Are Powerful Women Scrutinized? Media Coverage and the Careers of CEOs *

Valeria Ferraro

Boston College

September 29, 2020

Abstract

I study whether women in positions of power traditionally dominated by males attract higher public scrutiny relative to men. First, I link CEO positions in publicly listed companies in the U.S. to business and financial news, and find that *bad* news receive significantly more coverage when a company's CEO is a woman. I then show that bad media coverage negatively affects CEOs' careers, the effect being larger for women. I use a Bayesian learning model to show that these two facts may be linked: by being disproportionately exposed to bad media coverage, women's careers become more unstable. The results suggest that public information provided by the media can have unintended consequences on the careers of women executives.

JEL classification: J63, M51

*I would like to thank my advisor Claudia Olivetti for her invaluable guidance and support. I also thank all seminar participants of the Dissertation Workshop at Boston College for helpful comments. All errors are my own.

1 Introduction

Women are still largely underrepresented in top positions. As of 2017, women held 19.9% of board seats in Fortune 500 companies and covered only 5.8% of CEO positions in the same companies. This phenomenon, known as "glass ceiling", extends well beyond the corporate sector: in other professional environments, women account for 20% of law firm partners and 32% of university professors.[1] As a result, women's underrepresentation at the top of the earnings distribution remains extreme, although great progress has been made at closing the gender pay gap at the middle or the bottom (Bertrand, 2018; Blau and Kahn, 2017).

This paper contributes towards understanding women's absence from top positions by asking whether female leaders are more likely to attract public scrutiny relative to men. In particular, I study the role of public information provided by the news and how it affects the careers of CEOs in large US firms. The idea is that, by monitoring firms' performance and making editorial decisions, the media can influence the way in which CEO performance is perceived by the public opinion, thus impacting CEO reputation and her employment opportunities.

This paper makes three contributions. First, I show that the media are more likely to publish *bad* news when a firm's CEO is a woman. This result is not explained by systematic differences in firm performance or heterogeneity across firms. Second, I show that news matter for CEO turnover and her subsequent career, especially *bad* news. For women, the size of the effect is between two and three times as large as for men. Finally, I develop a Bayesian model of public learning in order to test whether the higher sensitivity of women's careers to the release of bad news is due to their higher exposure to bad media coverage. I test the model's predictions and show that they are supported in the data.

To the best of my knowledge, this is the first paper to ask whether the media play any role at explaining the glass ceiling. In the corporate environment, the idea that women – and minorities in general – in top roles may attract scrutiny is well known from an anedoctal point of view.[2] My paper confirms the popular wisdom that women in leadership positions may attract more media attention relative to men in similar roles, and shows that publishing decisions made by the media can have unintended consequences on the careers of top executives, even when such information is accurate.

In order to establish whether female CEOs attract more media attention relative to men,

[1] A current Glance at Women in the Law, American Bar Association (2016); National Center for Education Statistics, IPEDS Data Center, Fall Staff 2015 Survey (2016).

[2] See for example Financial Review, November 2017.

I link detailed data on business and financial news from RavenPack News Analytics to executive positions in BoardEx. Relative to other media databases – such as Factiva, commonly used by previous literature – RavenPack is particularly suitable for studying the effects of informational flows rather than specific events. There are several features of this dataset that make it appealing for my purposes. First, the dataset has information on a very large number of news articles from major sources of business and financial news, and allows identifying the main entities involved in a news story. Moreover, every news article is classified as conveying either positive or negative sentiment, and therefore I can define the information provided by a news article as either "good" or "bad" based on the sentiment score distribution.

I find that not only a business news at the bottom of the sentiment distribution receives more coverage when the company's CEO is a woman, but also that the media are slightly more likely to publish bad stories when covering female-led firms. The difference is statistically and economically significant. In contrast with the literature on media bias, I do not attempt to identify the reasons behind the differential media exposure of female executives. Instead, I take publishing decisions as given (Nimark, 2014; Chahrour et al., 2019). In fact, publishing decisions made by the media can be thought of as a *selection function* that maps states of the world to published stories (Nimark and Pitschner, 2019). The fact that female CEOs attract more media attention is consistent with empirical regularities found by previous literature: for example, extreme events are more newsworthy than mundane events (Shoemaker and Vos, 2009), and bad events are more newsworthy than positive events (Harrington, 1989; Soroka, 2012; Harcup and O'Neill, 2017).

CEOs are a special group of workers whose performance is publicly observable (Terviö, 2009). By making editorial decisions, the media can affect the way in which CEO performance is perceived. I show that not only media exposure predicts CEO turnover, but it also correlates with the CEO's subsequent employment opportunities. For example, increasing the proportion of bad news in a quarter from the 25th to the 75th percentile results in an increase in the probability of being dismissed from all job titles in the current firm by 55% (from 2.4% to 3.5%). For women, this effect is more than twice as large as for men. Taken together, my results suggest that the careers of female CEOs are more sensitive to the release of bad news relative to men's careers. The arrival of new information can be interpreted as a shock: in a given quarter, women's careers seem to be more at risk relative to men's careers after a "bad news shock" is realized. Can the different sensitivity of women's careers be explained by the fact that, at any point in their tenure, female CEOs are more likely to be exposed to bad media coverage?

To dig into the mechanism, I build on Nimark (2014) and construct a dynamic model of public learning with endogenous publishing decisions made by the media. At the beginning of CEO tenure, shareholders, investors, and potential employers have prior beliefs on the ability of the newly appointed CEO. Such prior beliefs can be thought of as the prior public reputation of the CEO, and need not to coincide with those of the board of directors, which most likely relies on private information not available to the public. CEO reputation evolves over time as shareholders, investors, and potential employers observe private and public signals of firm performance. The public signal is provided by the news. The key feature of publishing decisions in the model is that more negative outcomes – i.e. lower firm performance realizations – are more likely to be published by the media. Therefore, the availability of public information provided by the media is state-dependent: shareholders, investors, and potential employers are more likely to observe the public signal when realized firm performance is low. When it comes to differences between female- and male-led firms, the model's assumptions are minimal: shareholders, investors and potential employers have identical priors on the ability of female and male CEOs, and the underlying distribution of firm performance is the same in the two types of firms. These assumptions are motivated by empirical evidence. The only feature that differs in the two firms is the availability of the public signal: when performance is low, shareholders, investors and potential employers are *more likely* to observe the public signal for female-led firms. In other words, for female-led firms news selection acts as if the public signal was drawn from a "worse" distribution, even if the underlying distribution of firm performance is identical in male- and female-led firms.

In order to map the model to the data and form testable implications, I define an appointment "at risk" if the CEO has been exposed to bad news for more than a given fraction of her tenure. Intuitively, this threshold is such that an additional bad news borne by the CEO is likely to irreparably impair her reputation, thus resulting in appointment termination, demotion, or a career halt. The model delivers two testable implications: (i) holding firm performance constant, women are more likely to become at risk earlier in their appointment. This is a direct consequence of the fact that, at every point in their tenure, women are more exposed to bad media coverage. The second testable implication is that, (ii) conditional on being at risk, women's careers are more sensitive to the release of new bad information. This is due to the fact that women become at risk earlier in their appointment, when uncertainty on their ability is higher, and the weight of new information is larger. I show that both these predictions find support in the data.

I perform several checks in order to corroborate the robustness of my findings, and limit

the concern that my results are driven by unobservable differences across firms or alternative explanations. First, in order to check that my results on news coverage are not driven unobservable confounders that correlate with the appointment of female CEOs, I extend my main sample of CEOs to include lower-ranked executives, and match news articles that specifically mention an executive. The results confirm that female executives are more likely to attract media attention relative to males in a similar executive role, thus corroborating the finding that women executives may attract more media interest *per se*.

Finally, I check whether my results on the differential sensitivity of women's careers to the release of bad news are accounted for by alternative explanations. I explore the role of risk-aversion on the side of female CEOs, differences in prior beliefs – i.e. higher uncertainty on the ability of female CEOs –, and differences in CEO power. None of these explanations can convincingly account for my results.

Related Literature This paper is at the intersection of several literatures. First, it relates to the literature on the glass ceiling and the barriers to career advancement that women face in top positions. Many explanations have been put forward for the absence of women from the top echelons of the earnings distribution. These include, but are not limited to, gender differences in sorting across occupations and industries, differences in psychological traits, traditional gender roles and stereotypes, educational sorting, and family commitments.[3] Moreover, women face barriers to career advancement even when they do make it to the top, and the absence of a critical mass of women in professional environments poses challenges for those who succeed at climbing the ladder (Gagliarducci and Paserman, 2012; Blau et al., 2010).[4]

In the executive labor market, gender differences in pay or career advancement have been widely documented. Bertrand and Hallock (2001), for example, show that the gender gap in executive compensation is due to the fact that women are more likely to be employed in smaller firms, and usually cover lower-ranked positions. Albanesi, Olivetti, and Prados (2015) find that the compensation of female executives is more exposed to declines in firm

[3] For the role of gender differences in sorting across occupations and industries on the gender wage gap, see Blau and Kahn (2017). For gender differences along specific psychological traits that favor selection into high-paying career trajectories – such as risk-taking and willingness to compete – see Bertrand (2011) and Croson and Gneezy (2009) for a review. While the gender gap in years of schooling has reversed, women are still less likely to choose STEM fields, which typically give access to the highest-paying occupations (Patnaik et al., 2020; Kugler et al., 2017). Traditional gender roles and family commitments prevent women from pursuing high-paying careers, which often have inflexible schedules and require working long hours (Goldin, 2014).

[4] Gagliarducci and Paserman (2012) find that municipal governments in Italy are more unstable when led by a female mayor, especially when the council is entirely male. Blau et al. (2010) show that lack of mentoring and the absence of role models may hinder the success of women in the academic profession in economics.

value and less exposed to increases in firm value than that of males. Recent work shows that women in corporate executive roles exit the occupation at higher rates than men (Gayle, Golan, and Miller, 2012), and are more likely to be fired (Gupta et al., 2020).[5] To the best of my knowledge, my paper is the first one to ask whether the media play any role at hindering the advancement of women's careers in leadership positions. Anedoctally, the idea that women in executive roles may attract public scrutiny is a popular one.[6] This idea has also been proposed in the corporate finance literature, where the role of media attention for the career of female executives is usually analyzed in connection with CEO appointment (Gaughan and Smith, 2016; Lee and James, 2007).[7]

More generally, my paper relates to the role of public information in the labor market. While previous literature is concerned with studying the role of public information for hiring inefficiencies (Pallais, 2014; Terviö, 2009), I show that public information can lead to inefficient career outcomes for particular groups of workers, even when such information is accurate. Public information in the media is likely to play a crucial role for firm and CEO reputation (Hamilton and Zeckhauser, 2004); however, I am not aware of any former study analyzing the role of publicly available information in the media for individual CEOs' careers.

Finally, my paper relates to recent work on the effects of media focus on economic outcomes. In particular, my learning model builds on partial information models with endogenous news selection in the macroeconomics literature. For example, Nimark (2014) and Chahrour et al. (2019) show how events published in the media can shape agents' expectations and drive business cycles. From those papers I borrow the notion of news selection function – first introduced by Nimark and Pitschner (2019) – and show how news selection can influence public learning on the ability of workers in a special labor market.[8]

The rest of the paper is structured as follows. Section 2 introduces the data and the main estimating sample. Section 3 documents key facts on publishing decisions made by the media, and the fact that female CEOs are subject to more media attention relative to men. Section 4

[5]For gender differences in career advancements in other professional environments, see Sarsons (2017) on surgeons and Azmat et al. (2020) on lawyers.

[6]See for example Financial Review, November 2017.

[7] Gaughan and Smith (2016), for example, shows that the announcement of the appointment of a female CEO triggers negative investors' reactions, but only when it receives high media attention. A similar result is found by Lee and James (2007).

[8]A body of literature in political economy is concerned with studying the drivers of publishing decisions and media bias. These include, for example, Gentzkow and Shapiro (2006), Petrova (2008), Besley and Prat (2006). In these papers, media bias refers to the choice to publish biased or inaccurate information. The news selection function, instead, refers to the choice of which information to report, even when such information is accurate. News selection functions provide a flexible way to model state-dependent editorial decisions, without imposing structure on the mechanisms that drive those decisions.

documents the effects of media exposure on turnover and careers, for all CEOs and separately by gender. Section 5 introduces the model and its testable implications, which are tested in Section 6. Section 7 explores the role of alternative explanations. Section 6 concludes.

2 Data

2.1 Datasets and Sample Selection

CEOs BoardEx provides detailed data on executives in large companies around the world, including demographic characteristics, education, employment history, board interlocks, and network data. I select CEO positions in publicly listed US companies that started between 2000 and 2017. I exclude from the sample CEOs that cover dual positions or are also the company's President or CFO, and I exclude CEO Emeritus positions.

Companies I link CEOs to firm-level data using Compustat and CRSP, and obtain quarterly performance measures and stock price data. I use the firm-level files from BoardEx to obtain characteristics of the board and the the firm's management.

News News data are obtained from RavenPack News Analytics, a database that uses machine learning tools to organize unstructured content from news articles into structured data. RavenPack tracks news released by both press and web sources all around the world, and is used by private investors and across a broad range of academic research on the effects of media on financial markets.[9] The sources tracked by RavenPack include The Wall Street Journal, Dow Jones Newswires, Barron's, MarketWatch, as well as a very large number of industry and business publishers, national and local news, and blog sites (roughly 19,000 sources). Relative to other media databases – such as Factiva – RavenPack does not allow the user to directly access the content of an article, and every news entry is associated with variables containing structured information provided by the algorithm. Moreover, observations in RavenPack are at the entity-level, so that there may be multiple entries for the same news article, depending on the numbers of entities involved in a news story. Although it provides the user with less flexibility than Factiva, RavenPack is particularly suitable for studying the effects of informational flows rather than specific events, and is often used to analyze media sentiment around specific entities. In Appendix Figure B.1 I show how an article in Factiva

[9] https://www.ravenpack.com/

would look like in RavenPack.

Every news observation in the dataset is categorized by an "event taxonomy", which allows understanding the broad content of an article, and an entity tag, which allows identifying the main entities involved in a news story. I only match news that are very strongly related to the entity mentioned, i.e., I only match news in which the "relevance score" of a given entity is equal to 100.[10] For every entity-news entry, the database also provides a "sentiment score", which allows determining the sentiment content of the news article from the point of view of the entity mentioned. The score is derived from a collection of surveys in which financial experts rate entity-specific events as conveying either positive or negative sentiment, and to what extent. The analysts' ratings are then included in an algorithm that generates a score ranging from 0 to 100, where 50 indicates neutral sentiment, values above 50 indicate positive sentiment, and values below 50 indicate negative sentiment. I define a news as either "good" or "bad" based on the sentiment score distribution, with good news being below the 10th percentile of the distribution and good news above the 90th percentile.

There are several ways in which news data can be aggregated. An important feature of news data is that the same news story can be reported by multiple sources. In RavenPack, every news observation is associated to a "novelty" and a "similarity" score, which allow determining how "new" a news is and grouping news by similarity.

In order to analyze differences in news coverage between male- and female-headed firms, I aggregate news data at the story level and construct two measures of coverage. The first measure is given by the number of articles that a news story generates; the second measure is given by the number of days over which a news story is reported in the media.

In order to measure the propensity of media outlets to publish stories covering specific entities, I aggregate data at the quarterly level and count the number of stories published in every quarter, separately for good and bad stories.

Finally, to understand the effects of good and bad news on CEOs' careers, I construct a quarterly measure of media exposure, given by the fraction of good and bad news over the total number of news released in a quarter.

[10] For any news story that mentions an entity, the data provide a relevance score that indicates how strongly related the entity is to the underlying news story. A score of 0 means the entity was passively mentioned while a score of 100 means the entity was prominent in the news story.

2.2 Sample description

Table 1 shows the number of executives that were appointed in the sample companies between 2000 and 2017 by job title and gender, with the positions included in the main sample in the third row of the table. The positions in Table 1 are ranked by perceived importance (Albanesi et al., 2015; Bertrand and Hallock, 2001): clearly, women's underrepresentation increases the higher the perceived rank of the position.

I match news data to BoardEx using unique ISIN identifiers. Out of 3,126 positions in BoardEx, I am able to match 3,026 positions, 129 of which are covered by women.[11] Only 18% of these are CEO positions in very large companies (such as S&P 500, S&P MID CAP, and S&P SMALL CAP).[12] As shown by Table B.1 in the Appendix, the firms that I am able to match are on average larger than unmatched firms, and have larger boards. This is simply due to the fact that larger firms are more likely to be monitored by the media.

Table 2 shows the average characteristics of CEOs in the news-CEOs matched sample, separately by gender. Men and women CEOs are a homogeneous group in terms of observable characteristics such as age and education. Women tend to be appointed after longer tenures in the company, and their appointments are shorter on average, although these differences are not statistically significant. Women who make it to the top of the corporate ladder also have much larger networks, with a difference of 156 connections on average. More significant differences appear when comparing firms that appoint male and female CEOs. Out of 2,043 companies in the sample, only 105 ever appoint a woman CEO; the sample size decreases even more if I focus on companies in which there is variation in gender across appointments – only 53 companies. Consistent with previous literature, Table 2 shows that women tend to become CEOs in smaller firms, and are more likely to be appointed in firms operating in the consumer and service sector rather than the primary sector, which includes firms in energy, materials, industrials, and utilities (Bertrand and Hallock, 2001; Gayle et al., 2012).

Figure 2 shows the sentiment score distribution for the sample of matched news stories, with the two vertical bars representing the 10th and 90th percentiles of the distribution. Over 30% of the news stories reported have neutral sentiment, but there is substantial variation across news stories. Table 3 presents descriptive statistics for the same data. I present news stories by broad topic, separately by story sentiment. The most common news reported in the media include performance news and analysts' ratings. Bad news also involve legal and

[11] 20 positions are unmatched due to missing appointment dates in BoardEx, and 80 are unmatched due to missing news data.

[12] The rest of the positions are covered in public companies that are not part of any major index. Women are underrepresented in S&P 500, S&P MID CAP, and S&P SMALL CAP firms (12% of positions).

regulatory issues, whereas the top good stories are represented by the release of new products and services. There is substantial variation in the number of articles across good and bad stories, with much smaller variation when looking at the number of days: the overwhelming majority of news are "short lived" and are reported in the media for one day at most.

3 CEOs in the Media

Media outlets monitor firms' performance and deliver information that can be easily accessed by shareholders, investors, and the general public. Although it is possible for investors to monitor performance more directly, for example through the company's website or social media, most of the public will rely on processed information available in the news.[13] There are several reasons to expect that information provided by the media can be important for CEOs. CEOs are a special group of workers whose performance is publicly observable (Terviö, 2009). By making editorial decisions, the media can influence the way in which CEO performance is perceived by the public opinion. When assessing CEO performance, the Board of Directors most likely relies on private information that is not available to the public. However, the information provided by the media affects firm reputation, and informs the public opinion on the quality of the company-CEO match. Reputation is a crucial asset, both for firms and CEOs. For firms, reputation matters not only to attract consumers' demand, but also to attract and retain talented workers.[14] For CEOs, reputation is likely to affect current and future employment opportunities (Terviö, 2009).

When monitoring states of the world, the media make decisions as to which news stories to publish. Not only it would be impossible for the media to publish all events, but they also act as profit-maximizing market players that seek to publish stories that are appealing to the public. Publishing decisions made by the media can be thought of as a *selection function* that maps states of the world to published stories. The notion of news selection function was first introduced by Nimark and Pitschner (2019). News selection functions provide a flexible way to model editorial decisions, without imposing structure on the mechanisms that drive those decisions.

The journalism literature has identified empirical regularities on the features of news selection functions. In general, extreme events are more newsworthy than mundane events (Shoemaker and Vos, 2009). This feature of media reporting has already been used in the

[13] Examples here.

[14] Harvard Business Review, February 2007

macroeconomics literature: Nimark (2014) and Chahrour et al. (2019), for example, show how extreme events published in the media can shape agents' expectations and drive business cycles.[15] Another empirical regularity in news reporting is that bad events are more likely to be covered in the media (Harrington, 1989; Soroka, 2012; Harcup and O'Neill, 2017). For example, Harrington (1989) documents that network television news overemphasize bad economic news. Similarly, Soroka (2012) documents the *New York Times* is more likely to report bad news about unemployment, inflation, and interest rates rather than good news about the same variables.

In Appendix Tables B.2 and B.3 I check whether the empirical regularities documented by previous work at the aggregate level hold at the micro-level in my sample of firms. The crucial issue is that it is not possible to observe the distribution of all events, but only reported ones. However, by aggregating news data at the story level I can check whether the patterns hold *within* the sample of reported events, and understand how the characteristics of reported events correlate with observable firm characteristics. Therefore, I use the story-level dataset and divide news stories into five sub-samples based on their sentiment score. The idea is to check how CEO characteristics, firm performance, and news characteristics correlate with coverage for a news story within each subsample. In Table B.2 the dependent variable is represented by the number of articles for a news story (either press or web), whereas in Table B.3 the dependent variable is represented by the number of days over which the news story is reported by the media.

