Connections over Competence:
The Impact of Political Ties on Sell-Side Research

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Abstract

We show that Chinese state-owned (SOE) brokerage managers and board members may hire analysts connected with financial regulators to increase their promotional prospects. Using textual measures for analyst performance and kinship scores based on facial features, we find that politically connected analysts have less industry knowledge, lower recommendation profitability, and a higher tendency to plagiarize and follow trends compared with merit-based hires, while SOE brokerage officials are more likely to be promoted after hiring them. After China's anti-corruption campaign reaches the financial sector, research quality improves, and informational efficiency increases for firms most intensely covered by politically connected analysts. Contrary to the view that corruption merely redistributes resources to bureaucrats, our results suggest that corrupt hiring of financial intermediaries distorts the allocation of employment opportunities, reduces market efficiency, and imposes real costs on investors.

Keywords: Corruption; Cronyism; Political connection; Security analyst; Rent-seeking.
JEL classification: G15; G24; D73; P26.

1. Introduction

Due to the search frictions in the labor market, many hiring decisions are based on connections (Beaman, 2016; Munshi, 2003). Network referrals have both informational and relational value, as lower information asymmetry can facilitate the positive selection of competent employees (Karlan et al., 2009; Pallais and Sands, 2016), and long-term relationships can reduce moral hazard and monitoring costs (Heath, 2018). However, connection-based hiring can also facilitate favoritism and cronyism, reducing worker competence and work quality (Beaman and Magruder, 2012; Bramoullé and Goyal, 2016). Anecdotal evidence abounds of financial analysts with political connections in China.[1] This paper studies why Chinese state-owned brokerage officials hire security analysts connected with financial regulators.

As the performance of financial analysts has considerable variation and is publicly available, we can explore the reasons for and the social consequences of connection-based hiring. Because financial analysts have multi-dimensional skills, autonomy in research production and dissemination, and relatively high salaries, the costs of information asymmetry and moral hazard can be high for their employers. However, the highly regulated nature of the financial industry also makes it a hotbed of cronyism (Khwaja and Mian, 2005; Moon and Schoenherr, 2022). More interestingly, most large brokerages in China are state-owned enterprises (SOEs) whose managers and board directors are government officials from the Chinese Communist Party (CCP), so cronyism in this context is political rent extraction. SOEs can tolerate a relatively high level of rent extraction because they derive economic rents from state monopolies (Brødsgaard and Li, 2013; Unirule Institute of Economics, 2015, 2016).

Cronyism in China also has one unique mechanism due to its institutional features. After economic reforms in the late 1990s, China decentralized the control of economic resources and allowed SOEs autonomy in operational, financial, and technological decision-making. Despite

[1] For example, see JP Morgan's Sons and Daughters Program: https://archive.nytimes.com/dealbook.nytimes.com/2013/08/30/morning-agenda-jpmorgans-sons-and-daughters-program/, and the report of China's princelings in the finance industry: https://www.ft.com/content/e3e51a48-3b5d-11df-b622-00144feabdc0

their control over state resources, SOE managers and board directors are still centrally appointed by higher-ranked CCP officials. The China Securities Regulatory Commission (CSRC) oversees the Chinese stock market, and CSRC officials can appoint, promote, or demote SOE brokerage officials. SOE brokerage officials receive government-controlled salaries and have incentives to maximize their promotional prospects within the CCP. One way to achieve this goal is to recruit analysts connected with CSRC officials. In contrast to patronage hiring (Colonnelli et al., 2020) or cash-based corrupt hiring (Weaver, 2021), where recruiters receive either loyalty or bribes, corruption in our setting has the unique mechanism that lower-ranked SOE brokerage officials hire connected analysts to bribe higher-ranked CSRC officials, who can promote them in exchange, as illustrated in Figure 1.

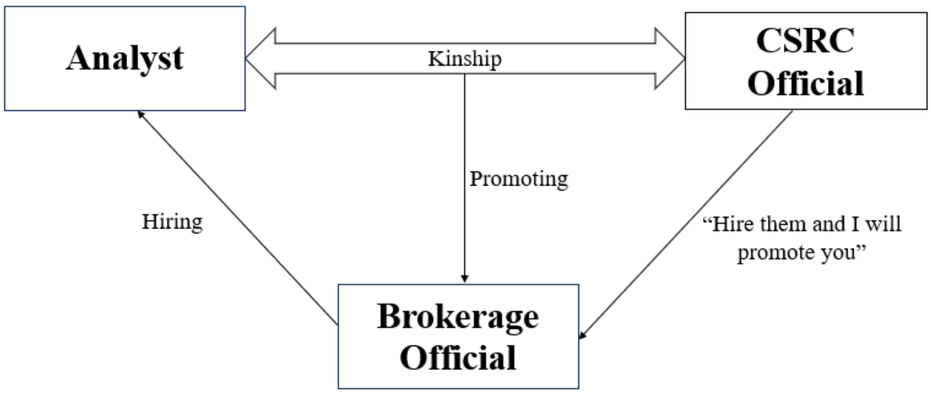

Figure 1. Illustration of the Cronyism

To test the economic channels and mechanisms, we select the healthcare industry for our sample, as clinical trials and medical products are publicly available so that we can measure analysts' industry knowledge, which institutional investors rank as analysts' most important quality (Bradley et al., 2017a; Brown et al., 2015 and 2016; Kadan et al., 2012). Our sample includes all listed healthcare firms that receive analyst coverage in China's primary stock market from 2012/1/1 to 2019/12/31. We measure industry knowledge as the frequency of industry-specific words in analyst reports because knowledge of firms' products and technology is necessary for information processing and cash flow forecasting. Besides industry knowledge, we also measure analyst performance based on their recommendation profitability, financial knowledge, trend following, and plagiarism tendency. Because kinship patronage is common in China (Khatri et al., 2006), we use machine learning to measure analysts' kinship connection with financial regulators based on their facial features. Our kinship prediction algorithm is based on the Oxford VGGFace project (Cao et al., 2018), which uses a ResNet architecture to balance efficiency with accuracy. To improve the accuracy of the prediction, we use photos of Chinese individuals as the training dataset for the algorithm.

There is a large variability in our sample analysts' research quality. We sort our sample analysts into quintiles based on their average industry knowledge. Analysts in the top quintile use more financial vocabulary, write longer reports, and are less likely to plagiarize than analysts in the bottom quintile, all with a 1% significance level. In addition, analysts in the top quintile also create more value for investors by generating more profitable recommendations.

We regress analyst performance on their political connection, controlling for other analyst characteristics, and find that politically connected analysts have lower levels of industry knowledge than nonconnected analysts. China's anti-corruption campaign reached the financial industry and severed many analysts' political ties in 2015, when the State Council of China changed the chairperson and most vice-chairpersons of the CSRC. Our sample analysts' average research quality significantly improves after 2015, including their industry knowledge, report originality and recommendation profitability, and they are also less likely to piggyback, or recommend overvalued stocks with recent runups after 2015. Politically connected analysts are less likely to be informed as they seem to follow salient news and plagiarize other analysts' reports, which may also explain their lower recommendation profitability.

To strengthen our causal interpretation, we use a difference-in-differences (DID) setting that exploits the exogenous shock of China's anti-corruption campaign. After 2015, the research quality of politically connected analysts significantly improves relative to nonconnected analysts in terms of the industry knowledge, length, originality of their reports, and their recommendation profitability. Relative to the pre-2015 period, an increase of one percentage point in analysts' political connection is associated with an increase of 3.54 and 6.45 percentage points in their one-month and two-month recommendation profitability after 2015, respectively. Despite skepticism about the campaign's motives (Griffin et al., 2022), it effectively reduces corruption (Chen and Kung, 2019; Giannetti et al., 2021), and the campaign is likely to discourage the new CSRC officials from corrupt practices. After unqualified analysts lose their connections, they may face greater competitive pressure and some of them are replaced by industry experts who can provide more valuable sell-side service.

The lower research caliber of politically connected analysts is consistent with cronyism, but brokerage managers may hire politically connected analysts to obtain business resources to increase brokerage profitability. To address the concern, we test the relationship between brokerage profitability and analysts' political connections. Across specifications, the effect of network hiring on brokerage profitability is insignificant, which dispels the alternative hypothesis that brokerages hire analysts connected with financial regulators to maximize profits. Before exploring our main mechanism, we test whether brokerage officials receive direct pecuniary benefits such as salary raises after hiring connected analysts. In our baseline regressions and DID tests, network hiring has insignificant effects on brokerage managers' and directors' compensation. Due to SOEs' operational autonomy, financial regulators cannot directly influence their compensation schemes. However, they can promote SOE brokerage officials for hiring their relatives, which is a covert way of returning brokerage officials' favors.

Then, we hand-collect SOE brokerage managers' and board members' employment history and regress their likelihood of being promoted on the average political connection of the analysts at their brokerages, controlling for official and brokerage characteristics. Officials at brokerages with more politically connected analysts are more likely to be promoted, which is significant at the 5% level. However, the relationship between analysts' political connection and brokerage officials' promotion is only statistically significant before 2015, during which a one percentage point increase in our kinship measure is associated with a 2.5 percentage points' increase in the probability of brokerage official promotion. In our DID test, brokerage officials who hire politically connected analysts are significantly less likely to be promoted in the period after 2015 than before 2015. After the anti-corruption campaign, the new financial regulators and brokerage officials are less likely to abuse their power than their predecessors.

Within our SOE brokerages, 23 officials of 19 brokerages were accused of misconduct after 2015, and most of them were promoted two to three times before 2015. On average, these brokerages' industry knowledge increases from 17.99 to 36.65, and their employee turnover increases from 9.92% to 11.06% after 2015. Among them, 13 officials were investigated and charged with corruption by the Central Commission for Discipline Inspection (CCDI), China's highest anti-corruption government body.

The results suggest that some SOE brokerage officials hire connected but unqualified analysts as bribes to CSRC officials to increase their promotional prospects. The exchange of favors between the higher- and lower-ranked CCP officials negatively affects sell-side research quality and investor returns from following analyst recommendations. In effect, cronyism transfers wealth from investors to CCP officials who oversee China's stock market, and the political rent extraction originates from the decentralized control over SOE resources and the centralized political appointment system within an autocracy.

Besides investor returns, we test how the quid pro quo affects financial market efficiency. Controlling for other factors that affect firms' information asymmetry, we find that firms more intensely covered by politically connected analysts have lower stock price informativeness and that average stock price informativeness across firms significantly improves after the anti-corruption campaign reaches China's financial sector in 2015. Although we lack strong causal evidence, crony hiring is likely to negatively affect financial market efficiency by crowding out more competent job candidates, reducing competition and analysts' effort levels, and reducing information production in the secondary market.

We contribute to network hiring. Previous studies show that less educated job seekers use referrals from close relatives (Bian, 1997; Granovetter, 1983), likely due to the higher moral hazard risk for underprivileged workers (Heath, 2018). In contrast, we show network hiring for privileged workers that is a form of cronyism and labor market discrimination.

