Playing favorites: How firms prevent the revelation of bad news. *Working Paper*. Retrieved from https://ssrn.com/abstract=2479542

Cornaggia, J., Cornaggia, K. J., and Israelson, R. (2017). Credit Ratings and the Cost of

Municipal Financing. Forthcoming in *Review of Financial Studies*. Retrieved from https://ssrn.com/abstract=2304373
Cornaggia, J., Cornaggia, K. J., and Xia, H. (2016). Revolving doors on Wall Street. *Journal of Financial Economics*, *120*(2), 400–419.
Custódio, C., and Metzger, D. (2014). Financial expert CEOs: CEO's work experience and firm's financial policies. *Journal of Financial Economics*, *114*(1), 125–154.
Deaves, R., Dine, C., and Horton, W. (2006). *How Are Investment Decisions Made? Report Commissioned by the Task Force to Mobilize Securities Legislation in Canada*.
Defond, M., Erkens, D. H., and Zhang, J. (2016). Do Client Characteristics Really Drive the Big N Audit Quality Effect ? New Evidence from Propensity Score Matching. *Management Science*. Retrieved from http://www.tandfonline.com/doi/abs/10.1198/jasa.2011.tm09599
DeHaan, E., Kedia, S., Koh, K., and Rajgopal, S. (2015). The Revolving Door and the SEC's enforcement outcomes: Initial Evidence from Civil Litigation. *Journal of Accounting and Economics*, *60*(2–3), 65–96.
Diamond, D. W. (1985). Optimal Release of Information By Firms. *Journal of Finance*, *40*(4), 1071–1094.
Diamond, D. W., and Verrecchia, R. E. (1991). Disclosure, Liquidity, and the Cost of Capital. *Journal of Finance*, *46*(4), 1325–1359.
Easley, D., and O'Hara, M. (2004). Information and the Cost of Capital Information and the Cost of Capital. *Journal of Finance*, *59*(4), 1553–1583.
Fan, J. S. (2016). Regulating Unicorns: Disclosure and the New Private Economy. *Boston College Law Review*, *57*(2), 583–642.
Fracassi, C., Petry, S., and Tate, G. (2016). Does rating analyst subjectivity affect corporate debt pricing? *Journal of Financial Economics*, *120*(3), 514–538.
Geiger, M. A., Lennox, C. S., and North, D. S. (2008). The hiring of accounting and finance officers from audit firms: How did the market react? *Review of Accounting Studies*, *13*(1), 55–86.
Geiger, M. A., North, D. S., and O'Connell, B. T. (2015). The Auditor-to-Client Revolving Door and Earnings Management. *Journal of Accounting, Auditing & Finance*, *20*(1), 1–26.
Goldberger, J. (2017, September 13). When Staffing an IRO Function, Embrace a Formalized Hiring Protocol. *IR Magazine*. Retrieved from https://www.irmagazine.com/articles/small-cap/22327/when-staffing-iro-function-embrace-formalized-hiring-protocol/
Green, T. C., Jame, R., Markov, S., and Subasi, M. (2014). Broker-hosted investor conferences. *Journal of Accounting and Economics*, *58*(1), 142–166.
Greene, W. (2004). The Behaviour of the Maximum Likelihood Estimator of Limited Dependent Variable Models in The Presence of Fixed Effects. *Econometrics Journal*, *7*(1), 98–119.
Harrison, C. (2010, May 1). Investor targetting: Hitting the bull's eye. *IR Magazine*. Retrieved from https://www.irmagazine.com/articles/shareholder-targeting-id/15900/investor-targeting-hitting-bulls-eye/#
Healy, P. M., Hutton, A. P., and Palepu, K. G. (1999). Stock Performance and Intermediation Changes Surrounding Sustained Increases in Disclosure. *Contemporary Accounting Research*, *16*(3), 485–520.
Healy, P. M., and Palepu, K. G. (2001). Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature. *Journal of Accounting and Economics*, *31*(1–3), 405–440.
Hoitash, R., Hoitash, U., and Kurt, A. C. (2016). Do Accountants Make Better Chief Financial

Officers? *Journal of Accounting and Economics*, *61*(2–3), 414–432.
Hong, H., and Kubik, J. D. (2003). Analyzing the Analysts: Career Concerns and Biased Earnings Forecasts. *Journal of Finance*, *LVIII*(1), 313–351.
Horton, J., Serafeim, G., and Wu, S. (2017). Career concerns of banking analysts. *Journal of Accounting and Economics*, *63*(2–3), 231–252.
Human, T. (2015, June 11). Are former sell-siders locking out the top jobs? *IR Magazine*. Retrieved from https://www.irmagazine.com/articles/people-careers/20824/are-former-sell-siders-locking-out-top-jobs/
Iacus, S. M., King, G., and Porro, G. (2011). Multivariate Matching Methods That Are Monotonic Imbalance Bounding. *Journal of the American Statistical Association*, *106*(493), 345–361.
Iacus, S. M., King, G., and Porro, G. (2012). Causal inference without balance checking: Coarsened exact matching. *Political Analysis*, *20*(1), 1–24.
IR Magazine. (2013). *Research Report: Measure for measure - How does your company measure IR?* Retrieved from https://media.irmagazine.com/library/research-sections/2013/measuring_ir_may_2013.pdf
IR Magazine. (2015). *Research Report: IR Challenges*.
IR Magazine. (2016). *Research Report: Direct Targeting of Investors - What's changed?* Retrieved from https://www.irmagazine.com/articles/shareholder-targeting-id/21609/direct-targeting-investors-whats-changed/
IR Magazine. (2017). *Research Report: Measuring and Demonstrating IR, Part II – Senior management*. Retrieved from https://www.irmagazine.com/articles/case-studies/21987/research-report-measuring-demonstrating-ir-part-ii-senior-management/
Jiang, J. X., Wang, I. Y., and Wang, K. P. (2017). Revolving Rating Analysts and Ratings of MBS and ABS: Evidence from LinkedIn. Forthcoming in *Management Science*.
Kafka, P. (2016, June 17). Spotify moves closer to an IPO by hiring a head of investor relations. *CNBC*. Retrieved from http://www.cnbc.com/2016/06/17/spotify-moves-closer-to-an-ipo-by-hiring-a-head-of-investor-relations.html
Karolyi, G. A., and Liao, R. C. (2017). The Economic Consequences of Investor Relations: A Global Perspective. *Working Paper*. Retrieved from http://ssrn.com/abstract=2591079
Kempf, E. (2017). The Job Rating Game: The Effects of Revolving Doors on Analyst Incentives. *Working Paper*. Retrieved from https://ssrn.com/abstract=2893903
King, G., Nielsen, R., Coberley, C., Pope, J. E., and Wells, A. (2011). Comparative Effectiveness of Matching Methods for Causal Inference. *Unpublished Manuscript*. https://doi.org/10.1.1.230.3451
Kirk, M. P., and Markov, S. (2016). Come on over: Analyst/investor days as a disclosure medium. *The Accounting Review*, *91*(6), 1725–1750.
Kirk, M. P., and Vincent, J. D. (2014). Professional investor relations within the firm. *The Accounting Review*, *89*(4), 1421–1452.
Korn Ferry Institute. (2012). *The investor relations officer: A 2010 survey of Fortune 500 companies*.
Korn Ferry Institute. (2015). *Investor Relations Officers - The 2014/15 Survey of IR Leaders in the Fortune 500*.
Lang, M. H., and Lundholm, R. J. (1996). Corporate Disclosure Policy and Analyst Behavior. *The Accounting Review*, *71*(4), 467–492.
Lang, M., and Lundholm, R. (1993). Cross-sectional determinants of analyst ratings of corporate

