Recipes for Success: Becoming a CEO

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ABSTRACT

This study employs novel machine learning techniques to analyze career determinants of first-time female and male chief executive officers (CEOs), thereby contributing to the ongoing discussion on leadership and gender. We find that female executives with strong social networks are more likely to become CEOs, whereas professional experience factors comprise the most important predictors for male CEOs, for whom social network, while still important, matters to a lesser extent. Our findings suggest that female and male executives encounter different criteria during the CEO selection process, where, in addition to professional qualifications, female candidates need exceptionally strong social networks to succeed.

Keywords: Leadership; Gender; CEOs; Machine Learning; Social Network
JEL Classification: G34, J16, J24, J20, G40

I. INTRODUCTION

The importance of effective leadership is uncontroversial and has been extensively studied, with characteristics of leaders shown to influence the performance of the organizations and economic growth, including at the national level[1]. However, the academic literature on what defines a leader in terms of upbringing remains largely unexplored, with an even larger knowledge gap when applied to the gender perspective. In this study, we focus on the characteristics of future corporate leaders and, using novel machine learning techniques, identify the most important predictors of CEO selection. Considering the current gender gap in corporate leadership, with only 10% of Fortune 500 companies led by female CEOs[2], we study this question from a gender perspective and explore whether determinants of leadership differ across male and female executives. Existing research on determinants of CEO selection is mostly gender-neutral and limited to small samples or anecdotal evidence[3]. In this study, we aim to bridge the gap in the literature by investigating what characteristics shape and define female and male leaders through the lens of CEO selection. We assess the universe of executives in the United States to understand what differentiates leaders who become CEOs from those holding executive positions and show how these characteristics differ by gender perspective.

Existing studies on leadership determinants and CEO selection are mostly based on interviewing approaches and personality assessments relying on small samples and soft information-gathering techniques (Kaplan, Klebanov, and Sorensen, 2012; Kaplan and Sorensen, 2021); Dillard and Lipschitz, 2014; Stevenson and Orr, 2017). Kaplan and co-authors (2012, 2021)

[1] See Jones and Olken (2005), Bertrand and Schoar (2003), Hambrick and Mason (1984).
[2] See S&P Global (2024), Elting (2023).
[3] See Kaplan et al. (2012, 2021), Dillard and Lipschitz (2014), Stevenson and Orr (2017).

studied CEO assessments by an executive search firm to analyze job interviews and differentiate how individuals selected as CEOs differ from other interviewees. Numerous other studies rely on anecdotal evidence, relying on interviews with CEOs and presenting findings on what they have in common (Dillard and Lipschitz, 2014; Stevenson and Orr, 2017). In terms of scope, existing studies isolate and investigate specific aspects of CEO selection determinants. Among these is the role of social networks, indicating that ties to firms or prior CEOs play an important role in the appointment (Wiersema, Nishimura, and Suzuki, 2018; Cziraki and Jenter, 2021). Another group of studies focuses on specific characteristics that may influence future leadership behaviors, including early-life conditions such as cognitive abilities and height, as well as formative early-life events such as natural disasters or economic depression (Adams, Keloharju, and Knüpfer, 2018; Bernile, Bhagwat, and Rau, 2017; Malmendier, Tate, and Yan, 2011). Although such qualitative, narrowly focused approaches are important for identifying potential personality traits of leaders, an in-depth empirical analysis of the determinants of leadership is lacking. Additionally, since these studies on CEO selection and leadership determinants are conducted from a gender-neutral perspective, little is known about which characteristics are crucial in the CEO selection process for female versus male candidates.

In this paper, we examine the determinants of leadership from a gender perspective by analyzing the characteristics of the universe of executives in the United States and identifying those that can predict the likelihood of becoming a CEO. We compiled an extensive dataset comprising over 100 distinct characteristics of executives in the United States, spanning nearly two decades. To effectively analyze this comprehensive set of executive characteristics, we introduce an algorithmic approach to CEO selection literature, building upon the increasing use of

machine learning techniques in finance[4]. These novel techniques allow us to consider a large number of covariates while avoiding overfitting and multicollinearity. A similar predictive algorithmic approach has been implemented in a seminal work on selecting board directors using machine learning by Erel et al. (2021), which specifically focused on director performance.

The closest study in the existing literature to ours compares a near-exhaustive sample of male CEOs with the Swedish male population, identifying traits that are necessary but not sufficient to become a CEO (Adams et al., 2018). Using data from the military, which includes virtually all Swedish males (military service was mandatory in Sweden during the sample period of 2004 to 2010), Adams and coauthors find that future CEOs score considerably higher on cognitive ability, noncognitive ability, and height compared to all 18-year-old males in Sweden who enter military service (Adams et al., 2018). Although early life indicators matter, one can argue that future leaders also evolve over time. We thus extend this research direction by focusing on the universe of executives in the United States and including a comprehensive set of factors, such as education, social networks, and experience, to identify what differentiates CEOs from other executives. This framework is then applied to female and male CEO selection to capture gender differences in this process.

We utilize a novel database of the entire population of executives in U.S. firms from 2000 to 2018. Our research design, which includes a comprehensive dataset of 342 first-time female and 4,457 male CEOs of public companies, as well as their characteristics, along with over 200,000 female and over 2 million male executives who did not become CEOs during that time, serves as a control group, enabling us to identify the important predictors of CEOs using machine-learning methods. We focus on first-time CEOs because being appointed for the first time is a significant

[4] See Athley and Imbens (2017), Mullainathan and Spiess (2017), Erel et al. (2021).

career milestone, after which prior experience as a CEO becomes a defining factor for future appointments (Tinsley and Purmal, 2019). Our sample comprises only public companies, as they exhibit greater homogeneity compared to private firms in terms of size, regulatory requirements, and governance. We employ similar frameworks for identifying determinants of female and male CEOs and find significant differences in the determinants of CEO selection based on the gender of the executives.

For ease of interpretation, we categorize executives' characteristics into eight broad groups: social network, professional experience, board experience, upper management experience, education, awards, affiliations, and other experience. To determine which of the eight groups of individual characteristics is the most important determinant of future CEOs, we calculate the sum of the importance scores for each variable within each model for each group. The results show that the three most important groups are social networks, upper management, and board experience across our models. Within these groups, we further disentangle which specific characteristics influence the likelihood that an executive will become a CEO. We find that social network factors are the most important for female CEOs, while professional experience factors are the most important for male candidates, for whom social network still plays an important, albeit lesser, role. Finally, we cross-fit the samples using the best-performing models for the opposite gender. Our results suggest that there are different criteria for female CEOs, and more women would become CEOs if they were selected using the male CEO selection model, whereas the reverse is true for male executives: fewer of them would be qualified for the role under the female CEO selection model. This finding highlights significant differences in the criteria applied during the CEO selection process by gender and underscores opportunities for further research in this area.

Our study contributes to existing literature in two primary ways. First, we contribute to the literature on leadership determinants by approaching the CEO selection process from a gender perspective. We respond to the explicit call for progressive research on economic perspectives of leadership and deepen our understanding of leadership determinants in corporate finance (Garretsen, Stoker, and Weber, 2020; Decressin, Kaplan, and Sorensen, 2025). By introducing a gender perspective to the CEO selection process, we contribute to a deeper understanding of gender differences in corporate leadership settings. We identify the characteristics that matter most for becoming a CEO and find that social networks and heterogeneous professional experience, including upper management and board roles, are the most important predictors of successful female CEO candidates. We then show how the set of predictors differs for male candidates, identifying the prevalence of professional experience and the lesser importance of social network factors.

Second, we contribute to the growing literature on machine learning applications in finance. We provide an overview of a set of machine-learning classification models and illustrate their application to the study of corporate finance. Building upon existing early corporate finance studies using machine learning, such as board selection and bankruptcy prediction (Erel et al., 2021; Jones, 2017), we incorporate these advanced techniques in our research design to provide a data-driven approach to identifying determinants of CEO selection from a gender perspective. We compiled a comprehensive dataset of over 100 characteristics of executives across various categories, including education, professional experience, board participation, social networks, affiliations, awards, and other experiences, to predict the likelihood of becoming a CEO. We then utilize state-of-the-art, interpretable machine learning techniques to extract meaning from traditional black-box machine learning models. Our paper is one of the earliest studies to use

machine learning in corporate governance research, following the seminal work by Erel et al. (2021), who first applied these techniques to board selection studies. We extend this algorithmic approach to identify the most important candidate characteristics predictive of CEO selection from a gender perspective.

II. LEADERSHIP AND GENDER

Leaders matter for growth and development, often playing crucial roles in governments, politics, and corporations. In a seminal study, Jones and Olken (2005) find that individual leaders play a significant role in national economic growth. In the corporate and strategic management context, leaders significantly affect the firms they manage (Hambrick and Mason, 1984; Bertrand and Schoar, 2003; Guenzel and Malmendier, 2020). However, existing literature often overlooks the study of the determinants of leadership success from a gender perspective, particularly in the corporate context. In this paper, we specifically examine the U.S. population of female and male executives to identify characteristics and traits that differentiate those executives who become CEOs from those who do not.

We are interested in exploring the differences in leadership characteristics from a gender perspective due to a historic underrepresentation of female leaders in the upper echelons of corporate leadership, despite the evidence that they often have superior managerial skills and are associated with the numerous benefits at the firms they manage, such as higher levels of innovation and corporate social responsibility, better disclosure practices and reduced risk, and greater stability and resilience[5]. Although women enter the workforce in approximately equal numbers to men, only one in eight C-suite leaders of publicly traded U.S. firms is a woman, and only 10% of

[5] See Cooper (2021), Wu et al. (2021), Post et al. (2020, 2011), Sahay and Cihak (2018).

Fortune 500 companies are led by female CEOs. Even though the number of female leaders is on the rise, women remain underrepresented in the upper echelons of the corporate world (Adams and Ferreira, 2009; Adams and Kirchmaier, 2016b). Of all S&P 500 companies, only 41 had female chief executive officers (CEOs) as of February 2023, representing about 8% of the index.[6] Female representation on boards of S&P 500 firms increased from 15% in 2008 to 34.7% at the beginning of 2024, but is still below France (over 45% female board representation), the UK, Spain, Italy, and Australia, each having over 40% of board seats held by women (Altrata, 2024). After a decade of proposals, in 2022, the European Union implemented mandatory gender quotas with the goal of allocating at least 40% of board seats to women by June 2026 (Rankin, 2022). According to the Women in the Workplace study by McKinsey & Company and LeanIn.Org in 2024, despite a positive trend in female representation in executive positions from 2015, female executives remain dramatically underrepresented, filling only 34% of vice president roles and only 29% of C-suite positions among the 281 companies surveyed (McKinsey & Company and LeanIn.Org, 2024). Although at the beginning of 2023, for the first time, over 10% of Fortune 500 companies were led by women CEOs, with the total number of female CEOs at a record 53, which since then remained largely flat at 10.4%, slightly decreasing to 52 female CEOs as of the 2024 Fortune 500 ranking (Elting, 2023; Hinchliffe, 2024).

Historically, women have faced several structural barriers to the upper echelons of management. Studies describe these barriers as stemming from corporate practices and from behavioral or cultural norms (Oakley, 2000; Schein, 2001; Hoyt and Murphy, 2016; Duchin, Simutin, and Sosyura, 2021). The extant literature suggests that female executives display behavioral and attitudinal differences compared to male executives. For example, Tannen (1994)

[6] Women CEOs of the S&P 500. (February 3, 2023). *Catalyst.*

concludes that women are less likely to engage in self-promoting behaviors, reducing their chances of being recognized and promoted. Additionally, compared to men, women tend to shy away from competition, which may also contribute to their relative underrepresentation in top leadership (Buser et al., 2014; Hogarth, Karelaia, and Trujillo, 2012). Sheryl Sandberg, the COO of Facebook, also points out in her bestselling book Lean In that women tend to pull back from career opportunities rather than lean in. She attributes this behavior to a myriad of internal and external (societal) factors (Sandberg, 2013).

Adams and Funk (2012) find that women in top management positions break through the glass ceiling because their decision-making processes and attitudes are similar to those of their male counterparts. Indeed, the characteristics of successful leaders are often aligned with traditional masculine stereotypes, such as being competent, determined, and industrious (Sczesny, 2013). Therefore, women are evaluated negatively if they exhibit a feminine leadership style, resulting in role-congruity prejudice toward female leaders. This perceived incongruity between female qualities and leadership roles can lead to prejudices in appointing female executives and evaluating their performance (Eagly and Karau, 2002). Moreover, although men are often expected to demonstrate strength, women need to demonstrate both sensitivity and strength to be perceived as effective leaders (Johnson, Murphy, Zewdie, and Reichard, 2008). Philipps and Prieto (2020) provide a historical perspective on women's leadership and develop a framework linking internal (motivation, ambition), organizational external (culture, support), and societal external (perceptions, expectations, policy) factors in order to explain gender social mobility.

Prior literature shows that leadership characteristics can differ across genders, as can perceptions of this dimension. Hiring a female CEO is considered an unconventional strategic choice. Markets typically lower a firm's value when it promotes a woman, indicating that because

women are underrepresented in CEO positions relative to men, the uncertainty is higher (Lee and James, 2007). Firms may hesitate to appoint women to leadership positions because they perceive female executives as too risk-averse or conservative. Huang and Kisgen (2013) find that firms led by female executives have lower growth rates and fewer acquisitions. At the same time, gender-based lower risk tolerance may result in fewer financial statement irregularities and higher accounting conservatism in firms with female chief financial officers (CFOs) (Gupta, Mortal, Chakrabarty, Guo, Turban, 2020; Francis, Hasan, Park, and Wu, 2015). Women managers have been shown to take on more "invisible work" during a crisis, including helping employees with work-life challenges, balancing workloads, and providing emotional support (Cooper, 2021). Female directors are associated with fewer employee layoffs, better environmental and innovative performance (Matsa and Miller, 2013; Hsu, Li and Pan, 2026; Griffin, Li and Xu, 2021), while female chief technology officers (CTOs) are associated with more innovation (Wu, Dbouk, Hasan, Kobeissi, and Zheng, 2021). CEO gender has been shown to affect merger and acquisition decisions, with female CEOs associated with a lower likelihood of engaging in corporate acquisitions, including initiating acquisition bids and offering lower bid premiums (Pan, Siegel, and Wang, 2020; Levi, Li, and Zhang, 2014). Instead, firms with gender diversity in top leadership tend to invest internally, having higher research and development (R&D) expenditures and more focus on change-oriented strategic renewal (Post, Lokshin, Boone, 2020). Gul, Srinidhi, and Ng (2011) find that gender-diverse boards disclose more information, which improves stock price informativeness. Faccio, Marchica, and Mura (2016) document that firms with female CEOs are associated with lower leverage, less volatile earnings, reduced corporate risk-taking, and higher survival rates. Gender-diverse firms outperform in corporate social responsibility (CSR), with more CSR strengths and fewer CSR concerns (Post, Rahman, and Rubow, 2011; Boulouta, 2013).

The International Monetary Fund (IMF) discussion note associates more female leaders in finance with improved stability and resilience in the banking system, suggesting that the benefits of female leadership extend beyond gender equality (Sahay and Cihak, 2018).

Female executives often find themselves on a "glass cliff," defined as a precarious or risky position, as firms tend to appoint female CEOs and board members in uncertain circumstances, such as after major scandals or financial distress (Ryan and Haslam, 2005; Cook and Glass, 2014; Ryan, Haslam, Morgenroth, Rink, Stoker, and Peters, 2016). However, even under adverse circumstances, female executives portray a valuable transformational leadership style by being open to communication and collaboration and achieving performance increases (Francis, Hasan, Shen, and Wu, 2021; Eagly and Carli, 2003). Adams and Ferreira (2009) suggest that female directors tend to be less conformist and express independent views more than male directors. They do not belong to the "old boys' club" and thus have no pressure to follow the group, which results in tougher monitoring that is especially beneficial for companies with weak shareholder rights. Moreover, gender effect has been shown to differ across countries where national cultural value of individualism encourages women to be more averse to competition (Li, Peng, Shen, R. and Wong, 2024). Overall, the presence of varying leadership skills based on gender has been well established in the literature from the standpoint of corporate outcomes. Our paper contributes to this literature by examining role of these skills and their differentiation base on gender in the context of CEO selection process.

Prior research finds a few factors, including education, as important determinants of effective leadership (Besley, Montalvo, and Reynal-Querol, 2011; Besley and Reynal-Querol, 2011). Although more women than men earn college degrees and about an equal number of both enter the workforce, fewer than 6% of the CEOs of the largest U.S. companies in the Russell 3000

Index are women (Fuhrmans, 2020).[7] Clearly, the difference in gender leadership is not in the absence or presence of a college degree, even though prior research finds that education is an important determinant of effective leadership (Besley, Montalvo, and Reynal-Querol, 2011; Besley and Reynal-Querol, 2011). There is some evidence of a persistent difference in math scores between male and female students, with the latter scoring lower, which affects the number of women in science, technology, engineering, and mathematics (STEM) fields, female directorship in STEM industries, and careers in finance (Adams and Kirchmaier, 2016a, 2016b; Adams, Barber, and Odean, 2023). Even with similar levels of academic ability, girls tend to experience lower levels of competitiveness, resulting in less prestigious academic tracks that have lower math and science intensity (Buser, Niederle, and Oosterbeek, 2014). Despite a decline in gender gaps in education, labor force participation, and earnings, women continue to make disadvantageous educational choices by opting out of math-intensive STEM fields, which tend to offer higher expected compensation and better career advancement opportunities based on meritocracy rather than gender biases (Bertrand, 2020). To investigate this issue, we include several variables related to educational attainment, including different types of degrees and academic institutions, to determine the influence of education on leadership skills in the context of CEO selection.

Conventional advice given to aspiring leaders includes going to an Ivy League school, getting an MBA, starting in consulting or investment banking, and seeking bigger roles. In fact, 52 percent of McKinsey alumni who left as senior partners later become CEOs, with the company's alumni leading 18 current Fortune 500 companies including Sundar Pichai of Alphabet and Jane Fraser of Citigroup (Umoh, 2025). Most of the CEO selection research is gender-neutral and does not allow to differentiate between the leadership characteristics preferred based on the gender of

[7] Women hold fewer than 12% of C-suite roles below CEO in Russell 3000 index companies (Fuhrmans, 2020).

CEO candidates. Prior literature shows that overconfident managers are more likely of being promoted to CEO, and that firms with higher risk-taking tendencies are likely to select outsider as a CEO or CEOs with high social capital while not differentiating on the role that the gender of candidate may play in the selection process (Goel and Thakor, 2008; Quigley, Hambrick, Misangyi and Rizzi, 2019; Abernethy, Kuang, and Qin, 2019). Anecdotal evidence suggests that women who become CEOs tend to follow two routes: spend a long time at a single company and eventually become the CEO or make a lateral move and become a CEO elsewhere (Dillard and Lipschitz, 2014). Prestigious schools or MBA degrees do not seem to matter much to most of the 24 interviewed female leaders of Fortune 500 companies, nor does banking or consulting experience (Dillard and Lipschitz, 2014). Another interview-based study of 57 female CEOs finds that 40% of the sample had a technical background in STEM fields; only about 20% had business, finance, or economics backgrounds (Stevenson and Orr, 2017). The Rockefeller Foundation partnered with executive search firm Korn Ferry on a CEO Pipeline Project to develop initiatives for female executive promotion, and among the resulting recommendations were gaining operational and sales experience early in the career, as well as exposure to governance and boards, finance, and external constituents, along with building professional networks (Spencer, Blazek, and Orr, 2019). However, a comprehensive investigation of the characteristics that determine female leadership success is missing from the existing literature. This is the first study to examine over 100 executive characteristics over a multiyear period and identify the ones most instrumental for aspiring leaders becoming CEOs.

We disentangle the leadership determinants among the other broad categories of executive characteristics. Specifically, we ground our variable selection in theoretical underpinnings and existing literature to determine a nearly exhaustive set of characteristics, which we then analyze

using advanced machine learning techniques. As a result, we offer a comprehensive investigation of the characteristics that determine leadership success, filling a gap in the literature until now. This is the first study to consider over 100 characteristics of female and male executives across a multi-year period and identify the ones most instrumental for success among executives aspiring to become CEOs. We contribute to research on corporate leadership from a gender perspective by adopting a data-driven approach to studying leadership characteristics.

III. MACHINE-LEARNING APPROACH

Machine learning has gained popularity in recent years in business literature, as it offers benefits over traditional parametric analysis. Machine learning enables the discovery of structures and patterns in data without requiring the specification of a functional form in advance, thereby allowing for greater flexibility in the models (Mullainathan and Spiess, 2017). Although the emphasis of traditional econometric models is on establishing causality, the main focus of machine-learning models is to enhance the algorithm's predictive power for new data (out-of-sample), which is achieved by training the algorithm using validation and cross-validation (Athey and Imbens, 2019). Similar to traditional econometrics, machine learning can be applied to regression problems (where the dependent variable is continuous) and classification problems (where the dependent variable is categorical). Additionally, machine learning can be applied in supervised learning (where the dependent and explanatory variables are clearly defined in the model) and unsupervised learning (where no dependent variable is defined, and exploratory data analysis is performed). We focus on classification algorithms and supervised machine learning because we have a clearly defined dependent variable with two categories: women who become CEOs and female executives who do not.

Machine learning can enhance the human decision-making process by helping discover complex patterns in data, predicting future outcomes based on a set of variables, as well as

conducting exploratory analysis (Kleinberg, Lakkaraju, Leskovec, Ludwig, and Mullainathan, 2018). Among recent studies with machine-learning applications in finance are numerous asset-pricing studies (Gu, Kelly, and Xiu, 2020; Bianchi, Büchner, and Tamoni, 2020), as well as a limited number of research papers in areas of corporate finance and accounting, including board selection, corporate culture, bankruptcy prediction, and relative valuation (Erel, Stern, Tan, and Weisbach, 2018; Li, Mai, Shen, and Yan, 2021; Jones, 2017; Geertsema and Lu, 2023; Li, Mai, Shen, Yang, and Zhang, 2026). It is important to note that machine-learning applications do not solely focus on numerical predictors. Textual, image, video, and voice analyses, that apply novel machine-learning methods, are also gaining traction in finance research. Researchers have used textual analysis to study the text of financial documents, including annual (10-K) and quarterly (10-Q) filings, as well as earnings conference calls and IPO prospectuses (Loughran and McDonald, 2016; Cohen, Malloy, and Nguyen, 2020; Li et al., 2021; Li et al., 2026; Hassan, Hollander, van Lent, and Tahoun, 2019). Textual analysis has also been increasingly applied to media data, such as employer reviews on Glassdoor and stock articles on Seeking Alpha (Green, Huang, Wen, and Zhou, 2019; Chen, De, Hu, and Hwang, 2014).

In this paper, we employ machine-learning techniques to identify specific factors influencing CEO selection, shedding light on the most important determinants of becoming a CEO. We compare the unique determinants and characteristics of executives who become CEOs with those of other executives who do not. Our primary objective is to conduct an exploratory analysis of the multidimensional determinants of CEO selection from a gender perspective. We assemble the most comprehensive (to our knowledge) dataset of executive characteristics to date. In our dataset, we identify over 100 attributes related to education, achievements, awards, affiliations, professional experience, and social networks. Because traditional models suffer from the curse of dimensionality (James, Witten, Hastie, and Tibshirani, 2013), we rely on machine-learning algorithms to identify the most important predictors of becoming a CEO.

Due to the high dimensionality of our setting, with numerous potential predictors of executives becoming CEOs, machine-learning algorithms offer significant advantages over traditional econometric techniques. First, machine-learning algorithms handle high dimensionality well, allowing us to identify the most important factors in an extensive set of features. Second, we train machine-learning algorithms using cross-validation to ensure the final models have predictive power on out-of-sample data as well, thereby addressing concerns about overfitting. Third, using novel methodology, we are able to interpret results of previously "black-box" machine learning models using explainable AI (XAI) techniques (Dwivedi et al., 2023; Klein and Walther, 2024). Therefore, our paper presents a unique approach for applying machine-learning techniques to investigate the determinants of career success, utilizing high-dimensional data to encompass a comprehensive set of potential predictors.

A few studies similar to ours focus on classification algorithms. Corporate governance structures in the context of selecting directors have been studied using machine learning classification algorithms, such as lasso, ridge, neural networks, and gradient boosting trees (Erel, Stern, Tan, and Weisbach, 2021). Governors' selection for provinces in China has been studied using lasso, bagging, random forest, and gradient-boosting algorithms (Gu, Hasan, Zhang, Zhao, and Zhu, 2019). Jones (2017) employs a gradient-boosting model to predict which firms will file for bankruptcy, utilizing a large number of potential explanatory variables. In addition to the models studied earlier, we consider a more comprehensive set of algorithms commonly used for classification in the broader machine learning literature. We include three sets of models in our analysis: classification models based on linear combinations of predictors and penalized methods, nonlinear classification models, and tree-based classification models (Kuhn and Johnson, 2013).

IV. DATA AND SAMPLE DESCRIPTION

Sample Selection

The data sample is organized on the individual-year level and includes all female executives who have held at least one executive position or sat on at least one board in a U.S. firm between 2001 and 2018, according to the BoardEx dataset. We exclude observations for executives with prior public CEO experience because we are only interested in first-time CEOs of publicly traded companies. The final sample for the female executive analysis consists of a total of 273,091 observations, including 342 female executives who became CEOs for the first time in public firms, and a control group of 272,749 observations for female executives who were never employed as CEOs in U.S. publicly traded firms. The final sample for the male executive analysis consists of a total of 2,016,377 observations, including 4,457 first-time male CEOs and a control group of 2,011,920 male executives who were never employed as CEOs in U.S. publicly traded firms.

BoardEx began its coverage in 1999, as reflected in the Organization Summary dataset, which started in that year. Other data files, including Employment, Education, Achievements, and Other Activities, contain biographical information and employment history dating back to the earliest available records for individuals included in BoardEx since 1999. For example, although we can only view the full data on an executive's salary, board positions, and other characteristics from the Organization Summary file starting in 1999, we can see her experience in the Employment dataset dating back as far as available. Similarly, other attributes from the Education, Affiliations, Achievements, and Other Activities datasets are available retrospectively. Therefore, we rely on the employment data to construct a panel dataset of active executives, meaning they held executive positions and/or served on boards during our sample period from 2001 to 2018. The data for 2018 is incomplete and was based on the data available at the time of data collection.

We limit our sample to observations for which we can calculate the combined network variables. Among the categories of network measures based on education, employment, other experiences, and combined, we keep the combined network measures, as they have the least number of missing values. The number of CEO appointments by year and the total number of executives each year are presented in Figure 1. We observe a generally positive trend in the female sample, with the number of female CEOs and executives increasing over the period, almost doubling for both measures from the beginning to the end. We observe a different trend for the first-time male CEOs, where the number decreases threefold from the beginning of the period (300 first-time male CEOs) to the end of the period (around 100 first-time male CEOs). This may be explained by higher rates of repeat male CEOs, who are significantly more likely to take on another CEO role after their initial appointment. The male executive pool increases slightly until 2012 and then remains relatively flat, with a slight downward trend.

[Figure 1 about here]

The distribution of first-time CEOs in public firms by state is presented in Figure 2. The largest number of first-time CEOs for both genders is appointed in companies headquartered in California, with 665 male CEOs and 58 female CEOs during our sample period. Texas has the second-largest number of male CEOs (492 total during our sample period), while New York has the second-largest number of female CEOs (34 total during our sample period). For the third-largest state, New York ranks third for male CEOs (362 total), while Texas ranks third for female CEOs (28 total). Among other states with a larger number of CEOs are Florida, Illinois, and Pennsylvania.

[Figure 2 about here]

The distribution of first-time CEOs by industry sector is presented in Figure 3. Some industries exhibit a higher proportion of female CEOs than male CEOs. Publishing has over 30% of first-time CEOs who are women, while General Retailers has over 20% of first-time CEOs who are women. More than 10% of first-time CEOs in the Pharmaceuticals and Biotechnology, Business Services, Clothing and Personal Products, Household Products, and Electricity industries are female. Slightly less than 10% of first-time CEOs in the Health, Leisure and Hotels, Real Estate, Telecommunication Services, Utilities, Insurance, Food Producers and Processors, Chemicals, Media and Entertainment, Food and Drug Retailers, Education, and Leisure Goods industries are women. The largest industries in terms of first-time male CEOs are Banking, Software and Computer Services, Pharmaceuticals and Biotechnology, Health, and Oil and Gas, with over 200 first-time male CEOs in each of these industries during our sample period.

[Figure 3 about here]

The list of all first-time female CEOs, along with the firm names and years of their appointments, is included in Table B1 in Appendix B.

Variables

We define the dependent variable – *First-time CEO* – as an indicator variable equal to 1 if an executive is in the first year of appointment as a first-time CEO in a publicly traded firm in the United States, and zero otherwise. The control group comprises U.S. executives listed in the BoardEx database who have never served as a CEO of a publicly traded U.S. firm.

We utilize 131 predictor variables across various categories, including affiliations, awards, board experience, education, professional experience, and social network. The machine learning setting enables us to engineer additional features by combining variables in groups without

encountering multicollinearity issues, as explained in the methodology section below. Definitions of all variables by category are included in Table A1. The overall categories are defined below.

Affiliations. Based on the Other Activities dataset, we identify individuals' affiliations across academic, art, business, female, foreign, health, humanities, international, law, science, and sports.

Awards. We identify the general award variable if the award is given to an individual. Among the specific types of awards in the Other Activities dataset are academic, business, city, government, humanitarian, law, leadership, media, military, royal, science, sports, women's, and other awards.

Board Experience. We identify individual board experience based on the Board and Director Committees file, including general committee experience and specific committee experience in audit, compensation, governance, nomination, and other committees as a chair or member.

Education. We identify whether an individual has a graduate degree, an honorary degree, or an Ivy League degree, as well as whether she went to a women's college and if she has a CPA, JD, MBA, MD, or Ph.D.

Professional Experience. We bring experience across various industries and firms, as well as diverse employment backgrounds in management, finance, marketing, law, the military, politics, academia, and other fields.

Social Network. Social network measures are widely used in the study of corporate behavior and other areas; they originated in graph theory. Network centrality refers to an individual's position within a social network, with higher centrality indicating more connections and a greater status hierarchy (Freeman, 1978; Burt, 1982). Social connectedness has been shown to play a key role in the appointment of board directors, increasing the likelihood of appointment for candidates who are connected to the CEO or other board members of the focal firms (Fracassi and Tate, 2012; Giannetti and Wang, 2023). While our study design does not readily lend itself to

examining the connection between candidates and the current board, we proxy an individual's social network centrality using four main measures: degree, closeness, betweenness, and eigenvector centrality. These measures can capture interconnectedness and social status in a network.

We calculate the four network measures following El-Khatib, Fogel, Jandik (2015) and Fracassi (2017). *Degree* counts the total number of direct ties an individual has:

$$D_i = \sum_{j \neq i} x_{ij} \tag{1}$$

where D_i is the degree level for individual *i*.x_{ij} is 1 for the presence of a social connection between *i* and *j*. We then normalize it by dividing by the maximum possible degrees in an N-actor network each year (Fracassi, 2017).

