Recipes for Female Success: Becoming a CEO

ABSTRACT

This study applies novel machine learning techniques to analyze career determinants of first-time female chief executive officers (CEOs) in corporate America, contributing to the ongoing discussion on leadership and gender. With a comprehensive dataset of over 100 characteristics of thousands of executives, we find that well-connected women with diverse experiences, including board exposure, are more likely to become CEOs. Comparing the predictive models for the male sample, we show that professional experience factors comprise the most important predictors for male CEOs for whom social network, while still important, is predictive to a lesser extent. We then cross-fit our predictive models for CEO selection across gender samples, with the results suggesting that more women would become CEOs if male CEO criteria were used, and fewer men would qualify if evaluated by criteria applied to female CEOs. Our findings suggest that female and male executives are judged by 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; Female CEOs; Machine Learning; Social Network

JEL Classification: G34, J16, J24, J20, G40

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I. INTRODUCTION

The importance of effective leadership is uncontroversial and has been extensively studied[1]. Female leaders 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[3]. Despite women entering the workforce in about equal numbers as men, only 1 in 8 C-suite leaders of the publicly traded U.S. firms is a woman, and only 10% of Fortune 500 companies are led by female CEOs[4]. However, existing research on determinants of CEO selection is mostly gender-neutral and limited to small samples or anecdotal evidence[5]. 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 lenses of CEO selection. We assess the whole universe of executives in the United States to understand what differentiates leaders becoming CEOs from everyone else holding executive positions and show how those characteristics are different from 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). Kaplan and co-authors (2012, 2021) study CEO assessments of an executive search firm to analyze job interviews and differentiate how individuals selected as CEOs are different from other interviewees. Numerous other studies rely on anecdotal evidence by interviewing just the CEOs and offering the 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

[1] See Jones and Olken (2005), Bertrand and Schoar (2003), Hambrick and Mason (1984).
[3] See Cooper (2021), Wu et al. (2021), Post et al. (2020, 2011), Sahay and Cihak (2018).
[4] See S&P Global (2024), Elting (2023).
[5] See Kaplan et al. (2012, 2021), Dillard and Lipschitz (2014), Stevenson and Orr (2017).

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 and narrowly focused approaches are important in identifying potential personality traits of leaders, in-depth empirical analysis of the determinants of leadership is lacking. Additionally, since these CEO selection and leadership-determinant studies 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 the ones that can predict the likelihood of becoming a CEO. We collect an extensive dataset of over 100 different characteristics of executives in the United States spanning almost 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[6]. These novel techniques allow us to consider a large number of covariates by avoiding overfitting and multicollinearity issues. 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 to ours in the existing literature compares a near-exhaustive sample of male CEOs to the Swedish male population, identifying traits that can be considered 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

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

extend this research direction by focusing on female executives and including a comprehensive set of factors such as education, social networks, and experience to identify what differentiates female CEOs from other female executives in the United States and following up with also applying this framework to male CEO selection.

We utilize a novel database of the entire population of female executives in U.S. firms from 2000 to 2018. Our research design and comprehensive dataset of 342 first-time female CEOs of public companies and their characteristics, as well as over 200,000 female executives who did not become CEOs during that time as a control group, allows us to identify the important predictors of female CEOs using machine-learning methods. We focus on first-time CEOs because being appointed for the first time is a breakthrough career moment, after which prior experience as a CEO is a defining factor for future appointments (Tinsley and Purmal, 2019). Our sample includes only public companies due to their greater homogeneity compared to private firms in terms of size, regulatory requirements, and governance. We follow up with a similar framework for determinants of male CEOs and find significant differences in CEO selection determinants based on the gender of the executives.

Our results demonstrate that all machine-learning models are in close agreement on the most influential individual-level characteristics. For the 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 find out which of the eight groups of individual characteristics is the most important determinant of upcoming CEOs, we compute the sum of the importance score of each variable for each model within each group. The results show that the three most important groups are social networks, upper management, and board experience. Within these groups, we further disentangle which specific characteristics influence the likelihood of a female executive becoming a CEO and show the overwhelming importance of the social network factors. We conduct the same estimation procedure for the first-time male CEO selection and find that professional experience factors are the most important for male candidates, for whom social network plays a lesser role compared to female CEO selection. Finally, we cross-fit the samples on the best-performing models of the

opposite genders. Our results suggest that there are different criteria for female CEOs, and more women would become CEOs if they were selected based on the male CEO selection model, with the reverse not true for the male executives, fewer of whom would be qualified for the role based on the female CEO selection model. This finding highlights the vast differences in the criteria applied during the CEO selection process based on the gender of the candidate and underscores the 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 the gender perspective. We answer the explicit call for progressive research of economic perspectives on leadership and deepen the understanding of leadership determinants in corporate finance (Garretsen, Stoker, and Weber, 2020). With the recent progress in decreasing glass ceiling obstacles for women, our paper brings a unique perspective to the study of female career outcomes. By looking at the universe of female executives in the United States, we identify the characteristics that matter most for becoming a CEO. We 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 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 how they apply to the study of corporate finance. Building upon existing early corporate finance studies using machine learning, such as bankruptcy prediction and board selection (Jones, 2017; Erel et al., 2021), we incorporate these advanced techniques in our research design to provide a data-driven approach to identifying determinants of CEO selection from gender perspective. We use a comprehensive set of over 100 characteristics of executives across broad categories of education, professional experience, board participation, social networks, affiliations, awards, and other experiences to predict the likelihood of becoming a CEO. We then utilize a state-of-the-art interpretable machine learning techniques to extract meaning from traditionally

black-box machine learning models. Our paper is one of the earliest studies that use machine learning to study corporate governance, following the seminal work in this area by Erel et al. (2021) who first applied these techniques to the board selection studies. We extend this algorithmic approach to identify the most important characteristics of candidates predictive of CEO selection from the 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. From a gender perspective, women's political leadership has affected policy decisions and is bolstered by mandated representation and initial electoral wins (Chattopadhyay and Duflo, 2004; Clots-Figueras, 2011; Besley and Case, 2003; Ferreira and Gyourko, 2014). 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 does not often study the determinants of the success of female leaders, particularly in the corporate context. In this paper, we specifically examine the U.S. population of female executives to identify characteristics and traits that differentiate women who become CEOs from those who do not.

Although 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). Out of all S&P 500 companies, only 41 had female chief executive officers (CEOs) as of February 2023, representing about 8% of the companies in the index.[7] 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 to reach at least 40% of seats on the board allocated to women by June 2026 (Rankin,

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

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 record 53, which since then remained largely flat at 10.4%, slightly decreasing to 52 female CEOs as of 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 those that stem from corporate practices and those rooted in behavioral or cultural norms (Oakley, 2000; Schein, 2001; Hoyt and Murphy, 2016). The extant literature suggests that female executives display behavioral and attitudinal differences compared to male executives. For example, Tannen (1994) 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 shy away from competition, which may also cause 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 away from career opportunities instead of leaning 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 processes and attitudes are similar to their male counterparts. Indeed, characteristics of successful leaders are aligned with masculine stereotypes, such as being competent, determined, and industrious (Sczesny, 2013). Therefore, women are evaluated negatively if they show a feminine leadership style, resulting in role-congruity prejudice toward female leaders where the perceived incongruity between female qualities and leadership roles leads to prejudices in appointing female executives and evaluating their performance (Eagly and Karau, 2002). Moreover, although men only need 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 research finds that education is an important determinant 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).[8] Clearly, the difference in gender leadership is not in the absence or presence of a college degree. However, there is 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 are still making disadvantageous education choices by opting out of math-intensive STEM fields that tend to have higher expected compensation and better career advancement opportunities that are 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 female leadership.

Career decisions and early choices in life, such as taking more math classes and pursuing STEM degrees in college, can be crucial for women's career advancement. Those few female leaders who rise to the top prove that it is not impossible. In this study, we investigate a comprehensive list of determinants of success for aspiring female leaders to incorporate into their career-planning process. These findings may

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

also inform policy decisions regarding early education programs to promote future gender equality in the workforce. We contribute to the research on corporate leadership from the gender perspective by incorporating a data-driven approach to studying the characteristics of female leaders.

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).

While the effects of differences in risk-taking behaviors may be mixed, studies suggest that there are numerous benefits to having female leaders in companies. Women managers demonstrate superior leadership skills and 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 (Matsa and Miller, 2013), and female chief technology officers (CTOs) are associated with more innovation (Wu, Dbouk, Hasan, Kobeissi, and Zheng, 2021). Levi, Li, and Zhang (2014) examine whether CEO gender affects merger and acquisition decisions, concluding that female CEOs are associated with a lower likelihood of initiating acquisition bids and lower bid premiums. 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).

Appointing a female CEO can be a strategic decision for a firm. 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. Overall, the presence of female managers brings informational and social diversity benefits, and it creates a collaborative and nurturing environment that fosters innovation and improvements in firm performance (Dezsö and Ross, 2012; Lyngsie and Foss, 2017). Therefore, having female executives bring different perspectives and information helps firms become more capable of dealing with complex issues.

