NETWORKS IN THE BOARD OF DIRECTORS : A CHOICE SET CONSIDERATION APPROACH.

BASILE DUBOIS[1]

PRELIMINARY VERSION

When landing a board of directors job, a significant portion of external candidates enjoys preexisting relationships with members of the board. These relationships may be entirely fortuitous, could reflect self-serving behavior on behalf of board members, or simply be used as a screening device to recruit individuals in extremely competitive positions. This paper uses a consideration sets framework to disentangle these explanations. I argue that estimates of the impact of pre-existing relationships on a director's probability of appointment are biased upwards in the literature. I make additional observations of the impact of a director's personal network on her likelihood of appointment.

[1]Toulouse School of Economics
Basile Dubois[2]: basile.dubois@tse-fr.eu
Under the supervision of Alexander GUEMBEL

1. INTRODUCTION

The board of directors is a peculiar institution. It is the backbone of modern corporate governance, its aim being to monitor the executive officers of the firm on behalf of the shareholders while providing expertise and leadership to the company. Its members are either executives or supervisory directors and have to take decisions collectively. It is difficult to become a member of a board of directors, as jobs are seldom posted and recruitments shrouded in mystery. Moreover, the selection and nomination of directors is a process far removed from the shareholders. Even though shareholders have the final say, director appointees are nominated by the board, on the advice of the CEO. Then, when shareholders vote on directors, they elect the ticket nominated by the board in almost all cases.

Recruitment in the board of directors involves many factors, which are hard to disentangle. It is in the firm's interest to have skilled directors and a board devoid of deadlock, and shareholders may want to appoint directors who are able to both advise and monitor the CEO. On the other hand, it might be in the interest of the CEO to pack the board with friends to ensure his continuation as a CEO, and he may prefer board members that vindicate his decisions and support him in front of the shareholders.

The problem is well known, and numerous pieces of legislation have been passed to ensure the alignment of shareholder and director interests. Among them are regulations on a minimum share of independent directors, which are directors that are not supposed to have any meaningful financial relationships with the supervised firm and its corporate officers outside of sitting fees.

It is worth noting that the above-described issues are not antithetic. A CEO may want skilled advisors who can provide advice when necessary, but vindicate his decisions. And a board that is cooperative and friendly towards the CEO will often be devoid of deadlock. There can be a gain in efficiency in appointing like-minded individuals to the board, and having a gridlocked board can reinforce the CEO's position as shown in Donaldson et al. (2020).

When thinking about the importance of preexisting relationships in the board's recruitment process, we accordingly end up with several intuitions. First, there is the aforementioned coordination concern, as it may be optimal to recruit like-minded individuals. Then, there is the screening concern: because of incomplete information, preexisting relationships may help with inference about the type of a director. That is, it may be easier for the board to reliably recruit skilled, fitting candidates through its network. Finally, there is the possibility of cronyism or nepotism. Bringing friends and cronies to the board may make governance easier while decreasing the supervision faced by the CEO and the board.

In this paper, I use insights and methods from the product market literature to produce reliable estimates of the role of networks in the appointment process. By aggregating the potential candidates into profiles based on observables, I can produce novel joint estimates of the importance of networks in the recruitment process relative to other candidate characteristics. Moreover, I can meaningfully interact firm characteristics and director characteristics, which helps me identify which type of firms prefers a particular type of directors. This is a very nice feature of my model, as it allows us to disentangle the various intuitions outlined above. For example, if the coordination concern is paramount, I expect larger multi-industry firms to recruit directors connected to the board. If recruitment through networks is mostly about CEO power, I would expect firms with longer CEO tenure to be more likely to recruit directors through the CEO's network.

This paper relates to three main strands of literature on CEO succession, director recruitment, and social networks.

The first strand of literature relates director appointment with the board's monitoring role. The seminal work of Hermalin and Weisbach (1998), show that independent boards are better monitors of their CEOs. Board independence decreases with CEO tenure, as a more skilled CEO requires less monitoring in equilibrium, and length of tenure is a signal for CEO skill. There is an alternative explanation for the decrease in the independence of the board observed when CEO tenure increases. As pointed out in Hermalin and Weisbach (1988), the board plays a major role in the CEO succession process. Since choosing the CEO is a key attribute of the board, one can only expect director recruitment to be connected in a way to CEO succession: a large fraction of the board is renewed when a new CEO is appointed. This is due to the fact that failed candidates leave the board to look for a job elsewhere. Since a CEO has less bargaining power at the beginning of his mandate, independent directors are often named at the beginning of CEO tenure.

Rosenstein and Wyatt (1990) show that there is a positive wealth reaction to the nomination of outsiders to the board. The appointment of outside directors benefits shareholders, which reinforces the intuition that they play a key monitoring role in the boardroom.

This strand of the literature, coupled with the corporate scandals of the 2000s, played a key role in the establishment of corporate governance regulations in the boardroom, namely the Sarbanes-Oxley Act of 2002 in the USA or the AFEP-MEDEF code in France. These regulations limit the number of insider directors, in order to assert the independence of the board. With the advent of these rules, the attention shifted to connected directors and homogenous boards.

The second strand of literature addresses the issue of connected boards. Kramarz and Thesmar (2013) study the case of the Grandes Ecoles in France and show that directors are more likely to be appointed to a board when they are part of the same social network as the CEO. Moreover, they show that CEOs who are former senior civil servants are less likely to be fired, are better paid, and make worst acquisitions.

Berger et al. (2013) study the German banking sector and show that it is more likely for an appointee to the board to be an outsider when the appointee shares social ties with the board and has a similar gender and age as the board. Boards also display homophily when considering director succession, as directors who are similar to the board enjoy longer tenures. They find weak evidence of reduced profitability when the board displays a high number of social ties.

Cai et al. (2021) use the BoardEx database to show that an appointee is much more likely to be connected to the board when the board already has a large fraction of coopted directors and the CEO has a long tenure. Moreover, boards with a larger fraction of independent directors also tend to recruit more connected directors. They also show in a separate binary logistic regression that firms are more likely to recruit candidates who are connected to the CEO or who exhibit a longer past relationship to a member of the board.

Liu (2010) finds that better-performing firms are more likely to appoint outside directors and that outside directors typically replace departed outsiders. Using a SURE setup, she shows that larger firms with better-networked CEOs are more likely to appoint a director connected to the CEO, while CEOs with shorter tenure are more likely to appoint non-connected directors.

The last strand of literature focuses on CEO succession. As the qualified candidates are few, it is much easier to recover a choice set when considering CEO succession. Therefore, this strand of the literature is much closer in terms of methods to this paper. Liu (2010) estimates a logit setup for CEO turnover, inside CEO hiring, and outside CEO hiring. She finds a significant effect of networks on CEO appointment and turnover. More connected candidates are more likely to be appointed, and CEOs who are more connected are more likely to keep their job.

Wang (2020) show that while connected candidates are more likely to be appointed, firm performance increases when a connected outsider is appointed while it decreases when a connected insider is appointed. This suggests that boards use connections to screen external candidates, while social ties distort the incentives when boards consider internal candidates, as their quality is already well known by the board.

My main contribution is twofold. First, I propose a rich and flexible specification inspired by the consideration set literature that allows me to jointly estimate the determinants of director choice and the composition of the choice set. This allows me to isolate the bias on parameters due to the composition of the choice set and recover the true parameter estimates. Secondly, I can exploit the vast dataset over 35 years and the structure of the model to get robust estimates on the relative importance of different observables in the recruitment process. This in turn allows me to shed light on which type of firm prefers to hire a given type of director and helps unravel the processes behind director appointment. For example, my setup allows me to jointly estimate the firms' preference for individuals connected to the board and individuals with large networks. As a candidate network is valuable in itself, and networked candidates are more likely to be connected to a board, this uniquely accounts for a very important source of misidentification.

The rest of the paper is organised as follows: In section 2, I briefly describe the datasets. In section 3, I describe the model used for estimation. In sections 4 and 5, I describe the estimation procedure and its results. In section 6, I detail a sanity check procedure, where I estimate the probability for a sitting director to be appointed on a committee. I conclude in section 7.

2. THE DATASET

The dataset is based on a combination of BoardEx data for the directors and network component, with CRSP-Compustat data for firms and market variables.

The BoardEx dataset is a business-oriented dataset focused on network data on business executives. It provides data on the board composition of firms and the background of individual directors. This includes information such as past positions, education, club membership, gender, age, and the dates of service of executives and senior managers. From the employment history of individuals and their extra-professional activities, the dataset provides complete information on professional and educational networks. Partial information on other kinds of social networks is also provided, through the observation of some club membership, NGO activities, and sitting on non-profits or academic boards.

As it is a corporate dataset targeted at business leaders, it suffers from a few shortcomings. Specifically, firm data is really sparse[1] and unreliable outside of board information. Moreover, it is likely that board data is incomplete for a particular firm or organization, as there are two ways for a firm-year to enter the dataset: Either it is added because the firm itself is being profiled, in which case every single individual sitting on its board will get a complete employment profile, or it is added because it is part of an individual director's employment profile[2]. There are 18 000 fully profiled organizations, among which nearly all publicly listed companies. Since I focus on publicly listed companies, the incomplete profiling issue is somewhat alleviated, but it remains present for older data. As data collection started in 1999, the farther I depart from 1999, the more likely I am to have partial data on board composition. In particular, I expect to miss all directors who retired before 1999.

[1] Both in the cross-section and in the time series.

[2] If a director sits on the board of firm A that is being profiled and also sits on the board of firm B that is not being profiled, firm B will enter the dataset by virtue of being on the Director's employment profile.

On the other hand, BoardEx is by far the most complete dataset on firm board composition and maintains an impressive array of director and executive profiles. The dataset inventories 1.4 million individual executive profiles, linked to over more than 300 000 identified firms and a million other various organizations. From these profiles' career and extra-professional history, it maps over 10 billion interpersonal relationships, with detailed information such as length of overlap, hierarchical positions, or the type of connection (educational, professional, social network, etc). Using the individual data on education and other activities, I can also identify the alumni networks, church memberships, academic fellowship, membership of a bar association, and other various formal social networks. The main limitation is that I can only strongly identify professional and educational networks, while data on other formal networks is partial and informal networks are not observed. This is both a blessing and a curse. Most of the endogeneity concern regarding networks goes away when we are limited to educational and professional networks since it is much harder to optimize these kinds of networking. Surely, ambitious individuals will attend better schools and switch jobs more often, which will have an impact on their professional network. But they cannot purely engage in networking, which would muddy the water in terms of the causal relationship between board appointments and connectedness. However, I may underestimate the true importance of connectedness and networks since I do not observe numerous informal relationships. I consider that two individuals share a relationship if they worked in the same company in the same city at the same time, if they sat on the same board (such as the board of a company, a NGO or a school district), were part of the same church in the same city in the same year, or if they were both studying the same topic at a given university in a given year. Membership in mandatory organizations such as Bar Associations and subscription to social charities such as the Friends of the Met are excluded from the relationship variable.

I complement the BoardEx dataset with CRSP-Compustat data on firms. Matching on various identifiers (CUSIP, CIK code, Ticker) and collapsing the duplicates[3], I get 1.35 million director-firm-year triplets over 35 years. A triplet represents a tenure year for a director in a given firm and includes all characteristics of the director and the firm for this given year. These triplets represent 9377 firms and 86 909 directors. I observe 110 447 first appointments of directors over roughly 35 years, of which 104 679 are outsiders, where I define an outsider director as being a director with no past employment history with the firm. Therefore, I depart from Hermalin and Weisbach (1988) and I do not make the distinction between outsiders and greys, who have no past employment with the firm but have business ties nonetheless. Once accounting for missing data, I get roughly 70 000 first appointments on which I can run the estimation. The summary statistics for these 70 000 observations do not differ substantially from the statistics of the broader 110 000 first appointments or 1.35 million triplets.