disclosures. *Journal of Accounting Research*, *31*(2), 246–271.
Lehavy, R., Li, F., and Merkley, K. (2011). The effect of annual report readability on analyst following and the properties of their earnings forecasts. *The Accounting Review*, *86*(3), 1087–1115.
Lehavy, R., and Sloan, R. G. (2005). Investor Recognition and Stock Returns. *Review of Accounting Studies*, *13*(January), 327–361.
Lennox, C. S., Francis, J. R., and Wang, Z. (2012). Selection Models in Accounting Research. *The Accounting Review*, *87*(2), 589–616.
Leuz, C., and Verrecchia, R. E. (2000). The Economic Consequences of Increased Disclosure. *Journal of Accounting Research*, *38*(2000), 91–124.
Li, F. (2008). Annual report readability, current earnings, and earnings persistence. *Journal of Accounting and Economics*, *45*(2–3), 221–247.
Lobo, G. J., Song, M., and Stanford, M. (2012). Accruals quality and analyst coverage. *Journal of Banking and Finance*, *36*(2), 497–508.
Loughran, T., and McDonald, B. (2011). When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks. *Journal of Finance*, *66*(1), 35–65.
Lourie, B. (2015). The Revolving-Door of Sell-Side Analysts: A Threat to Analysts' Independence? *Unpublished PhD thesis*. Retrieved from http://escholarship.org/uc/item/5j11w5cc#page-2
Luechinger, S., and Moser, C. (2014). The value of the revolving door: Political appointees and the stock market. *Journal of Public Economics*, *119*(November), 93–107.
Matsumoto, D., Pronk, M., and Roelofsen, E. (2011). What makes conference calls useful? The information content of managers' presentations and analysts' discussion sessions. *Accounting Review*, *86*(4), 1383–1414.
Mayew, W. J. (2012). Disclosure Outlets and Corporate Financial Communication: A Discussion of "Managers' Use of Language Across Alternative Disclosure Outlets: Earnings Press Releases versus MD&A." *Contemporary Accounting Research*, *29*(3), 838–844.
Mayew, W. J., and Venkatachalam, M. (2012). The Power of Voice: Managerial Affective States and Future Firm Performance. *The Journal of Finance*, *LXVII*(1), 1–43.
Menon, K., and Williams, D. D. (2004). Former audit partners and abnormal accruals. *The Accounting Review*, *79*(4), 1095–1118.
Merton, R. C. (1987). A Simple Model of Capital Market Equilibrium with Incomplete Information. *Journal of Finance*, *42*(3), 483–510.
Ng, B. S., and Troianovski, A. (2015, September 27). How Some Investors Get Special Access to Companies. *The Wall Street Journal*. Retrieved from https://www.wsj.com/articles/how-some-investors-get-special-access-to-companies-1443407097
NIRI. (2004). *Standards of Practice for Investor Relations* (3rd Editio). Vienna, VA, USA: National Investor Relations Institute. Retrieved from http://media.corporate-ir.net/media_files/priv/27585/standards_practice.pdf
NIRI. (2005). *NIRI Compensation Survey: An Assessment of Responsibilities, Staffing, And Salaries of Investor Relations Practitioners*. Alexandria, VA: National Investor Relations Institute.
NIRI. (2011). *Standards of Practice for Investor Relations: Vol III—Disclosure*. Alexandria, VA: National Investor Relations Institute.
O'Brien, P. C., and Bhushan, R. (1990). Analyst Following and Institutional Ownership. *Journal of Accounting Research*, *28*(May), 55–76.

Schipper, K. (1991). Analysts' Forecasts. *Accounting Horizons*, *5*(4), 105–121.
SEC. (2006, June 8). Speech by SEC Commissioner: "Complexity in Financial Reporting and Disclosure Regulation." *Remarks before the 25th Annual USC Leventhal School of Accounting SEC and Financial Reporting Institute Conference by Commissioner Cynthia A. Glassman*.
SEC. (2008). *Final Report of the Advisory Committee on Improvements to Financial Reporting to the United States Securities and Exchange Commission*. Washington, D.C.
Shipman, J. E., Swanquist, Q. T., and Whited, R. L. (2017). Propensity Score Matching in Accounting Research. *The Accounting Review*, *92*(1), 213–244.
Shive, S. A., and Forster, M. M. (2017). The Revolving Door for Financial Regulators. *Review of Finance*, *21*(4), 1445–1484.
Solomon, D. H. (2012). Selective Publicity and Stock Prices. *Journal of Finance*, *67*(2), 599–638.
Stuart, A. (2016, February 29). New Set of Skills Sought for Investor Relations. *The Wall Street Journal*. Retrieved from https://www.wsj.com/article_email/new-set-of-skills-sought-for-investor-relations-1456798033-lMyQjAxMTA2ODA5MTgwMzE5Wj
Sunder, J., Sunder, S. V., and Zhang, J. (2017). Pilot CEOs and corporate innovation. *Journal of Financial Economics*, *123*(1), 209–224.
Tucker, J. W. (2010). Selection Bias and Econometric Remedies in Accounting and Finance Research. *Journal of Accounting Literature*, *29*, 31–57.
Welker, M. (1995). Disclosure Policy, Information Asymmetry, and Liquidity in Equity Markets. *Contemporary Accounting Research*, *11*(2), 801–827.
Wu, J. S., and Zang, A. Y. (2009). What determine financial analysts' career outcomes during mergers? *Journal of Accounting and Economics*, *47*, 59–86.

Appendix A. Variable Definitions

Variable	*Definition*	*Data source*
Variable of interest		
AIRO	Indicator variable that takes the value 1 if the new IRO has prior experience as a financial analyst in the financial services industry and 0 otherwise.	Manually-collected data
Firm variables in the pre-IRO period		
Analyst Coverage	Average natural logarithm of 1 plus the number of analysts covering the company over the four quarters prior to the change in IRO.	IBES Detail File
#Institutional Investors	Average natural logarithm of 1 plus the number of institutional investors holding shares in the company over the four quarters prior to the change in IRO.	Thomson Reuters 13f
Stock Return Volatility	Standard deviation of daily stock return computed over the four quarters prior to the change in IRO.	CRSP
Bid-Ask Spread	Average daily bid-ask spread computed over the four quarters prior to the change in IRO. The daily bid-ask spread is computed as the highest ask price less the lowest bid price of that day divided by the midpoint between these two values.	CRSP
Market Capitalization	Average natural logarithm of market capitalization at quarter year-end computed over the four quarters prior to the change in IRO.	COMPUSTAT
Market-to-Book	Average market capitalization at quarter end divided by total equity for common shareholders (CEQ) at quarter end, computed over the four quarters prior to the change in IRO	COMPUSTAT
Litigation Risk	Indicator variable that takes the value 1 if the company's SIC code is one of the following: 2833-2836, 8731-8734, 3570-3577, 7370-7374, 3600-3674, 5200-5961, and 0 otherwise.	COMPUSTAT
Financing	Indicator variable that takes the value 1 if the yearly cash flow from sale of common and preferred stock (SSTK) is positive and 0 otherwise.	COMPUSTAT
R&D	Average quarterly research and development expense (XRDQ) divided by total assets at quarter end (ATQ) computed over the four quarters prior to the change in IRO. The variable is set to zero if research and development expense is missing. We multiply the ratio by 100 to improve result presentation.	COMPUSTAT
Return on Assets	Average quarterly net income (NIQ) divided by total assets at quarter end (ATQ) computed over the four quarters prior to the IRO change.	COMPUSTAT
Loss	Indicator variable that takes the value 1 if quarterly net income (NIQ) is negative and 0 otherwise.	COMPUSTAT
Leverage	Average leverage ratio computed as the sum of long-term debt (DLTTQ) and the short-term portion of long-term debt (DLCQ)	COMPUSTAT