Betweenness captures the extent to which a node lies between other nodes and facilitates pass-through communication within the network. This measure is the most effective in capturing an individual's absolute position within the network.

$$B_k = \sum_{i<j \neq k \in N} \frac{g_{ij(k)}/g_{ij}}{\frac{(n-1)(n-2)}{2}} \tag{2}$$

where B_k is the betweenness of individual *k,* g_{ij} denote the total number of shortest paths between individual *i* and *j*; $g_{ij(k)}$ equals 1 if the shortest paths between *i* and *j* also pass-through *k*. We normalize the betweenness value by the number of pairs in each year in the sample, which is calculated as $(n-1)(n-2)/2$ (El-Khatib et al., 2015).

Closeness is the inverse of the sum of the shortest distances between a node and every other node in the network, capturing the degree to which an individual is near all other individuals in the network. A person with high closeness plays a key role in information dissemination.

$$C_i = \frac{n-1}{\sum_{i \neq j \in N} d_{ij}} \times \frac{n}{N} \tag{3}$$

where C_i is the closeness for individual i; d_{ij} denotes the shortest distance between individual i and j, n is the size of the component i belongs to, and N is the size of the yearly network.

Eigenvector measures the relative importance of a node in the network. It takes into account the extent to which an individual is connected with other highly connected individuals. That means that if an individual is connected to others who are well-connected, they have greater influence within their network. E_i is solved by satisfying:

$$\lambda E' E = E' AE \tag{4}$$

where E is an individual's eigenvector. A represents the $n \times n$ matrix where n members are connected. λ is its associated eigenvalue. E_i is taken as the elements of the eigenvector E^* associated with A' principal eigenvalue, λ^*. Wasserman and Faust (1994) provide an extensive explanation of methods and applications of centrality measures.

In addition to calculating raw measures of network centrality described earlier, which we use to reference and compare to prior literature, we create ranking measures that we use in the models to simplify interpretation by ranking where each individual stands among all female executives who have available network measures in terms of percentile distribution, where 1 is the lowest centrality, and 100 is the highest centrality ranking of each measure for each individual (El-Khatib et al., 2015).

Although it is possible to calculate network centrality based on education, current or past employment, and other activities (Fracassi, 2017), we use the combined measure because it is the most comprehensive and has the fewest missing values due to its calculation method. Following Fracassi (2017), we aggregate social ties across all individuals based on employment, education, and other activities, and we create combined network measures. For example, if an individual has ties to other individuals based on at least one of the three dimensions (education, employment, or

other activities), we count it as a tie for each respective measure. If this tie is based on education, we can calculate education centrality; however, we consider the other two dimensions of centrality as missing. On the other hand, if two individuals have ties on all three dimensions, we would still assign the tie a value of 1 (not 3, even though all three dimensions are present) because we are only interested in identifying the presence of a connection between two individuals for our combined measure, not the number of dimensions on which they are connected. Therefore, the combined measure allows for the least number of missing values compared to the network measures based on the individual dimensions of education, employment, or other activities.

We also calculate a network heterogeneity measure, *Female Network*, that quantifies gender network diversity as the proportion of female connections in the individual's network (Fang, Francis, and Hasan, 2018). Finally, we include the total unscaled number of connections, *Total Executive Network*, which, along with the *Female Network*, facilitates easy comparison between female and male executives. Including six different measures of social network allows us to comprehensively capture different aspects of their strategic position in executive networks.

Other. This group of variables includes foreign nationality, mentor, volunteer, and author variables, as well as whether the female is an advisor, founder, treasurer, or trustee of any organization other than private and public companies.

Upper Management Experience. We generate variables for general upper management experience and experience in specific roles, including CFO, COO, CTO, executive VP, and president. Additionally, we account for heterogeneity in upper management experience across industries.

Descriptive Statistics

Descriptive statistics for all variables with the t-test for the means for the CEO and non-CEO samples are included in Table 1. Panel A presents a two-sample t-test with unequal variances for

the female sample's CEO and non-CEO subsamples. There are statistically significant differences across several characteristics. Specifically, among the employment category variables, we observe that female CEOs generally have more diverse employment experiences in terms of employment types and industries, and significantly more CFO, COO, and VP (quoted) roles, as well as experience in management and marketing. Female CEOs have significantly less experience in government, academia, and charity sectors. Among the board experience variables, female CEOs have more board experience in general (they sit on more boards), are more likely to have insider board experience, as well as more experience chairing the boards of quoted (public) companies, more committee experience in general, and specifically more governance, nomination, and audit committee experience. Among the social network variables, female CEOs score significantly higher across all measures of social network, including betweenness, closeness, degree, eigenvector centrality, and female network proportion. About 17 percent of the network of future CEOs consists of other women, compared to 11 percent for female executives who do not become CEOs. Among the education variables, female CEOs are more likely to have bachelor's and MBA degrees and less likely to have JDs and law affiliations or awards than other female executives. Finally, female CEOs tend to have more recognition and get more business, media, and women's awards.

Panel B of Table 1 presents a two-sample t-test with unequal variances for the male CEO and non-CEO subsamples. Male CEOs are more likely to have diverse industry experience, more upper-management experience (including CFO, COO, and VP), and less likely to have CTO or technology experience. Similar to female CEOs, male CEOs are more likely to have president, management, and marketing employment experience, compared to other executives. They are also less likely to have academic affiliations, academic, government, international, or charity employment experience. Similar to female CEOs, male CEOs are more likely to have more board and committee experience in general, as well as specific experience on compensation, nomination, and governance committees and as committee chairs, than their non-CEO counterparts. They are

also more likely to have board experience with publicly traded companies. Among the social network variables, male CEOs score higher in betweenness, closeness, degree, and eigenvector, although their total connections (executive network) tend to be smaller than those of other male executives. Male CEOs are also more likely to have bachelor's and honorary degrees, but less likely to have a graduate degree other than an MBA. Like female CEOs, male CEOs are less likely to hold a JD and to have law affiliations or awards than other executives. Male CEOs are less likely to be authors and to receive awards, including science awards, compared to other male executives. As with female CEOs, male CEOs are more likely to have received a business award. Male CEOs are less likely to have a foreign nationality, foreign affiliation, or experience as a foreign public firm CEO than other male executives.

[Table 1 about here]

While the mix of characteristics for CEOs of both genders is generally similar to that of other executives who do not become CEOs, our next step is to compare the differences between male and female CEOs specifically. Table 2 presents the *t*-test results for the means of all variables for male and female CEOs. Female CEOs exhibit lower heterogeneity in employment, industry, and international experience, are less likely to have military experience, but are more likely to have marketing experience than male CEOs. Female CEOs have slightly less upper management experience and are less likely to have experience as a US private firm CEO than male CEOs. Female CEOs tend to have fewer years of board experience (6.5 years compared to 9.5 years for male CEOs), both insider and outsider board experience, and are less likely to chair the board, but are more likely to have board and trustee experience in other organizations, and serve on committees in general, and governance, compensation, and audit committees specifically. Among the social network measures, female CEO score higher in betweenness, closeness, degree, eigenvector. Female CEOs tend to have more academic and humanities affiliations and awards compared to their male counterparts, and are more likely to have experience in advisory roles for non-public firms and organizations. Female CEOs also have more female affiliations and a larger

proportion of female network (17 percent compared to 11 percent for male CEOs). Female CEOs tend to have higher numbers of academic degrees and more PhD compared to male CEOs. Female CEOs are more likely to receive awards in general, as well as those in business, leadership, science, media, and women's categories.

[Table 2 about here]

V. METHODOLOGY

Overview and Model Descriptions

Machine-learning algorithms enable us to consider numerous features that may or may not be important in determining whether a person becomes a first-time female CEO. Unlike traditional logistic models, machine-learning models can easily handle a large number of predictors and prevent overfitting by implementing cross-validation (Athey and Imbens, 2019). The models in our analysis fall into three groups: linear classification models (logistic regression, lasso, GLM net), nonlinear classification models (KNN), and tree-based models (decision trees, bagged decision trees, random forest, gradient boosting, and XGBoost trees).

Logistic Regression. Logistic regression is a traditional parsimonious method of classification, allowing for the interpretability of the model. However, the logistic specification can suffer from high dimensionality in our setting if we include over 100 predictors for female CEOs. We run a logistic regression with all explanatory variables as a benchmark to compare its performance to other models.

Lasso. Lasso regression is often used for feature selection, as it penalizes variables with low explanatory power by assigning them zero coefficients. Therefore, the lasso allows us to select variables with higher explanatory power and drop variables with low explanatory power, thereby

reducing the dimensionality of parsimonious models, such as logistic regression, as described in the previous section. For tuning parameters, we use alpha equal to 1, so the model is specified as a Lasso.

GLM Net. GLM Net, also known as the elastic net, is a more flexible version of the generalized linear model (GLM). It uses the elastic net to penalize coefficient estimation by shrinking and/or setting coefficients to zero for features that do not significantly contribute to the model. The former technique is often called ridge regression, while the latter is known as lasso regression. GLM Net allows for combining these two techniques by choosing an appropriate tuning parameter, alpha, which ranges from 1 for Lasso regression to 0 for Ridge regression. Model tuning allows optimizing the alpha to maximize the model's ROC. The final model has alpha = 1 and lambda = 0.005, indicating that the optimal specification is closer to Lasso than to Ridge, with alpha close to 1 and lambda fairly low.

Boosted GLM. Boosted GLM is another flexible and powerful function for fitting generalized linear models using a boosting algorithm based on component-wise linear models (Bühlmann and Yu, 2003). Boosting is a general method for improving prediction accuracy by combining multiple simple models into a single composite model.

KNN. K-Nearest Neighbors (KNN) is a nonparametric algorithm that assumes similar features are close together, meaning the output object is based on the points most similar to it. We use generic model tuning for KNN with a tune length of 10, meaning the model is tuned 10 times on each of the 10 folds of cross-validation, using a different number of nearest neighbors to calculate the probability that a woman will become a CEO based on a set of characteristics. We specify ten options for nearest neighbors to train the model, ranging from a minimum of five

nearest neighbors to a maximum of 23, with an interval of 2. The final optimized value used for the model was k=23.

Decision Tree. The decision tree model is the most parsimonious tree-based model and is often used as an exploratory tool due to the ease of interpreting its results through visualization. The decision tree is a greedy algorithm, meaning that it starts the original split randomly and does not revisit it to change it even if more accurate splits become available later in its iterative process. This aspect of the decision tree is primarily responsible for its lackluster performance compared to tree-based ensemble methods, which allow it to combine multiple trees into one model and mitigate the greediness of the algorithm for each individual tree.

Bagged Decision Trees. Bagging is one of the first ensemble models that gained widespread acceptance. Bagging is a bootstrap aggregation technique that generates multiple training sets from the training data and combines these sets into a single learning algorithm. Bagging can be applied in conjunction with various techniques, including decision trees and support vector machines (SVMs). We employ bagging for the decision tree algorithm to enhance the performance of the decision tree model.

Random Forest. The random forest extends the bagging of decision trees by introducing random feature selection. Randomness is conducive to even further diversification of the trees, which the algorithm votes to combine for the final prediction. We employ a weighted-subspace random-forest algorithm that optimizes information gains within subsets of data using a weighting scheme (Zhao, Williams, and Huang, 2017). The tuning parameter for the random forest is the number of randomly selected features. The final model, fitted on the training data, used a tuning parameter that selected two variables at a time for random feature selection.

***Gradient Boosting*.** Gradient boosting is a version of the random forest algorithm. Whereas random forest uses the average of predictions from all trees for the final mode, gradient boosting uses the linear sum of all the trees.

***XGBoost Tree*.** Extreme Gradient Boosting (XGBoost) Trees is a scalable tree boosting system that combines multiple weak decision trees into a strong predictor (Chen and Guestrin, 2016).

Data Split and Preprocessing

We split our sample into training and test data using an approximate 75/25 split of the sample based on the rolling window, with the initial 6-year window categorized as training, followed by a 3-year window categorized as out-of-bag testing and continue rolling throughout our time period from 2001 to 2015; data from 2016-2018 is left out of the training and validation to be used as a test set for the out-of-sample predictions. Although random splitting is common in machine learning, the split can be based on time or other dimensions, depending on the task (Kuhn and Johnson, 2013). For instance, in face-recognition applications for machine learning, the time when the picture is taken probably does not have a significant effect, and the data can be split randomly. In contrast, for studying more time-sensitive phenomena such as stock returns or credit default rates, the data split into training and test sets based on years can be preferable. We follow numerous finance papers that split the data into training and test samples based on time, utilizing the rolling window technique in order to use historical data for training the models and to make predictions based on more recent data used as a test sample (Gu et al., 2020; Erel et al., 2021). As a result of the split, 207,347 observations are in the training set with 263 first-time female CEOs; the remaining 65,665 observations in the test set include 79 first-time female CEOs.

Because our predicted variable (*First-Time CEO*) is highly unbalanced, with 342 CEOs out of 273,091 female executives, we employ a subsampling method called the synthetic minority oversampling technique (SMOTE) during model training to enhance predictive ability. SMOTE is a "de facto" standard for learning from imbalanced data (Fernández, Garcia, Herrera, and Chawla, 2018). SMOTE combines oversampling of the minority class by creating synthetic minority class examples and undersampling of the majority class (Chawla, Bowyer, Hall, and Kegelmeyer, 2002). We incorporate the SMOTE sampling procedure into our train control function, which is performed on each fold of cross-validation on the test data, to minimize data leakage and biases. We do not use SMOTE to predict the final models on the test dataset.

We use a rolling window technique to train the models. The models are trained on a rolling 6-year window of training data, with the following 3 years used to validate model predictions; the last 3 years of data are left out of training and reserved as a test set. This partition results in eight training and validation windows. We use a tuning parameter of 10 for each model, meaning that we employ 10 different specifications of tuning parameters within each training window. We rely on built-in tuning parameters in most models unless otherwise specified when we choose to use a custom tuning grid.

In preprocessing, the variables in the sample are standardized by centering and scaling, except for tree-based models. First, we center the data by subtracting the variable's mean from each value of the variable. Next, we scale the data by dividing the centered value by the standard deviation. As a result, each variable is transformed to have a mean of 0 and a standard deviation of 1. We preprocess the training data in each of the eight training windows to minimize data leakage and bias. Preprocessing the test data is performed when predicting final models (excluding tree-based methods).

Model Evaluation and Performance

We evaluate our models using traditional evaluation metrics for the classification methodology. We use a receiver operating characteristic (ROC) curve to select the optimal model based on the maximum value obtained during training and validation. The ROC curve evaluates each model's class probabilities on a continuum of thresholds of tradeoffs between sensitivity and specificity (Kuhn and Johnson, 2013). For instance, even though we revert to the default classification boundary of 50% in all of our models, the ROC curve evaluates the continuum of classification boundaries (from 0 to 1) and how sensitivity and specificity trade off at each point of the continuum.

Sensitivity is the true positive rate (also referred to as recall), calculated as a ratio of the true positive cases to all positive cases identified by the model. For example, if a model identifies 100 individuals as CEOs, but out of those individuals, only 20 were CEOs in the original data (true CEOs) and the remaining 80 individuals identified by the model were false predictions, the sensitivity rate of the model would be 20 (true positive) over 100 (all positive cases identified by the model) resulting in 0.2 sensitivity rate.

$$Sensitivity = true\ positive/positive$$
$$= true\ postive/(true\ positive + false\ negative) \quad (5)$$

Specificity is the true negative rate calculated as the ratio of true negative cases to all negative cases identified by the model.

$$Specificity = true\ negative/negative$$
$$= true\ negative/(true\ negative + false\ positive) \quad (6)$$

Accuracy measures the model's overall ability to identify true cases across all data.

$$Accuracy = \frac{true\ positive + true\ negative}{true\ positive + false\ positive + true\ negative + false\ negative} \quad (7)$$

Balanced accuracy measures the model's average ability to identify true cases and is calculated as the sum of sensitivity and specificity divided by two.

$$Balanced\ Accuracy = (Sensitivity + Specificity)/2 \quad (8)$$

For example, in highly imbalanced data with a small proportion of positive cases relative to negative cases, the model may have low sensitivity, as it struggles to correctly identify true positives. On the other hand, in such a setting, the model would typically have high specificity, as it would be very accurate at identifying true negative cases, given the numerous observations available for training. Lowering the typical classification threshold from 50% to 30% may improve sensitivity because the threshold for classifying as a positive case is significantly lower. This, however, means that specificity is more likely to suffer, as more negative cases would be identified as false positives. Hence, there is a tradeoff between sensitivity and specificity. The ROC curve summarizes the model's ability to distinguish predicted classes. The area under the ROC curve (AUC) ranges from 1 to 0, with 1 indicating perfect predictive capability and 0 indicating none. The area of 0.5 indicates the model makes predictions as good as random. In addition to the ROC curve, we consider the tradeoff between sensitivity and specificity in classification problems to determine the best model.

We evaluate the performance of our final training models on the resampled data to obtain out-of-bag performance metrics, which assess the final model specifications chosen based on the optimized ROC on the resampled training dataset. A comparison of model performance for all the models is presented in Table 3. We include both out-of-bag performance metrics on the resampled

training data and out-of-sample performance metrics on the test data. Although machine-learning models achieve higher performance on the resampled training data, their performance is typically lower on the test data, which is new data not used for training the models. High performance on the resampled train data also indicates that some models are more prone to overfitting the data where they can achieve perfect AUC on the training sample but overfit the data and cannot achieve the same high performance on the new sample, such as a random forest with the near-perfect AUC of 0.99 on the training data, which decreases to 0.91 for the test data. Comparisons of the models are based on AUC, accuracy, sensitivity, specificity, and balanced accuracy. Random Forest, Gradient Boosting, and XGBoost have the highest test AUC on the out-of-sample (test data) performance for both male and female samples. In combination with the highest performance on other test metrics, such as accuracy, sensitivity, specificity, and balanced accuracy, the random forest is our best-performing model overall for the female sample, while the Boosted GLM is the best-performing model for the male sample.

[Table 3 about here]

Variable Importance Ranking

Because machine-learning models lack variable coefficients like traditional econometric models, they are often opaque and are called "black boxes." One of the most intuitive ways to gain insight into how machine-learning models arrive at their conclusions is to examine the variable-importance metrics. Variable-importance ranking is computed and validated on the training data. The importance of each feature is calculated based on its model specification, and the score is automatically scaled between 0 and 100. For example, for a linear model, the absolute value of the

t-statistic for each model parameter is used to rank the variable importance. A higher score indicates that a variable has greater importance in model prediction.

We group the most important variables into broader categories related to characteristics and present the variable importance using these categories: social network, upper management experience, professional experience, board experience, education, other experience, affiliation, and award, for each model in Figure 4. We also use the top 20 most important variables identified by the best-performing model as a feature selection and include only those top-ranked features in logistic models as a robustness check.

[Figure 4 about here]

SHAP (SHapley Additive exPlanations) Values

SHAP values present another opportunity for the interpretability of machine-learning algorithms. SHAP values come from the Shapley values, which are based on the theory of cooperative games developed by Nobel Laureate Lloyd S. Shapley in the 1950s.[8] Lundberg and Lee (2017) apply SHAP values in the context of machine learning by developing a framework to assess the strength and direction of the contribution of predictor variables in machine-learning algorithms. Because most machine-learning algorithms are black-box models with no coefficients assigned to the most important variables, we employ a novel SHAP interpretation method to identify the direction of the predictors' impact on the likelihood of female executives becoming CEOs. Figure 5 presents the directional effect of the top 20 predictors, based on SHAP values, using our best-performing

[8] Lloyd S. Shapley was awarded Nobel Prize in economic sciences in 2012, along with Alan E. Roth, for work in matching game theory (Shapley, 1953; Roth, 2016).

model (random forest). Although SHAP values do not claim causality, they provide an intuitive understanding of each variable's marginal contribution to predicting CEO selection.

[Figure 5 about here]

VI. MACHINE LEARNING RESULTS

To investigate the importance of various characteristics for both samples, we incorporate two techniques – grouping and individual variable importance. First, we aggregate all variables into eight general groups where, for example, the social network group comprises six social network-related variables included in the machine learning models. A few groups of characteristics matter most, based on the variable importance ranking among specific models, as presented in Figure 4, allowing us to summarize the variable importance scores for the individual variables within a group. In fact, all four of the top categories of variables for both gender subsamples are identical and include social network, upper management and board experience, and professional experience, respectively.

To assess the direction of the features' individual impact (positive or negative), we rely on the SHAP values in Figure 5. Although we find that group variables of social network, upper management experience, and board and professional experience most influence the likelihood of an executive becoming a CEO, the ranking of the individual variables in terms of importance differs based on the gender of the first-time CEO. Specifically, strategic positioning in social networks, heterogeneous professional experience, and upper management experience are positively associated with becoming a first-time female CEO in a publicly traded company. On the other hand, for first-time male CEOs, experience plays a much larger role than social network, as indicated by the variable importance as measured by SHAP values in Figure 5.

Social Network

The social network is the most influential group of characteristics for all tree-based models (including our best model, the random forest), as presented in Figure 4. Confirming the intuition and findings of the prior studies of the importance of connections for both female and male executives (Giannetti and Wang, 2023), Figure 4 shows that, as a group, the social network is a dominant category if we add the variable importance of all six social network variables to combine in a social network group. The models include six measures of a social network: degree, betweenness, closeness, eigenvector, total connections, and the proportion of women in the network.

All six social network measures are among the 20 most important determinants of female success in becoming a first-time CEO in our best-performing model, the random forest. As shown in Figure 5A, all six social network measures are positively associated with female CEO selection. This suggests that, for aspiring female executives, it is most beneficial to be a gatekeeper in a social network with pass-through communication (measured by betweenness), which provides quick access to information and powerful backers to aid career progression. In addition, having extensive social ties (measured by degree and total connections), as well as obtaining the most efficient information in the social network (measured by closeness), are among the most important predictive factors. The proportion of female connections in the network is also positively associated with becoming a CEO. Finally, it is also important to be connected with other highly connected individuals in the network (as measured by eigenvector).

For male CEOs, social network variables are not among the top 10 most important features as shown in Figure 5B. Social network (Closeness) is the only social network variable to appear among the top 20 and ranks 13th among the 20 most important variables, with a predictable

positive influence on the likelihood of a male executive becoming a CEO. To reconcile this finding with higher positive effect of connections for male candidates in becoming appointed to the board (Giannetti and Wang, 2023), it is important to note the differences in the way connections are measured. In our analysis, we use 6 measures of social network that are not specific to the particular company for which the CEO candidates are considered. In contrast, connections in Giannetti and Wang (2023) refer to prior connections between newly appointed directors and the board. Thus, we employ a broader definition of social networks and connectedness, encompassing the entire population of executives, rather than focusing on connections to board members of specific companies. This broader set of measures aligns better with our study setup, as we are examining executive selection questions from the individual's perspective, rather than the firm's, unlike most studies in this literature. The primary benefit of this approach is that it enables us to focus on the individual characteristics of executives and assess their importance in determining the likelihood of being selected as a CEO among all other candidates, taking into account their unique characteristics. Since we strive to make this study generalizable from the individual candidate's perspective, we plan to examine this question from the firm's perspective in a follow-up, separate study.

Upper Management Experience

Upper management experience is the second most important group of variables. In particular, heterogeneity and years of experience in upper management are the top two most influential predictors for female CEOs. Upper management heterogeneity is the number of different upper management positions multiplied by the corresponding years, which measures the diversity of upper management experience. As the SHAP values indicate, both the years of upper management

experience and the heterogeneity of experience are positively associated with the likelihood of becoming a CEO for the female sample, suggesting that breadth and depth (measured by years) of upper management experience are important.

Upper management employment experience and its heterogeneity are also in the top 20 predictors for the male model, albeit ranked much lower at 15th and 17th place, respectively. Again, we observe a positive association of upper management predictors with the likelihood of becoming a CEO, which holds for the male sample.

Board Experience

Board experience is the third most important predictor of the likelihood of becoming a CEO. Specifically, the number of years of board experience and the heterogeneity of board experience are among the top 10 most important variables and have positive predictive power in the female CEO prediction model. Serving as an insider board member for a number of years is also associated with a higher likelihood of becoming a female CEO, which is consistent with the finding that the majority of CEOs in public firms are insiders in general, which is a characteristic even more predominant among female CEOs (Cziraki and Jenter, 2021; Dillard and Lipschitz, 2014). Additionally, when examining only first-time female CEOs, board experience serves as a substitute for prior CEO experience in board hiring decisions (Tinsley and Purmal, 2019).

Board experience variables are not among the top 20 most important predictors for male CEOs. This result suggests that board experience may play a less important role as a substitute for prior CEO experience among first-time male CEOs.

Professional Experience

Professional experience is another influential group of variables. We find that the number of years of experience in both public and private firms is positively associated with the selection of female CEOs. Years of experience in public firms rank higher than years of work experience in private firms. This may be because exposure to public firms gives female executives greater familiarity with organizational frameworks and practices, ultimately improving their chances of selection for top roles. Employment experience heterogeneity, which is the number of different positions multiplied by the corresponding years of experience, is positively related to the selection of female CEOs.

For the male sample, public and private firm experience, measured by the number of firms, is the number one predictor of becoming a CEO. Given that upper management experience is ranked much lower than overall experience across different firms, it can be inferred that the quantity rather than the quality of the roles is more important for first-time male CEO candidates.

Experience in financial roles negatively affects the likelihood of becoming a CEO, in line with existing anecdotal evidence that suggests women may be better off avoiding business support roles if they want to increase their chances of becoming a CEO (Spencer et al., 2019). Another explanation for the negative relationship between finance experience and CEO title may be inferred from prior findings that female financial executives do not experience pay gaps and can even earn more than men in those roles (Francis, Hasan, Hovakimian, and Sharma, 2023). Finance experience, in general, and CFO experience, in particular, are also negatively related to the likelihood of becoming a CEO among male candidates.

International Employment Experience

Somewhat surprisingly, given the increasingly global nature of the business, overall international experience has a negative impact on female CEO selection, which may be due to the negative social network effects of being geographically separated from the primary executive network in the United States. This suggests that aspiring female executives should gain experience in various upper management positions rather than expanding into different countries.

Similarly, more granular variables related to international experience are negatively associated with the likelihood of becoming a CEO among male candidates. Specifically, Canadian employment experience is among the top 5 most important variables for the male sample, albeit in a negative direction for prediction, decreasing the likelihood of becoming a CEO. European and Asian employment experience is also among the top 20 variables, with a negative impact. However, the number of continents of employment overall has significant positive predictive power and ranks as the top 3 variable for the male CEO model, suggesting a potentially more nuanced role of global exposure for emerging leaders.

Education

The number of educational degrees is positively associated with the likelihood of becoming a CEO among male candidates, ranking 6th. However, specific degrees, such as bachelor's or master's, have a negative association separately. Perhaps engaging in different educational levels, such as executive degrees and certificates, helps male executives diversify their toolkits and better position them for CEO roles.

Advanced education (as measured by the attainment of master’s and other graduate degrees) is negatively associated with the likelihood of becoming a CEO in both samples.

Combined with the high positive predictive power of professional experience, it may be the case that joining the workforce and gaining experience creates better opportunities than investing time in an advanced degree.

Other Determinants

Although social networks, upper management experience, board, and professional experience dominate the top twenty predictors of female CEO selection, and other broader characteristics have relatively less predictive power, there are still some interesting findings. Academic affiliation also has negative predictive power, similarly indicating that work experience is more valuable than academic pursuits for female professionals interested in a CEO title. Second, although affiliation and award groups are somewhat more important in the categorical sense than education for the female sample, as shown in Figure 4, their variables are not among the top 20 most important predictors.

Similarly, none of the affiliation and award variables are among the top 20 for male CEOs.

CEO Selection Criteria by Gender Across Industries

To gain deeper insight into gender-specific determinants of first-time CEO appointments across industries, we rerun our best-performing machine learning models separately by gender – random forest for the female sample and boosted GLM for the male sample – within the five industries with the highest number of first-time CEO appointments: Software & Computer Services, Pharmaceuticals and Biotechnology, Banks, Health, and Business Services. We present the most important predictor ranking by industry for both samples in Figure 6.

[Figure 6 about here]

This industry-level analysis ensures that sufficient observations are included, and consistent target outcomes are achieved. For each industry, we extract the top 10 SHAP-valued predictors and compare them side-by-side across genders. The resulting patterns are remarkably consistent with those identified in the full sample: social network factors and upper management experience remain the most influential predictors for female CEOs, whereas professional experience dominates for their male counterparts.

For instance, in the Software and Computer Services sector, five of the six social network variables rank among the top ten predictors for female CEO selection, including degree centrality, total connections, betweenness, and closeness – highlighting the value of strategic positioning and gender-diverse networks. In contrast, male CEO predictors are centered on professional experience heterogeneity and breadth across firm types and industries. While closeness appears among the top predictors for both genders, other social network measures carry significantly more weight in the female models. These consistent patterns reinforce our broader finding that male and female executives face systematically different criteria in the CEO selection process.

VII. TRADITIONAL METHODS RESULTS

Univariate Analyses

We begin by comparing all 131 predictors for female and male CEOs, presenting the univariate analyses in Table 2. Based on the univariate analysis comparing the characteristics of first-time female and male CEOs, we observe that female CEOs are more likely to have affiliations and awards (including academic, scientific, and humanities awards), experience advising non-profit organizations, and receive awards (including business, leadership, and media awards). Female CEOs have a stronger social network (as measured by betweenness, closeness, degree, and

eigenvector), as well as a higher proportion of female network, with 17% of the network comprising female connections for female CEOs compared to 11% for male CEOs.

On the other hand, female CEOs are less likely to have board experience in public and large private corporations; however, they seem to compensate for this by having board and trustee experience in other types of organizations, such as nonprofits. For specific types of committees, female executives who become CEOs are more likely to be on compensation, governance, and audit committees, as well as on committees of non-profit organizations.

In terms of professional experience, female CEOs are less likely than male CEOs to have COO experience and heterogeneity in employment experience, both in terms of the number of industries and international experience. Female CEOs are more likely to have experience in law and marketing. Additionally, female CEOs typically have 23 years of professional experience by the time they are appointed to their first CEO role, compared to 37 years for first-time male CEOs. This, to some extent, may explain the differences in lower upper management experience (including serving as a CEO of a foreign or private company) among female CEOs compared to male CEOs.

Univariate Analyses of Most Important Variables

Next, we examine the top 20 most significant predictors of CEO selection by gender and present the univariate analyses for those in Panels A and B of Table 4. Some of the main differences discovered in the general univariate analysis are pronounced across the top 20 predictors. The most important predictors for female CEOs, comprising all six social network variables (betweenness, degree, female connections, closeness, total executive network connections, and eigenvector), are much higher for female CEOs compared to male CEOs, with statistically significant differences.