CRSP-Compustat Data is available for the fiscal year, which is convenient since most board tickets are presented at the same time as the fiscal year results, and director appointments are ratified during the annual general meeting of the fiscal year. It is therefore logical to consider that there is a causal relationship between the firm variables for a given fiscal year and director appointments in the following year.

Following Hermalin and Weisbach (1988), I include an array of firm variables such as firm size, firm earnings, leverage, firm performance relative to the industry, size of the board, Market to Book ratio and Tobin's Q, a measure of firm diversification and length of CEO tenure. In interacting these variables with the appointee-level variables, I should be able to understand

[3]Firms can change ticker after a merger or an acquisition, can get a different CUSIP when they stop being publicly traded only to become public again later, or following a corporate action.

how much a firm's own situation influences its board appointments.

Before continuing on with the model, some basic summary statistics are in order. The average number of connections of a newly appointed outside director to the board is 1.6 in the whole BoardEx sample. 31% of directors have preexisting relationships with the board and 21% to the CEO. In the CRSP-BoardEx linked dataset, there are only 1.08 connections on average. 26% of directors are connected to the board and 15% to the CEO. This is not that surprising. Firms in the CRSP subsample are public, which means that they are subject to stricter oversight, while a lot of firms in BoardEx are private firms: it is not surprising to find more connected directors in family-owned firms or firms financed through private equity. Moreover, it is reasonable to think that the data collection issues I pointed out above disproportionately affect non-connected directors: Because of the structure of the dataset, very connected directors had numerous jobs, which make them more likely to appear in non-profiled companies' boards.

When we restrict ourselves to S&P 500 data, there are 2.3 pre-existing connections to the board per appointee on average, 40% of the appointees are connected and 25% are connected to the CEO. This needs not necessarily indicate any causal relationships between networks and board appointments in the S&P500, since it may very well be that directors who are competent enough to lead an S&P500 company are few and know each other.

One concern is that the appointments of connected individuals may be mechanically driven by the size of the board. That is, it is simply more likely for a candidate to happen to randomly know a member of the board when the board is bigger. When looking at table C.I, this concern is alleviated: table C.I shows that while it is indeed more likely that bigger or more networked boards appoint connected directors, the size of the board does not seem to be the main force driving the appointment of connected individuals as the relationship between the size of the board and the distribution of connected appointees is nonlinear and nearly flat above the median board size (or above the median board network size).

[TABLE 1 about here.]

3. THE MODEL

The estimation of a discrete choice setup for board appointments is complicated by the fact that we cannot observe the choice set of the firm. This problem has been addressed in different ways in the literature.

Liu (2010) computed a binary probit where the dependent variable is the probability that the firm appoints a connected director. While this is a straightforward way to avoid the problem, a binary probit loses on the efficiency of the estimates, increases the potential error (as the choice set is collapsed), and does not allow for the computation of substitution patterns, as there are only two alternatives. Moreover, it cannot meaningfully include appointee characteristics as the alternative candidates are not accounted for in the model[4]. Therefore, this makes it difficult to thoroughly understand the complex interactions between firm characteristics and director characteristics.

Berger et al. (2013) estimate a binary logit where the dependent variable is the probability for a given appointee to be an outsider. While this also circumvents the issue of choice set generation, this obfuscates the causal relationship. Indeed, the causal relationship inferred by the model is that given an appointee profile, the firm decides to recruit her either as an insider or as an outsider, while in reality, the firm chooses a candidate who happens to be an outsider or an insider.

Cai et al. (2021) address the choice set selection issue in a creative way : they build a choice set from the potential directorial candidates, defined as appointees to firms of similar size in the same metropolitan area. While thoughtful and creative, this methodology is likely to introduce a large amount of bias if the choice set is misspecified. Let us make the mild assumption that people whe spent their career in a given industry are more likely to know eachother than people working in different industries[5]. Then, by forcing appointees to firms of similar size in different industries into the choice set, one would overestimate the importance of connections to the appointing board, as the appointee is simply more likely to know members of the board than the other candidates in the reconstructed choice set. Further, they report a different logistic regression on the characteristics of firms appointing connected directors. To my knowledge, they are the first to provide such a detailed outlook of which firm characteristic seem to drive the appointment of connected directors. However, this approach is also not devoid of bias. Because it is a separate regression that does not take into account individual directors' characteristics, this can introduce a large amount of bias: coefficients attributed to a connection to the board might simply identify a large network[6], industry experience[7] or an Ivy League education[8].

In the following, I first develop a simple multinomial logit model that takes into account firm observables and directors' observable and unobservable characteristics, then I build onto this model to account for choice set consideration.

[4]In order to see why, consider the following: If the researcher includes candidate characteristics in a binary appoint/don't appoint logit, the underlying assumption on the choice set is that the firm has to choose between recruiting the observed appointee or not recruiting anyone at all. As the firm probably choose between several potential appointees, this choice set is clearly wrong, and using it for estimation would result in too much weight put on the appointee's characteristics. Moreover, the problem is compounded by the fact that the researcher cannot include the firms that ended up not recruiting a director in the estimation, since their choice set (their candidate/appointee) is not observed, further reducing the identification of firm coefficients.

[5]Because of the way the BoardEx dataset is structured, observed connections mostly reflect career patterns.

[6]A larger network mechanically improves the odds of being connected to any given individual.

[7]Making it more likely to have worked with people sitting on the board.

[8]A lot of directors have studied in the same Ivy League schools.

3.1. *The choice set*

I aggregate the potential director appointees into profiles. These profiles are based on characteristics such as age, past tenure as a director, related work experience, number of connections to the board, connection to the CEO, size of network, etc. Note that I have to be very parsimonious in the characteristics I include in the profiles, as the number of potential profiles increases geometrically. Therefore, it is necessary that I further aggregate data for some of these characteristics : I group directors into age brackets, and I use the floor function of the logarithm with base 10 for the size of the network[9].

3.2. *The base model*

Let us denote firms by i and potential appointees profiles by j.

Let us consider a pairing between a firm i and a director with observable profile characteristics x_j. Assume that this match generates the following utility, that is fully captured by the firm.

$$u_{ijk} = V_{ij} + \epsilon_{ij}$$

With V_{ij} the match utility from observables x_j , and ϵ_{ij} the idiosyncratic component of utility. Under standard assumptions[10] on the distribution of ϵ (Gumbel extreme value) and normalizing the outside option, we get the following choice probabilities :

$$\mathbb{P}_{ij} = \frac{e^{V_{ij}}}{1 + \sum_m e^{V_{im}}} \tag{1}$$

I assume V_{ij} is a linear function of profile characteristics and firm attributes. Formally, let us denote :
x_j the profile's characteristics,
z_i the observed firm attributes,
ϵ_{ij} the idiosyncratic individual preferences.

$$\begin{aligned} u_{ij} &= V_{ij} + \epsilon_{ij} && (2) \\ &= \sum_l x_{jl}\tilde{\beta}_{il} + \epsilon_{ij} && (3) \\ &= \sum_l x_{jl}\bar{\beta}_l + \sum_{lr} x_{jl} z_{ir} \beta^o_{lr} + \epsilon_{ij} && (4) \end{aligned}$$

Where $\tilde{\beta}_{il} = \bar{\beta}_l + \sum_r z_{ir}\beta^o_{lr}$ is the taste of i for characteristic l, and the o superscript stands for observed firm attributes.

[9]To ease concerns about bias from arbitrary choices on aggregation level, I ran the estimation with many different cutoffs for the brackets and got quantitatively similar results.

[10]Standard assumptions for this kind of models, see McFadden (2001) for a detailed review of the discrete choice literature. Gumbel extreme value standard errors allow for the derivation of the logit specification.

3.3. *Unobserved characteristics*

As it turns out, the base model ignores potential unobserved characteristics. Let us again denote firms by i, individual directors by k, and the set of individuals sharing observables x_j as B_j.

Let us consider a pairing between a firm i and a director k with observables $x_k = x_j$. Assume that this match generates the following utility, that is fully captured by the firm.

$$u_{ijk} = V_{ij} + \omega_{ik} + \epsilon_{ijk}$$

With V_{ij} the match utility from observables x_j, ω_{ik} the match utility from unobservables of individual k, and ϵ_{ijk} the idiosyncratic component of utility.

In order to be able to identify the utility from unobservables, we need to make the key assumption that individual unobservables do not interact with firm characteristics[11]. In other words, the part of unobservables that is not correlated with the observables yields the same utility to all firms. Take a directorial candidate who has connections to the Washington establishment, and suppose that these connections cannot be predicted in any way from the observables. On a fundamental level, the model assumes that these connections yield the same utility to every firm. While this is the mildest assumptions one can make, it is quite restrictive.

Let us therefore rewrite ω_{ik} to account for the fact that we aggregate over profiles and that this utility is the same for all i. Define

$$\omega_{ik} = \bar{\xi}_j + \xi_{jk}$$

Where $\bar{\xi}_j$ is the average utility obtained from unobserved attributes of individuals with profile j.

Assuming that unobserved director characteristics do not interact with firm characteristics, we obtain the following model :

$$u_{ijk} = \sum_l x_{jl}\tilde{\beta}_{il} + \bar{\xi}_j + \xi_{jk} + \epsilon_{ijk}$$

Where I remind the reader that $\tilde{\beta}_{il} = \bar{\beta}_l + \sum_r z_{ir}\beta^o_{lr}$ is the taste of i for characteristic l, and the o superscript stands for observed firm attributes.

This rewrites

$$\begin{aligned} u_{ijk} &= \bar{\xi}_j + \sum_l x_{jl}\bar{\beta}_l + \sum_{lr} x_{jl} z_{ir}\beta^o_{lr} + \xi_{jk} + \epsilon_{ijk} \\ &= V_{ij} + \xi_{jk} + \epsilon_{ijk} \end{aligned}$$

And we get the following choice probabilities :

$$\mathbb{P}_{ij} = \frac{e^{V_{ij}+\Xi_j}}{1 + \sum_m e^{V_{im}+\Xi_m}} \tag{5}$$

where $\Xi_j = \ln \sum_{k\in B_j} e^{\xi_{jk}}$. This component deserves further comments. First of all, it is undistinguishable from $\bar{\xi}_j$. This is not problematic as we are only interested in unobservables to

[11]Please refer to the appendix A to see why this general model is not identified.

obtain better estimates of the β coefficients. Secondly, this term captures the cardinality of a given set B_j. This means that it can account for one of the main flaws of the aggregation design : some director profiles might be less likely to be chosen because they simply are rarer, i.e. there are less potential candidates with this profile. As we will see when going over the results, this leads to an underestimation of the value of connections in the base model. Thirdly, this formulation assumes that each firm has roughly the same choice set: it is as likely have access to a candidate with a given profile as is any other firm. This is a strong assumption, as one could easily consider that a board with a larger network would be more likely to have access to rarer profiles. I drop this assumption in the next section.

3.4. *Choice Set Consideration*

It is most likely that different firms face different choice set: finding a good candidate is a difficult process and not all options are available to every single firm. Some profiles are not only rarer, but also less likely to be encountered by a given firm. A consideration set framework can account for these nonrandom differences in choice set.

In a consideration set model, we jointly estimate the probability of one option to be present in the choice set and the probability for this option to be chosen. This requires that a characteristic that shifts the choice set does not enter the utility derived from a choice.