	divided by total assets (AT) at quarter end. The average is taken over the four quarters prior to the change in IRO.	
NASDAQ	Indicator variable that takes the value 1 if the company is listed on NASDAQ over the four quarters prior to IRO change and 0 otherwise.	COMPUSTAT
Firm Age	Natural logarithm of the number of years since IPO.	COMPUSTAT
Prior Change in Y	Change in *Y* between quarter Q−1 and quarter Q−4 prior to the IRO change, where *Y* is the dependent variable in any given regression.	See based on *Y*
Dependent variables		
Change Gunning Fog Index	Change in average of the Gunning Fog readability index for 8-K filings in the four quarters following the IRO change compared to the average over the four quarters prior to the IRO change. The Gunning Fog readability index is computed as $0.4 \times ((\#words/\#sentences + 100 \times (\#complex\ words/\#words))$ Higher values of the index reflect lower disclosure readability.	WRDS SEC Analytics
Change #Words	Change in the average natural logarithm of the number of words in 8-K filings over the four quarters following the change in IRO compared to the four quarters prior to the change in IRO. The word count ignores formatting characters and brackets.	WRDS SEC Analytics
Change #Complex Words	Change in the average natural logarithm of the number of complex words in 8-K filings over the four quarters following the change in IRO compared to the four quarters prior to the change in IRO. Complex words contain three or more syllables.	WRDS SEC Analytics
Change %Uncertain Words	Change in the average proportion of uncertainty words in 8-K filings over the four quarters following the change in IRO compared to the four quarters prior to the change in IRO. The proportion of uncertainty words is the number of Loughran and McDonald (2011) Financial-Uncertainty words in an 8-K filing divided by the total number of words in the document that occur in the master dictionary.	WRDS SEC Analytics
Change Analyst/Investor Days	Indicator variable for whether the company holds analyst-investor days in the four quarters following the change in IRO less indicator variable for whether the company holds analysts-investor days in the four quarters prior to the change in IRO.	FactSet Events Calendar
Change #Analyst/Investor Days	Change in the average number of analysts-investor days during the four quarters following the change in IRO compared to the four quarters prior to the change in IRO.	FactSet Events Calendar
Change Analyst Coverage	Change in average analyst coverage over the four quarters following the change in IRO compared to the four quarters prior to the change in IRO. Analyst coverage is computed as natural logarithm of 1 plus the number of analysts following the company.	IBES Detail File

Change #Institutional Investors	Change in average natural logarithm of 1 plus the number of institutional investors holding shares in the company over the four quarters following the change in IRO compared to the average over the four quarters prior to the change in IRO.	Thomson Reuters 13f
Change Amihud Ratio	Change in average Amihud ratio over the four quarters following the change in IRO compared to the average over the four quarters prior to the change in IRO. Amihud ratio is the average ratio of the daily absolute return to the dollar trading volume in that day, as defined by Amihud (2002). We multiply the ratio by 1,000 to improve result presentation.	CRSP
Change Bid-Ask Spread	Change in average daily bid-ask spread computed over the four quarters following the change in IRO compared to the four quarters prior to the change in IRO.	CRSP

Table 1: Sample Distribution

Panel A: Distribution by year

Year	Full sample Frequency	Full sample Percentage	AIRO = 1	AIRO = 0
2004	14	3.10%	1	13
2005	25	5.53%	4	21
2006	27	5.97%	8	19
2007	36	7.96%	5	31
2008	39	8.63%	6	33
2009	36	7.96%	11	25
2010	36	7.96%	14	22
2011	41	9.07%	11	30
2012	44	9.73%	15	29
2013	35	7.74%	9	26
2014	45	9.96%	9	36
2015	40	8.85%	9	31
2016	34	7.52%	16	18
Total	**452**	**100%**	**118**	**334**

Panel B: Distribution by industry

Industry	Full sample Frequency	Full sample Percentage	AIRO = 1	AIRO = 0
Consumer non-durables	42	9.29%	11	31
Consumer durables	13	2.88%	3	10
Manufacturing	51	11.28%	7	44
Energy	47	10.40%	14	33
Chemicals	26	5.75%	5	21
Business equipment	78	17.26%	26	52
Telecommunications	20	4.42%	8	12
Utilities	43	9.51%	11	32
Shops	49	10.84%	9	40
Healthcare	35	7.74%	10	25
Other	48	10.62%	14	34
Total	**452**	**100%**	**118**	**334**

Industry is based on the Fama-French 12 industry classification.

Panel C: Descriptive information about the IROs

	AIRO = 1 (N = 118)	AIRO = 0 (N = 334)	t-statistics for difference (1−0)
Gender			
Male	94	233	
Female	24	101	
Male%	79.66%	69.76%	2.07**
Education Highest Degree			
Bachelor%	27.12%	28.44%	−0.27
Master(non-MBA)%	5.93%	12.57%	−2.00**
MBA%	62.71%	51.20%	2.16**
Education University			
Ivy League%	19.49%	5.09%	4.85***

Statistical significance is based on two-tailed t-tests and is indicated as follows: *** p-value<0.01; ** p-value<0.05; * p-value<0.1.

Table 2: Firm Variables in the Pre-IRO Change Period

Panel A: Descriptive statistics

Variable	**N**	**Mean**	**S.D.**	**p25**	**p50**	**p75**
Analyst Coverage	452	2.928	0.463	2.646	3.004	3.261
#Institutional Investors	452	5.575	1.901	5.714	6.015	6.485
Bid-Ask Spread	452	0.024	0.010	0.017	0.022	0.029
Market Capitalization	452	9.598	1.145	8.769	9.411	10.320
Stock Return Volatility	452	0.018	0.008	0.013	0.016	0.022
Market-to-Book	452	3.758	5.997	1.934	2.861	4.260
Financing	452	0.837	0.341	1.000	1.000	1.000
R&D	452	0.766	1.326	0.000	0.106	0.925
Litigation Risk	452	0.283	0.451	0.000	0.000	1.000
Return on Assets	452	0.017	0.018	0.009	0.017	0.027
Loss	452	0.087	0.210	0.000	0.000	0.000
Leverage	452	0.246	0.154	0.128	0.228	0.350
NASDAQ	452	0.241	0.428	0.000	0.000	0.000
Firm Age	452	3.487	0.625	2.970	3.667	4.056

All continuous variables are winsorized at 1 and 99%. Variables are defined in Appendix A.

Panel B: Univariate statistics

	AIRO = 1 (N = 118)		**AIRO = 0** (N = 334)		Diff mean		Diff median	
Variable	Mean	Median	Mean	Median	(1−0)		(1−0)	
Analyst Coverage	2.978	3.056	2.911	2.994	0.067		0.062	*
#Institutional Investors	5.384	5.983	5.643	6.033	−0.259		−0.050	**
Bid-Ask Spread	0.027	0.024	0.024	0.021	0.003	***	0.003	***
Market Capitalization	9.395	9.349	9.670	9.439	−0.275	**	−0.090	*
Stock Return Volatility	0.020	0.018	0.018	0.016	0.002	**	0.002	***
Market-to-Book	4.380	2.631	3.538	2.924	0.842		−0.293	
Financing	0.826	1.000	0.841	1.000	−0.014		0.000	
R&D	0.894	0.076	0.721	0.114	0.173		−0.038	
Litigation Risk	0.297	0.000	0.278	0.000	0.018		0.000	
Return on Assets	0.014	0.014	0.018	0.018	−0.004	**	−0.003	**
Loss	0.129	0.000	0.073	0.000	0.057	**	0.000	**
Leverage	0.253	0.220	0.243	0.230	0.010		−0.009	
NASDAQ	0.339	0.000	0.207	0.000	0.132	***	0.000	***
Firm Age	3.364	3.341	3.530	3.744	−0.166	**	−0.403	**

This panel provides mean and median differences in prior-period (Q−1 to Q−4) variables between firms that hire an AIRO in Q0 and those that hire a regular IRO. All continuous variables are winsorized at 1 and 99%. Variables are defined in Appendix A. Statistical significance is based on two-tailed t-tests for means and Wilcoxon rank-sum test for medians, and is indicated as follows: *** p-value<0.01; ** p-value<0.05; * p-value<0.1.