As noted previously, board experience, including insider experience, as well as international employment and employment heterogeneity, is lower for female CEOs. Thus, we can infer that female candidates should have a significantly larger social network compared to male candidates in order to secure a CEO position. On the other hand, board experience for female CEOs, while still higher than that of other female candidates, tends to be lower than that of male CEOs-elect.

On the other hand, univariate results for the top 20 predictors from the male model, as presented in Panel B of Table 4, mostly yield non-statistically significant differences compared to female CEOs, suggesting that, in terms of the qualities male CEO candidates are evaluated on, female CEOs perform mostly on par. The most significant differences among the top 20 are related to professional experience with higher employment heterogeneity, upper management experience, and years of professional experience for male CEOs, although a larger number of public firms' experience for female CEOs before being selected.

[Table 4 about here]

Logistic Models

We apply traditional logistic regressions to assess how much variation in first-time CEO appointments can be explained by the top 20 variables identified by machine learning models for both male and female samples. The results are included in Table 5. Logistic models for female CEOs explain more variation in the dependent variable based on the 20 most important variables, accounting for approximately 10 percent of the total variation, whereas logistic regressions for male CEOs explain around 9 percent of the total variation. It is worth noting that one of the 20 most important features in the logistic model was dropped due to collinearity issues in both the female and male samples. This is one of the main distinguishing features of machine learning: it can effectively handle multicollinearity, whereas traditional models cannot. While most of the

direction and magnitude of the explanatory coefficients are consistent with SHAP values, some inconsistencies arise due to potential collinearity among the included variables.

Machine learning models can handle multicollinearity among numerous features, whereas logistic regression is prone to collinearity issues. Still, the results are mostly consistent, with the coefficients for social network variables being positive and statistically significant across logistic regressions for both female and male CEOs. While upper management experience heterogeneity retained its positive and statistically significant relation to the outcome variable of becoming a CEO in the female model, it is not significant for the male model without year fixed effects. Finance employment is negative for the female sample (consistent with SHAP) but positive for the male sample (inconsistent with SHAP), although CFO experience remained negative for the male sample (consistent with SHAP). Multicollinearity issues may also have contributed to a negative and statistically significant correlation between board experience (in years) and total executive network, whereas the combined experience of public and private firms (in the sample) is positive and statistically significant in the male sample.

Overall, our main machine learning predictions remain mostly consistent across univariate and traditional (logistic) model settings. Social networks are the most important predictor for first-time female CEOs and are even more important for aspiring female executives than for their male counterparts, for whom upper management experience is the strongest predictor. This can be explained at least in part by the lack of female representation, which is similar to the rates of male executives on boards and in upper management positions. Thus, social networks may serve as a substitute for the deficiency of board and management experience for women.

[Table 5 about here]

VIII. ADDITIONAL TESTS

Conditional Average Treatment Effect (CATE)

For our main analysis, we trained a set of 10 models separately on both subsamples based on gender. We also implemented a novel approach that allows us to train the machine learning model on a combined sample and use gender as a treatment variable, thereby estimating the conditional average treatment effect (CATE)[9]. This allows us to directly compare the selection probabilities and the significance of the defining characteristics between female and male candidates. We begin by comparing the CATE distribution of individual-level treatment effects across CEO candidates, stratified by gender, and present the aggregate effects of treatment in the combined sample in Figure 8. The treatment effect is equal to one if the candidate is female, and zero otherwise. The distribution shows negative mean and median values, which suggests that firms are less likely to select a female CEO than a male CEO candidate. About 24% of the CATE distribution for the treatment group (female CEO candidates) is above zero, meaning that only 24% of the firms are more likely to select a female CEO candidate.

[Figure 7 about here]

We next plot the feature importance for the top twenty variables driving heterogeneity of the outcome of becoming a CEO by gender treatment. Confirming our main result, Figure 8 presents the most important variables identified by the subsample models in the main analysis, which are also highlighted. Specifically, among the most important variables are upper management experience, board experience, social network variables (including degree, total number of connections, betweenness, female network, and closeness), and other measures of

[9] For details on the CATE methodology based on attribute-value groups, see Kallus (2023), Semenova and Chernozhukov (2021), Jacob (2021), and other related studies.

professional experience, including employment and industry heterogeneity, number and types of firms (public, private), and COO experience. The latter was not present in the subsample analyses.

[Figure 8 about here]

Next, we illustrate the magnitude of the effect of the top ten most important variables, based on gender treatment, in Figure 9. Most social network variables (including degree, betweenness, closeness, and eigenvector) exhibit far larger magnitudes for the female sample, whereas the total network is larger in magnitude of variable importance for male candidates. The proportion of females is relatively similar across both genders, albeit slightly larger in the male subsample. Years of employment experience, its heterogeneity (including industry and international heterogeneity), and the number of firms are slightly more important for the treated (female) subsample. Board experience measured in years is of about the same importance, although the number of boards and board heterogeneity are more important for female candidates.

[Figure 9 about here]

Finally, the CATE model allows us to estimate changes in the number of selected candidates from both pools using a gender-neutral approach. This analysis can be conducted only on the test subset of data since we need the trained model to estimate the test numbers. Compared to the 57 female CEOs predicted by the treated approach, the CATE model, which estimates counterfactual selection probabilities assuming gender neutrality, estimates that this number will be 92, an increase of over 160%. The number of selected male CEO candidates remained unchanged at 884 in the test sample when using this gender-neutral selection approach. These results are presented in Figure 10.

[Figure 10 about here]

Cross-Model Fit

We conduct a counterfactual analysis by cross-fitting models: the female sample is used to fit the final male prediction model, and vice versa. In this setup, it is essential to note that the qualifications predicted by our models differ for male and female candidates, as demonstrated by the analysis above. Thus, we are not comparing the same qualification requirements for both pools. Rather, we approximate how well male executives would perform wearing female shoes and vice versa. Our findings suggest that if men and women can switch genders while maintaining the same inherent qualifications, more women would be appointed to CEO positions, while only a fraction of male CEOs would be selected for the role.

In Table 6, Panel A, we compare the predicted observations identified by cross-models (female model for male sample, male model for female sample) with the actual number of CEOs. We find that the male model identifies 71% of the true female CEOs as CEOs, while only 30% of the actual male CEOs are identified by fitting the female model. The male model predicts higher rates of female CEOs compared to the female model prediction rates on the male sample.

Alternatively, we also estimate adjusted prediction models on the cross-samples in Table 6 Panel B. By comparing actual and predicted labels for CEOs and non-CEOs, our models identify a pool of candidates among all executives who meet the criteria of becoming CEO (based on a common set of characteristics shared by appointed CEOs) with about 1% of this highly qualified pool becoming CEOs for male sample and 2% for female sample. We then fit the female sample for the male CEO model to find out how many female executives would be in the highly qualified pool according to the male standards and, based on the 2% success rate for the highly qualified pool, how many females would have become CEOs if selected based on the male criteria (model). We find that based on the male qualifications, 526 female executives from our sample would have

become CEOs – compared to 342 actual female CEOs. This finding suggests that the number of female CEOs would be about 50 percent solely based on the qualifications that male CEOs were appointed on. Conversely, we fit the male sample to the female model and find that, if selected based on the characteristics required for female candidates, the male CEO pool would have consisted of 1,389 total CEOs, compared to the actual 4,457 male CEOs in our sample. These numbers suggest that only 31% of actual male CEOs would meet the qualification bar required for female CEO candidates. Additionally, in Table 6, Panels C and D, we present the breakdown of cross-model predicted rates by industry for female and male CEO samples, respectively.

Finally, we compared the cross-fit prediction rate across industries. In Table 6, Panel C, we examine the prediction rates when fitting a male model to the female sample and observe an overall high prediction accuracy, indicating that male predictive models can be applied to predict female CEOs. If we fit male CEO criteria, it is very likely that female executives will be well qualified based on the set of predictors. On the other hand, when we conduct a similar exercise with a fit female model on the male sample in Table 6 Panel D, the prediction rates across all industries are significantly lower. Only 2 industries – Tobacco and Whole Trade – have a 50 percent higher prediction accuracy rate. This suggests that the skills required of female CEOs may not be well matched to those in the male CEO pool.

Overall, our results in Table 6 suggest that, given male model standards, more women would become CEOs, whereas, given female model standards, fewer male executives would become CEOs. This finding suggests that stricter standards are applied to female CEOs than to male CEOs.

[Table 6 about here]

Placebo Social Network

Given that the social network is the strongest predictor of female CEO selection, we conduct a placebo test by replacing the statistically significant social network measures for both CEO and non-CEO executives with the average value for the other group. Since the four composite measures of social network (betweenness, closeness, degree, eigenvector) and the female network proportion are much lower for the non-CEO group, and these differences are statistically significant, we expect these placebo changes to affect the number of predicted CEOs for both groups. Indeed, with lower social networks, much fewer (less than half) actual CEOs are predicted to become CEOs, and over 50% more non-CEO executives are predicted to become CEOs. These results confirm our main finding that social networks play an important role in the probability that a female executive becomes a CEO, even when all other characteristics remain unchanged. The detailed results of the placebo analysis are presented in Table 7.

[Table 7 about here]

Temporal Differences in Female CEO Predictors

Given that our sample includes almost 20 years of data, we also examine potential changes in the predictors of female CEOs over this period. Specifically, we split our sample into pre- and post-financial crisis sub-samples and determined predictors for both. The Great Recession has been recognized as a significant turning point for banking, corporate finance, and governance, including increased attention to corporate social responsibility. In addition, debates in the existing literature diverge on whether there are differences in CEO selection and objectives before and after the crisis. One stream of literature argues that demand for social skills for executive selection has increased (Deming, 2017; Hansen, Sadun, Ramdas, and Fuller, 2021) while another group of scholars

suggests that not much has changed fundamentally in terms of characteristics of successful leaders (Pfeffer, 2015 and 2022; Decressin et al., 2025).

Our comprehensive dataset allows us to quantitatively assess this question by comparing the most important predictors from splitting the sample and training machine learning models on both pre- and post-2008 periods. The most important predictors of female CEOs in the split samples share some similarities – the number of firms and employment heterogeneity remain among the top ten predictors in both models. However, the number of education degrees and social network features became among the top ten predictors in the post-crisis period, suggesting an increase in the importance of less tangible characteristics of a new wave of female leaders. In addition, during the post-crisis period, the number of continents of employment and committee chair experience are added to the top twenty predictors, signaling better career prospects for female candidates with international and leadership experience. The top twenty most important predictors for the two sub-periods are presented in Figure 11.

[Figure 11 about here]

IX. SUMMARY AND DISCUSSION

This is the first paper to consider a comprehensive set of characteristics of female executives and to identify the most important factors in becoming a first-time CEO. We contribute to the literature on leadership and gender by building on the extensive population-level analysis by Adams et al. (2018) in the Swedish setting. Here, we extend this line of research to the entire population of female and male executives in the US and identify what distinguishes those who become CEOs from the broader executive population. By constructing a comprehensive dataset of first-time CEOs and their peers who did not reach the top of the corporate ladder between 2001 and 2018,

we use machine-learning techniques to uncover patterns in the data and build predictive models to identify the most important factors for becoming a CEO. We contribute to the existing literature on CEO selection, which is mainly based on the anecdotal and interview-based characteristics of CEOs, by providing data-driven evidence of why some women are better suited to compete with their peers and become CEOs.

These findings are consistent with some traits identified in the prior literature. Specifically, anecdotal evidence suggests negligible effects of prestigious schools or MBA degrees, and lack of defined career path such as through banking or consulting experience, that can lead to eventual CEO appointments. Instead, CEO interviews suggest that female executives tend to spend a long time at a single company and eventually become the CEO or make a lateral move and become a CEO elsewhere (Dillard and Lipschitz, 2014). Moreover, we find the support for recommendations developed by the Rockefeller Foundation and Korn Ferry on a CEO Pipeline Project where gaining operational and sales experience early in the career, as well as exposure to governance and boards, finance, and external constituents, along with building professional networks, were identified as worthy goals for aspiring executives (Spencer, Blazek, and Orr, 2019).

Overall, our findings suggest that the most important success factors for becoming a first-time female CEO are social network, upper management experience, and board and other professional experience. Advanced education, awards, affiliations, and other activities have adverse or negligible effects. Therefore, aspiring females may benefit from cultivating strong social networks and diverse professional experience to advance their careers and meet the demands and expectations of being a corporation's CEO.

For first-time male CEOs, the diversity of experience, as measured by the total number of firms (both public and private), plays the most important role in the CEO selection process. This

is followed by the number of continents where the candidates were previously employed, the number of educational degrees, and the types of employment experience, which are the most important predictors. Finally, social network (closeness), upper management experience, and its heterogeneity also have a positive impact and are still among the top 20 predictors, albeit with a much smaller magnitude. There is observed skewness in the most influential variables toward qualitative factors, such as the number of firms and heterogeneity of employment experience, rather than towards quantitative factors, such as the quality of those experiences (upper management, social networking), among male CEOs.

Some of the determinants for male and female CEOs have similarities, although the ranking of top predictors suggests that inspiring female CEOs have to place a much higher emphasis on their social network cultivation, while the top predictors for male CEOs are dominated by professional experience with the social networks having a much lesser role with only one out of top 20 predictors capturing social network relation. Professional experience is the top predictor for male candidates, whereas the importance of social networks is higher for female candidates, who comprise two out of the top five predictors for female CEOs, along with upper management and board experiences. This may suggest that women need to emphasize developing professional social networks more than men do, for whom only one social network measure is among the top 20 predictors, and even then, it is ranked 13th.

Acknowledging the importance of existing qualitative research on this topic, we believe our study provides a more comprehensive picture of the important factors in career progression. We carefully studied a population of executives in the United States over almost two decades, employing advanced machine-learning algorithms to examine over 100 potential determinants of leadership success. Our research highlights the importance of social networks as the primary

predictor of female CEO appointments. Our study confirms the importance of prioritizing professional experience, implying that building extensive expertise improves the likelihood of becoming a CEO. We find that upper management experience matters, suggesting that women who are comfortable in managerial roles also gain valuable leadership skills and expertise in self-promotion, thereby increasing their likelihood of becoming a CEO. Regarding the male sample, we find that heterogeneity of experience is most important, followed by heterogeneity of education (in terms of the number of degrees), and, to a lesser extent, the quality of those degrees. While upper management experience remains among the top 20 predictors for male CEOs, it is significantly less prevalent than for the female sample.

We also enhanced our machine learning approach by introducing a novel conditional treatment effect (CATE) model that directly compares the likelihood of an executive candidate being selected as a CEO, conditioning on gender as the treatment. This approach enables us to identify the characteristics that drive the probability of selection as a CEO, by gender, and the comparative magnitude of the most important characteristics for female and male executives. It also allows us to estimate the number of selected candidates using a gender-neutral approach, where we found that, while the number of male CEO selected using a gender-neutral approach remained the same, the number of selected female CEOs increased by over 160%.

These results advance our understanding of the determinants of career progression to high leadership roles among CEOs and can serve as a guide for aspiring professionals and corporate decision-makers. We identified differences in the predictors across genders: the social network was the top predictor for female CEOs, and professional experience was the top predictor for male CEOs. This suggests that female candidates, in addition to having stellar experience, must cultivate a robust social network to be appointed CEO, whereas for male candidates, quantitative measures

of experience matter more than qualitative measures such as upper management experience and social networks. In this paper, we contribute to the study of leadership and corporate governance by utilizing machine learning techniques to provide data-driven insights on the CEO selection process through the lens of gender.

REFERENCES

Adams, R. B., Barber, B. M. and Odean, T. (2023). The math gender gap and women's career outcomes. *The Journal of Investment Management, 21*(2).

Adams, R. B. and Ferreira, D. (2009). Women in the boardroom and their impact on governance and performance. *Journal of Financial Economics*, *94*(2), 291-309.

Adams, R. B. and Funk, P. (2012). Beyond the glass ceiling: Does gender matter? *Management Science, 58*(2), 219-235.

Adams, R., Keloharju, M. and Knüpfer, S. (2018). Are CEOs born leaders? Lessons from traits of a million individuals. *Journal of Financial Economics, 130*(2), 392-408.

Adams, R. B. and Kirchmaier, T. (2016a). Women in Finance. *SWIFT Institute, European Corporate Governance Institute (ECGI).*

Adams, R. B. and Kirchmaier, T. (2016b). Women on boards in finance and STEM industries. *American Economic Review*, *106*(5), 277-81.

Abernethy, M. A., Kuang, Y. F. and Qin, B. (2019). The relation between strategy, CEO selection, and firm performance. *Contemporary Accounting Research, 36*(3), 1575-1606.

Athey, S. and Imbens, G. W. (2019). Machine learning methods that economists should know about. *Annual Review of Economics, 11*, 685-725.

Altrata. (2024). *Global Gender Diversity Report*. https://boardex.com/reports/global-gender-diversity-2024

Bernile, G., Bhagwat, V. and Rau, P. R. (2017). What doesn't kill you will only make you more risk-loving: Early-life disasters and CEO behavior. *The Journal of Finance, 72*(1), 167-206.

Bertrand, M. (2020, May). Gender in the twenty-first century. *AEA Papers and Proceedings*, *110*, 1-24.

Bertrand, M. and Schoar, A. (2003). Managing with style: The effect of managers on firm policies. *The Quarterly Journal of Economics*, *118*(4), 1169-1208.

Besley, T. and Case, A. (2003). Political institutions and policy choices: Evidence from the United States. *Journal of Economic Literature, 41*(1), 7-73.

Besley, T. and Reynal-Querol, M. (2011). Do democracies select more educated leaders? *American Political Science Review*, 552-566.

Besley, T., Montalvo, J. G. and Reynal-Querol, M. (2011). Do educated leaders matter? *The Economic Journal, 121*(554), F205-227.

Bianchi, D., Büchner, M. and Tamoni, A. (2021). Bond risk premiums with machine learning. *The Review of Financial Studies, 34*(2), 1046-1089.

Boulouta, I. (2013). Hidden connections: The link between board gender diversity and corporate social performance. *Journal of Business Ethics, 113*(2), 185-197.

Bühlmann, P. and Yu, B. (2003). Boosting with the L 2 loss: regression and classification. *Journal of the American Statistical Association, 98*(462), 324-339.

Burt, R.S. (1982). *Toward a Structural Theory of Action: Network Models of Social Structure, Perception and Action.* Academic Press.

Buser, T., Niederle, M. and Oosterbeek, H. (2014). Gender, competitiveness, and career choices. *The Quarterly Journal of Economics*, *129*(3), 1409-1447.

Chattopadhyay, R. and Duflo, E. (2004). Women as policy makers: Evidence from a randomized policy experiment in India. *Econometrica, 72*(5), 1409-1443.

Chawla, N. V., Bowyer, K. W., Hall, L. O. and Kegelmeyer, W. P. (2002). SMOTE: synthetic minority oversampling technique. *Journal of Artificial Intelligence Research, 16,* 321-357.

Chen, H., De, P., Hu, Y. J. and Hwang, B. H. (2014). Wisdom of crowds: The value of stock opinions transmitted through social media. *The Review of Financial Studies, 27*(5), 1367-1403.

Chen, T. and Guestrin, C. (2016). Xgboost: A scalable tree boosting system. In *Proceedings of the 22nd ACM Sigkdd International Conference on Knowledge Discovery and Data Mining* (785-794).

Clots-Figueras, I. (2011). Women in politics: Evidence from the Indian States. *Journal of Public Economics, 95*(7-8), 664-690.

Cohen, L., Malloy, C. and Nguyen, Q. (2020). Lazy prices. *The Journal of Finance, 75*(3), 1371-1415.

Cook, A. and Glass, C. (2014). Above the glass ceiling: When are women and racial/ethnic minorities promoted to CEO? *Strategic Management Journal*, *35*(7), 1080-1089.

Cooper, M. (2021). Research: Women leaders took on even more invisible work during the pandemic. *Harvard Business Review Digital Articles*, 1–5.

Cziraki, P. and Jenter, D. (2021). The Market for CEOs. *Available at SSRN 3886752*.

Decressin, Y., Kaplan, S. N. and Sorensen, M. (2025). Have CEOs Changed? *Journal of Financial Economics, 173*, 104169.

Deming, D. J. (2017). The growing importance of social skills in the labor market. *The Quarterly Journal of Economics, 132*(4), 1593-1640.

Dezsö, C. L. and Ross, D. G. (2012). Does female representation in top management improve firm performance? A panel data investigation. *Strategic Management Journal, 33*(9), 1072-1089.

Dillard, S. and Lipschitz, V. (2014). How female CEOs actually get to the top. *Harvard Business Review.*

Duchin, R., Simutin, M. and Sosyura, D. (2021). The origins and real effects of the gender gap: Evidence from CEOs' formative years. *The Review of Financial Studies, 34*(2), 700-762.

Dwivedi, R., Dave, D., Naik, H., Singhal, S., Omer, R., Patel, P., Qian, B., Wen, Z., Shah, T., Morgan, G. and Ranjan, R. (2023). Explainable AI (XAI): Core ideas, techniques, and solutions. *ACM Computing Surveys, 55*(9), 1-33.

Eagly, A. H. and Carli, L. L. (2003). The female leadership advantage: An evaluation of the evidence. *The Leadership Quarterly, 14*(6), 807-834.

Eagly, A. H. and Karau, S. J. (2002). Role congruity theory of prejudice toward female leaders. *Psychological Review*, *109*(3), 573.

El-Khatib, R., Fogel, K. and Jandik, T. (2015). CEO network centrality and merger performance. *Journal of Financial Economics*, *116*(2), 349-382.

Elting, L. (2023, January 27). New Year, New Glass Heights: Women Now Comprise 10% Of Top U.S. Corporation CEOs. *Forbes*. https://www.forbes.com/sites/lizelting/2023/01/27/new-year-new-glass-heights-for-the-first-time-in-history-over-10-of-fortune-500-ceos-are-women/?sh=4c051eb8e77f

Erel, I., Stern, L., Tan, C. and Weisbach, M. S. (2018). Could machine learning help companies select better board directors? *Harvard Business Review.*

Erel, I., Stern, L. H., Tan, C. and Weisbach, M. S. (2021). Selecting directors using machine learning. *Review of Financial Studies, 34*(7), 3226-3264.

Faccio, M., Marchica, M. T. and Mura, R. (2016). CEO gender, corporate risk-taking, and the efficiency of capital allocation. *Journal of Corporate Finance*, *39*, 193-209.

Fang, Y., Francis, B. and Hasan, I. (2018). Differences make a difference: Diversity in social learning and value creation. *Journal of Corporate Finance, 48*, 474-491.

Fernández, A., Garcia, S., Herrera, F. and Chawla, N. V. (2018). SMOTE for learning from imbalanced data: progress and challenges, marking the 15-year anniversary. *Journal of Artificial Intelligence Research, 61*, 863-905.

Ferreira, F. and Gyourko, J. (2014). Does gender matter for political leadership? The case of U.S. mayors. *Journal of Public Economics, 112*, 24-39.

Fracassi, C. (2017). Corporate finance policies and social networks. *Management Science*, *63*(8), 2420-2438.

Fracassi, C., and Tate, G. (2012). External networking and internal firm governance. *The Journal of Finance, 67*(1), 153-194.

Francis, B., Hasan, I., Park, J. C. and Wu, Q. (2015). Gender differences in financial reporting decision making: Evidence from accounting conservatism. *Contemporary Accounting Research, 32*(3), 1285-1318.

Francis, B. B., Hasan, I., Hovakimian, G., and Sharma, Z. (2023). Gender pay gap in American CFOs: Theory and evidence. *Journal of Corporate Finance, 80*, 102404.

Francis, B., Hasan, I., Shen, Y. V. and Wu, Q. (2021). Do activist hedge funds target female CEOs? The role of CEO gender in hedge fund activism. *Journal of Financial Economics, 141*(1), 372-393.

Freeman, L. C. (1978). Centrality in social networks conceptual clarification. *Social Networks, 1(3*), 215-239.

Fuhrmans, V. (2020). Where are all the women CEOs? *The Wall Street Journal.* Retrieved from https://www.wsj.com/articles/why-so-few-ceos-are-women-you-can-have-a-seat-at-the-table-and-not-be-a-player-11581003276

Garretsen, H., Stoker, J. I. and Weber, R. A. (2020). Economic perspectives on leadership: Concepts, causality, and context in leadership research. *The Leadership Quarterly, 31*(3), 101410.

Geertsema, P., and Lu, H. (2023). Relative Valuation with Machine Learning. *Journal of Accounting Research, 61*(1), 329-376

Giannetti, M., and Wang, T. Y. (2023). Public attention to gender equality and board gender diversity. *Journal of Financial and Quantitative Analysis, 58*(2), 485-511.

Goel, A. M. and Thakor, A. V. (2008). Overconfidence, CEO selection, and corporate governance. *The Journal of Finance, 63*(6), 2737-2784.

Green, T. C., Huang, R., Wen, Q. and Zhou, D. (2019). Crowdsourced employer reviews and stock returns. *Journal of Financial Economics, 134*(1), 236-251.

Griffin, D., Li, K. and Xu, T. (2021). Board gender diversity and corporate innovation: International evidence. *Journal of Financial and Quantitative Analysis, 56*(1), 123-154.

Guenzel, M. and Malmendier, U. (2020). Behavioral corporate finance: The life cycle of a CEO career (No. w27635). *National Bureau of Economic Research.*

Gu, X., Hasan, I., Zhang, B., Zhao, L. and Zhu, Y. (2019). Up the Political Ladder: The Role of Political Networks. *SSRN Working Paper.*

Gu, S., Kelly, B. and Xiu, D. (2020). Empirical asset pricing via machine learning. *The Review of Financial Studies, 33*(5), 2223-2273.

Gul, F. A., Srinidhi, B. and Ng, A. C. (2011). Does board gender diversity improve the informativeness of stock prices? *Journal of Accounting and Economics*, *51*(3), 314-338.

Gupta, V. K., Mortal, S., Chakrabarty, B., Guo, X. and Turban, D. B. (2020). CFO gender and financial statement irregularities. *Academy of Management Journal, 63*(3), 802-831.

Hambrick, D. C. and Finkelstein, S. (1987). Managerial discretion: A bridge between polar views of organizational outcomes. *Research in Organizational Behavior*.

Hambrick, D. C. and Mason, P. A. (1984). Upper echelons: The organization as a reflection of its top managers. *Academy of Management Review, 9*(2), 193-206.

Hansen, S., Ramdas, T., Sadun, R. and Fuller, J. (2021). The demand for executive skills. *National Bureau of Economic Research*, No. w28959.

Hassan, T. A., Hollander, S., van Lent, L. and Tahoun, A. (2019). Firm-level political risk: Measurement and effects. *The Quarterly Journal of Economics, 134*(4), 2135-2202.

Hinchliffe, E. (2024, June 4). The share of Fortune 500 companies run by women CEOs stay flat at 10.4% as pace of change stalls. *Fortune*. https://fortune.com/2024/06/04/fortune-500-companies-women-ceos-2024/

Hogarth, R. M., Karelaia, N. and Trujillo, C. A. (2012). When should I quit? Gender differences in exiting competitions. *Journal of Economic Behavior & Organization*, *83*(1), 136-150.

Hoyt, C. L. and Murphy, S. E. (2016). Managing to clear the air: Stereotype threat, women, and leadership. *The Leadership Quarterly*, *27*(3), 387-399.

Hsu, P. H., Li, K. and Pan, Y. (2026). The eco-gender gap in boardrooms. *Management Science (Forthcoming)*.

Huang, J. and Kisgen, D. J. (2013). Gender and corporate finance: Are male executives overconfident relative to female executives? *Journal of Financial Economics*, *108*(3), 822-839.

Jacob, D. (2021). CATE meets ML: Conditional average treatment effect and machine learning. *Digital Finance, 3*(2), 99-148.

James, G., Witten, D., Hastie, T. and Tibshirani, R. (2013). *An Introduction to Statistical Learning* (Vol. 112, p. 18). New York: Springer.

Johnson, S. K., Murphy, S. E., Zewdie, S. and Reichard, R. J. (2008). The strong, sensitive type: Effects of gender stereotypes and leadership prototypes on the evaluation of male and female leaders. *Organizational behavior and human decision processes, 106*(1), 39-60.

Jones, S. (2017). Corporate bankruptcy prediction: a high dimensional analysis. *Review of Accounting Studies, 22*(3), 1366-1422.

Jones, B. F. and Olken, B. A. (2005). Do leaders matter? National leadership and growth since World War II. *The Quarterly Journal of Economics, 120*(3), 835-864.

Kallus, N. (2023). Treatment effect risk: Bounds and inference. *Management Science, 69*(8), 4579-4590.

Kaplan, S. N., Klebanov, M. M. and Sorensen, M. (2012). Which CEO characteristics and abilities matter? *The Journal of Finance*, *67*(3), 973-1007.

Kaplan, S. N. and Sorensen, M. (2021). Are CEOs different? *The Journal of Finance, 76*(4), 1773-1811.

Klein, T. and Walther, T. (2024). Advances in Explainable Artificial Intelligence (xAI) in Finance. *Finance Research Letters, 70*, 106358.

Kleinberg, J., Lakkaraju, H., Leskovec, J., Ludwig, J. and Mullainathan, S. (2018). Human decisions and machine predictions. *The Quarterly Journal of Economics, 133*(1), 237-293.

Kuhn, M. and Johnson, K. (2013). *Applied Predictive Modeling* (Vol. 26). New York: Springer.

Lee, P. M. and James, E. H. (2007). She'-e-os: Gender effects and investor reactions to the announcements of top executive appointments. *Strategic Management Journal*, *28*(3), 227-241.

Levi, M., Li, K. and Zhang, F. (2014). Director gender and mergers and acquisitions. *Journal of Corporate Finance*, *28*, 185-200.

Li, K., Mai, F., Shen, R. and Yan, X. (2021). Measuring corporate culture using machine learning. *Review of Financial Studies, 34*(7), 3265-3315.

Li, K., Mai, F., Shen, R., Yang, C., and Zhang, T. (2026). Dissecting corporate culture using generative AI. *The Review of Financial Studies, 39*(1), 253-296.

Li, K., Peng, Q., Shen, R. and Wong, G. (2024). Gender, competition, and performance: International evidence. *Journal of Financial and Quantitative Analysis,* 1-41.

Loughran, T. and McDonald, B. (2016). Textual analysis in accounting and finance: A survey. *Journal of Accounting Research, 54*(4), 1187-1230.

Lundberg, S. M. and Lee, S. I. (2017). A unified approach to interpreting model predictions. In *Advances in Neural Information Processing Systems*, 4765-4774.

Lyngsie, J. and Foss, N. J. (2017). The more, the merrier? Women in top-management teams and entrepreneurship in established firms. *Strategic Management Journal, 38*(3), 487-505.

Malmendier, U., Tate, G. and Yan, J. (2011). Overconfidence and early-life experiences: The effect of managerial traits on corporate financial policies. *The Journal of Finance, 66*(5), 1687-1733.

Matsa, D. A. and Miller, A. R. (2013). A female style in corporate leadership? Evidence from quotas. *American Economic Journal: Applied Economics*, *5*(3), 136-69.

