Predicting Authoritarian Selections: Theoretical and Machine Learning Predictions of Politburo Promotions for the 19th Party Congress of the Chinese Communist Party

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The starting argument for this paper is that elite selection and popular elections are both selection of leaders by a selectorate. Although the selectorates are small and their preference is largely hidden from public view, the Leninist institutions and established norms and rules drastically narrow the pool of potential candidates for high level offices, which can be narrowed further by observing elite social networks. Given the increasing availability of demographic, career, performance, and network data on senior Chinese officials, theoretically motivated and machine learning approaches can be used to make predictions about elite selection in China. Focusing on 19th Party Congress promotions into the Politburo, we make three sets of predictions based on theoretically motivated model specifications. We further use a variety of machine learning techniques to make multiple sets of predictions. Preliminary outcomes suggest that both the theoretically motivated models and machine learning approaches have their own pitfalls. For the theoretically motivated models, heavy reliance on informal ties variables will introduce multiple incorrect predictions if informal ties are mis-coded for otherwise competitive candidates. Meanwhile, the accuracy of machine learning predictions may suffer from fundamental shifts in the relationship between some input variables and outcomes in between congresses.

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The selection of authoritarian leaders is high stakes affairs. Despite waves of democratization, over 2 billion people still live under authoritarian regimes. Although some authoritarian regimes have directly or indirectly elected leadership, the largest authoritarian regimes, especially Leninist regimes such as China, Vietnam, and North Korea, still rely on intra-elite selection as the main mechanism for leadership turnover. Scholars of these regimes have used qualitative insights from historical cases to make predictions of promotions and purges of the top leadership, i.e. members of the Politburo Standing Committee and the chairman/ party secretary general (Lam 1999, 1995; Li 2012, 2000). There has been few efforts to systematically make predictions about lower level promotions, such as at the Politburo or Central Committee level (Li 2016). In sharp contrast to the thriving literature of predicting US presidential election outcomes, quantitatively driven predictions about elite selections have been stifled by the notion that elite selections were too opaque to gather data on, much less to provide consistent quantitative predictions. We disagree with this assumption and generate a set of predictions for promotions into the Politburo at the 19th Party Congress, scheduled to take place in October or November of 2017.

The starting argument for this paper is that elite selection and popular elections are both selection of leaders by a selectorate (Bueno de Mesquita et al. 2003; Bueno de Mesquita and Smith 2011). In the case of democracy, the selectorate contains millions of individuals, whose preference can be observed through surveys and inferred through economic conditions in the run-up to elections (Lewis-Beck and Tien 2004; Lewis-Beck and Stegmaier 2000; Lewis-Beck 2005; Leigh and Wolfers 2006; Hummel and Rothschild 2014). In the case of institutionalized Leninist parties, although the selectorates are small and their preference is largely hidden from public view, the Leninist institutions and established norms and rules drastically narrow the pool of potential candidates for high level offices. On top of that, given additional assumptions about the selectorates' preference for high performing officials or officials who are trusted by powerful leaders in these parties, one can further identify a list of possible winners in the next round of leadership selection.

Given the increasing availability of demographic, career, performance, and network data on senior Chinese officials, machine learning approaches can also be used to make predictions about elite selection in China (Meyer et al. 2015; Shih et al. 2008). Although we will not know the accuracy of the models until the fall 19th Party Congress, preliminary indications suggest that both the theoretical predictions and the machine learning predictions have their own pitfalls. The theoretically driven predictions suffer from two problems. First, because Politburo Standing Committee (PSC) composition, which is beyond the scope of this prediction, drives Politburo outcomes, we cannot provide precise predictions without knowing outcomes at the PSC level. This uncertainty forces us to make three sets of theoretically motivated predictions, depending on the realization of three plausible high level political scenarios at the 2017 19th Party Congress. We outline as specifically as possible about these three scenarios so that readers will have little doubt as to which scenario realizes in the fall of 2017. Second, if informal ties with certain top leaders are highly predictive of Politburo level promotion outcomes, even some mistakes in observing these ties due to incomplete information can introduce a significant share of incorrect predictions.

As for machine learning predictions, even very sophisticated algorithms may fall short because the top level power balance shifts between every party congress such that patterns observed in previous congresses may not apply to the current congress. In other words, regardless of how much one tries to cross validate with existing data, the emergence of unprecedented relationships or effects between input variables and the outcomes of interest will introduce a significant number of incorrect predictions. The machine learning results suggest that Politburo selection for the 19th Party Congress may follow a pattern that has not been witnessed since the 1990s.

Selection Versus Elections

In any political regime, leaders are selected by "the set of people whose endowments include the qualities or characteristics institutionally required to choose the government's leadership…" (Bueno de Mesquita et al. 2003: 42). In institutionalized democracies, the selectorate includes most adult citizens who cast their votes and directly or indirectly elect the next set of executives for the government (Schumpeter 1975). Because of the importance of voters' preference, scholars have predicted electoral outcomes in democracies by simply asking a sample of potential voters about their preferred choice among the candidates in the months or even days leading up to the election and by gauging the prevailing or expected economic conditions prior to elections, which presumably would affect voters' perception toward the incumbents (Lewis-Beck and Rice 1984; Lewis-Beck and Stegmaier 2000; Sigelman 1979; Wlezien and Erikson 2004). In recent years, scholars have taken advantage of potential information embedded in the betting market or even in social media as predictors of electoral outcomes in democracies (Wolfers and Zitzewitz 2004; Tumasjan et al. 2010).

To be sure, traditional polling or even social media data are far from perfect because, ultimately, many idiosyncratic factors determine who will actually vote on the day of the election, and thus no poll or online scraping effort can perfectly reflect the preference of the voting population (Hillygus 2011; Rothschild 2009). Still, because millions of people participate in elections in large democracies such as the US, traditional polls or online data on a large population provide important insights on electoral outcomes because such a large share of the population is expected to vote. Information on the current or expected economic conditions of the country also provides additional leverage in prediction models for democratic elections because the majority of voters presumably care a great deal about pocket-book issues (Lewis-Beck and Tien 2004; Lewis-Beck and Stegmaier 2000; Lewis-Beck 2005; Campbell 1992). This may not be true for authoritarian selections, where the selectorate number in the dozens of individuals, each with highly unrepresentative preferences.[1]

The institutions governing authoritarian selection, in contrast, are markedly different than those for democratic elections. Thus, a vastly different set of metrics need to be observed in making predictions about authoritarian selection. First of all, in institutionalized authoritarian regimes such as China,

[1] In recent works by Pan, Meng, and Yang, they found that roughly 50% of low to mid level officials in China are receptive to citizens' policy inputs, although that is far from saying that their preference s match those of the citizens'. See (Pan et al. 2014)

Vietnam, and even North Korea, the outcomes are reported clearly, just like in democracies. After a party congress or even after a purge, the official state media typically reported the new leaders of these countries more or less accurately until the next leadership reshuffling. Like democracies, institutionalized authoritarian regimes also have selectorates which decide on leadership outcomes. Unlike democracies, the selectorates in authoritarian regimes often are a small share of the population, sometimes numbering only in the dozens of individuals (Bueno de Mesquita and Smith 2011).

In the case of China, the Leninist Party Constitution clearly specifies that the five-yearly party congress, involving thousands of elite selectors, elected the Central Committee of around two hundred. The Central Committee in turn elected the Politburo, numbering around twenty individuals, and its standing committee, which ranged from five to nine individuals (Chinese Communist Party 2012). In reality, however, decades of historical and anecdotal research on elite politics suggest that a small handful of individuals had disproportional impact on the selection of Central Committee, Politburo, and the Standing Committee. For Politburo and Standing Committee members, the true selectorate may well be dozens of past and present Politburo Standing Committee members, especially the past and present party secretary generals (MacFarquhar 1997; MacFarquhar and Schoenhals 2006; Fewsmith 2001; Nathan and Gilley 2002).

Given the small handful of elite selectorate and their general inaccessibility to anyone outside of the party, it clearly is unrealistic for researchers to conduct opinion polls of them prior to a party congress. However, similar to the economic voting strand of the US prediction literature, scholars can, on the basis of historical knowledge and theoretical models, make assumptions about the policy or political preferences of the selectorate and derive prediction models for the Communist elite (Lewis-Beck and Stegmaier 2000; Lewis-Beck and Rice 1984). This is especially feasible for institutionalized authoritarian regimes such as the Chinese Communist Party because these regimes tended to provide both formal and informal institutions to govern leadership selection which encapsulated the preference of the selectorate either in the past or in the present (Thelen and Steinmo 1992; Pierson 1996). Furthermore, generations of scholars have studied the origins, functioning, and priorities in these institutions, which allowed scholars to theorize about and derive metrics which significantly impacted authoritarian leadership selection.

For the Chinese Communist regime, the existing scholarship points to three sets of variables that affected a Central Committee member's chance of entering the Politburo: basic biographical information, performance, and factional ties. First of all, since the reform and opening of China in 1978, Deng and others have fashioned institutions, such as the reserve cadre system and retirement rules, to groom younger and more educated officials for high offices (Cui 2003; Walder 2006; Yao 2016). These institutions have lowered the average age and raised the average education level of those entering the Politburo in the past thirty years (Shih et al. 2010b). During a particular tumultuous party congress in the 2002, the top leadership decided that those above the age of 67 should not serve another term in the Politburo Standing Committee, which also placed a hard age ceiling on those hoping to enter the Politburo (Miller 2008; Li 2016). At the Politburo level, women and minorities rarely made an appearance, likely reflecting inherent sexist and racist biases in the top leadership. Among the dozens of unique individuals who have served in the Politburo in the past twenty years, only three have been women or members of an ethnic minority. Furthermore, cadres of the same state or party rank holding different positions had varying probability of being promoted, reflecting a mix of factional affiliation placing them in important jobs in the first place and the regime's appreciation of individuals with experience in important organs or crucial specialization. Thus, past and current work experience in core party, military, or economic management positions may well affect promotion chances (Nathan 2003; Kiselycznyk and Saunders 2010; Wang and Minzner 2015).