Studying the selection process of female leaders and the supply and demand for them in the labor market can shed light on their underrepresentation and suggest potential solutions by identifying key characteristics that affect female leaders' progression to the highest corporate title. Of all board responsibilities, including allocating and securing resources, taking strategic actions, and performing administrative duties, choosing a new CEO is one of its most significant functions (Hambrick and Finkelstein, 1987). Boards exercise preferences and have real impacts on firm strategy, but they also experience external, organizational, and internal constraints. In particular, boards are subject to societal norms and expectations, external stakeholders, organizational resources, and their own internal dynamics. Therefore, investigating the determinants of female CEOs reveals not only the skills and experience

necessary for doing the actual job but also reveals board and societal perceptions of what defines female leadership.

Despite the conventional advice people often give to young females — go to an Ivy League school, get an MBA, start in consulting or investment banking, and seek bigger roles — 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). Moreover, prestigious schools or MBA degrees do not seem to matter much for most of the 24 interviewed females leading Fortune 500 companies, and neither does banking or consulting experience, according to the Harvard Business Review (Dillard and Lipschitz, 2014). Another interview-based study of 57 female CEOs finds that 40% of women in the sample had some 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 characteristics determining female leadership success is missing from the existing literature. This is the first study to consider over 100 characteristics of female executives over a multiyear period and identify the ones most instrumental for success among women aspiring to become CEOs.

III. MACHINE-LEARNING APPROACH

Machine learning has been gaining popularity in recent years in business literature, as it offers benefits compared to traditional parametric analysis. Machine learning helps discover structures and patterns in data without specifying the functional form in advance, allowing for flexibility in the models (Mullainathan and Spiess, 2017). Although the emphasis of traditional econometric models is to establish causality, the main focus of machine-learning models is to increase the algorithm's predictive power for new data (out-of-

sample), which occurs by training the algorithm using validation and cross-validation (Athey and Imbens, 2019). Similar to traditional econometrics, machine learning can apply to regression problems (where the dependent variable is continuous) and classification (where the dependent variable is categorical) problems. Additionally, machine learning can be introduced in supervised learning (where we clearly define dependent and explanatory variables in the model) and unsupervised learning (where no dependent variable is defined, and exploratory data analysis occurs). We focus on classification algorithms and supervised machine learning, as we have a clearly defined dependent variable with two categories: women who become CEO, and female executives who do not.

Machine learning can improve the human decision-making process, as it helps discover complex patterns in data and predict future outcomes given a set of variables, as well as conduct 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). It is important to note that machine-learning applications do not solely focus on numerical predictors. Textual, image, video, and voice analyses applying 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; 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 use machine-learning techniques to identify specific factors for female CEO selection to shed light on the most important determinants of becoming a CEO. We compare the unique determinants and characteristics of females who become CEOs to the characteristics of other female executives who do not become CEOs. Our primary objective is an exploratory analysis of multidimensional determinants of female CEO selection. We assemble the most comprehensive (to our knowledge) dataset

of characteristics for female executives to date. In our data, we identify over 100 female executives' attributes based on 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 for female executives becoming CEOs, machine-learning algorithms offer numerous advantages compared to 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, thus addressing overfitting concerns. Therefore, our paper offers a unique approach for applying machine-learning techniques to study determinants of female career success using high-dimensional data to account for 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, Zhao, and Zhu, 2019). Jones (2017) uses a gradient-boosting model to predict which firms will file for bankruptcy; that study uses a large number of potential explanatory variables. In addition to the models in the studies listed earlier, we consider a more comprehensive set of algorithms traditionally applied to classification problems 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 remove observations for executives who have prior public CEO employment experience because we are only interested in first-time CEOs of publicly traded companies. The final sample consists of a total of 273,091 observations with 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. About 4% of our sample comprises foreign nationals, including women from Canada, Europe, and other parts of the world.

BoardEx started its coverage in 1999, as reflected in the Organization Summary dataset that began in 1999. Other data files, including Employment, Education, Achievements, and Other Activities, contain biographical information and employment history going back as far as available for individuals included in BoardEx since 1999. For example, even though we can only see 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 going 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 the panel dataset of active female executives, meaning they held executive positions and/or served on boards during our sample period from 2001 to 2018.

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 combined network measures, as they have the least number of missing values. The number of female CEO appointments by year and the total number of female executives each year are presented in Figure 1. Distribution of first-time female CEOs in public firms by state and by industry sector

are presented in Figures 2 and 3, respectively. The list of all first-time female CEOs, along with the firm names and years of their appointments, is included in Appendix B.

[Figure 1 about here]

[Figure 2 about here]

[Figure 3 about here]

Variables

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

We use 131 predictor variables across the different categories, including affiliations, awards, board experience, education, professional experience, and social network. The machine learning setting allows us to engineer additional features by combining variables in groups without running into 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, including academic, art, business, female, foreign, health, humanities, international, law, science, and sports affiliations.

Awards. We identify the general award variable if the award recognizes an individual. Among the specific types of awards in the Other Activities dataset are academic, business, city, government, humanity, law, leadership, media, military, royalty, science, sports, women, 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, honorary degree, or 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 include experience across different industries and firms, as well as employment experience in management, finance, marketing, law, the military, politics, academia, and other roles.

***Social Network*.** Social network measures are extensively present in the study of corporate behaviors and in other areas; they have their origin in graph theory. Network centrality describes an individual's position in a social network, with higher centrality indicating more connections and greater status hierarchy (Freeman, 1978; Burt, 1982). We proxy an individual's social network centrality by using four measures including degree, closeness, betweenness, and eigenvector. 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 level of degree 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 others and makes pass-through communications within the network. This measure is the most effective in capturing the absolute position of an individual in 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 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 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. 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 if an individual is connected to others who are well-connected, this individual has greater influence in her 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 application 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, as it is the most comprehensive measure and has the least number of missing values due to the method of calculation. Following Fracassi (2017), we aggregate social ties for 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, other activities), we count it as a tie for each respective measure. If this tie is based on education, we can calculate education centrality, but we count 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*, which measures gender network diversity as a 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*, allows for the ease of comparison between female and male executives.

***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 the heterogeneity of upper management experience across different industries.

Descriptive statistics for all variables in the analysis are included in Table 1. Table 2 presents the *t*-test of the means for all variables for female CEOs in the year they become CEOs for the first time compared to other female executives.

[Table 1 about here]

[Table 2 about here]

V. METHODOLOGY

Overview and Model Descriptions

Machine-learning algorithms allow us to consider numerous features that may or may not be important in determining first-time female CEOs. 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 tree, 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 of a female CEO. 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 with a zero coefficient. Therefore, lasso allows us to select variables with higher explanatory power and drop variables with low explanatory power to reduce the dimensionality of parsimonious models, such as logistic regression described in the previous section. For tuning parameters, we use alpha equals 1, so the model is specified as lasso.

GLM Net. GLM Net, also known as the elastic net, is a more flexible generalized linear model (GLM). It uses the elastic net to penalize coefficient estimation by shrinking and/or assigning zero coefficients to features that do not add much information to the model. The former technique is often referred to as ridge regression; the latter technique is also known as lasso regression. GLM Net allows for combining these two techniques by choosing an appropriate tuning parameter alpha ranging 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, meaning that the optimal specification is much closer to lasso than to ridge, with alpha close to 1 and with penalty parameter lambda fairly low.

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

KNN. K-Nearest Neighbors (KNN) is a nonparametric algorithm that assumes similar features exist in close proximity, 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, which means the model is tuned ten times on each of the ten folds of cross-validation using a different number of nearest neighbors to calculate the probability of a female becoming a CEO based on a set of characteristics. We specify ten options for nearest neighbors to train the model, with a minimum of five nearest neighbors and a maximum of 23 nearest neighbors 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 interpretability of visualization of its results. The decision tree is a greedy algorithm, meaning that it starts the original split randomly and does not go back to change it even if more accurate splits are available later in its iterative process. This aspect of the decision tree is majorly responsible for its lackluster performance compared to tree-based ensemble methods that allow it to combine multiple trees in one model and ameliorate 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 multiple models into one learning algorithm. Bagging can be used with multiple techniques such as decision trees and support vector machines (SVM). We employ bagging for decision trees algorithm to improve decision-tree model performance.

Random Forest. The random forest extends the bagging of decision trees by introducing random feature selection. Randomness is conducive for even further diversification of the trees, which the algorithm votes to combine for the final prediction. We employ weighted-subspace random-forest algorithm, which optimizes information gains in 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 of two variables at a time for random selection of features.