First, and perhaps unsurprisingly, large firms are always more likely to be covered in the media. Second, the coefficient on the sentiment score is large and highly significant for news events at the tails of the sentiment score distribution, and insignificant in the middle. This is consistent with the first fact: more extreme events are more likely to be covered in the media. Moreover, the size of the coefficient is almost double in absolute value for very bad news stories (i.e. in the bottom 10%) relative to very good stories (i.e. in the top 90%). This is consistent with the second fact: bad news are more likely to be covered by the media relative to good news. Younger CEOs and CEOs at the beginning of their tenure also receive more media coverage on average. This may be due to the fact that there is more uncertainty around newly appointed CEOs, so that information becomes more valuable. Women CEOs, instead, seem to receive more media coverage for bad news only. This fact will be documented in detail in the next section. All in all, the results in Tables B.2 and B.3 suggest that the coverage

[15] Nimark (2014) developed a terminology for the tendency of media to publish extreme stories. A story on a dog biting a man would not be published, whereas a man biting a dog would most likely be published. Therefore, he labels public signals provided by the media as "man-bite-dog" signals.

patterns documented by previous literature are broadly confirmed in my data.

3.1 Are women CEOs scrutinized?

In this section, I document that a news concerning a company is more newsworthy when the CEO is a woman, the difference being entirely driven by *bad* news. This feature of the news selection function is consistent with the empirical regularities mentioned above. Women CEOs are still an exception in large firms: as of 2017, women held 4.8% of CEO positions in Fortune 500 companies. In this sense, women CEOs may be considered a "tail event". The fact that the difference is entirely driven by bad stories is consistent with bad events being inherently more newsworthy. This finding is consistent with several anedoctal stories suggesting that women in executive roles may face a high degree of scrutiny and monitoring, both in the private and the public sector.[16]

Bad news receive more coverage in female-headed firms First, I show that conditional on being reported, a *bad* news story receives more media coverage when a company is led by a female CEO. This result is not driven by systematic differences across firms or differences in firm performance.

I use the story-level dataset and estimate the following regression:

$$\text{news coverage}_{sijt} = \alpha + \beta \text{female}_{ijt} + X'_{ijt}\chi + Z'_{jt}\xi + \phi_j + \tau_t + \epsilon_{sijt} \tag{1}$$

where news coverage$_{sijt}$ represents the number of articles for story s linked to individual i in company j at time t, female$_{ijt}$ is a binary variable equal to 1 if the executive is a woman, X_{ijt} is a vector of individual-level controls including year of appointment fixed effects, a quadratic in age, education, network size, a quadratic in tenure, the number of board positions covered at the time of the appointment, and the tenure in the company at the time of the appointment. Z_{jt} is a vector of firm-level controls including quarterly sales and assets, and ϕ_j and τ_t represent firm and time fixed effects respectively. I estimate specification 1 on the full sample of news events, and then separately on different parts of the sentiment score distribution.

I focus on the small sample of firms in which I observe variation in gender across appointments (53 firms in total).[17] Of course, it is still possible that women CEOs get appointed in times of worse firm performance, which in turn would result in worse media coverage. Con-

[16] See for example Financial Review, November 2017.

[17] I repeat the same analysis on the full sample of firms, and replace firm fixed effects with sector fixed effects. The results for the full sample of firms are shown in Appendix Tables B.2 and B.3, and Appendix Figure B.2.

trolling for quarterly sales and assets mitigates this concern, but further robustness checks are presented in the next section.

Table 4 shows the results for the full sample of events. I use two alternative measures of news coverage, namely the number of articles for a news story and the number of days over which a news story is reported in the media. On average, a news story generates 0.6 additional articles for a female-headed firm; the difference is sizable, and corresponds to 22% relative to the sample mean. There is virtually no difference in coverage when measured by the number of days; as show by the summary statistics in Table 3, however, this variable shows very little variation in the data.

I then estimate the same specification on different parts of the sentiment score distribution, and plot the estimated coefficients on the female indicator in Figure 3. The difference in average news coverage is entirely driven by bad news, and is positive and significant both when looking at the number of articles and the number of days. The estimated coefficient on the female indicator is economically and statistically significant, with a difference of around 0.1 standard deviations above the mean.

More bad news stories are published for female-headed firms I then turn to the number of news stories published in a given quarter. The news selection function may be such that not only bad stories receive more coverage when they are published, but also more bad events are published. This second feature of the news selection function actually turns out to be less relevant.

I focus on the most frequent categories of news stories, which include performance-related news, analysts' rating, and legal issues.[18] In Table 5 I present coefficient estimates from an OLS regression and quantile regressions, separately for good and bad stories. On average, in either sample there is no significant difference in the number of news stories covering male- and female-led firms. A small positive difference shows up in the quantile regressions for the sample of bad news: at the 75th percentile of the distribution, the difference for female-headed firms is 0.14 news stories.

Women CEOs are more exposed to bad media coverage Finally, I construct a quarterly measure of good and bad media exposure. So far, I have "decomposed" media coverage into two components: an intensive margin, given by the number of articles per news story, and an

[18]The list of stories included in shown in Table in the Appendix. In Appendix Table I run the same analysis on the full sample of news stories, and find very similar results.

extensive margin, represented by the number of news stories published in a quarter. I now take a measure that conflates the two components, and simply consider the total number of articles published in a quarter. In every quarter, I count the number of good (bad) news articles released, and divide it by the total number of articles published in the same quarter. I define an article as "good" if the sentiment score of the article belongs to the top 10% of the distribution, whereas "bad" articles correspond to the bottom 10%. In Figure 4 I plot the distribution of media exposure, separately for good and bad exposure. Clearly, the share of bad news in female-headed firms first order stochastically dominates the distribution for male-headed firms, whereas no such effect appears when looking at the distribution of good news.[19] Table 6 shows that such difference persists conditional on observable firm performance and CEO characteristics, with a sizable and significant difference showing up at the average and in the upper part of the distribution. Taken together, these results are consistent with women CEOs being more exposed to *bad* media coverage relative to men, the difference not being driven by observable firm performance nor systematic differences across firms.

3.2 Robustness

I perform several robustness tests in order to corroborate the fact that women CEOs may attract more media interest *per se*, and that the results are not explained by systematic differences in firm performance or heterogeneity across firms.

First, I check more directly whether there are any significant differences in firm performance between male- and female-headed firms. If firms were more likely to appoint women in difficult times (the "glass cliff" hypothesis), then bad news for female-headed firms would simply be *worse* news, and thus they would be more likely to be covered in the media. I plot the distribution of sales and stock prices separately for male- and female-headed firms in Figure 5, and run OLS and quantile regressions in Table 7. While there seems to be virtually no difference in stock price returns between male- and female-led firms, the distribution of sales seems less dispersed for women. If anything, results from the quantile regressions show a slightly positive difference in sales for female-headed firms.[20]

Even if there seem to be little or no differences in observable firm performance for firms that appoint a female CEO, one might still be concerned that the results on news coverage

[19]The cumulative distribution functions and Kolmogorov-Smirnov tests are shown in Figure B.3.

[20]These differences are small, given that the 25th, 50th, and 75th percentiles of the log-sale distribution for male-led firms correspond to 3.08, 4.6, and 6.08.

reflect unobservable circumstances that coincide with the appointment of female CEOs. This could be the case, for example, if the company was undergoing a change in firm strategy and the board wanted to signal the change by appointing a female CEO. If this was the case, then the results in the previous section would just be reflecting a spurious correlation due to company circumstances that may have relatively little to do with the CEO. In order to check whether this is the case, I match to CEOs news articles that specifically *mention* the CEO as the main individual involved in a news story. I extend my main sample to include lower-ranked executives, and link news stories that mention either the CFO, COO, or other lower-ranked executives.[21] The results are presented in Tables B.5 and B.6. I standardize the dependent variable and transform it into z-scores to make the results comparable across executives. Clearly, the results show that female executives are more likely to attract media attention relative to male executives in the same position, with the largest relative effects observed for CEOs. This result assures – at least partially – against the concern that changing company characteristics fully drive the results, and corroborates the observation that women in executive positions may attract more media interest *per se*.

4 Media Exposure and CEOs' Careers

In this section, I document whether media exposure has any effect on CEOs' turnover and career. When assessing CEO performance, the board is likely to rely on private information not available in the media. However, the board may be reluctant to retain a CEO who performs poorly in the news. Moreover, the public information provided by the media may affect CEO reputation and her subsequent employment opportunities.

In order to document whether news release has any effect on CEO turnover or career, I estimate the following specification:

$$I(\text{Event}_{ijt}) = \alpha + \delta_1 \text{Share of bad news}_{ij,t-1} + \delta_2 \text{Share of good news}_{ij,t-1} + \theta \text{Number of news}_{ij,t-1} + X'_{ij,t-1}\gamma + Z'_{j,t-1}\eta + \phi_j + \tau_{t-1} + \nu_{ijt} \quad (2)$$

the dependent variable, $I(\text{Event}_{ijt})$, is an indicator for whether an event for CEO i in firm j occurs in quarter t. Such event can be CEO turnover, or moving to another firm, as I will explain below. I regress the event indicator on a number of lagged variables, including media exposure, and CEO and firm characteristics. The main coefficients of interest are δ_1 and

[21] I only match news stories in which the relevance score of the mentioned executive is equal to 100.

δ_2, namely the coefficients on the proportion of bad and good news: Share of bad news$_{ij,t-1}$ represents the share of news articles with sentiment score below the 10th percentile of the sentiment score distribution, and Share of good news$_{ij,t-1}$ represents the share of news articles above the 90th percentile. In every specification, I also control for the total number of news in quarter $t-1$, namely the denominator of the share variables. $X_{ij,t-1}$ is a vector of CEO characteristics, including a female indicator, network size, a quadratic in age, and a quadratic in tenure.[22] $Z_{j,t-1}$ is a vector of firm-level performance controls, namely monthly stock price returns averaged over the quarter preceding the event. Finally, ϕ_j and τ_{t-1} represent firm and time fixed effects; in some specifications, I replace firm fixed effects with sector fixed effects. Standard errors are clustered at the position level. In my most restrictive specification, I also control for two lags of the news and performance variables.

4.1 Turnover

I start by studying the effects of media exposure on CEO turnover. Differently from the corporate finance literature on CEO turnover, I do not attempt to classify the nature of turnover as due to resignation or firing.[23] Instead, I take an agnostic approach and define as turnover any quarter in which I observe a CEO ending her appointment. This is because a CEO may decide to resign or retire following good or bad media coverage. Moreover, the focus of the paper is understanding how the media can affect CEOs' careers rather than studying how the media influence boards' firing decisions, although this would be an interesting question for future research.

In Figure 6, I plot turnover probability as a function of quintiles of the share of bad news, measured in the quarter before turnover. The graph shows that exposure to bad information provided by the media seems to matter: the probability of turnover increases from 6.6% for the first quintile to 10% for the last quintile of the distribution. I then check more formally whether this result holds conditional on firm's and CEO appointment's characteristics in Table 8. In columns 1 and 2, I regress a turnover indicator at time t on the share of bad news in quarters $t-1$ and $t-2$, controlling for the total number of news, stock market performance, and CEO's tenure and characteristics.[24] Column 1 shows that the share of bad news in quarter

[22]The results are unchanged if I control for tenure non-parametrically, or if I allow tenure to have a differential effect by gender.

[23]In an influential paper, for example, Parrino (1997) provides a method for classifying CEO turnover as due to firing, resignation, or retirement.

[24]By including two lags in the news and performance measures I am excluding 10% of CEOs in the sample,

$t-1$ strongly predicts turnover probability at time t. The size of the coefficient is unchanged when adding firm fixed effects in column 2. In column 3, I further control for the share of good news at time $t-1$ and $t-2$: the share of good news at time $t-1$ seems to be negatively correlated with turnover in the following quarter, but the coefficient turns out to be smaller and insignificant when adding firm fixed effects in column 4. The magnitude of the coefficient on the share of bad news at time $t-1$ is fairly stable across specifications, including the hazard model in column 5.

My preferred estimate in column 4 implies that an increase in the fraction of bad news from the 25th to to 75th percentile is associated with an increase in the turnover probability of about 1 percentage point, from 6.4% to 7.5% – which corresponds to a 20% increase. This number is difficult to compare to previous work on CEO turnover, given that the corporate finance literature typically focuses on determinants of turnover other than the media. For example, Jenter and Lewellen (2019) find that turnover probability increases from 3.3% to 6.68% as stock market performance decreases from the 70th to the 20th percentile of the distribution in the preceding year; Jenter and Kanaan (2015) find that forced turnover probability increases from 2.05% to 4.14% as industry performance falls from the 90th to the 10th percentile in the preceding year. Relative to these estimates, my estimates for media exposure are smaller. This discrepancy may be due to several facts. First, the average turnover probability is higher in my sample. This is because I define as turnover any quarter in which I observe an appointment ending, whether it is due to resignation, firing, retirement, or even a change in job title. Moreover, it should be noted that my results reflect a correlation rather than a causal effect, and are most likely downward biased. I will discuss possible sources of endogeneity in the sext subsection.

Finally, Table 8 shows that conditional on the share of good and bad news released, the total number of news published in a quarter has no effect on turnover probability. In general, the other covariates have the expected sign. Low firm performance is associated with an increase in turnover probability, although the coefficient is never significant. CEOs with longer tenures are also more likely to terminate their appointment in a given quarter. Consistent with previous research and the descriptive statistics in Table 2, women CEOs have a higher probability of terminating their appointment relative to males, with a difference between 2 and 4 percentage points.

---

who had appointments that lasted less than 6 months.

4.2 Careers

Next, I turn to studying the effects of media exposure on CEOs' careers. All variables are measured in the same quarter in which I observe CEO turnover, and therefore the results represent the short-term effects of media exposure. Table 9 shows how much variation there is in the data, and the number individual observations for each indicator, separately by gender. First, I define two variables that are similar to the turnover indicator in spirit. The variable "Moved" indicates whether the CEO is no longer employed in the company under *any* job title. "Reappointed" is an indicator for whether the CEO started a new term as CEO in the same company. I then classify job moves according to the next job's characteristics. "Private firm" is an indicator for whether the CEO moves to a private company (i.e. not publicly listed); "Private/smaller firm" is an indicator for whether the CEO moves to a private company or a company with smaller sales relative to the departing company.[25] These two variables can only be defined for the subset of CEOs for which I observe the characteristics of the next job move, and therefore I exclude all other CEOs from the analysis. In the last measure ("Private/smaller/missing"), I also include CEOs for which the information on the next job move is missing. These include CEOs that have retired, dropped out from the occupation, had unemployment spells larger than a quarter, and CEOs for which I am not able to obtain exact information on the company in which they have started a new position.

The results are shown in Table 10. Column 1 replicates the regression in Table 8, column 4 for turnover. Similarly to the results in Table 8, a higher share of bad news in the current quarter predicts a career halt in the following quarter. In particular, exposure to bad news is strongly associated with leaving the company, and moving to a private or smaller firm. Bad news seem to have no significant effect on the probability of starting a new term as CEO in the same company.

Relative to turnover, the effects of bad media exposure are larger when considering the probability of moving to another company, or moving to a private or a smaller firm. Such estimates are closer to those produced by recent work on forced or perfirmance-induced CEO turnover, most likely because the definition of the dependent variable matches more closely to the turnover definition in previous research (Jenter and Lewellen, 2019; Jenter and Kanaan, 2015). Specifically, an increase in the proportion of bad news from the 25th to the 75th percentile increases the probability of moving to another firm of 55% (from 2.4% to 3.5%).

[25] In order to rank companies in terms of performance, I divide companies into two-digit SIC sectors and obtain deciles of yearly sales in a given sector-year. I define a company as "smaller" if the difference in yearly sales with the departing company is greater than two deciles in the fiscal year preceding the job move.

The same increase in the proportion of bad news has an even larger effect on the probability of moving to a smaller or private firm: the probability of moving to a smaller or private firm is 0.8% at the 25th percentile, and increases to 2.3% at the 75th percentile.

The results in Tables 8 and 10 show that *bad* media exposure strongly predicts turnover probability and employment in private or smaller companies. Good news, instead, seem to have very little effect. This asymmetry is consistent with a number of explanations. It is well known that people tend to put more weight on bad news relative to good news, a pattern that is known in psychology as negativity bias (Trussler and Soroka, 2014).[26] Another potential explanation is that when making hiring decisions, firms may seek to screen out particularly poor candidates in order to avoid very bad outcomes, rather than selecting the top ones (Bergman et al., 2020). An alternative interpretation has to do with reporting decisions made by the media. As discussed by section 3, the media are more likely to publish bad events relative to good ones. If this is the case, the distribution of events reported in the media does not reflect the unconditional distribution of all events. In other words, good news reported in the media are not good news in an unconditional sense, and for this reason they may be less relevant. This intuition will be formalized in detail in section 5.

It should be noted that the results presented in Tables 8 and 10 only reflect correlations and cannot be interpreted as the causal effect of media exposure on CEOs' careers. High-ability CEOs, for example, may be more able at communicating or manipulating the timing of news release. Under such hypothesis, the coefficient on the news variable would be downward biased. Moreover, firm performance at time $t-1$ is likely to be endogenous, since news information is typically incorporated into stock prices.[27] This also is likely to introduce a downward bias on the coefficient on the news variable. In Appendix Tables B.7 I show that the results do not change significantly if I exclude stock price performance at time $t-1$ and only include performance at time $t-2$. Another issue with firm performance is that I am able to obtain the performance variables only for a subset of company-quarters. In Appendix Table B.8 I exclude all performance controls – thus substantially increasing the number of observations – and obtain very similar results.

[26] As summarized by a famous quote: "It takes many good deeds to build a good reputation, and only one bad one to lose it" – Benjamin Franklin.

[27] I include average monthly stock price returns as a measure of firm performance for two reasons. First, the results are comparable to recent research on CEO turnover (Jenter and Kanaan, 2015; Jenter and Lewellen, 2019). Second, other performance measures – such as quarterly sales – are sparse and would significantly reduce sample sizes.

4.3 Turnover and careers, by gender

In section 3, I have documented than women CEOs are more exposed to *bad* media coverage relative to men. Are there any differences by gender when considering the effects of bad news on CEOs' careers? I answer this question in Table 11. I run the same regression as in Equation 2, and interact the exposure variable with a female indicator. Differently from Table 10, I only control for one lag of the news and performance variables in order to avoid selecting the sample and, most importantly, avoid differential selection by gender.

The results suggest that the careers of women CEOs seem to be more sensitive to the release of bad news relative to men's careers. While the differential effect on turnover is very close to zero, stark differences appear when considering the probability of leaving the company or moving to a smaller company. The differential is large and negative also when looking at the probability of reappointment, although the coefficient is imprecisely estimated. For men, the share of good news released in a quarter *decreases* the probability of turnover or leaving the company; women, on the other hand, seem to benefit less from the release of good news, although the difference is not statistically significant. In order to interpret the magnitudes of the coefficients, one should keep in mind that the share of bad news is drawn from a different distribution for men and women (see Figure 4). Moreover, as shown by Table 11, women have a higher baseline probability of ending their appointments or moving. Therefore, I rescale the estimates using the male distribution as the reference distribution for both groups. For men, the estimates imply an increase in the probability of moving to another firm (column 2) equal to 35% when the proportion of bad news increases from the 25th to the 75th percentile in the male distribution. For females, this effect is more than twice as large: on average, the probability of being employed in another firm increases by 85% when moving from the 25th to the 75th percentile in the male distribution. Similarly, the probability of moving to a private or smaller firm, or being missing from the dataset (column 6), increases by 30% for males when the proportion of bad news increases from the 25th to the 75th percentile; for females, such effect is at least three times as large, with the probability at the 25th percentile doubling when moving to the 75th percentile.[28]

The results show that, in any given quarter, the careers of women CEOs are more sensitive to the release of bad news relative to men's careers. The news variable can be interpreted as a

[28]More specifically, the probability of moving to another firm at the 25th percentile is 2.4% for males and 3.5% for females; at the 75th percentile, these probabilities increase to 3.2% for males and 6.3% for females. The probability of moving to a private or smaller firm, or being missing from the dataset, is 2% at the 25th percentile for both men and women; this probability increase to 2.6% for men and 4.7% for women at the 75th percentile of the distribution.

shock: in a given quarter, women's careers seem to be more at risk relative to men's careers after a "bad news shock" is realized. Can such different sensitivity be explained by the fact that, at any point in their tenure, women CEOs are more likely to be exposed to bad media coverage? This question will be answered in the next section through the lenses of a learning model, which will deliver simple testable implications in order to corroborate this conjecture.