Second, a large literature argues that authoritarian leaders in China value growth performance among their subordinates and reward them with promotions accordingly (Maskin et al. 2000; Li and Zhou 2005; Yao 2016; Jia et al. 2014). According to one dominant strand in the literature, relatively decentralized fiscal system allowed local party secretaries to outshine one another with growth and revenue collection performance, all in the hope of achieving promotions into the highest offices in China (Li and Zhou 2005; Chen et al. 2005). Indeed, qualitative research has found that growth performance has featured prominently in local cadres' performance evaluation, which formally makes up a large part of their evaluation prior to promotion (Edin 2003). The cadre evaluation procedures formally embed performance into the party's calculus in deciding which cadres would be promoted (Edin 2003; Whiting 2004).

Finally, an established qualitative literature on elite politics has shown that informal ties with top leaders constitute an important predictor of being highly placed in the party hierarchy (Tsou 1995; Nathan and Tsai 1995; Nathan 1973; Li 2016, 1994). In recent years, scholars have gathered more systematic data to show the impact of factional ties on the likelihood of cadres getting promotions across different levels of the Chinese government (Meyer et al. 2016; Shih et al. 2012; Jia et al. 2014; Keller 2016). Both the qualitative and the quantitative literature suggests that informal ties with top leaders in the regime exerted an important influence on cadre promotion, especially in the highest few levels of the Communist regime. Still, when deriving prediction models, one has to be careful about the exact impact that ties with various elite may have on promotion chances, since the literature and the history of the CCP have great disagreement on this issue. In the discussion below, we will specify how we deal with such disagreements when deriving prediction models for elite promotions in the CCP.

In sum, like elections in democracies, the outcomes of authoritarian selections in institutionalized Leninist regimes like the CCP were clearly announced. Unlike democratic elections, which typically involved the majority of a country's population, authoritarian selections involved hundreds or at most thousands of elite selectorates. Because of decades of research on the likely priorities of the secretive selectorate in the Chinese Communist regime, scholars predicting promotion outcomes in China can derive prediction models from our knowledge of the selectorate's preference, which have been encapsulated in various formal and informal institutions in the Chinese Communist Party.

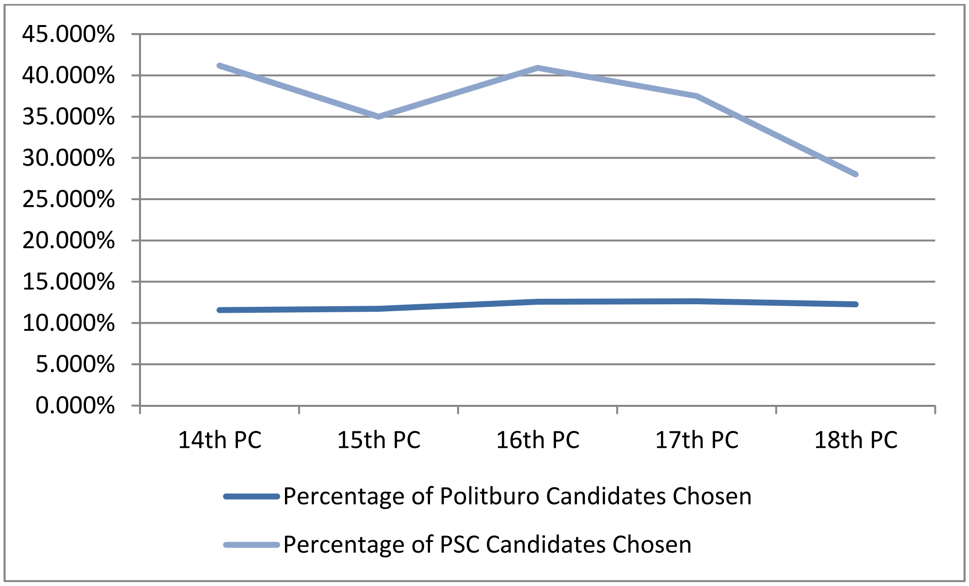
Politburo Selection as Testing Ground for Prediction Models

Similar to the literature on predicting presidential elections, predicting authoritarian selection must make assumptions about the preferences of the selectorate, measure variables that approximate the selectorate's preferences, and make predictions about the likely outcomes of the selection process. In the discussion below, we first explain why we chose promotions into the Politburo as the setting for predicting authoritarian selection outcomes. Along the way, we also explain who the selectorates are in the promotion of Politburo members, as far as we can ascertain. Finally, we provide an overview of the variables that may play a role in helping us predict Politburo promotion outcomes.

The foremost reason to predict Politburo outcomes in China is that they matter for future development both within the party and for policy trajectories, just as presidential elections matter in the US. The 25 or so members of the Politburo are the 25 most powerful officials in the country, among whom are vice premiers, party secretaries of the major provinces, and senior military and security officials. Much more so than even Central Committee members, Politburo members meet regularly to decide the fate of the country. To be sure, the most powerful officials in China are members of the Politburo Standing Committee (PSC), a collection of seven individuals. We refrain from trying to predict PSC outcomes for the 19th Party Congress because the candidate pool for PSC members, depending on seats available and the number of retiring Politburo members, number between 10 to 15 for 2 to 5 open seats at any given party congress. Because the candidates for the PSC are almost all Politburo members, who are among the most qualified and connected officials in the regime, selection into the PSC likely depended on highly idiosyncratic and mostly unobservable factors, such as support from surviving revolutionary elders, the bargaining power of various factions at the time of the congress, and scandals (Gilley 1998; Lam 1994; Li 2012; Huang 2000). In contrast, candidates for Politburo membership come from a much broader population, Central Committee members, who have diverse demographic profiles, job experience, and factional affiliations. The rich variation in these factors should allow researchers to narrow possible candidates considerably.

Furthermore, the same idiosyncratic factors driving PSC membership, especially power balance between the various factions, also dictate the number of seats in the PSC, which fluctuated widely in recent congresses from five to nine seats. As Figure 1 shows, this greatly affected the probability of an incumbent Politburo member entering the PSC in recent congresses. In contrast, the probability that a CC member from the previous party congress entering the Politburo at the current congress remained relatively stable at 11-12% throughout the recent congresses (Figure 1). The stability in the overall probability of a Central Committee member being selected into the Politburo makes predicting Politburo membership a much more tractable problem than predicting PSC membership. Nonetheless, as will be discussed below, we recognize that the composition of the PSC potentially has a profound impact on who will be promoted into the Politburo, which will need to be incorporated into our predictions of Politburo promotions.

Figure 1: Percentage of Candidates for Politburo and PSC Positions Chosen for Promotion: 14th-18th Party Congress



The extant qualitative literature paints a picture of fierce competition to enter the Politburo because Politburo membership constitutes one of the twenty-five or so most powerful positions in all of China. To be sure, everyone who was a candidate already underwent repeated rounds of formal evaluation by the party's powerful Central Organization Department, which took into account candidates' education, ethnicity, cadre evaluation performance, and evaluation by colleagues and superiors (Nathan and Gilley 2002: 25; Yao 2016). Presumably, several formal criteria, including gender, ethnicity, education level, current positions, and age, already eliminated the majority of potential candidates long before formal announcement of the decisions at party congresses.

The final candidates were further vetted by the political elite, which, after the Cultural Revolution, included current and past Politburo Standing Committee members, as well as current Central Committee members (Lieberthal 2004; Nathan and Gilley 2002; Kang Lim 2012). We know from anecdotal accounts that the most powerful elite, including current PSC members and the incumbent party secretary general, as well as past party secretary generals, at times bargained about promotions into the Politburo and the PSC even during a party congress (Lam 1995: 211). In the case of ordinary Central Committee members, the official media reported that during the 18th Party Congress, a straw poll took their preference in a semi-formal manner, although it remains unclear whether the same procedure will be repeated at the 19th Party Congress and what weight such a poll will have (Kang Lim 2012).

From our knowledge of these formal and informal procedures for selecting a Politburo member, we can safely say that a number of demographic, job experience, and even performance related variables may matter in predicting officials' promotion. According to some scholars, promotions in China are driven purely by the level of education, experience, and job performance (Yao 2016). As Yao (2016) puts it, an aspiring official in China joins the party at a young age and "…starts as a player in a life-long elimination tournament."

In addition to formal criteria, informal ties with various members of the top leadership may also have a significance influence, given their importance in the final vetting process. However, due to the high degree of uncertainties in elite power balance, we are forced to make at least two sets of predictions in models which include informal ties. First, we can make predictions assuming a relative *balance of power* between the top elite, where having overlapping work experience with a Politburo Standing Committee (PSC) member with different levels of formal power would help one's chances of promotion. Second, we can make predictions assuming that the current party secretary general is dominant and would help one's chance of promotion disproportionately, compared to ties with the other elite.