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, depending on the task, the split can be based on time or other dimensions (Kuhn and Johnson, 2013). For instance, for face-recognition applications in machine learning, 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 in 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 use a subsampling method called the synthetic minority oversampling technique (SMOTE) during the model training to increase predictive ability. SMOTE is a "de facto" standard for learning from imbalanced data (Fernández, Garcia, Herrera, and Chawla, 2018). SMOTE combines the minority class's oversampling by creating synthetic minority class examples and undersampling of the majority class (Chawla, Bowyer, Hall, and Kegelmeyer, 2002). We include the SMOTE sampling procedure in our train control function to be performed on each fold of cross-validation of 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 in the training process are fit on a rolling six years of training data, with the following rolling three years of data to validate the model predictions; the last three 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 use 10 specifications of tuning parameters in each window of training. We rely on built-in tuning parameters in most models unless otherwise specified when we choose to use a custom tuning grid.

In preprocessing procedures, the variables in the sample are standardized by centering and scaling, except for the 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 done when predicting final models on the test data (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 using the largest value during the training and validation process. 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 tradeoff shift 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.

$$\begin{aligned} Sensitivity &= true\ positive\ /\ positive \\ &= true\ positive\ /\ (true\ positive + false\ negative) \end{aligned} \tag{5}$$

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

$$\begin{aligned} Specificity &= true\ negative\ /\ negative \\ &= true\ negative\ /\ (true\ negative + false\ positive) \end{aligned} \tag{6}$$

Accuracy assesses the overall ability of the model to identify true cases among all the data.

$$\begin{aligned} Accuracy &= (true\ positive + true\ negative)\ / \\ &(true\ positive + false\ positive + true\ negative + false\ negative) \end{aligned} \tag{7}$$

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.

$$Balanced\ Accuracy = (Sensitivity + Specificity)\ /\ 2 \tag{8}$$

For example, for highly imbalanced data with a small proportion of positive cases compared to negative cases, the model may have low sensitivity as it struggles to identify the true positive cases correctly. On the other hand, in such a setting, the model would typically have high specificity, as it would be very accurate in identifying true negative cases; it has so many more observations to train on those. Lowering the typical classification boundary from 50% to 30% may improve sensitivity because the threshold to be classified as a positive case is much 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 the former indicating the perfect capability to predict the outcome and the latter indicating a lack thereof. 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 our final training models' performance on the resampled data to obtain out-of-bag performance metrics that evaluate the final model specifications chosen based on the optimized ROC on the resampled training data set. 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 usually lower on the test data, which is new data not used for the training of 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. In combination with the highest performance on other test metrics such as accuracy, sensitivity, specificity, and balanced accuracy, random forest is our best-performing model overall.

[Table 3 about here]

Variable Importance Ranking

Because the machine-learning models do not have variable coefficients similar to traditional econometric models, they are rather opaque and often called "black box." One of the most intuitive ways to take a glimpse into how machine-learning models come to their conclusions is to look at the variable-importance metrics. Variable-importance ranking is computed and validated on the training data. Each feature's importance is calculated based on each 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 for the variable-importance ranking. A higher score means a variable has higher importance in model prediction.

We group the most important variables into broader categories related to characteristics and present the variable importance using broader categories of the social network, upper management experience, professional experience, board experience, education, other experience, affiliation, and award for each model in Table 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.

[Table 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.[9] 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

[9] 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).

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. Table 5 presents the directional effect of the top 20 predictors based on SHAP values based on our best-performing model (random forest). Although SHAP values do not claim causality, they provide an intuitive understanding of the marginal contribution of each variable in predicting female CEO selection.

VI. RESULTS AND IMPLICATIONS

A few groups of characteristics matter most based on the variable importance ranking among specific models, as presented in Table 4. In order to assess the direction of their impact (positive or negative), we rely on the SHAP values in Table 5. Overall, we find that social network, upper management experience, and board and professional experience most influence the likelihood of a female executive becoming a CEO. Specifically, strategic positioning in social networks, heterogeneous professional experience, and upper management experience are positively associated with becoming a first-time CEO in a publicly traded company.

Social Network

Social network is the most influential group of characteristics for all tree-based models (including our best model – random forest) presented in Table 4. There are six measures of a social network included in the models: degree, betweenness, closeness, eigenvector, total connections, and proportion of women in the network. All six of these measures are among the 20 most important determinants of female success in our best model, random forest. As shown in Table 5, 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 communications (measured by betweenness), which

allows for quick access to information and powerful backers to aid in 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).

Upper Management Experience

Upper management experience is the second most important group of variables. In particular, heterogeneity and years of upper management experience are the most influential predictors. 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 show, both upper management experience in years and the heterogeneity of the experience are positively associated with the likelihood of becoming a CEO, suggesting that breadth and depth (measured by years) of upper management experience are important.

Board Experience

Board experience is the third most important group of variables for predicting the likelihood of becoming a CEO. Specifically, the number of years and heterogeneity of board experience are among the top 10 most important variables and have positive predictive power in the models. 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 looking only at first-time female CEOs, board experience is a substitute for prior CEO experience in board hiring decisions (Tinsley and Purmal, 2019).

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 related to female CEO selection. Years of work experience in public firms rank higher than years of work experience in private firms. This may be due to the possibility that exposure to public firms gives female executives more familiarity with organizational frameworks and practices that ultimately benefit their chances of selection for the top roles. Employment experience heterogeneity, which is the number of different positions multiplied by the corresponding years, is positively related to female CEO selection.

Experience in financial roles negatively affects the likelihood of becoming a CEO, in line with existing anecdotal evidence that women are better off avoiding business support roles if they want to increase their chances of becoming a CEO (Spencer et al., 2019). Another explanation for this negative relation between finance experience and CEO title may be inferred by prior findings that female financial executives do not experience pay gaps and can even make more than men in those roles (Francis, Hasan, Hovakimian, and Sharma, 2023). Interestingly, 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 pursue experience in various upper management positions instead of expanding to different countries.

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. First, advanced education (measured by the existence of master's degrees and other graduate degrees) has a negative association with the likelihood of becoming a CEO. 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. 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 higher in categorical importance than education, according to Table 4, their variables are not among the top 20 most important predictors.

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 focusing on cultivating strong social networks and diverse professional experience to advance their careers and meet the demands and expectations of being the CEO of a corporation.

VII. ADDITIONAL TESTS AND MALE SAMPLE ANALYSIS

Predictors for First-Time Male CEOs

As an extension to our main study, we conducted a follow-up analysis of predictors for first-time male CEOs and included our findings in Table A2. The best-performing model for a male sample is boosted GLM. Univariate analysis for the male sample is included in Table A3.

Professional experience comprises the top five predictors for male candidates, compared to the higher importance of social networks for female candidates, comprising two out of the top five predictors for female CEOs in addition to upper management and board experiences. This may suggest that women need to emphasize developing professional social networks more than men, for whom only one of the social network measures is identified among the top 20 predictors and, even then, ranked 13th. Finance experience, education, and some international experiences are negatively associated with the probability of becoming a CEO for male candidates, consistent with female sample analysis.

Some of the determinants 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.

[Table A2 about here]

[Table A3 about here]

Univariate Analyses

We start by comparing all 131 predictors for female and male CEOs and present the univariate analyses in Panel A of Table A4. Based on the univariate analysis comparing characteristics of the first-time female and male CEOs, we observe that female CEOs are much more likely to have affiliations and awards (including academic, science, and humanities), have experience advising non-profit organizations, and have awards (including business, leadership, and media awards). Female CEOs have stronger social network (as measured by betweenness, closeness, degree, and eigenvector), as well as a higher proportion of female network, with 17% of 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, but they seem to compensate for it by having board and trustee experience in other types of organizations, such as non-profits. 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 experiences, female CEOs are less likely than male CEOs to have COO experience and heterogeneity in employment experience, both in terms of a number of industries and international experience. Female CEOs are more likely to have law and marketing experience. Also, on average, female CEOs have 23 years of professional experience by the time they get appointed as CEO for the first time, compared to 37 years of professional experience for first-time male CEOs. This, to some extent, may explain the differences in lower upper management experience (including being a CEO of foreign or private companies) for female CEOs compared to male CEOs.

Next, we explore the top 20 most important predictors for CEO selection for each gender and present the univariate analyses for those in Panels B and C of Table A4. 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, along with international employment and employment heterogeneity, is lower for female CEOs. Thus, we can imply that female candidates should have a much higher social network compared to male candidates in order to get a CEO position. On the other hand, board experience for female CEOs, while still needing to be higher compared to other female candidates, tends to be lower compared to male CEO-elect.

On the other hand, univariate results for the top 20 predictors from the male model, as presented in Panel C of Table A4, mostly yield non-statistically significant differences when compared to female CEOs, suggesting that on the qualities that male CEO candidates get evaluated, 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 A4 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 A5. Logistic models for female CEOs explain more variation in dependent variables based on the 20 most important variables included at around 10 percent of total variation, while logistic regressions for male CEOs explain around 9 percent of total variation. It is worthwhile noting that one of the 20 most important features included in the logistic model dropped out

due to collinearity issues for both female and male samples. This is one of the main distinguishing features of machine learning that is capable of dealing with multicollinearity issues effectively, and traditional models that are not. While most of the direction and magnitude of explanatory coefficients are consistent with SHAP values, there are some inconsistencies due to potential collinearity of the included variables.