5 Model

I build a learning model with endogenous news selection in order to formalize and understand how public information provided by the media affects the evolution of public beliefs on CEO ability – that is, the public reputation of the CEO. I build on Nimark (2014), and add endogenous news selection to an otherwise standard Bayesian model of public learning. Nimark (2014) shows how the tendency of media to publish extreme events can shape agents' expectations and drive aggregate uncertainty. Differently from Nimark (2014), I model another aspect of news reporting – namely the fact that bad outcomes are more newsworthy relative to good outcomes – and derive a tractable framework that maps to the empirical results presented in the previous sections.[29]

5.1 Homogeneous firms

5.1.1 Model set-up

I start from an environment in which there is only one type of firm-CEO. At the time of CEO appointment ($t = 0$), shareholders, investors, and potential employers have a prior belief on CEO ability that is normally distributed:

$$a \sim N\left(\mu_a, \frac{1}{\tau_a}\right)$$

where $\tau_a > 0$. I normalize $\mu_a = 0$ for simplicity. Such prior beliefs need not to coincide with those of the board of directors, which most likely relies on private information not available to the public. Prior beliefs on CEO ability of shareholders, investors, and potential employers can be thought of as the prior public reputation of the CEO. Such public reputation evolves over time as shareholders, investors, and potential employers observe private and public

[29] In my setting what really matters is the asymmetry between male- and female-headed firms when it comes to *bad* media coverage. Alternatively, one could think of modeling the news selection function such that outcomes on the tails are more newsworthy – as in Nimark (2014) – and more so on the left tail.

signals of firm performance. In every period of CEO tenure t, firm performance q_t is realized, where q_t is a function of CEO ability and a random shock:

$$q_t = a + \epsilon_t$$

$$\epsilon_t \sim N\left(0, \frac{1}{\tau_\epsilon}\right),\ \tau_\epsilon > 1$$

In every period, shareholders, investors, and potential employers form posterior beliefs based on a private and public signal of firm performance. The private signal of firm performance, s_t, is a function of firm performance q_t and a random shock:

$$s_t = q_t + \tilde{\eta}_t$$

$$\tilde{\eta}_t \sim N\left(0, \frac{1}{\tau_{\tilde{\eta}}}\right),\ \tau_{\tilde{\eta}} > 1$$

where $\tilde{\eta}_t$ is a random observation error independent of q_t, normally distributed and centered around zero.[30] With probability ω, in every period shareholders, investors, and other firms also observe a pubic signal of firm performance, y_t, which is provided by the media:

$$y_t = q_t + \eta_t$$

$$\eta_t \sim N\left(0, \frac{1}{\tau_\eta}\right),\ \tau_\eta > 1$$

where η_t is a normally distributed random publication or observation error, independent of the particular realization q_t.

In line with previous work on CEO turnover, I assume that here exists a threshold μ_a^* – set exogenously – such that the CEO is fired in period t if $\hat{\mu}_{a,t} < \mu_a^*$, where $\hat{\mu}_{a,t}$ is inferred CEO ability at time t. μ_a^* is common to all employers, so that the CEO will not be hired by a prospective employer in period t if $\hat{\mu}_{a,t} < \mu_a^*$.

5.1.2 News selection

Publishing decisions are made by the media through the news selection function. The news selection function monitors performance realizations q_t and decides which realizations to make public. Every particular realization q_t can be thought of as representing a different

[30] Note that I assume no heterogeneity in the observation error $\tilde{\eta}_t$. The model is identical if I assume J error draws – so that $\tilde{\eta}_{jt}$ denotes the observation error for individual j at time t – and consider aggregate belief updating.

state of the world. Publishing decisions are represented by the random variable S_t: when the media decide to publish state q_t, $S_t = 1$ is realized, and the signal $y_t = q_t + \eta_t$ is made public.[31] The availability of the public signal y_t depends on the realized state of the world: the key assumption on the publication rule is that more negative states are considered more newsworthy by the news selection function. This assumption is in line with the empirical evidence presented in the previous sections, and is an empirical regularity when looking at news reporting (see Section 3).

Definition 1. Negative outcomes are considered more newsworthy by the news selection function if $\frac{P(S_t=1|q_t)}{P(S_t=0|q_t)}$ is decreasing in q_t.

Definition 1 states that the relative probability of the public signal being available increases as firm performance decreases. It can be shown that under the publication rule in Definition 1, the distribution of unpublished states first order stochastically dominates the distribution of published states.

Proposition 1. *If* $\frac{P(S_t=1|q_t)}{P(S_t=0|q_t)}$ *is decreasing in* q_t*, then* $P(q_t \leq q|S_t = 0) \leq P(q_t \leq q|S_t = 1)$.

Proof. In the Appendix.

The proposition states the distribution of published states ($S_t = 1$) is "worse" relative to the distribution of unpublished states ($S_t = 0$) . In other words, when $S_t = 1$, it is as if realized firm performance was drawn from a worse distribution relative to the case in which $S_t = 0$. This is because the news selection function is more likely to publish realizations of q_t on the left tail of the unconditonal distribution $P(q_t)$.

From first order stochastic dominance, it follows that the mean of published states is lower than the mean of unpublished states: $E(q_t|S_t = 1) \leq E(q_t|S_t = 0)$: on average, the value of firm performance is lower when it is made public relatively to when it is not.

The next proposition states that the mean of published states is also lower than the unconditional mean of all states:

Proposition 2. *The mean of published states is lower than the unconditional mean of all states, that is:* $E(q_t|S_t = 1) \leq E(q_t)$.

Proof. In the Appendix.

[31] The assumption is that media outlets can perfectly observe q_t, but can only provide a noisy signal to the public. This is equivalent to assuming that the media observe a noisy signal of output quality y_t, which is made public without noise.

Figure 7 helps visualizing these results. Figure 7 plots the unconditional distribution of firm performance $P(q_t)$, the conditional probability of publication $P(S_t = 1|q_t)$, and the distribution of published firm performance, $P(q_t|S_t = 1)$. The unconditional distribution $P(q_t)$ – the blue solid line – is centered around zero by assumption. For a given realization q_t with distribution $P(q_t)$, the conditional probability of the state being reported, $P(S_t = 1|q_t)$, increases monotonically as q_t decreases, and approaches 1 for very low values of q_t. The distribution of reported states $P(q_t|S_t = 1)$ – the blue dashed line in Figure 7 – is shifted to the left relative to the unconditional distribution $P(q_t)$: the average event published by the media is a "worse" event relative to the average event in the true underlying distribution.

5.1.3 Belief updating

In every period t, rational investors, shareholders, and other firms use the private signal s_t and the public signal y_t – whenever available – to inform their posterior beliefs on firm performance and CEO ability. At the beginning of period t, the mean and variance of the posterior distribution of firm performance are a function of all private and public signals up to $t-1$:

$$E(q_t|h_t) = \frac{\tau_{\tilde{\eta}} \sum_{j=1}^{t-1} s_j + \tau_\eta \sum_{j=1}^{t-1} y_j \cdot I(S_j = 1)}{\tau_q + (t-1)\tau_{\tilde{\eta}} + \tau_\eta \sum_{j=1}^{t-1} I(S_j = 1)} \tag{3}$$

$$Var(q_t|h_t) = \left(\tau_q + (t-1)\tau_{\tilde{\eta}} + \tau_\eta \sum_{j=1}^{t-1} I(S_j = 1)\right)^{-1} \tag{4}$$

Equation 4 shows that the variance of the posterior distribution of firm performance is lower when y_t is available. Whenever y_t is available, the additional information provided by the media reduces uncertainty. Proposition 3 helps formalizing this intuition:

Proposition 3. *The weight on the realization q_t is larger when y_t is available relative to when it is not available.*

Proof. In the Appendix.

Propositon 3 states that, when y_t is available, the agent puts more weight on the new observation (relative to her prior) compared to the case in which y_t is not available. Whether the posterior mean firm performance (ability) is higher or lower when y_t is available depends on the particular realization y_t.[32] However, given that S_t is more likely to "switch on" for low realizations of firm performance, the agent will be likely to put more weight on the signals when the underlying state is low.

[32]Depending on the realization of the observation error η_t, y_t can be arbitrarily large in absolute value.

In Figure 9, I simulate the evolution of posterior public beliefs on CEO ability with and without the public signal provided by the news.[33] In every period, the posterior mean in the model with news selection – the dark blue dots – is below the posterior mean of the model with private signals only – the light blue dots. Figure 8 plots the distribution of realized signals. Whereas the distribution of the private signal is centered around zero, mirroring the unconditional distribution of firm performance – and CEO ability –, the distribution of the realized public signal is skewed to the left. This is due to the bias introduced by news selection, which is such that low realizations of firm performance are more likely to be published; with an observation error normally distributed around zero, realized public signals are likely to be low as well.[34]

The model assumes that there is a threshold μ_a^* such that the CEO is fired (or not hired) if $\hat{\mu}_{a,t} < \mu_a^*$. The challenge with mapping the model to the data is that the econometrician does not observe the evolution of public beliefs, $\hat{\mu}_{a,t}$, but only a discrete choice:

$$I(\text{End of appointment})_t = I(\hat{\mu}_{a,t} < \mu_a^*)$$

In order to map the model to the data, consider an intermediate threshold $\bar{\mu}_a > \mu_a^*$ such that the appointment becomes "at risk" if $\hat{\mu}_{a,t}$ falls below $\bar{\mu}_a$. $\bar{\mu}_a$ can be interpreted as a threshold such that the marginal effect of an additional bad news on CEO career becomes large, since for any additional bad news CEO's inferred ability will likely fall below the threshold μ_a^*. Intuitively, any additional bad news borne by the CEO at this threshold is likely to irreparably impair her reputation, thus resulting in appointment termination, demotion, or a career halt.

5.2 Heterogeneous firms

I now turn the case of heterogenous firms. I consider two types of firms: female- and male-headed firms ($g = F, M$). The two types of firms are identical in terms of prior distribution of CEO ability, unconditional distribution of firm performance, and ability thresholds, but differ with respect to one feature: the media are more likely to publish a low performance

[33] This requires making assumptions on the distributions' parameters such that the publication rule is satisfied. In Appendix A.2 I describe exactly how the distributional assumptions on CEO ability and output q and the structure imposed by the news selection function allow characterizing the family of conditional distributions $P(q|S=0)$ and $P(q|S=1)$ such that the publication rule in Definition 1 is satisfied.

[34] It should be noted that the simulation in Figure 9 represents a particular path of infinitely many paths: depending on the realizations of the random errors, there will be paths in which the posterior mean in presence of the public signal will be above the posterior mean with the private signal only. However, if we could average across infinitely many paths, we would see something similar to Figure 9, with the posterior mean in a model with news selection being below the baseline model with private signals only.

realization for female-headed firms relative to male-headed firms.

More formally, the model's assumptions on female- and male-headed firms are:

(i) The prior ability distribution is the same in the two firms: $a^F \sim a^M \sim N\left(0, \frac{1}{\tau_a}\right)$

(ii) The unconditional distribution of firm performance is the same in the two firms: $P^F(q_t) \sim P^M(q_t)$;

(iii) The firing (not hiring) and "riskiness" thresholds are the same in the two firms: $\mu_a^{*^F} = \mu_a^{*^M}$ and $\bar{\mu}_a^F = \bar{\mu}_a^M$

(iv) Any given low performance realization is more likely to be published for a female-headed firm relative to a male-headed firm, whereas a high performance realization is more likely not to be published for a female-headed firm relative to a male-headed firm: $\frac{P^F(S_t=1|q_t)}{P^M(S_t=1|q_t)}$ is decreasing in q_t and $\frac{P^F(S_t=0|q_t)}{P^M(S_t=0|q_t)}$ is increasing in q_t.

The model's assumptions are supported by empirical evidence. I discuss the fitness of Assumption (i) and present corroborating evidence in Section 7.2. Assumption (ii) has been discussed in Section 3.2, where I verify that there is no significant difference in performance between the two types of firms, neither when looking at sales or stock price returns. Assumption (iii) states that the firing and "riskiness" thresholds μ_a^* and $\bar{\mu}_a$ are the same in the two firms. In order to understand whether this assumption is satisfied, I check the history of bad media coverage at the time of CEO departure. This is given by the ratio between the total number of bad news and the total number of news cumulated over CEO's appointment. From the model's point of view, this measure represents a sufficient statistics for all past public signals, and thus allows to "back out" $\hat{\mu}_{a,T}$, where T is the time of appointment termination. The distribution of history of bad media coverage is plotted in Figure 10. The Kolmogorov-Smirnov test is unable to reject the equality of the two distributions (p-value =0.835).[35]

Given these assumptions, the intuition from the homogeneous case carries through the case of heterogeneous firms. When performance is low, shareholders, investors and potential employers are *more likely* to observe the public signal for female-led firms relative to male-led firms. This implies that, for the same firm performance distribution, at any point in time the posterior mean ability of females will be more likely to be below the posterior mean ability of males (see Figure 9). Recall that the model assumes that there exists a threshold $\bar{\mu}_a$ such that

[35] On average, the ratio of bad news over the total is at the time of CEO dismissal is 18% for both male and female CEOs.

the appointment becomes "at risk" if $\hat{\mu}^g_{a,t}$ falls below $\bar{\mu}_a$, and that such threshold is identical in the two types of firms. The model delivers three testable implications:

(0) For all CEOs, their career should be more sensitive to an additional bad news when they become "at risk";

(1) Women are more likely to become "at risk" earlier in their appointments;

(2) Conditional on being at risk, the weight of the public signal is larger for women.

Prediction (0) relies on the existence of the threshold $\bar{\mu}_a$ – namely the threshold such that the marginal effect of an additional bad news on CEO career becomes large. Prediction (1) follows from the fact that, at every point in their tenure and keeping firm performance constant, the value of the public signal is lower for women (see Figure 8). Therefore, since posterior mean ability is a function of all signals, at any given point in time the posterior mean ability of females will be more likely to be below that of males. As a consequence, women's mean posterior ability will be more likely to cross the threshold $\bar{\mu}_a$ earlier in the appointment. Prediction (2) follows from Prediction (1): conditional on being at risk, women are at an earlier stage of their appointment, and therefore the weight of new information is larger for them. This is a consequence of Bayesian learning: as time moves on, the relative sensitivity of the update to the arrival of new information becomes smaller.

6 Empirical Tests

Prediction (1) states that women are more likely to become "at risk" earlier in the appointment. I define a quarter t "risky" if *any* bad news is released at time t.[36] I define an appointment "at high risk" in quarter t if up to time t the CEO experienced more than 50% risky quarters, and "at low risk" otherwise. In Table 12 I show the sample's characteristics by risk, separately for men and women. In line with the first prediction, on average women's appointments become at risk three quarters earlier than males' appointments. Table 12 also shows that, conditional on being at risk, the share of bad news up to time t is higher for women. In Figure B.4 I plot CEO tenure separately for the high- and low-risk sample, and by gender. The corresponding cumulative distribution functions are plotted in Figure B.5. The figures show that shorter tenures are more frequent for women in the high-risk sample, whereas the two distributions look very similar in the low-risk sample.

[36]The median share of bad news in a quarter is 9.5%.

Prediction (2) states that the careers of women should be more sensitive to the release of new (bad) information in the high-risk sample. I replicate the same specification as in Table 11 separately for the two subsamples. Table 13 shows that Prediction (2) finds support in the data. The estimated coefficients on the interaction terms are large and have the expected sign in the high-risk sample, whereas they are much smaller (and often have the opposite sign) in the low-risk sample. In other words, the results in Table 11 – unconditional on past media history – are entirely driven by the high-risk, high-exposure sample.

In line with Prediction (0), for men the effect of new bad information is larger in the high-risk sample. Men in the high-risk sample have a higher chance of crossing the threshold μ_a^*, and therefore an additional bad signal has a large marginal effect on career.[37] [38]

The structure imposed by the learning model provides a way for linking together the results on differential media exposure and the differential effect of media on women's careers. In fact, there are two confounding factors that correlate with each other and cannot be controlled for simultaneously: CEO tenure and past media history. The analysis in Table 11 does not control for past media history, and shows that, conditional on tenure, women's careers are more sensitive to the release of bad information *in any given quarter*. In Table 13 I split the sample into two-sub samples based on past media history: by keeping history constant and letting tenure vary "endogenously", I show that women's careers are more unstable in the high-exposure sample.

The evidence presented in this section intends to corroborate a mechanism rather than estimating the causal effect of media exposure on women's careers. In fact, a crucial issue that I am not addressing is that of sample selection. If the mechanism is relevant, we may expect CEOs with longer tenures – who bared long periods of media exposure – to have higher unobserved ability. Selection issues would be even more relevant for female CEOs, as they are more exposed to bad media coverage. By inspecting the data, selection could represent a concern: women are underrepresented in the high-risk sample (3.58%) relative to the low-risk sample (4.17%).[39] If there is differential attrition between men and women, such that women with higher unobservable ability are more likely to remain in office, the estimated

[37] One should not confuse the sensitivity of the posterior mean update with the sensitivity of CEOs' careers. Whereas the sensitivity of the posterior mean update is likely to decrease as $\mu_{a,t} > \bar{\mu}_a$, the sensitivity of CEOs' careers is largest as $\mu_{a,t} > \bar{\mu}_a$.

[38] Note that, however, men in the high-risk sample have longer tenures than men in the low-risk sample. In additional robustness checks, I focus my attention on tenures below 1 or 2 years in an attempt to keep tenure constant. The results are broadly consistent with the pattern in Table .

[39] The difference is smaller when looking at the sample for which I have non-missing values in the control variables and that are used in the estimation: 3.66% in the low-risk sample versus 3.49% in the high-risk sample.

coefficients would represent a lower bound of the true effect of media exposure on women's careers.

7 Alternative Explanations

In this section, I propose a (non-exhaustive) list of alternative explanations that may account for my results, and check whether they hold in the data. Admittedly, the proposed empirical tests will not be perfect and alternative explanations cannot be ruled out completely. However, I do provide evidence assuring against the concern that alternative explanations fully account for my results.

7.1 Risk Aversion

A first possibility could be that the differential effect of bad media exposure observed for women is the result of women's choices rather than the effect of public reputation. If women executives are more risk averse than men, they may be more likely than men to choose to move to a smaller or private firm, for the same amount of bad news in the preceding quarter. This consideration stems from the fact that women are known to be more risk averse than men (Croson and Gneezy, 2009). However, it should be noted that this statement may not hold for women executives, who are a highly selected group (Blau and Kahn, 2017). Adams and Funk (2012), for example, find that the risk attitudes of women directors in Sweden are not in line with the average in the population, and that female directors are actually more risk loving than male directors.

In order to check whether my results are driven by risk aversion on the side of female CEOs, I analyze whether the arrival of bad news in female-led firms has any "spillover" effects on the appointment of women in high-ranked roles within the same firm.[40] The idea is that, if the result is due to learning rather than the CEO being risk averse, a female-headed firm may be reluctant to promote a woman into a high-ranked role if its (female) CEO is performing poorly in the media. Note that, however, this requires assuming that the company (more precisely, the board of directors) uses the information available in the media to learn about

[40] Another way to test this would be checking whether bad media coverage for a female CEO in a given firm decreases the chances of appointing a woman in other firms, for example in the same sector. However, such "peer effect" is hard to identify empirically due to the "reflection problem" and the fact that firms' decisions in the same industry are highly correlated.

the ability of a group – female executives in general – rather than the CEO only.[41]

In order to test this hypothesis, I regress a binary variable indicating whether a female executive is appointed as the company's Chair, CFO, or COO, on news exposure in the preceding quarter, interacted with a female CEO indicator. The idea is to check whether the likelihood of appointing a female executive decreases in female-headed firms as the fraction of bad news increases – that is, the interaction term should be negative. Table 14 shows that this is indeed the case. Moreover, the result is driven by Chairs, the highest rank by perceived importance in the corporate ladder. Although these findings somewhat assure against the concern that the results are fully explained by female CEOs being more risk averse, it should be noted that it may still be possible that less women apply for a high-ranked position when a female CEO is performing poorly in the news. Unfortunately, as I only observe appointments rather than potential applicants, I am not able to address this concern.