We cannot exactly determine which state of the world will prevail because events immediately before or even during a party congress can radically transform the relative power balance at the top, which transform the impact of ties with various leaders on a candidate's chance of entering the Politburo. For example, although Jiang Zemin initially did not look like he could dominate the 1997 15th Party Congress, he convened an enlarged Politburo meeting in the middle of the congress, itself an unusual move, where retired revolutionary elder Bo Yibo insisted on the immediate retirement of two of Jiang's rivals, Qiao Shi and Liu Huaqing, which gave Jiang and his allies a majority in the PSC (Lam 1999: 333). This unusual set of events allowed Jiang to dominate the congress and to promote his cronies into higher offices. Another example was the 16th Party Congress, where Hu Jintao was slated to take over all the formal positions from Jiang until the congress announced that Jiang would retain control over the military and promoted several of his close followers into Politburo Standing Committee (Fewsmith 2003). In a subsequent discussion, we will clearly identify the conditions for identifying which state of the world China will be in during the 19th Party Congress.

Data

The biographical data used for these predictions come from an updated biographical data base of the Chinese elite compiled by Shih, Meyer, and Lee (Meyer et al. 2015) , which is based on an earlier version of the Central Committee data compiled by Shih, Shan, Liu (Shih et al. 2008). These data record all publicly available demographic information on full and alternate Central Committee members, as well as all jobs held by them, which allow us to derive variables to record factional affiliation. Following much of the existing literature, we measure factional ties as overlapping job experience between a more senior level official and a junior official for over one year prior to the senior official's entry into the Politburo (Shih et al. 2012; Jia et al. 2014). The latest version of the data also ensure that overlapping school ties denote not just alumnus relationship, but attendance of the same university at the same time, a degree of precision that was not captured in previous versions of the data. All the variables available for our analysis are explained on Table 1 in Appendix A.

One should note that some available variables are never used in any of our models. This is because the theoretically motivated models only choose a limited subset of theoretically significant variables for inclusion in the analysis. The summary statistics for the variables used in the theoretical models are provided on Table 2 of Appendix A. The For the machine learning models, many variables are thrown out because they lead to inefficient estimates.

It is important to note that we are mainly using information of Central Committee members as of the 2012 18th Party Congress to predict outcomes at the 19th Party Congress. The only exception is the positions that CC members held, which is updated as of the end of 2015. Although the wide-ranging purge that President Xi carried out since 2012 already eliminated several Central Committee members from the running, we consider these removals part of what we are trying to predict. For the position variables, purged officials are presumed to still hold their last position, even if they are purged by the end of 2015. In other words, because we are mainly relying on information from prior to 2012 to make our predictions, we do not try to "cheat" by eliminating officials purged since 2012 from our predictions. In our reporting of the results, we will highlight officials who already have been removed on our prediction lists. In other words, we can already begin to assess the accuracy of the various prediction models.

For all of our theoretical models and some of the machine learning models (the GLM models), we use logistic regressions to generate predicted probability of entering the Politburo for 18th Party Congress CC members, as shown on Equation 1. In our reporting of the results below, we rank 18th Party Congress CC members by their predicted probabilities of entering the Politburo in the fall of 2017. As we specify below, our explanatory variables include biographical variables, performance variables, and factional ties variables (Table 2, Appendix A).

$$\hat{P}_{i18} = \exp[X'_{i18}\,\beta]/(1+\exp[X'_{i18}\,\beta]) \qquad (1)$$

Theoretically Motivated Predictions: Three Scenarios

As we alluded previously, the theory driven approaches generate three sets of predictions based on three possible states of the world in the fall of 2017. For the theory driven models, we use existing theories about elite Chinese politics to guide our variable selection process and estimate the impact of these variables on Politburo promotion outcomes in the 14th through 18th Party Congress using logit estimations. These estimates are then applied to predicting the likelihood of 18th Party Congress Central Committee members to enter the Politburo at the 19th Party Congress.

First of all, regardless of which world we are in, the formal institutions governing cadre selection in the past three decades likely will exert a profound influence on cadre selection regardless of which world we will find ourselves. Appendix 1 lists common variables across all three theory-driven models, including age, gender, minority ethnicity, current bureaucratic group (*xitong*), and current specialization. A rich literature already points out that Deng Xiaoping and Chen Yun engaged in a comprehensive campaign to rejuvenate the party by imposing increasingly strict age limit on officials at various levels, including the highest level (Cui 2003; Manion 1993). Subsequent leaders have maintained the status quo or have made the age limit even stricter (Dittmer 2001; Lam 1999). In the case of bureaucratic grouping dummies, the representation of local, central, and military officials in the CC and in the Politburo has been relatively stable and can affect one's chance of entering the Politburo (Li 2005; Shih et al. 2010b; Lieberthal 2004). Also, a CC member's current specialization in party affairs, economic affairs, civil affairs, defense, and leadership positions may also affect one's probability of being promoted. Thus, we also include dummy variables for an official's specialization as of late 2015. The summary statistics of these variables are presented on Table 2 in Appendix A.

We first use meritocratic variables to predict Politburo promotions because one strand of the literature argues strongly that promotions in China are done in more or less meritocratic manner. We want to test this hypothesis by seeing how well promotions in the fall of 2017 match predictions using only meritocratic variables, as outlined on Appendix 1. Because we aim to score the performance of all Central Committee members similarly to accurately capture the performance effect, we cannot include provincial growth performance variables in this model because only a subset of Central Committee candidates to the Politburo is serving in provincial leadership positions. For the remaining CC members in the State Council, the military, and central party apparatus, their performance criteria are very different from those of provincial leaders. It would be grossly inaccurate to assign "zero" growth performance to these CC members.

Instead, formal rules within the party placed the most promising officials early in their careers in the reserve cadre list, which afforded them frequent rotations to positions in various ministerial level units, including provinces, State Council ministries, and central party apparatus (Cui 2003; Yao 2016). Although theorists of factions would argue that placements in the reserve cadre list were influenced by factional ties in the first place, such placements occurred early enough in one's career that likely many performance related attributes, which were difficult for outsiders to observe, were incorporated into the consideration. As such, we include two sets of variables to capture whether a person had been identified as a promising cadre early on. First, we include variables which measure whether a CC member served a stint in the central government or the military in the first twenty years of her career. Because these units are considered the "nucleus" (核心) of the regime, the party may value cadres who had work experience in these units. Second, we include variables which measure the number of local and central positions held. If one rotated to new positions both within and between ministerial level units, this variable would count upward. Presumably, the party would consider a cadre with a long duration party membership, controlling for age, to be a merit. Again, if models containing these variables are able to make the most accurate predictions for Politburo promotions, China's political system may operate on the basis of merit.

As for predictions based on CC members' informal ties, we generate two sets of predictions due to high uncertainties about high level political intrigues leading up to the 19th Party Congress, which can drastically shift elite political equilibria. On Table 1, we outline the manifestation of a power balance scenario versus the incumbent (Xi) dominant scenario. As Table 1 reveals, if the party secretary general is able to both achieve a majority in the PSC and ensure that the vast majority of newly appointed PSC members come from his faction, one would have to put greater weight on the predictions of the incumbent dominant model. On the other hand, if no single faction achieves a majority in the PSC and newly promoted PSC members come from various factions, one would put more weight on the predictions generated by the power balance model.

Concretely, relative balance of power at the top suggests that direct and indirect ties with any member of the Politburo Standing Committee should all help one get ahead of the pact in the upcoming contest for a Politburo seat to some degree. Existing works suggest that work or school ties with Politburo Standing Committee members in general helped one's career (Li 2016; Shih et al. 2012). We suspect that given the fierce competition for Politburo seats, not every PSC member will have equal say in Politburo promotions, even if power balance between the major factions is relatively equal. Thus, we break CC members' ties with PSC members into ties with the premier, executive vice premier, head of the National's People's Congress, head of the Chinese People's Political Consultative Conference, head of the Central Discipline and Inspection committee, and the first secretary of the Central Secretariat, some of whom traditionally occupied seats in the PSC (Appendix 1). We also include princeling status in the power balance model because princelings, defined as children of officials with ministerial or above ranking, were not necessarily allied with the incumbent party secretary general, even if that person was a princeling himself.

Table 1: Manifestations of Power Balance Versus Incumbent Domination

Scenarios	Manifestations
Power Balance	• No single faction has a clear majority in the PSC • No single faction dominates the promotion of new PSC members • The number of seats in the PSC remains the same (7)
Incumbent Dominance	• One faction, likely that of the party secretary general, achieves a majority in the PSC • The party secretary's faction is able to dominate new promotions into the PSC • The party secretary general may change the number of PSC seats in order to obtain a majority in the PSC

Finally, the earliest theorists of elite CCP politics posited that power at the highest level of the party was "monistic, unified, and indivisible," suggesting that the head of the party would eventually acquire total power over the party, including power over top level appointments (Tsou 1976). If this were true, we would expect ties with the incumbent party secretary general (PSG) to have a dominant influence over important outcomes such as promotions into the Politburo. To account for such a world, we include variables which record various ties with the PSG, including work ties, education ties, birth province ties (Appendix 1). According to qualitative observations, party secretaries of the home provinces of the party secretary general may also enjoy extra patronage, mainly because they can meet more frequently with the family and friends of China's top leaders (Li 2016; Lam 1995). Furthermore, China watchers have noted that the current party secretary general, Xi Jinping, might have consolidated power more so than any reform-era leader, including Deng Xiaoping (Johnson and Kennedy 2015; Li 2016; Ansfield 2014). Given such an unprecedented scenario, we further increase the effect of party secretary general ties by one standard deviation when generating predicted probabilities for the incumbent dominant model.