Machine learning models are able to handle the multicollinearity of numerous features, while logistic regression suffers from collinearity issues. Still, results are mostly consistent with social network variables coefficients 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 pushed board experience (years) and total executive network into negative and statistically significant correlation, while public and private experience combined (firms) are positive and statically significant in the male sample.

Overall, our main machine learning prediction findings remain mostly consistent in 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 similar to male executives' rates on board and in upper management positions; thus, social networks may be a substitute for the deficiency of board and management experience for women.

[Table A5 about here]

Cross-Model Fit

We conduct a counterfactual analysis test by cross-fitting models where the female sample is fitted for the final male prediction model and vice versa. In this setup, it is important to note that the qualifications predicted by our models are different for male and female candidates, as has been demonstrated by the analysis above. Thus, we are not comparing the same qualifications 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 having the same inherent qualifications, more women would find themselves in CEO positions, while only a fraction of male CEOs will be selected for the role.

In Table A6 Panel A, we compare predicted observations identified by cross models (female model for male sample, male model for female sample) to the actual number of respective 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 A6 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 got appointed on. Reversely, we fit the male sample for the female model and find that, if selected based on the characteristics required for female candidates, the male CEO pool would have been 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. Also, in Table A6, Panel C and Panel D, we show the breakdown of cross-model predicted rates across industries for female and male CEO samples, respectively.

Overall, our results in Table A6 suggest that given the male model standards, more women would become CEOs, while given female model standards, a lower number of male executives would become CEOs. This finding suggests stricter standards are applied for female CEOs compared to male CEOs.

[Table A6 about here]

Placebo Social Network

Considering that the social network is the strongest predictor for the female CEO selection, we conduct a placebo test replacing the statistically significantly different social network measures of both CEO and non-CEO executives with the average value for the opposite 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 network plays an outstanding role in the probability of a female executive becoming a CEO, even if all other characteristics do not change. The detailed results of the placebo analysis are presented in Table A7.

[Table A7 about here]

Temporal Differences in Female CEO Predictors

Given our sample includes almost twenty years of data, we also examine the potential changes in the predictors of female CEO over this time. Specifically, we split our sample into the pre- and post- financial crisis and determine predictors to both sub-samples. Great recession has been recognized as a significant steppingstone for banking, corporate finance and governance issues, including but not limited to increased

attention to and focus on 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 suggest that not much has changed fundamentally in terms of characteristics of successful leaders (Pfeffer, 2015 and 2022; Decressin, Kaplan, and Sorensen, 2024).

Our comprehensive data set allows us to quantitatively assess this question by comparing most important predictors from splitting the sample and training machine learning models on pre- and post- 2008 periods. Most important predictors of female CEOs in the split samples share some similarities – 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 become among the top ten predictors in the post-crisis period, suggesting an increase in importance of less tangible characteristics of a new wave of female leaders. In addition, during the post-crisis period number of continents of employments 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 two sub periods are presented in Table A8.

[Table A8 about here]

VIII. SUMMARY AND DISCUSSION

This is the first paper to consider a comprehensive set of characteristics of female executives and identify the most important factors of success in becoming a first-time CEO. We contribute to the literature on leadership and gender, building on the extensive analysis of the population level proposed by Adams et al. (2018) in the Swedish setting. Here, we extend this line of research to the whole population of female and male executives in the US and identify what differentiates those who become CEOs from the executive population. By constructing a comprehensive dataset of first-time female CEOs and their peers who did

not make it to the very top of the corporate ladder between 2001 and 2018, we utilize machine-learning techniques to uncover patterns in the data and build predictive models to identify the most important factors for female success in 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 better compete with their peers and become CEOs.

Gender equality spans a broad field of social research, including sociology, psychology, and organizational behavior, and has numerous avenues for future research and discovery. As academic journals, popular press, and business practitioners note, much is needed to develop and change society's perceptions and definitions of leaders. Acknowledging the importance of existing qualitative research on this topic, we believe our study provides a more comprehensive picture of important factors in career progression as we carefully study a population of female executives in the United States over almost two decades by employing advanced machine-learning algorithms to examine over 100 potential determinants of female success. Our research points out the importance of social networks, which are the main 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 comfortable in managerial roles also gain valuable leadership skills and expertise in self-promotion, resulting in a greater likelihood of becoming a CEO. These results advance our understanding of the determinants of career progression for female CEOs and can serve as a guide for aspiring female professionals and corporate decision-makers to promote gender diversity and inclusion in their organizations.

We also compare female and male CEO candidates, as it is commonly known and acknowledged that women need to work longer and harder, combine both masculine and feminine leadership styles, and still face numerous obstacles and cognitive bias while competing with male professionals. As a result of such comparison, we can confirm this prior with the finding that more women would become CEOs if the male criteria were applied, but the reverse is not true if the standards are flipped for male candidates. We also identified differences in the predictors across genders, with the social network being the top predictor

for female CEOs but professional experience as 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, experience matters more than social networks.

In this paper, we contribute to corporate governance studies by utilizing machine learning techniques to provide data-driven insights on the CEO selection process through the lens of gender. Over the decades, society and the business world have come a long way in promoting and instilling gender diversity on boards and in corporate settings. Now is the time to equip corporate policymakers with advanced algorithmic techniques to engage in instituting change, leadership, and mentorship structures to nurture diversity and equality, offer fair access to opportunities, and increase shareholder value by empowering highly qualified underrepresented candidates to have a seat at the table and build inclusive organizations.

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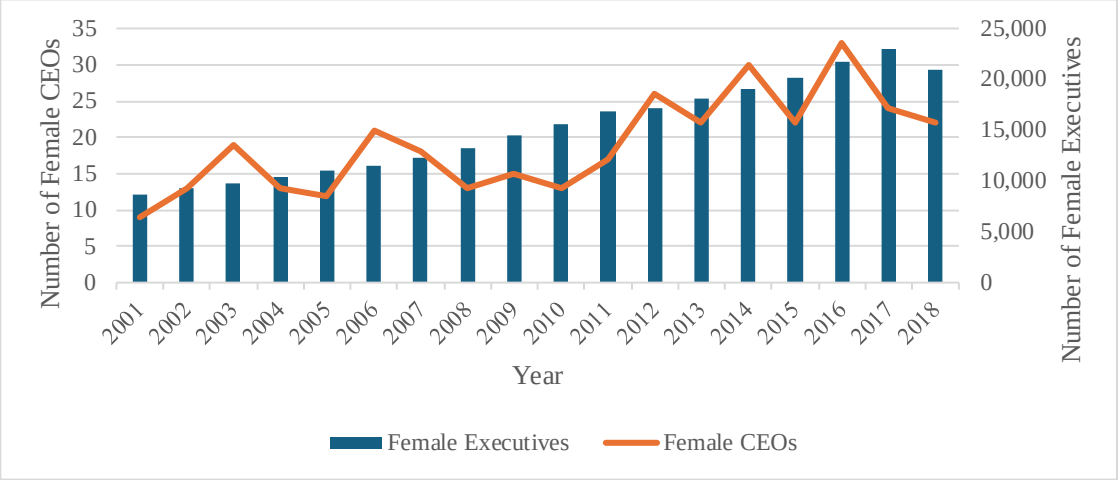
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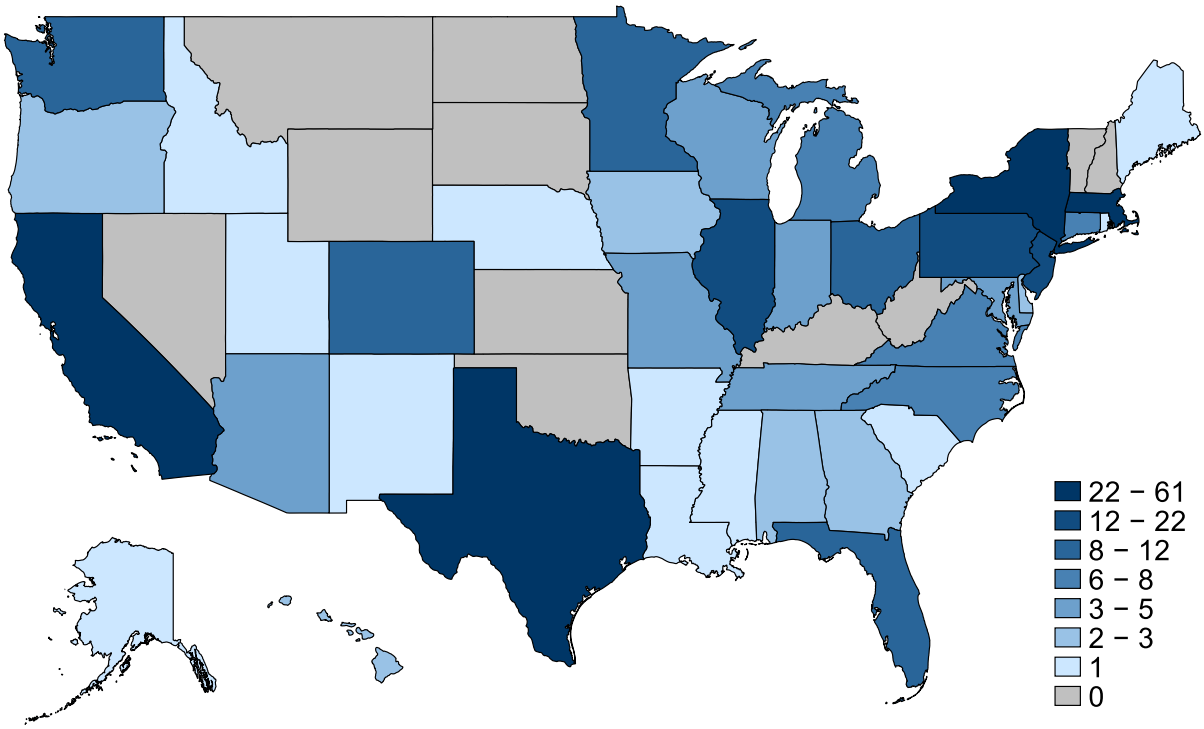
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Figure 1: Data Distribution by Year