Table 3: Changes in Economic Consequences and Disclosure Characteristics from Pre- to Post-IRO Change

Panel A: Descriptive statistics

Variable	N	Mean	S.D.	p25	p50	p75
Change Gunning Fog Index	452	0.121	2.333	−0.716	0.097	0.970
Change #Words	452	0.068	0.898	−0.231	0.038	0.326
Change #Complex Words	452	0.070	0.873	−0.229	0.041	0.338
Change %Uncertain Words	452	0.000	0.003	−0.002	0.000	0.002
Change Analyst/Investor Days	452	0.021	0.187	0.000	0.000	0.000
Change #Analyst/Investor Days	452	0.020	0.230	0.000	0.000	0.000
Change Analyst Coverage	452	0.026	0.132	−0.052	0.018	0.094
Change #Institutional Investors	452	0.129	0.636	−0.013	0.023	0.095
Change Amihud Ratio	452	-0.020	0.154	−0.038	-0.009	0.009
Change Bid-ask Spread	452	0.000	0.010	−0.005	0.000	0.004

All continuous variables are winsorized at 1 and 99%. Variables are defined in Appendix A.

Panel B: Univariate statistics

	AIRO = 1 (N = 118)		**AIRO = 0** (N=334)		Diff mean (1−0)		Diff median (1−0)	
Variable	Mean	Median	Mean	Median				
Change Gunning Fog Index	−0.369	−0.187	0.294	0.202	−0.663	***	−0.389	***
Change #Words	−0.072	−0.021	0.117	0.063	−0.188	**	−0.084	***
Change #Complex Words	−0.066	−0.035	0.118	0.068	−0.185	**	−0.103	***
Change %Uncertain Words	−0.001	−0.001	0.000	0.000	−0.001	***	−0.001	***
Change Analyst/Investor Days	0.051	0.000	0.010	0.000	0.041	**	0.000	*
Change #Analyst/Investor Days	0.056	0.000	0.008	0.000	0.048	**	0.000	**
Change Analyst Coverage	0.055	0.053	0.016	0.005	0.040	***	0.049	***
Change #Institutional Investors	0.177	0.022	0.111	0.025	0.066		−0.004	
Change Amihud Ratio	−0.049	−0.011	−0.010	−0.007	−0.039	***	−0.004	*
Change Bid-Ask Spread	−0.001	−0.002	0.001	0.000	−0.002	**	−0.002	**

This panel provides mean and median differences in changes in economic and disclosure variables in the four quarters before and after the IRO change (quarter 0). All continuous variables are winsorized at 1 and 99%. Variables are defined in Appendix A. Statistical significance is based on one-tailed t-tests for means and Wilcoxon rank-sum test for medians, and is indicated as follows: *** p-value<0.01; ** p-value<0.05; * p-value<0.1.

Table 4: Determinants of Appointing an IRO with Prior Experience as Financial Analyst

Variables	(1) **AIRO**	(2) **AIRO**
Analyst Coverage	0.4071**	0.1230**
	(0.1864)	(0.0579)
#Institutional Investors	−0.0054	−0.0010
	(0.0330)	(0.0112)
Bid-Ask Spread	19.4904	6.5003
	(27.3932)	(8.6393)
Market Capitalization	−0.1964**	−0.0572**
	(0.0784)	(0.0232)
Stock Return Volatility	−17.3375	−5.4940
	(35.5460)	(11.2007)
Market-to-Book	0.0225*	0.0072*
	(0.0126)	(0.0041)
Financing	−0.1303	−0.0417
	(0.2221)	(0.0710)
R&D	−0.0464	−0.0137
	(0.0653)	(0.0222)
Litigation Risk	−0.1054	−0.0255
	(0.2359)	(0.0695)
Return on Assets	−2.4495	−0.8424
	(5.5990)	(1.7871)
Loss	0.1467	0.0451
	(0.4714)	(0.1624)
Leverage	0.4481	0.1352
	(0.5159)	(0.1632)
NASDAQ	0.3996**	0.1225*
	(0.1923)	(0.0648)
Firm Age	−0.0330	−0.0092
	(0.1259)	(0.0400)
Constant	−0.0181	0.4296
	(0.9638)	(0.3015)
Industry Fixed Effects	YES	YES
Observations	452	452
Pseudo R^2	0.0728	
Adjusted R^2		0.0295

This table presents the results of a Probit model (model 1) and Linear Probability Model (LPM; model 2) to test the determinants of hiring an AIRO. The dependent variable is *AIRO* which takes the value 1 if the IRO appointed in quarter 0 was previously employed as a financial analyst in the financial services industry and 0 otherwise. The independent variables are measured over the four quarters prior to the IRO change. All specifications include industry fixed effects defined based on Fama-French 12 industry classification. Standard errors robust and clustered at firm-level are reported in parentheses. All continuous variables are winsorized at 1 and 99%. Variables are defined in Appendix A. Statistical significance is based on two-sided t-tests and is indicated as follows: *** p-value<0.01; ** p-value<0.05; * p-value<0.1.

Table 5: Changes in Firm Disclosure Characteristics after Changing the IRO

Panel A: Gunning Fog Index

Variable	Pred.	(1)	(2)	(3)
AIRO	**−**	**−0.5957*** **	**−0.6870*** **	**−0.5512** **
		(0.2277)	**(0.2508)**	**(0.2408)**
Prior Change Gunning Fog Index		0.0798	0.0572	0.1195*
		(0.0608)	(0.0758)	(0.0609)
Analyst Coverage		−0.2147	−0.3535	−0.4087
		(0.3105)	(0.3370)	(0.3978)
#Institutional Investors		−0.0485	−0.0568	−0.0593
		(0.0619)	(0.0832)	(0.0759)
Bid-Ask Spread		62.5316	22.6117	48.4346
		(56.4001)	(66.1370)	(63.0039)
Market Capitalization		0.2156*	0.2415	0.2368
		(0.1296)	(0.1944)	(0.1496)
Stock Return Volatility		−106.9056	−45.1904	−98.6979
		(72.9492)	(84.9005)	(81.8904)
Market-to-Book		−0.0198	−0.0229	−0.0189
		(0.0136)	(0.0204)	(0.0138)
Financing		0.1506	−0.1157	0.0466
		(0.2506)	(0.3550)	(0.2715)
R&D		0.0918	0.1346	0.0466
		(0.1126)	(0.1370)	(0.1152)
Litigation Risk		−0.0987	0.1614	0.1849
		(0.4428)	(0.5546)	(0.4419)
Return on Assets		−14.9419*	−7.5974	−20.1197**
		(9.0212)	(10.3953)	(10.0310)
Loss		−0.4270	−0.3539	−0.4468
		(0.6435)	(0.7400)	(0.6698)
Leverage		−0.4852	−0.5737	−0.5934
		(0.6787)	(0.8399)	(0.7210)
NASDAQ		−0.0129	−0.1198	0.1333
		(0.3538)	(0.4021)	(0.3535)
Firm Age		−0.3873*	−0.3456	−0.4859*
		(0.2200)	(0.2381)	(0.2513)
Constant		1.2742	1.1904	2.4376
		(1.3848)	(1.7415)	(1.5271)
Industry Fixed Effects		YES	YES	YES
Adjusted R^2		0.0137	0.0086	0.0483
Observations		452	349	401