As Figure 1 and 2, shows, not every theoretically generated variable had a significant impact on Politburo promotions from the 14th to the 18th Party Congress. Among the demographic and job variables, which are included in all the models, both age and age quartile variables exerted a systematic, mostly negative influence on promotion chances. Being a woman actually helped promotion, while being a minority is detrimental. Although females were obviously discriminated against in the CCP hierarchy and had low representation in the Central Committee, every Politburo since the early 1990s has had at least one woman, which means that the few women in the Central Committee enjoyed significantly higher odds of entering the Politburo than their male colleagues, all else being equal.

In terms of current positions, both central party positions and military positions exerted a significant positive influence on a full Central Committee member's chance of entering the Politburo compared to the null category of working in the legal *xitong* and party-backed mass organizations such as the Writers' Union. Surprisingly, holding positions in the rubber stamp National People's Congress or the CPPCC exerted a positive influence on one's promotion chances, although that impact is not significant at the 95% level. Equally surprising to us, a CC member who worked in a State Council position (Posi_Cgov) was no more likely to obtain a promotion into Politburo than someone in the legal bureaucracy or in a mass organization.

Figure 1: Logit Coefficients of the Demographic and Job Variables Across the Three Theoretical Models with 95% Confidence Intervals

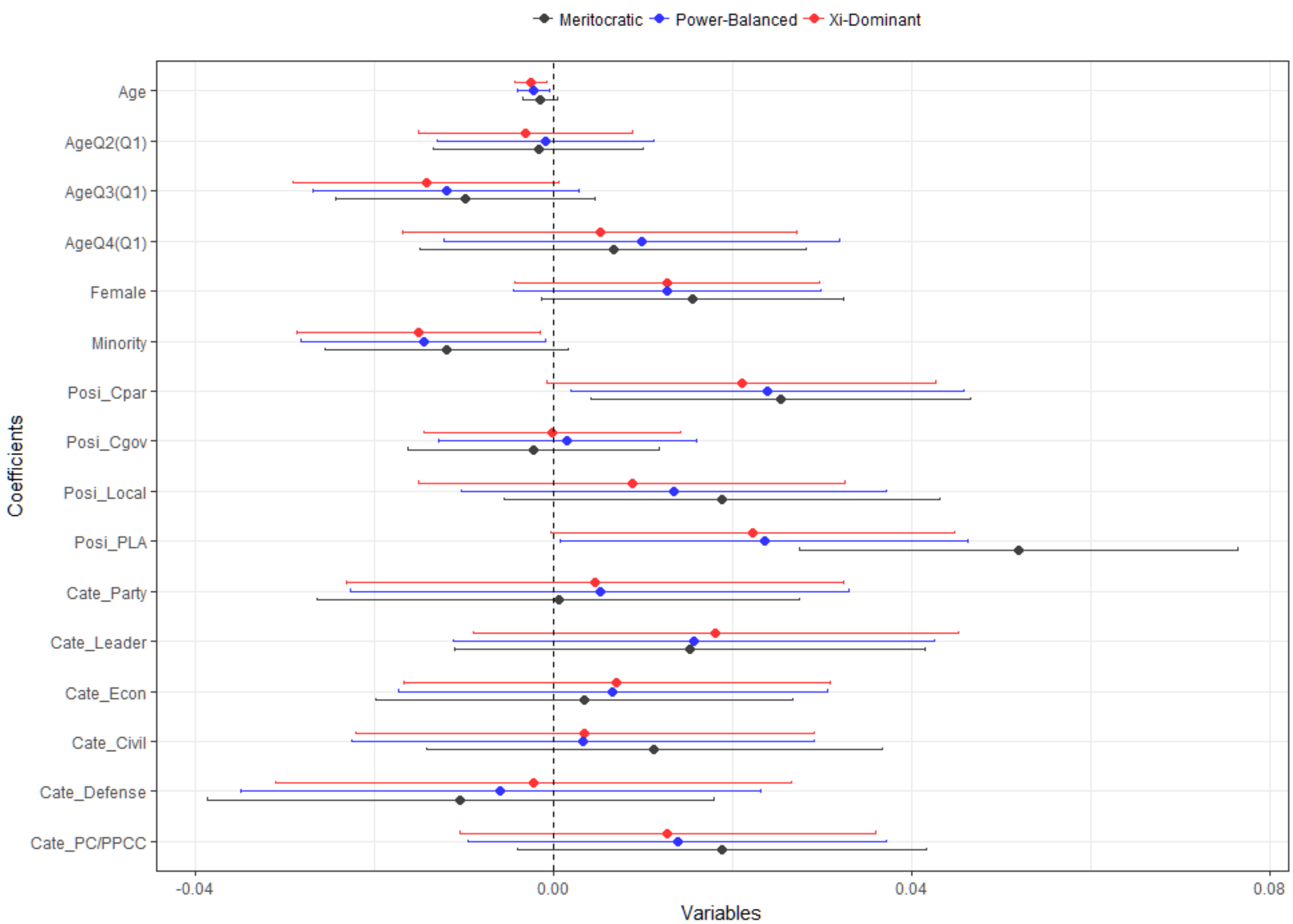


Figure 2: Logit Coefficients of the Key Variables in the Meritocratic, Power Balance, and Incumbent Dominant Models with 95% Confidence Intervals

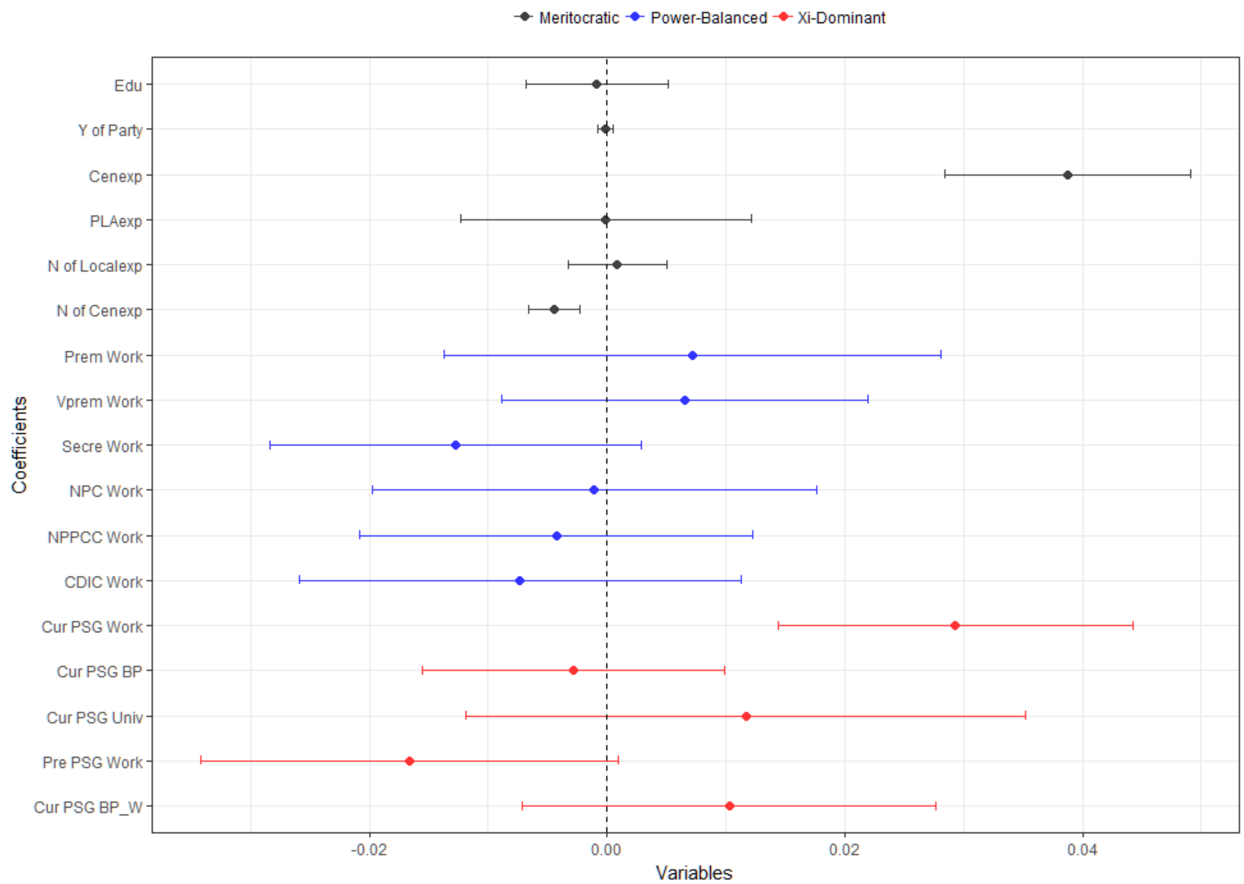


Figure 2 reports the logit coefficients for the key theoretical variables. As expected, having central experience in the first 20 years of one's career exerted a very positive influence, although that variable may be capturing personal secretary experience of cadres, which provided very strong bases for factional ties (Li and Pye 1992). Contrary to our expectation, the number of local positions held did not exert any influence on one' s promotion chances, while the number of central experience actually exerted a negative influence. This may reflect an "old doughnut" effect whereby an official who is well known in Beijing may become disqualified because members of the selectorate know her weaknesses or pitfalls all too well.