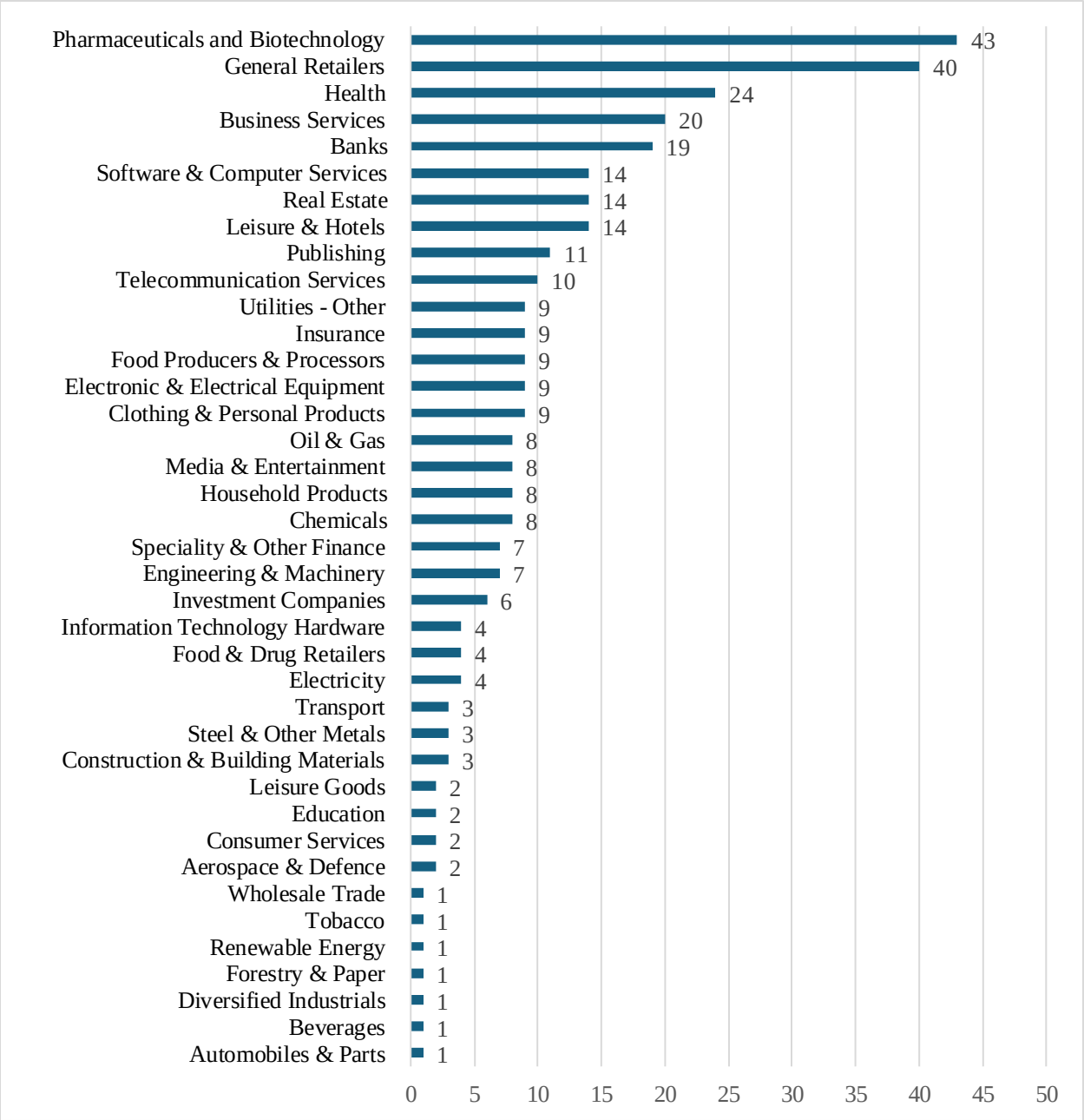
This figure shows the sample distribution by year with the number of first-time female CEO appointments by year on the left-hand side y-axis, as well as the total number of female executives by year on the right-hand side y-axis. *First-time CEO* is equal to 1 in a year when a female executive becomes 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 2: Female CEO Distribution by State



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.

Figure 3: Female CEO Sector Distribution



This figure shows the sample distribution of female CEOs across industry sectors. There are 342 first-time female CEOs of publicly traded firms in the sample from 2001 to 2018.

Table 1: Descriptive Statistics

This table presents summary statistics for all variables used in the data analysis. There is a total of 131 characteristics across 273,091 observations, including 342 female CEOs. Definitions of all variables are included in Table A1.

	Mean	SD	P25	Median	P75
Academic affiliation	0.24	0.43	0.00	0.00	0.00
Academic award	0.12	0.32	0.00	0.00	0.00
Academic emp exp	0.10	0.30	0.00	0.00	0.00
Advisor (other)	0.07	0.26	0.00	0.00	0.00
Africa emp exp	0.01	0.07	0.00	0.00	0.00
Americas emp exp	0.01	0.08	0.00	0.00	0.00
Art affiliation	0.06	0.23	0.00	0.00	0.00
Asia emp exp	0.03	0.18	0.00	0.00	0.00
Audit committee chair exp	0.03	0.16	0.00	0.00	0.00
Audit committee exp	0.10	0.29	0.00	0.00	0.00
Author	0.03	0.18	0.00	0.00	0.00
Award	0.40	0.49	0.00	0.00	1.00
Bachelor's degree	0.71	0.45	0.00	1.00	1.00
Betweenness	43.40	36.13	1.00	50.00	75.00
Board exp (firms)	0.96	2.09	0.00	0.00	1.00
Board exp (years)	5.40	14.91	0.00	0.00	5.00
Board exp Heterogeneity	30.25	462.37	0.00	0.00	6.21
Board member (other)	0.06	0.24	0.00	0.00	0.00
Business affiliation	0.08	0.27	0.00	0.00	0.00
Business award	0.15	0.36	0.00	0.00	0.00
Canada emp exp	0.09	0.29	0.00	0.00	0.00
CFO emp exp	0.11	0.32	0.00	0.00	0.00
Chair exp (quoted)	0.02	0.15	0.00	0.00	0.00
Chairwoman (other)	0.15	0.36	0.00	0.00	0.00
Charity emp exp	0.05	0.21	0.00	0.00	0.00
Child affiliation	0.03	0.17	0.00	0.00	0.00
City award	0.00	0.05	0.00	0.00	0.00
Closeness	50.48	28.87	25.00	50.00	75.00
Clubs emp exp	0.00	0.07	0.00	0.00	0.00
Committee (other)	0.09	0.28	0.00	0.00	0.00
Committee chair exp	0.08	0.27	0.00	0.00	0.00
Committee exp	0.25	0.43	0.00	0.00	0.00
community school degree	0.00	0.07	0.00	0.00	0.00
Compensation committee chair exp	0.03	0.17	0.00	0.00	0.00
Compensation committee exp	0.10	0.30	0.00	0.00	0.00
COO emp exp	0.06	0.24	0.00	0.00	0.00
Countries exp	1.23	0.62	1.00	1.00	1.00
CPA	0.10	0.30	0.00	0.00	0.00
CTO emp exp	0.01	0.09	0.00	0.00	0.00
Degree	48.39	30.67	23.00	49.00	75.00
Eigenvector	48.63	31.40	25.00	50.00	75.00
Employment exp (types)	1.45	0.79	1.00	1.00	2.00
Employment exp Heterogeneity	33.96	26.49	16.00	29.00	48.00
Europe emp exp	0.07	0.25	0.00	0.00	0.00
Exec VP exp (quoted)	0.01	0.11	0.00	0.00	0.00
Female affiliation	0.07	0.25	0.00	0.00	0.00
Female network (proportion)	0.11	0.15	0.00	0.00	0.19
Finance emp exp	0.19	0.39	0.00	0.00	0.00
Foreign affiliation	0.01	0.12	0.00	0.00	0.00
Foreign firm CEO emp exp	0.02	0.15	0.00	0.00	0.00
Foreign Nationality	0.04	0.20	0.00	0.00	0.00
Foreign private firm CEO emp exp	0.02	0.14	0.00	0.00	0.00
Foreign public firm CEO emp exp	0.01	0.08	0.00	0.00	0.00
Founder (other)	0.01	0.11	0.00	0.00	0.00
Founder emp exp	0.02	0.15	0.00	0.00	0.00
Gov award (US)	0.01	0.11	0.00	0.00	0.00
Gov emp exp	0.04	0.19	0.00	0.00	0.00
Governance committee chair exp	0.03	0.17	0.00	0.00	0.00
Governance committee exp	0.09	0.29	0.00	0.00	0.00
Graduate degree	0.50	0.50	0.00	1.00	1.00
Health affiliation	0.07	0.26	0.00	0.00	0.00