McKinsey & Company and LeanIn.Org. (2024). *Women in the Workplace 2024: The 10th Anniversary Report.*

Mullainathan, S. and Spiess, J. (2017). Machine learning: an applied econometric approach. *Journal of Economic Perspectives, 31*(2), 87-106.

Oakley, J. G. (2000). Gender-based barriers to senior management positions: Understanding the scarcity of female CEOs. *Journal of Business Ethics*, *27*(4), 321-334.

Pan, Y., Siegel, S. and Wang, T.Y. (2020). The cultural origin of CEOs' attitudes toward uncertainty: Evidence from corporate acquisitions. *The Review of Financial Studies, 33*(7), 2977-3030.

Pfeffer, J. (2015). *Leadership BS: Fixing Workplaces and Careers One Truth at a Time*. Harper Business.

Pfeffer, J. (2022). *7 Rules of Power: Surprising -- but True -- Advice on How to Get Things Done and Advance Your Career*. BenBella Books.

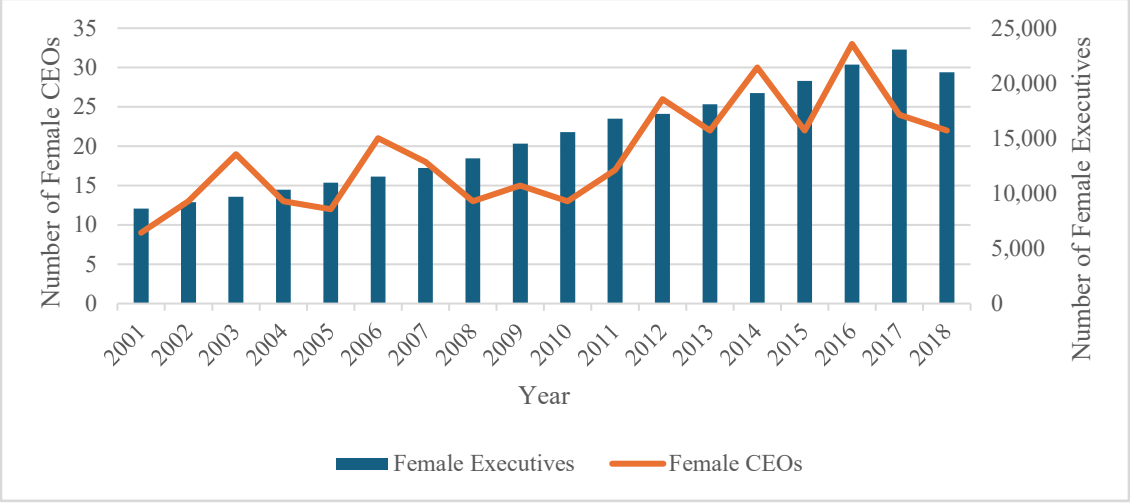
Phipps, S. T. and Prieto, L. C. (2020). Leaning in: A historical perspective on influencing women's leadership. *Journal of Business Ethics*, 1-15.

Post, C., Lokshin, B. and Boone, C. (2020). What changes after women enter top management teams? A gender-based model of strategic renewal. *Academy of Management Journal, 65*(1).

Post, C., Rahman, N. and Rubow, E. (2011). Green governance: Boards of directors' composition and environmental corporate social responsibility. *Business & Society*, *50*(1), 189-223.
Quigley, T. J., Hambrick, D. C., Misangyi, V. F. and Rizzi, G. A. (2019). CEO selection as risk-taking: A new vantage on the debate about the consequences of insiders versus outsiders. *Strategic Management Journal, 40*(9), 1453-1470.
Rankin, J. (2022, June 10). EU agrees 'landmark' 40% quota for women on corporate boards. *Guardian*. https://www.theguardian.com/business/2022/jun/07/eu-agrees-landmark-40-quota-for-women-on-corporate-boards
Roth, A. E. (2016). Lloyd Shapley (1923-2016): A founding father of game theory. *Nature, 532*(7598), 178-179.
Ryan, M. and A. Haslam (2005). The glass cliff: Evidence that women are over-represented in precarious leadership positions. *British Journal of Management*, *16*, 81−90.
Ryan, M. K., Haslam, S. A., Morgenroth, T., Rink, F., Stoker, J. and Peters, K. (2016). Getting on top of the glass cliff: Reviewing a decade of evidence, explanations, and impact. *The Leadership Quarterly, 27*(3), 446-455.
Sahay, R., Čihák other IMF Staff, M. and Adrian, T. (2018). Women in finance: A case for closing gaps. *IMF Staff Discussion Note, 2018*(5), 1-42.
Sandberg, S. (2013). *Lean in: Women, work, and the will to lead.* New York: Alfred A. Knopf.
Schein, V. E. (2001). A global look at psychological barriers to women's progress in management. *Journal of Social Issues, 57*(4), 675-688.
Sczesny, S. (2003). A closer look beneath the surface: Various facets of the think-manager–think-male stereotype. *Sex Roles*, *49*(7-8), 353-363.
Semenova, V. and Chernozhukov, V. (2021). Debiased machine learning of conditional average treatment effects and other causal functions. *The Econometrics Journal, 24*(2), 264-289.
S&P Global (2024). *Elusive Parity: Key Gender Parity Metric Falls for First Time in 2 Decades.*
Shapley, L. S. (1953). A value for n-person games. *Contributions to the Theory of Games, 2*(28), 307-317.
Spencer, S. M., Blazek, E. S. and Orr, J. E. (2019). Bolstering the female CEO pipeline: Equalizing the playing field and igniting women's potential as top-level leaders. *Business Horizons, 62*(5), 567-577.
Stevenson, J. E. and Orr, E. (2017). We interviewed 57 female CEOs to find out how more women can get to the top. *Harvard Business Review.*
Tannen, D. (1994). *Gender and discourse*. Oxford University Press.
Tinsley, C.H. and Purmal, K. (2019). Board experience is helping more women get CEO jobs. *Harvard Business Review.*
Umoh, R. (2025, October 27). *The McKinsey CEO pipeline: How the consulting giant built an empire of influence and filled the world's corner offices with its alumni*. Fortune. https://fortune.com/2025/09/25/mckinsey-ceo-pipeline-fortune-500-global-500-consulting-ai/
Wasserman, S. and Faust, K. (1994). *Social network analysis: Methods and applications* (Vol. 8). Cambridge University Press.
Wiersema, M. F., Nishimura, Y. and Suzuki, K. (2018). Executive succession: The importance of social capital in CEO appointments. *Strategic Management Journal, 39(5)*, 1473-1495.
Wu, Q., Dbouk, W., Hasan, I., Kobeissi, N. and Zheng, L. (2021). Does gender affect innovation? Evidence from female chief technology officers. *Research Policy, 50*(9), 104327.
Zhao, H., Williams, G. J. and Huang, J. Z. (2017). WSRF: An R package for classification with scalable weighted subspace random forests. *Journal of Statistical Software, 77*(i03), 1.

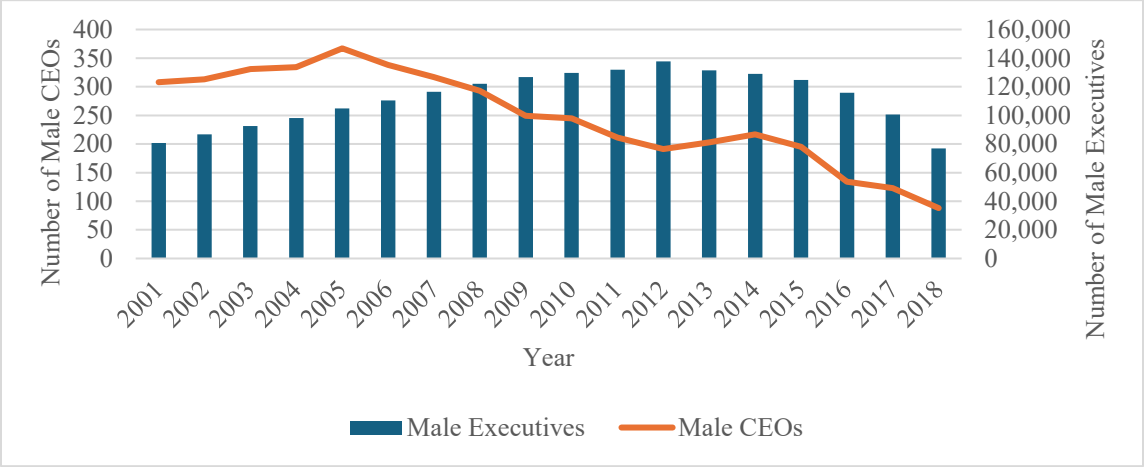
Figure 1: Data Distribution by Year

Figure 1A. Female Sample



This figure shows the sample distribution by year with the number of first-time female CEO appointments by year on the left-hand side y-axis, as well as the total number of female executives by year on the right-hand side y-axis. *First-time CEO* is equal to 1 in a year when a female executive becomes a CEO in a publicly traded U.S. firm for the first time; it equals 0 otherwise. There are 342 first-time female CEOs in our sample and 273,091 observations.

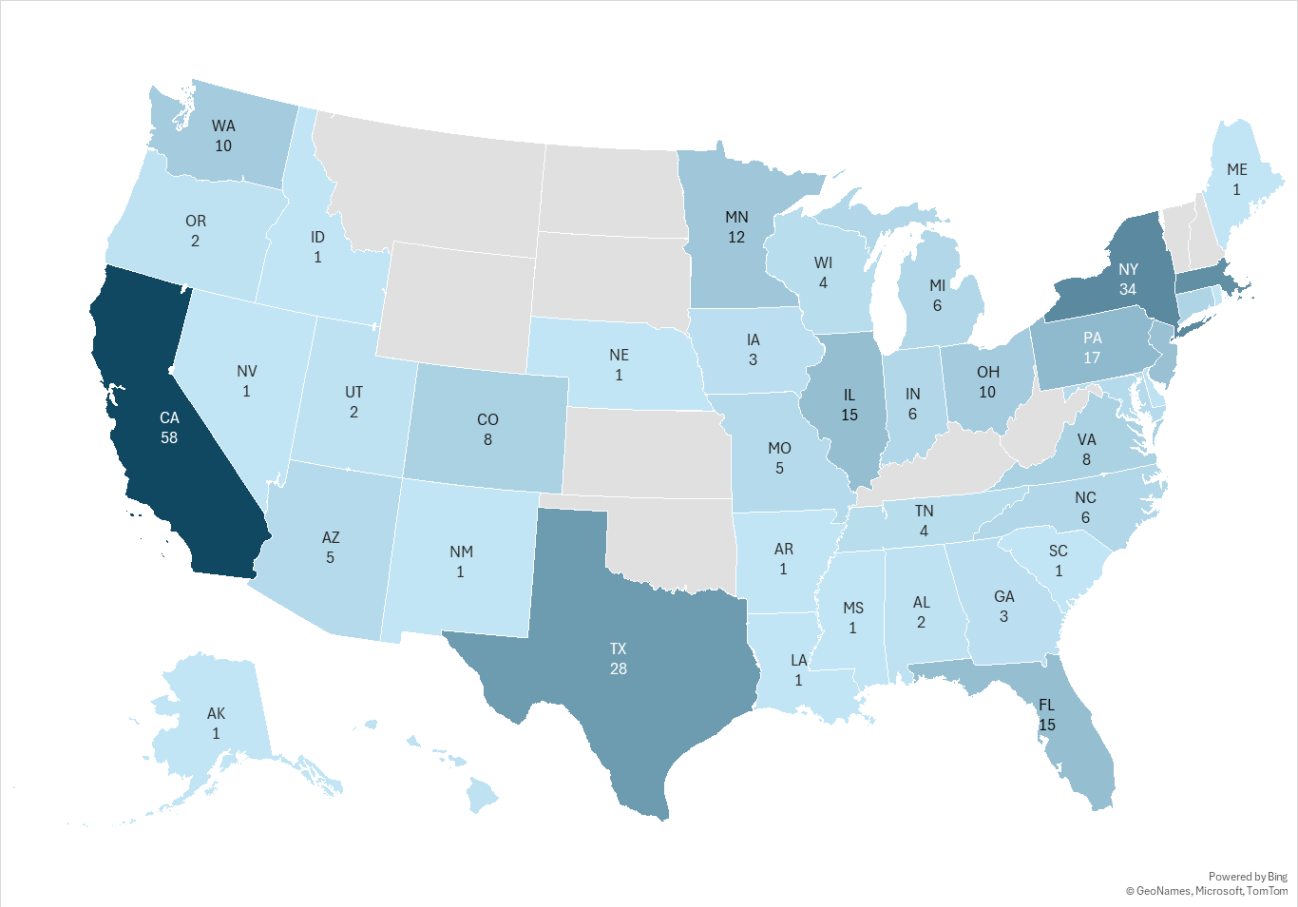
Figure 1B. Male Sample



This figure shows the sample distribution by year with the number of first-time male CEO appointments by year on the left-hand side y-axis, as well as the total number of male executives by year on the right-hand side y-axis. *First-time CEO* is equal to 1 in a year when a male executive becomes a CEO in a publicly traded U.S. firm for the first time; it equals 0 otherwise. There are 4,457 first-time male CEOs in our sample and 2,016,377 observations.

Figure 2: CEOs Distribution by State

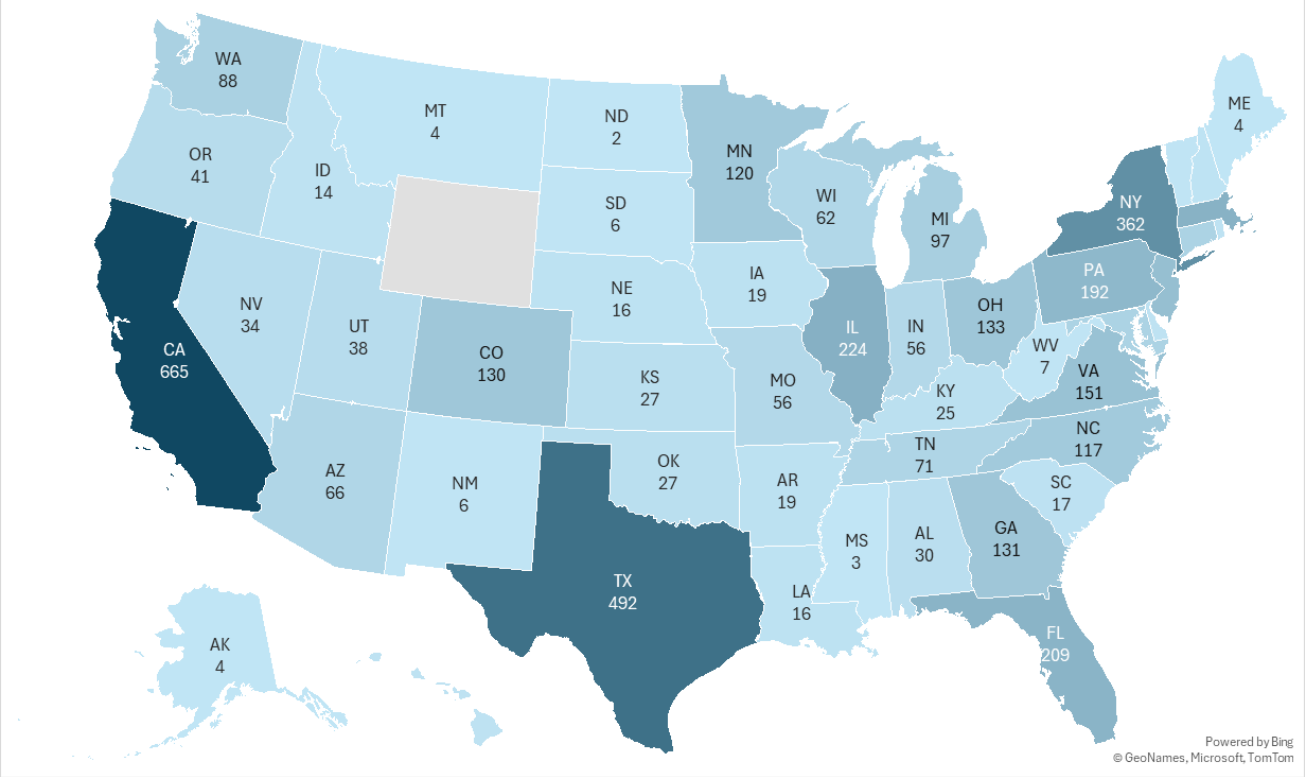
Figure 2A. Female CEOs



This figure shows the geographic distribution of first-time female CEOs of publicly listed companies across the states in the United States. There are 342 first-time female CEOs of publicly traded firms in the sample from 2001 to 2018 (note: 5 of the companies were not headquartered in the U.S. at the time of CEO appointment and thus those observations were excluded from the map). The darker color corresponds to the higher number of first-time CEOs appointed during our sample period. Gray color corresponds to the absence of the CEOs' appointments during the sample period. The map was generated using Microsoft Excel.

Figure 2 (continued): CEOs Distribution by State

Figure 2B. Male Sample



This figure shows the geographic distribution of first-time female CEOs of publicly listed companies across the states in the United States. There are 4,457 first-time male CEOs of publicly traded firms in the sample from 2001 to 2018 (note: 65 of the companies were not headquartered in the U.S. at the time of CEO appointment and thus those observations were excluded from the map). The darker color corresponds to the higher number of first-time CEOs appointed during our sample period. Gray color corresponds to the absence of the CEOs' appointments during the sample period. The map was generated using Microsoft Excel.

Figure 3: First-time CEO Industry Distribution

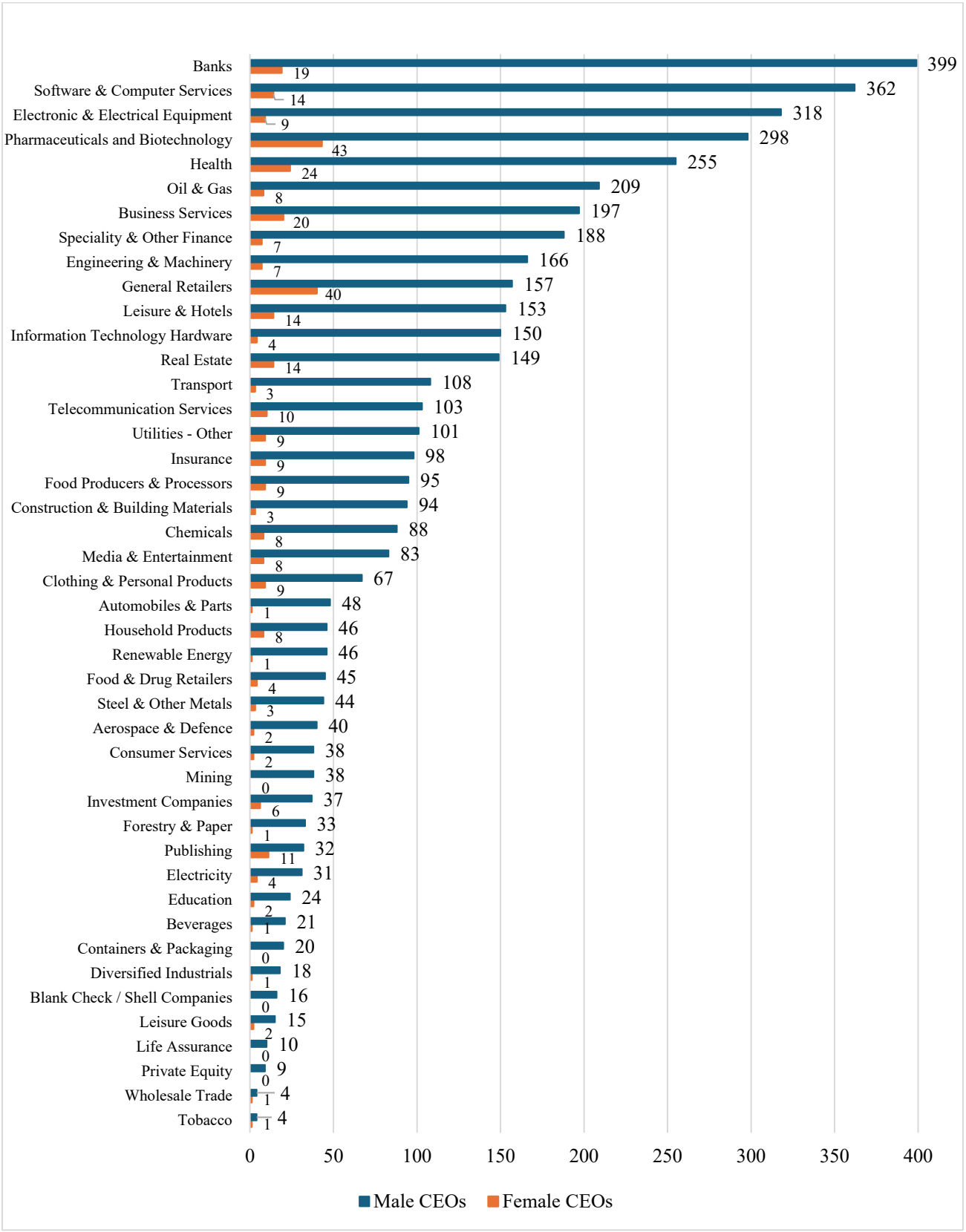


Figure 4: Feature Importance by Group

This figure shows the variable importance grouped into the following categories: social network, upper management experience, board experience, professional experience, education, affiliation, award, and other experience. Grouping the variables follows the categories defined in Table A1. A total of 131 explanatory variables are included in the models. The horizontal axis contains all 10 models in the analysis. The color gradient shows the importance of the features, where the darker colors indicate the most important and the lighter colors indicate the least important groups identified by the model. The groups are sorted based on the best performing model for each sample (Random Forest for Panel A, boosted GLM for Panel B).

Panel A. Female Sample

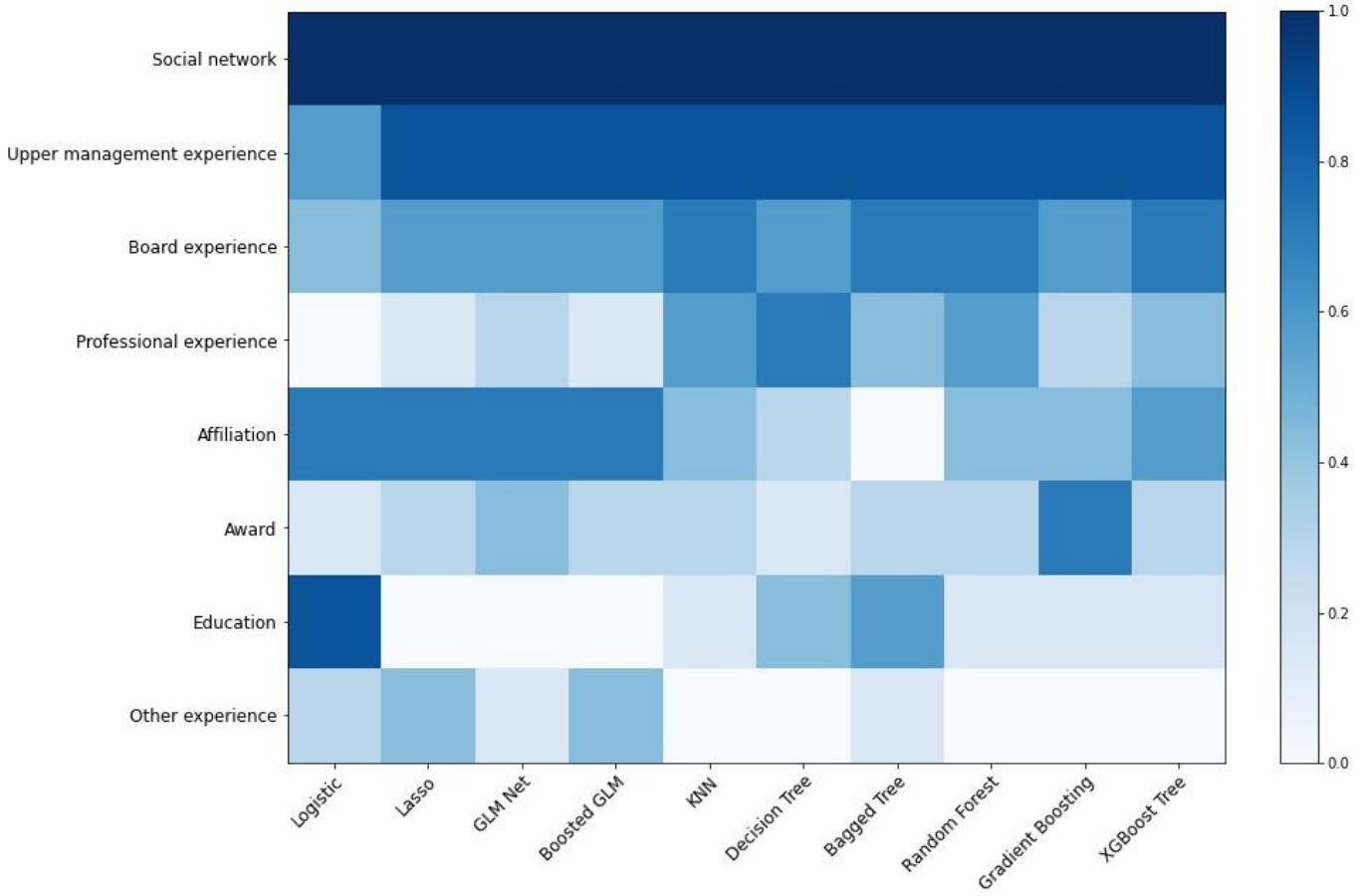


Figure 4 (continued): Feature Importance by Group

This figure shows the variable importance grouped into the following categories: social network, upper management experience, board experience, professional experience, education, affiliation, award, and other experience. Grouping the variables follows the categories defined in Table A1. A total of 131 explanatory variables are included in the models. The horizontal axis contains all 10 models in the analysis. The color gradient shows the importance of the features, where the darker colors indicate the most important and the lighter colors indicate the least important groups identified by the model. The groups are sorted based on the best performing model for each sample (Random Forest for Panel A, boosted GLM for Panel B).

Panel B. Male Sample

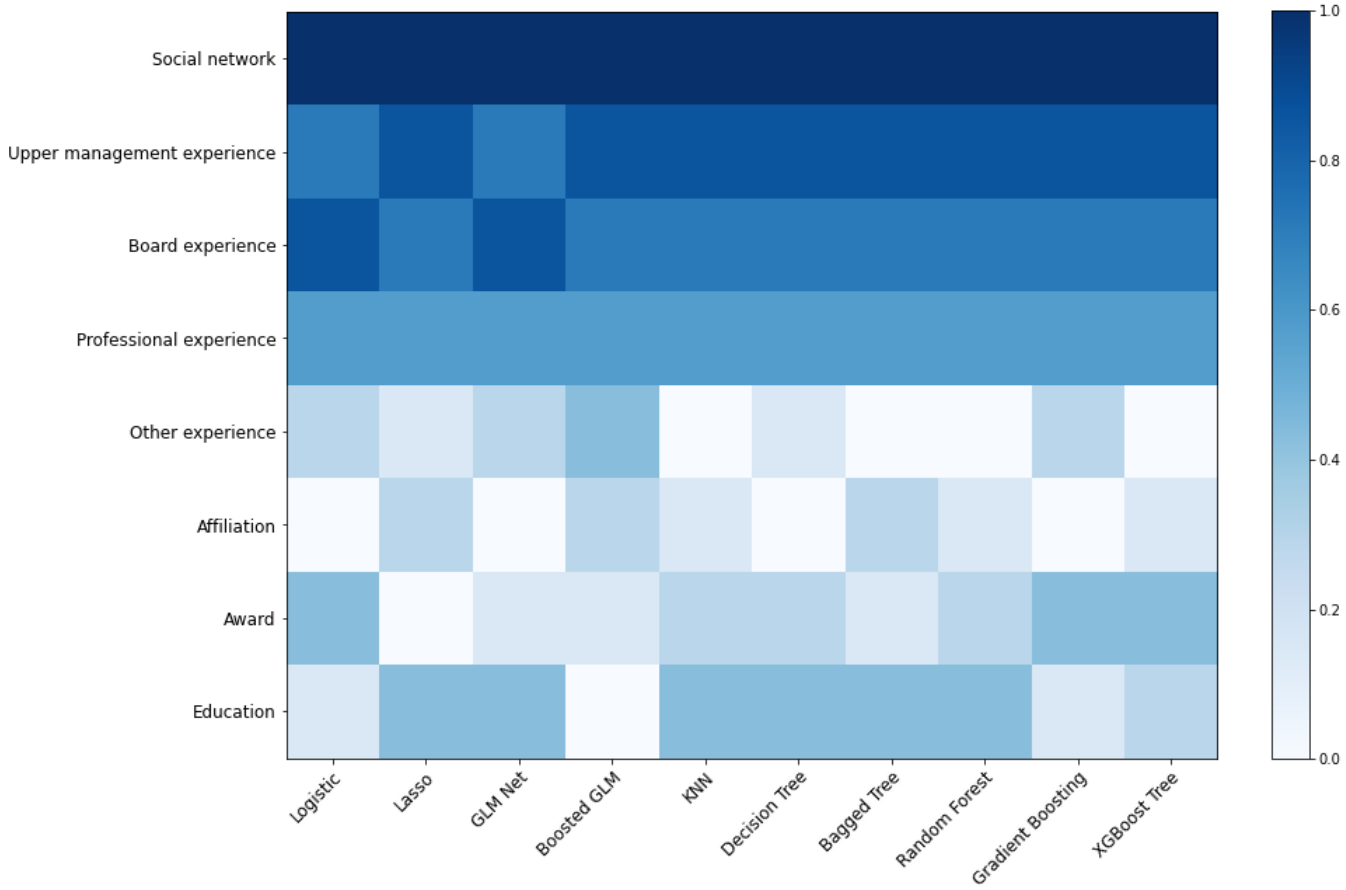


Figure 5: SHAP Values for Top 20 Variables

This figure presents the results for the best performing model for each sample (Random Forest for Panel A, boosted GLM for Panel B), with SHAP values indicating the direction and magnitude of the explanatory variable's impact on the prediction of the outcome variable. SHAP values are presented for the top 20 variables with the largest impact on the prediction. Darker color indicates a positive impact, while lighter color indicates a negative impact. Definitions of all variables are included in Table A1.