In our power balance model, ties with PSC members who served as Premier, Executive Vice Premier, first secretary of the central secretariat, chairman of the NPC, CPPCC, and CDIC did not exert any obviously positive impact on one's chance of promotion. In fact, being affiliated with the first secretary of the central secretariat may bias one's promotion chances downward. This is very different from the findings of the extant literature, which focuses on the promotion chances of alternate members of the Central Committee (ACC). Affiliation with PSC members helped ACC members become full CC members

(Shih et al. 2010a). These findings suggest that while PSC members exerted systematic influence on followers' ability to enter the Central Committee, they were not able to systematically help followers enter the elite Politburo.

Finally, Figure 2 shows that work ties with the incumbent party secretary general exerted a large positive effect on one's chances of entering the Politburo. Although birth province ties did not exert a positive influence, university ties and work experience in the party secretary general's home province also tended to have a positive influence on one's chance of entering the Politburo, although these effects are not significant at the 95% level. Ties with the previous party secretary general, in contrast, exerted a negative influence on one's chance of entering the Politburo. The disparity in the effect of ties with the current and with the past secretary general suggest a large difference between holding formal power as the incumbent secretary general and informal power as the previous one. Although not the main objective of this paper, these findings suggest that the contests for entry into the Central Committee and into the Politburo are in some ways quite different from each other. In the latter case, only patronage by the highest formal leader in the regime can systematically boost one's chance of promotion.

Table 2: Predicted Politburo Promotions at the 19th PC by Meritocratic, Power Balance, and Incumbent Dominant Models

Rank	Meritocratic	Power-Balanced	Xi-Dominant
1	Su Shulin	Su Shulin	**<u>Chen Miner</u>**
2	Lu Hao	Zhang Guoqing	**<u>Zhao Hongzhu</u>**
3	Li Hongzhong	Lu Hao	Lu Hao
4	Peng Qinghua	Zhang Qingwei	**<u>Wang Chen</u>**
5	Zhang Qingwei	**<u>Chen Miner</u>**	Zhang Guoqing
6	Lu Xinshe	Ma Xingrui	**<u>Wang Xuejun</u>**
7	Wang Anshun	Wang Yongqing	**<u>Xia Baolong</u>**
8	Shen Yueyue (F)	Ling Jihua	Su Shulin
9	Wang Dongming	Li Jiheng	**<u>Huang Xingguo</u>**
10	Jia Ting'an	Peng Qinghua	Zhang Qingwei
11	Tie Ning (F)	Xiao Jie	Ma Xingrui
12	Sun Jianguo	Shen Yueyue (F)	**<u>Lu Zhangong</u>**
13	Xu Dazhe	Guo Shuqing	**<u>Chen Xi</u>**
14	Du Qinglin	Wang Dongming	Xiao Jie
15	Li Xueyong	Xu Dazhe	**<u>Hu Zejun (F)</u>**
16	Guo Shuqing	Li Hongzhong	Wang Yongqing
17	Wang Jun	Wang Guosheng	Li Jiheng
18	Li Jianhua	Wang Anshun	Peng Qinghua
19	**<u>Zhao Hongzhu</u>**	Zhou Qiang	Wang Anshun
20	Xiao Jie	Lu Xinshe	**<u>Bayinchaolu (M)</u>**
Percent of Likely Errors in Top 20 as of 2/13/2017	**25%**	**15%**	**20%**

Table 2 lays out the top 20 predictions of the theoretical models, ranked by predicted probability of entering the Politburo at the 19th Party Congress. We further draw a line under the 11th name across the three models because assuming fixed Politburo and PSC sizes and status quo for retirement age, eleven seats are expected to open up at the 19th Party Congress. On Table 2, we also underline and make bold identified followers of Xi Jinping. Obviously, they feature very prominently in the incumbent dominant predictions. It is noteworthy that several names appear on all of the lists, including Zhang Qingwei, Lu Hao, Xiao Jie, and Su Shulin. Lu Hao especially is ranked among the top three in all three models, as well as other model specifications not reported in Appendix A. The combination of their rich administrative experience and their relative youth made them attractive Politburo candidates regardless of the political situation. Obviously, the reality of elite politics suggests that major political shocks can undermine even strong candidates such as Su Shulin, who is affiliated with purged leader Zhou Yongkang.

Besides these common predictions, there are notable differences between the three models. First Figures 3-5 shows that overall rankings predicted by the meritocratic model are very different from the predictions of the power balance and incumbent dominant models. Among the top 20, there is 50% overlap between the meritocratic and power balance models, but even among the overlapping names, their respective ranks are different. Li Hongzhong, for example, is ranked third in the meritocratic model but 13 in the power balance model. Between the meritocratic and incumbent (Xi) dominant models, there is 35% overlap, but the ranks of the overlaps are very different. Peng Qinghua, for example, ranks fourth in the meritocratic model but 18th in the incumbent dominant model.

Figure 3: Predicted Probability Rankings of the Meritocratic Model in Quartiles

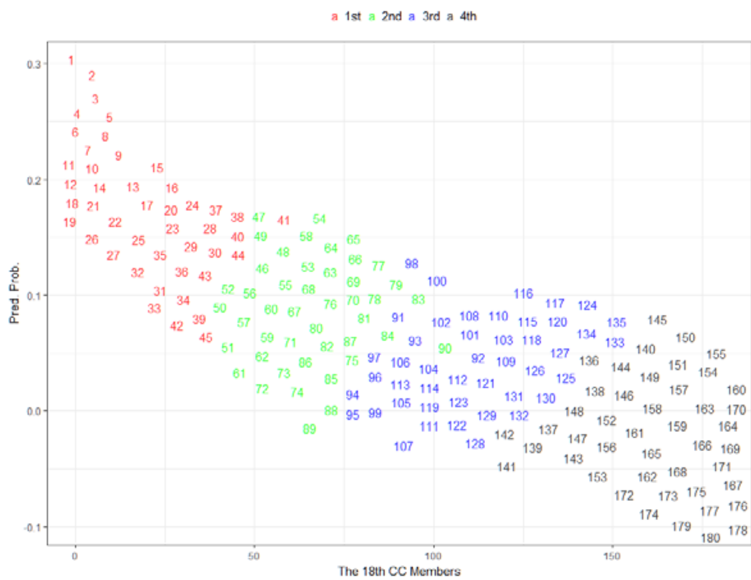


Figure 4: Predicted Probability Rankings of the Power-Balance Model in Meritocratic Quartiles

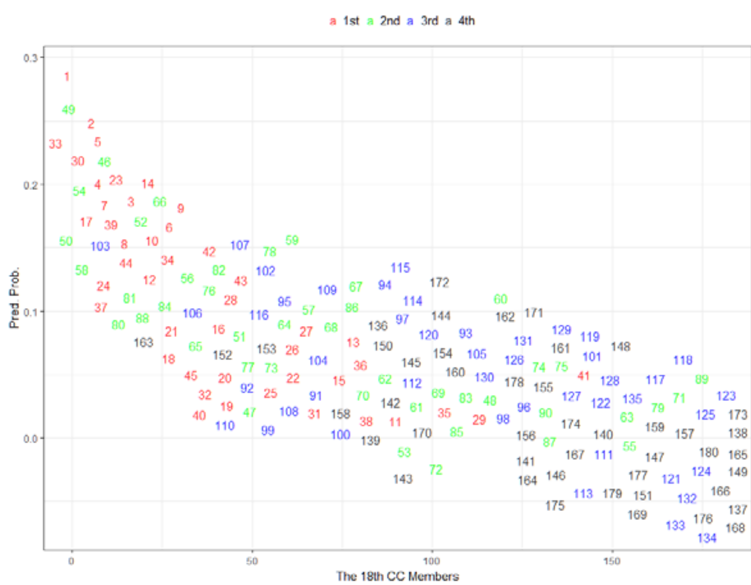
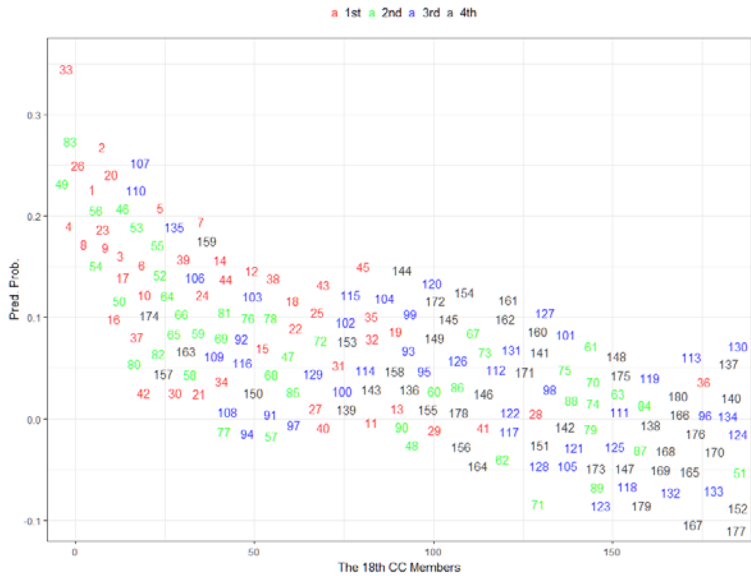


Figure 5: Predicted Probability Rankings of the Incumbent Dominant Model in Meritocratic Quartiles



Besides the ranking, findings on Table 2 also allow readers to begin assessing the accuracy of the various models. First, the names shaded in red are cadres who have been arrested for corruption since the 18th Party Congress. There is no chance that they will be promoted into the Politburo in the fall of 2017. Second, cadres shaded in grey are those holding ceremonial positions as of January 2017, who are unlikely to receive a promotion into the Politburo. Thus, the shaded cadres likely are on the top 20 list incorrectly. Thus, even in early 2017, we can already say that the top 20 predictions for the meritocratic model are at least 25% incorrect, while the top predictions of the power balance and incumbent dominant models are 15% and 20% incorrect, respectively.