Formally, let us define the consideration function ϕ_{ij}, defining the probability of profile j being considered by firm i.

$$\phi_{ij} = \frac{e^{\gamma_{ij}}}{1 + e^{\gamma_{ij}}}$$

Where γ_{ij} is a function of firm characteristics and director characteristics.
Then, the probability that choice set $\mathcal{C}$ is being considered by firm i is given by

$$\pi_i^{\mathcal{C}} = \prod_{j \in \mathcal{C}} \phi_{ij} \prod_{k \notin \mathcal{C}} (1 - \phi_{ik})$$

This yields the formal choice probabilities:

$$p_{ij} = \sum_{\mathcal{C}} \prod_{l \in \mathcal{C}} \phi_{il} \prod_{k \notin \mathcal{C}} (1 - \phi_{ik}) \mathbb{P}_{ij}(x_j, z_i | \mathcal{C})$$

With $\mathbb{P}_{ij}$ as defined in equation (1). Because of the increased computational complexity of this model, it must be estimated via simulation, as described in Goeree (2008) and Abaluck and Adams-Prassl (2021). Details of the estimation procedure are provided in the appendix B.

Such a consideration set model allows for the endogenous determination of the choice set for each and every firm according to a set of parameters. I allow the choice set to be a function of the director's experience, the director's network, the director's preexisting relationship with the board, and the size of the board's network. The inherent logic is that while profiles that are more connected, with a larger network and a more relevant job experience should be rarer, a board with a larger network should be more likely to access such potential candidates. This captures two fundamentally different effects. The first is in essence purely mechanical: A board with a larger network is more likely to have pre-existing connections with a randomly chosen appointee. Therefore, candidates with pre-existing relationships are more likely to be "considered" if the board has a larger network. The second effect stems from the proposed board recruitment mechanism. Anecdotic evidence[12] shows that directors are using their network to

[12] See Cai et al. (2021)

search for suitable candidates. If we follow this line of thought, rare profiles are relatively more likely to be considered by firms with large networks than firms with small board networks. Consequently, the estimated positive coefficients for the board network parameters show that boards do indeed use their networks to find suitable applicants.

4. ESTIMATION PROCEDURE AND IDENTIFICATION

Given the choice set of a firm, the outside option is defined as the recruitment of an insider director. I remind the reader that outsider directors are defined as directors who do not have a past employment history with the hiring firm. Since there are many legal and governance constraints on the recruitment of insider directors, firm will try to allocate directorships to outsiders as often as possible. Arguably, another suitable outside option would be to renew the mandate of a currently sitting director. However, the board recruitment process seems not to be driven by such concerns: the decision to replace a director is often taken months before a suitable candidate is found, and the search process is usually lengthy and quite costly for the firm.

I follow Keane and Nada (2012) and randomly sample 20 profiles for each firm to create the choice set when estimating the baseline model and the observed characteristic model.

I estimate all of the models by maximising the logarithm of their likelihood function. While this is quite straightforward for the base model, the unobserved characteristics model and the consideration set model deserve some comments.

4.1. *Unobserved Characteristics*

In the unobserved characteristics model, I run a nested loop based on the BLP[13] contraction mapping.

Let us first define the *observed* mean utility from good j, δ_j as

$$\delta_j = \sum_l x_{jl}\bar{\beta}_l + \Xi_j$$

This mean utility encompasses the utility from unobserved characteristics, Ξ_j, and the intercepts of the utility derived from observed characteristics. Without further assumptions on the distribution of Ξ_j, the $\bar{\beta}$ coefficients are unidentified and only δ_j is[14]. From the main specification, only the β^o can be recovered with this procedure. However, this provides a good sanity check for the standard errors of the baseline model, as not accounting for unobservables biases standard errors and overestimates precision (Murdock, 2006).

I follow Murdock (2006) and I estimate the log-likelihood through standard optimisation techniques[15], but each time the log-likelihood is computed, the vector of mean utilities δ is recovered by the BLP algorithm. Therefore, the estimation algorithm is a nested loop, with an outer loop consisting of the maximum likelihood estimation, and an inner loop consisting of the BLP contraction mapping. As the analytical gradient is misspecified (it cannot take into account the impact of the change of parameters on the coefficients δ), convergence is slow, but

[13] Berry et al. (1995)

[14] Assuming $\mathbb{E}(\Xi_j) = 0$, we could recover $\bar{\beta}$ with a simple OLS regression of δ_j on characteristics. However, this would be quite unreasonable, as $E(\Xi_j)$ is proportional to the cardinality of B_j as we discussed earlier.

[15] Specifically, the Berndt–Hall–Hall–Hausman algorithm.

this algorithm is still more stable and faster than estimating the δ together with the β using gradient methods[16].

Specifically, the inner loop consists in the following. Let us define the predicted market share $\hat{s}_j = \sum_{i=1}^{n} \frac{\mathbb{P}_{ij}}{n}$, and the observed market share for profile j as s_j. Starting from an arbitrary vector δ_0, I find the vector of δ by iterating the subsequent equation until convergence.

$$\delta_t = \delta_{t-1} + \ln s_j - ln(\hat{s}_j|\delta_{t-1})$$

4.2. *Consideration Set Model*

As explained in section 3.4, the estimation procedure relies on simulation and is described in details in the appendix. In short, I first simulate R choice sets for each firm, and then, given the simulated choice sets and the parameter values, I compute the choice probabilities of choosing a given profile for each firm. Finally, I average the likelihoods I obtain from the R simulations to get the simulated likelihood function.

To simulate firm i's choice set, I first fix $R/2$ draws of uniform random variables over the available profiles $j \in \{1, ..., J\}$. I then generate their $R/2$ antithetic covariates[17] to obtain R draws of J uniform random variables. Using parameter values, I compute ϕ_{ij} for each j, and compare it to the corresponding uniform draw. If the value of the probability is higher than the draw, it is in the choice set. By repeating this process for profile and each firm for each of the R draws, I obtain R choice sets for each firm.

Once the choice set are determined, I estimate the choice probabilities for each firm-draw, conditional on choice set and parameter values. Importantly, choice probabilities are computed using importance sampling with reference to the initial choice set, so as to ensure convergence of the estimates[18]. Averaging the likelihood functions resulting from these choice probabilities yield the simulated likelihood, that can then be maximised. I use the Berndt–Hall–Hall–Hausman algorithm, but I compute the final Hessian numerically so that I can allow for potential heteroskedasticity[19].

Identification relies on the crucial assumption that the board's network enters the consideration function, but does not enter the choice function. That is to say, the size of the network of the board will shift the choice set that is available to a given firm, but will not play any role in the choice of director nominees by the board, conditional on choice set. Such an exclusion restriction is necessary to provide point identification.

5. RESULTS

5.1. *Firm and director controls*

Firm and director characteristics used in the estimation are summarised in Table C.II. Director controls are all characteristics that are likely to be correlated to the number of pre-existing relationships a director has with the board, therefore leading to spurious estimates were they

[16] As the δ are alternative specific coefficients, maximum likelihood is notably prone to dramatic overfitting when they are estimated through gradient methods. See Bierlaire et al. (1997) for a discussion.

[17] Antithetic acceleration drastically reduces the variance from simulation and is less costly in terms of computer memory. See Geweke (1988).

[18] Indeed, a change in choice set could induce a very large change in choice probabilities, which would induce discontinuities in the log-likelihood. A discontinuous log-likelihood might not converge to its maximum using standard optimisation procedures.

[19] The BHHH approximated Hessian is equal to the 'meat' of the Huber-White sandwich estimator, which yields mathematical equivalence between the HW covariance variance matrix and the BHHH covariance matrix.

not taken into account. Firm controls are fundamentals that are likely to influence the marginal value of pre-existing relationships with board members, or the marginal the value of director controls such as industry experience or the size of the network of the appointee. Summary statistics are provided in the tables C.XII and C.XIII in the appendix.

[TABLE 2 about here.]

5.2. *Terminology*

In this model, firm characteristics are interacted with candidate (profile) characteristics, which makes economic interpretation of the results difficult, both in terms of magnitude and economic significance. In order to streamline the discussion, let me define some terminology: In the following will refer to the mean effect of a variable and to the standard effect of a variable. The mean effect of variable l is to be defined as

$$\text{MEf}_l = \bar{\beta}_l + \sum_r \mathbb{E}(z_{ir})\beta^o_{lr}$$

And represents the effect of an increase of one unit in the variable l on the choice utility of the average firm in the sample.
Similarly, the standard effect of variable l given firm characteristic r is defined as

$$\text{StEf}_{lr} = \sigma(z_{ir})\beta^o_{lr}$$

And represents the effect of a standard deviation of firm characteristic r on the choice utility provided by variable l.
This terminology will help quantify the economic magnitude of effects. When the mean effect of characteristic l is negative, an increase in characteristic l will decrease the probability that a given profile is chosen. Further, a very small standard effect relative to the mean effect can be interpreted as an interaction coefficient being economically insignificant, as the variation found in the data will have little impact on the magnitude and directionality of the estimate.
Finally, I will make the distinction between a networked and a connected director. A networked director has a large network of interpersonal relationships observable in the dataset, acquired through past work experiences or through her studies. A connected director has a pre-existing relationship with at least one member of the board.

5.3. *Preliminary Regression: Baseline model*

[TABLE 3 about here.]
[TABLE 4 about here.]

Our two variables of interest are the number of pre-existing relationships of the appointee with the board, and the size of the network of the appointee.

Baseline estimation results presented in table C.III show that firms appointing a director who has a connection with a member of the board tend to be bigger, more leveraged, have a lower ROA, and a higher Q ratio. In other words, firms that are either overvalued, underperforming or behemoths tend to nominate connected directors more often. This points towards the cronyism hypothesis, where underperforming and entrenched boards exhibit nepotistic behaviour. On the other hand, there is some mixed evidence pointing towards the coordination or the screening hypothesis. Firms that changed CEOs recently tend to recruit connected directors, and executive directors are more likely to be connected to a member of the board than supervisory directors. Executive directors are extremely important in the day to day management of the firm but it is frowned upon to have them sit in the audit and compensation committees. Therefore, nepotistic boards should not prefer appointing executive directors rather than supervisory directors, whereas boards concerned with the proper screening and the proper coordination of the executive team might rely on personal connections to recruit and screen executive officers. Similarly, a firm that changed CEO will not have an entrenched CEO but will often be going through a process of renewal of the executive team, where coordination and screening are of paramount importance. Finally, there are three relationships that I posit to be purely mechanical. Firms with a larger board and firms with a larger network are more likely to appoint connected directors because the probability of a director being connected to a member of the board is mechanically higher, and firms spanning few industries are more likely to appoint a connected directors because the pool of candidates is smaller when one considers that such firms would probably prefer to hire an industry specialist. This intuition is somewhat reinforced by looking at results in table C.XIV, that show that firms spanning few industries are much more likely to recruit directors with past job experience in the main industry of the firm.

Results presented in table C.IV indicate that firms recruiting directors with larger networks are bigger, less leveraged, have a slightly lower Tobin's Q than average and are more likely to have a recently appointed CEO. Further, firms with larger boards are slightly less likely to appoint directors with a large network, but boards with a large network are much more likely to hire a networked director. I argue that this evidence points towards the board referral process described in Fahlenbrach et al. (2018), wherein boards screen potential directors by using other directors as referees.

Finally, I have to discuss the mean effect of pre-existing relationship and of the size appointee's network. In this specification, having an additional pre-existing relationship with a board member will, on average, make a candidate less likely to be appointed to the board. Conversely, having a larger overall network will make an appointee more likely to be appointed to the board. While the baseline specification has its own biases[20] that makes it difficult to make any definitive conclusion at this point, this hints to a mis-identification of the impact of pre-existing relationships in previous literature. In such case, directors with a larger network are mechanically more likely to have pre-existing relationships with members of the board, but have a higher likelihood of appointment because of the director referral process described in Fahlenbrach et al. (2018) and not particularly because of direct connections to the board. We will see in the following that this intuition is confirmed in the choice set consideration model.

5.4. *Unobserved Characteristics model*

[TABLE 5 about here.]

[TABLE 6 about here.]