Panel A. Female Sample

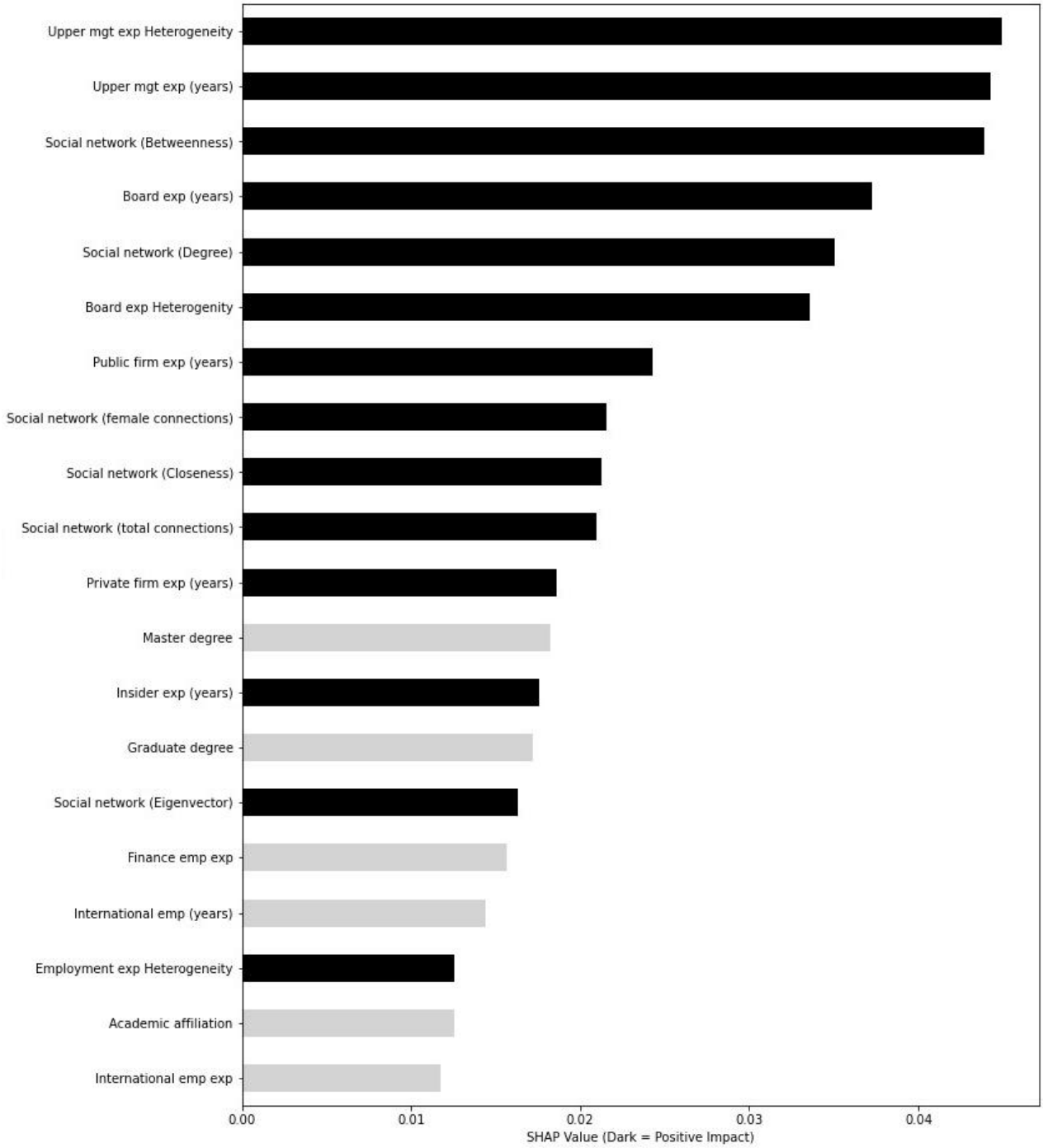


Figure 5 (continued): SHAP Values for Top 20 Variables

This figure presents the results for best performing model for each sample (Random Forest for Panel A, boosted GLM for Panel B), with SHAP values indicating the direction and magnitude of the explanatory variable's impact on the prediction of the outcome variable. SHAP values are presented for the top 20 variables with the largest impact on the prediction. Darker color indicates a positive impact, while lighter color indicates a negative impact. Definitions of all variables are included in Table A1.

Panel B. Male Sample

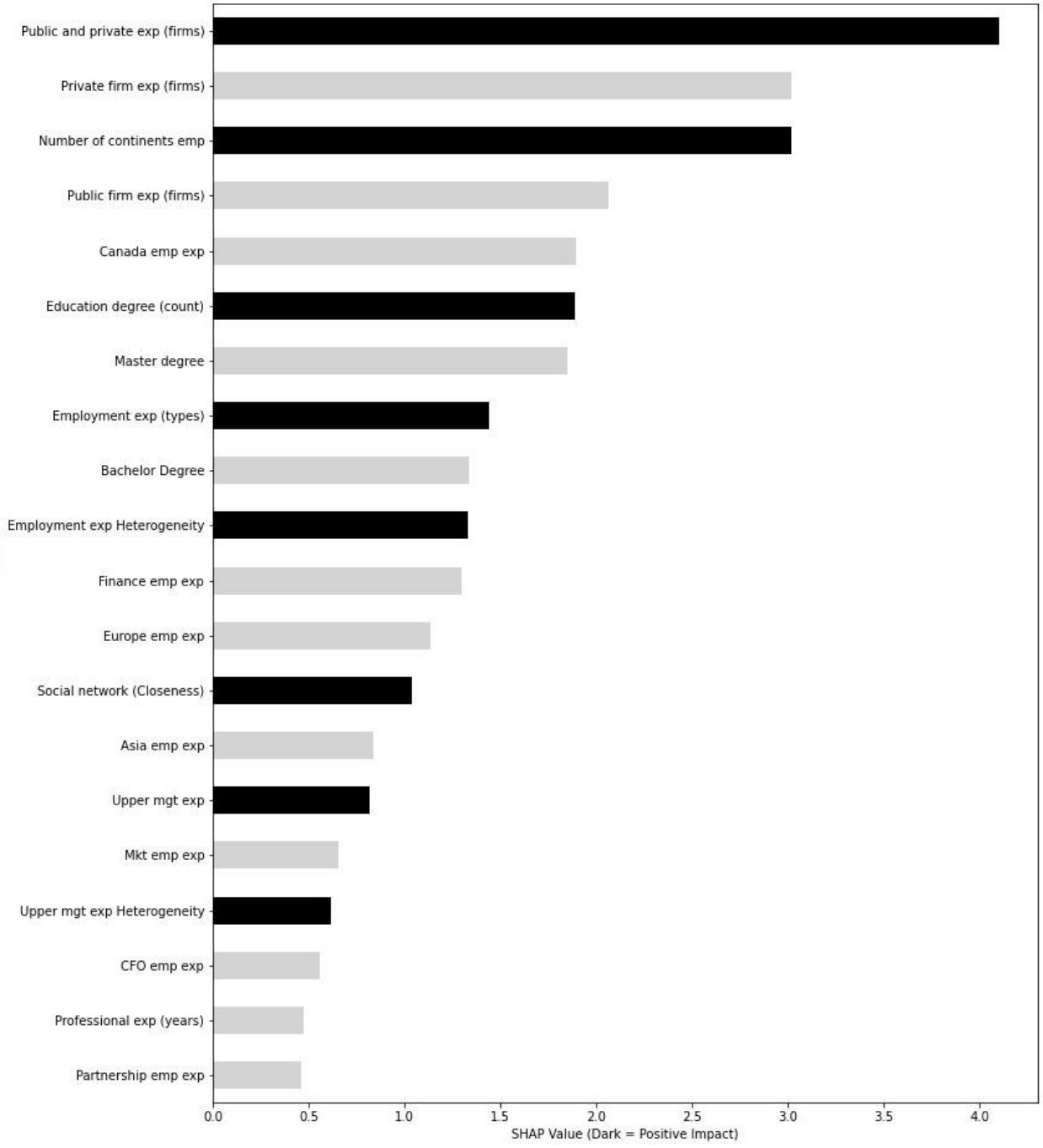


Figure 6: SHAP Values by Industry

This figure presents the results for best performing model for each sample (Random Forest for female sample, boosted GLM for male sample) by industry, with SHAP values indicating the direction and magnitude of the explanatory variable's impact on the prediction of the outcome variable. SHAP values are presented for the top 20 variables with the largest impact on the prediction. Darker color indicates a positive impact, while lighter color indicates a negative impact. Definitions of all variables are included in Table A1.

Panel A. Software and Computer Services Industry

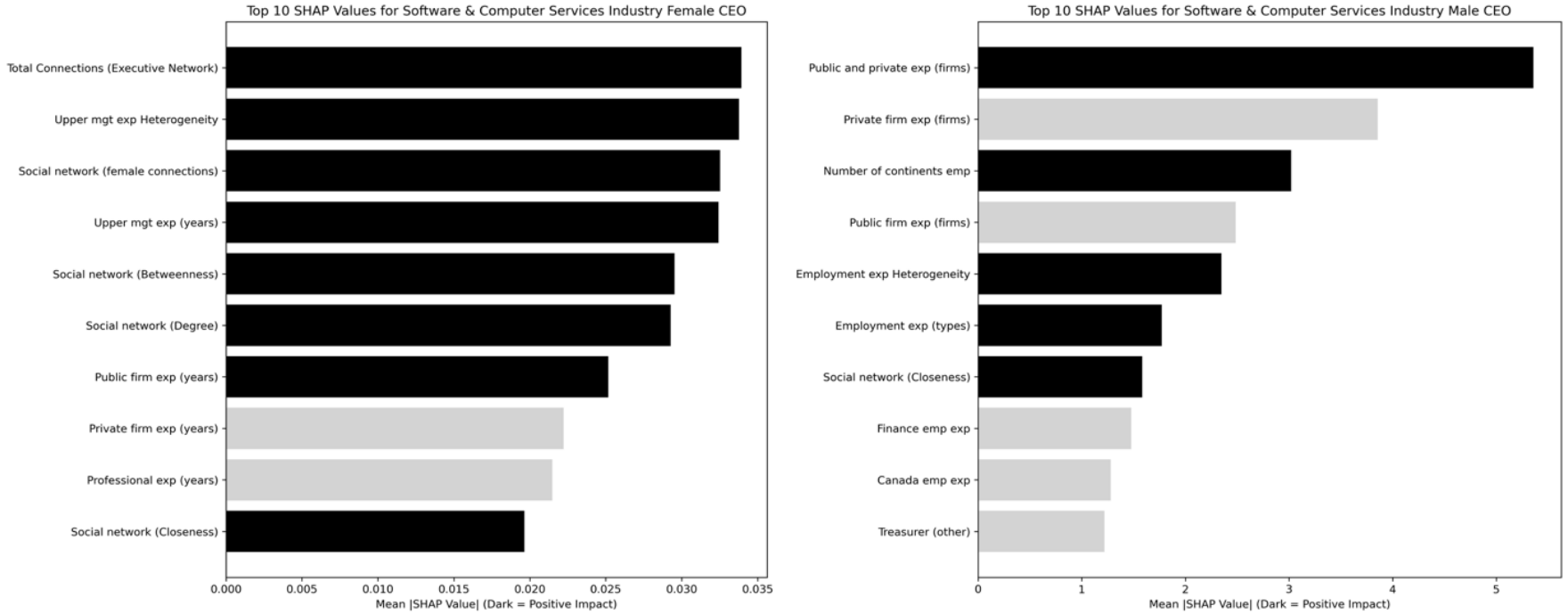


Figure 6 (continued): SHAP Values by Industry

This figure presents the results for best performing model for each sample (Random Forest for female sample, boosted GLM for male sample) by industry, with SHAP values indicating the direction and magnitude of the explanatory variable's impact on the prediction of the outcome variable. SHAP values are presented for the top 20 variables with the largest impact on the prediction. Darker color indicates a positive impact, while lighter color indicates a negative impact. Definitions of all variables are included in Table A1.

Panel B. Pharmaceuticals and Biotechnology Industry

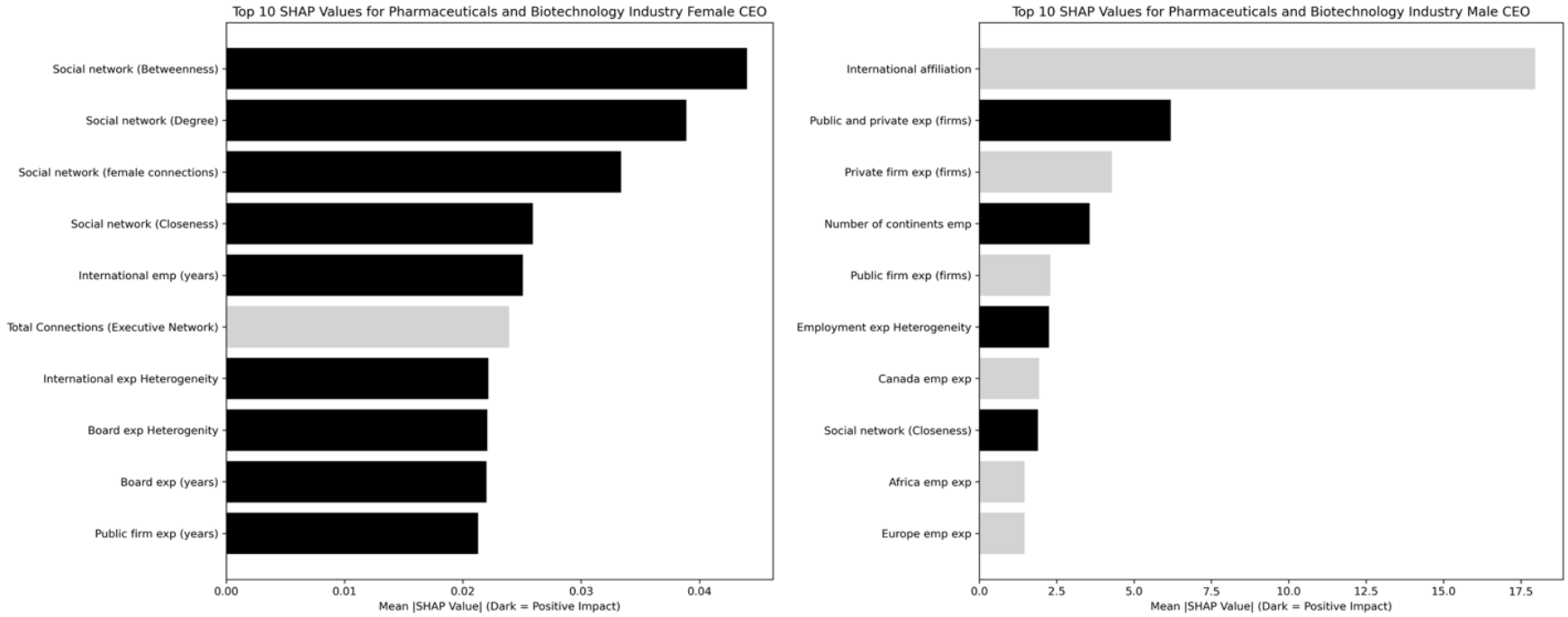


Figure 6 (continued): SHAP Values by Industry

This figure presents the results for best performing model for each sample (Random Forest for female sample, boosted GLM for male sample) by industry, with SHAP values indicating the direction and magnitude of the explanatory variable's impact on the prediction of the outcome variable. SHAP values are presented for the top 20 variables with the largest impact on the prediction. Darker color indicates a positive impact, while lighter color indicates a negative impact. Definitions of all variables are included in Table A1.

Panel C. Banking Industry

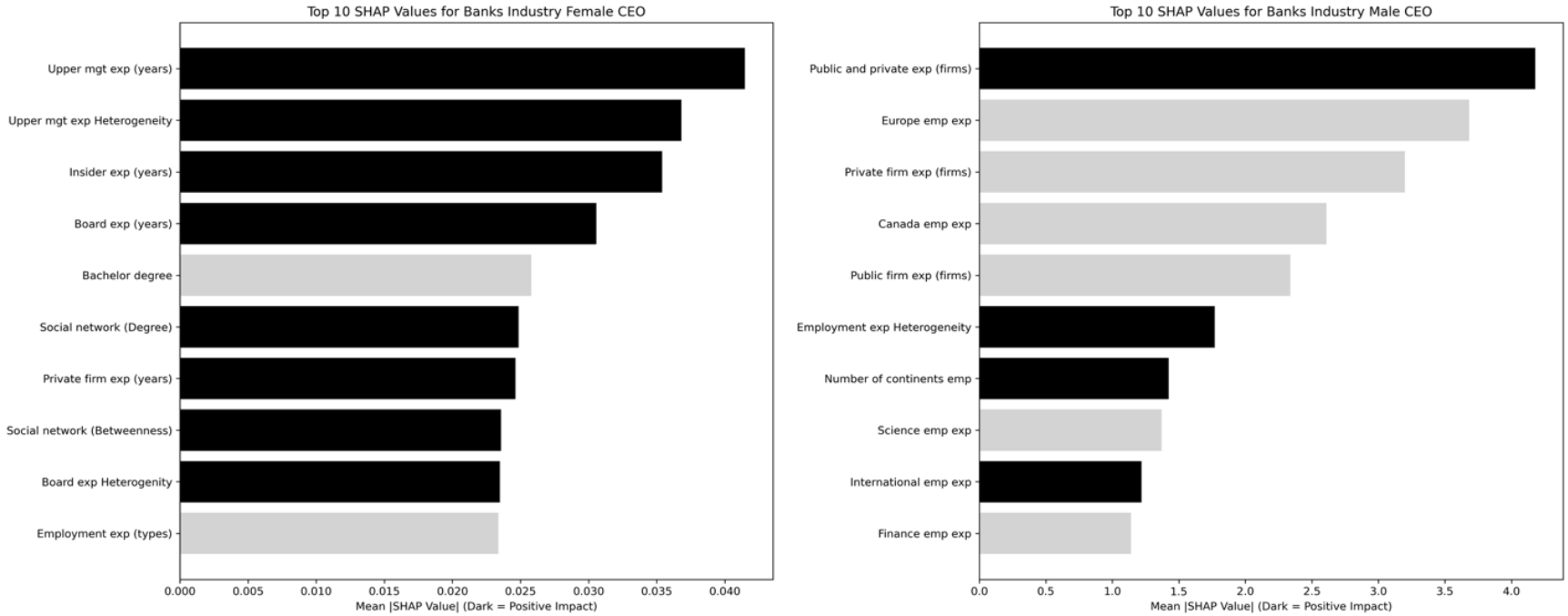


Figure 7: Heterogeneity of Treatment Effect by Gender – CATE

This figure presents the CATE distribution of individual-level treatment effects across CEO candidates based on gender (treatment effect is equal to one if the candidate is female; and zero otherwise). The distribution presents the aggregate effects of treatment in the sample. Since the mean and median are negative, the plot suggests that firms are less likely to select female CEO compared to male CEO candidate. Specifically, about 24% of the CATE distribution for female candidates are above 0, meaning that 24% of firms would be more likely to select female CEO candidate.

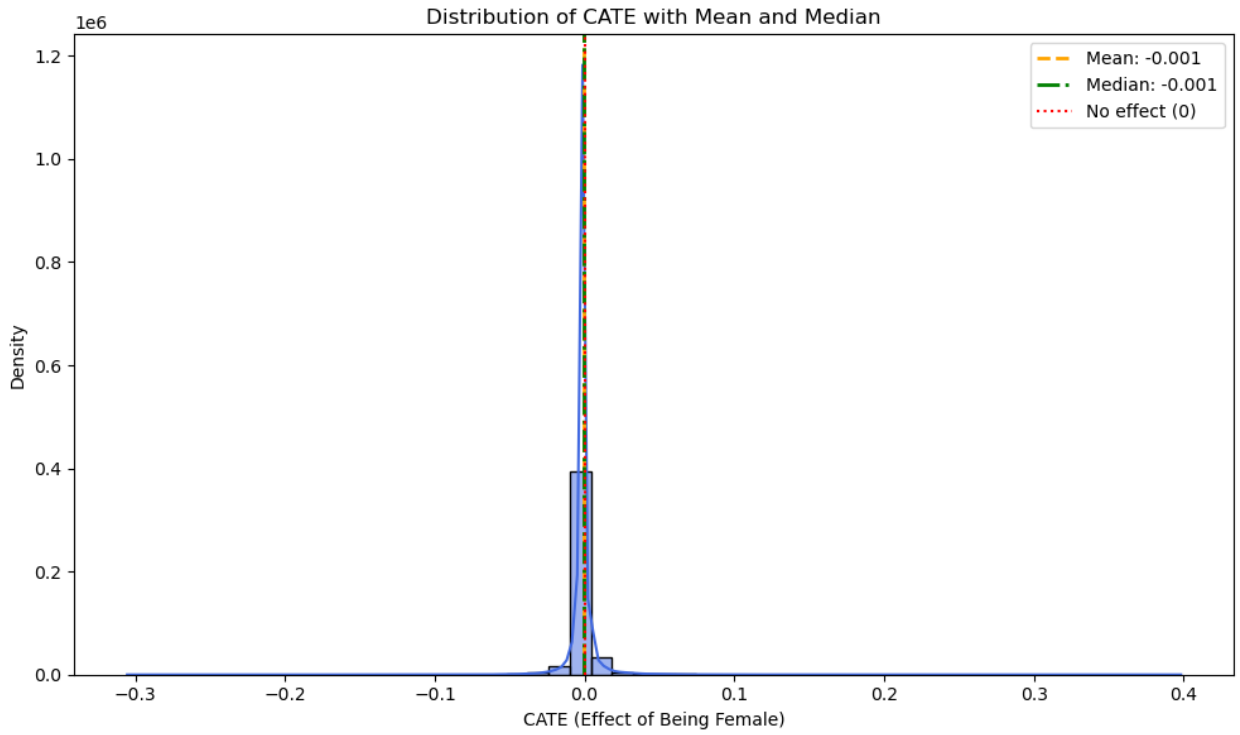


Figure 8: Feature Importance for Top 20 Variables Driving Heterogeneity by Gender – CATE

This figure presents the feature importance for the top 20 variables driving heterogeneity by gender in predicting CEOs. Values are presented for the top 20 variables with the largest impact on the prediction. Longer bar indicates a larger impact (importance), while shorter bars indicate a smaller impact (importance). Definitions of all variables are included in Table A1.

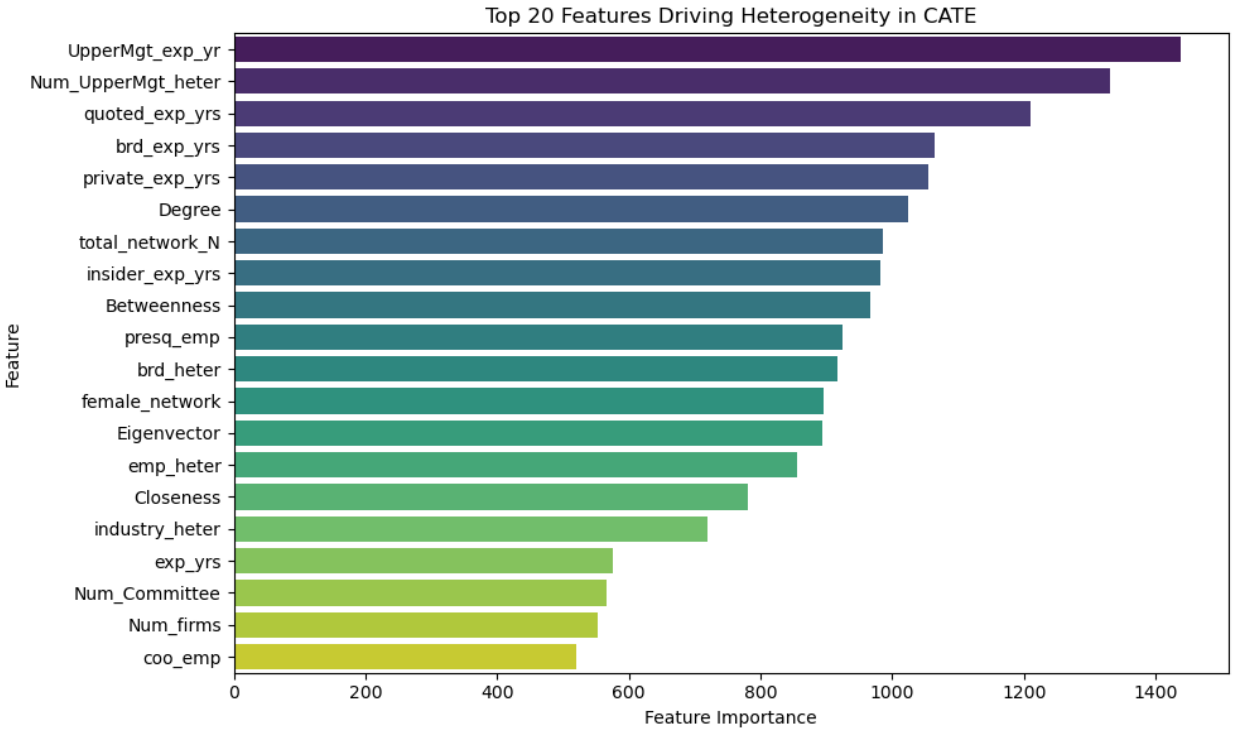


Figure 9: Subgroup Analysis – CATE

This figure presents the interpretation of the effect of the top 10 variables by feature importance that driving heterogeneity by gender in predicting CEOs. Values are presented for the top 10 variables with the largest impact on the prediction by treatment split where Lighter color indicates the effect for treated (female) group, and darker color indicates the control (male) group. Definitions of all variables are included in Table A1.

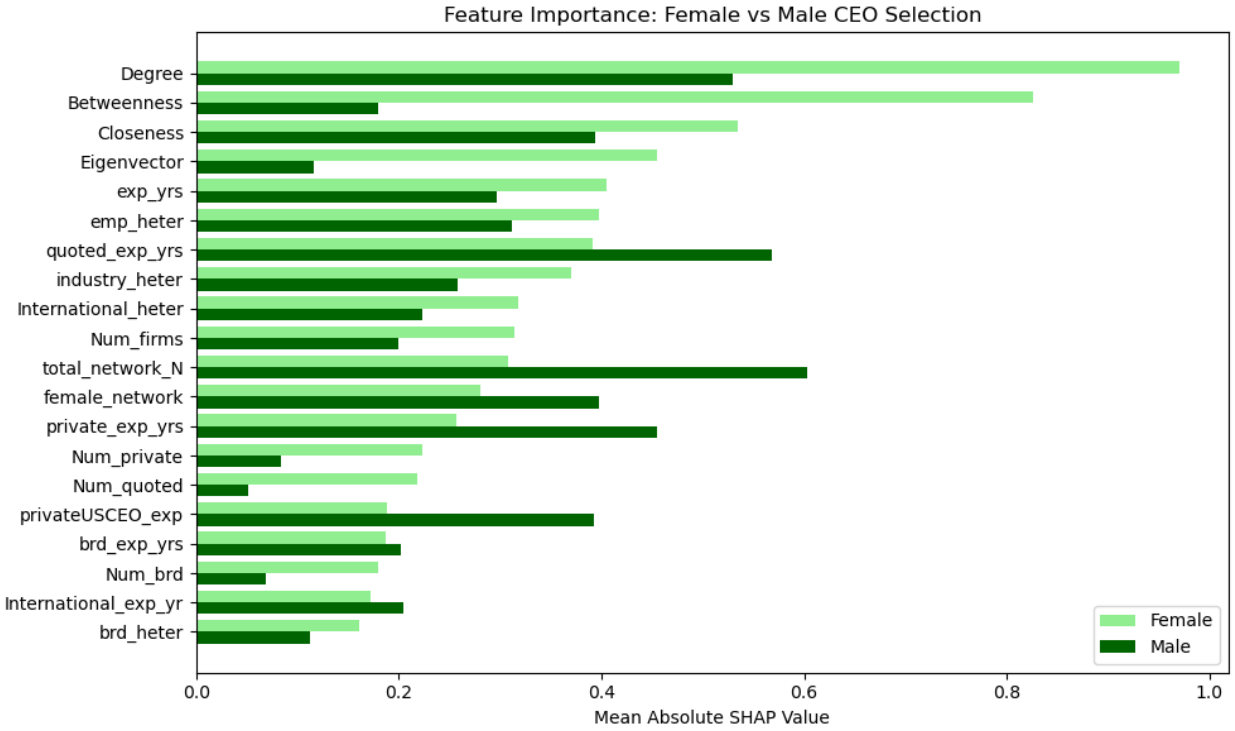


Figure 10: Gender-Neutral Selection Analysis – CATE

This figure presents changes in the number of selected candidates using gender neutral approach. In the test subset of data, 57 female CEOs are actually selected – if CATE model estimates counterfactual selection probabilities assuming gender neutrality, the total number of female CEOs, this number increases to 92 female CEOs, an increase of over 160%. Number of selected male CEO candidates remains unchanged (884) using gender-neutral selection approach.

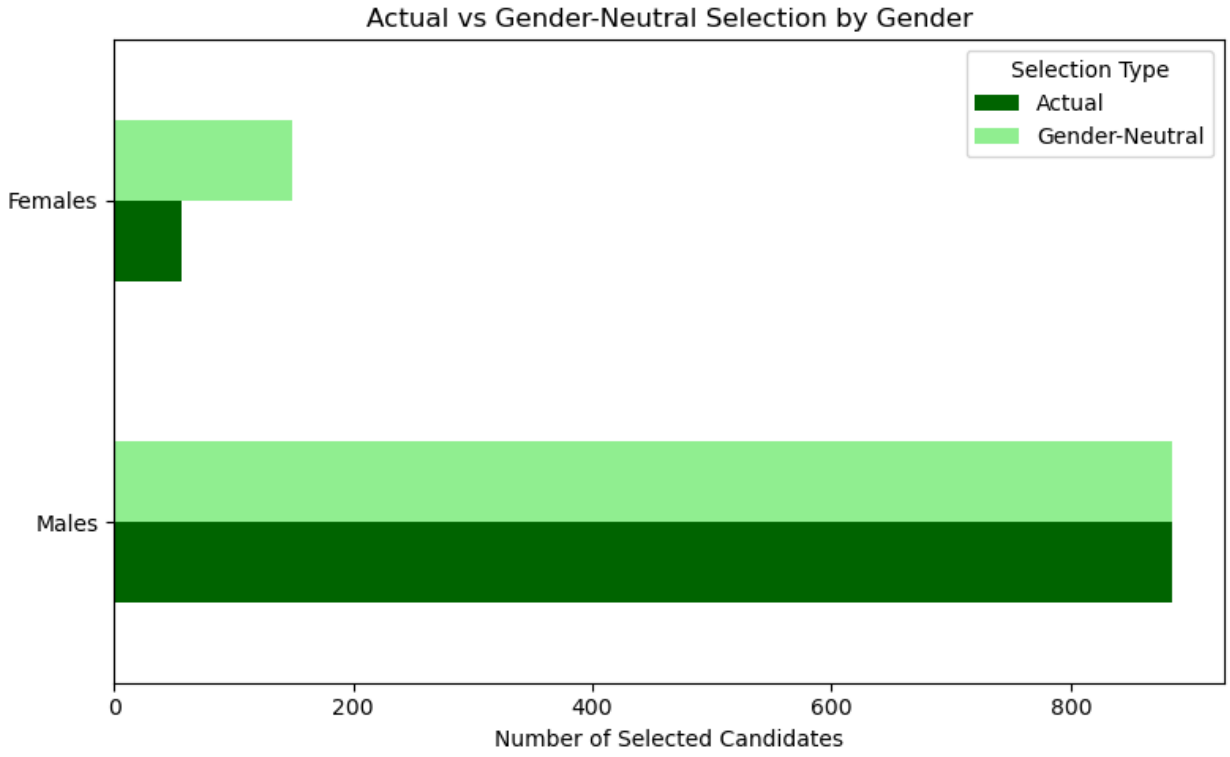


Figure 11: SHAP Values for Top 20 Variables – Pre- and Post-Crisis Subsamples

This figure presents the results for the female CEO top-performing model for pre- (Panel A) and post-crisis (Panel B) subsamples, XGBoost tree specification, with SHAP values indicating the direction and magnitude of the explanatory variable's impact on the prediction of the outcome variable. SHAP values are presented for the top 20 variables with the largest impact on the prediction. Darker color indicates a positive impact, while lighter color indicates a negative impact. Definitions of all variables are included in Table A1.