7.2 Uncertainty

Shareholders, investors, and potential employers may have more dispersed beliefs on prior ability of female CEOs. This would explain why women's careers are more sensitive to the release of new information relative to males' careers. In fact, the relative weight of new information depends on the precisions of prior information and the signal. For the same level of signal precision, the weight of new information is larger when prior information is less precise.[42] [43]

In order to understand investors' prior beliefs at the start of a female appointment, I check the evolution of firm-level uncertainty and beliefs around the appointment of a new CEO, comparing male-to-female transitions to male-to-male transitions.[44] In order to gain statistical power, in this section I extend my sample of 3,026 CEOs to include CEOs that are also the company's President. [45]

As a measure of firm-level uncertainty, I use data on the volatility of firm equity options,

[41]The argument goes through even if the company uses public information to learn about the ability of the CEO in office, but is aware that a fraction of other firms and the general public will update about the group, in a spirit similar to Bohren et al. (2019)

[42]As shown by Phelps (1972), this would be a particular case of statistical discrimination.

[43]Figure 5 does not show evidence of higher variance in firm performance for female-led firms. However, given their minority status, ex-ante prior uncertainty on the ability of female CEOs may still be higher.

[44]For male-to-male appointments, a transition is defined as appointing a new individual, and drop change in job titles for the same individual CEO.

[45]This is due to the very small number of matches of expectation and volatility data with my original sample, corresponding to roughly 12% of the sample.

calculated by OptionMetrics.[46] I form two portfolios of firms, corresponding to male-to-male and male-to-female transitions, and check the evolution of average monthly volatility of firm equity options around CEO appointment, separately for the two portfolios. The results are plotted in Figure B.6. In the 6 months before the appointment, the two portfolios closely follow each other. Firm-level uncertainty increases slightly in the month of CEO transition, but only for male-to-male appointments. In Appendix Figure B.7, I "zoom-in" closer and focus on 10-day volatility calculated in each of the 25 days around CEO appointment. CEO appointment increases firm-level uncertainty in both groups of firms, and the two portfolios very closely follow each other.

In order to have a even more direct measure of dispersion in beliefs, I use IBES data on analysts' expectations.[47] I match to firms analysts' monthly forecasts of earnings per share (EPS) at a one-year horizon, and form two portfolios of firms, corresponding to male-to-male and male-to-female transitions. In order to proxy for uncertainty in analysts' beliefs, I focus on two measures. First, I calculate the forecast error, defined as the difference between realized EPS and the average forecast. As a second measure, I use the standard deviation of analysts' forecasts. The results are plotted in Figures B.8 and B.9. Again, I do not detect any significant increase in uncertainty following the appointment of a female CEO. In fact, the average forecast error – overoptimistic before appointment in both portfolios – converges to zero more quickly following the appointment of a female CEO. For male-to-male appointments, the transition is smoother and I do not detect any deviation from the trend around the month of CEO appointment. In general, Figure B.8 suggests that analysts do not revise their forecasts dramatically following the appointment of a new CEO, and that expectations are highly-path dependent, at least in the short term.[48] Similarly, Figure B.9 shows no evidence of higher disagreement among analysts when evaluating female-led firms: the trend is flat both before and after the appointment, with no significant change in the intercept around the time of CEO appointment.

[46] These data are commonly used in the corporate finance and macroeconomics literature to measure firm-level uncertainty. Two prominent examples include Baker, Bloom, and Davis (2016), and Kelly, Pástor, and Veronesi (2016).

[47] Such data are becoming increasingly common in recent work in corporate finance. Examples include Ben-David, Graham, and Harvey (2013), Greenwood and Shleifer (2014), Gennaioli, Ma, and Shleifer (2016), Bouchaud, Krueger, Landier, and Thesmar (2019) and Bordalo, Gennaioli, Porta, and Shleifer (2019).

[48] I find similar results when looking at forecasts of long-term earnings growth. On the persistency of forecast errors, see for example Ma et al. (2020).

7.3 CEO power

As a final test, I check whether female CEOs are less powerful than their male counterparts, or more likely to be appointed following powerful CEOs. In fact, if women are systematically appointed following particularly influential or long-tenured leaders, investors' uncertainty regarding the new leadership may arise, even if not due to gender per se. This hypothesis is similar in spirit with the previous one, and is in line with the so called "glass cliff", according to which women and other minorities are more likely to be appointed in particularly difficult or precarious positions. In Table B.9, I focus on my main estimating sample of CEOs and check the characteristics of the current CEO and his or her predecessor, separately by gender. In the first panel, I compare male and female CEOs across firms and show that, on average, female CEOs are not less powerful than their male counterparts. The only significant difference arises when looking at the share of independent board members, as female-led firms tend to have slightly more independent boards. In the second panel, I check how male and female CEOs compare when considering their predecessors: again, I do not find evidence that women are more likely to be appointed following particularly powerful leaders, at least on average. Taken together, these results suggest that female CEOs are not less powerful than their male counterparts, and that uncertainty regarding female leadership is unlikely to account for the observed patterns.

8 Conclusions

This paper documents that women CEOs are more likely to attract public scrutiny relative to their male counterparts. I show that this phenomenon can account for differences in career trajectories between male and female top executives, thus contributing at explaining the absence of women from top leadership positions.

My work tackles a specific mechanism that can apply to an extraordinarily special group of workers: CEOs. More research is needed in order to understand how to promote the career advancement of women in professional environments and at the top echelons of the earnings distribution, a goal that has been shown to improve efficiency (Hsieh et al., 2019).

As argued by Terviö (2009), public information plays a crucial role in highly-paid professions in which performance on the job is publicly observable. Further research is needed in order to understand more broadly how the media influence the executive labor market – for example, through executive compensation – and how such information affects boards' decisions.

My paper is concerned with studying the consequences of media focus rather than the rea-

sons behind specific editorial decisions. Admittedly, this would be an important question to answer in order to understand the sources of inefficiencies, and better guide policymaking. I defer the answer to such important question to future research.

9 Figures

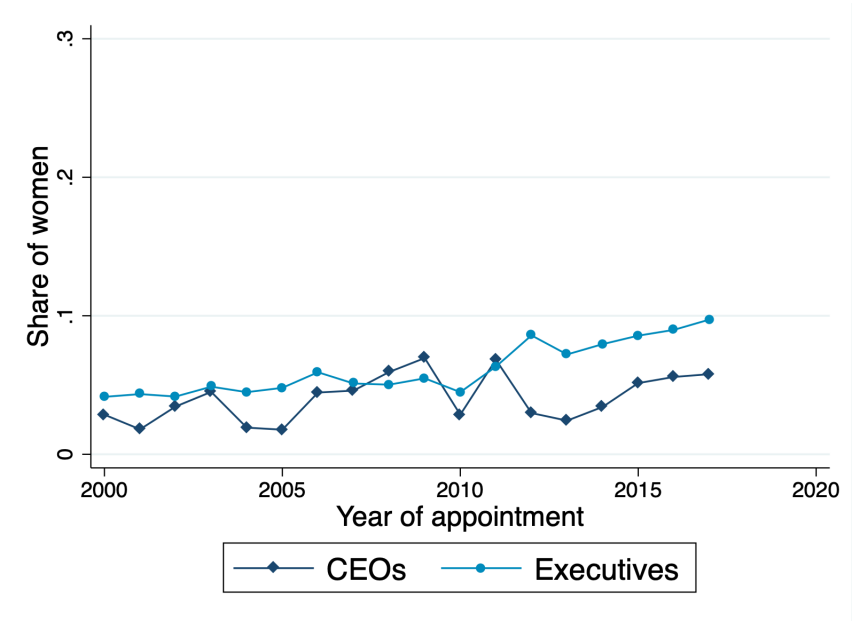


Figure 1: Share of female executives, by year of appointment

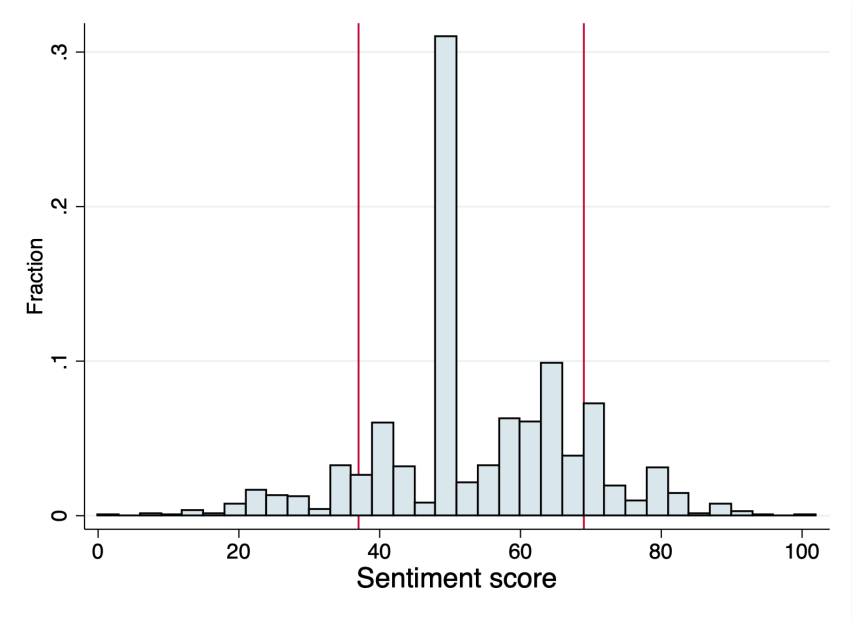
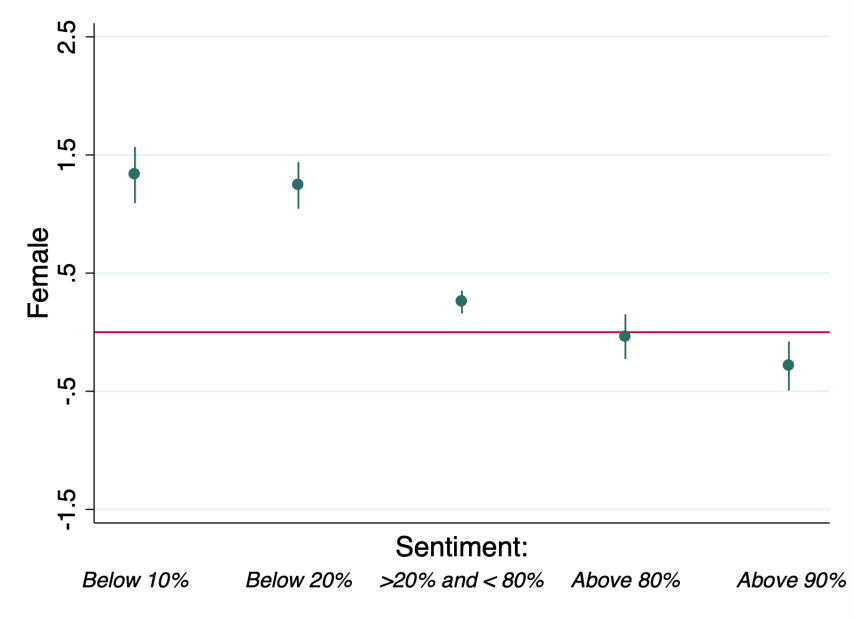
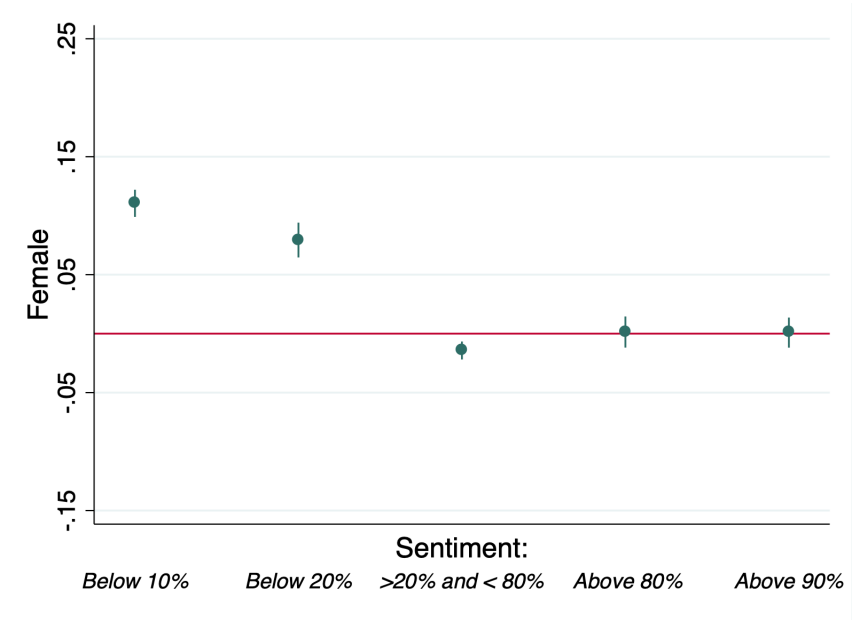


Figure 2: Sentiment score distribution

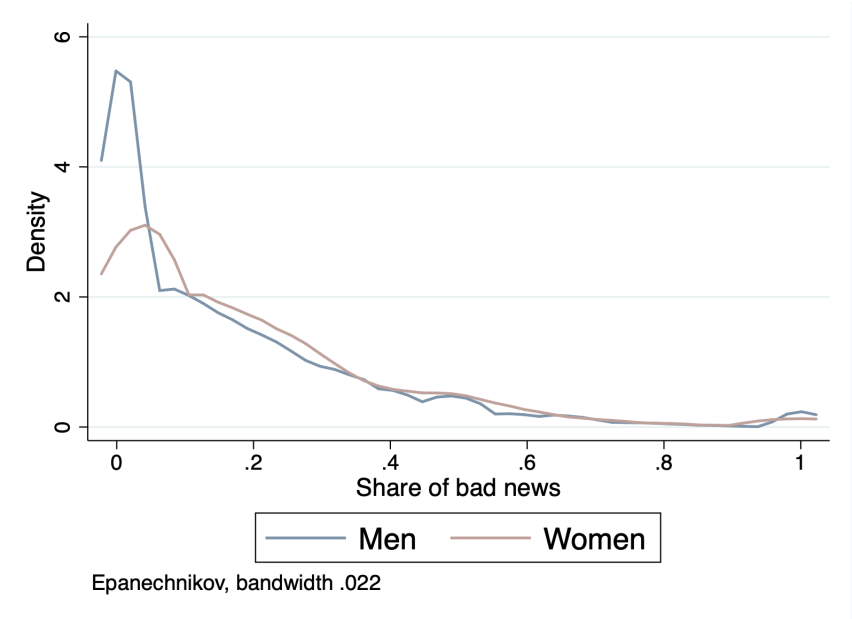


(a) Number of articles

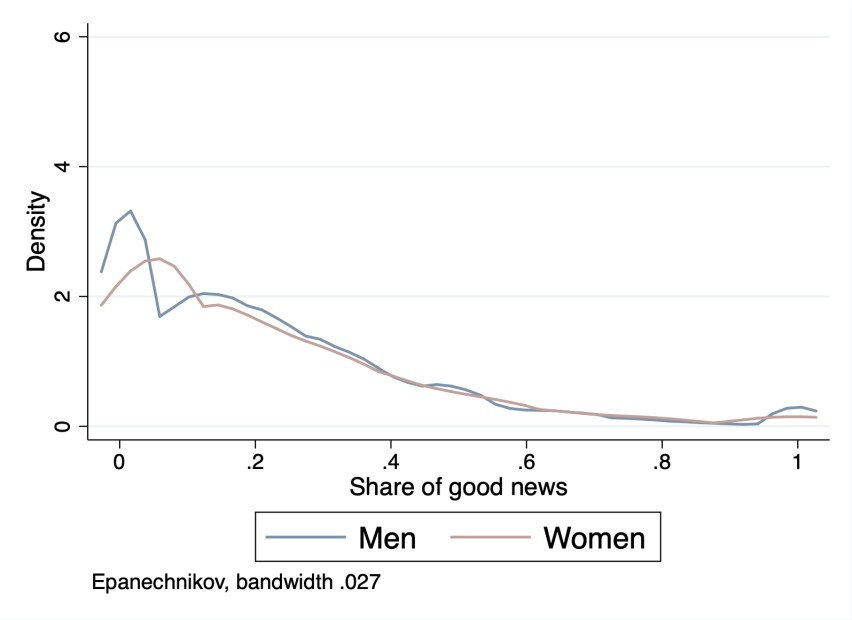


(b) Number of days

Figure 3



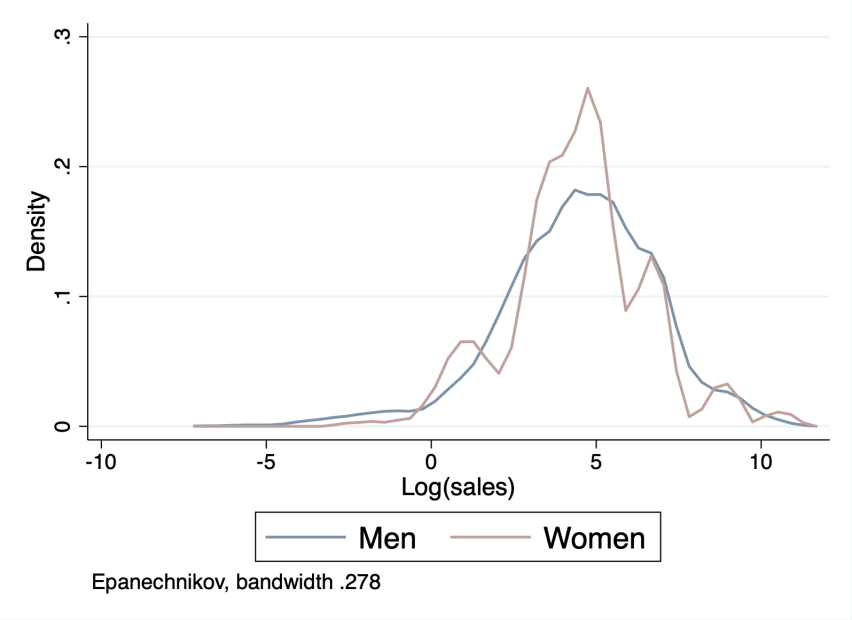
(a) Share of bad news



(b) Share of good news

Figure 4

(a) Monthly stock price returns



(b) Log(sales)

Figure 5

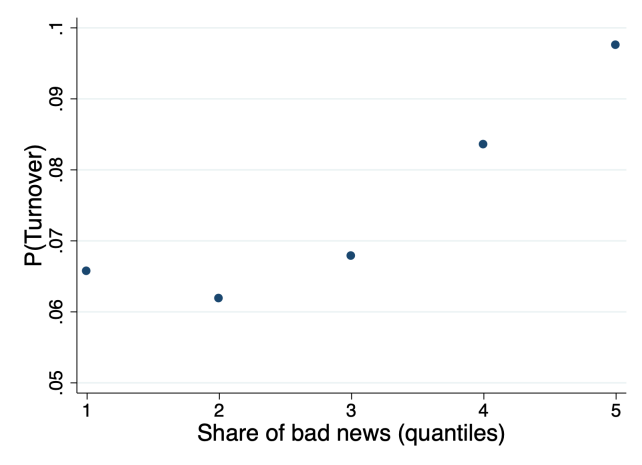


Figure 6: Conditional turnover probability

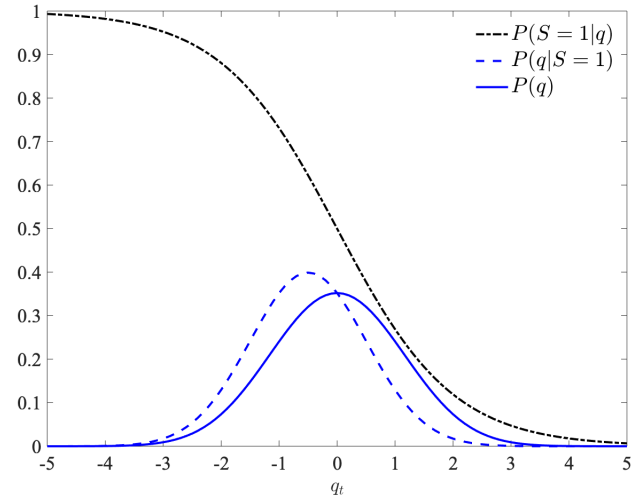


Figure 7: News selection

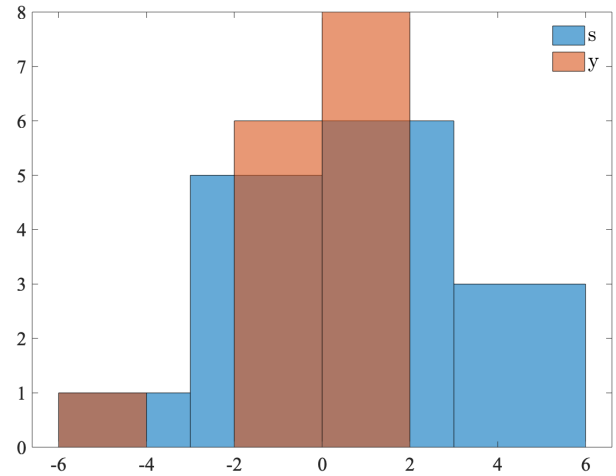


Figure 8: Distribution of realized signals

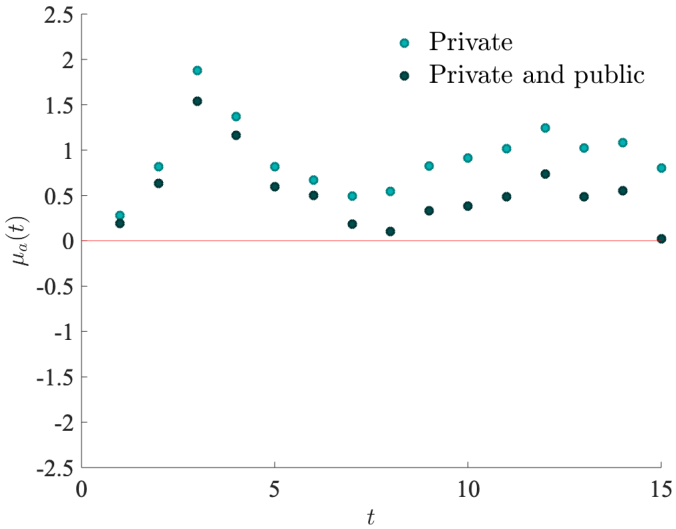


Figure 9

Notes: Posterior mean $\hat{\mu}_a(t)$ over time, in a learning model with and without the public signal provided by the media.