Estimates of the unobserved characteristics model are presented in tables C.V and C.VII. As expected, accounting for the rarity of profiles through mean utilities negates the board network coefficient for rare profiles. It becomes insignificant when interacted when the appointee's network, and becomes negative when interacted with the number of pre-existing relationships of the appointee with the board[21]. The fact that small change in model specification changes the estimates in a predictable fashion further motivates the consideration set specification: Proper

[20] As discussed above, biases are mostly related to the composition of the choice set given the aggregation procedure. Profiles with a large number of pre-existing relationships are likely to be uncommon, whereas they represent a large number of the aggregated profiles.

[21] Boards with large networks will be more likely to choose all profiles over the outside option in this specification, as there is a large positive intercept coefficient for board networks. Because of the way the multinomial logit function is setup, this effect will be proportionally much bigger for profiles with a low mean utility, as they start with a lower

consideration of how the choice set is selected is necessary to obtain reliable estimates.
Table C.V presents coefficient estimates for the interaction of the appointee's number of pre-existing relationships. The interaction coefficient with Q, Industries and leverage are not statistically significant in this specification, but the other coefficients retain both their statistical significance and economic magnitude. Importantly, firms with a larger ROA are less likely to recruit directors connected to the board, executive directors are more likely to be connected to the board, and a firm that recently changed CEO is more likely to recruit directors connected to the board.
On the other hand, results presented in table C.VII show that in this specification, most interaction coefficients with the appointee's network are insignificant. It seems that firms recruiting candidates with large networks are bigger, less leveraged, and have a lower Q-ratio.
As I stay agnostic regarding the distribution of mean utilities, I cannot recover the intercept of the estimates, and I therefore cannot compute the mean effect of a change in profile characteristics with this specification.

5.5. *Consideration Set Model*

[TABLE 7 about here.]
[TABLE 8 about here.]
[TABLE 9 about here.]

Parameter estimates in the consideration set model are to be taken as the value of the estimate *conditional on the profile being considered*. The full results including consideration parameters estimates are reported in table C.XV of the appendix.
Results of the consideration estimation regarding the candidate's pre-existing relationships, network and experience are presented in table C.VII, C.VIII, and C.IX, respectively. Before delving into the details, several comments are in order. First, accounting for consideration has a very large impact on the mean effect of the coefficients. Second, it appears that the size of the candidate's network is the single most important variable in determining the appointment to a board, followed by the experience of the candidate (or lack thereof). Lastly, the economic magnitude of the interaction coefficients is quite small comparatively to their mean effects: despite firm fundamentals being somewhat predictive of recruitment behaviour, their economic significance is only marginal. The size of the board, the number of industries that the firm is spanning and the type of position (supervisory vs executive) seem to be the only consistently economically significant firm characteristics in the recruitment decision.

Interestingly, even when accounting for the probability of consideration, a candidate with pre-existing relationships with members the board is **not** more likely to be appointed. If anything, the existence of a relationship with a member of the board might be detrimental to the candidate. Further, most of the significant interaction coefficients are arguably mechanical. A larger board will have a higher probability to be connected to a random candidate *ceteris paribus*, and it is probable that larger firms and firms spanning few industries recruit from a smaller pool of interconnected candidates[22]. While firms recruiting connected directors are significantly larger, have a higher Q and higher leverage, the ROA coefficient is now statistically insignificant. This does not provide a lot of evidence for a coordination or a cronyism hypothesis.

---

utility, and the probability of choice is proportional to the ratio $\frac{e^{U_j}}{1+\sum e^{U_k}}$. Therefore, it is not surprising to have a lower board network coefficient for rare profiles, considering that its marginal impact on choice is larger.

[22]Suitable candidates to the board of a S&P500 firm are presumably few, and single industry firms might be interested in specialists of the industry.

On the other hand, it is self-evident that the candidate's network plays a very large role in her appointment probability when looking at table C.VIII. The mean effect of an increase in magnitude in the network of the director is very large, but firms with more members on the board tend to be less likely to appoint networked directors. This evidence points towards the screening hypothesis: as described in Fahlenbrach et al. (2018), director candidates would be recruited through a referral process. Having a larger network increases the likelihood of getting a relevant referral, be it by a mutual acquaintance or a well established expert in her field. Surprisingly, it seems that the size of the network matters more for supervisory director appointees than for executive director appointees. While I do not have a definitive explanation for this fact, it might be due to the nature of the job: It is relatively easy to evaluate the performance of an executive using the past performance of her firm or her division, whereas it is very difficult to ascertain the value of a supervisory director. In such case, referrals would carry more weight for supervisory director than for executive directors.

Finally, table C.IX shows that past industry experience matters a lot conditional on consideration. Even though the mean effect was negative in the baseline model, it is now strongly positive. As I argued above, the baseline model underestimates the value of rare characteristics such as relevant industry experience. Experience seems to be particularly valuable for firms with a recently appointed CEO. This is not surprising, as the board might want to ensure that a newcomer gets the right advice during his first few years on the job. Larger companies, spanning few industries, with a higher ROA and low leverage also tend to value experience, but the magnitude of the standard effect is small. The interaction coefficient of experience and supervisory director is positive, of relatively large magnitude, and I contend that this is again due to the nature of the job: past experience in the industry is one of the rare quality signals for supervisory directors, while an executive director can be evaluated on numerous metrics.

6. APPOINTMENT TO COMMITTEES

6.1. *Board committees*

While the choice set for board appointments is unobserved, the choice set for committee appointments is easily observed: To be appointed to the a board committee, one needs to be a director. As the Boardex dataset also reports committee appointments, I can estimate whether or not pre-existing relationships increase the likelihood of being appointed to a committee.

Two committees are of particular interest: The Audit committee, which oversights the financial auditing process, and the compensation committee, which determines the structure and amount of compensation for executives and board members (and often manages the recruitment process). These committees arguably carry out the most important missions of the board, as they supervise the incentive-setting process, and control the truthfulness of the financial reporting process.

If directors who have pre-existing relationships with members of the board are recruited to reinforce CEO power or to stack the board with friends, one would expect connected directors to be more likely to be appointed as committee members. By contrast, if networked directors are recruited because they are on average of higher quality, directors appointed to committees should have a larger network at the date of their nomination to the board.

I run the estimation over all observed appointments of directors to committees in the Boardex database. I exclude observations where I cannot observe the complete choice set at the time of the appointment (such as when a committee member has been appointed before the firm entered the dataset) or when the CEO is the appointee (as I consider such committee appointment to have a different nature). Accordingly, the choice set is composed of all directors sitting on the board, excluding the CEO. The outside option is to appoint a director who was an insider at the time of recruitment.

6.2. *Results*

Strikingly, results are extremely similar for compensation committee and audit committee appointments, despite a minority of directors cumulating appointments in both committees. In either case, the influence of pre-existing relationships on the likelihood of appointments to the committee is negligible. Contrastingly, the most important factors in getting appointed to a committee are being a supervisory director and having a large network.

[TABLE 10 about here.]

[TABLE 11 about here.]

Further, the appointee's network seems to have decreasing returns to scale: the larger the network of the board, the less decisive the size of appointee's network is in her probability of committee appointment. On the other hand, a large board network makes it more likely overall to appoint an outsider to a committee rather than an insider. This suggests that boards with larger networks can rely on their own network to gauge the quality of an appointee. Finally, the larger the company, the less valuable are pre-existing connections to the board, but the more valuable the size of the overall network.

Again, the evidence does not point towards the coordination hypothesis nor the nepotism hypothesis: pre-existing relationships barely matter and networks seem to be used as screening devices.

7. CONCLUDING REMARKS

7.1. *Summary: What matters for director appointments?*

I believe the evidence is overall favourable to the screening hypothesis, and not so much to the cronyism hypothesis nor to the coordination hypothesis. Pre-existing relationships with board members do not make appointment likelier once accounting for endogenous choice set consideration, but past experience and a larger network do.

As in the previous literature, there is some evidence suggesting that some firms are hiring connected directors because of nepotism or coordination concerns. Nonetheless, the magnitude of these estimates is small, and this seems to be of second order importance. Namely, firms hiring connected directors seem to have a slightly lower adjusted ROA, a slightly higher leverage, a higher Tobin's Q and are larger on average. They also tend to have a recently appointed CEO[23].

Overall, having a pre-existing relationship to a member of the board seems to be unfavourable to the potential appointee. This can be explained by the fact that shareholders may have a strong negative reaction towards obvious cronyism (Cai et al., 2021), but also by the fact that board members barely benefit from appointing their friends to the board: helping a relationship to become a director to another board expands the joint network of the appointed director and the refereeing director, while appointing them to the referee's own board does not expand their joint network (Fahlenbrach et al., 2018). On the other hand, the size of a director's network and a relevant past job experience have a large positive impact on her probability of appointment. This is coherent with a market where screening and referrals play an important role.

7.2. *Summary: Why consideration sets?*

While discrete choice models are relatively robust to misspecification, the mathematical structure of such models may lead to large biases in the estimates when the actual choice

[23] In estimations not reported in this paper, I find that these results are quantitatively similar when considering only connections to the CEO or only connections to non-CEO members of the board

sets are not observable. In the director/CEO appointments literature, it is extremely difficult to recover the set of candidates for a board of directors job, and the choice set has to be created on an ad hoc basis. Unfortunately, this will bias the estimates depending on the way the choice set has been built. Let us consider the simple case, where there are two dummy characteristics A and B. If one consistently introduces more candidates with characteristic A than there were in the choice sets faced by the board, and undershoots the number of candidates with characteristic B, then the estimate for A will be biased down and the estimate for characteristic B will be biased up, irrelevant of the true value for these characteristics. Indeed, the estimates rationalise the choice conditional on a choice set.

I posit that this is exactly what happens in my baseline model, where I underestimate the value of networks and the value of experience as I force too many candidates with rare profiles (including network/past experience) in the choice set. I argue that this is also what happens when choice sets are built from appointees in comparable firms in the literature. For example, if people with large networks are more likely to be appointed in general, they will be more likely to be appointed in comparable firms, and therefore overrepresented in the choice set. This with lead to an underestimation of the importance of networks.

I contend that consideration set models are a satisfying solution to this problem. The estimation is ran over all possible choice sets, and the model jointly rationalises the considered choice set and the choice probability. If the consideration part of the model is reasonably specified, such models should provide better estimates of parameters while having the advantage of being point-identified. The main cost for the researcher is computational[24], but computers able to run such estimations in a reasonable time have become accessible to most professionals. In the results I presented above, we have seen that the introduction of a consideration set model corrected the biases in the estimates in a predictable way: estimates for the value of rare characteristics are higher.

Consideration set models are suitable in numerous other settings in the Finance literature. When studying household investor behaviour, investor preferences, executive appointment & turnover, credit markets or financial contagion, discrete choice models are already a common ocurrence. Whether it is to simulate inattention, nonrandom choice sets, or brokered markets, consideration set models can help lower the bias of estimates at a reasonable computational cost[25].

[24]Because of simulation, and because an analytical gradient cannot be provided for consideration parameters.

[25]See Crawford et al. (2021) for a survey of such models, based on the notion of sufficient sets.

REFERENCES

ABALUCK, J. AND A. ADAMS-PRASSL (2021): "What do consumers consider before they choose? Identification from asymmetric demand responses," *The Quarterly Journal of Economics*, 136, 1611–1663.

ATHEY, S. AND G. W. IMBENS (2007): "Discrete choice models with multiple unobserved choice characteristics," *International Economic Review*, 48, 1159–1192.

BERGER, A. N., T. KICK, M. KOETTER, AND K. SCHAECK (2013): "Does it pay to have friends? Social ties and executive appointments in banking," *Journal of Banking & Finance*, 37, 2087–2105.

BERRY, S., J. LEVINSOHN, AND A. PAKES (1995): "Automobile prices in market equilibrium," *Econometrica: Journal of the Econometric Society*, 841–890.

——— (2004): "Differentiated products demand systems from a combination of micro and macro data: The new car market," *Journal of political Economy*, 112, 68–105.