The incorrect predictions in the power balance and incumbent dominant models suggest one pitfall of the theoretically driven models. Because ties with the incumbent leader of China exerted such an important influence on one's promotion probability, mis-coding of that tie can incorrectly place a candidate among the top contenders. Similarly, missing such a tie may incorrectly exclude a person from the top contender list. Among the top predictions of the incumbent dominant model, for example, Wang Xuejun is identified as a follower of Xi Jinping because he overlapped with Xi while they were both junior officials in Hebei Province in the 1980s. However, historical evidence suggests that the two cadres did not know each other very much, but in order to be consistent with our coding, Wang is identified as a Xi follower (Li 2016). Similarly, although China scholars have identified Li Xi as a likely beneficiary of Xi's patronage, he never worked or studied with Xi and was born in a different province from Xi (Li 2016). Instead, Li's ties with Xi stemmed from the fact that he served as the private secretary of a good friend of Xi Zhongxun, Xi's father. Given that it is impossible to systematically collect this kind of personal data, theoretically driven predictions which rely on informal tie variables will generate a certain number mistakes due to data miscoding.

Nonetheless, the Xi dominant model still generated 10 potential Xi followers among the top-20 list, as well as quite a few highly qualified cadres with ties to other factions, such as Lu Hao and Ma Xingrui. Despite mis-coding for some Xi Jinping followers, the qualitative literature suggests that quite a few of Xi followers on the top 20 list, including Chen Min'er, Wang Chen, Xia Baolong, Chen Xi, and Bayinchaolu, are indeed followers of Xi Jinping with some chance of entering the Politburo at the 19th Party Congress (Li 2016).

Machine Learning Predictions

Besides theoretically guided predictions, we also use machine learning techniques to generate a set of predictions. The bases of these predictions are promotion patterns from the 14th Party Congress to the 18th Party Congress. For machine learning approaches, there are generally three major steps: 1) variable selection, 2) model training, and 3) prediction. For machine learning approaches, we make as few assumptions about the promotion process as possible. Thus, we first include as many variables as possible (Table 1, Appendix A). Then, we will choose the relevant variables scored by an Area Under the Curve (AUC) of the Receiver Operating Characteristic (ROC) curve. Next, for some approaches, we will train the model by means of bagging (bootstrap aggregation), ie applying the selected model on a set of randomly chosen observations to see if its predicted power remains the consistent. Lastly, the trained model will predict the list of the Politburo members in the 19th Party Congress.

To be sure, there are a number of statistical techniques that broadly perform the above steps in different fashions. This paper will use one parametric model, the Generalized Linear Model (GLM), and one non-parametric model, the random forests model (RF) for variable selection.

1. **Generalized Linear Model with Stepwise Selection**

For the GLM variable selection process, we use a classic logistic regression to predict the list of the next Politburo members. In Equation 2, P_i denotes whether a CC member *i* is promoted to the Politburo at the next Party Congress. The predictors indicate each individual i's characteristics such as biographical, career, contextual, factional, and network variables as described in Appendix I. Out of the 48 variables, we implement a backward elimination technique to select variables that can maximize the area under the curve (AUC) of receiver operating characteristics (ROC) curve of the model. For binary outcome variables, maximizing AUC for model's ROC essentially minimizes the incorrect predictions relative to correct predictions of the model and has been a canonical technique in machine learning for years (Bradley 1997). In the backward elimination technique, we include all the variables in the initial model, and identify a variable whose contribution to the model's AUC is the smallest among the candidates.

In each subsequent round, we remove the identified variable if adding the variable is no better than a random generated dichotomous variable. Here, we do not choose the predictor combination where the AUC of the model is maximized. This is because even adding a randomly generated variable would slightly increase an AUC by a small margin. The optimal model instead is where all the predictors increase AUC more so than replacing them with a randomly generated variable.

$$P_i = \gamma Bio_i + \delta Car_i + \varepsilon Con_i + \theta Fac_i + \pi Net_i + \sum \omega(V_i^1 * V_i^2) + \square_i \tag{2}$$

The next step is including interaction terms between the selected variables (Equation 2). We use a forward inclusion technique for the models with interaction variables. If adding interaction terms between two variables increases the model's AUC greater than adding a randomly generated variable, the model accepts the interaction term which otherwise is dropped. Table 1 in Appendix A shows the final model selection. The rankings generated from this model are reported on the "naïve GLM" column (1) of Table 3.

Based on the final model, we calculate the predicted probabilities for the 18th CC members to be promoted to the Politburo member in the 19th Party Congress. In order to boost the predictive power of the fitted model, we use a bagging technique where we generate a model from different subsamples of the dataset (5 folds and 1000 iterations in our case), which will result in different coefficients for the model. From the bagging model, we average out the predicted values of each new entry and produce the list of the 18th CC members whose predicted probability of promotion to the Politburo is higher than others. However, this GLM model with stepwise selection might suffer from the over-fitting problem where the model perfectly conforms to the existing dataset. Therefore, we apply the holdout cross-validation method where we split the dataset into a training set (80% of randomly selected observations) and a test set (the remaining 20% of observations), and then select the variables which perform better than a randomly generated variable in terms of AUC. The final model is chosen when the AUC of the test set is the highest among the multiple rounds (1000 iterations in our case). One should note that because of the small number of promotions into the Politburo, we exclude test sets which contain less than 9 promotions in them, which is around 20% of the total number (42) of Politburo promotions in our data set. The results are reported on column two of Table 3.

2. Random Forest Variable Selection

Random forests model is one of the most popular nonparametric methods for classification. It begins with a standard machine learning technique called a 'decision tree,' which tests the predictive power of input variables along a given sequence. At each branch, the decision tree algorithm chooses the value of the input variable that best predicts outcomes (Calle et al. 2011). By the time one arrives at the lowest branch, a sequence of values for all input variables will have been chosen. The random forests model is designed to construct multiple, independent decision trees in order to overcome the over-fitting problem a single tree (Breiman 2001). First, the random forest algorithm splits the training set into N bootstrap samples with replacement and then estimates individual decision trees to the samples. Each individual decision tree is deliberately over-fitted and grown to the largest extent possible without pruning (Breiman 2001). Next, the random forest reduces correlation between different trees by eliminating highly correlated trees in the test set. Then, a subset of the remaining forest in the test set can classify the outcome of a given observation. Predicted probability of the random forest algorithm is the proportion of trees in the test set predicting or "voting" for a given outcome, or "classifying." It is a simple non-parametric algorithm with good performance in practice and substantially resistant to over-fitting (Breiman 2001).

We select the input variables by optimizing the AUC of the random forests. This strategy also uses a backward elimination technique on the basis of the initial ranking of variables (Calle et al. 2011). Among 1000 iterations, we choose the best predictor combination which maximizes the out-of-bag AUC. The list of the variables selected is shown in Appendix I. With the variables selected by the random forests AUC maximization process, we further predict the top 20 list using other machine learning algorithms, including Least Absolute Shrinkage and Selection Operator (LASSO), Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), and K-nearest neighbors (KNN)[2]. Finally, we build an ensemble model that synthesizes all the results from the above machine learning methods in order to maximize the overall prediction accuracy measured by the AUC.

Various machine-learning techniques are equipped with their own algorithms to select important variables, to remove irrelevant ones, or to decide a sufficient set for predictions. However, we restrict the scope to the variables previously chosen by the random forests procedures. We use the other machine learning algorithms to improve predictions in other ways. LASSO is one type of the regression analysis which penalizes large regression coefficients. Because unusually large coefficients may be the result of random shocks which will not be repeated in the future, LASSO reduces prediction errors by shrinking large coefficients similarly to ridge regressions (Tibshirani 1996). LDA is a classification method to search for a linear combination of variables that best separates two classes or targets by calculating a scoring function originally introduced by Fisher (1936). The produced combination results are used for dimensionality reduction where insignificant features are removed, while preserving as much of the class discrimination information as possible.

The SVM is one of the well-known supervised learning algorithms for classification. This algorithm first finds a linearly separable boundary of one class from the other. When the decision boundary is not linearly separable, unlike the LDA which stops to find, the SVM also uses a nonlinear mapping to transform the data into a higher dimension (Cortes and Vapnik 1995). This method has high accuracy and is particularly effective in high dimensional features as the SVM looks for complex high dimensional non-linear boundaries. KNN is a widely used non-parametric method for classification. It classifies a case depending on the classification of its K nearest neighbors as measured by either Euclidean distance for discrete variables or the share of overlaps for dummy variables between the input values of the test observation and those of the training observations. It is one of the simplest machine learning techniques without any model training, and there is no need to manipulate complicate parameters to implement the method. However, it is computationally expensive as it determines each distance from all other data point (Shakhnarovich et al. 2005).