Honorary Degree	0.02	0.13	0.00	0.00	0.00
Humanities affiliation	0.13	0.33	0.00	0.00	0.00
Humanity award	0.11	0.32	0.00	0.00	0.00
Industries exp	1.41	0.90	1.00	1.00	2.00
Industry exp Heterogeneity	33.30	32.96	16.00	25.00	38.00
Insider exp (firms)	0.06	0.32	0.00	0.00	0.00
Insider exp (years)	0.42	2.59	0.00	0.00	0.00
International affiliation	0.05	0.22	0.00	0.00	0.00
International emp (years)	3.43	9.96	0.00	0.00	0.94
International emp exp	0.19	0.39	0.00	0.00	0.00
International exp Heterogeneity	3.48	13.96	0.00	0.00	0.00
Ivy degree	0.17	0.37	0.00	0.00	0.00
JD	0.16	0.37	0.00	0.00	0.00
Law affiliation	0.08	0.27	0.00	0.00	0.00
Law award	0.16	0.37	0.00	0.00	0.00
Law emp exp	0.06	0.24	0.00	0.00	0.00
Leader award	0.08	0.26	0.00	0.00	0.00
Master's degree	0.47	0.50	0.00	0.00	1.00
MBA	0.19	0.39	0.00	0.00	0.00
MD	0.02	0.13	0.00	0.00	0.00
Media award	0.12	0.32	0.00	0.00	0.00
Medical emp exp	0.01	0.08	0.00	0.00	0.00
Mentor	0.01	0.07	0.00	0.00	0.00
Mgt emp exp	0.84	0.37	1.00	1.00	1.00
Military award	0.00	0.04	0.00	0.00	0.00
Military emp exp	0.01	0.08	0.00	0.00	0.00
Mkt emp exp	0.12	0.33	0.00	0.00	0.00
Nomination committee chair exp	0.03	0.16	0.00	0.00	0.00
Nomination committee exp	0.09	0.29	0.00	0.00	0.00
Num of academic degree	1.44	1.04	1.00	1.00	2.00
Number of continents emp	0.21	0.47	0.00	0.00	0.00
Number of different committees	0.49	1.17	0.00	0.00	0.00
Oceania emp exp	0.01	0.10	0.00	0.00	0.00
Other awards	0.09	0.29	0.00	0.00	0.00
Other committee chair exp	0.01	0.12	0.00	0.00	0.00
Other committee exp	0.02	0.14	0.00	0.00	0.00
Outsider exp (firms)	0.12	0.61	0.00	0.00	0.00
Outsider exp (years)	0.85	5.00	0.00	0.00	0.00
Partnership emp exp	0.06	0.23	0.00	0.00	0.00
PhD degree	0.07	0.25	0.00	0.00	0.00
Political emp exp	0.04	0.20	0.00	0.00	0.00
President (other)	0.08	0.27	0.00	0.00	0.00
President exp (quoted)	0.02	0.14	0.00	0.00	0.00
Private firm exp (firms)	2.02	2.23	1.00	1.00	3.00
Private firm exp (years)	10.77	14.25	0.51	7.01	16.42
Professional exp (years)	21.85	9.98	15.00	22.00	29.00
Public and private exp (firms)	3.25	3.12	1.00	3.00	5.00
Public firm exp (firms)	1.23	1.60	0.00	1.00	2.00
Public firm exp (years)	7.89	11.19	0.00	4.00	12.17
Royalty award	0.00	0.06	0.00	0.00	0.00
Science affiliation	0.02	0.16	0.00	0.00	0.00
Science award	0.06	0.24	0.00	0.00	0.00
Science emp exp	0.05	0.22	0.00	0.00	0.00
Secretary (other)	0.02	0.16	0.00	0.00	0.00
Sport affiliation	0.01	0.10	0.00	0.00	0.00
Sport award	0.00	0.05	0.00	0.00	0.00
Sporting emp exp	0.00	0.02	0.00	0.00	0.00
Tech emp exp	0.04	0.18	0.00	0.00	0.00
Total Executive Network	24.16	63.62	0.00	6.00	20.00
Treasurer (other)	0.03	0.16	0.00	0.00	0.00
Trustee (other)	0.11	0.32	0.00	0.00	0.00
University emp exp	0.04	0.19	0.00	0.00	0.00
Upper mgt exp	0.18	0.38	0.00	0.00	0.00
Upper mgt exp (industries)	0.12	0.37	0.00	0.00	0.00
Upper mgt exp (years)	1.28	4.02	0.00	0.00	0.00
Upper mgt exp Heterogeneity	1.39	4.84	0.00	0.00	0.00
US private firm CEO emp exp	0.11	0.31	0.00	0.00	0.00
Volunteer	0.01	0.07	0.00	0.00	0.00
Women award	0.15	0.36	0.00	0.00	0.00
Women's College	0.04	0.19	0.00	0.00	0.00

Table 2: T-test of Sample Means

This table presents a two-sample *t*-test with unequal variances for the CEO and non-CEO subsamples. 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 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.

	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 4: Feature Importance by Group

This table 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 Random Forest, the best performing model.