BESANKO, D., S. GUPTA, AND D. JAIN (1998): "Logit demand estimation under competitive pricing behavior: An equilibrium framework," *Management Science*, 44, 1533–1547.

BIERLAIRE, M., T. LOTAN, AND P. TOINT (1997): "On the overspecification of multinomial and nested logit models due to alternative specific constants," *Transportation Science*, 31, 363–371.

BROWNSTONE, D. AND P. LI (2018): "A model for broad choice data," *Journal of choice modelling*, 27, 19–36.

CAI, J., T. NGUYEN, AND R. WALKLING (2021): "Director Appointments: It Is Who You Know," *The Review of Financial Studies*.

COBB, B. R., R. RUMI, AND A. SALMERÓN (2012): "Approximating the distribution of a sum of log-normal random variables," *Statistics and Computing*, 16, 293–308.

CRAWFORD, G. S., R. GRIFFITH, AND A. IARIA (2021): "A survey of preference estimation with unobserved choice set heterogeneity," *Journal of Econometrics*, 222, 4–43.

DONALDSON, J. R., N. MALENKO, AND G. PIACENTINO (2020): "Deadlock on the Board," *The Review of Financial Studies*, 33, 4445–4488.

DRAGANSKA, M. AND D. JAIN (2004): "A likelihood approach to estimating market equilibrium models," *Management Science*, 50, 605–616.

DUFRESNE, D. (2008): "Sums of lognormals," in *Actuarial Research Conference*, 1–6.

FAHLENBRACH, R., H. KIM, A. LOW, ET AL. (2018): "The importance of network recommendations in the director labor market," *Swiss Finance Institute Research Paper*.

GEWEKE, J. (1988): "Antithetic acceleration of Monte Carlo integration in Bayesian inference," *Journal of Econometrics*, 38, 73–89.

GOEREE, M. S. (2008): "Limited information and advertising in the US personal computer industry," *Econometrica*, 76, 1017–1074.

HABIBI, S., E. FREJINGER, AND M. SUNDBERG (2019): "An empirical study on aggregation of alternatives and its influence on prediction in car type choice models," *Transportation*, 46, 563–582.

HAUSMAN, J. A. AND D. A. WISE (1978): "A conditional probit model for qualitative choice: Discrete decisions recognizing interdependence and heterogeneous preferences," *Econometrica: Journal of the econometric society*, 403–426.

HERMALIN, B. E. AND M. S. WEISBACH (1988): "The determinants of board composition," *The RAND Journal of Economics*, 589–606.

——— (1998): "Endogenously chosen boards of directors and their monitoring of the CEO," *American Economic Review*, 96–118.

KEANE, M. P. AND W. NADA (2012): *Estimation of discrete choice models with many alternatives using random subsets of the full choice set: With an application to demand for frozen pizza*, Nuffield College.

KRAMARZ, F. AND D. THESMAR (2013): "Social networks in the boardroom," *Journal of the European Economic Association*, 11, 780–807.

LIU, Y. (2008): "Employment networks and the CEO labor market," *Available at SSRN 1361776*.

——— (2010): "The role of networks in the CEO and director labor market," Ph.D. thesis.

MABIT, S. L. (2011): "Vehicle type choice and differentiated registration taxes," in *ETC 2011*.

MCFADDEN, D. (2001): "Economic choices," *American economic review*, 91, 351–378.

MURDOCK, J. (2006): "Handling unobserved site characteristics in random utility models of recreation demand," *Journal of environmental economics and management*, 51, 1–25.

ROSENSTEIN, S. AND J. G. WYATT (1990): "Outside directors, board independence, and shareholder wealth," *Journal of financial economics*, 26, 175–191.

WANG, J. X. (2020): "Board Connections and CEO succession," *Available at SSRN 3551748*.

WEISBACH, M. S. (1988): "Outside directors and CEO turnover," *Journal of financial Economics*, 20, 431–460.

WONG, T., D. BROWNSTONE, AND D. S. BUNCH (2019): "Aggregation biases in discrete choice models," *Journal of choice modelling*, 31, 210–221.

WU, J., N. B. MEHTA, AND J. ZHANG (2005): "Flexible lognormal sum approximation method," in *GLOBECOM'05. IEEE Global Telecommunications Conference, 2005.*, IEEE, vol. 6, 3413–3417.

APPENDIX A: THE GENERAL MODEL IS UNIDENTIFIED

Let us denote firms by i, individual directors by k, and the set of individuals sharing observables x_j as B_j.

Let us consider a pairing between a firm i and a director k with observables $x_k = x_j$. Assume that this match generates the following utility, that is fully captured by the firm.

$$u_{ijk} = V_{ij} + \omega_{ik} + \epsilon_{ijk}$$

With V_{ij} the match utility from observables x_j, ω_{ik} the match utility from unobservables of individual k, and ϵ_{ijk} the idiosyncratic component of utility. Under standard assumptions on the distribution of ϵ (Gumbel extreme value) and normalizing the outside option, we get the following choice probabilities

$$\begin{aligned}\mathbb{P}_{ij} &= \frac{\sum\limits_{k \in B_j} e^{V_{ij}+\omega_{ik}}}{1 + \sum\limits_{l} \sum\limits_{k \in B_l} e^{V_{il}+\omega_{ik}}} \\ &= \frac{e^{V_{ij}+\Omega_{ij}}}{1 + \sum\limits_{l} e^{V_{il}+\Omega_{il}}}\end{aligned}$$

Where $\Omega_{ij} = \ln \sum_{k \in B_j} e^{\omega_{ik}}$. It is quite clear that Ω_{ij} cannot be identified without further assumptions. However, making assumptions on Ω_{ij} amounts to making assumptions on the distribution of ω_{ik} and on the distribution of $Card(B_j)$. The problem is well known in the consumer choice literature (Hausman and Wise, 1978) and it has been shown that while aggregation by averaging over observables may bias down the estimates and increase standard errors (Mabit (2011), Habibi et al. (2019)), aggregation ignoring hidden heterogeneity is even more problematic (Brownstone and Li (2018), Wong et al. (2019)).

APPENDIX B: ESTIMATION PROCEDURE

Remember that we wish to approximate the likelihood

$$\prod_i \sum_j \mathbf{1}(y_i = j) \cdot p_{ij}(\theta) = \prod_i \sum_j \mathbf{1}(y_i = j) \cdot \sum_{\mathcal{C}} \prod_{l \in \mathcal{C}} \phi_{il} \prod_{k \notin \mathcal{C}} (1 - \phi_{ik}) \mathbb{P}_{ij}(x_j, z_i | \mathcal{C}, \theta)$$

Where $\mathbf{1}(y_i = j)$ is the indicator function taking a value of 1 whenever firm i chose profile j, and θ is the vector of parameters.. This is computationally unfeasible, as it would require us to sum over all possible choice sets $\mathcal{C}$, or at least over the subset of choice sets $\mathcal{C}_j$ including option j. As there are more than 800 different profiles, this represents over an overwhelming number of possible combinations.

The obvious solution is to use numerical simulation. We have

$$p_{ij} = \sum_{\mathcal{C}} \prod_{l \in \mathcal{C}} \phi_{il} \prod_{k \notin \mathcal{C}} (1 - \phi_{ik}) \mathbb{P}_{ij}(x_j, z_i | \mathcal{C}, \theta) \simeq \frac{\sum_{r=1}^{R} \mathbb{P}_{ij}(x_j, z_i | \mathcal{C}_r, \theta)}{R}$$

with $C_r \sim \prod_{l \in \mathcal{C}} \phi_{il} \prod_{k \notin \mathcal{C}} (1 - \phi_{ik})$

For R large enough, we have a good approximation of p_{ij}. Fortunately, when using antithetic covariates, we can achieve a good approximation for a relatively small number of simulations R. Unfortunately, when R is relatively small, this approximation is not smooth: a change in parameters θ may lead to a change in consideration probabilities $\prod_{l \in \mathcal{C}} \phi_{il} \prod_{k \notin \mathcal{C}} (1 - \phi_{ik})$ that leads to a vastly different choice set. Then, the choice probabilities can jump, as the choice set is different: an infinitely small change in parameters θ may lead to an abrupt change in value.

I follow the solution proposed in Goeree (2008), and I implement an importance sampling to resolve this issue. For ease of notation, let us denote

$$\Phi(\mathcal{C}|\theta) = \prod_{l \in \mathcal{C}} \phi_{il}(\theta) \prod_{k \notin \mathcal{C}} (1 - \phi_{ik}(\theta))$$

We have

$$p_{ij}(\theta) = \sum_{\mathcal{C}} \Phi(\mathcal{C}|\theta) \cdot \mathbb{P}_{ij}(x_j, z_i | \mathcal{C}, \theta)$$

We can rewrite the equation using Φ evaluated at the initial guess of parameters, θ^0

$$p_{ij}(\theta) = \sum_{\mathcal{C}} \frac{\Phi(\mathcal{C}|\theta)}{\Phi(\mathcal{C}|\theta^0)} \cdot \Phi(\mathcal{C}|\theta^0) \cdot \mathbb{P}_{ij}(x_j, z_i | \mathcal{C}, \theta)$$

Therefore,

$$p_{ij} \simeq \frac{1}{R} \sum_r \frac{\Phi(\mathcal{C}_r|\theta)}{\Phi(\mathcal{C}_r^0|\theta^0)} \cdot \mathbb{P}_{ij}(x_j, z_i | \mathcal{C}_r^0, \theta)$$

with $C_r^0 \sim \Phi(\mathcal{C}|\theta^0); C_r \sim \Phi(\mathcal{C}|\theta)$ drawn from the same underlying uniform distribution[26].

[26] That is, $C_r^0 \sim \Phi(\mathcal{C}|\theta^0); C_r \sim \Phi(\mathcal{C}|\theta)$ are drawn as transformations of the same draw from the uniform distribution, drawn once and for all at the beginning of the procedure.

As the choice probabilities are evaluated over the initial choice sets, there is no jump in probabilities when the realised choice set changes, as this only affects the ratio $\Phi(\mathcal{C}_r|\theta)/\Phi(\mathcal{C}_r^0|\theta^0)$, which is much smoother. This allows the standard optimisation procedures to work their magic and converge to consistent estimates.

The estimation proceeds as follows:

1. To set up the initial choice set
   (a) Draw R uniform random variables u_{ijr} over $\mathcal{U}_{0,1}$ for each firm-profile pair (i,j). These draws will remain fixed for the duration of the estimation to ensure consistent convergence.
   (b) Draw their antithetic covariates $u_{ij-r} = 1 - u_{ijr}$, to obtain $2R$ draws for each firm-profile pair.
   (c) Set an initial value θ^0 for parameters.
   (d) Calculate $\phi_{ij}(\theta^0)$ for each firm-profile pair.
   We will store the $\phi_{ij}(\theta^0)$ and u_{ij} in memory for the rest of the estimation.
   (e) For each firm, define the $2R$ choice sets $\mathcal{C}_{ir}^0$ such that

$$j \in \mathcal{C}_{ir}^0 \Leftrightarrow \phi_{ij}(\theta^0) > u_{ijr}$$

2. At each iteration:
   (a) Calculate $\phi_{ij}(\theta)$ for each firm-profile pair.
   (b) For each firm, define the $2R$ choice sets $\mathcal{C}_{ir}$ such that

$$j \in \mathcal{C}_{ir} \Leftrightarrow \phi_{ij}(\theta) > u_{ijr}$$

   (c) Compute

$$\mathbb{P}_{ij}(x_j, z_i|\mathcal{C}_r^0, \theta)$$

   (d) Calculate

$$\begin{aligned} p_{ij}(\theta) &\simeq \frac{1}{2R}\sum_{r=-R}^{R} \frac{\Phi(\mathcal{C}_r|\theta)}{\Phi(\mathcal{C}_r^0|\theta^0)} \cdot \mathbb{P}_{ij}(x_j, z_i|\mathcal{C}_r^0, \theta) \\ &\simeq \frac{1}{2R}\sum_{r=-R}^{R} \frac{\prod_{l\in\mathcal{C}_{ir}} \phi_{il}(\theta) \prod_{k\notin\mathcal{C}_{ir}} (1-\phi_{ik}(\theta))}{\prod_{l\in\mathcal{C}_{ir}^0} \phi_{il}(\theta^0) \prod_{k\notin\mathcal{C}_{ir}^0} (1-\phi_{ik}(\theta^0))} \cdot \mathbb{P}_{ij}(x_j, z_i|\mathcal{C}_r^0, \theta) \end{aligned}$$

   Note that the choice set will change over time, but this will only be taken into account in $\Phi(\mathcal{C}_r|\theta)$. $\mathbb{P}$ will be evaluated over the initial choice set using the updated parameter values θ, and $\Phi(C_r^0|\theta^0)$ will remain constant over the course of the estimation.
   (e) The log-likelihood is calculated as usual

$$LogLik = \sum_i \ln\left(\sum_j \mathbf{1}(y_i = j) \cdot p_{ij}(\theta)\right)$$

3. Iterate until convergence.

APPENDIX C: TABLES

[TABLE 12 about here.]
[TABLE 13 about here.]
[TABLE 14 about here.]
[TABLE 15 about here.]