Most studies show the benefits of political connections to firms (Acemoglu et al., 2016; Amore and Bennedsen, 2013; Bertrand et al., 2014; Cooper et al., 2010; Faccio, 2006; Ferguson and Voth, 2008; Fisman, 2001; Goldman et al., 2009; Vidal et al., 2012), but connections can also facilitate rent extraction when the interests of politicians are misaligned with those of the organizations, as in patronage-based hiring (Colonnelli et al., 2020). Colonnelli, Li and Liu (2022) find that the net benefits of political connection to nonconnected private equity investors are negative in China. Cruz et al. (2017) show that candidates in the center of social networks tend to win public sector jobs due to their ability to practice clientelism. Individuals connected with current politicians obtain better-paying jobs (Fafchamps and Labonne, 2017; Gagliarducci and Manacorda, 2020), potentially from the exchange of favors between politicians and firms.

We contribute to the debate on whether corruption is socially efficient. Although corruption may allow economic resources to be allocated to individuals who value them the most (Beck and Maher, 1986; Leff, 1964; Lien, 1986; Lui, 1985), it benefits the wealthy and privileged (Colonnelli et al., 2020; Esteban and Ray, 2006; Krueger, 1974; Shleifer and Vishny, 1993; Xu, 2018). We find that crony hires perform worse than merit-based hires, while Weaver (2021) shows that corrupt hiring does not reduce community health service quality, possibly because the health workers use cash bribes to compete for positions with limited autonomy and privilege and because performance dispersion is lower in the public than the private sector (Borjas, 2002). Most studies show adverse effects of corruption, including trade costs (Sequeira, 2016), regulatory non-compliance, and worker mortality (Fisman and Wang, 2015), as well as distortions in investment efficiency (Duchin and Sosyura, 2012; Mauro, 1995), license allocation (Bertrand et al., 2007) and knowledge production (Fisman et al., 2018). Although corruption facilitates the exchange of resources in an autocracy, it occurs among the privileged few at the expense of citizens, which maintains its power distribution.

We also contribute to the literature on the cross-sectional variation of analyst performance (Asquith et al., 2005; Clement and Tse, 2003; Kadan et al., 2012; Stickel, 1992). Analysts' relative performance has significant variability, and only a small group of skilled analysts issue influential reports persistently (Li, 2005; Loh and Stulz, 2011; Mikhail et al., 2004). Our study suggests that institutional frictions may cause analyst performance variability.

The remainder of this paper is organized as follows. Section 2 presents the background and our hypotheses. Section 3 describes the data and our methods, and Section 4 presents the results and discussion of our main tests. Section 5 presents our additional tests, and Section 6 reports our robustness tests. Section 7 concludes the paper.

2. Background and hypothesis development

2.1. Background

In autocratic countries, bureaucrats are not fully accountable to citizens, corruption is rampant and economic efficiency is low (Chen and Kung, 2019; Djankov et al., 2010; Fisman et al., 2018; Fisman and Svensson, 2007; Fisman and Wang, 2015; Pei, 2016; Shleifer and Vishny, 1993; Treisman, 2000). Since China's economic reform in 1978, the political competition in China has increased relative to the pre-reform period, as the local politicians have gained de jure control over local resources such as land, and their promotions within the CCP have become more closely tied with economic growth. Although Li and Zhou (2005) show that local economic performance is positively associated with provincial officials' promotional prospects, the rule of the game is often violated. To win the political tournament, local officials may react strategically to environmental monitoring (He et al., 2020) and sell land at steep discounts to princelings, or top CCP officials (Chen and Kung, 2019). Because the economic reform has barely changed the political power distribution between the elites and the average Chinese citizens, the de facto performance criteria for government officials, such as economic growth, may not be used. Political elites in China enjoy dynastic political rents, and their exchange of favors between Chinese politicians for rent extraction has been documented in the real estate industry (Chen and Kung, 2019) and the banking sector (Agarwal et al., 2020).

Does the rampant corruption mean that the political tournament within CCP is ineffective and policies do not benefit citizens? Because China does not practice an old-school dictatorship like North Korea after the reform in 1978, its central government balances political elites' and citizens' interests to achieve political stability. Although the concentration of power is high within the CCP with relatively few checks and balances compared to democratic countries, there are grassroots elections of village chairmen in China, as the villagers' monitoring can reduce information asymmetry between top and local officials to reduce local officials' rent extraction, especially for remote villages and for periods with less bureaucratic capacity (Martinez-Bravo et al., 2022). In addition to villages, state-owned enterprises (SOEs) represent another type of institution characterized by decentralized control and local activity, i.e., with high information asymmetry between SOE officials and top officials. To address information asymmetry and maintain vertical control, the central government sets up various regulatory agencies, such as the China Securities Regulatory Commission (CSRC), to monitor firms in the securities industry, including SOE brokerages.

The within-party monitoring is unlikely to be as effective as the grassroots monitoring in villages, as SOE officials can select the employees at their discretion. In addition, SOEs enjoy economic rents due to state monopoly on resources and various benefits such as government subsidies, which cushion the bottom line so SOEs can tolerate a relatively high level of rent extraction. Although SOE officials' lack of performance incentives and potential rent-seeking does not benefit SOE performance, the discontent from minority shareholders is unlikely to cause widespread protests and uprisings. Due to SOEs' lower political importance than villages, China's political elites may allow higher rent extraction and lower political accountability in SOEs. Where political accountability is relatively low, the rules for the political tournament are less based on performance but more on privileges endowed from birth, such as connections and wealth, as the SOE officials with more resources can pay higher bribes to get promotions.

2.2. Hypotheses

We examine political accountability at SOEs by investigating why SOE brokerage officials hire security analysts connected to financial regulators. Because bribery and cronyism are generally secretive, we select the sell-side sector, as financial analysts' performance is publicly observable, which allows us to test the impact of crony hiring directly.

The tension in connection-based hiring is that connections can work in two ways: reducing information asymmetry and moral hazard, or facilitating cronyism. Financial analysts enjoy relatively high salaries and autonomy in report issuance, company visits, and client communication, so their skills are multi-dimensional and complex. To find suitable candidates with relevant skills and good work ethics, brokerage managers may use their informational advantage to hire competent candidates in their social circles, which include CSRC officials' friends and relatives. Besides positively selecting job candidates using informational advantage, network hiring may also reduce moral hazard risks and monitoring costs after hiring, as long-term relationships tend to induce cooperative behavior (Heath, 2018).

However, the institutional features of China also suggest that cronyism may explain the network hiring. SOE brokerage managers and board directors are CCP officials who receive government-controlled salaries that are not linked to brokerage performance, and their promotions are decided by financial regulators from the CSRC, who are ranked one level up in the CCP hierarchy. Promotions within the CCP are highly valuable, as higher-ranked officials control more public resources besides enjoying higher salaries and more stipends. The centralized political appointment and decentralized control over state resources may incentivize lower-ranked SOE officials to hire analysts connected with higher-ranked financial regulators to increase their promotional prospects. The mechanism of the quid pro quo is similar to that in Chen and Kung (2019), where provincial party secretaries move up the political ladder by bribing "princelings" in the politburo with land price discounts. In our setting, the bribe is the nonmeritocratic hiring of politically connected analysts. If politically connected analysts are less competent and brokerage officials hire them as bribes to CSRC officials for their political careers, then corruption explains the connection-based hiring, which indicates a low level of political accountability in SOEs.

Our two opposing hypotheses are as follows:

The Connection Benefit Hypothesis: SOE brokerage directors and managers hire analysts connected with CSRC officials because network hiring allows them to select more competent candidates and reduce monitoring costs.

The Cronyism Hypothesis: SOE brokerage directors and managers hire less qualified analysts connected with financial regulators to increase their promotional prospects.

If analysts' political connection is associated with better analyst and brokerage performance, then connection benefits are likely to explain the hiring decisions. If analysts' political connection is associated with worse analyst and brokerage performance and brokerage officials are likely to be promoted after hiring connected analysts, then the connection-based hiring is likely to be an exchange of favors between higher and lower-ranked CCP officials.

3. Data and Methodology

3.1. Data

We select Chinese A-share healthcare industry firms and the analysts who cover these firms for our sample.[2] Because the healthcare industry has high technological barriers to entry, rapid innovation, and transparency, we study analysts who cover healthcare firms so that we can directly measure their industry knowledge based on their reports and public information. Although Kadan et al. (2012) study the industry expertise of firm analysts and strategists, we only study firm analysts because strategists' analysis entails more macroeconomic than industry-specific knowledge. In addition, the bulk of sell-side service is within-industry investment consulting. Using the Wind financial database, we find that around 70% of analyst reports are firm-level reports, while strategy reports make up 30% of the total number of A-share reports from 2006 to 2020.

We identify the healthcare industry according to Wind, which follows the Global Industry Classification Standard (GICS). Crane and Crotty (2020) show that the proportion of skilled analysts has increased over time, and most Chinese brokerages started sell-side research services after 2000, so more recent samples may be more relevant.[3] Our sample consists of all listed healthcare firms that receive analyst coverage in the Chinese A-share market from 2013/1/1 to 2019/12/31, as most analyst reports issued before 2013 are not publicly available. We collect company financial data from the Wind Financial Terminal, and the observation period for firms is from 2012/1/1 to 2020/12/31. We use all available data within the sample period for newly listed shares and firms with missing data. We download analyst reports from Hexun.com, Huibo, and Wind.

Because all sell-side analysts must register their profiles on the Securities Association of China (SAC), we collect analysts' education level and sell-side employment history on the SAC website. For all the analysts who have left the sell side within our sample period, we search online to find their next employer. Our sources for pre-analyst and post-analyst work experience include financial websites like Hexun.com and Eastmoney.com, as well as the websites of asset management firms. SAC also provides brokerage ranking and revenue and profit data. We collect data on brokerage managers and directors (or brokerage officials for

[2] Chinese A-share firms are those listed on the Shanghai Stock Exchange and the Shenzhen Stock Exchange.

[3] The New Fortune magazine in China started ranking sell-side analysts in June, 2003.

short) from brokerage disclosures and the Shanghai and Shenzhen Stock Exchange, including their age, gender, qualification, and employment history. We collect analysts' photos from the Securities Association of China (SAC) website, financial news sites, and social media platforms, as well as financial regulators' photos from the corresponding official websites, annual reports, financial news sites, and social media platforms. We record the details of our photo collection and preprocessing procedures in Section B4.1 of Appendix B.

For analyst recommendation profitability, we use all analysts' ratings, including forecast revisions, initial coverages, and other events. Although analyst recommendation value is more accurate with time stamp data (Bradley et al., 2020), many large brokerage houses in China do not share their recommendations or reports on financial terminals or websites. In addition, the report release dates on Huibo are generally several days later than when the reports are released to the brokers' paying clients. Therefore, we only use the report release date in the reports, which are at a daily frequency. Our textual data cleaning details are in Section B1 of the Appendix.