Panel A. Pre-Crisis Subsample

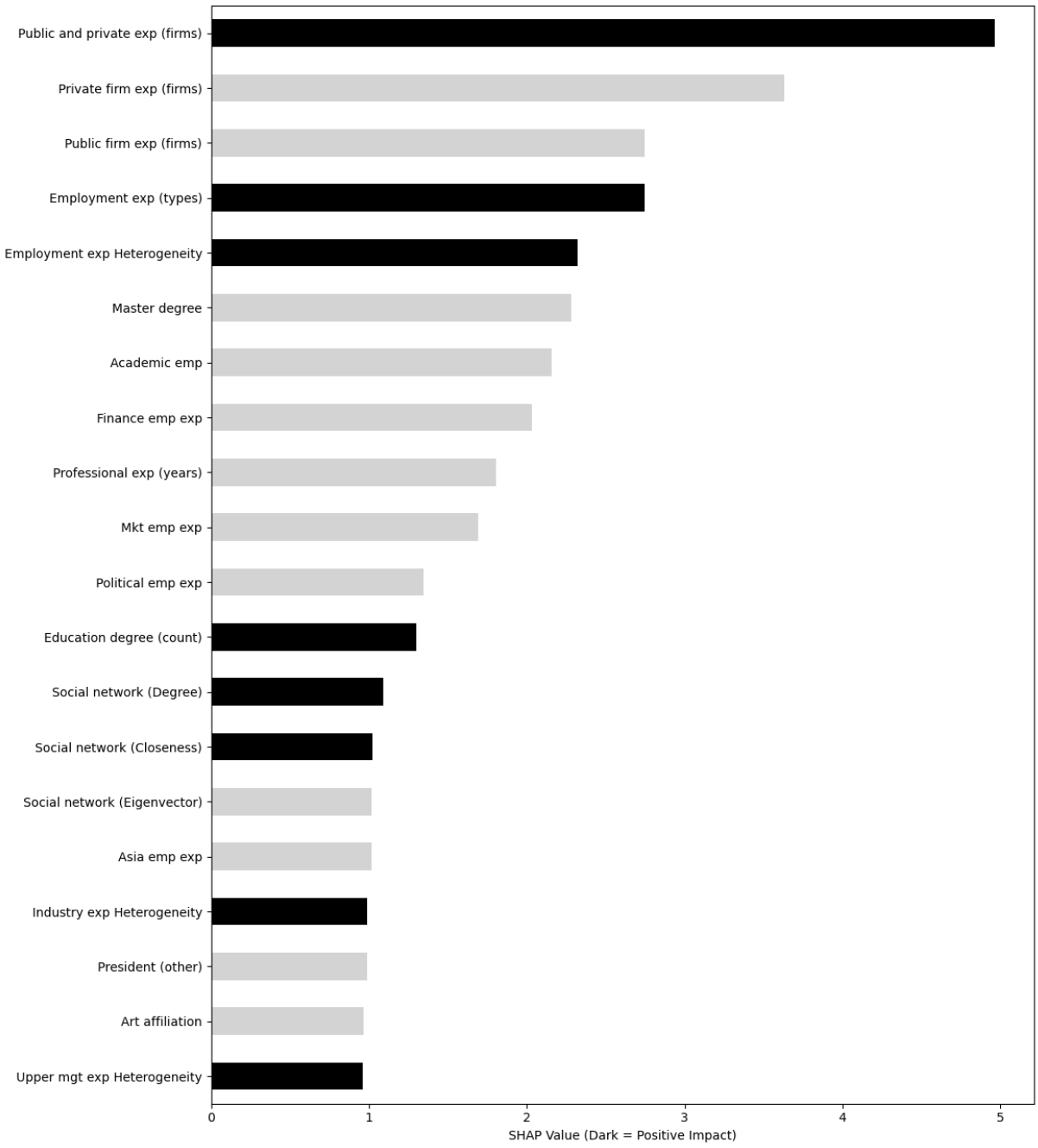


Figure 11 (continued): SHAP Values for Top 20 Variables – Pre- and Post-Crisis Subsamples

This figure presents the results for the female CEO top-performing model for pre- (Panel A) and post-crisis (Panel B) subsamples, XGBoost tree specification, with SHAP values indicating the direction and magnitude of the explanatory variable's impact on the prediction of the outcome variable. SHAP values are presented for the top 20 variables with the largest impact on the prediction. Darker color indicates a positive impact, while lighter color indicates a negative impact. Definitions of all variables are included in Table A1.

Panel B. Post-Crisis Subsample

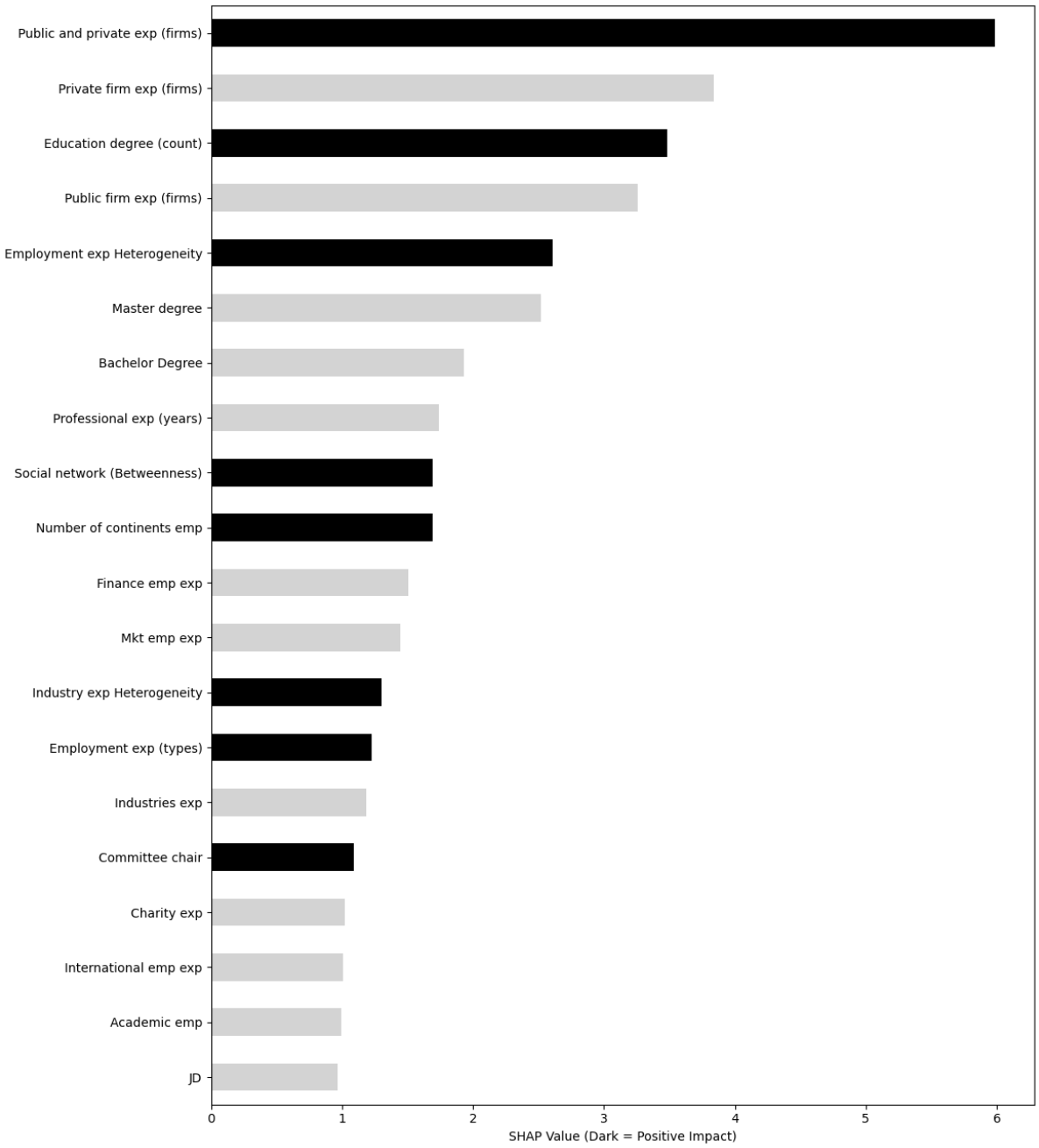


Table 1: Descriptive Statistics

This table presents a two-sample t-test with unequal variances for the CEO and non-CEO subsamples for all variables used in the data analysis. Definitions of all variables are included in Table A1.

Panel A. Female Sample

This table presents a two-sample *t*-test with unequal variances for the CEO and non-CEO subsamples for female sample. The CEO subsample consists of female executives who became first-time CEOs in a given year. Definitions of all variables are included in Table A1. *p < 0.10; **p < 0.05; ***p < 0.01.

	CEO	Non-CEO	Difference	T-stat
Academic affiliation	0.16	0.24	-0.07	-3.22**
Academic award	0.11	0.12	-0.01	-0.29
Academic emp exp	**0.02**	**0.10**	**-0.08**	**-5.05*** **
Advisor (other)	0.07	0.07	-0.01	-0.38
Africa emp exp	0.01	0.01	0.00	0.16
Americas emp exp	0.01	0.01	0.00	-0.23
Art affiliation	0.03	0.06	-0.03	-2.15*
Asia emp exp	0.03	0.03	-0.01	-0.75
Audit committee chair exp	0.05	0.03	0.02	2.80**
Audit committee exp	**0.16**	**0.10**	**0.07**	**4.23*** **
Author	0.01	0.03	-0.02	-2.13*
Award	0.41	0.40	0.01	0.31
Bachelor's degree	**0.79**	**0.71**	**0.08**	**3.36*** **
Betweenness	**77.50**	**43.36**	**34.14**	**17.47*** **
Board exp (firms)	**1.61**	**0.96**	**0.65**	**5.73*** **
Board exp (years)	6.53	5.40	1.13	1.40
Board exp Heterogeneity	27.80	30.26	-2.46	-0.10
Board member (other)	0.06	0.06	0.00	0.05
Business affiliation	0.05	0.08	-0.03	-2.20*
Business award	**0.23**	**0.15**	**0.09**	**4.45*** **
Canada emp exp	0.07	0.09	-0.03	-1.61
CFO emp exp	**0.20**	**0.11**	**0.08**	**4.85*** **
Chair exp (quoted)	**0.07**	**0.02**	**0.05**	**6.10*** **
Chairwoman (other)	0.11	0.15	-0.04	-2.33*
Charity emp exp	**0.00**	**0.05**	**-0.05**	**-4.03*** **
Child affiliation	0.01	0.03	-0.02	-2.21*
City award	0.00	0.00	0.00	-0.87
Closeness	**68.42**	**50.46**	**17.96**	**11.50*** **
Clubs emp exp	0.00	0.00	0.00	-1.21
Committee (other)	**0.04**	**0.09**	**-0.05**	**-3.30*** **
Committee chair exp	0.13	0.08	0.05	3.15**
Committee exp	**0.34**	**0.25**	**0.09**	**4.03*** **
Community college degree	0.01	0.00	0.00	1.21
Compensation committee chair exp	0.04	0.03	0.01	1.40
Compensation committee exp	**0.20**	**0.10**	**0.10**	**5.93*** **
COO emp exp	**0.32**	**0.06**	**0.26**	**19.77*** **
Countries exp	1.31	1.23	0.08	2.34*
CPA	0.08	0.10	-0.02	-1.06
CTO emp exp	0.01	0.01	0.00	-0.33
Degree	**76.81**	**48.36**	**28.46**	**17.16*** **
Eigenvector	**65.32**	**48.61**	**16.71**	**9.84*** **
Employment exp (types)	**1.61**	**1.45**	**0.16**	**3.80*** **
Employment exp Heterogeneity	38.19	33.95	4.24	2.96**

Europe emp exp	0.09	0.07	0.02	1.58
Exec VP exp (quoted)	**0.05**	**0.01**	**0.04**	**6.08*** **
Female affiliation	0.04	0.07	-0.03	-2.24*
Female network (proportion)	**0.17**	**0.11**	**0.06**	**7.78*** **
Finance emp exp	0.19	0.19	0.00	0.15
Foreign affiliation	0.01	0.01	-0.01	-1.30
Foreign firm CEO emp exp	0.02	0.02	0.00	-0.44
Foreign Nationality	0.02	0.04	-0.02	-1.84
Foreign private firm CEO emp exp	0.02	0.02	0.00	0.07
Foreign public firm CEO emp exp	0.00	0.01	0.00	-0.77
Founder (other)	0.01	0.01	0.00	-0.49
Founder emp exp	0.03	0.02	0.00	0.44
Gov award (US)	0.01	0.01	-0.01	-1.13
Gov emp exp	**0.00**	**0.04**	**-0.04**	**-3.75*** **
Governance committee chair exp	0.02	0.03	-0.01	-1.05
Governance committee exp	**0.17**	**0.09**	**0.08**	**4.79*** **
Graduate degree	0.47	0.50	-0.03	-1.17
Health affiliation	0.04	0.07	-0.03	-2.39*
Honorary Degree	0.01	0.02	0.00	-0.47
Humanities affiliation	0.08	0.13	-0.04	-2.40*
Humanity award	0.10	0.11	-0.01	-0.65
Industries exp	**1.70**	**1.41**	**0.29**	**5.95*** **
Industry exp Heterogeneity	**41.63**	**33.28**	**8.34**	**4.68*** **
Insider exp (firms)	**0.14**	**0.06**	**0.08**	**4.73*** **
Insider exp (years)	0.73	0.42	0.32	2.25*
International affiliation	**0.01**	**0.05**	**-0.04**	**-3.50*** **
International emp (years)	1.74	3.44	-1.70	-3.15**
International emp exp	0.17	0.19	-0.02	-0.92
International exp Heterogeneity	1.45	3.49	-2.03	-2.69**
Ivy degree	0.19	0.17	0.03	1.34
JD	**0.08**	**0.16**	**-0.08**	**-4.23*** **
Law affiliation	**0.01**	**0.08**	**-0.06**	**-4.33*** **
Law award	**0.08**	**0.17**	**-0.09**	**-4.43*** **
Law emp exp	0.04	0.06	-0.02	-1.74
Leader award	0.10	0.08	0.02	1.47
Master's degree	0.44	0.47	-0.03	-1.21
MBA	**0.30**	**0.19**	**0.11**	**5.10*** **
MD	0.02	0.02	0.00	0.33
Media award	**0.20**	**0.12**	**0.09**	**5.14*** **
Medical emp exp	0.00	0.01	-0.01	-1.41
Mentor	0.00	0.01	-0.01	-1.34
Mgt emp exp	**0.98**	**0.84**	**0.14**	**7.24*** **
Military award	0.00	0.00	0.00	-0.82
Military emp exp	0.00	0.01	-0.01	-1.41
Mkt emp exp	**0.27**	**0.12**	**0.15**	**8.55*** **
Nomination committee chair exp	0.03	0.03	0.00	-0.13
Nomination committee exp	**0.15**	**0.09**	**0.06**	**3.86*** **
Num of academic degree	1.39	1.44	-0.04	-0.72
Number of continents emp	0.19	0.21	-0.02	-0.86
Number of different committees	**1.02**	**0.49**	**0.53**	**8.35*** **
Oceania emp exp	0.01	0.01	-0.01	-0.93
Other awards	0.06	0.09	-0.03	-1.96
Other committee chair exp	**0.04**	**0.01**	**0.02**	**3.48*** **
Other committee exp	**0.06**	**0.02**	**0.04**	**4.89*** **
Outsider exp (firms)	0.07	0.12	-0.05	-1.62
Outsider exp (years)	0.30	0.85	-0.56	-2.05*

Partnership emp exp	**0.01**	**0.06**	**-0.04**	**-3.42*****
PhD degree	0.06	0.07	-0.01	-0.73
Political emp exp	0.01	0.04	-0.03	-2.76**
President (other)	**0.02**	**0.08**	**-0.05**	**-3.72*****
President exp (quoted)	**0.31**	**0.02**	**0.29**	**37.72*****
Private firm exp (firms)	**2.65**	**2.02**	**0.63**	**5.21*****
Private firm exp (years)	12.45	10.77	1.68	2.18*
Professional exp (years)	23.20	21.85	1.34	2.49*
Public and private exp (firms)	**4.87**	**3.25**	**1.63**	**9.65*****
Public firm exp (firms)	**2.23**	**1.23**	**1.00**	**11.58*****
Public firm exp (years)	**14.10**	**7.88**	**6.22**	**10.27*****
Royalty award	0.00	0.00	0.00	-1.12
Science affiliation	0.02	0.02	0.00	-0.15
Science award	0.08	0.06	0.01	1.14
Science emp exp	0.06	0.05	0.02	1.34
Secretary (other)	0.01	0.02	-0.01	-1.57
Sport affiliation	0.01	0.01	0.00	-0.75
Sport award	0.01	0.00	0.00	1.12
Sporting emp exp	0.00	0.00	0.00	-0.41
Tech emp exp	0.03	0.04	-0.01	-0.92
Total Connections (Executive Network)	21.25	24.17	-2.92	-0.85
Treasurer (other)	0.01	0.03	-0.01	-1.45
Trustee (other)	0.11	0.11	0.00	-0.05
University emp exp	0.01	0.04	-0.03	-3.04**
Upper mgt exp	**0.51**	**0.18**	**0.33**	**16.07*****
Upper mgt exp (industries)	**0.47**	**0.12**	**0.35**	**17.10*****
Upper mgt exp (years)	**3.07**	**1.28**	**1.79**	**8.23*****
Upper mgt exp Heterogeneity	**4.00**	**1.38**	**2.62**	**10.00*****
US private firm CEO emp exp	**0.35**	**0.11**	**0.24**	**13.89*****
Volunteer	0.00	0.01	-0.01	-1.37
Women award	**0.25**	**0.15**	**0.10**	**5.02*****
Women's College	0.04	0.04	0.00	0.21
Observations	342	272,749	273,091	

Table 1 (continued): Descriptive Statistics

This table presents a two-sample t-test with unequal variances for the CEO and non-CEO subsamples for all variables used in the data analysis. Definitions of all variables are included in Table A1.

Panel B. Male Sample

This table presents a two-sample *t*-test with unequal variances for the CEO and non-CEO subsamples for male sample. The CEO subsample consists of male executives who became first-time CEOs in a given year. Definitions of all variables are included in Table A1. *p < 0.10; **p < 0.05; ***p < 0.01.

	CEO	Non-CEO	Difference	T-stat
Academic affiliation	**0.10**	**0.12**	**-0.02**	**-3.49*****
Academic award	0.06	0.06	0.00	0.11
Academic emp exp	**0.03**	**0.08**	**-0.04**	**-10.82*****
Advisor (other)	0.02	0.03	-0.01	-2.80**
Africa emp exp	0.00	0.01	0.00	-3.04**
Americas emp exp	0.01	0.01	0.00	-1.57
Art affiliation	0.02	0.02	0.00	-1.63
Asia emp exp	0.05	0.06	-0.01	-2.23*
Audit committee chair exp	0.04	0.04	0.01	2.30*
Audit committee exp	**0.11**	**0.09**	**0.02**	**4.72*****
Author	**0.01**	**0.02**	**-0.01**	**-3.72*****
Award	**0.19**	**0.25**	**-0.05**	**-8.13*****
Bachelor's degree	**0.79**	**0.75**	**0.04**	**5.95*****
Betweenness	**57.01**	**32.18**	**24.83**	**46.62*****
Board exp (firms)	**2.07**	**1.34**	**0.72**	**17.68*****
Board exp (years)	**9.50**	**8.13**	**1.37**	**4.92*****
Board exp Heterogeneity	48.05	51.28	-3.23	-0.40
Board member (other)	0.02	0.02	0.00	-1.89
Business affiliation	0.03	0.04	-0.01	-2.58**
Business award	**0.08**	**0.05**	**0.02**	**7.33*****
Canada emp exp	**0.06**	**0.12**	**-0.06**	**-12.15*****
CFO emp exp	**0.19**	**0.13**	**0.06**	**12.09*****
Chair exp (quoted)	**0.21**	**0.08**	**0.12**	**29.91*****
Chairwoman (other)	0.07	0.08	0.00	-0.63
Charity emp exp	**0.00**	**0.01**	**-0.01**	**-4.87*****
Child affiliation	0.01	0.01	0.00	-0.39
City award	0.00	0.00	0.00	-1.61
Closeness	**58.69**	**35.38**	**23.31**	**46.51*****
Clubs emp exp	0.00	0.00	0.00	-1.21
Committee (other)	**0.01**	**0.04**	**-0.02**	**-8.56*****
Committee chair exp	**0.11**	**0.09**	**0.02**	**4.17*****
Committee exp	**0.24**	**0.19**	**0.06**	**10.12*****
Community college degree	0.00	0.00	0.00	-0.67
Compensation committee chair exp	0.04	0.03	0.01	2.66**
Compensation committee exp	**0.12**	**0.09**	**0.03**	**7.28*****
COO emp exp	**0.41**	**0.10**	**0.31**	**69.51*****
Countries exp	1.35	1.32	0.03	2.38*
CPA	**0.07**	**0.05**	**0.03**	**8.09*****
CTO emp exp	**0.01**	**0.03**	**-0.01**	**-5.62*****
Degree	**59.27**	**34.18**	**25.09**	**49.75*****
Eigenvector	**56.69**	**33.65**	**23.04**	**44.25*****
Employment exp (types)	**1.53**	**1.45**	**0.09**	**7.27*****
Employment exp Heterogeneity	58.12	59.10	-0.98	-1.65
Europe emp exp	0.09	0.09	0.00	0.34
Exec VP exp (quoted)	**0.04**	**0.01**	**0.02**	**15.29*****
Female affiliation	0.00	0.00	0.00	-1.32
Female network (proportion)	0.11	0.12	-0.01	-3.11**
Finance emp exp	0.19	0.18	0.01	1.69

Foreign affiliation	**0.00**	**0.01**	**-0.01**	**-3.53*** **
Foreign firm CEO emp exp	0.06	0.07	-0.01	-1.95
Foreign Nationality	**0.03**	**0.04**	**-0.01**	**-3.94*** **
Foreign private firm CEO emp exp	0.04	0.05	0.00	-0.70
Foreign public firm CEO emp exp	**0.02**	**0.03**	**-0.01**	**-4.39*** **
Founder (other)	0.00	0.00	0.00	-1.92
Founder emp exp	0.04	0.04	0.00	-0.18
Gov award (US)	0.00	0.01	0.00	-2.20*
Gov emp exp	**0.00**	**0.02**	**-0.02**	**-8.73*** **
Governance committee chair exp	0.03	0.03	0.00	-0.22
Governance committee exp	**0.09**	**0.08**	**0.02**	**4.83*** **
Graduate degree	**0.44**	**0.51**	**-0.06**	**-8.11*** **
Health affiliation	0.03	0.03	-0.01	-2.16*
Honorary Degree	**0.02**	**0.01**	**0.01**	**4.16*** **
Humanities affiliation	0.04	0.05	-0.01	-2.97**
Humanity award	0.04	0.04	-0.01	-1.91
Industries exp	**1.56**	**1.35**	**0.21**	**16.26*** **
Industry exp Heterogeneity	**59.95**	**55.30**	**4.65**	**7.19*** **
Insider exp (firms)	**0.41**	**0.11**	**0.30**	**41.58*** **
Insider exp (years)	**2.21**	**0.84**	**1.37**	**22.02*** **
International affiliation	0.02	0.02	0.00	-2.27*
International emp (years)	**9.41**	**11.70**	**-2.29**	**-5.17*** **
International emp exp	**0.20**	**0.26**	**-0.07**	**-9.94*** **
International exp Heterogeneity	**8.13**	**11.67**	**-3.53**	**-6.02*** **
Ivy degree	0.15	0.17	-0.02	-2.91**
JD	**0.06**	**0.13**	**-0.07**	**-14.35*** **
Law affiliation	**0.01**	**0.05**	**-0.04**	**-11.18*** **
Law award	**0.05**	**0.13**	**-0.08**	**-15.86*** **
Law emp exp	**0.02**	**0.05**	**-0.03**	**-9.27*** **
Leader award	0.02	0.02	0.00	0.60
Master's degree	**0.42**	**0.47**	**-0.05**	**-6.40*** **
MBA	**0.28**	**0.24**	**0.05**	**7.37*** **
MD	**0.01**	**0.02**	**-0.01**	**-4.25*** **
Media award	0.04	0.03	0.00	1.05
Medical emp exp	0.00	0.00	0.00	-4.10***
Mentor	0.00	0.00	0.00	-1.75
Mgt emp exp	**0.98**	**0.84**	**0.14**	**26.36*** **
Military award	0.00	0.00	0.00	0.41
Military emp exp	0.03	0.03	0.00	1.49
Mkt emp exp	**0.17**	**0.09**	**0.08**	**18.40*** **
Nomination committee chair exp	0.03	0.03	0.00	0.09
Nomination committee exp	**0.10**	**0.08**	**0.02**	**4.74*** **
Num of academic degree	1.25	1.28	-0.03	-2.49*
Number of continents emp	**0.23**	**0.30**	**-0.08**	**-9.15*** **
Number of different committees	**0.75**	**0.42**	**0.33**	**21.08*** **
Oceania emp exp	0.01	0.02	0.00	-2.33*
Other awards	**0.04**	**0.05**	**-0.01**	**-4.24*** **
Other committee chair exp	0.02	0.01	0.00	2.71**
Other committee exp	**0.06**	**0.02**	**0.04**	**16.64*** **
Outsider exp (firms)	0.21	0.17	0.03	3.01**
Outsider exp (years)	**0.92**	**1.24**	**-0.32**	**-3.43*** **
Partnership emp exp	**0.02**	**0.09**	**-0.07**	**-17.23*** **
PhD degree	**0.04**	**0.06**	**-0.02**	**-5.75*** **
Political emp exp	**0.01**	**0.03**	**-0.01**	**-5.88*** **
President (other)	**0.02**	**0.04**	**-0.02**	**-6.77*** **
President exp (quoted)	**0.35**	**0.06**	**0.29**	**83.16*** **
Private firm exp (firms)	**2.73**	**2.28**	**0.45**	**11.81*** **
Private firm exp (years)	14.56	14.12	0.45	1.62
Professional exp (years)	**37.29**	**40.11**	**-2.82**	**-16.05*** **
Public and private exp (firms)	**4.69**	**3.57**	**1.12**	**21.56*** **
Public firm exp (firms)	**1.96**	**1.29**	**0.67**	**27.01*** **
Public firm exp (years)	**12.84**	**8.79**	**4.05**	**19.54*** **

Royalty award	0.00	0.00	0.00	-3.13**
Science affiliation	0.01	0.01	-0.01	-2.82**
Science award	**0.02**	**0.04**	**-0.01**	**-3.82*** **
Science emp exp	**0.06**	**0.09**	**-0.03**	**-6.30*** **
Secretary (other)	0.00	0.01	0.00	-2.74**
Sport affiliation	0.00	0.01	0.00	-0.64
Sport award	0.00	0.00	0.00	-1.56
Sporting emp exp	0.00	0.00	0.00	-0.35
Tech emp exp	**0.03**	**0.06**	**-0.03**	**-9.62*** **
Total Connections (Executive Network)	**15.58**	**40.88**	**-25.29**	**-18.03*** **
Treasurer (other)	0.01	0.01	0.00	-2.31*
Trustee (other)	**0.06**	**0.05**	**0.01**	**3.38*** **
University emp exp	**0.00**	**0.02**	**-0.02**	**-8.70*** **
Upper mgt exp	**0.62**	**0.26**	**0.36**	**54.50*** **
Upper mgt exp (industries)	**0.37**	**0.12**	**0.25**	**45.33*** **
Upper mgt exp (years)	**3.26**	**1.71**	**1.56**	**9.72*** **
Upper mgt exp Heterogeneity	**4.18**	**1.96**	**2.22**	**12.99*** **
US private firm CEO emp exp	**0.48**	**0.18**	**0.30**	**51.25*** **
Volunteer	0.00	0.00	0.00	-2.47*
Women award	0.00	0.00	0.00	0.35
Women's College	0.00	0.00	0.00	-1.00
Observations	4,457	2,011,920	2,016,377	

Table 2: T-test of Sample Means – Comparison of Male and Female CEOs

This table presents a two-sample *t*-test with unequal variances for the female and male CEO subsamples. Definitions of all variables are provided in Table A1. *p < 0.10; **p < 0.05; ***p < 0.01.