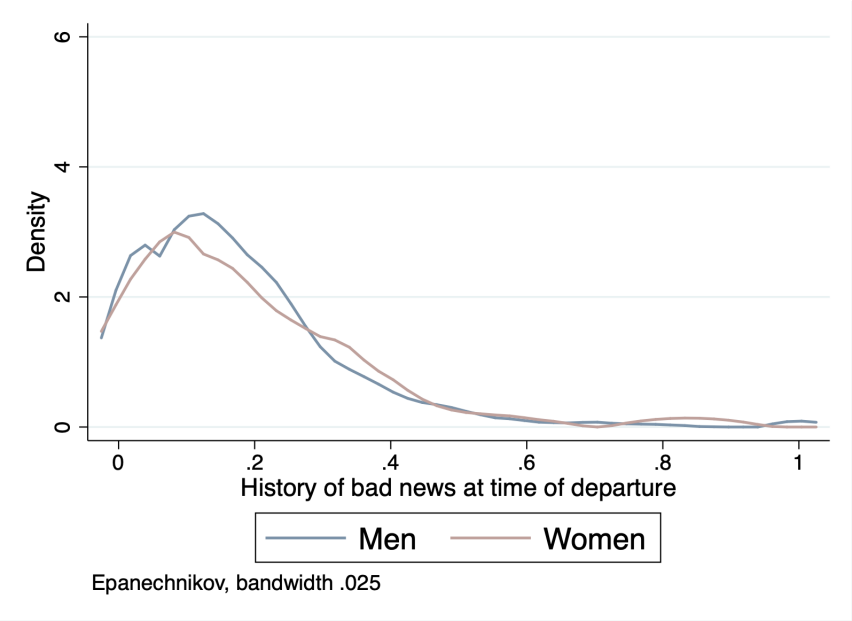


Figure 10

Notes: Proportion of bad news cumulated during CEO appointment over the total number of news at the time of CEO departure.

10 Tables

Table 1: Job titles, by gender

	Women	Men	Total
Chair	134 2.1 %	6,247 97.9 %	6,381 100 %
CEO	131 4.19 %	2,995 95.81 %	3,126 100 %
President	167 6.02 %	2,607 93.98 %	2,774 100 %
COO	239 8 %	2,750 92 %	2,989 100 %
CFO	774 11.46 %	5,981 88.54 %	6,755 100 %
Other Chief Officer	505 17.68 %	2,351 82.32 %	2,856 100 %
Total	2,471 6.17 %	37,576 93.83 %	40,047 100 %

Table 2: CEOs, by gender

	Women		Men		Difference	p-value
	Mean	Standard deviation	Mean	Standard deviation		
Panel A. Individual characteristics						
Age	52.59	7.06	52.60	8.22	-0.01	0.993
Born in the US	0.94	0.24	0.92	0.28	0.02	0.574
Bachelor's degree	0.35	0.48	0.29	0.45	0.07	0.115
Master's/MBA/Prof. degree	0.36	0.48	0.45	0.50	-0.09	0.055
Doctorate degree	0.16	0.36	0.15	0.36	0.00	0.914
Number of qualifications	1.89	1.20	1.92	1.09	-0.03	0.801
Appointment dur. (days)	650.42	730.26	697.77	765.54	-47.35	0.514
Tenure in company (years)	7.32	9.37	6.53	8.29	0.79	0.374
Network size	1,325.24	1,617.72	1,169.26	1,420.68	155.97	0.229
Total number of boards	2.01	1.61	1.93	1.65	0.08	0.662
Panel B. Board characteristics						
Gender ratio	0.76	0.11	0.91	0.10	-0.15	0.000
Number of directors	8.23	2.06	8.46	2.51	-0.24	0.378
Panel C. Firm characteristics						
Assets	5,214.55	20,908.14	8,123.41	73,910.11	-2908.87	0.686
Employees	9.70	29.61	8.37	28.74	1.32	0.644
Sales	3,523.68	16,343.86	2,555.31	9,929.19	968.37	0.343
Gross profits	921.21	3,071.22	842.44	3,397.51	78.77	0.815
Market value	2,889.77	8,973.50	3,698.14	16,623.82	-808.37	0.623
Primary sector	0.03	0.18	0.15	0.35	-0.11	0.000
Consumer sector	0.26	0.44	0.15	0.35	0.12	0.000
Service sector	0.71	0.46	0.71	0.46	0.00	0.946
Number of positions	129		2,897			
Number of firms	105		1,938			

Notes: Source: Panel A and B: BoardEx, 2000-2017, Panel C: Compustat, 2000-2017. Individual and board characteristics are measured in the year of the appointment (except *Appointment duration*), whereas firm characteristics are measured the year before the appointment.

Table 3: News, by sentiment

	Number of stories published	Share of total	Sentiment score: Mean	Sentiment score: SD	Articles per story: Mean	Articles per story: SD	Days per story: Mean	Days per story: SD
Panel A. Bad news (< 10th ptile)								
earnings	29,466	0.30	26.94	7.89	2.02	4.47	1.06	0.26
analyst-ratings	18,577	0.49	31.50	6.37	1.32	1.13	1.03	0.18
order-imbalances	13,757	0.64	32.96	0.51	1.37	0.77	1.12	0.39
legal	12,109	0.76	22.10	1.98	5.09	11.89	1.30	0.70
revenues	4,626	0.81	24.84	6.73	2.81	9.40	1.11	0.38
regulatory	3,582	0.84	22.30	0.71	3.21	5.87	1.22	0.58
price-targets	3,464	0.88	25.87	7.32	1.18	0.71	1.02	0.15
products-services	3,153	0.91	28.87	5.84	4.47	14.86	1.23	0.71
credit-ratings	2,366	0.94	29.52	4.94	2.13	1.79	1.03	0.18
Panel B. Good news (> 90th ptile)								
products-services	82,220	0.20	66.31	5.14	3.95	24.51	1.20	1.25
earnings	54,526	0.32	72.00	8.80	2.20	4.40	1.06	0.25
technical-analysis	46,004	0.43	58.96	1.65	1.09	0.41	1.04	0.24
analyst-ratings	37,148	0.52	71.21	10.85	1.19	0.62	1.02	0.14
stock-prices	34,630	0.60	63.00	0.00	2.45	6.55	1.14	0.43
acquisitions-mergers	28,369	0.67	66.46	7.10	2.26	6.43	1.10	0.35
partnerships	23,371	0.73	61.04	0.19	2.97	5.53	1.12	0.42
equity-actions	20,373	0.78	64.35	6.67	1.98	4.31	1.07	0.29
revenues	18,351	0.82	66.70	11.31	2.15	3.88	1.06	0.30

Table 4: Gender differences in news coverage

	Number of articles (1)	Number of days (2)
Female	0.591***	0.009*
	(0.041)	(0.004)
Network size	-0.000***	-0.000
	(0.000)	(0.000)
Number of qualifications	-0.126	0.003
	(0.146)	(0.019)
Age	-0.365***	-0.029***
	(0.067)	(0.006)
Age sq.	0.003***	0.000***
	(0.001)	(0.000)
Tenure	-0.054***	-0.004*
	(0.017)	(0.002)
Tenure sq.	0.000**	0.000
	(0.000)	(0.000)
Sentiment score	-0.028	-0.001*
	(0.017)	(0.001)
Log(sales)	0.011	-0.005
	(0.091)	(0.011)
Log(assets)	0.187	0.024
	(0.173)	(0.016)
Firm FE	Y	Y
Year FE	Y	Y
Year of appointment FE	Y	Y
N	12,030	12,030
Mean	2.764	1.111

Notes: Observations are news stories released between 2000 and 2017 in the sample of matched news-CEO firms. The sample is restricted to firms in which I observe variation in gender across appointments (53 firms). The dependent variable in column (1) is the total number of articles for a news story. The dependent variable in column (2) is the total number of days over which a news story is reported in the press. The estimating specification is Equation 1 in the text. Standard errors are clustered at the position level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. .

Table 5: Number of bad and good stories

	OLS	Q(0.25)	Q(0.5)	Q(0.75)
		A. Bad stories		
	(1)	(2)	(3)	(4)
Female	0.063	0.021**	0.120***	0.142***
	(0.053)	(0.009)	(0.034)	(0.044)
Tenure	-0.006**	0.000	-0.000	-0.002
	(0.003)	(0.001)	(0.001)	(0.003)
Tenure sq.	0.000	-0.000	-0.000**	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Number of news	0.049***	0.028***	0.053***	0.076***
	(0.004)	(0.001)	(0.001)	(0.003)
Age	-0.013	-0.002*	0.002	0.007
	(0.015)	(0.001)	(0.004)	(0.010)
Age sq.	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Log(sales)	-0.000	-0.006***	-0.012***	-0.008
	(0.007)	(0.001)	(0.004)	(0.005)
Log(assets)	0.016	0.000	0.004	0.018***
	(0.010)	(0.001)	(0.004)	(0.007)
Year FE	Y	Y	Y	Y
N	18133	18133	18133	18133
		B. Good stories		
	(1)	(2)	(3)	(4)
Female	-0.039	-0.010	-0.008	0.049
	(0.067)	(0.023)	(0.038)	(0.053)
Tenure	0.012***	0.013***	0.015***	0.010***
	(0.003)	(0.001)	(0.002)	(0.002)
Tenure sq.	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Number of news	0.063***	0.050***	0.067***	0.098***
	(0.004)	(0.002)	(0.002)	(0.003)
Age	-0.014	0.007	0.011	0.004
	(0.015)	(0.005)	(0.009)	(0.009)
Age sq.	0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Log(sales)	0.077***	0.039***	0.055***	0.066***
	(0.007)	(0.003)	(0.004)	(0.006)
Log(assets)	0.041***	0.024***	0.035***	0.033***
	(0.011)	(0.004)	(0.005)	(0.006)
Year FE	Y	Y	Y	Y
N	18133	18133	18133	18133

Table 6: Share of bad and good news

	OLS	Q(0.25)	Q(0.5)	Q(0.75)
		A. Share of bad news		
	(1)	(2)	(3)	(4)
Female	0.022**	0.000**	0.027***	0.034***
	(0.010)	(0.000)	(0.009)	(0.011)
Tenure	-0.001**	0.000	-0.001*	-0.002***
	(0.000)	(0.000)	(0.000)	(0.001)
Tenure sq.	0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Age	-0.005**	-0.000*	-0.001	-0.005
	(0.003)	(0.000)	(0.002)	(0.003)
Age sq.	0.000**	0.000*	0.000	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Number of news	0.000***	0.000***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Log(sales)	-0.004***	-0.000**	-0.005***	-0.003
	(0.001)	(0.000)	(0.001)	(0.002)
Log(assets)	0.001	0.000	0.001	-0.001
	(0.002)	(0.000)	(0.002)	(0.003)
Year FE	Y	Y	Y	Y
N	17385	17385	17385	17385
		B. Share of good news		
	(1)	(2)	(3)	(4)
Female	0.000	0.001	-0.007	0.006
	(0.011)	(0.003)	(0.006)	(0.010)
Tenure	0.002***	0.002***	0.003***	0.002***
	(0.001)	(0.000)	(0.000)	(0.001)
Tenure sq.	-0.000*	-0.000***	-0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Age	0.002	0.001	0.002	0.005
	(0.002)	(0.001)	(0.002)	(0.004)
Age sq.	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Number of news	-0.001***	0.000	-0.000***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Log(sales)	0.013***	0.009***	0.018***	0.018***
	(0.002)	(0.001)	(0.001)	(0.002)
Log(assets)	0.003	0.006***	0.004**	0.001
	(0.002)	(0.001)	(0.002)	(0.003)
Year FE	Y	Y	Y	Y
N	17385	17385	17385	17385

Table 7: Log(sales)

	OLS	Q(0.25)	Q(0.5)	Q(0.75)
		A. Stock price returns		
	(1)	(2)	(3)	(4)
Female	-0.008	-0.005	-0.001	0.001
	(0.017)	(0.004)	(0.003)	(0.006)
Tenure	-0.000	0.001***	0.000*	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Tenure sq.	-0.000	-0.000***	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Age	0.000	0.001**	0.002***	0.001
	(0.002)	(0.001)	(0.001)	(0.001)
Age sq.	-0.000	-0.000**	-0.000***	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Number of news	0.000	-0.000***	-0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Log(assets)	-0.014***	0.006***	0.002***	-0.003***
	(0.003)	(0.000)	(0.000)	(0.000)
Firm FE	Y	N	N	N
Year FE	Y	Y	Y	Y
N	15742	15742	15742	15742
		B. Log(sales)		
	(1)	(2)	(3)	(4)
Female	-0.020	0.256***	0.309***	0.401***
	(0.053)	(0.088)	(0.055)	(0.056)
Tenure	-0.001	0.004	0.014***	-0.006**
	(0.003)	(0.006)	(0.003)	(0.003)
Tenure sq.	0.000	-0.001***	-0.001***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Age	0.030**	0.006	0.039***	0.001
	(0.015)	(0.016)	(0.010)	(0.011)
Age sq.	-0.000*	0.000	-0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Number of news	-0.000	0.010***	0.006***	0.003***
	(0.000)	(0.001)	(0.001)	(0.001)
Log(assets)	0.754***	0.789***	0.849***	0.882***
	(0.032)	(0.008)	(0.005)	(0.005)
Year FE	Y	Y	Y	Y
Firm FE	Y	N	N	N
N	18133	18133	18133	18133

Table 8: Turnover

	(1) I(Turnover)	(2) I(Turnover)	(3) I(Turnover)	(4) I(Turnover)	(5) Hazard
Share bad news t-1	0.053***	0.055***	0.040**	0.048***	0.484**
	(0.016)	(0.017)	(0.016)	(0.018)	(0.189)
Share bad news t-2	0.020	0.016	0.017	0.014	0.198
	(0.014)	(0.014)	(0.014)	(0.015)	(0.190)
Share good news t-1			-0.032***	-0.016	-0.425**
			(0.012)	(0.014)	(0.195)
Share good news t-2			-0.007	-0.006	-0.076
			(0.012)	(0.014)	(0.179)
Female	0.021*	0.045	0.021	0.044	0.262
	(0.013)	(0.071)	(0.013)	(0.071)	(0.161)
Number of news t-1	-0.000*	-0.000	-0.000*	-0.000	-0.010*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.006)
Number of news t-2	-0.000	-0.000	-0.000	-0.000	-0.003
	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)
Return t-1	-0.025	-0.017	-0.021	-0.016	-0.026
	(0.027)	(0.027)	(0.027)	(0.027)	(0.381)
Return t-2	-0.002	0.011	-0.000	0.012	0.169
	(0.025)	(0.026)	(0.025)	(0.026)	(0.378)
Network size	-0.000	0.000	-0.000	0.000	
	(0.000)	(0.000)	(0.000)	(0.000)	
Tenure	-0.002	0.011***	-0.002	0.011***	
	(0.002)	(0.002)	(0.002)	(0.002)	
Tenure sq.	-0.000	-0.000***	-0.000	-0.000***	
	(0.000)	(0.000)	(0.000)	(0.000)	
Age	-0.001	0.013	-0.001	0.013	0.022***
	(0.003)	(0.010)	(0.003)	(0.010)	(0.004)
Age sq.	0.000	-0.000	0.000	-0.000	
	(0.000)	(0.000)	(0.000)	(0.000)	
Firm_FE	N	Y	N	Y	N
Sector_FE	Y	N	Y	N	Y
Year_FE	Y	Y	Y	Y	N
Year_appointed_FE	Y	Y	Y	Y	Y
N	13204	13204	13204	13204	13204
Mean	0.072	0.072	0.072	0.072	

Table 9: Career moves, by gender

Variable name	Summary statistics			
	Women		Men	
	Mean	N	Mean	N
Moved	0.50	129	0.46	2897
Reappointed	0.39	127	0.34	2868
Private firm	0.22	90	0.17	1987
Private/smaller firm	0.22	90	0.17	1979
Private/smaller/missing	0.43	129	0.42	2897

Table 10: Career moves

	(1)	(2)	(3)	(4)	(5)	(6)
				Characteristics of next job move:		
	Turnover	Moved	Reappointed	Private firm	Private/ smaller firm	Private/ smaller/ missing
Share bad news t-1	0.048***	0.050***	0.002	0.062***	0.062***	0.040***
	(0.018)	(0.014)	(0.008)	(0.014)	(0.014)	(0.012)
Share bad news t-2	0.014	0.014	-0.005	0.002	0.002	0.006
	(0.015)	(0.011)	(0.008)	(0.011)	(0.011)	(0.010)
Share good news t-1	-0.016	-0.012	-0.004	0.004	0.005	-0.010
	(0.014)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)
Share good news t-2	-0.006	-0.006	-0.005	-0.009	-0.009	-0.010
	(0.014)	(0.009)	(0.008)	(0.008)	(0.009)	(0.009)
Female	0.044	0.017	0.031	0.014	0.014	-0.003
	(0.071)	(0.049)	(0.029)	(0.028)	(0.028)	(0.042)
Number of news t-1	-0.000	-0.000	-0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of news t-2	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Return t-1	-0.016	0.028	-0.017	0.053**	0.053**	0.014
	(0.027)	(0.022)	(0.013)	(0.023)	(0.023)	(0.020)
Return t-2	0.012	0.026	-0.002	0.039**	0.039**	0.014
	(0.026)	(0.020)	(0.013)	(0.019)	(0.019)	(0.018)
Network size	0.000	0.000	-0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tenure	0.011***	0.007***	0.002	0.006***	0.006***	0.006***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Tenure sq.	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age	0.013	0.005	0.003	0.006	0.006	0.004
	(0.010)	(0.006)	(0.005)	(0.007)	(0.007)	(0.006)
Age sq.	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm_FE	Y	Y	Y	Y	Y	Y
Year_FE	Y	Y	Y	Y	Y	Y
Year_appointed_FE	Y	Y	Y	Y	Y	Y
N	13204	13204	13005	7742	7734	13204
Mean	0.072	0.032	0.022	0.018	0.018	0.026

Table 11: Career moves, by gender

	(1)	(2)	(3)	(4)	(5)	(6)
				Characteristics of next job move:		
	Turnover	Moved	Reappointed	Private firm	Private/ smaller firm	Private/ smaller/ missing
Share bad news t-1	0.035***	0.035***	0.004	0.043***	0.044***	0.027***
	(0.013)	(0.009)	(0.008)	(0.009)	(0.009)	(0.008)
F × Share bad news t-1	0.005	0.090*	-0.028	0.086**	0.085**	0.082*
	(0.073)	(0.048)	(0.043)	(0.043)	(0.043)	(0.044)
Share good news t-1	-0.020*	-0.015*	-0.004	-0.001	-0.001	-0.015**
	(0.012)	(0.008)	(0.007)	(0.008)	(0.008)	(0.007)
F × Share good news t-1	0.008	0.039	-0.002	0.019	0.020	0.040
	(0.061)	(0.041)	(0.036)	(0.041)	(0.041)	(0.037)
Female	0.005	0.002	-0.001	-0.010	-0.009	-0.008
	(0.044)	(0.029)	(0.026)	(0.027)	(0.027)	(0.027)
Return t-1	-0.008	0.031**	-0.017	0.039***	0.039***	0.019
	(0.022)	(0.015)	(0.013)	(0.014)	(0.014)	(0.013)
Network size	0.000	0.000	-0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tenure	0.011***	0.005***	0.003***	0.003***	0.003***	0.005***
	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Tenure sq.	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age	0.013**	0.004	0.004	-0.002	-0.005	0.003
	(0.006)	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)
Age sq.	-0.000*	-0.000	-0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm_FE	Y	Y	Y	Y	Y	Y
Year_FE	Y	Y	Y	Y	Y	Y
N	15231	15231	14994	9002	8992	15231
Mean_m	0.071	0.029	0.024	0.016	0.016	0.025
Mean_f	0.092	0.043	0.033	0.025	0.025	0.031