3.2. Analyst performance measures

3.2.1. Industry knowledge

Sell-side analysts are more specialized than buy-side analysts by industry sectors (Brown et al., 2016) and generally cover fundamentally related firms or industry peers (Ali and Hirshleifer, 2020; Parsons et al., 2020), potentially due to similarity in technology and R&D as analysts need technological expertise to understand and forecast firm performance (Tan et al., 2019). We use industry knowledge as one of our analyst performance measures, as knowledge is the prerequisite of skills, and many papers show the importance of industry knowledge in investment. Hutton et al. (2012) find that analysts can forecast earnings as accurately as managers and attribute this to their industry expertise. Industry knowledge can help venture capital firms select and nurture innovative startups (Chemmanur et al., 2014), can benefit firms' innovation via knowledge spillovers (Martens and Sextroh, 2021), can improve corporate monitoring and reduce agency conflicts (Bradley et al., 2017b). A qualified analyst must possess adequate industry knowledge to understand firms' business models, competitiveness, and growth potential to forecast future cash flows and estimate intrinsic values. However, long-term cash flows are uncertain and cannot be predicted based on knowledge of existing facts alone. Hence, industry knowledge is a necessary, but insufficient condition for analyst skill.

Industry knowledge reflects analysts' value to investors, as most buy-side analysts care more about the industry experience of sell-side analysts than their star status or company size (Brown et al., 2016). In addition, standard measures of brokerage prestige, such as size, may not accurately reflect research quality in China, where most large brokerage houses are state-owned enterprises with political goals. In our sample, 20.7% of star analysts are in central SOEs and 62.1% in local SOEs, although most central SOE brokerages are much larger than either local SOEs or private brokerages.

Using a bag-of-words approach, we measure industry knowledge as the number of occurrences of industry-specific terms in analyst reports because knowledge of industry-specific jargon is necessary for understanding business operations and forecasting growth. Insightful analyst reports focus on the key drivers of firm operations and growth, including the products, R&D, patents, and services, rather than general policies or past financial performance. The key drivers of firm profits differ across sectors within the healthcare industry. Products, patents, and R&D are highly relevant for pharmaceutical and biotech firms, while services are more critical for Clinical Research Organizations (CROs) and hospitals. Unlike pharmaceutical and biotech firms, active pharmaceutical ingredient (API) manufacturers care less about innovation and more about the costs of ingredients. We aggregate the sector-specific terms into a healthcare industry knowledge dictionary to reflect the focuses of different sectors.

We rely on public sources to build our industry knowledge dictionary to ensure that our industry knowledge measure is unaffected by inside information. First, we gather names of drugs, medical devices, equipment, clinical services, and drug targets from the websites of governments, companies, and third parties. These terms encompass the approved products and services of all the sectors in the healthcare industry, and the websites contain useful information for analysts and investors. For example, Klein et al. (2020) show that healthcare analysts directly access US FDA (Food and Drug Administration) website information. A list of our word sources is in Section B2.1 of the Appendix.

Second, we add key terms from firm disclosures that are contextually similar to the jargon above. Based on previous studies, we use annual reports and IPO prospectus as our additional corpus, which include information that is both investment relevant and industry-specific, such as firms' leading products, R&D, and competitors. Hoberg and Phillips (2016) use 10-k business descriptions to classify firms' industries because firms generally discuss their main products in annual fillings. Gibbons et al. (2021) find that analysts write more informative recommendation reports when directly accessing corporate disclosures via EDGAR. Brown et al. (2016) show that financial reports like 10-k filings are more important for buy-side analysts than conference calls or management earnings guidance. We scrape A-share healthcare firms' filings (including annual, semiannual, quarterly reports, and IPO prospectus) during the period 2010-2020 from the official website CNINFO, which is the equivalent of EDGAR in China. We use word embedding, a method also used by Li et al. (2021), to find terms in disclosures that are contextually similar to our precompiled words above. We provide the technical details in Section B2.2 of the Appendix. We give the same weight to all the words in our industry knowledge dictionary, as different word weighting schemes are unlikely to change our results significantly.

Our textual measure of industry knowledge is independent of analysts' professional connections, which captures analysts' industry expertise across portfolio firms and over time. Unlike our direct approach, Kadan et al. (2012) indirectly measure industry expertise as analysts' across-industry recommendation profitability, which is affected by many confounding factors and disconnected from the term's practical meaning of within-industry expertise (Bradshaw, 2012)—Bradley et al. (2017a) proxy industry knowledge as pre-analyst work experience. The drawback is that previous work experience may lead to access to insiders and private information, which is still analysts' competitive advantage after Regulation Fair Disclosure (Green et al., 2014).

3.2.2. Other performance measures

This section reports the other proxies for analyst performance besides industry knowledge.

First, we calculate analysts' recommendation profitability based on the investment recommendations from their reports.[4] We use one-month to three-month recommendation profitability, rather than announcement day abnormal return, because we cannot differentiate among reports issued before or after trading hours, and the large percentage of retail investors in China means that short-term price impact measures are highly noisy for most stocks. We study the investment profitability of analysts' ratings by trading on their recommendations at report issuance date T with a holding period of 30 to 90 days. We follow the literature and use buy-and-hold abnormal returns to measure analysts' recommendation profitability (Crane and Crotty, 2020; Jegadeesh and Kim, 2010). The abnormal return ABR(i) for recommendation i is as follows:

$$ABR_i(\mathrm{T}) = D_i(\prod_{t=T}^{T+n}\left(1 + r_{i,t}\right) - \prod_{t=T}^{T+n}\left(1 + r_{m,t}\right)), n = 30, 60, 90$$

Where $r_{i,t}$ is the return on the target stock in report i, $r_{m,t}$ is the market return, and D_i is equal to 1, 0, and -1 for upgrades, neutral opinions, and downgrades, respectively. We use all reports, including revisions, initial coverages, and other non-revisions. We buy the target stock at the market price if the stock receives a Buy recommendation (including Strong Buy and Buy), do not trade for Hold ratings, and sell the stock for Sell ratings. Then, we recalculate the ABR for all the analyst recommendations in our sample. We aggregate recommendation profitability at the report level to the analyst level by averaging each measure for each analyst in each year.

Second, we use analysts' tendency to follow stock price trends or earnings announcements. Industry experts are more likely to provide new information to investors (Li, et al., 2015; Luo and Nagarajan, 2015), rather than to piggyback on financial news without providing new insight or investment value (Altinkilic and Hansen, 2009; Loh and Stulz, 2011). We measure an analyst's piggybacking tendency as his or her average pre-recommendation returns, which is related to the recommendation screening approach in Loh and Stulz (2011).

[4] We first extract investment recommendations by algorithms and then manually check their accuracy.

Third, we also proxy analyst performance by their employment outcome. We define Employment as a dummy variable that is equal to 1 if an analyst has a promotion or moves to a higher ranked brokerage or the buy-side during the year, and to 0 otherwise.

Fourth, we also use plagiarism tendency to measure research quality. Due to the relatively weak protection on intellectual property rights in China (Fang et al., 2017), some financial analysts may directly copy the reports of other analysts. We measure the likelihood of plagiarism as the maximum cosine similarity between a report and all the reports issued within seven days before, whose details are reported in Section B3 of the Appendix.

3.3. Analysts' political connection

We measure analysts' political connection as the probability of their kinship connection with financial regulators. Based on anecdotal evidence, some investment banking and sell-side analysts are Chinese officials' relatives, especially children, nephews or nieces.[5] There are also evidence of top Chinese officials' relatives profiting in the financial industry from political power.[6] In literature on social connections, ethnographic or genealogical data can be used to measure kinship tightness (Benzell and Cooke, 2021; Diao and Zhan, 2023; Enke, 2019; Giuliano and Nunn, 2018; Moscona et al., 2020). Because the family relationship of most analysts is private information, we estimate the probability of their kinship with financial regulators based on their facial features using analyst photos from SAC website and financial regulator photos from CSRC annual reports. Individuals with greater facial similarity have greater genetic similarity and are more likely to be kins (Torosin et al., 2020).

We use an analyst's and a financial regulator's photos to compute their kinship score, ranging from 0 to 1, where higher values signify a higher probability of a blood relationship between the two. Our kinship prediction algorithm is based on one of the best-performing algorithms from the competition "Northeastern SMILE Lab - Recognizing Faces in the Wild"

[5] For example, see JP Morgan's Sons and Daughters Program: https://archive.nytimes.com/dealbook.nytimes.com/2013/08/30/morning-agenda-jpmorgans-sons-and-daughters-program/

[6] See the report of China's princelings in the finance industry: https://www.ft.com/content/e3e51a48-3b5d-11df-b622-00144feabdc0

(Howard et al., 2019). Following Xie et al. (2017), we use the procedures and methods in Oxford VGGFace project (Parkhi et al., 2015; Cao et al., 2018), including the ResNet-50 architecture. The ResNet architecture balances efficiency with accuracy via skip connections and bottleneck residual blocks. The network selects the most discriminative aspects and prominent features of the faces, but also computes the average of features, making the kinship scoring mechanism more robust.

Our training set for the machine learning algorithm comprises the frontal face photos of 310 Chinese parent-child pairs from the KinFaceW Dataset (Lu et al., 2012, 2014). We define analyst-year level kinship as each analyst's highest kinship score with all the CSRC senior officials in each year. The details of our algorithm are in Section B4.2 of Appendix B.

3.4. Main tests

To test our hypotheses on connection-based hiring at SOE brokerages, we first investigate whether politically connected hires are more competent than nonconnected hires in Equation (1).

$$\begin{aligned}\text{Analyst performance}_{i,t} &= \alpha + \beta \cdot \text{Political connection}_{i,t} \\ &\quad + \gamma \cdot \text{Controls}_{i,t} + \delta_t + \varepsilon_{i,t}\end{aligned} \tag{1}$$

The subscript i denotes each analyst and t denotes each year. We aggregate industry knowledge, recommendation profitability and other report level variables to the analyst year or brokerage year level. We use heteroskedasticity-robust standard errors for regressions based on Equation (1). Because an analyst's industry knowledge and other measures of performance are likely to contain time-invariant components that are absorbed by analyst fixed effects, we do not include analyst fixed effects in Equation (1). We cluster robust standard errors at the analyst level.

For the regressions on analyst performance, our control variables include analyst experience, education and portfolio complexity. Clement (1999) shows that analysts' experience and portfolio complexity affect their forecast accuracy. Mikhail et al. (1997, 2003) find that analysts tend to become more accurate as they become more experienced covering a firm. Bradley et al. (2017a) show that brokerages sometimes allocate analysts without related work experiences to covered firms, but these inexperienced analysts are not necessarily unqualified because analysts can acquire their industry knowledge through prior work experience or self-learning after becoming an analyst. For high-technology industries, education in relevant fields may contribute to an analyst's industry knowledge. To address analyst learning effects, we add analysts' work experience as a control variable. Besides experience, education level can also affect analysts' expertise and investment insight. Portfolio complexity, as measured by the number of firms covered by an analyst per year, may negatively affect analysts' accuracy, as busy analysts are likely to devote less time to each portfolio firm.