	Female CEO	Male CEO	Difference	T-stat
Academic affiliation	**0.16**	**0.10**	**0.06**	**3.80*****
Academic award	**0.11**	**0.06**	**0.05**	**3.54*****
Academic emp exp	0.02	0.03	-0.01	-1.28
Advisor (other)	**0.07**	**0.02**	**0.05**	**5.55*****
Africa emp exp	0.01	0.00	0.00	0.58
Americas emp exp	0.01	0.01	0.00	-0.74
Art affiliation	0.03	0.02	0.01	1.68
Asia emp exp	0.03	0.05	-0.02	-1.82
Audit committee chair exp	0.05	0.04	0.01	0.90
Audit committee exp	**0.16**	**0.11**	**0.06**	**3.34*****
Author	0.01	0.01	0.00	0.16
Award	**0.41**	**0.19**	**0.22**	**9.66*****
Bachelor's degree	0.79	0.79	0.01	0.24
Betweenness	**77.50**	**57.01**	**20.49**	**11.53*****
Board exp (firms)	1.61	2.07	-0.46	-3.28**
Board exp (years)	**6.53**	**9.50**	**-2.97**	**-3.75*****
Board exp Heterogeneity	27.80	48.05	-20.25	-1.97*
Board member (other)	**0.06**	**0.02**	**0.04**	**5.37*****
Business affiliation	0.05	0.03	0.02	2.06*
Business award	**0.23**	**0.08**	**0.16**	**9.92*****
Canada emp exp	0.07	0.06	0.00	0.21
CFO emp exp	0.20	0.19	0.00	0.19
Chair exp (quoted)	**0.07**	**0.21**	**-0.14**	**-6.15*****
Chairwoman (other)	0.11	0.07	0.03	2.20*
Charity emp exp	0.00	0.00	0.00	-0.73
Child affiliation	0.01	0.01	0.00	-0.48
City award	0.00	0.00	0.00	-0.28
Closeness	**68.42**	**58.69**	**9.73**	**6.23*****
Clubs emp exp	0.00	0.00	0.00	-0.62
Committee (other)	**0.04**	**0.01**	**0.03**	**4.13*****
Committee chair exp	0.13	0.11	0.02	1.25
Committee exp	**0.34**	**0.24**	**0.10**	**4.02*****
Community college degree	0.01	0.00	0.01	1.81
Compensation committee chair exp	0.04	0.04	0.00	-0.09
Compensation committee exp	**0.20**	**0.12**	**0.07**	**3.78*****
COO emp exp	0.32	0.41	-0.09	-3.18**
Countries exp	1.31	1.35	-0.04	-0.98
CPA	0.08	0.07	0.01	0.59
CTO emp exp	0.01	0.01	-0.01	-1.25
Degree	**76.81**	**59.27**	**17.54**	**11.16*****
Eigenvector	**65.32**	**56.69**	**8.63**	**5.08*****
Employment exp (types)	1.61	1.53	0.08	2.05*
Employment exp Heterogeneity	**38.19**	**58.12**	**-19.93**	**-11.27*****
Europe emp exp	0.09	0.09	0.00	-0.11
Exec VP exp (quoted)	0.05	0.04	0.01	1.31
Female affiliation	**0.04**	**0.00**	**0.04**	**12.17*****
Female network (proportion)	**0.17**	**0.11**	**0.06**	**6.83*****
Finance emp exp	0.19	0.19	0.00	0.01
Foreign affiliation	0.01	0.00	0.00	0.36

Foreign firm CEO emp exp	0.02	0.06	-0.04	-3.02**
Foreign Nationality	0.02	0.03	-0.01	-0.55
Foreign private firm CEO emp exp	0.02	0.04	-0.02	-2.08*
Foreign public firm CEO emp exp	0.00	0.02	-0.02	-2.41*
Founder (other)	0.01	0.00	0.01	1.81
Founder emp exp	0.03	0.04	-0.01	-1.08
Gov award (US)	0.01	0.00	0.00	0.50
Gov emp exp	0.00	0.00	0.00	-1.24
Governance committee chair exp	0.02	0.03	-0.01	-0.67
Governance committee exp	**0.17**	**0.09**	**0.07**	**4.44*** **
Graduate degree	0.47	0.44	0.03	0.94
Health affiliation	0.04	0.03	0.01	1.58
Honorary Degree	0.01	0.02	-0.01	-0.66
Humanities affiliation	**0.08**	**0.04**	**0.04**	**3.63*** **
Humanity award	**0.10**	**0.04**	**0.06**	**5.78*** **
Industries exp	1.70	1.56	0.13	2.59**
Industry exp Heterogeneity	**41.63**	**59.95**	**-18.32**	**-7.51*** **
Insider exp (firms)	**0.14**	**0.41**	**-0.27**	**-5.69*** **
Insider exp (years)	**0.73**	**2.21**	**-1.48**	**-4.80*** **
International affiliation	0.01	0.02	-0.01	-0.98
International emp (years)	**1.74**	**9.41**	**-7.67**	**-7.52*** **
International emp exp	0.17	0.20	-0.02	-1.02
International exp Heterogeneity	**1.45**	**8.13**	**-6.68**	**-5.44*** **
Ivy degree	0.19	0.15	0.04	1.95
JD	0.08	0.06	0.02	1.47
Law affiliation	0.01	0.01	0.00	0.57
Law award	0.08	0.05	0.02	1.87
Law emp exp	0.04	0.02	0.02	2.70**
Leader award	**0.10**	**0.02**	**0.07**	**8.26*** **
Master's degree	0.44	0.42	0.02	0.84
MBA	0.30	0.28	0.01	0.53
MD	0.02	0.01	0.01	1.62
Media award	**0.20**	**0.04**	**0.17**	**14.18*** **
Medical emp exp	0.00	0.00	0.00	-0.28
Mentor	0.00	0.00	0.00	-0.48
Mgt emp exp	0.98	0.98	0.00	-0.33
Military award	0.00	0.00	0.00	-0.92
Military emp exp	**0.00**	**0.03**	**-0.03**	**-3.35*** **
Mkt emp exp	**0.27**	**0.17**	**0.10**	**4.64*** **
Nomination committee chair exp	0.03	0.03	0.00	-0.14
Nomination committee exp	0.15	0.10	0.05	2.92**
Num of academic degree	**1.39**	**1.25**	**0.15**	**3.45*** **
Number of continents emp	0.19	0.23	-0.03	-1.24
Number of different committees	**1.02**	**0.75**	**0.27**	**3.95*** **
Oceania emp exp	0.01	0.01	-0.01	-1.12
Other awards	0.06	0.04	0.02	2.12*
Other committee chair exp	0.04	0.02	0.02	2.48*
Other committee exp	0.06	0.06	0.00	0.03
Outsider exp (firms)	**0.07**	**0.21**	**-0.14**	**-3.38*** **
Outsider exp (years)	0.30	0.92	-0.63	-2.71**
Partnership emp exp	0.01	0.02	0.00	-0.31
PhD degree	**0.15**	**0.04**	**0.11**	**9.60*** **
Political emp exp	0.01	0.01	0.00	-0.31
President (other)	0.02	0.02	0.01	0.90
President exp (quoted)	0.31	0.35	-0.05	-1.73
Private firm exp (firms)	2.65	2.73	-0.08	-0.64

Private firm exp (years)	12.45	14.56	-2.12	-2.52*
Professional exp (years)	**23.20**	**37.29**	**-14.09**	**-23.46*****
Public and private exp (firms)	4.87	4.69	0.19	1.05
Public firm exp (firms)	2.23	1.96	0.27	2.98**
Public firm exp (years)	14.10	12.84	1.26	1.88
Royalty award	0.00	0.00	0.00	-0.28
Science affiliation	0.02	0.01	0.01	2.52*
Science award	**0.08**	**0.02**	**0.05**	**5.49*****
Science emp exp	0.06	0.06	0.00	0.26
Secretary (other)	0.01	0.00	0.01	2.02*
Sport affiliation	0.01	0.00	0.00	0.23
Sport award	0.01	0.00	0.00	2.50*
Sporting emp exp	0.00	0.00	0.00	-0.39
Tech emp exp	0.03	0.03	0.00	0.01
Total Executive Network	21.25	15.58	5.67	2.87**
Treasurer (other)	0.01	0.01	0.01	0.94
Trustee (other)	**0.11**	**0.06**	**0.05**	**3.89*****
University emp exp	0.01	0.00	0.00	0.58
Upper mgt exp	**0.51**	**0.62**	**-0.11**	**-4.00*****
Upper mgt exp (industries)	0.47	0.37	0.10	3.22**
Upper mgt exp (years)	3.07	3.26	-0.19	-0.62
Upper mgt exp Heterogeneity	4.00	4.18	-0.18	-0.38
US private firm CEO emp exp	**0.35**	**0.48**	**-0.13**	**-4.71*****
Volunteer	0.00	0.00	0.00	-0.28
Women award	**0.25**	**0.00**	**0.24**	**36.50*****
Women's College	**0.04**	**0.00**	**0.04**	**11.84*****
Observations	342	4,457	4,799	

Table 3: Comparison of Model Performance

This table presents the out-of-bag and out-of-sample performance metrics for all the models. Out-of-bag performance is assessed on the resampled training data, and out-of-sample performance is based on the test subsample data. We split the sample into training data based on rolling window, with the initial 6 years as training subsample, and the following 3 years as validation subsample rolling throughout 2001 to 2015; and test sample for 2016-2018. *AUC* is the area under the ROC curve. *Sensitivity* is the ratio of true positive cases to all positive cases identified by the model. *Specificity* is the ratio of true negative cases to all negative cases identified by the model. *Accuracy* assesses the model's overall ability to identify true cases among all of the data. *Balanced Accuracy* measures the model's average ability to identify true cases and is the sum of sensitivity and specificity divided by two. *Random Forest* is the best-performing model based on the highest test AUC among all models.

Panel A. Female Sample

	AUC	*Accuracy*	*Sensitivity*	*Specificity*	*Balanced Accuracy*
Out-of-Bag Performance					
Logistic Regression	0.80	0.52	0.93	0.52	0.73
Lasso	0.86	0.93	0.55	0.93	0.74
GLM Net	0.87	0.93	0.56	0.93	0.74
Boosted GLM	0.86	0.93	0.55	0.93	0.74
KNN	0.85	0.94	0.43	0.94	0.68
Decision Tree	0.90	0.91	0.70	0.91	0.81
Bagged Decision Trees	0.99	0.94	0.99	0.94	0.97
Random Forest	**0.99**	**0.95**	**1.00**	**0.95**	**0.97**
Gradient Boosting	0.91	0.94	0.57	0.94	0.76
XGBoost	0.93	0.94	0.69	0.94	0.81
Out-of-Sample Performance					
Logistic Regression	0.69	0.51	0.75	0.51	0.63
Lasso	0.77	0.93	0.37	0.93	0.65
GLM Net	0.78	0.92	0.41	0.92	0.66
Boosted GLM	0.78	0.93	0.37	0.93	0.65
KNN	0.75	0.94	0.30	0.94	0.62
Decision Tree	0.84	0.91	0.53	0.91	0.72
Bagged Decision Trees	0.88	0.94	0.48	0.94	0.71
Random Forest	**0.91**	**0.95**	**0.54**	**0.95**	**0.75**
Gradient Boosting	0.89	0.95	0.42	0.95	0.68
XGBoost	0.89	0.94	0.49	0.94	0.72

Table 3 (continued): Comparison of Model Performance

This table presents the out-of-bag and out-of-sample performance metrics for all the models. Out-of-bag performance is assessed on the resampled training data, and out-of-sample performance is based on the test subsample data. We split the sample into training data based on rolling window, with the initial 6 years as training subsample, and the following 3 years as validation subsample rolling throughout 2001 to 2015; and test sample for 2016-2018. *AUC* is the area under the ROC curve. *Sensitivity* is the ratio of true positive cases to all positive cases identified by the model. *Specificity* is the ratio of true negative cases to all negative cases identified by the model. *Accuracy* assesses the model's overall ability to identify true cases among all of the data. *Balanced Accuracy* measures the model's average ability to identify true cases and is the sum of sensitivity and specificity divided by two. *Random Forest* is the best-performing model based on the highest test AUC among all models.

Panel B. Male Sample

	AUC	*Accuracy*	*Sensitivity*	*Specificity*	*Balanced Accuracy*
Out-of-Bag Performance					
Logistic Regression	0.83	0.69	0.81	0.69	0.75
Lasso	0.84	0.80	0.74	0.80	0.77
GLM Net	0.82	0.67	0.81	0.67	0.74
Boosted GLM	**0.84**	**0.79**	**0.75**	**0.79**	**0.77**
KNN	0.83	0.90	0.51	0.90	0.71
Decision Tree	0.90	0.89	0.75	0.89	0.82
Bagged Decision Trees	0.99	0.92	1.00	0.92	0.96
Random Forest	0.99	0.92	0.99	0.92	0.96
Gradient Boosting	0.91	0.93	0.61	0.93	0.77
XGBoost	0.91	0.93	0.61	0.93	0.77
Out-of-Sample Performance					
Logistic Regression	0.75	0.72	0.66	0.72	0.69
Lasso	0.81	0.81	0.68	0.81	0.75
GLM Net	0.75	0.70	0.67	0.70	0.69
Boosted GLM	**0.81**	**0.81**	**0.68**	**0.81**	**0.75**
KNN	0.76	0.92	0.33	0.92	0.62
Decision Tree	0.81	0.92	0.42	0.92	0.67
Bagged Decision Trees	0.85	0.94	0.43	0.94	0.69
Random Forest	0.88	0.96	0.35	0.96	0.66
Gradient Boosting	0.89	0.97	0.38	0.97	0.67
XGBoost	0.89	0.96	0.40	0.96	0.68

Table 4: T-test of Sample Means – Comparison of Male and Female CEOs

This table presents a two-sample *t*-test with unequal variances for the female and male CEO subsamples. Definitions of all variables are provided in Table A1. *p < 0.10; **p < 0.05; ***p < 0.01.

Panel A. Top 20 Most Important Variables (Female Model)

	Female CEO	Male CEO	Difference	T-stat
Upper mgt exp Heterogeneity	4.00	4.18	-0.18	-0.38
Upper mgt exp (years)	3.07	3.26	-0.19	-0.62
Social network (Betweenness)	**77.50**	**57.01**	**20.49**	**11.53*** **
Board exp (years)	**6.53**	**9.50**	**-2.97**	**-3.75*** **
Social network (Degree)	**76.81**	**59.27**	**17.54**	**11.16*** **
Board exp Heterogeneity	27.80	48.05	-20.25	-1.97*
Public firm exp (years)	14.10	12.84	1.26	1.88
Social network (Female connections)	**0.17**	**0.11**	**0.06**	**6.83*** **
Social network (Closeness)	**68.42**	**58.69**	**9.73**	**6.23*** **
Social network (Total Executive Network)	**21.25**	**15.58**	**5.67**	**2.87** **
Private firm exp (years)	12.45	14.56	-2.12	-2.52*
Master's degree	0.44	0.42	0.02	0.84
Insider exp (years)	**0.73**	**2.21**	**-1.48**	**-4.80*** **
Graduate degree	0.47	0.44	0.03	0.94
Social network (Eigenvector)	**65.32**	**56.69**	**8.63**	**5.08*** **
Finance emp exp	0.19	0.19	0.00	0.01
International emp (years)	**1.74**	**9.41**	**-7.67**	**-7.52*** **
Employment exp Heterogeneity	**38.19**	**58.12**	**-19.93**	**-11.27*** **
Academic affiliation	**0.16**	**0.10**	**0.06**	**3.80*** **
International emp exp	0.17	0.20	-0.02	-1.02

Panel B. Top 20 Most Important Variables (Male Model)

	Female CEO	Male CEO	Difference	T-stat
Public and private exp (firms)	4.87	4.69	0.19	1.05
Private firm exp (firms)	2.65	2.73	-0.08	-0.64
Number of continents emp	0.19	0.23	-0.03	-1.24
Public firm exp (firms)	**2.23**	**1.96**	**0.27**	**2.98** **
Canada emp exp	0.07	0.06	0.00	0.21
Num of academic degree	**1.39**	**1.25**	**0.15**	**3.45*** **
Master's degree	0.44	0.42	0.02	0.84
Employment exp (types)	1.61	1.53	0.08	2.05*
Bachelor's degree	0.79	0.79	0.01	0.24
Employment exp Heterogeneity	**38.19**	**58.12**	**-19.93**	**-11.27*** **
Finance emp exp	0.19	0.19	0.00	0.01
Europe emp exp	0.09	0.09	0.00	-0.11
Social network (Closeness)	**68.42**	**58.69**	**9.73**	**6.23*** **
Asia emp exp	0.03	0.05	-0.02	-1.82
Upper mgt exp	**0.51**	**0.62**	**-0.11**	**-4.00*** **
Mkt emp exp	**0.27**	**0.17**	**0.10**	**4.64*** **
Upper mgt exp Heterogeneity	4.00	4.18	-0.18	-0.38
CFO emp exp	0.20	0.19	0.00	0.19
Professional exp (years)	**23.20**	**37.29**	**-14.09**	**-23.46*** **
Partnership emp exp	0.01	0.02	0.00	-0.31

Table 5: Logistic Models with Most Important Variables

This table presents the prediction of first-time CEOs from logistic models. The variables for the logistic models were selected based on the top 20 most important variables predicted by the best-performing model for each sample. Definitions of all variables are provided in Table A1. Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Panel A. Female CEOs

	(1) First-time Female CEO	(2) First-time Female CEO
Upper mgt exp Heterogeneity	0.036***	0.036***
	(0.013)	(0.013)
Upper mgt exp (years)	-0.017	-0.017
	(0.019)	(0.019)
Social Network (Betweenness)	0.033***	0.033***
	(0.004)	(0.004)
Board exp (years)	-0.041***	-0.041***
	(0.008)	(0.008)
Social Network (Degree)	0.023***	0.023***
	(0.005)	(0.005)
Board exp Heterogeneity	0.000	0.000
	(0.001)	(0.000)
Public firm exp (years)	0.014***	0.014***
	(0.003)	(0.003)
Female network (proportion)	1.324***	1.362***
	(0.314)	(0.316)
Social Network (Closeness)	-0.002	-0.002
	(0.007)	(0.007)
Total Executive Network	-0.004***	-0.004**
	(0.002)	(0.002)
Private firm exp (years)	0.010**	0.011**
	(0.005)	(0.005)
Master's degree	-0.232	-0.229
	(0.281)	(0.281)
Insider exp (years)	0.035*	0.034*
	(0.018)	(0.019)
Graduate degree	-0.031	-0.038
	(0.283)	(0.283)
Social Network (Eigenvector)	-0.006	-0.007
	(0.006)	(0.006)
Finance emp exp	-0.357**	-0.361**
	(0.154)	(0.154)
International emp exp	-0.486***	-0.470***
	(0.151)	(0.151)
Employment exp Heterogeneity	-0.005**	-0.005*
	(0.003)	(0.003)
Academic affiliation	-0.639***	-0.636***
	(0.153)	(0.153)
Constant	-9.410***	-9.658***
	(0.244)	(0.411)
Year fixed effects	No	Yes
Observations	273,091	273,091
Pseudo R-squared	0.106	0.109

Table 5 (continued): Logistic Models with Most Important Variables

This table presents the prediction of first-time CEOs from logistic models. The variables for the logistic models were selected based on the top 20 most important variables predicted by the best-performing model for each sample. Definitions of all variables are provided in Table A1. Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1.

Panel B. Male CEOs

	(1) First-time Male CEO	(2) First-time Male CEO
Public and private exp (firms)	0.033***	0.041***
	(0.008)	(0.007)
Private firm exp (firms)	-0.036***	-0.033***
	(0.011)	(0.010)
Number of continents emp	-0.191**	-0.167*
	(0.094)	(0.094)
Canada emp exp	-0.708***	-0.691***
	(0.114)	(0.113)
Education degree (count)	-0.303***	-0.326***
	(0.077)	(0.077)
Master's degree	0.151*	0.182**
	(0.084)	(0.084)
Employment exp (types)	-0.099	-0.136*
	(0.068)	(0.073)
Bachelor's degree	0.513***	0.494***
	(0.087)	(0.087)
Employment exp Heterogeneity	-0.005***	-0.004**
	(0.002)	(0.002)
Finance emp exp	0.157***	0.170***
	(0.053)	(0.053)
Europe emp exp	0.114	0.100
	(0.110)	(0.110)
Social Network (Closeness)	0.018***	0.017***
	(0.001)	(0.001)
Asia emp exp	0.109	0.110
	(0.119)	(0.119)
Upper mgt exp	1.714***	1.705***
	(0.035)	(0.035)
Mkt emp exp	0.889***	0.903***
	(0.048)	(0.048)
Upper mgt exp Heterogeneity	0.001	0.001**
	(0.000)	(0.000)
CFO emp exp	-0.802***	-0.792***
	(0.050)	(0.050)
Professional exp (years)	-0.014***	-0.008***
	(0.003)	(0.003)
Partnership emp exp	-1.149***	-1.096***
	(0.118)	(0.118)
Constant	-6.707***	-6.565***
	(0.107)	(0.125)
Year fixed effects	No	Yes
Observations	2,016,377	2,016,377
Pseudo R-squared	0.090	0.096

Table 6: Cross-Model Fit

This table presents the prediction of first-time CEOs from cross-fitted models where the female sample is fitted for the final male prediction model and vice versa.

Panel A. Predictions on Cross-Model Fit

In this panel, we propose an alternative measure of cross-model fit. We look at observations correctly identified as CEOs by cross-model fit (best-performing model for the other sample) and compare them to the actual number of respective CEOs.

	Female CEOs	**Male CEOs**
Number of CEOs predicted by the cross-model fit	244	1,344
Actual number of CEOs	342	4,457
Rate of Prediction	0.71	0.30

Panel B. Adjusted Prediction Models on Cross-Samples

In this panel, we propose an alternative measure of cross-model fit. We look at observations correctly identified as CEOs by cross-models (best performing model for the other sample) and compare them to the actual number of respective CEOs. About 1% of the predicted male CEOs who meet the overall criteria to become a CEO identified by the model actually become CEOs. In fitting the female sample for the male CEO prediction model, we use this percentage as a proxy of how many of the predicted female CEOs who meet the male criteria of becoming a CEO would plausibly become CEOs in real life (matching 1% of qualified males who become CEOs). For the female CEO model, about 2% of the predicted female CEOs who meet the overall criteria to become a CEO identified by the model actually become CEOs. In fitting the male sample for the male CEO prediction model, we use this percentage as a proxy of how many of the predicted male CEOs who meet the male criteria of becoming a CEO would plausibly become CEOs in real life (matching 2% of qualified females who become CEOs).

	Female CEOs	**Male CEOs**
Adjusted Number of CEOs predicted by the cross-model fit	526	1,389
Actual number of CEOs	342	4,457
Adjusted Rate of Prediction	1.54	0.31

Table 6 (continued): Cross-Model Fit

This table presents the prediction of first-time CEOs from cross-fitted models where the female sample is fitted for the final male prediction model and vice versa.

Panel C. Cross-Model Fit Predictions by Industry on Female Sample with Male Model

	Predicted		Actual	
	CEO	Not CEO	Total	Prediction Rate (%)
Pharmaceuticals and Biotechnology	**19**	**24**	**43**	**44**
General Retailers	**25**	**15**	**40**	**63**
Health	**13**	**11**	**24**	**54**
Business Services	**10**	**10**	**20**	**50**
Banks	**11**	**8**	**19**	**58**
Leisure & Hotels	**9**	**5**	**14**	**64**
Real Estate	**9**	**5**	**14**	**64**
Software & Computer Services	**8**	**6**	**14**	**57**
Publishing	**9**	**2**	**11**	**82**
Telecommunication Services	**8**	**2**	**10**	**80**
Clothing & Personal Products	**4**	**5**	**9**	**44**
Electronic & Electrical Equipment	**5**	**4**	**9**	**56**
Food Producers & Processors	**5**	**4**	**9**	**56**
Insurance	**7**	**2**	**9**	**78**
Utilities - Other	**5**	**4**	**9**	**56**
Chemicals	3	5	8	38
Household Products	**4**	**4**	**8**	**50**
Media & Entertainment	1	7	8	13
Oil & Gas	**4**	**4**	**8**	**50**
Engineering & Machinery	**4**	**3**	**7**	**57**
Specialty & Other Finance	**4**	**3**	**7**	**57**
Investment Companies	0	6	6	0
Electricity	**3**	**1**	**4**	**75**
Food & Drug Retailers	1	3	4	25
Information Technology Hardware	**2**	**2**	**4**	**50**
Construction & Building Materials	1	2	3	33
Steel & Other Metals	**2**	**1**	**3**	**67**
Transport	1	2	3	33
Aerospace & Defense	**2**	**0**	**2**	**100**
Consumer Services	0	2	2	0
Education	**2**	**0**	**2**	**100**
Leisure Goods	**2**	**0**	**2**	**100**
Automobiles & Parts	0	1	1	0
Beverages	**1**	**0**	**1**	**100**
Diversified Industrials	0	1	1	0
Forestry & Paper	**1**	**0**	**1**	**100**
Renewable Energy	**1**	**0**	**1**	**100**
Tobacco	**1**	**0**	**1**	**100**
Wholesale Trade	**1**	**0**	**1**	**100**
Total	188	154	342	55

Table 6 (continued): Cross-Model Fit

Panel D. Cross-Model Fit Predictions by Industry on Male Sample with Female Model

	Predicted		Actual	
	CEO	Not CEO	Total	Prediction Rate (%)
Banks	88	311	399	22
Software & Computer Services	64	298	362	18
Electronic & Electrical Equipment	94	224	318	30
Pharmaceuticals and Biotechnology	59	239	298	20
Health	64	191	255	25
Oil & Gas	45	164	209	22
Business Services	37	160	197	19
Specialty & Other Finance	35	153	188	19
Engineering & Machinery	31	135	166	19
General Retailers	59	98	157	38
Leisure & Hotels	33	120	153	22
Information Technology Hardware	43	107	150	29
Real Estate	38	111	149	26
Transport	34	74	108	31
Telecommunication Services	19	84	103	18
Utilities - Other	**41**	**60**	**101**	**41**
Insurance	28	70	98	29
Food Producers & Processors	21	74	95	22
Construction & Building Materials	25	69	94	27
Chemicals	24	64	88	27
Media & Entertainment	18	65	83	22
Clothing & Personal Products	17	50	67	25
Automobiles & Parts	10	38	48	21
Household Products	13	33	46	28
Renewable Energy	6	40	46	13
Food & Drug Retailers	14	31	45	31
Steel & Other Metals	**19**	**25**	**44**	**43**
Aerospace & Defense	11	29	40	28
Consumer Services	5	33	38	13
Mining	3	35	38	8
Investment Companies	2	35	37	5
Forestry & Paper	12	21	33	36
Publishing	8	24	32	25
Electricity	9	22	31	29
Education	6	18	24	25
Beverages	**10**	**11**	**21**	**48**
Containers & Packaging	**9**	**11**	**20**	**45**
Diversified Industrials	1	17	18	6
Blank Check / Shell Companies	0	16	16	0
Leisure Goods	4	11	15	27
Life Assurance	0	10	10	0
Private Equity	0	9	9	0
Tobacco	**2**	**2**	**4**	**50**
Wholesale Trade	**3**	**1**	**4**	**75**
Total	1,064	3,393	4,457	24

Table 7: Placebo Test

This table presents the prediction of first-time female CEOs from placebo models where the most important predictor variable (social network) is switched for female executives with CEO-level social network assigned to non-CEO female executives and vice versa. This table shows the resulting changes in prediction.

Panel A. Differences in Social Network Predictors for CEO and Non-CEO Executives

This panel displays the difference in means in social network variables between CEO and non-CEO female executives. In the placebo sample, statistically significantly different social network variables were replaced by the mean values of the opposite group (CEO for non-CEO and vice versa).

	CEO		Non-CEO			
	N	**Mean**	**N**	**Mean**	**Difference**	**T-stat**
Betweenness	342	77.50	272,749	43.36	34.14	17.47***
Closeness	342	68.42	272,749	50.46	17.96	11.50***
Degree	342	76.81	272,749	48.36	28.46	17.16***
Eigenvector	342	65.32	272,749	48.61	16.71	9.84***
Female network (proportion)	342	0.17	272,749	0.11	0.06	7.78***
Total Connections (Executive Network)	342	21.25	272,749	24.17	-2.92	-0.85

Panel B. Predicted CEO Rates for CEO and Non-CEO Executives – Placebo Social Network

This panel presents prediction results for the actual full sample and the placebo full sample. In the actual sample, our best-performing model accurately identifies 89% of the actual CEOs as CEOs, while in the placebo sample where we replace key social network measures with the median measures for non-CEO sample, it only identifies 34%. This result may imply that with a lowered placebo social network, less than half of female executives who actually became CEOs would be able to get appointed. For the non-CEO sample with their actual social network, only 5% of the pool can meet the prediction expectation of becoming a CEO, while 11% of the non-CEO sample with a placebo (higher) social network can meet such prediction. This translated to doubling in the probability prediction of becoming CEOs for non-CEO executives if they increase their social network to match the average social network of female executives who actually become CEOs.

	CEOs		Non-CEOs	
	Actual Sample	Placebo Sample	Actual Sample	Placebo Sample
Number of CEOs predicted	306	116	14,747	29,824
Number Actual	342	342	272,749	272,749
Rate of Prediction	0.89	0.34	0.05	0.11

Appendix A

Table A1: Variable Definitions

Variable	Definition
Affiliations	
Academic affiliation	Equals 1 if individual has an academic affiliation; 0 otherwise.
Art affiliation	Equals 1 if individual has an arts affiliation; 0 otherwise.
Business affiliation	Equals 1 if individual has a business affiliation; 0 otherwise.
Child affiliation	Equals 1 if individual has a child organization affiliation; 0 otherwise.
Female affiliation	Equals 1 if individual has an affiliation with a women's organization; 0 otherwise.
Foreign affiliation	Equals 1 if individual has a foreign country affiliation; 0 otherwise.
Health affiliation	Equals 1 if individual has an affiliation with a health organization; 0 otherwise.
Humanities affiliation	Equals 1 if individual has a humanities affiliation; 0 otherwise.
International affiliation	Equals 1 if individual has an international organization affiliation; 0 otherwise.
Law affiliation	Equals 1 if individual has a law affiliation; 0 otherwise.
Science affiliation	Equals 1 if individual has an affiliation with a science organization; 0 otherwise.
Sport affiliation	Equals 1 if individual has a sports affiliation; 0 otherwise.
Awards	
Award	Equals 1 if individual has won any awards including academic, business, city, government, humanity, law, leadership, media, military, royalty, science, sports, women, or other awards; 0 otherwise.
Academic award	Equals 1 if individual has been recognized by an academic organization; 0 otherwise.
Business award	Equals 1 if individual has been recognized by a business organization; 0 otherwise.
City award	Equals 1 if individual has been recognized by a municipal government; 0 otherwise.
Gov award (US)	Equals 1 if individual has been recognized by the U.S. government; 0 otherwise.
Humanity award	Equals 1 if individual has been recognized by a humanities organization; 0 otherwise.
Law award	Equals 1 if individual has been recognized by the legal field including JD, admission to courts, law awards; 0 otherwise.
Leadership award	Equals 1 if individual has been recognized as a leader; 0 otherwise.
Media award	Equals 1 if individual has been recognized by a media organization; 0 otherwise.
Military award	Equals 1 if individual has been recognized by a military organization; 0 otherwise.
Other awards	Equals 1 if individual has won any other award; 0 otherwise.
Royalty award	Equals 1 if individual has been recognized by a royal organization; 0 otherwise.
Science award	Equals 1 if individual has been recognized by a scientific organization; 0 otherwise.
Sport award	Equals 1 if individual has been recognized by a sports organization; 0 otherwise.
Women award	Equals 1 if individual has been recognized by a women's organization; 0 otherwise.
Board Experience	
Audit committee chair exp	Equals 1 if individual has experience as a chair of the audit committee; 0 otherwise.
Audit committee exp	Equals 1 if individual has experience as a member of the audit committee; 0 otherwise.
Board exp (firms)	Cumulative number of unique firms i the individual's board experience.
Board exp (years)	Cumulative number of years of the individual's board experience.