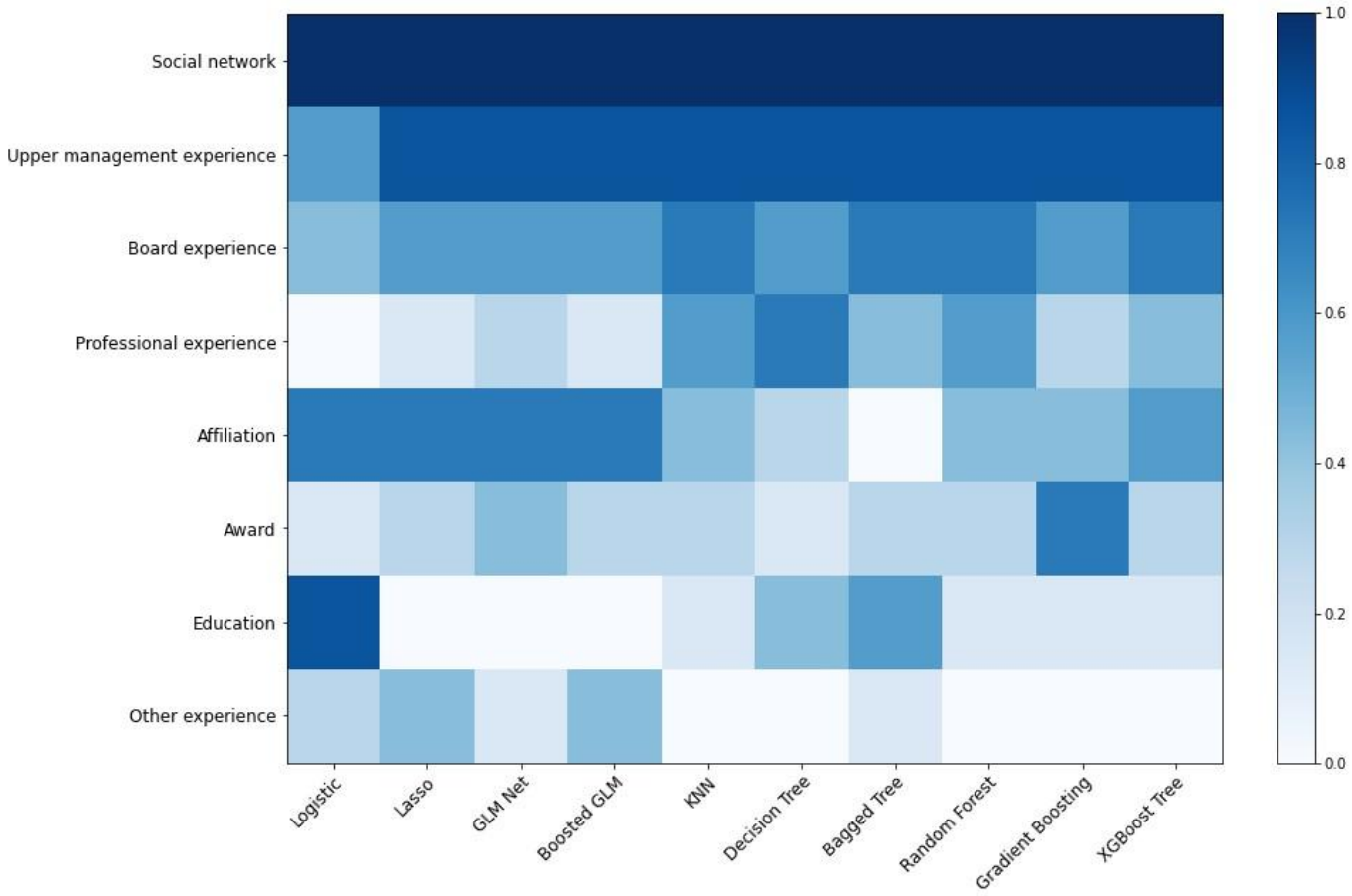
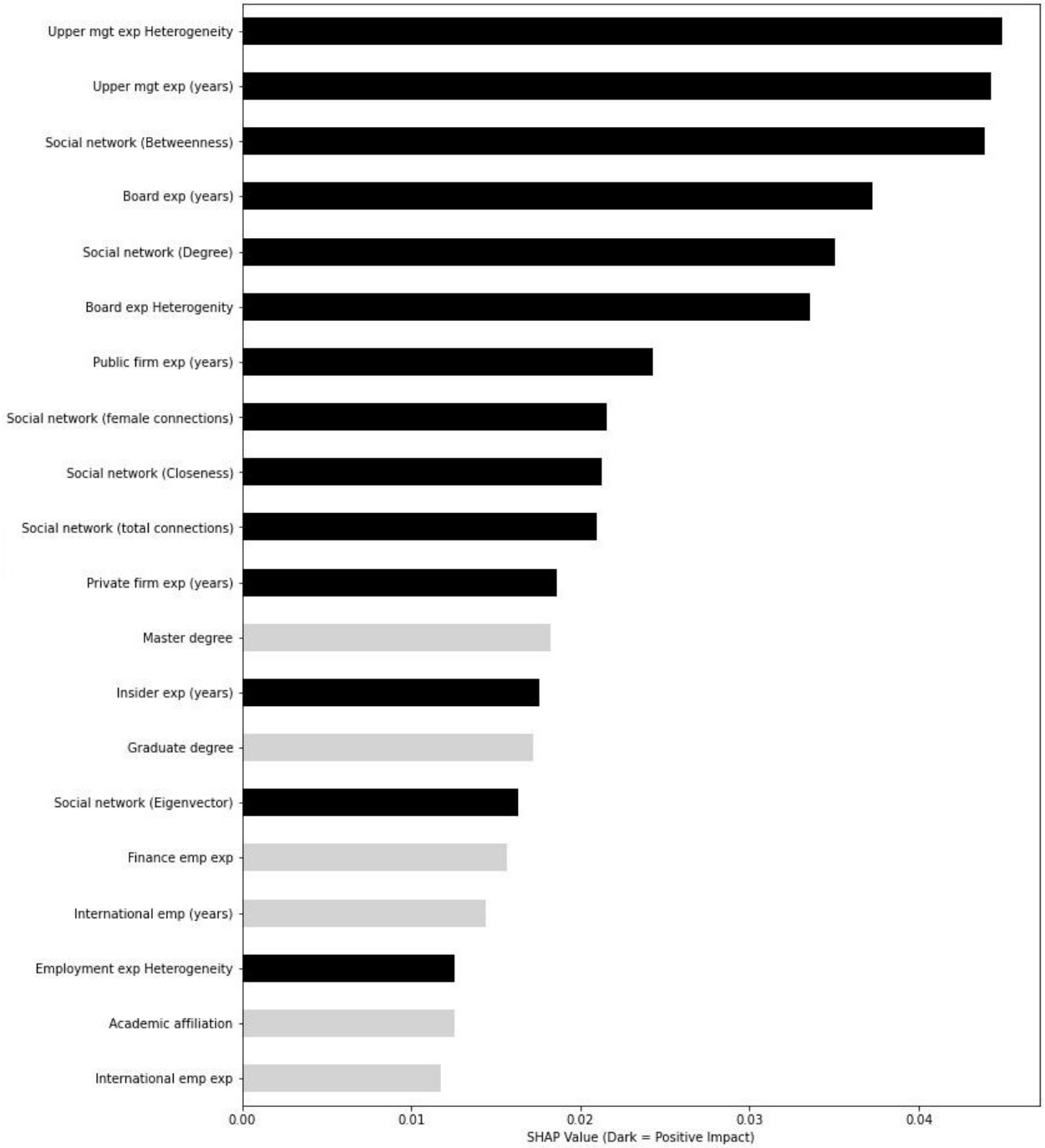


Table 5: SHAP Values for Top 20 Variables

This table presents the results for the top-performing model, Random Forest 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.



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.

Table A2: SHAP Values for Top 20 Variables – Male Sample

This table presents the results for the top-performing model for male sample, boosted GLM 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.

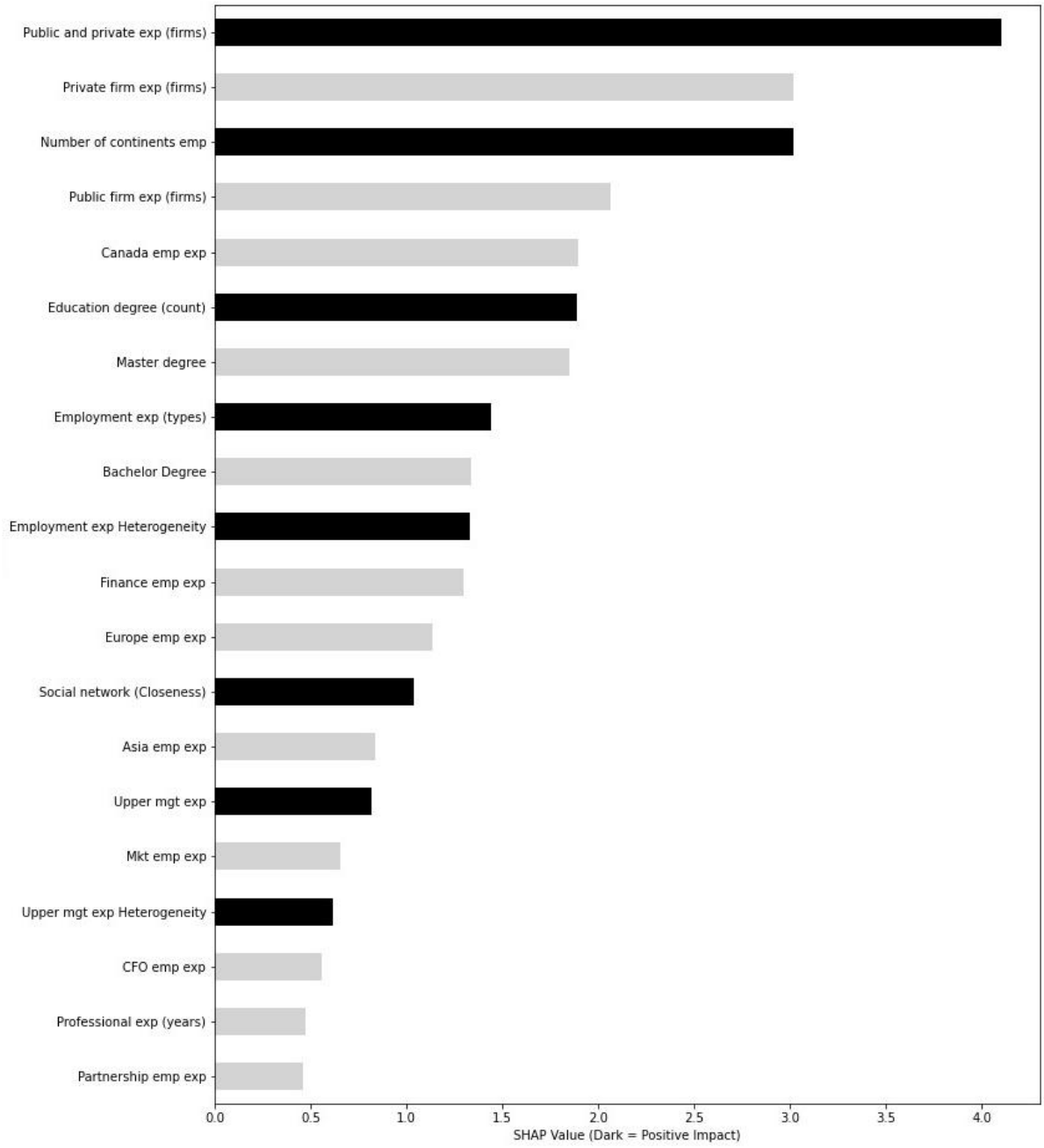


Table A3: T-test of Sample Means – Male Sample

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 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 A4: 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. All Variables