To address endogeneity concerns and strengthen the causal inference, we use a differences-in-differences setting by exploiting the exogenous change in analysts' political connection due to the anti-corruption campaign. China's anti-corruption campaign launched by Xi Jinping touched the financial industry in 2015, starting from the banking sector.[7] In 2015, the campaign also reached the China Securities Regulatory Commission (CSRC), which is the highest oversight committee for the securities and asset management industry in China. In table A2, we list the turnover in CSRC top officials each year, who include CSRC chairman, vice chairmen, chairman assistants, and the leader of discipline inspection and supervision team. In 2015, 10 CSRC top officials left their positions, including the chairman and three out of the four vice-chairmen, and 4 were investigated for corruption. As CSRC top officials have the power to appoint SOE brokerage officials, to allocate brokerage business licenses and to approve IPOs, the drastic turnover in CSRC severs many analysts' political ties, so that the previously politically connected analysts become less valuable to SOE brokerages and may be fired or work harder to avoid being fired afterwards.

The DID test is specified by Equation (2) below, where Post is a dummy variable that equals one after China's anti-corruption campaign reached China's stock market in 2015 and zero otherwise. The coefficient on $\text{Political connection}_{i,t} \cdot \text{Post}_t$ is the DID coefficient and it captures the effect of losing political connection on analysts' performance.

[7] https://www.ft.com/content/e50b1036-ab73-11e4-8070-00144feab7de

$$\text{Analyst performance}_{i,t} = \alpha + \beta_1 \cdot \text{Political connection}_{i,t} \cdot \text{Post}_t + \beta_2 \cdot \text{Political connection}_{i,t} + \beta_3 \cdot \text{Post}_t + \gamma \cdot \text{Controls}_{i,t} + \delta_t + \varepsilon_{i,t} \tag{2}$$

As additional evidence, we test whether brokerage officials are likely to be promoted after hiring politically connected analysts. If politically connected analysts are more competent and their hiring benefits brokerage profitability, brokerage officials may be promoted for increasing SOE profits. If politically connected analysts are less competent and brokerage officials are promoted for hiring them despite the negative effects on brokerage profitability, then the nonmeritocratic hiring is likely to be a form of bribe that brokerage officials give to financial regulators. Our baseline and DID test for brokerage officials' career outcome are specified in Equation (3) and (4), respectively, where the subscript k denotes each brokerage.

$$\text{Official promotion}_{k,t} = \alpha + \beta \cdot \text{Political connection}_{k,t} + \gamma \cdot \text{Controls}_{k,t} + \delta_t + \eta_k + \varepsilon_{k,t} \tag{3}$$

$$\text{Official promotion}_{k,t} = \alpha + \beta_1 \cdot \text{Political connection}_{k,t} \cdot \text{Post}_t + \beta_2 \cdot \text{Political connection}_{k,t} + \beta_3 \cdot \text{Post}_t + \gamma \cdot \text{Controls}_{k,t} + \delta_t + \eta_k + \varepsilon_{k,t} \tag{4}$$

We use Cox regression models to estimate Equation (3) and (4). Official promotion $_{k,t}$ is a dummy that equals one if any of the managers or directors at brokerage k is promoted in a specific year, and zero otherwise, where promotion includes moving to a higher ranked position at the current brokerage, other SOE brokerages or mutual funds, stock exchanges or the CSRC. Political connection $_{k,t}$ is the average value of political connections of the analysts working in brokerage k in year t. Equation (3) is estimated first on the whole sample, and then on the pre-2015 and post-2015 subsamples.

For the regressions on brokerage official promotion, our control variables include brokerage revenue, brokerage official age, gender, education and certification. The definitions of all the variables are in Table A1 of Appendix A.

4. Empirical results and discussion

4.1. Summary statistics

We have downloaded 34,788 reports from Hexun.com, Huibo and Wind. The pharmaceuticals sector accounts for 24.9% of total coverage, the largest among all healthcare sectors. The second most popular sector is the traditional Chinese medicine sector, accounting for 21.30%, which slightly outnumbers the biotechnology sector (20.56%). We have 126 brokerages, 411 analysts, and 250 healthcare firms. After excluding analysts who do not issue reports with ratings and those with missing observations, we have 300 analysts with observations including photos. Each analyst has been issuing reports on average for 4.85 years and covers 11 firms on average over our sample period. Only one report has a "Sell" rating, while 86.31% of all reports give positive ratings, ranging from "Hold-outperform" to "Strong Buy". Most revision reports are upgrades.

Table 1 reports summary statistics of the variables used in analyst performance analysis. We collapse report-level observations to the analyst-brokerage-year level. The average value of kinship of the whole sample is 0.633, with a significant degree of variation across analysts, brokerages, and years. We classify the analysts with kinship bigger than 0.7 as connected and the others as nonconnected, with their respective description statistics shown in Panel B and Panel C.

[Insert Table 1 here]

Politically connected analysts have more education and work experience, potentially because the politically connected enjoy many privileges and advantages such as greater wealth levels and more opportunities or because there is positive selection in network hiring, or both. Table 1 shows that connected analysts on average have 0.7 more years of experience in the security sector (5.26 years for connected analysts, and 4.56 years for nonconnected analysts) and higher education levels than nonconnected analysts, allowing them to accumulate more industry knowledge and financial knowledge. For other variables, there are also variations across analysts and years. The variation of recommendation profitability is larger for longer time horizons.

We report the pairwise correlation between the analyst characteristics in Table 2. The performance measures are highly correlated, including industry knowledge, financial knowledge, report length, and plagiarism tendency. The recommendation profitability for each analyst is quite persistent over different holding horizons. The correlation of our industry knowledge measure with analyst and brokerage characteristics is relatively low, suggesting that there is research quality heterogeneity even among analysts with similar background. If the low correlation is driven by time-series variation, analysts' research caliber changes over time. There could be convergence or divergence in sell-side research quality across SOE and non-SOE brokerages over our sample period.

[Insert Table 2 here]

Table 3 displays the characteristics of analysts across brokerages of different ownership categories, including their performance. The average values of kinship are similar across non-SOEs, local SOEs, and central SOEs. While the analysts working in non-SOEs tend to be more experienced than those working in SOEs, they are slightly less educated and perform worse. There are 121, 488, and 347 observations for analysts at non-SOEs, local SOEs and central SOEs, respectively. The central SOE brokerages are larger than local SOE brokerages, potentially due to more government resources. Qin et al. (2018) find that local governments are more profit-oriented while the central government cares more about political goals in China.

[Insert Table 3 here]

Table 4 provides descriptive statistics for variables at the brokerage-year level, including brokerage official characteristics. The mean value of brokerage official promotion is 0.214, meaning that on average, 21.4% of the brokerage officials experience promotions in a given year during the sample period.

[Insert Table 4 here]

For Table 5, we investigate the performance variability of analysts with high and low levels of industry expertise. We first sort our sample analysts into quintiles based on their industry knowledge and then conduct t-tests on the other measures of their performance. Compared with analysts in the bottom quintile, those in the top quintile have significantly higher financial knowledge, tend to plagiarize less, and produce longer analyst reports. The patterns support the validity of our bag-of-words industry knowledge measure for distinguishing competent and incompetent analysts.

[Insert Table 5 here]

Analysts can create value for investors by collecting private information or processing public information. Some studies argue that analysts' value is in their collection of private information (Clement and Tse, 2005; Frankel et al., 2006; Ivkovic and Jegadeesh, 2004), while others cast doubt on the information discovery role of analysts (Kim and Song, 2015; Livnat and Zhang, 2012). As knowledge of vocabulary or jargons is a minimum requirement for fundamental analysis, unqualified analysts may hide their lack of industry knowledge for gathering and interpreting information by copying the content of news or other analysts' reports. This strategy takes little efforts and is not risky in a country of weak protection on intellectual property rights.[8]

The lack of industry knowledge may be one of the reasons for Chinese sell-side analysts' low forecast accuracy, which has been criticized in a Bloomberg article.[9] While Bradley et al. (2017a) show that 73% of US stock forecasts in the US are from analysts with previous work experience and 37% from those with industry-related experience during the period 2008 to 2011, we find that most of our sample analysts lack healthcare industry work experience. For example, Chinese securities regulator fined Wu Chaoze for her unsubstantiated reports, who is the head of research of China Securities Co., Ltd.[10] Wu Chaoze is also the head of the telecommunications research group, but she has neither related degree nor industry work experience.

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[8] China receives very low score on IPR protection. For example, see https://www.gtipa.org/publications/2021/11/30/release-2021-international-property-rights-index

[9] https://www.bloomberg.com/news/articles/2016-05-02/china-stock-analysts-were-among-world-s-worst-amid-surprise-rout

[10] https://news.stcn.com/sd/202012/t20201218_2640416.html

4.2. Connection benefits or cronyism

4.2.1. Analyst performance and political connection

This section reports the results for our hypothesis testing. Table 6 presents the results of our baseline regressions of analysts' performance on their political connection. The coefficients on kinship for piggybacking tendency and recommendation profitability are significant while the ones for other performance measures are not significant, but most of them suggest that politically connected analysts have worse performance, except that politically connected analysts use more financial vocabulary in their reports. Because most of the politically connected analysts are at SOEs, which have more resources and benefits such as subsidies than non-SOEs, the performance of analysts may be driven by these confounding factors. However, coinciding with the anti-corruption campaign, the average research quality of our sample analysts improves after 2015 along some dimensions, including their recommendation profitability.

[Insert Table 6 here]

To mitigate endogeneity issues, we use the DID design in Equation (2) to isolate the effect of losing political connection on analysts' performance. Before showing our DID results, we first examine the strength and relevance of the exogenous shock. Table A2 in Appendix A shows CSRC official turnover in each year. In 2015, 10 CSRC officials were replaced or newly positioned and 4 of them were investigated for corruption and punished by the CCP, which exceeds the turnover in any year before or after 2015. The drastic turnover at the top of CSRC is likely to sever the political connection of many analysts, which is exogenous to performance confounders.

Table 7 reports our DID results for which the dependent variables are analysts' industry knowledge, financial knowledge, report length, plagiarism and piggybacking tendency. The coefficient of the DID terms Post × Kinship is significantly positive for industry knowledge and report length. After the exogenous shock in 2015 that severs many analysts' political ties, the average industry knowledge improves by 15.756 for each one percentage point increase in our kinship measure, which is significant at the 10% level. This result is consistent with Panel A of Figure 2, which shows that the connected analysts increase their industry knowledge more than the unconnected ones.