Board exp Heterogeneity	Number of boards served multiplied by number of years of board experience.
Board member (other)	Equals 1 if individual has board member experience in organizations other than publicly listed or private companies; 0 otherwise.
Chairwoman exp (quoted)	Equals 1 if individual has chairwoman experience in a quoted (public) firm; 0 otherwise.
Committee chair exp	Equals 1 if individual has audit/compensation/governance/nomination/other committee chair experience; 0 otherwise.
Committee exp	Equals 1 if individual has committee experience; 0 otherwise.
Committee (other)	Equals 1 if individual has committee experience in organizations other than publicly listed or private companies; 0 otherwise.
Compensation committee chair exp	Equals 1 if individual has compensation committee chair experience; 0 otherwise.
Compensation committee exp	Equals 1 if individual has compensation committee experience; 0 otherwise.
Governance committee chair exp	Equals 1 if individual is chair of the governance committee; 0 otherwise.
Governance committee exp	Equals 1 if individual is a member of the governance committee; 0 otherwise.
Insider exp (firms)	Cumulative number of unique firms for the individual's insider board experience.
Insider exp (years)	Cumulative number of years of the individual's insider board experience.
Nomination committee chair exp	Equals 1 if individual is chair of the nomination committee; 0 otherwise.
Nomination committee exp	Equals 1 if individual is a member of the nomination committee; 0 otherwise.
Number of different committees	Number of different committees on which the individual has served.
Other committee chair exp	Equals 1 if individual is chair of a committee other than compensation, audit, governance, or nomination; 0 otherwise.
Other committee exp	Equals 1 if individual is a member of a committee other than compensation, audit, governance, or nomination; 0 otherwise.
Outsider exp (firms)	Cumulative number of unique firms for the individual's outsider board experience.
Outsider exp (years)	Cumulative number of years of the individual's outsider board experience.
CEO Appointment	
First-time CEO	Equals 1 in the year a female executive becomes a CEO in a publicly traded U.S. firm for the first time; 0 otherwise.
Education	
Bachelor degree	Equals 1 if individual has a bachelor degree; 0 otherwise.
Community college degree	Equals 1 if individual has a community college degree; 0 otherwise.
CPA	Equals 1 if individual holds a CPA; 0 otherwise.
Graduate degree	Equals 1 if individual has a graduate degree (MD, Ph.D., JD, MBA, masters); 0 otherwise.
Honorary degree	Equals 1 if individual had earned an honorary degree; 0 otherwise.
Ivy degree	Equals 1 if attended an Ivy league school; 0 otherwise.
JD	Equals 1 if individual holds a JD degree; 0 otherwise.
Master degree	Equals 1 if individual holds a master's degree; 0 otherwise.
MBA	Equals 1 if individual holds an MBA degree; 0 otherwise.
MD	Equals 1 if individual holds an MD degree; 0 otherwise.
Number of academic degrees	Number of academic degrees.
PhD	Equals 1 if individual holds a Ph.D. degree; 0 otherwise.
Women's College	Equals 1 if attended an all-women school; 0 otherwise.
Professional Experience	
Academic emp exp	Equals 1 if individual has academic employment experience; 0 otherwise.
Africa emp exp	Equals 1 if individual has employment experience in Africa; 0 otherwise.
Americas emp exp	Equals 1 if individual has employment experience in the Americas (except for Canada and the United States); 0 otherwise.

Asia emp exp	Equals 1 if individual has employment experience in Asia; 0 otherwise.
Canada emp exp	Equals 1 if individual has employment experience in Canada; 0 otherwise.
Charity emp exp	Equals 1 if individual has charity employment experience; 0 otherwise.
Clubs emp exp	Equals 1 if individul has club employment experience; 0 otherwise.
Countries exp	Number of home countries of the companies in which an individual has work experience.
Europe emp exp	Equals 1 if individual has employment experience in Europe; 0 otherwise.
Employment exp Heterogeneity	Number of employment types multiplied by number of years of employment experience.
Employment exp (types)	Number of types of employment experience including academic, law, management, marketing, military, political, science, technology, and finance.
Finance emp exp	Equals 1 if individual has finance employment experience; 0 otherwise.
Foreign co emp exp	Equals 1 if individual has foreign employment experience; 0 otherwise.
Founder exp	Equals 1 if individual has experience as a founder; 0 otherwise.
Global exp	Equals 1 if individual has international or foreign work experience or international or foreign affiliation.
Gov emp exp	Equals 1 if individual has government employment experience; 0 otherwise.
Industries exp	Number of industries in which an individual has experience.
Industry exp Heterogeneity	Number of industries multiplied by number of years of employment experience.
International emp exp	Equals 1 if individual has employment experience at a company with a non-U.S. home country; 0 otherwise.
International emp (years)	Number of years of international employment experience.
International exp Heterogeneity	Number of continents multiplied by the number of years of international employment experience.
Law emp exp	Equals 1 if individual has law employment experience; 0 otherwise.
Medical emp exp	Equals 1 if individual has medical employment experience; 0 otherwise.
Mgt emp exp	Equals 1 if individual has managerial employment experience; 0 otherwise.
Military emp exp	Equals 1 if individual has military employment experience; 0 otherwise.
Mkt emp exp	Equals 1 if individual has marketing employment experience; 0 otherwise.
Number of continents emp	Number of continents in which the individual has work experience.
Oceania emp exp	Equals 1 if individual has employment experience in Oceania; 0 otherwise.
Partnership emp exp	Equals 1 if individual has partnership employment experience; 0 otherwise.
Political emp exp	Equals 1 if individual has political employment experience; 0 otherwise.
Private firm exp (firms)	Cumulative number of unique firms for the individual's private firm experience.
Private firm exp (years)	Cumulative number of years of the individual's private firm experience.
Professional exp (years)	Cumulative number of years of professional experience measured from the start year of the first job in the employment file to the current year.
Public and private exp (firms)	Cumulative number of unique firms for the individual's public and private firm experience.
Public firm exp (firms)	Cumulative number of unique firms for the individual's public firm experience.
Public firm exp (years)	Cumulative number of years of the individual's public firm experience.
Science emp exp	Equals 1 if individual has science employment experience; 0 otherwise.
Sporting emp exp	Equals 1 if individual had been employed by a sports organization; 0 otherwise.
Tech emp exp	Equals 1 if individual has technology employment experience; 0 otherwise.
University emp exp	Equals 1 if individual had been employed by a university; 0 otherwise.
Upper Management Experience	
CFO emp exp	Equals 1 if individual has CFO experience; 0 otherwise.

COO emp exp	Equals 1 if individual has COO experience; 0 otherwise.
CTO emp exp	Equals 1 if individul has CTO experience; 0 otherwise.
Exec VP exp (quoted)	Equals 1 if individual has executive VP experience at a publicly traded company; 0 otherwise.
Foreign firm CEO emp exp	Equals 1 if individual has foreign firm CEO experience; 0 otherwise.
Foreign private firm CEO emp exp	Equals 1 if individual has foreign private firm CEO experience; 0 otherwise.
Foreign public firm CEO emp exp	Equals 1 if individual has foreign public firm CEO experience; 0 otherwise.
President exp (quoted)	Equals 1 if individual has president experience in publicly traded (quoted) company; 0 otherwise.
Upper mgt exp	Equals 1 if individual has upper management (COO, CFO, CTO, President) employment experience; 0 otherwise.
Upper mgt exp (industries)	Number of industries in which the individual has upper management experience.
Upper mgt exp (years)	Number of years of upper management experience.
Upper mgt exp Heterogeneity	Number of upper management roles (CFO, COO, CTO) multiplied by the number of years of upper management experience.
US private firm CEO emp exp	Equals 1 if individual has CEO experience at a U.S. private firm; 0 otherwise.
Social Network	
Betweenness	Betweenness is the percentile ranking of betweenness, with 1 being the lowest value and 100 being the highest value; Betweenness captures the extent to which a node lies between others and makes pass-through communications within the network.
Closeness	Closeness is the percentile ranking of closeness, with 1 being the lowest value and 100 being the highest value; Closeness is the inverse of the sum of the shortest distance between a node and every other node in the network and captures the degree to which an individual is near all other individuals in a network.
Degree	Degree is the percentile ranking of the degree, with 1 being the lowest value and 100 being the highest value; Degree centrality counts total number of direct ties an executive has.
Eigenvector	Eigenvector is the percentile ranking of the eigenvector, with 1 being the lowest value and 100 being the highest value; Eigenvector measures the relative importance of a node in the network, taking into account the extent to which an individual is connected with other highly connected individuals.
Female network (proportion)	Proportion of women in the individual's network.
Total Connections (Executive Network)	Total number of connections in the executive network.
Other Experience	
Advisor (other)	Equals 1 if individual has experience as an advisor in organizations other than publicly listed or private companies; 0 otherwise.
Author	Equals 1 if individual is an author of a book; 0 otherwise.
Chairwoman (other)	Equals 1 if individual has chairwoman experience in organizations other than publicly listed or private companies; 0 otherwise.
Foreign nationality	Equals 1 if individual's nationality is not American; 0 otherwise.
Founder (other)	Equals 1 if individual has experience as a founder in organizations other than publicly listed or private companies; 0 otherwise.
Mentor	Equals 1 if individual has experience as a mentor; 0 otherwise.
President (other)	Equals 1 if individual has president experience in organizations other than publicly listed or private companies; 0 otherwise.
Secretary (other)	Equals 1 if individual has secretary experience in organizations other than publicly listed or private companies; 0 otherwise.
Treasurer (other)	Equals 1 if individual has treasurer experience in organizations other than publicly listed or private companies; 0 otherwise.
Trustee (other)	Equals 1 if individual has trustee experience in organizations other than publicly listed or private companies; 0 otherwise.
Volunteer	Equals 1 if individual has volunteer experience; 0 otherwise.

Appendix B

Table B1: List of Female CEOs

This table presents the names of first-time female CEOs, the year they become first-time CEOs, the corresponding company and the SIC code. There is a total of 342 first-time female CEO of U.S. publicly traded companies (with non-missing data for the sample's set of predictors).

Female CEO Name	Year Became First-time CEO	Company Name	SIC
Adelene Perkins	2010	Infinity Pharmaceuticals Inc	2834
Adena Friedman	2017	Nasdaq Inc	6200
Agnes Ngo	2015	Central Pacific Financial Cp	6020
Alison May	2002	Redenvelope Inc	5961
Amy Lee	2017	Fiduciary/Claymore Energy Infrastructure Fund	6726
Amy Miles	2009	Regal Entertainment Group	7830
Andi Owen	2018	Miller (Herman) Inc	2520
Andrea Ayers	2012	Convergys Corp	7389
Angela Braly	2007	Anthem Inc	6324
Angelica Berrie	2003	Kid Brands Inc	3990
Anna Chagnon	2003	Bitstream Inc	7372
Anna Manning	2017	Reinsurance Group Amer Inc	6311
Anna Protopapas	2017	Mersana Thrpeutic Inc	2836
Anne Ackerley	2009	BlackRock Defined Opportunity Credit Trust	6726
Anne Mulcahy	2001	Xerox Holdings Corp	3577
Anne Noonan	2016	Omnova Solutions Inc	2821
Anne Stevens	2006	Carpenter Technology Corp	3312
Anne Whitaker	2014	Synta Pharmaceuticals Corp	2834
Anne-Marie Ainsworth	2012	Oiltanking Partners L.P.s	5171
B Beasley	2017	Beasley Broadcast Group Inc	4832
Barbara Rentler	2014	Ross Stores Inc	5651
Barbara Smith	2017	Commercial Metals	3312
Beth Garvey	2018	Bg Staffing Inc	7363
Beth Mooney	2011	Keycorp	6020
Bethany Mayer	2014	Ixia	3825
Betsy Holden	2001	Mondelez International Inc	2052
Bonnie Anderson	2013	Veracyte Inc	2835
Brittany McKinney	2011	Analysts International Corp	7371
Caren Mason	2004	Quidel Corp	2835
Carin Stutz	2012	Cosi Inc	5812
Carissa Rodeheaver	2016	First United Corp	6020
Carol Bramson	2014	Summer Infant Inc	3990
Carol Meyrowitz	2007	TJX Companies Inc (The)	5651
Carol Nelson	2002	Cascade Financial Corp	6020
Carolyn Logan	2002	Salix Pharmaceuticals Ltd	2834
Carrie Bourdow	2018	Trevena Inc	2836
Carrie Gunnerson	2010	Arts Way Manufacturing Inc	3523
Cathy McCarthy	2007	Sm&A Corp	7370
Cheryl Bachelder	2007	Popeyes Louisiana Kitchen	6794
Cheryl Henry	2018	Ruths Hospitality Group Inc	5812
Christina Gold	2006	Western Union Co	6099
Christine Day	2008	Lululemon Athletica Inc	2300
Christine King	2001	Amis Holdings Inc	3674
Cindy Baier	2018	Brookdale Senior Living Inc	8050
Cindy Collins	2012	Genvec Inc	2834
Cindy Taylor	2007	Oil States Intl Inc	3533
Claire Tucker	2016	Capstar Financial Holdings Inc	6020
Clara Conti	2004	Ipix Corp	7373
Colleen Brown	2005	Fisher Communications Inc	4833
Connie Lau	2006	Hawaiian Electric Industries	4911
Connie Mixon	2011	Mycelx Technologies Corp	3580
Connie Moore	2005	Bre Properties Inc	6798

Cynthia Passmore-Mclaughin	2005	Enesco Group Inc	5190
Cynthia Sullivan	2001	Immunomedics Inc	2835
Dawn Lepore	2004	Drugstore.Com Inc	5961
Dawn Robertson	2016	Stein Mart Inc	5651
Dawn Zier	2012	Nutrisystem Inc	5961
Dawne Hickton	2007	Rti Intl Metals Inc	3490
Debbie Fretz	2001	Energy Transfer Partners	4922
Debbie Osteen	2018	Acadia Healthcare Co Inc	8060
Debbie Perelman	2018	Revlon Inc	2844
Debbie Reed-Klages	2011	Sempra Energy	4931
Denise Morrison	2011	Campbell Soup Co	2030
Denise Ramos	2011	Itt Inc	3561
Denny Post	2016	Red Robin Gourmet Burgers	5812
Diana Adams	2013	Ambac Financial Group Inc	6351
Diane Goostree	2006	Artes Medical Inc	2836
Diane Irvine	2008	Blue Nile Inc	5944
Diane Sullivan	2011	Caleres Inc	3140
Doctor Abbie Celniker	2014	Sesen Bio Inc	2836
Doctor Annalisa Jenkins	2015	Dimension Therapeutics Inc	2836
Doctor Aoife Brennan	2018	Synlogic Inc	2834
Doctor Catherine Corrigan	2018	Exponent Inc	8742
Doctor Claire Kruger	2007	Spherix Inc	2836
Doctor Deborah Dunsire	2005	Millennium Pharmaceuticals	2835
Doctor Deirdre Gillespie	2006	La Jolla Pharmaceutical Co	2836
Doctor Gail Seneca	2003	Luminent Mortgage Capital	6798
Doctor Helen Torley	2014	Halozyme Therapeutics Inc	2836
Doctor Irene Rosenfeld	2006	Mondelez International Inc	2052
Doctor Jennifer Simpson	2015	Delcath Systems Inc	3841
Doctor Jill Milne	2015	Catabasis Pharmaceuticals	2836
Doctor Julia Owens	2018	Millendo Therapeutics Inc	2836
Doctor Kim Mink	2015	Innophos Holdings Inc	2810
Doctor Kris Zsebo	2014	Eiger Biopharmaceuticals Inc	2836
Doctor Laura Shawver	2018	Synthorx Inc	2836
Doctor Linda Grais	2013	Ocera Therapeutics Inc	2836
Doctor Lisa Su	2014	Advanced Micro Devices	3674
Doctor Loretta Mayer	2016	Senestech Inc	2870
Doctor Lucy Lu	2017	Avenue Therapeutics Inc	2834
Doctor M Berrey	2014	Chimerix Inc	2836
Doctor Maria Fardis	2016	Iovance Biotherapeutics Inc	2836
Doctor Max Gowen	2014	Trevena Inc	2836
Doctor Michelle Dipp	2013	Ovascience Inc	2836
Doctor Nancy Simonian	2016	Syros Pharmaceuticals Inc	2836
Doctor Pam Marrone	2013	Marrone Bio Innovtions	2870
Doctor Prabha Fernandes	2012	Cempra Inc	2834
Doctor Robin Smith	2006	Caladrius Biosciences Inc	2836
Doctor Sharon Mates	2014	Intra-Cellular Therapies Inc	2836
Doctor Susan Molineaux	2014	Calithera Biosciences Inc	2836
Doctor Tina Nova	2007	Genoptix Inc	8071
Donita Rudy	2006	Omega Financial Corp	6020
Donna Coughey	2005	Willow Finl Bancorp Inc	6035
Dunia Shive	2008	Belo Corp	4833
Eileen Drake	2015	Aerojet Rocketdyne Holdings	3760
Eileen Schaefer	2003	Claires Stores Inc	5600
Eileen Scott	2002	Pathmark Stores Inc	5411
Elisa Steele	2015	Jive Software Inc	7372
Elizabeth Cholawsky	2014	Support.Com Inc	7370
Elizabeth Hance	2006	Magyar Bancorp Inc	6036
Ellen Alemany	2016	Cit Group Inc	6020
Ellen Cotter	2016	Reading Intl Inc	7830
Ellen Gordon	2015	Tootsie Roll Industries Inc	2060
Ellen Kullman	2009	Du Pont (E I) De Nemours	2820
Elly Mackus	2011	Cf Bankshares Inc	6035
Emma Walmsley	2017	Glaxosmithkline Plc	2834
Ev Graham	2008	Raptor Pharmaceutical Corp	2834
Fran Horowitz-Bonadies	2017	Abercrombie & Fitch	5651
Frances Conley	2002	Cutter & Buck Inc	2320

Gail Boudreaux	2017	Anthem Inc	6324
Gail Goodman	2007	Constant Contact Inc	7310
Gail Page	2005	Aspira Womens Health Inc	2835
Gayla Delly	2012	Benchmark Electronics Inc	3672
Geisha Williams	2017	PG&E Corp	4931
Gerry Frost	2015	Amerisafe Inc	6331
Ginger Graham	2003	Amylin Pharmaceuticals Inc	2834
Ginni Rometty	2012	Intl Business Machines Corp	7370
Gracia Martore	2011	Tegna Inc	4833
Greta Guggenheim	2017	Tpg Re Finance Trt Inc	6798
Gretchen McClain	2011	Xylem Inc	3561
H Eberhart	2011	Cdi Corp	7363
Heidi Stanley	2009	Sterling Financial Corp	6036
Holli Ladhani	2017	Select Energy Services Inc	1389
Ilene Gordon	2009	Ingredion Inc	2040
Indra Nooyi	2006	Pepsico Inc	2080
Jackie Lemke	2013	Bioanalytical Systems Inc	8731
Jane Aggers	2005	Hancock Fabrics Inc	5940
Jane Elfers	2010	Childrens Place Inc	5600
Jane Hollingsworth	2010	Nupathe Inc	2834
Jane Murray	2007	Qmed Inc	9995
Jane Sun	2016	Trip Com Group Ltd	4700
Jane Trust	2015	Western Asst Inv Grd Incm Fd	6726
Janet Matricciani	2015	World Acceptance Corp	6141
Janet Robinson	2004	New York Times Co	2711
Janet Steinmayer	2006	Centerplate Inc	5812
Jennifer Cue	2012	Jones Soda Co	2086
Jennifer Good	2006	Penwest Pharmaceuticals Co	2834
Jennifer Murphy	2016	Western Asset Mtg Capital Cp	6798
Jennifer Sherman	2016	Federal Signal Corp	3711
Jenniffer Deckard	2014	Fairmount Santrol Holdings	1400
Jenny Scanlon	2016	Usg Corp	3270
Jill Granoff	2008	Cole Kenneth Prod Inc	3140
Jill Smith	2009	Digitalglobe Inc	4899
Jo Young	2003	Phoenix Companies Inc	6311
Joanne Kim	2008	Wilshire Bancorp Inc	6020
Judith Henkels	2002	Access Plans Usa Inc	7389
Judy McReynolds	2010	Arcbest Corp	4213
Julia Gregory	2014	Contrafect Corp	2836
Julia Stewart	2002	Dine Brands Global Inc	6794
Julie Dill	2012	Spectra Energy Partners L.P.	4922
Julie Howard	2012	Navigant Consulting Inc	8742
Julie Laulis	2017	Cable One Inc	4841
Julie Smith	2015	Raptor Pharmaceutical Corp	2834
Karel Czanderna	2012	Flexsteel Industries Inc	2510
Karen Colonias	2012	Simpson Manufacturing Inc	3420
Karen Magee	2006	Planetout Inc	7370
Karen Murray	2017	Sequential Brands Group Inc	6794
Karen Puckett	2015	Harte Hanks Inc	7331
Karen Richardson	2003	E.Piphany Inc	7372
Karen Sammon	2016	Par Technology Corp	3578
Karen van Lith	2011	Makemusic Inc	7372
Karen Wright	2004	Nyer Medical Group Inc	5912
Kate Duchene	2016	Resources Connection Inc	8721
Kathleen Ligocki	2003	Tower Automotive Inc	3460
Kathleen Skarvan	2012	Electromed Inc	3845
Kathryn Bufano	2014	Bon-Ton Stores Inc	5311
Kathy Harless	2006	Supermedia Inc	2741
Kathy Marinello	2006	Ceridian Corp	8721
Katrina Lake	2017	Stitch Fix Inc	5961
Katrine Bosley	2016	Editas Medicine Inc	2836
Katy McCarthy	2013	Geeknet Inc	5961
Kay Krill	2005	Ann Inc	5621
Keri Jones	2018	Christopher & Banks Corp	5621
Kerrii Anderson	2006	Wendy's International Inc	5812
Kim Kelly	2002	Insight Communications Co	4841

Kim Korth	2011	Supreme Industries Inc	3713
Kim Lubel	2013	Cst Brands Inc	5500
Kim McWaters	2003	Universal Technical Inst	8200
Kim Popovits	2009	Genomic Health Inc	2835
Kim Schaefer	2009	Great Wolf Resorts Inc	7011
Kimberly Till	2008	Harris Interactive Inc	8700
Kitty Iverson	2003	Cyberoptics Corp	3827
Kristine Juster	2018	Kimball International	2520
Laura Alber	2010	Williams-Sonoma Inc	5961
Laura Fergerson	2009	Franklin Universal Trust	6726
Laura Hamilton	2008	Mts Systems Corp	3829
Laura Sen	2009	Bj's Wholesale Club Inc	5399
Lauralee Martin	2013	Healthpeak Properties Inc	6798
Laurie Stewart	2012	Sound Financial Bancorp Inc	6035
Leone Patterson	2018	Adverum Biotechnologies	2836
Lesa Kennedy	2009	Intl Speedway Corp	7948
Leslie Hale	2018	Rlj Lodging Trust	6798
Liane Pelletier	2003	Alaska Communications Systems Group	4813
Limor Ganot	2013	Alon Blue Square Israel	6510
Linda Farthing	2007	Stein Mart Inc	5651
Linda Heasley	2018	J Jill Inc	5621
Linda Lang	2005	Jack In The Box Inc	5812
Linda Massman	2013	Clearwater Paper Corp	2670
Linda Zecher	2013	Houghton Mifflin Harcourt Co	2731
Lisa Earnhardt	2014	Intersect Ent Inc	3842
Lisa Gersh	2012	Martha Stewart Living Omnimedia	4888
Lisa Harper	2001	Gymboree Corp	2300
Lisa Hook	2010	Neustar Inc	4899
Lisa Jones	2014	Pioneer Diversified High Income	6726
Lisa Roskens	2003	America First Apt Investors	6798
Lisa Wardell	2016	Adtalem Global Education Inc	8200
Liz Fetter	2013	Symmetricom Inc	3661
Liz Smith	2012	Bloomin' Brands Inc	5812
Loretta Bush	2007	Xinhua Sports & Entertainment Ltd	7311
Lori Holmes-Woods	2018	Isoray Inc	2836
Lori Jones	2004	Axion Intl Holdings Inc	3089
Lorna Nagler	2007	Christopher & Banks Corp	5621
Luann Via	2012	Christopher & Banks Corp	5621
Lynda Nahra	2004	Community West Bancshares	6020
Lynn Dugle	2016	Engility Holdings Inc	8711
Lynn Elsenhans	2008	Sunoco Inc	2911
Lynn Good	2013	Duke Energy Corp	4931
Lynn Jurich	2015	Sunrun Inc	3620
Lynn Powers	2009	Gaia Inc	7370
Maggie Wilderotter	2004	Frontier Communications Corp	4813
Mandy Ginsberg	2017	Match Group Inc	7370
Margaret Keane	2014	Synchrony Financial	6141
Margaret Kelly	2013	Re/Max Holdings Inc	6531
Margo Georgiadis	2017	Mattel Inc	3942
Marguerite Nader	2013	Equity Lifestyle Properties	6798
Maria Hawthorne	2016	Ps Business Parks	6798
Maria Pope	2018	Portland General Electric Co	4911
Marillyn Hewson	2013	Lockheed Martin Corp	3760
Marissa Mayer	2012	Altaba Inc	7370
Marita Zuraitis	2013	Horace Mann Educators Corp	6331
Marla Schaefer	2003	Claires Stores Inc	5600
Marti Morfitt	2001	Cns Inc	3842
Mary Barra	2014	General Motors Co	3711
Mary Berner	2007	Readers Digest Assn Inc	2731
Mary Burton	2006	Zale Corp	5944
Mary Dillon	2010	Us Cellular Corp	4812
Mary Forte	2002	Zale Corp	5944
Mary Heino	2015	Lantheus Holdings Inc	2835
Mary Junck	2001	Lee Enterprises Inc	2711
Mary Kipp	2015	El Paso Electric Co	4911
Mary Laschinger	2014	Veritiv Corp	5110

Mary Puma	2002	Axcelis Technologies Inc	3559
Mary Sammons	2003	Rite Aid Corp	5912
Mary Tolan	2010	R1 Rcm Inc	8741
Meenu Chhabra	2016	Proteostasis Therapeutics	2836
Meg Gentle	2017	Tellurian Inc	1311
Melissa Payner-Gregor	2004	Bluefly Inc	5961
Melissa Reiff	2016	Container Store Group	5700
Melissa Smith	2014	Wex Inc	7374
Michele Buck	2017	Hershey Co	2060
Michele Paige	2003	Cadus Corporation	6552
Michelle Gass	2018	Kohl's Corp	5311
Michelle Heying-Wilver	2012	Dynavox Inc	7373
Min Kim	2006	Hope Bancorp Inc	6020
Mina Sooch	2016	Gemphire Therapeutics Inc	2836
Mindy Grossman	2008	Hsn Inc	5961
Mindy Meads	2010	Aro Liquidation Inc	5621
Molly Hemmeter	2015	Landec Corp	2033
Nancy Harris	2009	Asure Software Inc	7370
Nancy Li	2008	Neulion Inc	7370
Nancy Lurker	2008	Interpace Biosciences Inc	8071
Natasha Giordano	2017	Plx Pharma Inc	2834
Nicole Ossenfort	2018	Franchise Group Inc	7200
Pam Patsley	2009	Moneygram International Inc	6099
Pamela Little	2011	Ats Corp	7373
Pat Kampling	2012	Alliant Energy Corp	4931
Pat Russo	2002	Lucent Technologies Inc	7373
Pat Scheller	2016	Viveve Medical Inc	3845
Pat Vincent-Collawn	2010	Pnm Resources Inc	4911
Pat Woertz	2006	Archer-Daniels-Midland Co	2070
Patti Poppe	2016	Cms Energy Corp	4931
Peggy Montana	2014	Shell Midstream Partners L.P.	4610
Peyton Patterson	2003	Newalliance Bancshares Inc	6036
Phebe Novakovic	2013	General Dynamics Corp	3721
Rachel King	2014	Glycomimetics Inc	2836
Rose Crane	2011	Epocrates Inc	7370
Safra Catz	2014	Oracle Corp	7370
Sally Smith	2003	Buffalo Wild Wings Inc	5812
Sandra Stephens	2005	Southfirst Bancshares Inc	6035
Sandy Cochran	2004	Books-A-Million Inc	5940
Sara Mathew	2010	Dun & Bradstreet Corp	7323
Sarah Eames	2004	Allied Healthcare Intl Inc	8082
Selina Lo	2012	Ruckus Wireless Inc	3576
Shannon Greene	2016	Tandy Leather Factory Inc	5990
Sharon John	2013	Build-A-Bear Workshop Inc	5945
Sharon Leite	2018	Vitamin Shoppe Inc	5400
Sharon Patrick	2003	Martha Stewart Living Omnimedia	4888
Sharon Rowlands	2014	Reachlocal Inc	7370
Sheila Marcelo	2014	Care.Com Inc	7370
Shelley Broader	2015	Chicos Fas Inc	5621
Shelly Ibach	2012	Sleep Number Corp	2510
Sheri McCoy	2012	Avon Products	2844
Sheri Miksa	2004	Rubio's Restaurants Inc	5812
Sheryl Palmer	2013	Taylor Morrison Home Corp	1531
Shira Goodman	2016	Staples Inc	5110
Shirley Singleton	2002	Edgewater Technology Inc	7370
Simone Lagomarsino	2011	Heritage Oaks Bancorp	6020
Stephanie Hayano	2006	Natural Health Trends Corp	5122
Stephanie Kushner	2016	Broadwind Inc	3510
Stephanie Pugliese	2015	Duluth Holdings Inc	5961
Stephanie Sonnabend	2003	Sonesta Intl Hotels	7011
Stephanie Streeter	2002	Banta Corp	2750
Sue Swenson	2015	Inseego Corp	3661
Sue Vogt	2008	Seracare Life Sciences Inc	2835
Sue Washer	2014	Applied Genetic Technologies	2836
Susan Cameron	2004	Reynolds American Inc	2111
Susan Ciallella	2005	Fibrocell Science Inc	2836

Susan DeVore	2013	Premier Inc	5122
Susan Givens	2014	New Senior Investment Group	6798
Susan McGalla	2011	Wet Seal Inc	5621
Susan Salka	2005	Amn Healthcare Services Inc	7361
Susan Still	2016	Hometown Bankshares Corp	6020
Susan Story	2014	American Water Works Co Inc	4941
Suzanne Miglucci	2015	Charles & Colvard Ltd	3290
Suzanne Sitherwood	2012	Spire Inc	4924
Sylvia Summers	2007	Trident Microsystems Inc	3674
Talbott Roche	2016	Blackhawk Network Holdings Inc	7374
Tamara Lundgren	2006	Schnitzer Steel Inds	5093
Tawny Lam	2017	Nova Lifestyle Inc	2510
Teresa Elder	2017	Wideopenwest Inc	4813
Tricia Griffith	2016	Progressive Corp-Ohio	6331
Tricia Stitzel	2018	Tupperware Brands Corp	3089
Trish Gilligan	2001	Navisite Inc	7374
Trudy Sullivan	2007	Talbots Inc	5621
Ursula Burns	2009	Xerox Holdings Corp	3577
Valerie Palmieri	2015	Aspira Womens Health Inc	2835
Vicki Hollub	2016	Occidental Petroleum Corp	1311
Vicki Holt	2010	Spartech Corp	3080
Vogt Faro	2016	Jetpay Corp	6099
Wellington Denahan-Norris	2012	Annaly Capital Management	6798
Wendy Silverstein	2017	New York Reit Inc	6798
Wendy Simpson	2007	Ltc Properties Inc	6798
Zee Hakimoglu	2007	Clearone Inc	3663