	72.5%	75%	77.5%	80%	82.5%	85%	87.5%	90%	92.5%	95%	97.5%
All appointees	0.00	0.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00	2.00	4.00
Less than median board size	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	2.00
Median board size and higher	0.00	0.00	0.00	1.00	1.00	1.00	1.00	1.00	2.00	3.00	5.00
8th decile board size and higher	0.00	0.00	1.00	1.00	1.00	1.00	1.00	2.00	2.00	4.00	7.00
Less than median board network	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.00	1.00	3.00
Median board network and higher	0.00	0.00	1.00	1.00	1.00	1.00	1.00	1.00	2.00	3.00	5.00
8th decile board network and higher	0.00	1.00	1.00	1.00	1.00	1.00	1.00	2.00	2.00	3.00	4.00

TABLE C.I

THIS TABLE DISPLAYS THE QUANTILES OF THE NUMBER OF CONNECTIONS TO THE BOARD PER APPOINTEE. THE FIRST ROW DESCRIBES THE QUANTILES FOR ALL APPOINTEES, THE THREE NEXT ROWS PRESENT THE QUANTILES FOR DIRECTORS APPOINTED TO BOARDS OF VARYING SIZE QUANTILES, AND THE LAST THREE ROWS PRESENT QUANTILES FOR DIRECTORS APPOINTED TO BOARDS WITH VARYING NETWORK SIZE.

TABLE C.II

VARIABLES DESCRIPTION

Director characteristic	Aggregated Values
Age	- 40, 40-50, 50-60, 60-70, 70 +
Network size (log 10)	0, 1, 2, 3, 4
Contacts in the board	0, 1, 2, 4
Bachelor	0,1
Graduate diploma (MD, PhD, Masters)	0,1
Juris Doctorate	0,1
MBA	0,1
Industry experience (SIC code at the 3 digit level)	0,1

Firm Characteristic	Description
Board Size	Size of the board
Size	Logarithm of the Asset holdings
ROA	Deviation from the firm's industry ROA
Leverage	Leverage ratio
Tobin's Q	Tobin's Q ratio
Supervisory director	Non-executive appointment
Industries	Number of 3 digit SIC the company is spanning
NEWCEO	New CEO appointed in the last 3 years
Board Network	log of the board's network

TABLE C.III

BASELINE MODEL: IMPACT OF PRE-EXISTING RELATIONSHIPS.

THIS TABLE DISPLAYS THE RESULT OF THE BASELINE MODEL ESTIMATION. THE DEPENDENT VARIABLE IS THE LIKELIHOOD FOR A FIRM TO APPOINT A DIRECTOR WITH THE OBSERVED APPOINTEE'S PROFILE. THE FIRST COLUMN DISPLAYS THE RAW ESTIMATE FOR THE IMPACT OF ONE ADDITIONAL PRE-EXISTING RELATIONSHIP INTERACTED WITH THE DISPLAYED FIRM CHARACTERISTIC ON u_{ij}, THE SECOND COLUMN DISPLAYS THE IMPACT OF A STANDARD DEVIATION IN FIRM CHARACTERISTIC ON u_{ij} (ESTIMATE $\times$ STANDARD DEVIATION OF THE CHARACTERISTIC), THE THIRD COLUMN DISPLAYS THE T-STATISTIC AND THE FOURTH COLUMN DISPLAYS THE SIGNIFICANCE LEVEL (*=10%, **=5%, ***=1%).

THE ANTEPENULTIMATE OF THE TABLE DISPLAYS THE MEAN AVERAGE EFFECT OF ONE ADDITIONAL RELATIONSHIP CONSIDERING THE AVERAGE VALUE FOR FIRM CHARACTERISTICS. IN THIS SPECIFICATION, THE IMPACT OF AN ADDITIONAL PRE-EXISTING RELATIONSHIP IS NEGATIVE.

Firm Variable	Estimate	Std Effect	t-stat	
boardsize	0.05	0.15	25.82	***
ROA	-0.13	-0.03	-4.93	***
Size	0.07	0.15	20.19	***
leverage	0.01	0.01	2.77	***
Q	0.08	0.08	12.38	***
Industries	-0.08	-0.06	-11.82	***
NEWCEO	0.18	0.09	17.23	***
Board Network	0.07	0.10	13.37	***
Supervisory Director	-0.10	-0.04	-6.78	***
Intercept	-2.67		-66.83	***
Mean effect of a relationship	-1.272695			
Number of observations	69843			
Log-Likelihood	-130696.2	Pseudo R^2	0.39229	

TABLE C.IV

BASELINE MODEL: IMPACT OF APPOINTEE'S NETWORK.

THIS TABLE DISPLAYS THE RESULT OF THE BASELINE MODEL ESTIMATION. THE DEPENDENT VARIABLE IS THE LIKELIHOOD FOR A FIRM TO APPOINT A DIRECTOR WITH THE OBSERVED APPOINTEE'S PROFILE. THE FIRST COLUMN DISPLAYS THE RAW ESTIMATE FOR THE IMPACT OF AN INCREASE IN MAGNITUDE OF THE APPOINTEE'S NETWORK INTERACTED WITH THE DISPLAYED FIRM CHARACTERISTIC ON u_{ij}, THE SECOND COLUMN DISPLAYS THE IMPACT OF A STANDARD DEVIATION IN FIRM CHARACTERISTIC ON u_{ij} (ESTIMATE $\times$ STANDARD DEVIATION OF THE CHARACTERISTIC), THE THIRD COLUMN DISPLAYS THE T-STATISTIC AND THE FOURTH COLUMN DISPLAYS THE SIGNIFICANCE LEVEL (*=10%, **=5%, ***=1%).
THE ANTEPENULTIMATE ROW OF THE TABLE DISPLAYS THE MEAN AVERAGE EFFECT OF AN INCREASE IN MAGNITUDE OF THE APPOINTEE'S NETWORK CONSIDERING THE AVERAGE VALUE FOR FIRM CHARACTERISTICS. IN THIS SPECIFICATION, THE IMPACT OF AN INCREASE IN MAGNITUDE IN THE SIZE OF THE NETWORK IS POSITIVE.

Firm Variable	Estimate	Std Effect	t-stat	
boardsize	-0.02	-0.08	-8.74	***
ROA	-0.04	-0.01	-1.24	
Size	0.06	0.14	14.25	***
leverage	-0.02	-0.05	-6.07	***
Q	-0.02	-0.02	-2.17	**
Industries	0.01	0.01	1.38	
NEWCEO	0.06	0.03	3.85	***
Board Network	0.19	0.28	30.37	***
Supervisory Director	0.13	0.05	5.58	***
Intercept	-1.81		-34.41	***
Mean effect of log_{10} network	0.2524255			
Number of observations	69843			
Log-Likelihood	-130696.2	Pseudo R^2	0.3922	

TABLE C.V

UNOBSERVED CHARACTERISTICS MODEL: IMPACT OF PRE-EXISTING RELATIONSHIPS.
THIS TABLE DISPLAYS THE RESULT OF THE ESTIMATION OF THE SPECIFICATION WITH MEAN UTILITIES ACCOUNTING FOR UNOBSERVED CHARACTERISTICS SUCH AS THE RARITY OF A PROFILE. THE DEPENDENT VARIABLE IS THE LIKELIHOOD FOR A FIRM TO APPOINT A DIRECTOR WITH THE OBSERVED APPOINTEE'S PROFILE. THE FIRST COLUMN DISPLAYS THE RAW ESTIMATE FOR THE IMPACT OF ONE ADDITIONAL PRE-EXISTING RELATIONSHIP INTERACTED WITH THE DISPLAYED FIRM CHARACTERISTIC ON u_{ij}, THE SECOND COLUMN DISPLAYS THE IMPACT OF A STANDARD DEVIATION IN FIRM CHARACTERISTIC ON u_{ij} (ESTIMATE $\times$ STANDARD DEVIATION OF THE CHARACTERISTIC), THE THIRD COLUMN DISPLAYS THE T-STATISTIC AND THE FOURTH COLUMN DISPLAYS THE SIGNIFICANCE LEVEL (*=10%, **=5%, ***=1%).

Firm Variable	Estimate	Std Effect	t-stat	
boardsize	0.03	0.10	8.02	***
ROA	-0.08	-0.02	-1.67	*
Size	0.02	0.04	2.45	**
leverage	0.01	0.02	1.40	
Q	-0.01	-0.01	-1.26	
Industries	-0.02	-0.02	-1.50	
NEWCEO	0.06	0.03	2.93	***
Board Network	-0.09	-0.13	-14.77	***
Supervisory Director	-0.09	-0.03	-3.65	***
Number of observations	69843			
Log-Likelihood	-17748.91	Pseudo R^2	0.91747	

TABLE C.VI

UNOBSERVED CHARACTERISTICS MODEL: IMPACT OF APPOINTEE'S NETWORK.
THIS TABLE DISPLAYS THE RESULT OF THE ESTIMATION OF THE SPECIFICATION WITH MEAN UTILITIES ACCOUNTING FOR UNOBSERVED CHARACTERISTICS SUCH AS THE RARITY OF A PROFILE. THE DEPENDENT VARIABLE IS THE LIKELIHOOD FOR A FIRM TO APPOINT A DIRECTOR WITH THE OBSERVED APPOINTEE'S PROFILE. THE FIRST COLUMN DISPLAYS THE RAW ESTIMATE FOR THE IMPACT OF AN INCREASE IN MAGNITUDE OF THE APPOINTEE'S NETWORK INTERACTED WITH THE DISPLAYED FIRM CHARACTERISTIC ON u_{ij}, THE SECOND COLUMN DISPLAYS THE IMPACT OF A STANDARD DEVIATION IN FIRM CHARACTERISTIC ON u_{ij} (ESTIMATE $\times$ STANDARD DEVIATION OF THE CHARACTERISTIC), THE THIRD COLUMN DISPLAYS THE T-STATISTIC AND THE FOURTH COLUMN DISPLAYS THE SIGNIFICANCE LEVEL (*=10%, **=5%, ***=1%).

Firm Variable	Estimate	Std Effect	t-stat	
boardsize	0.00	0.00	0.13	
ROA	-0.15	-0.04	-1.25	
Size	0.05	0.12	3.03	***
leverage	-0.02	-0.06	-1.90	*
Q	-0.11	-0.11	-4.33	***
IndustriesSpanning	0.03	0.03	0.98	
NEWCEO	0.05	0.03	0.94	
logBoardNetwork	-0.01	-0.01	-0.48	
SupervisoryDirector	-0.01	-0.00	-0.22	
Number of observations	69843			
Log-Likelihood	-17748.91	Pseudo R^2	0.91747	

TABLE C.VII

CONSIDERATION SET MODEL: IMPACT OF PRE-EXISTING RELATIONSHIPS.