This table presents the results of three models that estimate the effect of hiring an AIRO on the readability of the firm's 8-K filings. The dependent variable is the change in average Gunning Fog Index over four quarters before and after the change in IRO (*Change Gunning Fog Index*). Higher values of the Gunning Fog Index reflect lower disclosure readability, so a negative change in the index reflects an improvement in disclosure readability. Model (1) is a difference-in-differences OLS regression run over the full sample of IRO changes. Models (2) and (3) are difference-in-differences regressions on a matched sample of treated (AIRO) and control (regular IRO) observations obtained using Coarsened Exact Matching (CEM). In model (2), the matching is done based on exact matching on industry and coarsened match on market capitalization (1-to-n matching), therefore matching a treatment and control observations based on firm characteristics. In model (3), the matching is exact on IRO gender, Ivy League university education, graduation from an MBA program and the Fama-French 12 industry classification of their new employer, therefore matching treatment and control observations based primarily on IRO characteristics (1-to-n matching). Sample size is different across models (1) and (2) since the CEM algorithm determines empirically the number of observations that can be matched. All specifications include industry fixed effects based on Fama-French 12 industry classification. Standard errors are robust and clustered at firm level, and reported in parentheses. All continuous variables are winsorized at 1 and 99%. Variables are defined in Appendix A. Statistical significance is based on one-tailed test where there is a prediction and based on two-tailed test otherwise, and is indicated as follows: *** p-value<0.01; ** p-value<0.05; * p-value<0.1.

Panel B: Word counts in 8-K filings

Variable	Pred.	*Change #Words* (1)	(2)	(3)	*Change #Complex Words* (4)	(5)	(6)	*Change %Uncertain Words* (7)	(8)	(9)
AIRO	−	**−0.1603****	**−0.1725****	**−0.1446***	**−0.1551****	**−0.1703****	**−0.1395***	**−0.0009*****	**−0.0009*****	**−0.0009****
		(0.0913)	**(0.0999)**	**(0.0982)**	**(0.0888)**	**(0.0972)**	**(0.0954)**	**(0.0003)**	**(0.0004)**	**(0.0004)**
Prior Change #Words		0.1697***	0.1670***	0.1669***						
		(0.0537)	(0.0581)	(0.0556)						
Prior Change #Complex Words					0.1627***	0.1609***	0.1647***			
					(0.0531)	(0.0574)	(0.0554)			
Prior Change %Uncertain Words								0.0867***	0.0855**	0.1106***
								(0.0319)	(0.0340)	(0.0361)
Other controls		YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry FE		YES	YES	YES	YES	YES	YES	YES	YES	YES
Adjusted R^2		0.0686	0.0741	0.1024	0.0643	0.0691	0.0982	0.0380	0.0324	0.0506
Observations		452	349	401	452	349	401	452	349	401

This table presents the results of models that estimate the effect of hiring an AIRO on total number of words (*Change #Words*), number of complex words (*Change #Complex Words*), and number of uncertain words (*Change #Uncertain Words*) in the firm's 8-K filings. The dependent variables are computed as the change in average number of words (total, complex, or uncertain) in 8-K filings over the four quarters before and after the change in IRO. Models (1), (4), and (7) are difference-in-differences OLS regressions run over the full sample of IRO changes. The other models are difference-in-differences regressions run on a matched sample of treated (AIRO) and control (regular IRO) observations obtained using Coarsened Exact Matching (CEM). In models (2), (5), and (8) the matching is done based on exact matching on industry and coarsened match on market capitalization (1-to-n matching), therefore matching treatment and control observations based on firm characteristics. In models (3), (6), and (9) the matching is exact on IRO gender, Ivy League university education, graduation from an MBA program and the Fama-French 12 industry classification of their new employer, therefore matching treatment and control observations based primarily on IRO characteristics (1-to-n matching). Sample size is different across models run on matched observations since the CEM algorithm determines empirically the number of observations that can be matched. All specifications include industry fixed effects based on Fama-French 12 industry classification. Standard errors are robust and clustered at firm level, and reported in parentheses. All continuous variables are winsorized at 1 and 99%. Variables are defined in Appendix A. Statistical significance is based on one-tailed test where there is a prediction and based on two-tailed test otherwise, and is indicated as follows: *** p-value<0.01; ** p-value<0.05; * p-value<0.1.

Table 6: Changes in Decision to Host Analyst/Investor Days after Changing the IRO

		Change Analyst/Investor Days			*Change #Analyst/Investor Days*		
Variables	Pred.	(1)	(2)	(3)	(4)	(5)	(6)
AIRO	**+**	**0.0389****	**0.0253**	**0.0368***	**0.0431***	**0.0221**	**0.0438***
		(0.0230)	**(0.0241)**	**(0.0243)**	**(0.0282)**	**(0.0290)**	**(0.0302)**
Prior Change in Y		−0.0025	−0.0145	0.0052	0.0015	−0.0075	0.0168
		(0.0206)	(0.0266)	(0.0217)	(0.0275)	(0.0330)	(0.0270)
Analyst Coverage		−0.0046	−0.0028	−0.0108	−0.0079	−0.0090	−0.0059
		(0.0220)	(0.0245)	(0.0271)	(0.0311)	(0.0343)	(0.0367)
#Institutional Investors		0.0032	0.0006	0.0050	0.0044	0.0003	0.0067
		(0.0044)	(0.0046)	(0.0050)	(0.0057)	(0.0063)	(0.0065)
Bid-Ask Spread		0.1535	3.9734	−1.2484	1.0325	5.8326	−0.8543
		(3.3133)	(3.8550)	(3.8217)	(4.0215)	(4.5724)	(4.6436)
Market Capitalization		0.0078	0.0056	0.0082	0.0087	0.0211	0.0066
		(0.0110)	(0.0133)	(0.0120)	(0.0146)	(0.0191)	(0.0155)
Stock Return Volatility		0.2199	−5.2767	2.2169	0.0792	−6.5326	2.9109
		(4.5033)	(5.2253)	(5.2218)	(5.4122)	(6.1648)	(6.2889)
Market-to-Book		−0.0002	0.0031	−0.0002	−0.0005	0.0034	−0.0005
		(0.0025)	(0.0021)	(0.0026)	(0.0033)	(0.0026)	(0.0035)
Financing		−0.0186	−0.0492	−0.0211	−0.0200	−0.0467	−0.0154
		(0.0292)	(0.0354)	(0.0341)	(0.0365)	(0.0456)	(0.0421)
R&D		0.0043	0.0011	0.0061	0.0032	0.0009	0.0048
		(0.0084)	(0.0088)	(0.0099)	(0.0099)	(0.0104)	(0.0116)
Litigation Risk		−0.0134	0.0174	0.0025	−0.0145	0.0144	0.0007
		(0.0344)	(0.0373)	(0.0368)	(0.0386)	(0.0385)	(0.0420)
Return on Assets		−0.3531	0.3777	−0.5276	−0.1960	0.5702	−0.3119
		(0.7042)	(0.8409)	(0.7525)	(0.8230)	(0.9531)	(0.8822)
Loss		−0.0233	0.0381	−0.0354	−0.0090	0.0625	−0.0166
		(0.0639)	(0.0656)	(0.0667)	(0.0839)	(0.0866)	(0.0889)
Leverage		0.0190	−0.0207	−0.0136	0.0700	0.0360	0.0459
		(0.0648)	(0.0725)	(0.0670)	(0.0817)	(0.0890)	(0.0873)
NASDAQ		−0.0488*	−0.0671**	−0.0553**	−0.0441	−0.0551	−0.0492
		(0.0255)	(0.0300)	(0.0273)	(0.0296)	(0.0337)	(0.0322)
Firm Age		−0.0325**	−0.0365**	−0.0292*	−0.0363*	−0.0418*	−0.0238
		(0.0152)	(0.0163)	(0.0154)	(0.0201)	(0.0213)	(0.0180)
Constant		0.0503	0.1352	0.0489	0.0538	0.0179	0.0069
		(0.1300)	(0.1406)	(0.1429)	(0.1668)	(0.1843)	(0.1788)
Industry Fixed Effects		YES	YES	YES	YES	YES	YES
R^2		0.0428	0.0669	0.0464	0.0376	0.0568	0.0416
Observations		452	349	401	452	349	401