[Insert Table 7 here]

[Insert Figure 2 here]

Table 8 reports our DID results for which the dependent variables are different specifications of analysts' recommendation profitability. The coefficient for Post × Kinship is positive across all specifications, as well as statistically significant for most columns. Relative to the period before 2015, one percentage point increase in analysts' likelihood of kinship connection with financial regulators increase the one-month abnormal return from following their recommendations by 3.54 after 2015.

[Insert Table 8 here]

The results support the cronyism hypothesis over the connection benefit hypothesis. Although politically connected analysts enjoy more resources, their research quality is not better than nonconnected analysts at lower ranked brokerages, and their research quality relatively improves after they lose their political connection due to the exogenous shock of the anti-corruption campaign. Both the loss of political ties and China's clamp-down on corruption likely reduce the rent seeking at SOEs, which may incentivize the crony analysts to work harder or leave the sell-side sector after 2015. Our results also suggest that top-down monitoring may be effective in reducing corruption (Olken, 2007), and that anti-corruption campaigns may reduce corruption and improve economic efficiency (Colonnelli and Prem, 2022).

In addition, in Figure 3 and 4, we show that the analysts hired after 2015 tend to perform better than those hired before 2015 across all performance measures, except for piggybacking tendency. This provides further evidence that China's crackdown on corruption leads to a more merit-based approach in hiring.

[Insert Figure 3 here]

[Insert Figure 4 here]

Political connection is a barrier to entry into the sell-side market, which protects unqualified analysts from market competition. If the market is efficient, investors that lose money due to unqualified investment recommendations will exit the market and the unqualified analysts will lose their client and their job. While we show large variability in analyst performance in China, Crane and Crotty (2020) find that the majority of sell-side analysts in the US market are skilled. In more democratic countries with higher transparency and less political intervention, unqualified workers are less likely to obtain and stay in high-paying positions than more autocratic countries with more political rent-seeking.

One concern for the exogenous shock is that the new CSRC officials may continue to exchange favors with brokerage officials, so that new connections are formed after old ones are severed due to the anti-corruption campaign. Unlike cyclical political turnover, the anti-corruption campaign not only disrupts smooth successions within the CCP, but also reduces politicians' rent extraction by increasing the costs of corruption. According to the organization Transparency International, China's corruption perception score increases from 37 in 2015 to 45 in 2022, where a higher score indicates less corruption.[11] Zhang (2023) finds that the anti-corruption campaign launched by Xi Jinping reduces the level of corruption in China's judicial system and improves firms' investment and output in areas with poor initial legal infrastructure and in industries with high contract intensity. The campaign effectively reduces nationwide corruption, so cronyism is likely to decrease as the new CSRC and SOE officials are unlikely to abuse their powers as much as their predecessors.

4.2.2. Brokerage director promotion and analyst political connection

The above findings only tell one side of the cronyism story. The CSRC officials' relatives benefit from the analyst positions, but the crony hirings lower brokerages' research quality and financial performance. As SOE officials' salaries are government-controlled, the brokerage managers and directors may not lose much personally after they hire inept employees, and they can increase their promotion prospects after giving the favors to their superiors at CSRCs. This

[11] https://www.transparency.org/en/cpi/2022/index/chn

section reports the relationship between SOE brokerage officials' promotional probability and the crony hiring.

Table 9 reports our whole sample and subsample estimation results for Equation (3). Officials at brokerages with more politically connected analysts, proxied by their average kinship with CSRC officials, are significantly more likely to be promoted, which is only statistically significant before 2015. One percentage point increase in the average analyst kinship measure increases the likelihood of brokerage official promotion by 2.459 percentage points, which is significant at the 5% level. The pattern is robust to alternative control variable specifications.

[Insert Table 9 here]

Table 10 reports our DID estimation results based on Equation (4). The coefficient of Post × Kinship is significantly negative, so brokerage officials who hire politically connected analysts are less likely to be promoted after 2015 than before. The loss of political ties also affects brokerage officials. In an autocracy with ill-defined rights and weak rules, the proceeds of corruption hinges on the officials receiving the bribes remaining in power. The financial regulators personally benefit from the favor exchange, and political rent-seeking can explain politicians' high rates of asset growth, as documented by Fisman et al. (2014) for Italian politicians.

[Insert Table 10 here]

Besides the indirect evidence above, we find direct evidence of brokerage director corruption. Within our sample SOE brokerages, 23 directors of 19 brokerages (15 local SOEs and 4 central SOEs) are accused of misconduct and punished after 2015. Most of them were promoted to highly ranked positions at brokerages, mutual funds and stock exchanges before 2015. These brokerages' industry knowledge score increased from 17.99 to 36.65, and their employee turnover rate increased from 9.92% to 11.06% on average, from the period before to that after 2015. Among them, 13 directors are investigated and charged with corruption by the Central Commission for Discipline Inspection (CCDI), the highest anti-corruption government body in China. The additional evidence suggests that securities regulators promote brokerage directors in their exchange of favors, and these directors tend to engage in various forms of rent-seeking.

None of the directors above are charged with giving positions to unqualified analysts, though. The cronyism we report is a relatively mild form of corruption, and is quite indirect and difficult to uncover. In contrast to the exchange of favors between princeling firms and local officials in Chen and Kung (2019), CSRC officials are much lower ranked than the supreme rulers in the Politburo, and employment opportunities are a much less valuable form of bribe than the cheap land given to the princelings. However, corruption-prone directors are likely to misuse their power in many ways, consistent with both their corruption charges and the improvement in their brokerages' research quality after 2015.

5. Additional tests

5.1. Cronyism and financial market efficiency

In this section, we test whether the crony hiring has real effects on market efficiency. Previous studies document the distortionary effects of cronyism on the public sector (Xu, 2018) and the private sector (Moon and Schoenherr, 2022; Nian and Wang, 2023). In addition, countries with weak legal institutions tend to have smaller, less valuable and less efficient capital markets (La Porta et al., 1997, 2002; Shleifer and Wolfenzon, 2002), where information intermediaries tend to be less specialized. China has relatively weak legal institutions and investor protection, as well as a less competitive capital market compared with the U.S. (Allen et al., 2005; Cheung et al., 2006; Jiang et al., 2010;). Does low-quality investment research from crony analysts also contribute to the inefficient capital market in China?

Studies on the US market show that analysts are important information intermediaries who can affect firm policies (Derrien and Kecskes, 2013; Guo et al., 2019). We test how crony analysts affect Chinese financial market efficiency in the baseline and DID tests specified by Equation (5) to (7).

$$\text{Price informativeness}_{j,t} = \alpha + \beta \cdot \text{Post}_{j,t} + \gamma \cdot \text{Controls}_{j,t} + \delta_t + \eta_j + \varepsilon_{j,t} \quad (5)$$

$$\text{Price informativeness}_{j,t} = \alpha + \beta \cdot \text{Political connection}_{j,t} + \gamma \cdot \text{Controls}_{j,t} + \delta_t + \eta_j + \varepsilon_{j,t} \quad (6)$$

$$\text{Price informativeness}_{j,t} = \alpha + \beta_1 \cdot \text{Political connection}_{j,t} \cdot \text{Post}_t + \beta_2 \cdot \text{Political connection}_{j,t} + \beta_3 \cdot \text{Post}_t + \gamma \cdot \text{Controls}_{j,t} + \delta_t + \eta_j + \varepsilon_{j,t} \quad (7)$$

Where the subscript j denotes each healthcare firm. The firm year level $\text{Political connection}_{j,t}$ measures the intensity of firms receiving coverage from politically connected analysts. Equation (6) is estimated first on the whole sample and then on the pre-2015 and post-2015 subsamples.

We proxy for stock price informativeness by Amihud's stock illiquidity measure (2002). We control for factors that could affect firms' information asymmetry, including firms' market capitalization, stock price and return volatility, momentum, trading volume, R&D intensity, institutional ownership, book to market, leverage, ROA, number of covering analysts, following Harford et al. (2019) and Weller's (2018). Because the shares of SOEs face more trading restrictions, we also control for firms' ownership category. In addition, we use firm and year fixed effects to control for time invariant or macroeconomic confounders. Besides CCP officials from the CSRC, we also include financial regulators from the Shanghai Stock Exchange and Shenzhen Stock Exchange who are higher ranked than SOE brokerage officials.

Relative to private brokerages, large SOE brokerages have comparative advantage in broker services, which are often bundled with security research services, and more than 70% of money in the Chinese stock market is from retail investors, institutional investors are likely to continue using the service of a brokerage even if its research in certain industries is not useful due to crony hiring. In addition, the Chinese government has administrative monopoly on the financial market, so the unqualified financial analysts crowd out more competent competitors due to the limited brokerage licenses and jobs available. The lower research quality means less informative analysis on companies and less timely responses to changes in fundamentals, but the connected analysts may have access to more insider information that increases the price informativeness of the stocks they cover, so crony hiring has overall ambiguous effects on financial market efficiency.

In Table 11, stock illiquidity is positively correlated with the intensity of coverage from politically connected analysts, which is significant at the 5% level before 2015 but insignificant after 2015. Before 2015, one percentage point increase in the average kinship of covering analysts is associated with 1.79 percentage points' increase in the stock's Amihud illiquidity measure. Before the anti-corruption campaign, stocks most intensely covered by politically connected analysts have lower informational efficiency, which may be driven by selection effects or the relatively worse research coverage provided by politically connected analysts.

[Insert Table 11 here]

To sharpen the identification, we use DID tests based on the exogenous shock of the anti-corruption campaign and report the results in Table 12. In Column (1) and (2), the time dummy Post has significantly negative coefficients. After 2015, the average illiquidity of our sample firms decreases by around 0.24, which suggests that the anti-corruption campaign improves China's financial market efficiency by reducing cronyism and low-quality research. Consistent with our cronyism hypothesis, the DID term $\text{Political connection}_{j,t} \cdot \text{Post}_t$ has negative coefficients, suggesting that the price informativeness improves for stocks that are more intensely covered by politically connected analysts after 2015, though the coefficients are not statistically significant.

[Insert Table 12 here]

A larger number of analysts covering an industry can improve information efficiency in the U.S. market (Merkley et al., 2017). However, we show that politically connected analysts do not contribute to financial market efficiency. Due to the state monopoly on brokerage licenses and business resources in our context, crony hires can crowd out potentially more competent analysts and cronyism may also negatively affect analysts' effort level by lowering competition. However, the cronyism has relatively limited impact on the financial market, possibly because investors can select the research service from competent analysts or conduct their own analysis. In addition, the Chinese market has capital control, a high percentage of retail investors and stringent short-sale constraints (Mei et al., 2009), where the roles of institutional investors are relatively limited.[12] These characteristics contribute to speculations, leading to drastic bubbles and busts in the A-share market (Xiong and Yu (2011), which is another reason for the negligible effects of crony hiring on average.