THIS TABLE DISPLAYS THE RESULT OF THE ESTIMATION OF THE CHOICE SET CONSIDERATION SPECIFICATION. THE DEPENDENT VARIABLE IS THE LIKELIHOOD FOR A FIRM TO APPOINT A DIRECTOR WITH THE OBSERVED APPOINTEE'S PROFILE. THE FIRST COLUMN DISPLAYS THE RAW ESTIMATE FOR THE IMPACT OF ONE ADDITIONAL PRE-EXISTING RELATIONSHIP INTERACTED WITH THE DISPLAYED FIRM CHARACTERISTIC ON u_{ij}, THE SECOND COLUMN DISPLAYS THE IMPACT OF A STANDARD DEVIATION IN FIRM CHARACTERISTIC ON u_{ij} (ESTIMATE $\times$ STANDARD DEVIATION OF THE CHARACTERISTIC), THE THIRD COLUMN DISPLAYS THE T-STATISTIC AND THE FOURTH COLUMN DISPLAYS THE SIGNIFICANCE LEVEL (*=10%, **=5%, ***=1%).
THE ANTEPENULTIMATE OF THE TABLE DISPLAYS THE MEAN AVERAGE EFFECT OF ONE ADDITIONAL RELATIONSHIP CONSIDERING THE AVERAGE VALUE FOR FIRM CHARACTERISTICS. IN THIS SPECIFICATION, THE IMPACT OF AN ADDITIONAL PRE-EXISTING RELATIONSHIP IS NEGATIVE.

Firm Variable	Estimate	Std Effect	t-stat	
boardsize	0.05	0.15	21.45	***
ROA	-0.07	-0.017	-1.87	*
Size	-0.01	-0.011	-1.29	
leverage	0.02	0.04	6.73	***
Q	0.07	0.01	5.84	***
Industries	-0.14	-0.11	-18.37	***
NEWCEO	0.08	0.037	5.64	***
Supervisory Director	-0.16	-0.055	-8.61	***
Intercept	-1.76		-53.84	***
Mean effect of a relationship	-1.533248			
Number of observations	69843			
Log-Likelihood	-68523.18			

TABLE C.VIII

CONSIDERATION SET MODEL: IMPACT OF APPOINTEE'S NETWORK.

THIS TABLE DISPLAYS THE RESULT OF THE ESTIMATION OF THE CHOICE SET CONSIDERATION SPECIFICATION. THE DEPENDENT VARIABLE IS THE LIKELIHOOD FOR A FIRM TO APPOINT A DIRECTOR WITH THE OBSERVED APPOINTEE'S PROFILE. THE FIRST COLUMN DISPLAYS THE RAW ESTIMATE FOR THE IMPACT OF AN INCREASE IN MAGNITUDE OF THE APPOINTEE'S NETWORK INTERACTED WITH THE DISPLAYED FIRM CHARACTERISTIC ON u_{ij}, THE SECOND COLUMN DISPLAYS THE IMPACT OF A STANDARD DEVIATION IN FIRM CHARACTERISTIC ON u_{ij} (ESTIMATE $\times$ STANDARD DEVIATION OF THE CHARACTERISTIC), THE THIRD COLUMN DISPLAYS THE T-STATISTIC AND THE FOURTH COLUMN DISPLAYS THE SIGNIFICANCE LEVEL (*=10%, **=5%, ***=1%). THE ANTEPENULTIMATE OF THE TABLE DISPLAYS THE MEAN AVERAGE EFFECT OF ONE ADDITIONAL RELATIONSHIP CONSIDERING THE AVERAGE VALUE FOR FIRM CHARACTERISTICS. IN THIS SPECIFICATION, THE IMPACT OF AN ADDITIONAL PRE-EXISTING RELATIONSHIP IS NEGATIVE.

Firm Variable	Estimate	Std Effect	t-stat	
boardsize	-0.09	-0.29	-18.68	***
ROA	0.15	0.0366	2.14	**
Size	-0.01	-0.032	-1.74	*
leverage	-0.01	-0.015	-1.19	
Q	-0.05	-0.049	-2.53	**
Industries	0.05	0.042	3.26	***
NEWCEO	0.02	0.00	0.54	
Supervisory Director	0.92	0.33	24.16	***
Intercept	2.84		43.49	***
Mean effect of log_{10} network	2.82782			
Number of observations	69843			
Log-Likelihood	-68523.18			

TABLE C.IX

CONSIDERATION SET MODEL: IMPACT OF PAST INDUSTRY EXPERIENCE.

THIS TABLE DISPLAYS THE RESULT OF THE ESTIMATION OF THE CHOICE SET CONSIDERATION SPECIFICATION. THE DEPENDENT VARIABLE IS THE LIKELIHOOD FOR A FIRM TO APPOINT A DIRECTOR WITH THE OBSERVED APPOINTEE'S PROFILE. THE FIRST COLUMN DISPLAYS THE RAW ESTIMATEFOR THE IMPACT OF PAST INDUSTRY EXPERIENCE AT THE 3-DIGIT SIC LEVEL INTERACTED WITH THE DISPLAYED FIRM CHARACTERISTIC ON u_{ij}, THE SECOND COLUMN DISPLAYS THE IMPACT OF A STANDARD DEVIATION IN FIRM CHARACTERISTIC ON u_{ij} (ESTIMATE $\times$ STANDARD DEVIATION OF THE CHARACTERISTIC), THE THIRD COLUMN DISPLAYS THE T-STATISTIC AND THE FOURTH COLUMN DISPLAYS THE SIGNIFICANCE LEVEL (*=10%, **=5%, ***=1%).
THE ANTEPENULTIMATE OF THE TABLE DISPLAYS THE MEAN AVERAGE EFFECT OF ONE ADDITIONAL RELATIONSHIP CONSIDERING THE AVERAGE VALUE FOR FIRM CHARACTERISTICS. IN THIS SPECIFICATION, THE IMPACT OF AN ADDITIONAL PRE-EXISTING RELATIONSHIP IS NEGATIVE.

Firm Variable	Estimate	Std Effect	tstat	
boardsize	-0.07	-0.23	-5.93	***
ROA	-0.16	-0.039	-0.74	
Size	-0.07	-0.17	-3.33	***
leverage	-0.03	-0.085	-2.32	**
Q	0.17	0.162	1.73	*
Industries	-0.08	-0.061	-2.26	**
NEWCEO	0.56	0.27	7.14	***
Supervisory Director	0.83	0.30	7.28	***
Intercept	5.71		25.52	***
Mean effect of industry experience	5.682979			
Number of observations	69843			
Log-Likelihood	-68523.18			

TABLE C.X

AUDIT COMMITTEE APPOINTMENTS

THIS TABLE DISPLAYS THE RESULT OF THE ESTIMATION OF THE CHOICE SET CONSIDERATION SPECIFICATION. THE DEPENDENT VARIABLE IS THE LIKELIHOOD FOR A BOARD TO APPOINT A GIVEN DIRECTOR TO THE AUDIT COMMITTEE. THE CHOICE SET IS COMPOSED OF ALL MEMBERS OF THE BOARD APART FROM THE CEO. THE FIRST COLUMN DISPLAYS THE ESTIMATES, THE SECOND COLUMN DISPLAYS THE T-STATISTIC AND THE FOURTH COLUMN DISPLAYS THE SIGNIFICANCE LEVEL (*=10%, **=5%, ***=1%) THE GENDER VARIABLE TAKES A VALUE OF 1 FOR MEN AND 0 FOR WOMEN.

	Estimates	t-stat	p.value
Board size-Intercept	-4.84e-01	-30.38	***
Size-Intercept	8.28e-02	2.91	***
ROA-Intercept	3.04e-01	1.61	
Board Network-Intercept	9.84e-01	20.55	***
Leverage-Intercept	9.64e-02	4.74	***
Intercept-Intercept	-9.24	-23.84	***
Board Size-Contacts.at.nomination	3.33e-02	16.16	***
Size-Contacts.at.nomination	-2.93e-02	-5.73	***
ROA-Contacts.at.nomination	5.83e-02	1.46	
Board Network-Contacts.at.nomination	6.23e-03	0.65	
Leverage-Contacts.at.nomination	1.99e-03	0.59	
Intercept-Contacts.at.nomination	-1.11e-01	-1.35	
Board Size-NetworkSize	7.31e-02	19.49	***
Size-NetworkSize	4.25e-02	5.34	***
ROA-NetworkSize	-1.47e-01	-2.58	***
Board Network-NetworkSize	-4.82e-01	-30.95	***
Leverage-NetworkSize	-2.17e-02	-4.03	***
Intercept-NetworkSize	3.79	29.51	***
Gender	-3.41e-01	-17.60	***
Age	-6.70e-03	-8.79	***
Supervisory	5.05	58.75	***
Bachelor	2.64e-01	13.17	***
MBA	2.11e-01	14.08	***
GraduateDegree	-3.84e-01	-24.91	***
Experience	-2.81e-01	-13.66	***
Nobservations	34941	Log-Likelihood	-50492

TABLE C.XI

COMPENSATION COMMITTEE APPOINTMENTS

THIS TABLE DISPLAYS THE RESULT OF THE ESTIMATION OF THE CHOICE SET CONSIDERATION SPECIFICATION. THE DEPENDENT VARIABLE IS THE LIKELIHOOD FOR A BOARD TO APPOINT A GIVEN DIRECTOR TO THE AUDIT COMMITTEE. THE CHOICE SET IS COMPOSED OF ALL MEMBERS OF THE BOARD APART FROM THE CEO. THE FIRST COLUMN DISPLAYS THE ESTIMATES, THE SECOND COLUMN DISPLAYS THE T-STATISTIC AND THE FOURTH COLUMN DISPLAYS THE SIGNIFICANCE LEVEL (*=10%, **=5%, ***=1%) THE GENDER VARIABLE TAKES A VALUE OF 1 FOR MEN AND 0 FOR WOMEN.

	Estimates	t-stat	p.value
Board size-Intercept	−0.46	-30.71	***
Size-Intercept	−2.16e-2	-0.77	
ROA-Intercept	0.65	3.53	***
Board Network-Intercept	0.81	17.17	***
Leverage-Intercept	3.84e-2	1.98	**
Intercept-Intercept	−7.17	-18.20	***
Board Size - Contacts at nomination	3.03e-2	15.00	***
Size - Contacts at nomination	−1.38e-2	-2.71	***
ROA - Contacts at nomination	−5.52e-3	-0.15	
Board Network - Contacts at nomination	1.81E-2	2.03	**
Leverage - Contacts at nomination	−1.67e-3	-0.55	
Intercept - Contacts at nomination	−0.30	-3.93	***
Mean :	−8.02e-2		
Board Size - Network Size	6.72e-2	17.40	***
Size - Network Size	8.02e-2	9.72	***
ROA - Network Size	−0.25	-4.34	***
Board Network - Network Size	−0.43	-27.29	***
Leverage - Network Size	−8.39e-2	-1.49	
Intercept - Network Size	3.32	25.14	***
Mean:	0.45		
Gender	−0.23	-11.43	***
Age	−7.56e-3	-9.62	***
Supervisory	4.35	67.39	***
Bachelor	2.47e-2	1.22	
MBA	−1.61e-3	-0.10	
GraduateDegree	−7.36e-2	-4.69	***
Experience	−0.21	-9.89	***
Nobservations	33400	Log-Likelihood	-49938

TABLE C.XII

SUMMARY STATISTICS

THIS TABLE PROVIDES DESCRIPTIVE STATISTICS FOR THE FIRM VARIABLES. THESE VARIABLES HAVE BEEN WINSORIZED AT THE 2.5% AND THE 97.5% LEVEL.