This table presents the results of models that estimate the effect of hiring an AIRO on the firm's decision to host analyst/investor days (*Change Analyst/Investor Days*) and the change in average number of analyst/investor days (*Change #Analyst/Investor Days*) from before to after the change in IRO. Models (1) and (4) are difference-in-differences OLS regressions run over the full sample of IRO changes. The other models are difference-in-differences regressions run on a matched sample of treated (AIRO) and control (regular IRO) observations obtained using Coarsened Exact Matching (CEM). In models (2) and (5) the matching is done based on exact matching on industry and coarsened match on market capitalization (1-to-n matching), therefore matching treatment and control observations based on firm characteristics. In models (3) and (6) the matching is exact on IRO gender, Ivy League university education, graduation from an MBA program and the Fama-French 12 industry classification of their new employer, therefore matching treatment and control observations based primarily on IRO characteristics (1-to-n matching). Sample size is different across models run on matched observations since the CEM algorithm determines empirically the number of observations that can be matched. All specifications include industry fixed effects based on Fama-French 12 industry classification. Standard errors are robust and clustered at firm level, and reported in parentheses. All continuous variables are winsorized at 1 and 99%. Variables are defined in Appendix A. Statistical significance is based on one-tailed test where there is a prediction and based on two-tailed test otherwise, and is indicated as follows: *** p-value<0.01; ** p-value<0.05; * p-value<0.1.

Table 7: Changes in Analyst and Institutional Investor Following after Changing the IRO

Panel A: Analyst coverage

Variables	Pred.	(1)	(2)	(3)	(4)	(5)	(6)
AIRO	+	**0.0370*****	**0.0365*****	**0.0394*****	**0.0369*****	**0.0362*****	**0.0406*****
		(0.0126)	**(0.0132)**	**(0.0130)**	**(0.0128)**	**(0.0135)**	**(0.0131)**
Prior Change Analyst Coverage		0.2666***	0.2884***	0.2572***	0.2667***	0.2885***	0.2562***
		(0.0470)	(0.0535)	(0.0489)	(0.0473)	(0.0538)	(0.0488)
Change Gunning Fog Index					−0.0001	−0.0004	0.0020
					(0.0020)	(0.0025)	(0.0021)
Analyst Coverage		−0.0963***	−0.1106***	−0.1212***	−0.0963***	−0.1107***	−0.1205***
		(0.0239)	(0.0286)	(0.0174)	(0.0240)	(0.0288)	(0.0176)
#Institutional Investors		0.0007	0.0007	0.0025	0.0006	0.0006	0.0026
		(0.0032)	(0.0033)	(0.0035)	(0.0032)	(0.0033)	(0.0036)
Bid-Ask Spread		1.5256	2.2605	−0.5208	1.5319	2.2690	−0.6055
		(2.5543)	(2.9602)	(2.5202)	(2.5644)	(2.9614)	(2.5142)
Market Capitalization		0.0168**	0.0231**	0.0187***	0.0168**	0.0232**	0.0182***
		(0.0076)	(0.0095)	(0.0069)	(0.0077)	(0.0096)	(0.0069)
Stock Return Volatility		2.2287	2.3743	5.0338	2.2175	2.3565	5.2223
		(3.3144)	(3.9258)	(3.2819)	(3.3354)	(3.9218)	(3.2839)
Market-to-Book		−0.0007	−0.0007	−0.0012	−0.0007	−0.0008	−0.0012
		(0.0010)	(0.0014)	(0.0010)	(0.0010)	(0.0014)	(0.0010)
Financing		0.0075	−0.0001	0.0232	0.0075	−0.0001	0.0231
		(0.0192)	(0.0237)	(0.0201)	(0.0192)	(0.0238)	(0.0201)
R&D		−0.0015	−0.0004	−0.0014	−0.0015	−0.0003	−0.0015
		(0.0067)	(0.0077)	(0.0071)	(0.0067)	(0.0077)	(0.0071)
Litigation Risk		0.0224	0.0156	0.0294	0.0224	0.0157	0.0289
		(0.0225)	(0.0291)	(0.0234)	(0.0225)	(0.0291)	(0.0234)
Return on Assets		0.5002	0.2256	0.5224	0.4985	0.2223	0.5640
		(0.5593)	(0.6335)	(0.5217)	(0.5620)	(0.6337)	(0.5223)
Loss		−0.0203	−0.0511	−0.0214	−0.0204	−0.0513	−0.0206

	(0.0494)	(0.0550)	(0.0513)	(0.0494)	(0.0551)	(0.0513)
Leverage	0.0445	0.0638	0.0565	0.0445	0.0635	0.0580
	(0.0457)	(0.0538)	(0.0478)	(0.0459)	(0.0540)	(0.0482)
NASDAQ	−0.0179	−0.0194	−0.0023	−0.0179	−0.0194	−0.0025
	(0.0200)	(0.0250)	(0.0201)	(0.0200)	(0.0250)	(0.0201)
Firm Age	−0.0099	−0.0119	−0.0086	−0.0099	−0.0120	−0.0076
	(0.0111)	(0.0118)	(0.0116)	(0.0110)	(0.0117)	(0.0117)
Constant	0.0532	0.0473	0.0685	0.0534	0.0478	0.0634
	(0.0771)	(0.0928)	(0.0794)	(0.0772)	(0.0930)	(0.0797)
Industry Fixed Effects	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.1897	0.2126	0.2258	0.1878	0.2102	0.2249
Observations	452	349	401	452	349	401

This table presents the results of models that estimate the effect of hiring an AIRO on the number of analysts covering the firm. The dependent variable is the change in the number of analyst covering the firm over the four quarters before and after the change in IRO (*Change Analyst Coverage*). Compared to the first three models, the last three models also include as control the change in average 8-K readability from before to after the change in IRO (*Change Gunning Fog Index*). Models (1) and (4) are difference-in-differences OLS regressions run over the full sample of IRO changes. The other models are difference-in-differences regressions on a matched sample of treated (AIRO) and control (regular IRO) observations obtained using Coarsened Exact Matching (CEM). In models (2) and (5) the matching is done based on exact matching on industry and coarsened match on market capitalization (1-to-n matching), therefore matching a treatment and control observations based on firm characteristics. In models (3) and (6) the matching is exact on IRO gender, Ivy League university education, graduation from an MBA program and the Fama-French 12 industry classification of their new employer, therefore matching treatment and control observations based primarily on IRO characteristics (1-to-n matching). Sample size is different across models run on matched observations since the CEM algorithm determines empirically the number of observations that can be matched. All specifications include industry fixed effects based on Fama-French 12 industry classification. Standard errors are robust and clustered at firm level, and reported in parentheses. All continuous variables are winsorized at 1 and 99%. Variables are defined in Appendix A. Statistical significance is based on one-tailed test where there is a prediction and based on two-tailed test otherwise, and is indicated as follows: *** p-value<0.01; ** p-value<0.05; * p-value<0.1.