[1] We excluded the results of some basic machine learning methods such as Naïve Bayes classifier, ID3 Tree, and the Classification and Regression Tree (CART) because their prediction performance is s poor (i.e. their AUCs are barely over 0.5).

Our final model is the ensemble model which incorporates all the prediction results from the above machine learning methods. Based on the classification decisions made by each method, the ensemble model stacks all the methods into one model by using a weighted majority vote. In our case, among the eight machine learning algorithms we tested including Naïve Bayes, ID3 Tree, CART, RF, LASSO, LDA, SVM, KNN, we select the last five algorithms, whose AUC is at least over 0.6 and whose average correlation with the other models are below 0.7 for the ensemble building. This is because a shortlist composed of more accurate models with less correlation with each other is better for the final ensemble prediction. In order to minimize the situation where the inferior models overrule the superior models, we also weight each model based on the AUC of the test set, when it comes to voting for the final ensemble model. On average, the rankings of the test set AUC of our selected models as the following: 1) RF 2) SVM 3) LASSO 4) LDA 5) KNN. For each model including the ensemble, we tested the data with different randomly selected subsamples multiple times. The final AUC of each model on Table 3 is calculated as the average AUC of the out-sample test set among 1000 iterations.

The top 20 predictions of all these approaches are reported on Table 3. Again, we attempt to evaluate the accuracy of these predictions even at the beginning of 2017 by identifying purged cadres and cadres serving in rubber stamp organs, who are shaded in red and grey respectively. All of these approaches, except for KNN, already contain over 30% of likely errors, even for predictions with high AUC. To be sure that doesn't mean that these approaches won't in the end contain many accurate predictions, since the fate of 60-70% of the top 20 lists remain up in the air. However, the high AUC of these approaches, which measures their fit with existing observations, however drawn, suggests that these specifications should have high accuracy in future data. However, that is not so.

The exception to the relatively poor performance of the machine learning techniques is KNN, which places two Xi Jinping followers (by work ties) among the top eleven and four among the top four. Moreover, it only so far contains 15% of likely mistakes instead of over 30% as the other approaches. The model does well despite relatively low AUC with out of sample predictions of the existing data. Since RF has chosen most of the factional and network variables, the KNN algorithm will find "neighbors" whose characteristics, including factional attributes, most resemble a current CC member and "vote" on whether this person will receive a promotion similarly to the promotion of her closest neighbors. Thus, those on the top 20 list for KNN share many attributes of past CC members who received a promotion into the Politburo.

On average, each of the machine learning model predicts only three Xi Jinping followers among the top 20. In reality, China scholars have guessed at a congress that is potentially dominated by Xi, which would result in many more Xi followers promoted into the Politburo (Li 2016). Fundamentally, the thus far poor accuracy of machine learning predictions may stem from the usually high level of power enjoyed by Xi Jinping, which renders other variables unimportant for the coming party congress even though they mattered for promotion in previous congresses. Given the vector of input variables selected by random forests, many cadres that would have been classified for promotion in previous congresses may not receive one in the coming congress.

Table 4 reports the most frequently predicted cadres among the top 20 lists of the machine learning approaches. Even on this list, 1/3 of the cadres are unlikely to make it into the Politburo later this year because they are already holding largely ceremonial positions or have been removed. The top five on the list include Su Shulin, Lu Hao, Jia Ting'an, Li Hongzhong, and Li Jianhua. Again, Su Shulin clearly is a mistaken prediction due to data limitation. In general, current positions suggest that 35% of the top 20 on this list likely will not enter the Politburo. Lu Hao and Jia Ting'an, meanwhile, made it on to nearly every prediction list. In the case of Jia, he is associated with former president Jiang Zemin, who may be losing power rapidly. Thus, this prediction may not be so accurate. Lu Hao has multiple characteristics which are associated with promotion into the Politburo. He features among the top 20 in both theoretically motivated predictions and in the machine learning models. By all indications, Lu should make it into the Politburo in the fall of 2017, if past data are of any help in making future predictions in elite politics. Given his close association with Hu Jintao, however, promotion into the Politburo may not occur for him.

Table 3: 19th Politburo Predictions Using Various Machine Learning Techniques

Rank	Naïve GLM	CV GLM	Random Forest	LASSO	LDA	SVM	KNN	Ensemble
1	**Bayinchaolu(M)**	**Bayinchaolu(M)**	Lu Hao	Lu Hao	Lu Hao	Liu Yazhou	**Chen Miner**	Wang Anshun
2	Su Shulin	Su Shulin	Su Shulin	Su Shulin	Wang Anshun	Jia Ting'an	Lu Hao	Cai Fuchao
3	Li Hongzhong	**Wang Xuejun**	**Chen Miner**	Jia Ting'an	Jia Ting'an	Li Wei	Cai Mingzhao	Lu Hao
4	**Wang Xuejun**	Li Hongzhong	Cai Fuchao	Wang Anshun	Shen Deyong	Lu Hao	Su Shulin	Su Shulin
5	Lu Hao	Lu Hao	Cai Mingzhao	Peng Qinghua	Su Shulin	Wang Anshun	Wang Sanyun	Jia Ting'an
6	Li Jianhua	**Zhao Hongzhu**	Wang Anshun	Li Jianhua	**Zhao Hongzhu**	Huang Qifan	Wang Yong	Li Hongzhong
7	Luo Zhijun	Li Jianhua	**Lou Jiwei**	Li Hongzhong	Liu Yazhou	Shen Deyong	Xiao Gang	Shen Deyong
8	Cai Mingzhao	Luo Zhijun	Peng Qinghua	Che Jun	**Wang Xuejun**	**Lou Jiwei**	Zhou Qiang	Wang Guosheng
9	**Zhao Hongzhu**	**Chen Miner**	Luo Huining	Cai Fuchao	Peng Qinghua	Che Jun	Zhang Guoqing	Li Jianhua
10	Peng Qinghua	Wang Dongming	Ling Jihua	Song Xiuyan (F)	Huang Qifan	Cai Fuchao	Bateer	Wang Xinxian
11	You Quan	Che Jun	**Hu Zejun (F)**	**Zhao Hongzhu**	Li Hongzhong	Su Shulin	**Bayinchaolu(M)**	Luo Zhijun
12	Wang Dongming	Peng Qinghua	Wang Guosheng	Huang Qifan	**Chen Miner**	Cai Mingzhao	Cao Jianming	Quanzhezhu (M)
13	Che Jun	Jia Tingan	Zhao Zhengyong	You Quan	Tie Ning (F)	Zhao Zhengyong	Che Jun	Shen Yueyue (F)
14	**Lu Zhangong**	**Lu Zhangong**	Li Hongzhong	Shen Deyong	**Bayinchaolu(M)**	Zhao Shi (F)	Chen Quanguo	**Xia Baolong**
15	Jia Ting'an	**Huang Xingguo**	Tie Ning (F)	Zhang Qingwei	Che Jun	Cao Jianming	**Chen Xi**	Peng Qinghua
16	Ji Bingxuan	You Quan	Wang Xinxian	Jiang Dingzhi	**Lu Zhangong**	Yuan Chunqing	**Hu Zejun (F)**	**Guo Gengmao**
17	**Wang Chen**	Lu Xinshe	Jiang Jiemin	Wang Yongqing	Cai Fuchao	Wu Aiying (F)	Huang Qifan	Xu Shousheng
18	Li Xueyong	Cai Fuchao	Li Jianhua	**Bayinchaolu(M)**	Li Jianhua	Luo Huining	Jia Ting'an	**Lou Jiwei**
19	**Chen Miner**	Ji Bingxuan	Huang Qifan	**Wang Xuejun**	You Quan	**Hu Zejun (F)**	Jiang Jiemin	Li Xueyong
20	Huang Qifan	**Guo Gengmao**	Zhang Qingwei	**Chen Miner**	**Hu Zejun (F)**	Shen Yueyue (F)	Leng Rong	Wang Dongming
Final AUC:	0.951	0.771	0.872	0.769	0.744	0.811	0.645	0.886
Error Rate:	35%	40%	40%	30%	30%	35%	15%	40%

Table 4: Top Predictions Among Machine Learning Approaches, Ranked by the Number of Appearances on Top 20 Lists

Rank	Name	Count
1	Su Shulin	8
2	Lu Hao	7
3	Jia Ting'an	7
4	Li Hongzhong	6
5	Li Jianhua	6
6	Peng Qinghua	6
7	Che Jun	6
8	Huang Qifan	6
9	Wang Anshun	6
10	Cai Fuchao	6
11	**Bayinchaolu (M)**	5
12	**Chen Miner**	5
13	Shen Deyong	5
14	**Wang Xuejun**	4
15	Cai Mingzhao	4
16	**Zhao Hongzhu**	4
17	You Quan	4
18	**Hu Zejun (F)**	4
19	**Lu Zhangong**	3
20	Li Xueyong	3
20	Lou Jiwei	3

Conclusions

Predicting authoritarian selection is much more challenging than predicting election because the elite selectorate cannot be polled by scholars in most cases. Instead, similar to the economic voting literature, scholars have to make assumptions about the selectorate's preferences, develop metrics that approximate the preferences of the elite selectorate, and make predictions. The Leninist institutions and established norms and rules drastically narrow the pool of potential candidates for high level offices. Furthermore, elite social network variables may provide additional predictive power. We make predictions based both on existing theories of leadership selection in China and on atheoretical machine learning algorithms. For the theoretically motivated models, heavy reliance on informal ties variables introduces multiple incorrect predictions when informal ties are mis-coded for otherwise competitive candidates. Meanwhile, the accuracy of machine learning predictions may suffer from fundamental shifts in the relationship between some input variables and outcomes in between congresses. For now, in-indepth knowledge of China and more accurate coding of elite informal networks still seem to yield more accurate predictions at the Politburo level.