Table 12: Sample characteristics, by risk

	High risk		
	Women	Men	p-value diff:
Tenure	8.95	11.868	0.000
Share of “risky" quarters	0.751	0.723	0.000
Share of bad news, from 0 to t	0.245	0.194	0.000
N	262	7,236	
	Low risk		
	Women	Men	p-value diff:
Tenure	8.688	8.519	0.760
Share of “risky" quarters	0.316	0.296	0.053
Share of bad news, from 0 to t	0.12	0.111	0.322
N	295	7,765	

Table 13: Career moves, by risk

	(1)	(2)	(3)	(4)	(5)	(6)
				Characteristics of next job move:		
	Turnover	Moved	Reappointed	Private firm	Private/ smaller firm	Private/ smaller/ missing
			A. High Risk			
Share bad news t-1	0.046**	0.055***	0.007	0.061***	0.061***	0.042***
	(0.019)	(0.013)	(0.010)	(0.014)	(0.014)	(0.012)
F × Share bad news t-1	0.055	0.139**	-0.100**	0.119**	0.119**	0.137**
	(0.094)	(0.066)	(0.051)	(0.061)	(0.061)	(0.060)
Share good news t-1	-0.037*	-0.024*	-0.007	-0.010	-0.010	-0.019*
	(0.020)	(0.014)	(0.011)	(0.015)	(0.015)	(0.013)
F × Share good news t-1	-0.029	-0.002	-0.027	0.025	0.024	0.025
	(0.092)	(0.065)	(0.051)	(0.071)	(0.072)	(0.059)
Female	0.037	-0.005	0.047**	-0.018	-0.019	-0.027
	(0.035)	(0.025)	(0.020)	(0.025)	(0.025)	(0.023)
Individual-level controls	Y	Y	Y	Y	Y	Y
Performance controls	Y	Y	Y	Y	Y	Y
Sector_FE	Y	Y	Y	Y	Y	Y
Year_FE	Y	Y	Y	Y	Y	Y
N	7498	7498	7335	4221	4209	7498
Mean_m	0.071	0.033	0.019	0.021	0.021	0.028
Mean_f	0.107	0.057	0.039	0.034	0.034	0.038
			B. Low Risk			
Share bad news t-1	0.038**	0.038***	0.002	0.030***	0.031***	0.029***
	(0.017)	(0.010)	(0.011)	(0.009)	(0.009)	(0.010)
F × Share bad news t-1	-0.031	-0.063	0.066	0.001	-0.000	-0.042
	(0.087)	(0.054)	(0.055)	(0.046)	(0.046)	(0.050)
Share good news t-1	-0.035***	-0.025***	-0.002	-0.007	-0.007	-0.025***
	(0.013)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)
F × Share good news t-1	0.050	-0.009	0.035	0.029	0.029	-0.001
	(0.069)	(0.042)	(0.044)	(0.040)	(0.040)	(0.040)
Female	-0.001	0.014	-0.017	-0.006	-0.006	0.005
	(0.029)	(0.018)	(0.018)	(0.017)	(0.017)	(0.016)
Individual-level controls	Y	Y	Y	Y	Y	Y
Performance controls	Y	Y	Y	Y	Y	Y
Sector_FE	Y	Y	Y	Y	Y	Y
Year_FE	Y	Y	Y	Y	Y	Y
N	8060	8060	7986	4949	4944	8060
Mean_m	0.071	0.025	0.027	0.012	0.012	0.022
Mean_f	0.078	0.031	0.027	0.014	0.014	0.024

Table 14: "Spillover" to the appointment of other executives

	(1) Female Chair/CFO/COO	(2) Female Chair	(3) Female CFO	(4) Female COO
Share bad news t-1	-0.001	0.001	-0.000	0.002
	(0.004)	(0.002)	(0.003)	(0.002)
F × Share bad news t-1	-0.065***	-0.016*	-0.021	0.003
	(0.022)	(0.008)	(0.016)	(0.013)
Share good news t-1	-0.002	0.001	-0.001	0.002
	(0.004)	(0.001)	(0.003)	(0.002)
F × Share good news t-1	-0.051***	0.000	-0.024*	-0.017*
	(0.019)	(0.007)	(0.014)	(0.011)
Female	0.011	0.004	0.031***	-0.022***
	(0.013)	(0.005)	(0.010)	(0.008)
Return t-1	-0.017**	0.003	-0.013**	0.000
	(0.007)	(0.002)	(0.005)	(0.004)
Network size	0.000	0.000	0.000	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Tenure	0.000	0.000**	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Tenure sq.	-0.000	-0.000*	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Age	0.001	-0.000	0.000	0.002*
	(0.002)	(0.001)	(0.001)	(0.001)
Age sq.	-0.000	0.000	-0.000	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.002	0.001	-0.004	-0.042
	(0.050)	(0.019)	(0.037)	(0.030)
Firm_FE	Y	Y	Y	Y
Year_FE	Y	Y	Y	Y
N	15231	15231	15231	15231
Mean_m	0.004	0.000	0.003	0.002
Mean_f	0.041	0.014	0.004	0.004

References

Renee Adams and Patricia Funk. Beyond the glass ceiling: Does gender matter? *Management Science*, 58(2):219–235, 2012. URL https://EconPapers.repec.org/RePEc:inm:ormnsc:v:58:y:2012:i:2:p:219-235.

Stefania Albanesi, Claudia Olivetti, and Maria José Prados. Gender and Dynamic Agency: Theory and Evidence on the Compensation of Top Executives. In Solomon W. Polachek, Konstantinos Tatsiramos, and Klaus F. Zimmermann, editors, *Gender in the Labor Market*, volume 42 of *Research in Labor Economics*, pages 1–59. Emerald Publishing Ltd, January-M 2015. URL https://ideas.repec.org/h/eme/rleczz/s0147-912120150000042001.html.

Ghazala Azmat, Vicente Cuñat, and Emeric Henry. Gender promotion gaps: Career aspirations and workplace discrimination. 2020.

Scott R Baker, Nicholas Bloom, and Steven J Davis. Measuring economic policy uncertainty. *The quarterly journal of economics*, 131(4):1593–1636, 2016.

Itzhak Ben-David, John R Graham, and Campbell R Harvey. Managerial miscalibration. *The Quarterly Journal of Economics*, 128(4):1547–1584, 2013.

Peter Bergman, Danielle Li, and Lindsey Raymond. Hiring as exploration. *Available at SSRN 3630630*, 2020.

Marianne Bertrand. New Perspectives on Gender. In O. Ashenfelter and D. Card, editors, *Handbook of Labor Economics*, volume 4 of *Handbook of Labor Economics*, chapter 17, pages 1543–1590. Elsevier, 2011.

Marianne Bertrand. The glass ceiling. Working Paper No. 2018-38, University of Chicago, June 2018.

Marianne Bertrand and Kevin F. Hallock. The gender gap in top corporate jobs. *ILR Review*, 55(1):3–21, 2001. doi: 10.1177/001979390105500101. URL https://doi.org/10.1177/001979390105500101.

Timothy Besley and Andrea Prat. Handcuffs for the grabbing hand? media capture and government accountability. *American economic review*, 96(3):720–736, 2006.

Francine D. Blau and Lawrence M. Kahn. The gender wage gap: Extent, trends, and explanations. *Journal of Economic Literature*, 55(3):789–865, September 2017. doi: 10.1257/jel.20160995. URL https://www.aeaweb.org/articles?id=10.1257/jel.20160995.

Francine D Blau, Janet M Currie, Rachel TA Croson, and Donna K Ginther. Can mentoring help female assistant professors? interim results from a randomized trial. *American Economic Review*, 100(2): 348–52, 2010.

J Aislinn Bohren, Alex Imas, and Michael Rosenberg. The dynamics of discrimination: Theory and evidence. *American economic review*, 109(10):3395–3436, 2019.

Pedro Bordalo, Nicola Gennaioli, Rafael La Porta, and Andrei Shleifer. Diagnostic expectations and stock returns. *The Journal of Finance*, 74(6):2839–2874, 2019.

Jean-Philippe Bouchaud, Philipp Krueger, Augustin Landier, and David Thesmar. Sticky expectations and the profitability anomaly. *The Journal of Finance*, 74(2):639–674, 2019.

Ryan Chahrour, Kristoffer Nimark, and Stefan Pitschner. Sectoral Media Focus and Aggregate Fluctuations. Boston College Working Papers in Economics 987, Boston College Department of Economics, October 2019. URL https://ideas.repec.org/p/boc/bocoec/987.html.

Rachel Croson and Uri Gneezy. Gender differences in preferences. *Journal of Economic Literature*, 47 (2):448–74, June 2009. doi: 10.1257/jel.47.2.448. URL https://www.aeaweb.org/articles?id=10.1257/jel.47.2.448.

Stefano Gagliarducci and M. Daniele Paserman. Gender Interactions within Hierarchies: Evidence from the Political Arena. *Review of Economic Studies*, 79(3):1021–1052, 2012. URL https://ideas.repec.org/a/oup/restud/v79y2012i3p1021-1052.html.

Kevin Gaughan and Edward Bishop Smith. Better in the shadows? media coverage and market reactions to female ceo appointments. In *Academy of Management Proceedings*, volume 2016, page 13997. Academy of Management Briarcliff Manor, NY 10510, 2016.

George-Levi Gayle, Limor Golan, and Robert A. Miller. Gender differences in executive compensation and job mobility. *Journal of Labor Economics*, 30(4):829–872, 2012. doi: 10.1086/666615. URL https://doi.org/10.1086/666615.

Nicola Gennaioli, Yueran Ma, and Andrei Shleifer. Expectations and investment. *NBER Macroeconomics Annual*, 30(1):379–431, 2016.

Matthew Gentzkow and Jesse M Shapiro. Media bias and reputation. *Journal of political Economy*, 114(2):280–316, 2006.

Claudia Goldin. A grand gender convergence: Its last chapter. *American Economic Review*, 104(4): 1091–119, 2014.

Robin Greenwood and Andrei Shleifer. Expectations of returns and expected returns. *The Review of Financial Studies*, 27(3):714–746, 2014.

Vishal K Gupta, Sandra C Mortal, Sabatino Silveri, Minxing Sun, and Daniel B Turban. You're fired! gender disparities in CEO dismissal. *Journal of Management*, 46(4):560–582, 2020.

James T Hamilton and Richard Zeckhauser. Media coverage of ceos: who? what? where? when? why? *Unpublished working paper, Stanford Institute of International Studies*, 2004.

Tony Harcup and Deirdre O'Neill. What is news? *Journalism Studies*, 18(12):1470–1488, 2017. doi: 10.1080/1461670X.2016.1150193. URL https://doi.org/10.1080/1461670X.2016.1150193.

David E. Harrington. Economic news on television: The determinants of coverage. *The Public Opinion Quarterly*, 53(1):17–40, 1989. ISSN 0033362X, 15375331. URL http://www.jstor.org/stable/2749237.

Chang-Tai Hsieh, Erik Hurst, Charles I Jones, and Peter J Klenow. The allocation of talent and us economic growth. *Econometrica*, 87(5):1439–1474, 2019.

Dirk Jenter and Fadi Kanaan. Ceo turnover and relative performance evaluation. *the Journal of Finance*, 70(5):2155–2184, 2015.

Dirk Jenter and Katharina Lewellen. Performance-induced ceo turnover. *Available at SSRN 1570635*, 2019.

Bryan Kelly, L'uboš Pástor, and Pietro Veronesi. The price of political uncertainty: Theory and evidence from the option market. *The Journal of Finance*, 71(5):2417–2480, 2016.

Adriana D Kugler, Catherine H Tinsley, and Olga Ukhaneva. Choice of majors: Are women really different from men? Technical report, National Bureau of Economic Research, 2017.

Peggy M Lee and Erika Hayes James. She'-e-os: gender effects and investor reactions to the announcements of top executive appointments. *Strategic Management Journal*, 28(3):227–241, 2007.

Yueran Ma, Tiziano Ropele, David Sraer, and David Thesmar. A quantitative analysis of distortions in managerial forecasts. Technical report, National Bureau of Economic Research, 2020.

Kristoffer P. Nimark. Man-bites-dog business cycles. *American Economic Review*, 104(8):2320–67, August 2014. doi: 10.1257/aer.104.8.2320. URL https://www.aeaweb.org/articles?id=10.1257/aer.104.8.2320.

Kristoffer P. Nimark and Stefan Pitschner. News media and delegated information choice. *Journal of Economic Theory*, 181(C):160–196, 2019. doi: 10.1016/j.jet.2019.02.001.

Amanda Pallais. Inefficient hiring in entry-level labor markets. *American Economic Review*, 104(11): 3565–99, 2014.

Robert Parrino. Ceo turnover and outside succession a cross-sectional analysis. *Journal of financial Economics*, 46(2):165–197, 1997.

Arpita Patnaik, Matthew J Wiswall, and Basit Zafar. College majors. Working Paper 27645, National Bureau of Economic Research, August 2020. URL http://www.nber.org/papers/w27645.

Maria Petrova. Inequality and media capture. *Journal of public Economics*, 92(1-2):183–212, 2008.

Edmund Phelps. The statistical theory of racism and sexism. *American Economic Review*, 62(4):659–61, 1972. URL https://EconPapers.repec.org/RePEc:aea:aecrev:v:62:y:1972:i:4:p:659-61.

Heather Sarsons. Interpreting signals in the labor market: evidence from medical referrals. *Job Market Paper*, 2017.

Pamela J. Shoemaker and Timothy Vos. *Gatekeeping Theory*. Routledge, 2009.

Stuart N. Soroka. The gatekeeping function: Distributions of information in media and the real world. *The Journal of Politics*, 74(2):514–528, 2012. ISSN 00223816, 14682508. URL http://www.jstor.org/stable/10.1017/s002238161100171x.

Marko Terviö. Superstars and mediocrities: Market failure in the discovery of talent. *The Review of Economic Studies*, 76(2):829–850, 2009. ISSN 00346527, 1467937X. URL http://www.jstor.org/stable/40247622.

Marc Trussler and Stuart Soroka. Consumer demand for cynical and negative news frames. *The International Journal of Press/Politics*, 19(3):360–379, 2014.

A Appendix

A.1 Proofs

Proof of Proposition 1

Proof. Rewrite $P(S=1|q)$ and $P(S=0|q)$ using Bayes' rule:

$$P(S=1|q) = \frac{P(q|S=1)\cdot P(S=1)}{P(q)}$$

$$P(S=0|q) = \frac{P(q|S=1)\cdot P(S=0)}{P(q)}$$

Therefore:

$$\frac{P(S=1|q)}{P(S=0|q)} = \frac{P(q|S=1)}{P(q|S=0)} \cdot \frac{P(S=1)}{P(S=0)}$$

For fixed $\frac{P(S=1)}{P(S=0)}$, this implies that $\frac{P(q|S=1)}{P(q|S=0)}$ is decreasing in q, and therefore $\frac{P(q|S=0)}{P(q|S=1)}$ is increasing in q.

Denote $f_0(q)$ and $f_1(q)$ the density functions of $P(q|S=0)$ and $P(q|S=1)$. We have:

$$\frac{f_0(q_i)}{f_1(q_i)} \geq \frac{f_0(q_j)}{f_1(q_j)} \ \forall q_i \geq q_j$$

or equivalently:

$$f_0(q_i)f_1(q_j) \geq f_0(q_j)f_1(q_i) \ \forall q_i \geq q_j \tag{5}$$

Integrate both sides of the last expression from the minimum in the range of q to q_j, with respect to q_j:

$$\int_{\min q \in Q}^{q_j} f_0(q_i)\cdot f_1(q_j)dq_j \geq \int_{\min q \in Q}^{q_j} f_0(q_j)\cdot f_1(q_i)dq_j$$

which simplifies to:

$$\frac{f_0(q)}{f_1(q)} \geq \frac{F_0(q)}{F_1(q)} \tag{6}$$

Integrate both sides of equation 5 from q_i to the maximum in the range of q, with respect to q_i:

$$\int_{q_i}^{\max q \in Q} f_0(q_i)\cdot f_1(q_j)dq_j \geq \int_{q_i}^{\max q \in Q} f_0(q_j)\cdot f_1(q_i)dq_j$$

which simplifies to:

$$\frac{1-F_0(q)}{1-F_1(q)} \geq \frac{f_0(q)}{f_1(q)} \tag{7}$$

Combine inequalities 6 and 7 and rearrange terms to obtain:

$$F_0(q) \leq F_1(q)$$

□

Proof of Proposition 2

Proof. From Proposition (1), $P(q_t \leq q|S_t = 0) \leq P(q_t \leq q|S_t = 1)$, which implies that $E(q_t|S_t = 0) \geq E(q_t|S_t = 1)$. Therefore, since $E(q_t) = 0$:

$$E(q_t) = E(q_t|S_t = 0) \cdot P(S_t = 0) + E(q_t|S_t = 1) \cdot P(S_t = 1) = 0$$

Since $E(q_t|S_t = 0) \geq E(q_t|S_t = 1)$, it must be $E(q_t|S_t = 1) \leq 0$, which in turn implies that $E(q_t|S_t = 1) \leq E(q_t)$.

□

Proof of Proposition 3

Proof. Suppose that $t = 1$ (the proof is identical for $t > 1$).
If $S_1 = 1$:

$$E(q_1|S_1 = 0, s_1, y_1) = \frac{\tau_{\tilde{\eta}} s_1 + \tau_\eta y_1}{\tau_q + \tau_{\tilde{\eta}} + \tau_\eta}$$

If $S_1 = 0$:

$$E(q_1|S_1 = 0, s_1) = \frac{\tau_{\tilde{\eta}} s_1}{\tau_q + \tau_{\tilde{\eta}}}$$

Take the expectation of these expressions, conditional on q_1:

$$E\left(E(q_1|S_1 = 0, s_1, y_1)|q_1\right) = \frac{\tau_{\tilde{\eta}} + \tau_\eta}{\tau_q + \tau_{\tilde{\eta}} + \tau_\eta} \cdot q_1 \tag{8}$$

$$E\left(E(q_1|S_1 = 0, s_1)|q_1\right) = \frac{\tau_{\tilde{\eta}}}{\tau_q + \tau_{\tilde{\eta}}} \cdot q_1 \tag{9}$$

Since τ_q, τ_η, and $\tau_{\tilde{\eta}}$ are all positive, expression 8 is always greater than expression 9. □

A.2 Parametrization

The distributional assumptions of the learning model and the structure imposed by the news selection function give enough conditions to set the parameters of the distributions and produce simulations. Definition 1 states that the publication rule is such that $\frac{P(S=1|q)}{P(S=0|q)}$ is decreasing in q.
Using Bayes' rule:

$$P(S = 1|q) = \frac{P(q|S = 1) \cdot P(S = 1)}{P(q)}$$

$$P(S = 0|q) = \frac{P(q|S = 1) \cdot P(S = 0)}{P(q)}$$

which imply that the odds ratio can be rewritten as:

$$\frac{P(S=1|q)}{P(S=0|q)} = \frac{P(q|S=1)}{P(q|S=0)} \cdot \frac{P(S=1)}{P(S=0)} = \frac{P(q|S=1)}{P(q|S=0)} \cdot \frac{\omega}{(1-\omega)}$$

The unconditional probability $P(q)$ is a mixture of two distributions:

$$P(q) = P(S=1) \cdot P(q|S=1) + P(S=0) \cdot P(q|S=0) = \omega \cdot P(q|S=1) + (1-\omega) \cdot P(q|S=0)$$

Under the assumption that $P(q|S=1)$ and $P(q|S=0)$ are normal distributions, then $P(q)$ is also a normal distribution. Assume that:

$$P(q|S=0) \sim N(\mu_0, \sigma_0^2)$$

$$P(q|S=1) \sim N(\mu_1, \sigma_1^2)$$

Set $\sigma_0^2 = \gamma\sigma_1^2$. Then we have:

$$\frac{P(S=1|q)}{P(S=0|q)} = \sqrt{\gamma} e^{\frac{1}{2\sigma_1}\left[\left(\frac{q-\mu_0}{\sqrt{\gamma}}\right)^2 - (q-\mu_1)^2\right]}$$

The right hand side is decreasing in q if the exponent is decreasing in q. Therefore, the following condition must be met:

$$q\left(\frac{1}{\sqrt{\gamma}} - 1\right) < \mu_0 - \mu_1$$

Setting $\gamma = 1$, the condition is met for every q if $\mu_0 - \mu_1 > 0$. Since we have imposed that $E(q) = 0$, then $\mu_0 > 0$ and $\mu_1 < 0$ (see Proposition 2).[49] Note, moreover, that we must choose values ω, $\mu_0 > 0$, and $\mu_1 < 0$ such that:

$$E(q) = \mu_1 \cdot \omega + \mu_0 \cdot (1-\omega) = 0$$

[49] Some values of μ_0, μ_1 and σ_1 may introduce kurtosis in $P(q)$. In order to avoid bimodality in $P(q)$ one must set $\mu_0 - \mu_1 < 2\sigma_1$.