Panel B: Number of institutional shareholders

Variables	Pred.	(1)	(2)	(3)	(4)	(5)	(6)
AIRO	+	**0.0642***	**0.0661***	**0.0767****	**0.0619***	**0.0624***	**0.0742****
		(0.0409)	**(0.0432)**	**(0.0426)**	**(0.0406)**	**(0.0426)**	**(0.0419)**
Prior Change #Institutional Investors		1.4085***	1.3957***	1.3872***	1.4088***	1.3978***	1.3872***
		(0.0945)	(0.1299)	(0.1113)	(0.0947)	(0.1300)	(0.1115)
Change Gunning Fog Index					−0.0037	−0.0051	−0.0042
					(0.0035)	(0.0042)	(0.0041)
Analyst Coverage		0.0121	0.0281	0.0258	0.0113	0.0262	0.0242
		(0.0243)	(0.0343)	(0.0271)	(0.0240)	(0.0338)	(0.0266)
#Institutional Investors		−0.0362*	−0.0496*	−0.0299	−0.0364*	−0.0498*	−0.0302
		(0.0200)	(0.0286)	(0.0206)	(0.0201)	(0.0287)	(0.0206)
Bid-Ask Spread		−5.3049	−7.7526	−3.3473	−5.0905	−7.6399	−3.1718
		(4.9369)	(6.2252)	(5.7036)	(4.9084)	(6.2161)	(5.7024)
Market Capitalization		0.0170	0.0059	0.0215	0.0177	0.0071	0.0224
		(0.0197)	(0.0199)	(0.0212)	(0.0198)	(0.0198)	(0.0213)
Stock Return Volatility		7.4451	12.5018	5.1360	7.0643	12.2679	4.7468
		(6.7434)	(8.4297)	(7.9738)	(6.7016)	(8.4078)	(7.9721)
Market-to-Book		−0.0024	−0.0049	−0.0028	−0.0024	−0.0050	−0.0028
		(0.0021)	(0.0030)	(0.0023)	(0.0021)	(0.0030)	(0.0023)
Financing		0.0473	0.0290	0.0578*	0.0479	0.0284	0.0580*
		(0.0322)	(0.0340)	(0.0310)	(0.0322)	(0.0339)	(0.0309)
R&D		−0.0143	−0.0097	−0.0134	−0.0140	−0.0091	−0.0133
		(0.0121)	(0.0157)	(0.0133)	(0.0121)	(0.0157)	(0.0133)
Litigation Risk		−0.0025	−0.0227	−0.0074	−0.0026	−0.0215	−0.0064
		(0.0278)	(0.0429)	(0.0309)	(0.0274)	(0.0426)	(0.0303)
Return on Assets		0.3262	0.8513	0.2877	0.2690	0.8090	0.2032
		(1.0639)	(1.3059)	(1.1477)	(1.0474)	(1.2925)	(1.1283)
Loss		0.1227	0.1334	0.1205	0.1214	0.1318	0.1190
		(0.0857)	(0.0930)	(0.0971)	(0.0852)	(0.0926)	(0.0966)

Leverage	−0.0443	0.0474	0.0110	−0.0465	0.0442	0.0078
	(0.0812)	(0.0970)	(0.0823)	(0.0810)	(0.0969)	(0.0821)
NASDAQ	−0.0348	−0.0339	−0.0271	−0.0348	−0.0345	−0.0267
	(0.0429)	(0.0451)	(0.0416)	(0.0429)	(0.0452)	(0.0415)
Firm Age	−0.0100	−0.0050	−0.0135	−0.0114	−0.0069	−0.0155
	(0.0272)	(0.0298)	(0.0285)	(0.0272)	(0.0298)	(0.0287)
Constant	0.0664	0.1624	−0.0654	0.0715	0.1684	−0.0545
	(0.1427)	(0.2266)	(0.1383)	(0.1429)	(0.2272)	(0.1397)
Industry Fixed Effects	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.8169	0.7883	0.8204	0.8167	0.7880	0.8201
Observations	452	349	401	452	349	401

This table presents the results of three models that estimate the effect of hiring an AIRO on the number of institutional investors with ownership in the firm. The dependent variable is the change in the number of institutional investors over the four quarters before and after the change in IRO (*Change #Institutional Investors*). Compared to the first three models, the last three models also include as control the change in average 8-K readability from before to after the change in IRO (*Change Gunning Fog Index*). Models (1) and (4) are difference-in-differences OLS regressions run over the full sample of IRO changes. The other models are difference-in-differences regressions on a matched sample of treated (AIRO) and control (regular IRO) observations obtained using Coarsened Exact Matching (CEM). In models (2) and (5) the matching is done based on exact matching on industry and coarsened match on market capitalization (1-to-n matching), therefore matching a treatment and control observations based on firm characteristics. In models (3) and (6) the matching is exact on IRO gender, Ivy League university education, graduation from an MBA program and the Fama-French 12 industry classification of their new employer, therefore matching treatment and control observations based primarily on IRO characteristics (1-to-n matching). Sample size is different across models run on matched observations since the CEM algorithm determines empirically the number of observations that can be matched. All specifications include industry fixed effects based on Fama-French 12 industry classification. Standard errors are robust and clustered at firm level, and reported in parentheses. All continuous variables are winsorized at 1 and 99%. Variables are defined in Appendix A. Statistical significance is based on one-tailed test where there is a prediction and based on two-tailed test otherwise, and is indicated as follows: *** p-value<0.01; ** p-value<0.05; * p-value<0.1.

Table 8: Changes in Stock Liquidity after Changing the IRO

Panel A: Amihud (2002) ratio

Variables	Pred.	(1)	(2)	(3)	(4)	(5)	(6)
AIRO	−	**−0.0307****	**−0.0385*****	**−0.0325****	**−0.0310****	**−0.0380*****	**−0.0324****
		(0.0155)	**(0.0154)**	**(0.0175)**	**(0.0155)**	**(0.0153)**	**(0.0174)**
Prior Change Amihud Ratio		0.5173***	0.4802***	0.4808***	0.5173***	0.4799***	0.4807***
		(0.1034)	(0.1031)	(0.1073)	(0.1034)	(0.1032)	(0.1073)
Change Gunning Fog Index					−0.0005	0.0007	0.0003
					(0.0020)	(0.0021)	(0.0022)
Analyst Coverage		0.0120	−0.0034	0.0102	0.0119	−0.0032	0.0103
		(0.0180)	(0.0216)	(0.0212)	(0.0180)	(0.0216)	(0.0212)
#Institutional Investors		0.0012	−0.0024	0.0019	0.0012	−0.0023	0.0019
		(0.0040)	(0.0034)	(0.0047)	(0.0040)	(0.0034)	(0.0047)
Bid-Ask Spread		−0.9663	−0.5027	1.7631	−0.9361	−0.5177	1.7523
		(3.8725)	(4.2391)	(3.3759)	(3.8696)	(4.2401)	(3.3667)
Market Capitalization		0.0043	0.0087	0.0049	0.0044	0.0085	0.0049
		(0.0072)	(0.0086)	(0.0077)	(0.0073)	(0.0087)	(0.0079)
Stock Return Volatility		−2.9623	−4.3280	−6.5558	−3.0164	−4.2944	−6.5310
		(4.5937)	(5.1136)	(4.1407)	(4.5948)	(5.1055)	(4.1206)
Market-to-Book		−0.0015	−0.0006	−0.0012	−0.0015	−0.0005	−0.0012
		(0.0009)	(0.0009)	(0.0010)	(0.0009)	(0.0009)	(0.0010)
Financing		0.0023	−0.0081	−0.0035	0.0023	−0.0080	−0.0035
		(0.0197)	(0.0237)	(0.0214)	(0.0196)	(0.0238)	(0.0214)
R&D		0.0185***	0.0219***	0.0166**	0.0185***	0.0219***	0.0166**
		(0.0069)	(0.0076)	(0.0070)	(0.0069)	(0.0076)	(0.0070)
Litigation Risk		0.0106	0.0098	0.0064	0.0106	0.0097	0.0063
		(0.0238)	(0.0376)	(0.0253)	(0.0239)	(0.0376)	(0.0252)
Return on Assets		−0.4103	−0.6810	−0.5865	−0.4184	−0.6749	−0.5811
		(0.5026)	(0.5915)	(0.5547)	(0.4960)	(0.5868)	(0.5440)