5.2. Cronyism and brokerage performance

Besides its effects on financial market efficiency, we also test the impact of the cronyism on brokerage performance, to address the concern that some brokerage managers may hire unqualified analysts connected with financial regulators to obtain more business resources such as licenses, which can benefit their firms. We report the relationship between analysts' political connections and brokerage profitability in Table 13 and that between analysts' political connections and brokerage wage level in Table 14. Neither yields statistically significant results. On average, crony security analysts do not benefit their employers, while the SOE managers personally benefit from the hiring.

[Insert Table 13 here]

[Insert Table 14 here]

6. Robustness tests

Our results are robust to various variable and estimation method specifications. We change our proxy for stock price informativeness to Weller's price jump ratio (2018). We rerun the baseline and DID tests using winsorized kinship and analyst performance. We also use a binary variable $Kinship_{cat}$ that equals 1 when the continuous kinship measure is bigger or equals 0.7. We also change age to a dummy variable Age_{cat}, which equals 1 if the official's age is between 50 and 60. The results do not change qualitatively.

Instead of using linear probability models, we use logistic regressions to estimate the likelihood of brokerage official promotions, with various specifications for control variables. We also regress brokerage official promotion on lagged brokerage-level kinship. The results

[12] Institutional investors own only 18.7% of Chinese A-shares in 2021 and less than 10% in 2014 (Lin and Puchniak, 2021).

are qualitatively similar to the main results, which are omitted for the sake of brevity.

7. Conclusions

We document a form of connection-based corrupt hiring at state-owned brokerages and show that the nonmeritocratic hires tend to lack industry knowledge and investment insight, which negatively affects financial market efficiency and imposes real costs on Chinese A-share investors. In exchange for favors, securities regulators are likely to promote brokerage directors after they hire unqualified analysts. However, political connection is only one of the possible explanations for unqualified professionals in a state-regulated industry, where political barriers to entry and ill-defined property rights result in imperfect market competition. In addition, we only investigate one form of corrupt hiring at Chinese SOE brokerages. Besides hiring analysts connected with financial regulators, SOE brokerage directors may hire analysts connected with themselves to transfer resources to their networks. In addition, not all CSRC officials have the power to appoint personnel so that some SOE directors may receive other forms of benefits in return, such as business advantages or nonpublic information.

Unlike Weaver (2021), we find that corrupt hires are less competent and corrupt hiring negatively affects market efficiency. Compared with community health workers in Weaver’s sample, financial analysts require more specialized knowledge and higher skills to deliver useful services to investors, and their performance variation is much more significant. In addition, financial analysts are likely to have more rent extraction opportunities on the job than community health workers. For example, security analysts could issue biased reports for brokerage commissions and investment banking fees (Groysberg et al., 2011). Besides the difference in worker skill, task complexity, and autonomy, our results differ from Weaver's (2021) due to the different institutional contexts. The inter-generational correlations of wealth are relatively high in China, so wealth may not indicate individuals' job performance, especially where abstract thinking and initiatives are required. In autocratic countries with low social mobility, corruption based on political connections creates significant distortions in resource allocation and negatively impacts social welfare.

Our findings also suggest low political accountability in Chinese SOEs and regulatory agencies. Stable autocracies generally have some democratic institutions at the grassroots level, such as the elections of village heads in China to address the information asymmetry between central and local officials (Martinez-Bravo et al., 2022). CSRC officials’ rent extraction suggests that within-party monitoring is less effective than villages' grassroots monitoring. This may be due to the different political mobility of SOE officials and village heads in China. Although both villages and SOEs have autonomy and local activity, village heads are not eligible for promotions within the CCP, so village elections, unlike the appointment of SOE officials, do not threaten the rent extraction ability of the existing political elites. Besides reducing information asymmetry between local and central officials, the vertical control of SOEs may also maintain political elites’ dynastic rents by incentivizing SOE officials to pay bribes to win the political tournament.

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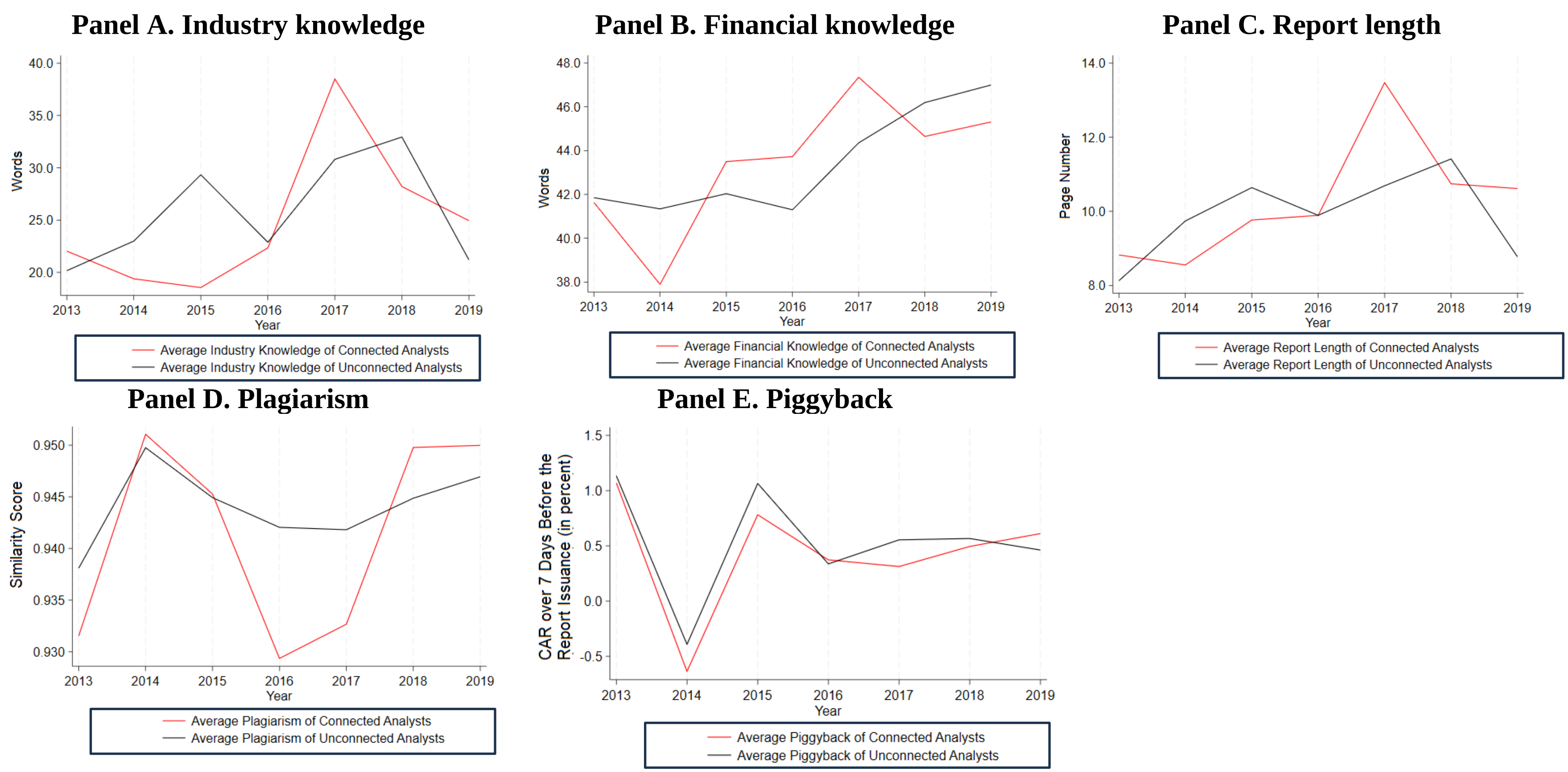
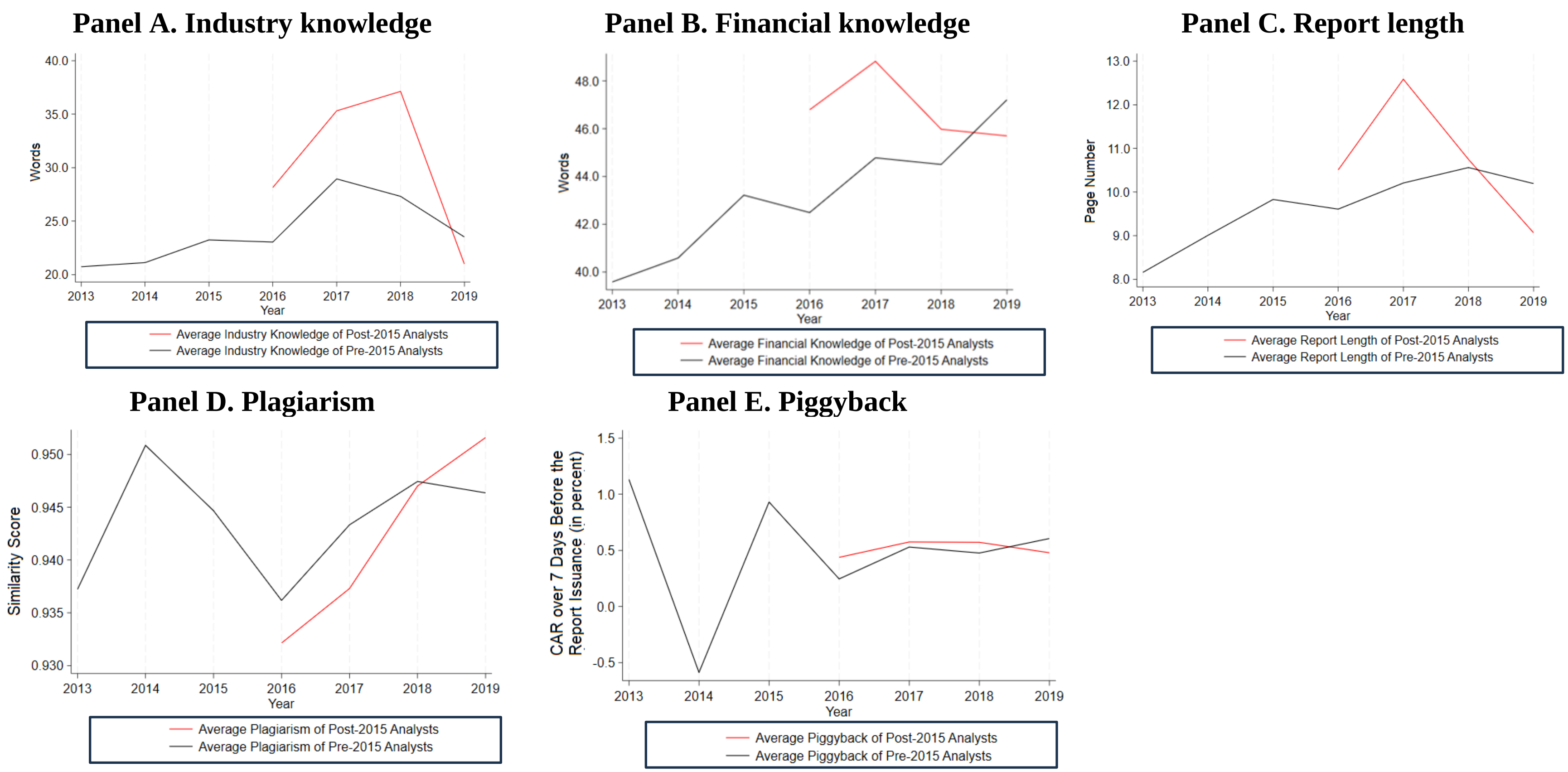
Figure 2. Time trends of performance of analysts who are connected vs. those who are nonconnected.