	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	

Panel B. 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 C. 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 A5: 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

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 A6: 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

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

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 A7: Placebo Test

This table presents the prediction of first-time 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

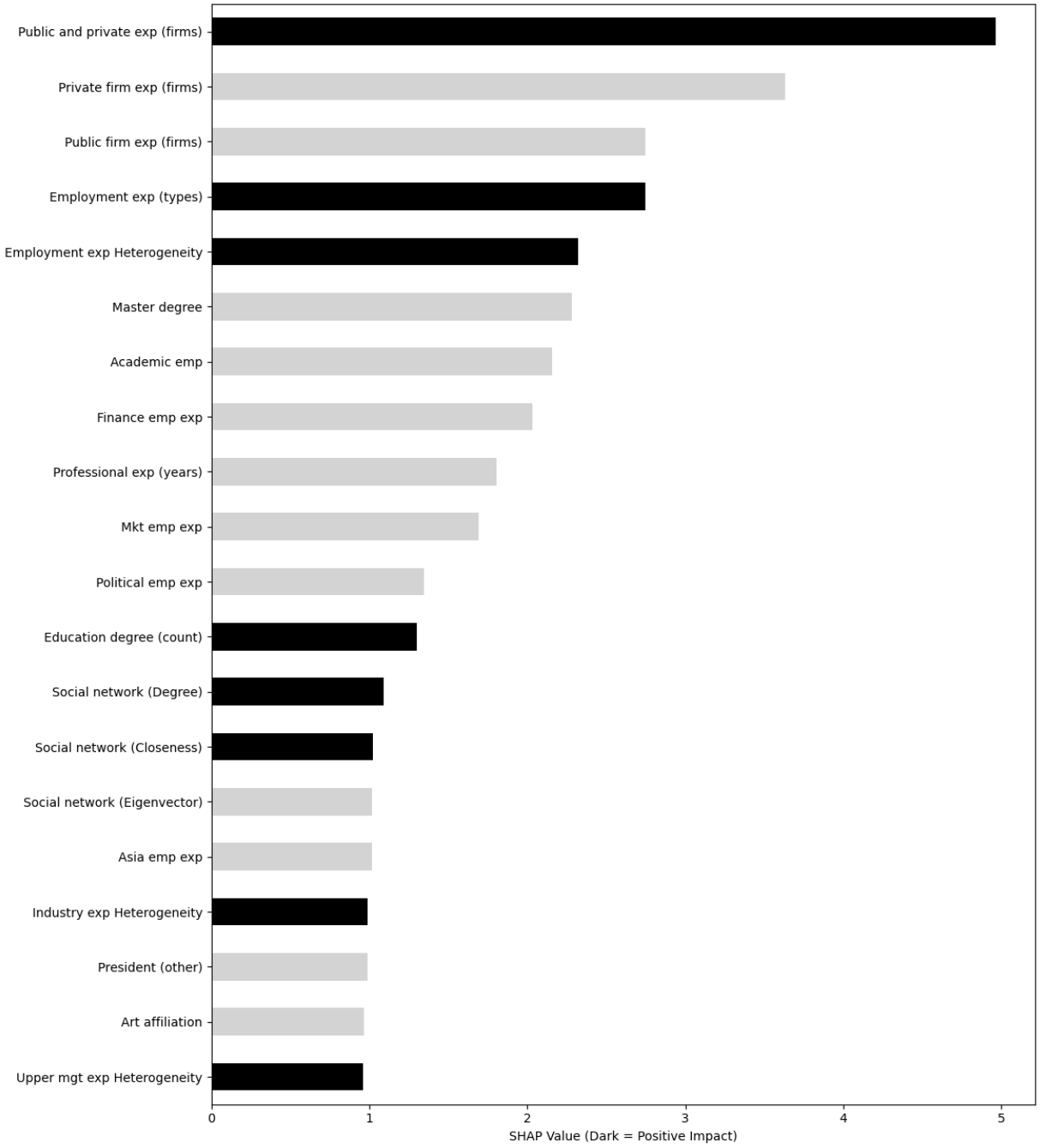
This panel presents prediction results for the actual full sample and the placebo full sample. In the actual sample, our best-performing model accurately identifies 89% of the actual CEOs as CEOs, while in the placebo sample where we replace key social network measures with the median measures for non-CEO 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

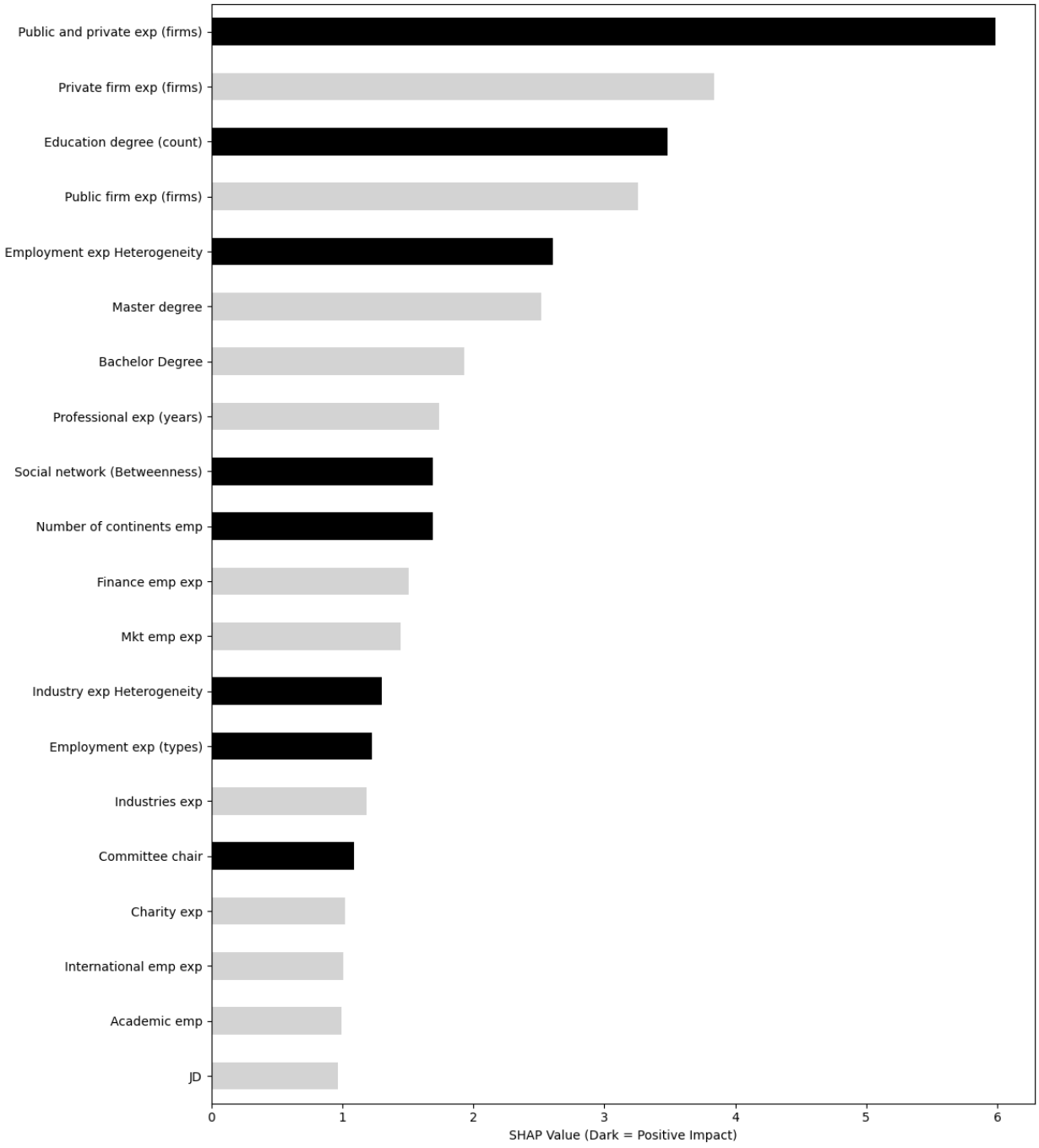
Table A8: SHAP Values for Top 20 Variables – Pre- and Post-Crisis Subsamples

This table presents the results for the top-performing model for pre- and post-crisis 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



Panel B. Post-Crisis Subsample



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