Loss	−0.0234	−0.0731	−0.0288	−0.0236	−0.0728	−0.0287
	(0.0546)	(0.0490)	(0.0583)	(0.0544)	(0.0490)	(0.0581)
Leverage	0.0233	0.0978**	0.0258	0.0230	0.0983**	0.0260
	(0.0567)	(0.0420)	(0.0632)	(0.0573)	(0.0422)	(0.0640)
NASDAQ	0.0015	0.0246	0.0062	0.0015	0.0247	0.0062
	(0.0180)	(0.0177)	(0.0216)	(0.0180)	(0.0178)	(0.0215)
Firm Age	0.0096	0.0067	0.0159	0.0094	0.0069	0.0160
	(0.0119)	(0.0133)	(0.0135)	(0.0120)	(0.0134)	(0.0137)
Constant	−0.0442	−0.0117	−0.0655	−0.0434	−0.0128	−0.0662
	(0.1070)	(0.1278)	(0.1154)	(0.1066)	(0.1276)	(0.1149)
Industry Fixed Effects	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.2887	0.2877	0.2699	0.2871	0.2856	0.2679
Observations	452	349	401	452	349	401

This table presents the results of models that estimate the effect of hiring an AIRO on the firm's stock liquidity. The dependent variable is the change in Amihud (2002) ratio over the four quarters before and after the change in IRO (*Change Amihud Ratio*). Compared to the first three models, the last three models also include as control the change in average 8-K readability from before to after the change in IRO (*Change Gunning Fog Index*). Models (1) and (4) are difference-in-differences OLS regressions run over the full sample of IRO changes. The other models are difference-in-differences regressions on a matched sample of treated (AIRO) and control (regular IRO) observations obtained using Coarsened Exact Matching (CEM). In models (2) and (5) the matching is done based on exact matching on industry and coarsened match on market capitalization (1-to-n matching), therefore matching a treatment and control observations based on firm characteristics. In models (3) and (6) the matching is exact on IRO gender, Ivy League university education, graduation from an MBA program and the Fama-French 12 industry classification of their new employer, therefore matching treatment and control observations based primarily on IRO characteristics (1-to-n matching). Sample size is different across models run on matched observations since the CEM algorithm determines empirically the number of observations that can be matched. All specifications include industry fixed effects based on Fama-French 12 industry classification. Standard errors are robust and clustered at firm level, and reported in parentheses. All continuous variables are winsorized at 1 and 99%. Variables are defined in Appendix A. Statistical significance is based on one-tailed test where there is a prediction and based on two-tailed test otherwise, and is indicated as follows: *** p-value<0.01; ** p-value<0.05; * p-value<0.1.

Panel B: Bid-ask spreads

Variables	Pred.	(1)	(2)	(3)	(4)	(5)	(6)
AIRO	**−**	**−0.0014***	**−0.0016***	**−0.0012**	**−0.0016***	**−0.0018****	**−0.0014**
		(0.0010)	**(0.0010)**	**(0.0011)**	**(0.0011)**	**(0.0010)**	**(0.0011)**
Prior Change Bid-Ask Spread		0.1923***	0.1410***	0.1804***	0.1899***	0.1408***	0.1781***
		(0.0476)	(0.0447)	(0.0478)	(0.0476)	(0.0450)	(0.0479)
Change Gunning Fog Index					−0.0003**	−0.0003*	−0.0003**
					(0.0001)	(0.0002)	(0.0001)
Analyst Coverage		0.0003	0.0010	0.0004	0.0002	0.0009	0.0003
		(0.0012)	(0.0014)	(0.0014)	(0.0012)	(0.0014)	(0.0014)
#Institutional Investors		−0.0003	−0.0005	−0.0004	−0.0003	−0.0005*	−0.0005
		(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Bid-Ask Spread		−0.3167	−0.2934	−0.1947	−0.2970	−0.2869	−0.1796
		(0.2396)	(0.2517)	(0.2395)	(0.2395)	(0.2512)	(0.2391)
Market Capitalization		−0.0022***	−0.0026***	−0.0023***	−0.0022***	−0.0025***	−0.0022***
		(0.0005)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Stock Return Volatility		−0.5074	−0.5765	−0.6878**	−0.5407*	−0.5899*	−0.7190**
		(0.3222)	(0.3526)	(0.3216)	(0.3236)	(0.3519)	(0.3222)
Market-to-Book		0.0000	0.0001	0.0000	0.0000	0.0001	0.0000
		(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Financing		−0.0005	−0.0007	−0.0017	−0.0004	−0.0007	−0.0017
		(0.0015)	(0.0016)	(0.0015)	(0.0015)	(0.0016)	(0.0015)
R&D		0.0017***	0.0020***	0.0019***	0.0018***	0.0020***	0.0019***
		(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Litigation Risk		0.0031**	0.0021	0.0026	0.0031*	0.0022	0.0027
		(0.0016)	(0.0020)	(0.0016)	(0.0016)	(0.0020)	(0.0016)
Return on Assets		0.0169	0.0275	0.0069	0.0118	0.0250	0.0000
		(0.0338)	(0.0376)	(0.0318)	(0.0343)	(0.0379)	(0.0320)
Loss		0.0013	−0.0007	0.0000	0.0011	−0.0008	−0.0001
		(0.0032)	(0.0030)	(0.0032)	(0.0031)	(0.0030)	(0.0032)

Leverage	0.0010	0.0017	−0.0001	0.0008	0.0015	−0.0004
	(0.0032)	(0.0033)	(0.0033)	(0.0032)	(0.0033)	(0.0033)
NASDAQ	−0.0017	−0.0007	−0.0022*	−0.0017	−0.0007	−0.0022*
	(0.0012)	(0.0014)	(0.0013)	(0.0012)	(0.0013)	(0.0013)
Firm Age	−0.0008	−0.0014	−0.0008	−0.0009	−0.0015	−0.0010
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Constant	0.0399***	0.0445***	0.0428***	0.0403***	0.0449***	0.0436***
	(0.0064)	(0.0074)	(0.0066)	(0.0064)	(0.0075)	(0.0067)
Industry Fixed Effects	YES	YES	YES	YES	YES	YES
Adjusted R^2	0.2671	0.3138	0.2814	0.2705	0.3165	0.2851
Observations	452	349	401	452	349	401

This table presents the results of models that estimate the effect of hiring an AIRO on the firm's stock liquidity. The dependent variable is the change in average bid-ask ratio over the four quarters before and after the change in IRO (*Change Bid-Ask Spread*). Compared to the first three models, the last three models also include as control the change in average 8-K readability from before to after the change in IRO (*Change Gunning Fog Index*). Models (1) and (4) are difference-in-differences OLS regressions run over the full sample of IRO changes. The other models are difference-in-differences regressions on a matched sample of treated (AIRO) and control (regular IRO) observations obtained using Coarsened Exact Matching (CEM). In models (2) and (5) the matching is done based on exact matching on industry and coarsened match on market capitalization (1-to-n matching), therefore matching a treatment and control observations based on firm characteristics. In models (3) and (6) the matching is exact on IRO gender, Ivy League university education, graduation from an MBA program and the Fama-French 12 industry classification of their new employer, therefore matching treatment and control observations based primarily on IRO characteristics (1-to-n matching). Sample size is different across models run on matched observations since the CEM algorithm determines empirically the number of observations that can be matched. All specifications include industry fixed effects based on Fama-French 12 industry classification. Standard errors are robust and clustered at firm level, and reported in parentheses. All continuous variables are winsorized at 1 and 99%. Variables are defined in Appendix A. Statistical significance is based on one-tailed test where there is a prediction and based on two-tailed test otherwise, and is indicated as follows: *** p-value<0.01; ** p-value<0.05; * p-value<0.1.