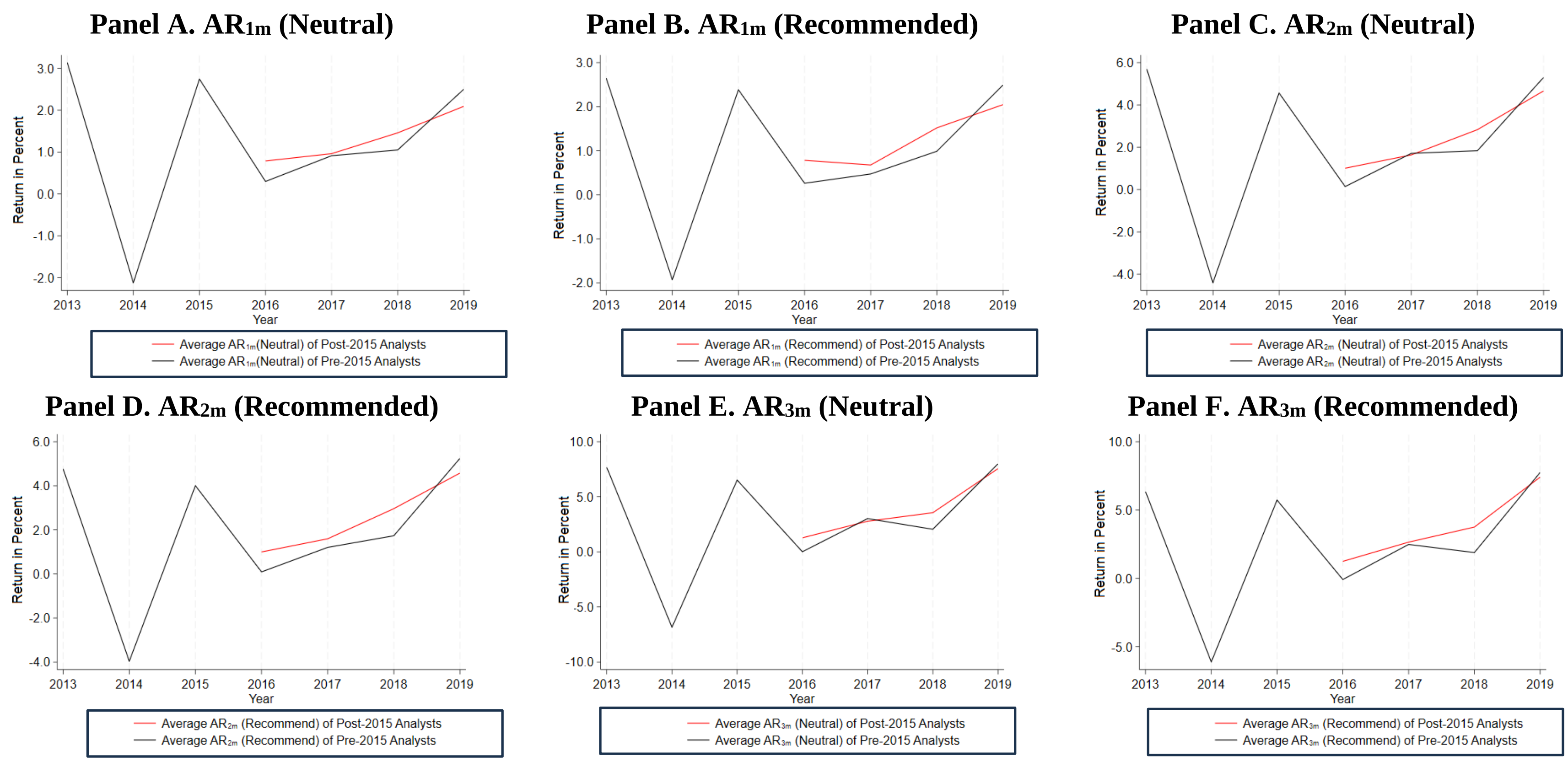
Notes: This figure shows the performance time trends of respectively connected und nonconnected analysts. Analyst performance can be measured by: (1) Industry Knowledge: the average number of occurrences of medical words by an analyst in a report written by the analyst in a particular year; (2) Financial Knowledge: the average number of occurrences of financial technical words in a report written by the analyst in a particular year; (3) Report Length: the average number of pages in a report written by the analyst in a particular year; (4) Plagiarism: the average of the highest cosine similarity between the reports, written by an analyst within a specific year, and other reports within the seven days preceding its publication (excluding the reports written by the same authors and those written by some of the same authors in the same brokerages; (5) Piggyback is cumulative abnormal return of the seven days before analyst report issuance. Connected analysts are defined as analysts whose kinship scores are bigger than 0.7; others are nonconnected analysts.

Figure 3. Time trends of performance of analysts who started to work in the security sector before vs. after 2015.



Notes: This figure shows the performance time trends of analysts who started to work in the security sector respectively before and after 2015. Analyst performance can be measured by: (1) Industry Knowledge: the average number of occurrences of medical words by an analyst in a report written by the analyst in a particular year; (2) Financial Knowledge: the average number of occurrences of financial technical words in a report written by the analyst in a particular year; (3) Report Length: the average number of pages in a report written by the analyst in a particular year; (4) Plagiarism: the average of the highest cosine similarity between the reports, written by an analyst within a specific year, and other reports within the seven days preceding its publication (excluding the reports written by the same authors and those written by some of the same authors in the same brokerages; (5) Piggyback is cumulative abnormal return for seven days before analyst report issuance. Pre-2015 refers to the analysts who started to work in security sector before 2015, and Post-2015 refers to the analysts who started to work in security sector after 2015.

Figure 4. Time trends of recommendation profitability of analysts before vs. after 2015.



Notes: This figure shows the time trends of recommendation profitability of analysts who started to work in the security sector respectively before and after 2015. Recommendation profitability is measured using AR, calculated by multiplying the corresponding abnormal return of following analyst recommendation and holding for the respective periods as indicated in subscript (e.g. "1m" means one month), with a ternary variable, which takes the value 1 if the rating is better than the threshold, as indicated in the bracket in the header of the corresponding column; 0 if the rating equals the threshold; -1 if the rating is worse than the threshold. Pre-2015 refers to the analysts who started to work in security sector before 2015, and Post-2015 refers to the analysts who started to work in security sector after 2015.

Table 1

Descriptive statistics for analyst performance.

This table reports the summary statistics of the variables related to analyst performance analysis in this paper. We report the number of observations (Obs.), mean (Mean), standard deviation (Std. Dev.), minimum value (Min), 1st percentile (P1), 50th percentile (P50), and 99th percentile (P99), maximum value (Max.), skewness (Skew.), kurtosis (Kurt.). All variables are defined in Table A1 of Appendix A. All variables in this table are at the analyst-brokerage-year level.

	Obs.	Mean	Std. Dev.	Min	P1	P50	P99	Max	Skew.	Kurt.
Panel A: Full sample										
Kinship	956	0.633	0.180	0.134	0.141	0.675	0.922	0.944	-0.732	2.814
Employment at Central SOE	956	0.363	0.481	0	0	0	1	1	0.570	1.325
Employment at Local SOE	956	0.510	0.500	0	0	1	1	1	-0.042	1.002
Employment at SOE	956	0.873	0.333	0	0	1	1	1	-20.250	6.046
Analyst Experience	956	4.856	3.292	0	0	4	14	16	0.712	2.951
Analyst Education	956	0.934	0.248	0	0	1	1	1	-3.499	13.245
Portfolio Complexity	956	11.017	18.098	0	0	3	79	190	3.625	23.271
Industry Knowledge	956	24.835	26.109	0.500	2	18	146.500	320	3.979	29.695
Financial Knowledge	956	43.860	11.455	6	17.667	44	71	100	0.118	3.896
Report Length	956	9.906	8.080	2	2	7.873	44	81	3.240	20.004
Plagiarism	956	0.944	0.037	0.492	0.793	0.952	0.990	1	-3.836	33.343
Piggyback	536	0.064	0.159	-0.307	-0.216	0.055	0.464	1.327	1.896	15.508
AR_{1m} (Neutral)	536	0.969	2.742	-5.883	-5.170	0.814	8.609	21.509	1.233	9.750
AR_{1m} (Recommend)	536	0.797	2.625	-16.069	-5.788	0.680	7.993	13.415	-0.015	7.374
AR_{2m} (Neutral)	536	1.643	5.193	-11.121	-10.498	1.398	15.449	26.342	0.710	5.251
AR_{2m} (Recommend)	536	1.427	4.951	-12.425	-10.498	1.168	14.673	25.333	0.529	4.786
AR_{3m} (Neutral)	536	2.287	7.607	-16.242	-14.388	2.053	23.669	40.141	0.658	5.072
AR_{3m} (Recommend)	536	1.970	7.272	-19.029	-14.388	1.663	22.061	39.662	0.540	4.961
Panel B: Connected Analysts										
Kinship	400	0.797	0.058	0.701	0.701	0.793	0.944	0.944	0.381	2.536
Employment at Central SOE	400	0.393	0.489	0	0	0	1	1	0.440	1.194
Employment at Local SOE	400	0.475	0.500	0	0	0	1	1	0.100	1.010
Employment at SOE	400	0.868	0.339	0	0	1	1	1	-2.168	5.700

Table 1
(*continued*)