B Figures

DOWJONES | Newswires

UPDATE:Societe Generale Up On Talk of Citigroup Interest

304 words
10 March 2006
10:59 AM
Dow Jones News Service
DJ
English
(c) 2006 Dow Jones & Company, Inc.

By Steve Goldstein

LONDON (Dow Jones)--Shares of the French bank Societe Generale advanced on Friday on a report speculating that Citigroup may have contacted the country's government about making a bid.

The French magazine Le Nouvel Observateur reported that a large U.S. bank has contacted the French government about the possibility of making an offer for a bank in that country. The magazine believes it to be Citigroup (C) .

The report speculated that Societe Generale would be first in line for a Citigroup bid.

Societe Generale rose 3.9% in Paris in a moderately advancing stock market.

BNP Paribas, another French bank, added 0.8%.

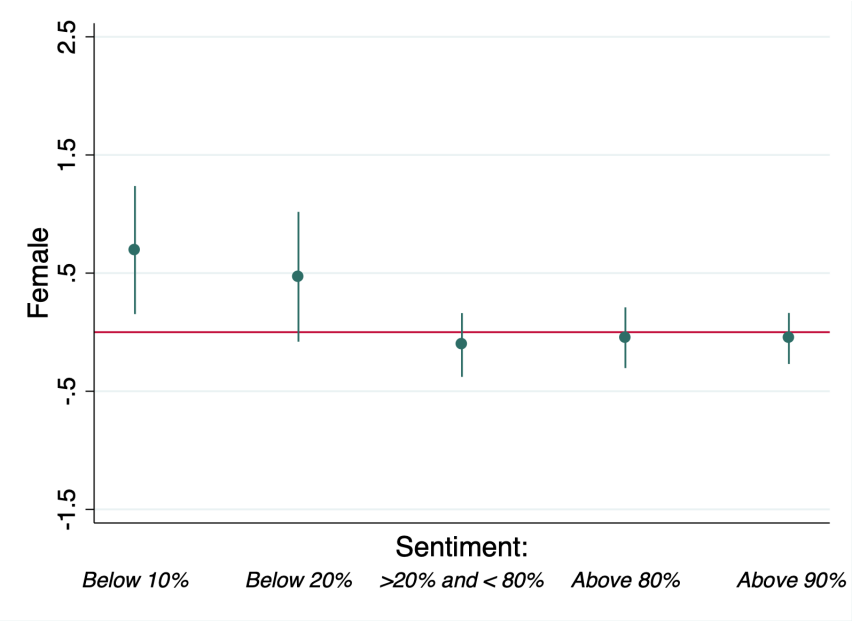
Hugues Doumenc, an analyst at French brokerage Fideuram Wargny, said rumors of Citigroup interest frequently appear, and he doubts that it will launch a bid for the French bank.

(a) Factiva

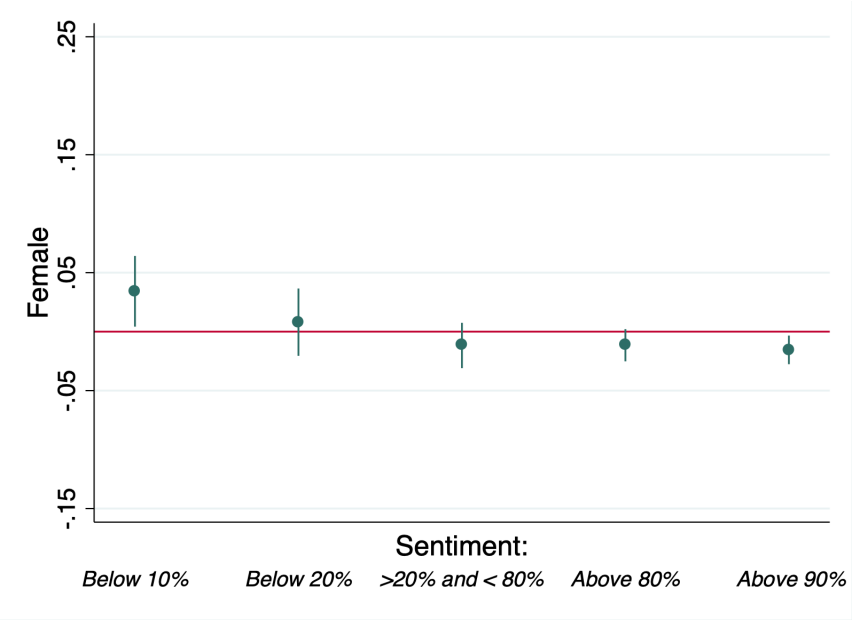
Entity id	Relevance	Source	Date	Time	Story category	Story group	Sentiment
CITI	100	DJNS	10mar2006	10:59 AM	public-offering	equity-actions	43
SG	100	DJNS	10mar2006	10:59 AM	stock-prices	stock-gain	63

(b) RavenPack

Figure B.1: Factiva and RavenPack



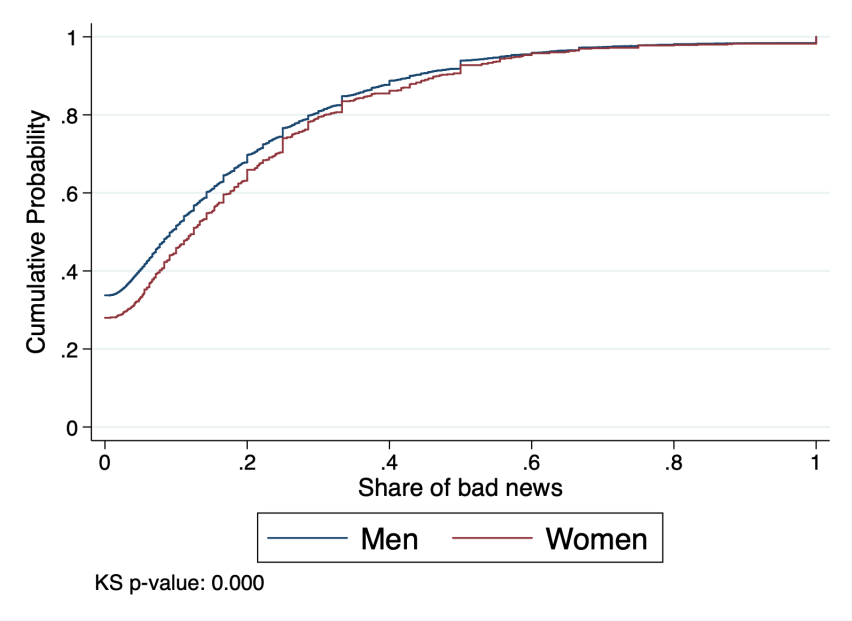
(a) Number of articles



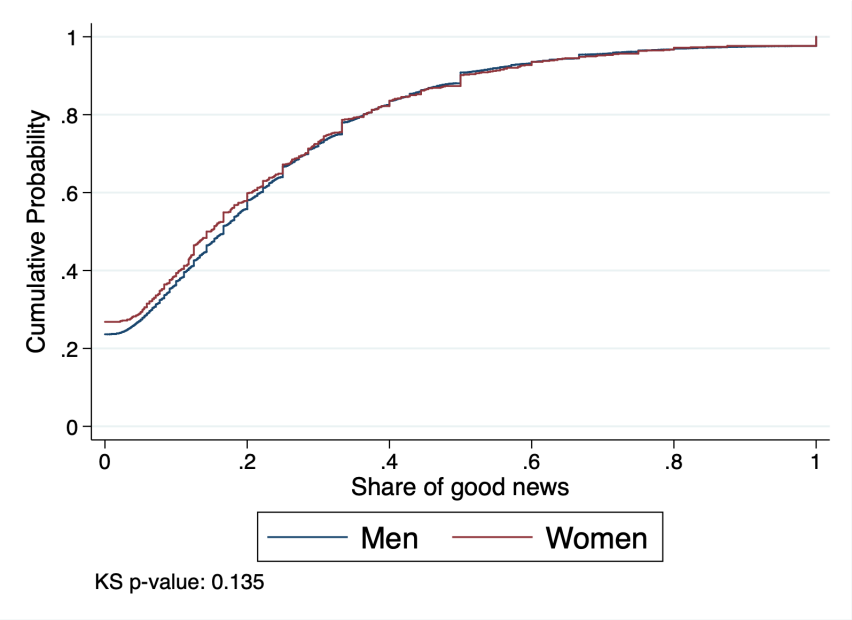
(b) Number of days

Figure B.2: Gender difference in news coverage, full sample of firms

Notes: Figure A plots the estimated coefficient on the female indicator in Table B.2; Figure B plots the estimated coefficient on the female indicator in Table B.3. The estimating specification is equation 1 in the text.



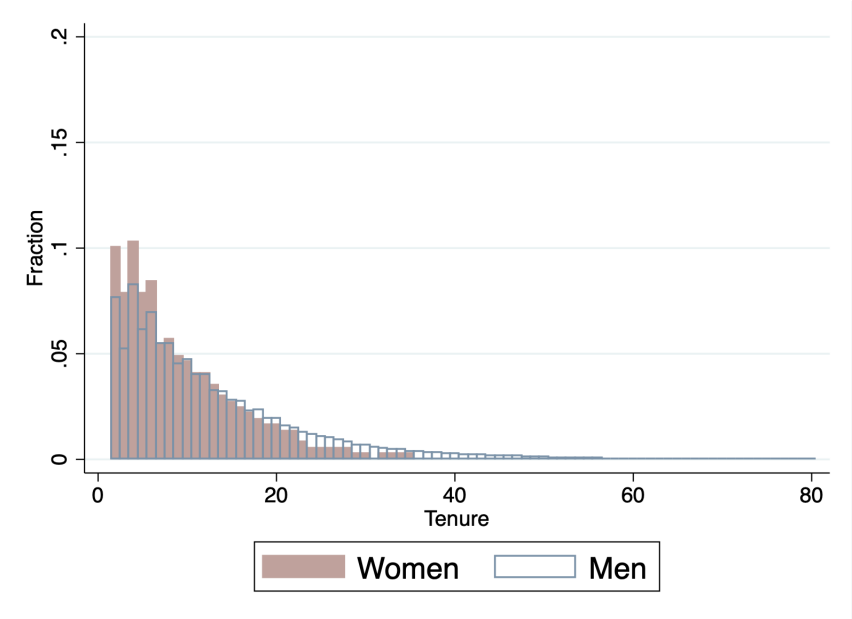
(a) Share of bad news



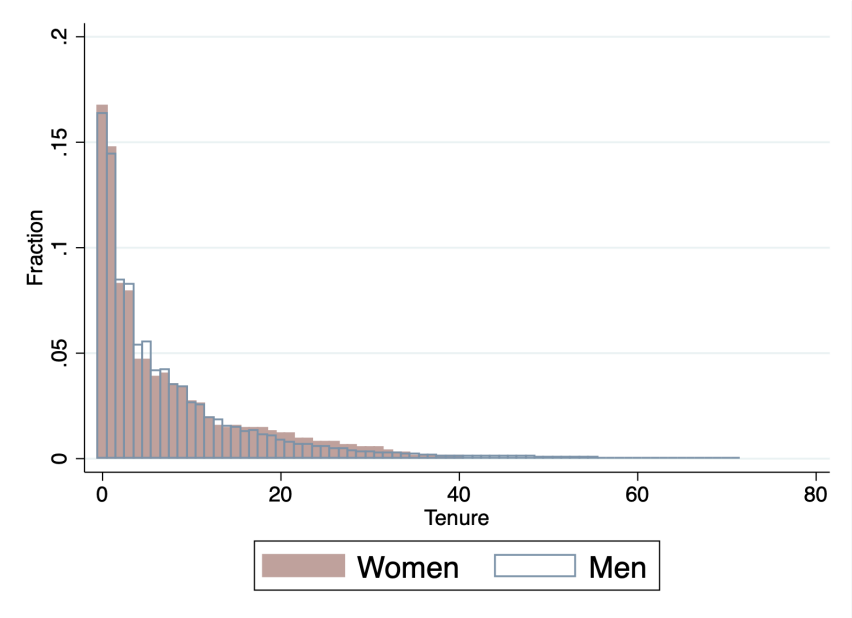
(b) Share of good news

Figure B.3: CDFs of the share of bad/good news, by gender

Notes: Cumulative distribution functions (CDFs) for the distributions in Figure 4. The reported p-values are from the Kolmogorov-Smirnov test for the equality of the distributions.



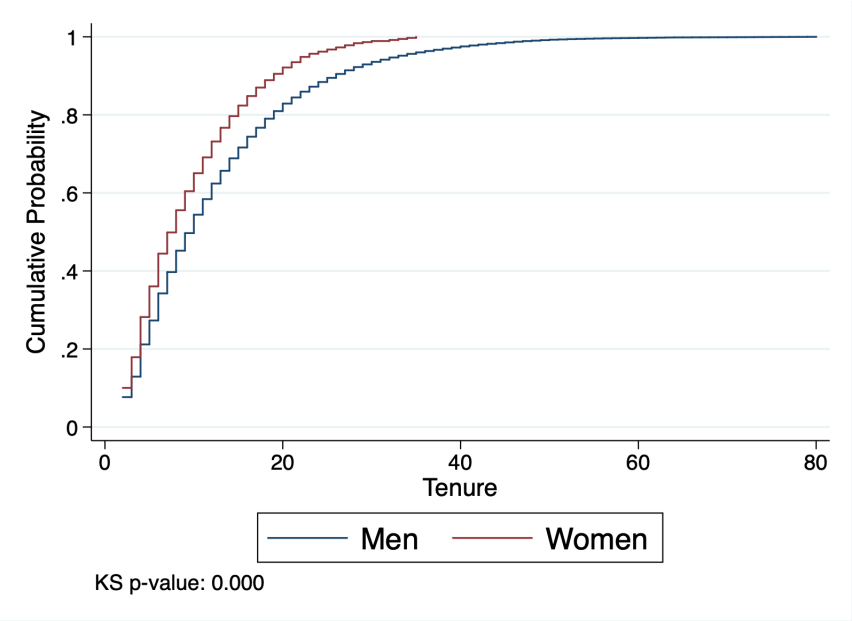
(a) High-risk sample



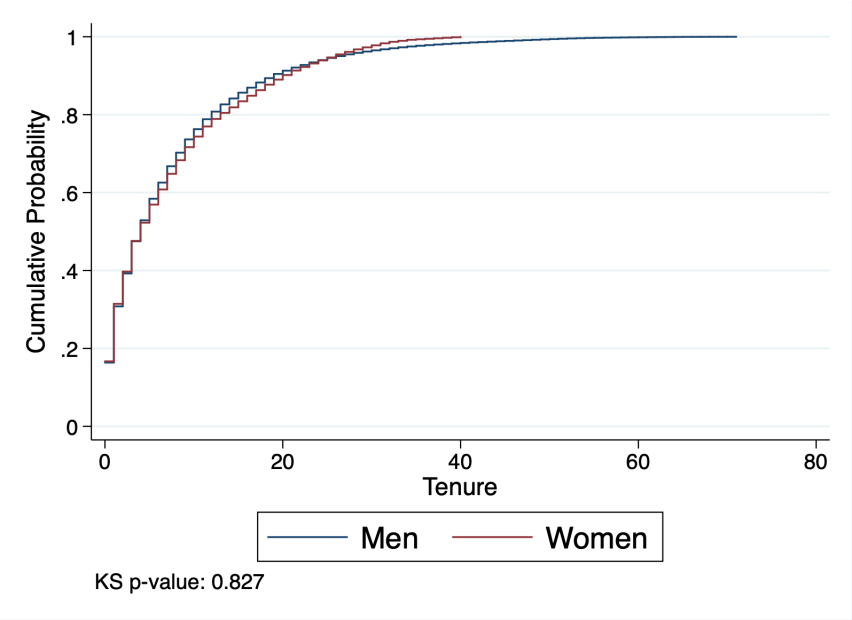
(b) Low-risk sample

Figure B.4: Distribution of tenure (quarters), by gender

Notes: Distribution of tenure (in quarters), separately by risk and gender.



(a) High-risk sample



(b) Low-risk sample

Figure B.5: CDFs of tenure (quarters), by gender

Notes: Cumulative distribution functions (CDFs) of the distributions in Figure B.4. The reported p-values are from the Kolmogorov-Smirnov test for the equality of the distributions.

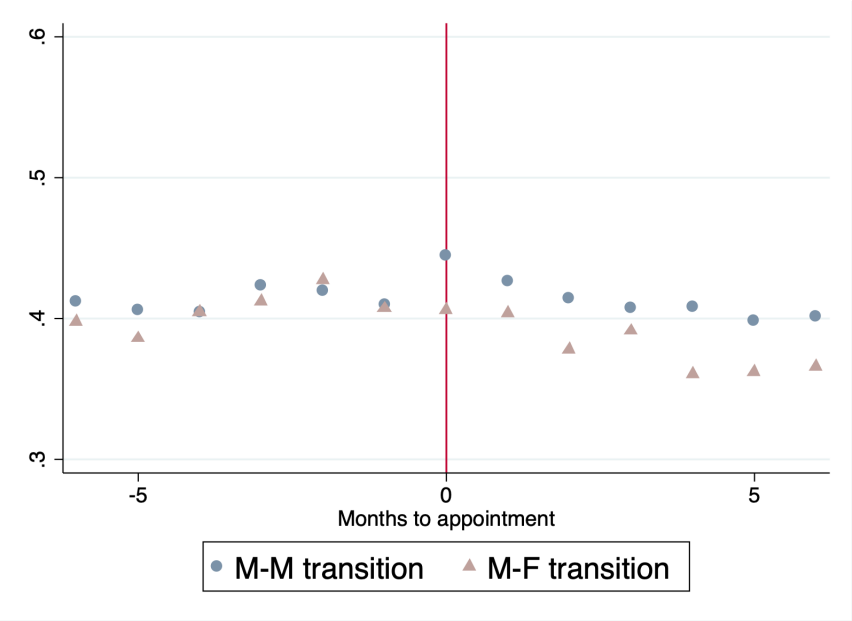


Figure B.6

Notes: Average volatility of firm equity options, measured on the last trading day of the month and calculated in the preceding 30-day horizon. The sample includes 117 male-to-female transitions and 1,817 male-to-male transitions.