Appendix A: Variable List and Summary Statistics

Table 1: Variable List and Explanations for All Models

Type	Name	Measurement	M	P	X	G	R
Biographical Variables	Age	Year – Birth Year	O	O	O		O
	Age2	(Age)2				O	O
	AgeQ	Age Quartiles (Q1 ~ Q4)	O	O	O		
	Age62	Whether Age is over 62					
	Edu	0=High Below; 1=High or Tech; 2=College; 3=Post-graduate	O				O
	Female	Whether Male or Female	O	O	O		O
	Minority	Whether Han or Minority	O	O	O		
Career Variables	Y of Party	The Number of Years since the CCP entry	O				O
	Cenexp	Whether had worked in the Central Departments	O			O	O
	PLAexp	Whether had worked in the People's Liberation Army	O				O
	CYLexp	Whether had worked in the Communist Youth League					O
	Secreexp	Whether had worked as a Central or Provincial Secretariat					O
	N of Localexp	The Number of Positions Held Before (Local Government)	O				O
	N of Cenexp	The Number of Positions Held Before (Central Government)	O			O	O
Contextual Variables	Midterm	Whether holding a CC membership in the 14th or 16th PC				O	O
	Posi_Cpar	Whether currently working in the Central Party Organization	O	O	O	O	O
	Posi_Cgov	Whether currently working in the Central State Organization	O	O	O		
	Posi_Local	Whether currently working in the Local Government	O	O	O	O	O
	Posi_PLA	Whether currently working in the PLA Department	O	O	O	O	O
	Cate_Party	Whether currently working in the Party Affairs-related Job	O	O	O		O
	Cate_Econ	Whether currently working in the Economy-related Job	O	O	O		O
	Cate_Civil	Whether currently working in the Civil Affairs-related Job	O	O	O		
	Cate_Leader	Whether currently working in the Leadership Jobs: local party secretaries, governors, central ministers	O	O	O		O
	Cate_Defense	Whether currently working in the Military or Foreign Affairs-related Job	O	O	O		
	Cate_PC/PPCC	Whether currently working in the NPC or CPPCC-related Job	O	O	O		O
	Cate_Others	Whether currently working in the Court or Mass Organization-related Job	O	O	O		
Factional Variables	Deng	Whether had worked with Deng Xiaoping in the same ministerial level unit					O
	TsinghuaU	Whether obtained a BA Degree from Qinghua University					O
	PekingU	Whether obtained a BA Degree from Beijing University					O
	PartySchool	Whether obtained a BA Degree from the Central Party School					O
	Princeling	Whether an Offspring of the Central Committee Member				O	O
	Shanghai_W	Whether had worked in the Shanghai municipality					O
Network Variables	Degree	Rescaled Degree Centrality				O	O
	Btwness	Rescaled Betweenness Centrality					O
	Closeness	Rescaled Closeness Centrality					O
	Cur PSG Work	Whether had worked with the Current PSG			O	O	O
	Cur PSC Work	Whether had worked with the Current Politburo Standing Committee Members					O
	Cur Poli Work	Whether had worked with the Current Politburo Members					O
	Pre PSG Work	Whether had worked with the Previous PSG			O	O	O
	Pre PSC Work	Whether had worked with the Previous Politburo Standing Committee Members					O
	Pre Poli Work	Whether had worked with the Previous Politburo Members					O

			M	P	X	G	R
	Inc PSG Work	Whether had worked with the Incoming PSG					O
	Cur PSG BP	Whether born in the same province with the Current PSG			O		O
	Pre PSG BP	Whether born in the same province with the Previous PSG					O
	Inc PSG BP	Whether born in the same province with the Incoming PSG					
	Cur PSG Univ	Whether obtained a BA Degree from the same university with the Current PSG			O		
	Pre PSG Univ	Whether obtained a BA Degree from the same university with the Previous PSG					
	Inc PSG Univ	Whether obtained a BA Degree from the same university with the Incoming PSG					
	Cur PSG BP_W	Whether had worked in the birth province of the Current PSG			O		O
	Pre PSG BP_W	Whether had worked in the birth province of the Previous PSG					O
	Inc PSG BP_W	Whether had worked in the birth province of the Incoming PSG					
	Prem Work	Whether had worked with the Current Premier		O			
	Vprem Work	Whether had worked with the Current Vice Premier		O			
	Secre Work	Whether had worked with the Current Secretariat General		O			
	NPC Work	Whether had worked with the Current NPC Chairman		O			
	NPPCC Work	Whether had worked with the Current NPPCC Chairman		O			
	CDIC Work	Whether had worked with the Current CDIC Secretary		O			

Column Labels M=meritocratic model, P=power balance, X=Xi Jinping Dominant, G=GLM, R=random forest

Table 2: Summary Statistics of Variables in Theory Driven Models, By Party Congress*

	14^{th}PC	15^{th}PC	16^{th}PC	17^{th}PC	18^{th}PC
N	167	169	173	178	180
Biographical:					
Age	59.82	58.74	58.31	58.83	58.93
Age62	61 (36.53%)	48 (28.4%)	39 (22.54%)	56 (31.46%)	36 (20%)
Female	12 (7.19%)	7 (4.14%)	4 (2.31%)	12 (6.74%)	8 (4.44%)
Ethnic	14 (8.38%)	14 (8.28%)	14 (8.09%)	15 (8.43%)	9 (5%)
Job Position:					
Central Party	14 (8.38%)	15 (8.88%)	11 (6.36%)	20 (11.24%)	20 (11.11%)
Central Gov.	32 (19.16%)	32 (18.93%)	32 (18.5%)	27 (15.17%)	36 (20%)
Local Institution	51 (30.54%)	48 (28.4%)	44 (25.43%)	37 (20.79%)	50 (27.78%)
PLA	35 (20.96%)	34 (20.12%)	38 (21.97%)	30 (16.85%)	37 (20.56%)
Others	35 (20.96%)	40 (23.67%)	48 (27.75%)	64 (35.96%)	37 (20.56%)
Job Category:					
Leadership	56 (33.53%)	49 (28.99%)	48 (27.75%)	40 (22.47%)	54 (30%)
Party Affairs	15 (8.98%)	15 (8.88%)	12 (6.94%)	21 (11.8%)	23 (12.78%)
Economy	27 (16.17%)	23 (13.61%)	30 (17.34%)	29 (16.29%)	32 (17.78%)
Civil Affairs	13 (7.78%)	17 (10.06%)	13 (7.51%)	9 (5.06%)	15 (8.33%)
Defense/Foreign	39 (23.35%)	41 (24.26%)	45 (26.01%)	40 (22.47%)	46 (25.56%)
PC/PPCC	13 (7.78%)	19 (11.24%)	23 (13.29%)	39 (21.91%)	8 (4.44%)
Others	8 (4.79%)	8 (4.73%)	4 (2.31%)	3 (1.69%)	10 (5.56%)
Meritocratic:					
Party Exp.	39.02	35.04	33.3	34.97	37.02
Education	1.75	1.92	2.08	2.29	2.6
N of Central Exp.	3.34	3.56	3.58	3.63	3.4
N of Local Exp.	1.07	1.11	1.21	1.37	1.35
Central Exp.	96 (57.49%)	109 (64.5%)	112 (64.74%)	119 (66.85%)	120 (66.67%)
PLA Exp.	54 (32.34%)	53 (31.36%)	60 (34.68%)	55 (30.9%)	54 (30%)
Power-Balanced:					
Premier Tie	3 (1.8%)	7 (4.14%)	6 (3.47%)	6 (3.37%)	25 (13.89%)
Vice Premier Tie	11 (6.59%)	3 (1.78%)	7 (4.05%)	26 (14.61%)	11 (6.11%)
Secretariat General Tie	12 (7.19%)	8 (4.73%)	12 (6.94%)	10 (5.62%)	12 (6.67%)
NPC Chairman Tie	21 (12.57%)	0 (0%)	6 (3.47%)	5 (2.81%)	13 (7.22%)
CPPCC Chairman Tie	14 (8.38%)	13 (7.69%)	5 (2.89%)	4 (2.25%)	12 (6.67%)
CDIC Chairman Tie	0 (0%)	10 (5.92%)	7 (4.05%)	11 (6.18%)	11 (6.11%)
Incumbent-Dominant:					
Current PSG Work Tie	22 (13.17%)	16 (9.47%)	13 (7.51%)	18 (10.11%)	10 (5.56%)
Previous PSG Work Tie	7 (4.19%)	16 (9.47%)	13 (7.51%)	18 (10.11%)	11 (6.11%)
PSG Birth Place Tie	23 (13.77%)	30 (17.75%)	9 (5.2%)	8 (4.49%)	5 (2.78%)
PSG University Tie	1 (0.6%)	2 (1.18%)	11 (6.36%)	3 (1.69%)	4 (2.22%)
Working in PSG Birthplace Tie	8 (4.79%)	8 (4.73%)	8 (4.62%)	13 (7.3%)	5 (2.78%)

*For dummy variables, both the raw number of CC members with those attributes and the percentage of CC members with those attributes, in parentheses, are reported. For all other variables, the mean values are reported.

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