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
boardsize	69843	7.501	3.296	0	5	9	33
ROA	69843	0.002	0.247	-1.428	-0.015	0.098	0.463
Size	69843	6.654	2.275	1.6	5.061	8.167	12.495
leverage	69843	0.974	2.56	-7.354	0.044	1.153	17.537
Q	69843	0.933	0.958	0.249	0.579	0.931	7.964
Industries	69843	0.407	0.809	0	0	1	10
Board Network	69843	8.738	1.458	3.219	8.062	9.677	12.634
NEWCEO	69843						
... No	43265	61.9%					
... Yes	26578	38.1%					
SupervisoryDirector	69843						
... No	10550	15.1%					
... Yes	59293	84.9%					

TABLE C.XIII

SUMMARY STATISTICS

THIS TABLE PROVIDES DISTRIBUTION OF THE PROFILE VARIABLES, WHEN AN OUTSIDER DIRECTOR HAS BEEN GIVEN THE DIRECTORSHIP. FOR THE 9950 OBSERVATIONS WHERE AN INSIDER DIRECTOR HAS BEEN RECRUITED RATHER THAN AN OUTSIDER, THESE VALUES (AS WELL AS THE VALUE OF THE INTERCEPT) ARE SET TO 0.

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
ncontacts	64615	0.316	0.828	0	0	0	4
networksize	64615	2.36	0.673	1	2	3	4
ages	64615	55.071	8.657	40	50	60	70
experience	64615						
... No	56362	87.2%					
... Yes	8253	12.8%					
Bachelor	64615						
... No	25519	39.5%					
... Yes	39096	60.5%					
MBA	64615						
... No	43718	67.7%					
... Yes	20897	32.3%					
Graduate	64615						
... No	49274	76.3%					
... Yes	15341	23.7%					
JD	64615						
... No	56946	88.1%					
... Yes	7669	11.9%					

TABLE C.XIV

IMPACT OF INDUSTRY EXPERIENCE.

THIS TABLE DISPLAYS THE RESULT OF THE BASELINE MODEL ESTIMATION. THE DEPENDENT VARIABLE IS THE LIKELIHOOD FOR A FIRM TO APPOINT A DIRECTOR WITH THE OBSERVED APPOINTEE'S PROFILE. THE FIRST COLUMN DISPLAYS THE RAW ESTIMATE FOR THE IMPACT OF PAST INDUSTRY EXPERIENCE AT THE 3-DIGIT SIC LEVEL INTERACTED WITH THE DISPLAYED FIRM CHARACTERISTIC ON u_{ij}, THE SECOND COLUMN DISPLAYS THE IMPACT OF A STANDARD DEVIATION IN FIRM CHARACTERISTIC ON u_{ij} (ESTIMATE $\times$ STANDARD DEVIATION OF THE CHARACTERISTIC), THE THIRD COLUMN DISPLAYS THE T-STATISTIC AND THE FOURTH COLUMN DISPLAYS THE SIGNIFICANCE LEVEL (*=10%, **=5%, ***=1%).

	Estimates	Std Effect	t-stat	
boardsize	-0.04	-0.13	-6.23	***
ROA	0.01	0.00	0.25	
Size	-0.01	-0.02	-0.77	
M2B	0.01	0.07	5.34	***
leverage	-0.04	-0.11	-7.33	***
Q	0.10	0.09	7.05	***
Industries	-0.47	-0.38	-22.65	***
NEWCEO	0.36	0.18	13.78	***
Board Network	0.46	0.68	31.39	***
Supervisory Director	-0.04	-0.01	-0.81	
Intercept	-5.64		-44.52	***
Mean effect of industry experience	-1.914566			
Number of observations	69843			
Log-Likelihood	-130696.2	Pseudo R^2	0.3922	

TABLE C.XV

CONSIDERATION SET ESTIMATION RESULTS.

THIS TABLE DISPLAYS THE RESULT OF THE CONSIDERATION SET ESTIMATION. THE DEPENDENT VARIABLE IS THE LIKELIHOOD FOR A FIRM TO APPOINT A DIRECTOR WITH THE OBSERVED APPOINTEE'S PROFILE. THE FIRST COLUMN DISPLAYS THE RAW ESTIMATES, THE SECOND COLUMN DISPLAYS THE IMPACT OF A STANDARD DEVIATION IN FIRM CHARACTERISTIC ON u_{ij} (ESTIMATE $\times$ STANDARD DEVIATION OF THE CHARACTERISTIC), THE THIRD COLUMN DISPLAYS THE T-STATISTIC AND THE FOURTH COLUMN DISPLAYS THE SIGNIFICANCE LEVEL (*=10%, **=5%, ***=1%).

$z_i \cdot x_j$	Estimate	StdEffect	pvalue
boardsize-ages	-9.20e-05	-3.03e-04	7.67e-01
deviationfrommeanROA-ages	-4.13e-04	-1.02e-04	9.25e-01
logat-ages	4.55e-03	1.04e-02	3.92e-19
leverage-ages	-5.51e-04	-1.41e-03	7.94e-02
Q-ages	1.09e-03	1.04e-03	3.52e-01
IndustriesSpanning-ages	1.27e-03	1.03e-03	2.23e-01
NEWCEO-ages	-1.09e-03	-5.28e-04	5.55e-01
SupervisoryDirector-ages	5.92e-02	2.12e-02	1.91e-96
Intercept-ages	-7.70e-02	-0.00e+00	3.57e-73
boardsize-experience	-7.27e-02	-2.40e-01	2.99e-09
deviationfrommeanROA-experience	-1.59e-01	-3.91e-02	4.60e-01
logat-experience	-7.48e-02	-1.70e-01	8.76e-04
leverage-experience	-3.36e-02	-8.59e-02	2.06e-02
Q-experience	1.70e-01	1.63e-01	8.44e-02
IndustriesSpanning-experience	-7.59e-02	-6.14e-02	2.36e-02
NEWCEO-experience	5.56e-01	2.70e-01	9.55e-13
SupervisoryDirector-experience	8.34e-01	2.98e-01	3.26e-13
Intercept-experience	5.71e+00	0.00e+00	6.05e-143
boardsize-MBA	1.45e-02	4.77e-02	2.76e-02
deviationfrommeanROA-MBA	-8.86e-02	-2.19e-02	3.29e-01
logat-MBA	9.64e-02	2.19e-01	3.00e-21
leverage-MBA	-2.10e-03	-5.39e-03	7.40e-01
Q-MBA	-6.64e-03	-6.36e-03	7.96e-01
IndustriesSpanning-MBA	1.01e-02	8.20e-03	6.14e-01
NEWCEO-MBA	1.91e-01	9.27e-02	2.06e-07
SupervisoryDirector-MBA	-2.78e-01	-9.94e-02	1.41e-07
Intercept-MBA	-1.86e+00	-0.00e+00	4.90e-109
boardsize-JD	2.80e-02	9.23e-02	3.16e-04
deviationfrommeanROA-JD	-5.81e-02	-1.43e-02	6.25e-01
logat-JD	8.79e-02	2.00e-01	2.03e-12
leverage-JD	1.62e-02	4.16e-02	4.04e-02
Q-JD	9.76e-02	9.36e-02	4.82e-03
IndustriesSpanning-JD	6.56e-02	5.31e-02	6.15e-03
NEWCEO-JD	-2.46e-02	-1.20e-02	5.94e-01
SupervisoryDirector-JD	-5.01e-02	-1.79e-02	4.87e-01
Intercept-JD	-3.88e+00	-0.00e+00	2.63e-276
boardsize-networksize	-9.08e-02	-2.99e-01	1.12e-77
deviationfrommeanROA-networksize	1.48e-01	3.66e-02	3.24e-02
logat-networksize	-1.41e-02	-3.20e-02	8.25e-02
leverage-networksize	-5.93e-03	-1.52e-02	2.33e-01
Q-networksize	-5.17e-02	-4.95e-02	1.14e-02
IndustriesSpanning-networksize	5.30e-02	4.28e-02	1.13e-03
NEWCEO-networksize	1.58e-02	7.65e-03	5.86e-01
SupervisoryDirector-networksize	9.24e-01	3.31e-01	1.96e-128
Intercept-networksize	2.84e+00	0.00e+00	0.00e+00
boardsize-ncontacts	4.63e-02	1.53e-01	9.49e-102
deviationfrommeanROA-ncontacts	-7.28e-02	-1.80e-02	6.21e-02
logat-ncontacts	-5.19e-03	-1.18e-02	1.96e-01
leverage-ncontacts	1.63e-02	4.16e-02	1.74e-11
Q-ncontacts	6.61e-02	6.34e-02	5.10e-09
IndustriesSpanning-ncontacts	-1.43e-01	-1.15e-01	3.46e-75
NEWCEO-ncontacts	7.62e-02	3.70e-02	1.67e-08
SupervisoryDirector-ncontacts	-1.56e-01	-5.57e-02	7.51e-18
Intercept-ncontacts	-1.76e+00	-0.00e+00	0.00e+00
boardsize-Bachelor	-2.39e-02	-7.87e-02	9.33e-04
deviationfrommeanROA-Bachelor	-2.45e-01	-6.06e-02	3.25e-02
logat-Bachelor	1.21e-01	2.74e-01	1.05e-21
leverage-Bachelor	-1.83e-02	-4.68e-02	2.14e-02
Q-Bachelor	-4.33e-02	-4.15e-02	1.55e-01
IndustriesSpanning-Bachelor	1.08e-01	8.76e-02	2.77e-05
NEWCEO-Bachelor	2.96e-01	1.44e-01	3.89e-11
SupervisoryDirector-Bachelor	5.44e-01	1.95e-01	2.15e-19
Intercept-Bachelor	1.52e-01	0.00e+00	1.26e-01
boardsize-Graduate	-2.04e-03	-6.72e-03	8.02e-01
deviationfrommeanROA-Graduate	-1.56e-01	-3.86e-02	1.98e-01
logat-Graduate	1.34e-01	3.05e-01	5.05e-23
leverage-Graduate	-4.15e-02	-1.06e-01	3.46e-06
Q-Graduate	8.36e-03	8.01e-03	8.00e-01
IndustriesSpanning-Graduate	9.92e-02	8.02e-02	3.13e-04
NEWCEO-Graduate	2.59e-01	1.26e-01	8.82e-08
SupervisoryDirector-Graduate	4.95e-01	1.77e-01	1.01e-12
Intercept-Graduate	-1.46e+00	-0.00e+00	2.28e-41
boardsize-Intercept	-7.51e-02	-2.47e-01	2.36e-04
deviationfrommeanROA-Intercept	2.05e-01	5.06e-02	4.57e-01
logat-Intercept	-5.84e-01	-1.33e+00	7.36e-64
leverage-Intercept	1.33e-01	3.40e-01	9.34e-10
Q-Intercept	2.19e-02	2.10e-02	7.68e-01
IndustriesSpanning-Intercept	-2.03e-01	-1.64e-01	4.24e-03
NEWCEO-Intercept	-4.56e-01	-2.21e-01	1.94e-04
SupervisoryDirector-Intercept	-2.28e-02	-8.16e-03	8.95e-01
Intercept-Intercept	2.77e+00	0.00e+00	5.57e-26
logBoardNetwork-ncontacts	7.50e-01	1.09e+00	0.00e+00
Intercept-ncontacts	-7.00e+00	-0.00e+00	0.00e+00
logBoardNetwork-networksize	3.75e-01	5.47e-01	0.00e+00
Intercept-networksize	-5.00e+00	-0.00e+00	0.00e+00
logBoardNetwork-experience	1.12e+00	1.63e+00	0.00e+00
Intercept-experience	-1.71e+01	-0.00e+00	0.00e+00
logBoardNetwork-Intercept	7.00e-02	1.02e-01	0.00e+00
Intercept-Intercept	-1.19e+00	-0.00e+00	0.00e+00
Number of observations	69843	Log-Likelihood	-68523.18