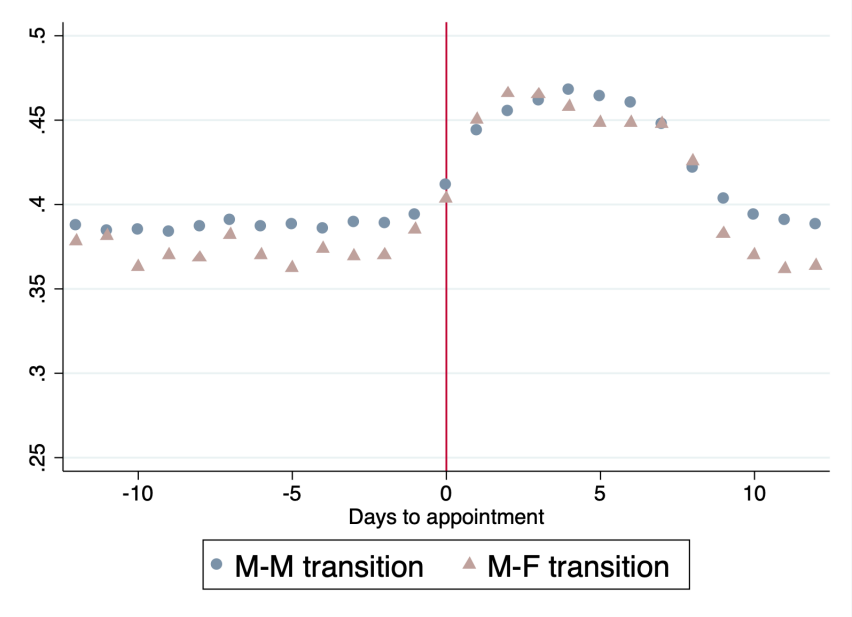


Figure B.7

Notes: Volatility of firm equity options, measured daily and calculated over the preceding 10-day horizon. The red vertical bar corresponds to the day of CEO appointment. The sample includes 89 male-to-female transitions and 1,396 male-to-male transitions. and

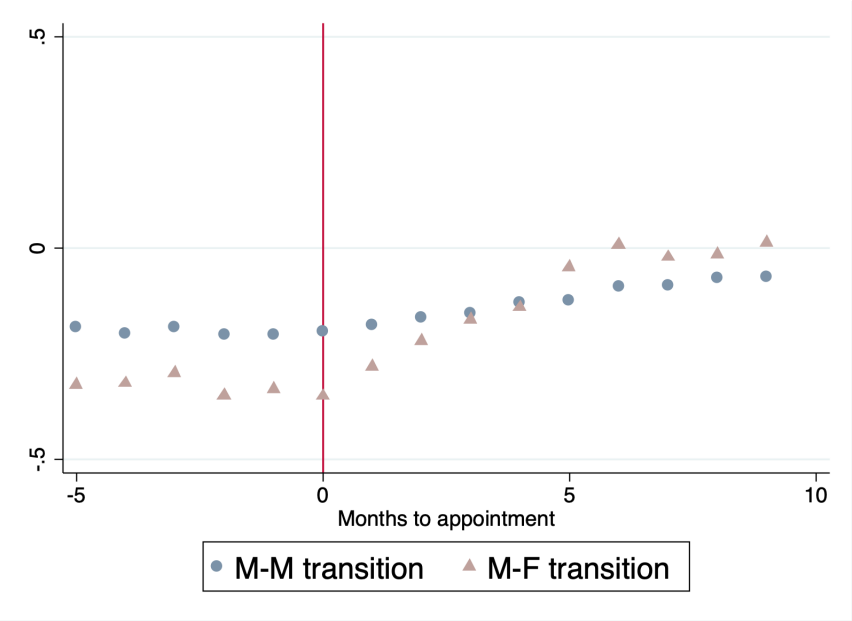


Figure B.8

Notes: Average forecast error, calculated as the difference between actual EPS and the average forecasted EPS. The forecast period corresponds to one year. The sample includes 53 male-to-female transitions and 1,047 male-to-male transitions.

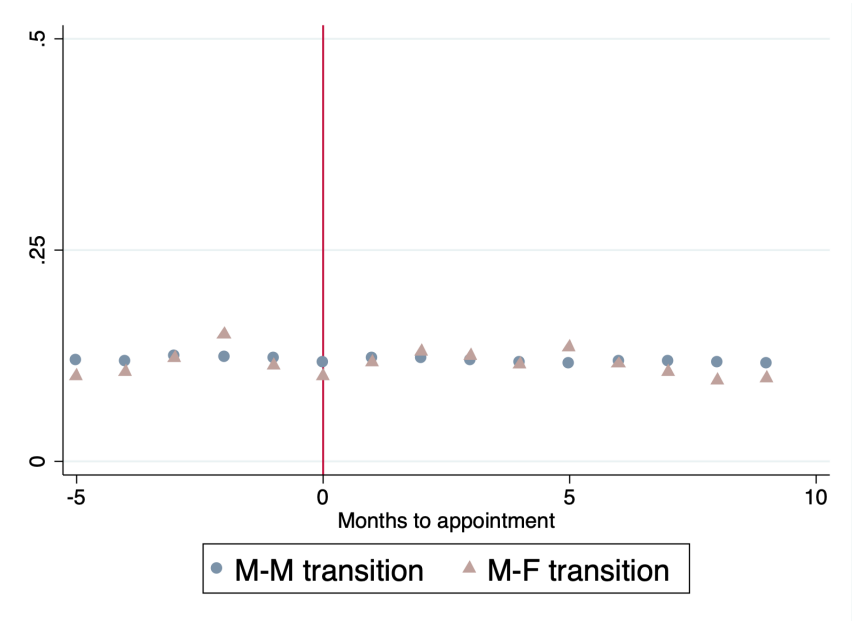


Figure B.9

Notes: Average standard deviation of analysts' EPS expectations. The forecast period corresponds to one year. The sample includes 53 male-to-female transitions and 1,047 male-to-male transitions.

Table B.1: Comparison between unmatched and matched positions and firms

	Unmatched			Matched				
	Mean	Standard deviation	N	Mean	Standard deviation	N	Difference	p-value
Panel A. Individual characteristics								
Female	0.02	0.141	100	0.043	0.202	3,026	-0.023	0.267
Age	51.156	8.977	77	52.6	8.174	2,970	-1.444	0.127
Appointed after 2010	0.41	0.494	100	0.527	0.499	3,026	-0.117	0.021
Born in the US	0.778	0.424	27	0.919	0.273	1,329	-0.141	0.009
Bachelor's degree	0.287	0.455	87	0.288	0.453	2,756	-0.001	0.982
Master's/MBA/Professional degree	0.425	0.497	87	0.449	0.497	2,756	-0.024	0.664
Doctorate degree	0.149	0.359	87	0.152	0.359	2,756	-0.003	0.954
Number of qualifications	2.033	1.326	30	1.919	1.09	2,070	0.114	0.571
Appointment duration (days)	676.068	693.603	74	695.772	764.012	2,749	-19.704	0.826
Tenure in company (years)	3.217	3.962	30	6.569	8.338	2,070	-3.352	0.028
Network size	920.798	1338.01	99	1175.933	1429.706	2,970	-255.135	0.080
Total number of boards	1.867	1.57	30	1.936	1.649	2,029	-0.069	0.818
Number of positions			100			3,026		
Panel B. Board characteristics								
Gender ratio	0.97	0.08	30	0.91	0.11	2,070	0.06	0.001
Number of directors	6.90	1.52	30	8.45	2.50	2,070	-1.55	0.001
Panel C. Firm characteristics								
Assets	2,243.82	8,572.30	38	7,997.51	72,424.21	2,449	-5753.69	0.624
Employees	3.22	10.04	37	8.43	28.77	2,376	-5.21	0.271
Sales	1,227.37	4,300.95	38	2,597.52	10,289.15	2,432	-1370.15	0.413
Gross profits	501.79	2,154.67	38	845.87	3,383.40	2,432	-344.09	0.532
Market value	3,311.84	17,723.33	36	3,660.20	16,344.71	2,216	-348.37	0.899
Primary sector	0.08	0.28	96	0.14	0.35	2,870	-0.06	0.104
Consumer sector	0.17	0.38	96	0.15	0.36	2,870	0.02	0.664
Service sector	0.75	0.44	96	0.71	0.46	2,870	0.04	0.369
Number of firms			75			2,039		

Notes: Source: Panel A and B: BoardEx, 2000-2017, Panel C: Compustat, 2000-2017. Individual and board characteristics are measured in the year of the appointment (except *Appointment duration*), whereas firm characteristics are measured the year before the appointment.

Table B.2: Number of articles, all firms

Sentiment score:	*Below 10%* (1)	*Below 20%* (2)	*20% – 80%* (3)	*Above 80%* (4)	*Above 90%* (5)
Female	0.695**	0.469	-0.108	-0.047	-0.053
	(0.329)	(0.334)	(0.164)	(0.156)	(0.131)
Network size	0.000**	0.000	0.000**	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Born in the US	0.214***	0.243**	0.151	0.133***	0.123**
	(0.077)	(0.109)	(0.105)	(0.048)	(0.051)
Number of qualifications	-0.076***	-0.011	0.009	-0.006	0.011
	(0.029)	(0.040)	(0.032)	(0.021)	(0.020)
Age	-0.013	-0.137**	-0.036	-0.035	-0.031
	(0.036)	(0.063)	(0.038)	(0.031)	(0.030)
Age sq.	-0.000	0.001*	0.000	0.000	0.000
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Tenure	-0.023**	-0.034**	-0.013	-0.015**	-0.009
	(0.011)	(0.015)	(0.011)	(0.007)	(0.007)
Tenure sq.	0.000**	0.000***	0.000**	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sentiment score	-0.056***	-0.030***	0.024	0.029***	0.028***
	(0.008)	(0.006)	(0.018)	(0.005)	(0.005)
Log(sales)	-0.036	-0.061**	-0.011	-0.015	-0.005
	(0.025)	(0.031)	(0.027)	(0.021)	(0.020)
Log(assets)	0.287***	0.305***	0.158***	0.154***	0.145***
	(0.035)	(0.043)	(0.036)	(0.022)	(0.022)
Quarter FE	Y	Y	Y	Y	Y
Year of appointment FE	Y	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y	Y
N	62,384	123,344	351,837	116,047	93,128
Mean	2.361	2.189	2.292	2.131	2.179

Notes: Observations are news stories released between 2000 and 2017 in the full sample of matched news-CEO firms. The dependent variable is represented by the total number of articles for a news story. The estimating specification is equation 1 in the text, where company fixed effects are replaced with sector fixed effects. Standard errors are clustered at the position level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. .

Table B.3: Number of days in the press, all firms

Sentiment score:	*Below 10%* (1)	*Below 20%* (2)	*20% – 80%* (3)	*Above 80%* (4)	*Above 90%* (5)
Female	0.034*	0.008	-0.012	-0.012	-0.015**
	(0.018)	(0.017)	(0.012)	(0.008)	(0.007)
Network size	0.000***	0.000***	0.000***	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Born in the US	0.015**	0.013**	0.011	0.008*	0.010***
	(0.006)	(0.006)	(0.008)	(0.004)	(0.004)
Number of qualifications	-0.005**	-0.001	-0.001	0.001	-0.000
	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)
Age	-0.004	-0.008***	-0.001	-0.003	-0.003
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Age sq.	0.000	0.000**	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tenure	-0.000	-0.000	-0.000	-0.002***	-0.001*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Tenure sq.	0.000	0.000	0.000**	0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sentiment score	-0.004***	-0.001***	0.004***	0.000	0.001***
	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)
Log(sales)	0.001	-0.001	0.001	-0.005**	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Log(assets)	0.016***	0.017***	0.015***	0.016***	0.010***
	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)
Quarter FE	Y	Y	Y	Y	Y
Year of appointment FE	Y	Y	Y	Y	Y
Sector FE	Y	Y	Y	Y	Y
N	62,384	123,344	351,837	116,047	93,128
Mean	1.107	1.101	1.080	1.077	1.069

Notes: Observations are news stories released between 2000 and 2017 in the full sample of matched news-CEO firms. The dependent variable is represented by the total number of days over which a news story is reported in the press. The estimating specification is equation 1 in the text, where company fixed effects are replaced with sector fixed effects. Standard errors are clustered at the position level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. .

Table B.4: CEOs: Gender Differences in News Coverage

Dependent Variable: News Coverage (z-scores)					
	(1)	(2)	(3)	(4)	(5)
Female	0.032	−0.005	0.314***	0.327***	0.387***
	(0.058)	(0.044)	(0.109)	(0.111)	(0.117)
Network size		0.000***	−0.000	−0.000	−0.000*
		(0.000)	(0.000)	(0.000)	(0.000)
Born in the US		0.035*	−0.029	−0.044	−0.048
		(0.020)	(0.101)	(0.098)	(0.099)
Number of qualifications		0.003	-0.015	−0.022	−0.048
		(0.010)	(0.049)	(0.047)	(0.048)
Age		0.019	0.026	0.033	0.010
		(0.014)	(0.029)	(0.029)	(0.029)
Age sq.		−0.000	−0.000	−0.000	−0.000
		(0.000)	(0.000)	(0.000)	(0.000)
Tenure		−0.007***	−0.004	−0.004	−0.004
		(0.002)	(0.004)	(0.004)	(0.004)
Tenure sq.		0.000***	0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)
Appointment news=1				0.213***	0.212***
				(0.028)	(0.029)
Resignation news=1				0.442***	0.448***
				(0.066)	(0.067)
Sentiment score				0.000	0.000
				(0.001)	(0.001)
Number of listed boards					0.066*
					(0.038)
Tenure in company					−0.010**
					(0.004)
Year FE	Y	Y	Y	Y	Y
Year of appointment FE	N	Y	Y	Y	Y
Firm FE	N	N	Y	Y	Y
N	18703	18703	18703	18703	18300

Notes: Source: CEOs data from BoardEx and news data from Ravenpack News Analytics. Observations are news stories released between 2000 and 2017. Standard errors are clustered at the position level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.5: CEOs: Gender Differences in News Coverage

Dependent Variable: News Coverage (z-scores)					
	(1)	(2)	(3)	(4)	(5)
Female	0.032	−0.005	0.314***	0.327***	0.387***
	(0.058)	(0.044)	(0.109)	(0.111)	(0.117)
Network size		0.000***	−0.000	−0.000	−0.000*
		(0.000)	(0.000)	(0.000)	(0.000)
Born in the US		0.035*	−0.029	−0.044	−0.048
		(0.020)	(0.101)	(0.098)	(0.099)
Number of qualifications		0.003	-0.015	−0.022	−0.048
		(0.010)	(0.049)	(0.047)	(0.048)
Age		0.019	0.026	0.033	0.010
		(0.014)	(0.029)	(0.029)	(0.029)
Age sq.		−0.000	−0.000	−0.000	−0.000
		(0.000)	(0.000)	(0.000)	(0.000)
Tenure		−0.007***	−0.004	−0.004	−0.004
		(0.002)	(0.004)	(0.004)	(0.004)
Tenure sq.		0.000***	0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)
Appointment news=1				0.213***	0.212***
				(0.028)	(0.029)
Resignation news=1				0.442***	0.448***
				(0.066)	(0.067)
Sentiment score				0.000	0.000
				(0.001)	(0.001)
Number of listed boards					0.066*
					(0.038)
Tenure in company					−0.010**
					(0.004)
Year FE	Y	Y	Y	Y	Y
Year of appointment FE	N	Y	Y	Y	Y
Firm FE	N	N	Y	Y	Y
N	18703	18703	18703	18703	18300

Notes: Observations are news stories released between 2000 and 2017. Standard errors are clustered at the position level. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table B.6: Other Chief Officers: Gender Differences in News Coverage

Dependent Variable: News Coverage (z-scores)								
	CFOs/COOs				Other Chief Officers (CAOs, CMOs, CTOs)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	0.031	−0.003	0.355**	0.263**	0.037	−0.000	0.238+	0.231+
	(0.052)	(0.054)	(0.166)	(0.135)	(0.086)	(0.090)	(0.179)	(0.174)
Network size		0.000***	−0.000	−0.000		0.000**	−0.000+	−0.000+
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
Born in the US		−0.001	−0.305***	−0.191**		0.039	−0.404	−0.417
		(0.035)	(0.107)	(0.082)		(0.062)	(0.351)	(0.355)
Number of qualifications		0.016	0.091**	0.075**		−0.040	−0.092	−0.076
		(0.014)	(0.040)	(0.035)		(0.033)	(0.107)	(0.106)
Age		0.038	0.163**	0.182***		0.015	0.125	0.152+
		(0.024)	(0.080)	(0.065)		(0.029)	(0.104)	(0.102)
Age sq.		−0.000	−0.002**	−0.002***		−0.000	−0.001	−0.001+
		(0.000)	(0.001)	(0.001)		(0.000)	(0.001)	(0.001)
Tenure		−0.008**	0.002	0.001		−0.001	0.026	0.024
		(0.003)	(0.004)	(0.003)		(0.007)	(0.032)	(0.029)
Tenure sq.		0.000***	0.000**	0.000		0.000	0.000+	0.000
		(0.000)	(0.000)	(0.000)		(0.000)	(0.000)	(0.000)
COO=1		−0.011	0.089	0.102				
		(0.040)	(0.093)	(0.077)				
Appointment news=1				0.786***				0.445+
				(0.061)				(0.321)
Resignation news=1				1.576***				0.680+
				(0.265)				(0.425)
Sentiment score				−0.000				0.006
				(0.002)				(0.027)
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Year of appointment FE	N	Y	Y	Y	N	Y	Y	Y
Firm FE	N	N	Y	Y	N	N	Y	Y
Observations	11295	11295	11295	11295	1271	1271	1271	1271

Notes: Observations are news stories released between 2000 and 2017. Standard errors are clustered at the position level. $+p < 0.20$ $*p < 0.10$, $**p < 0.05$, $***p < 0.01$.

Table B.7: Career moves, excluding the first lag in the performance variable

	(1)	(2)	(3)	(4)	(5)	(6)
				Characteristics of next job move:		
	Turnover	Moved	Reappointed	Private firm	Private/ smaller firm	Private/ smaller/ missing
Share bad news t-1	0.049***	0.048***	0.003	0.059***	0.059***	0.040***
	(0.018)	(0.014)	(0.008)	(0.014)	(0.014)	(0.012)
Share bad news t-2	0.014	0.015	-0.005	0.003	0.003	0.006
	(0.015)	(0.011)	(0.008)	(0.011)	(0.011)	(0.010)
Share good news t-1	-0.016	-0.011	-0.004	0.006	0.006	-0.010
	(0.014)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)
Share good news t-2	-0.005	-0.006	-0.004	-0.010	-0.010	-0.010
	(0.014)	(0.009)	(0.008)	(0.008)	(0.009)	(0.009)
Female	0.044	0.018	0.031	0.014	0.013	-0.003
	(0.071)	(0.049)	(0.029)	(0.027)	(0.027)	(0.042)
Number of news t-1	-0.000	-0.000	-0.000	0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of news t-2	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Return t-2	0.013	0.024	-0.001	0.036*	0.036*	0.013
	(0.026)	(0.020)	(0.012)	(0.019)	(0.019)	(0.018)
Network size	0.000	0.000	-0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tenure	0.011***	0.007***	0.002	0.006***	0.006***	0.006***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Tenure sq.	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age	0.012	0.005	0.003	0.007	0.006	0.004
	(0.010)	(0.006)	(0.005)	(0.007)	(0.007)	(0.006)
Age sq.	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm_FE	Y	Y	Y	Y	Y	Y
Year_FE	Y	Y	Y	Y	Y	Y
Year_appointed_FE	Y	Y	Y	Y	Y	Y
N	13241	13241	13042	7764	7755	13241
Mean	0.071	0.031	0.022	0.018	0.018	0.026

Table B.8: Career moves, excluding performance variables

	(1)	(2)	(3)	(4)	(5)	(6)
				Characteristics of next job move:		
	Turnover	Moved	Reappointed	Private firm	Private/ smaller firm	Private/ smaller/ missing
Share bad news t-1	0.042***	0.042***	0.001	0.049***	0.049***	0.036***
	(0.015)	(0.011)	(0.007)	(0.012)	(0.012)	(0.010)
Share bad news t-2	0.011	0.015	-0.002	-0.001	-0.000	0.010
	(0.013)	(0.010)	(0.007)	(0.010)	(0.010)	(0.009)
Share good news t-1	-0.016	-0.013	-0.003	-0.001	-0.000	-0.014*
	(0.012)	(0.008)	(0.007)	(0.008)	(0.008)	(0.007)
Share good news t-2	-0.008	-0.009	-0.002	-0.010	-0.010	-0.010
	(0.012)	(0.008)	(0.007)	(0.008)	(0.008)	(0.008)
Female	0.043	0.006	0.038	0.035	0.035	-0.019
	(0.057)	(0.049)	(0.023)	(0.041)	(0.041)	(0.042)
Number of news t-1	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Number of news t-2	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Network size	0.000	0.000	0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tenure	0.012***	0.007***	0.002**	0.005***	0.005***	0.006***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Tenure sq.	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Age	0.005	0.009*	-0.004	0.013*	0.010	0.007
	(0.009)	(0.005)	(0.004)	(0.007)	(0.007)	(0.005)
Age sq.	-0.000	-0.000	0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm_FE	Y	Y	Y	Y	Y	Y
Year_FE	Y	Y	Y	Y	Y	Y
Year_appointed_FE	Y	Y	Y	Y	Y	Y
N	17157	17157	16934	10232	10216	17157
Mean	0.075	0.033	0.024	0.019	0.019	0.028

Table B.9: CEO power: current CEOs and their predecessors

Current CEO is:	*Female*		*Male*			
	Mean	N	Mean	N	Diff.	p-val.
Current CEO:						
First appointment	0.581	129	0.624	2897	−0.04	0.324
Tenure in company (years)	8.272	101	7.916	2226	0.36	0.673
Founder	0.101	129	0.075	2892	0.03	0.288
Share of indep. board members	0.891	101	0.852	2225	0.04	0.014
Appointment duration (days)	662	118	707	2660	−45	0.531
Predecessor CEO:						
Female	0.514	109	0.015	2389	0.50	0.000
Tenure in company (years)	10.444	95	10.612	2029	−0.17	0.874
Founder	0.138	109	0.128	2387	0.01	0.764
Chair	0.349	109	0.31	2389	0.04	0.392
Share of indep. board members	0.853	95	0.832	2028	0.02	0.234
Appointment duration (days)	1415	109	1463	2388	−48	0.777