	Obs.	Mean	Std. Dev.	Min	P1	P50	P99	Max	Skew.	Kurt.
Panel B: Connected Analysts										
Analyst Experience	400	5.263	3.354	0	0	5	14.500	16	0.680	3.010
Analyst Education	400	0.920	0.272	0	0	1	1	1	-3.096	10.587
Portfolio Complexity	400	10.912	20.796	0	0	2	106	190	4.179	26.999
Industry Knowledge	400	26.617	32.244	.5	2.250	17.197	168.700	320	4.018	26.529
Financial Knowledge	400	44.135	11.563	6	17.500	44.659	71.200	79	-0.160	3.130
Report Length	400	10.460	9.653	2	2	8	56	81	3.435	19.698
Plagiarism	400	0.942	0.035	0.740	0.799	0.951	0.991	0.993	-2.187	10.401
Piggyback	214	0.073	0.153	-0.216	-0.187	0.062	0.456	0.466	0.395	2.577
AR_{1m} (Neutral)	214	1.165	2.953	-5.883	-5.883	0.730	10.624	13.745	0.722	4.763
AR_{1m} (Recommend)	214	1.079	2.854	-5.883	-5.883	0.726	8.609	13.415	0.633	4.819
AR_{2m} (Neutral)	214	2.071	5.847	-11.121	-11.121	1.407	21.265	25.426	0.764	4.654
AR_{2m} (Recommend)	214	1.959	5.608	-11.121	-11.121	1.407	20.066	25.333	0.738	4.796
AR_{3m} (Neutral)	214	2.858	8.644	-15.596	-14.388	1.670	31.103	40.141	0.833	4.951
AR_{3m} (Recommend)	214	2.636	8.325	-15.596	-14.388	1.587	29.291	39.662	0.795	5.053
Panel C: Unconnected Analysts										
Kinship	556	0.515	0.152	0.134	0.141	0.562	0.695	0.699	-0.743	2.543
Employment at Central SOE	556	0.342	0.475	0	0	0	1	1	0.667	1.445
Employment at Local SOE	556	0.536	0.499	0	0	1	1	1	-0.144	1.021
Employment at SOE	556	0.878	0.328	0	0	1	1	1	-2.306	6.316
Analyst Experience	556	4.563	3.218	0	0	4	13	14	0.736	2.877
Analyst Education	556	0.944	0.230	0	0	1	1	1	-3.872	15.995
Portfolio Complexity	556	11.092	15.897	0	0	4	70	115	2.494	10.649
Industry Knowledge	556	23.553	20.533	1	2	18.829	90.867	186	2.627	14.451
Financial Knowledge	556	43.662	11.383	11.333	17.667	43.731	70	100	0.327	4.516
Report Length	556	9.508	6.707	2	2	7.822	36	51	2.203	9.867
Plagiarism	556	0.945	0.038	0.492	0.793	0.953	0.990	1	-4.745	44.859
Piggyback	322	0.058	0.164	-0.307	-0.237	0.052	0.477	1.327	2.732	22.442
AR_{1m} (Neutral)	322	0.838	2.588	-5.883	-4.480	0.818	7.993	21.509	1.688	15.217
AR_{1m} (Recommend)	322	0.609	2.448	-16.069	-5.170	0.667	7.053	9.495	-0.780	9.722
AR_{2m} (Neutral)	322	1.358	4.697	-11.121	-9.553	1.398	14.349	26.342	0.525	5.389
AR_{2m} (Recommend)	322	1.074	4.435	-12.425	-9.924	1.075	14.278	15.449	0.095	3.705
AR_{3m} (Neutral)	322	1.908	6.820	-16.242	-13.938	2.112	18.603	33.463	0.296	4.264
AR_{3m} (Recommend)	322	1.528	6.455	-19.029	-14.093	1.736	17.692	22.061	0.021	3.515

Table 2

Analyst performance correlations.

This table shows correlations across the full sample for the key variables about analysts as defined in Table A1 of Appendix A. The granularity of the regression is analyst-brokerage-year. *, **, and ***denote significance at the 10%, 5%, and 1% level, respectively.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1) Kinship	1.00													
(2) Central SOE	0.00	1.00												
(3) Local SOE	-0.01	-0.79***	1.00											
(4) Industry Knowledge	-0.01	0.03	0.00	1.00										
(5) Financial Knowledge	0.06	0.20***	-0.17***	0.25***	1.00									
(6) Report Length	0.04	0.08*	-0.09**	0.74***	0.37***	1.00								
(7) Plagiarism	-0.04	-0.10***	0.11***	-0.50***	-0.37***	-0.71***	1.00							
(8) Piggyback	-0.03	-0.06	0.05	-0.03	-0.01	-0.01	-0.02	1.00						
(9) AR_{1m} (Neutral)	0.00	-0.05	0.05	-0.05	0.03	-0.01	-0.05	0.69***	1.00					
(10) AR_{1m} (Recommend)	0.06	-0.03	0.02	-0.08*	0.07*	-0.01	-0.04	0.43***	0.86***	1.00				
(11) AR_{2m} (Neutral)	0.02	-0.04	0.05	-0.04	0.07	0.01	-0.07	0.66***	0.98***	0.88***	1.00			
(12) AR_{2m} (Recommend)	0.05	-0.03	0.03	-0.05	0.10**	0.01	-0.07	0.51***	0.88***	0.96***	0.93***	1.00		
(13) AR_{3m} (Neutral)	0.02	-0.03	0.05	-0.02	0.08*	0.02	-0.07*	0.65***	0.96***	0.87***	0.99***	0.92***	1.00	
(14) AR_{3m} (Recommend)	0.04	-0.03	0.04	-0.04	0.12***	0.02	-0.08*	0.53***	0.86***	0.93***	0.92***	0.99***	0.93***	1.00

Table 3

Descriptive statistics for analyst characteristics by brokerage ownership categories.

This table reports the distribution of connected and nonconnected analysts in central, local SOEs and non-SOE brokerages in this paper, as well as the summary statistics of their respective characteristics and performance. We report the number of observations (Obs.), mean (Mean), standard deviation (Std. Dev.), minimum value (Min), 1st percentile (P1), 50th percentile (P50), and 99th percentile (P99), maximum value (Max.), skewness (Skew.), kurtosis (Kurt.). All variables are defined in Table A1 of Appendix A. All variables in this table are at the analyst-brokerage-year level.

	Obs.	Mean	Std. Dev.	Min	P1	P50	P99	Max	Skew.	Kurt.
Panel A: Non-SOE										
Kinship	121	0.634	0.182	0.141	0.141	0.676	0.854	0.896	-0.824	2.820
Analyst Experience	121	5.223	3.646	0	0	5	15	16	0.605	2.757
Analyst Education	121	0.917	0.276	0	0	1	1	1	-3.032	10.190
Portfolio Complexity	121	7.405	10.978	0	0	3	55	63	2.769	11.843
Industry Knowledge	121	21.718	23.560	1	3	15.571	149	163.400	3.546	19.354
Financial Knowledge	121	43.302	10.836	15	18	43	70	74	0.115	3.638
Report Length	121	10.734	8.921	2	3	8	44	44.500	1.983	6.938
Plagiarism	121	0.942	0.033	0.758	0.847	0.949	0.988	0.990	-2.181	10.636
Piggyback	60	0.065	0.128	-0.187	-0.187	0.057	0.348	0.348	0.034	2.237
AR_{1m} (Neutral)	60	0.953	2.181	-4.039	-4.039	1.097	6.286	6.286	-0.239	2.969
AR_{1m} (Recommend)	60	0.947	2.183	-4.039	-4.039	1.097	6.286	6.286	-0.232	2.958
AR_{2m} (Neutral)	60	1.384	4.274	-8.589	-8.589	1.817	12.822	12.822	-0.223	3.189
AR_{2m} (Recommend)	60	1.385	4.273	-8.589	-8.589	1.817	12.822	12.822	-0.224	3.191
AR_{3m} (Neutral)	60	1.537	6.433	-13.481	-13.481	1.887	19.105	19.105	-0.257	3.357
AR_{3m} (Recommend)	60	1.548	6.430	-13.481	-13.481	1.887	19.105	19.105	-0.262	3.366
Panel B: Local SOEs										
Kinship	488	0.633	0.187	0.134	0.167	0.675	0.891	0.913	-0.671	2.781
Analyst Experience	488	4.625	3.234	0	0	4	14	15	0.794	3.037
Analyst Education	488	0.932	0.251	0	0	1	1	1	-3.444	12.860
Portfolio Complexity	488	13.025	21.826	0	0	4	115	190	3.443	19.518
Industry Knowledge	488	24.575	22.236	0.500	1.500	19.100	114.600	208	3.057	18.749
Financial Knowledge	488	42.587	11.311	11.333	17.333	43.133	69	100	0.351	4.817
Report Length	488	9.313	7.401	2	2	7.702	41.500	73	3.655	24.949
Plagiarism	488	0.946	0.032	0.707	0.793	0.955	0.990	1	-2.810	16.169
Piggyback	286	0.072	0.175	-0.216	-0.204	0.074	0.491	1.327	2.534	18.507

Table 3
(*continued*).

	Obs.	Mean	Std. Dev.	Min	P1	P50	P99	Max	Skew.	Kurt.
Panel B: Local SOEs										
AR_{1m} (Neutral)	286	1.105	2.802	-5.883	-4.480	0.897	9.495	21.509	1.921	13.546
AR_{1m} (Recommend)	286	0.844	2.699	-16.069	-5.788	0.684	8.609	13.415	-0.188	9.785
AR_{2m} (Neutral)	286	1.864	5.162	-11.121	-9.553	1.582	20.066	26.342	0.945	6.048
AR_{2m} (Recommend)	286	1.576	4.925	-12.425	-10.118	1.221	15.449	25.333	0.690	5.410
AR_{3m} (Neutral)	286	2.641	7.585	-15.596	-13.938	2.279	29.291	40.141	0.806	5.630
AR_{3m} (Recommend)	286	2.246	7.246	-19.029	-14.388	1.967	23.669	39.662	0.683	5.694
Panel C: Central SOE										
Kinship	347	0.633	0.183	0.141	0.177	0.675	0.907	0.944	-0.793	2.858
Analyst Experience	347	5.052	3.228	0	0	5	13	15	0.631	2.900
Analyst Education	347	0.942	0.233	0	0	1	1	1	-3.796	15.411
Portfolio Complexity	347	9.452	13.383	0	0	3	61	66	2.063	7.091
Industry Knowledge	347	26.287	31.424	2	2.500	18	174	320	4.200	29.854
Financial Knowledge	347	45.845	11.622	6	17.667	45.308	71.400	79	-0.208	3.205
Report Length	347	10.452	8.631	2	3	8.015	48	81	3.260	20.468
Plagiarism	347	0.940	0.043	0.492	0.784	0.951	0.993	1	-4.495	39.754
Piggyback	190	0.051	0.142	-0.307	-0.307	0.045	0.441	0.441	0.273	2.978
AR_{1m} (Neutral)	190	0.769	2.808	-5.883	-5.883	0.624	10.624	10.624	0.408	4.047
AR_{1m} (Recommend)	190	0.679	2.647	-5.883	-5.883	0.521	7.053	10.624	0.313	3.919
AR_{2m} (Neutral)	190	1.391	5.506	-11.121	-11.121	1.125	21.265	21.265	0.551	4.270
AR_{2m} (Recommend)	190	1.218	5.199	-11.121	-11.121	0.808	14.673	21.265	0.460	4.105
AR_{3m} (Neutral)	190	1.991	7.980	-16.242	-15.517	1.661	31.103	31.103	0.600	4.370
AR_{3m} (Recommend)	190	1.688	7.575	-16.242	-14.388	1.040	22.061	31.103	0.501	4.137

Table 4
Descriptive statistics at the brokerage level.

This table reports the summary statistics of the variables involved in official promotion analysis in this paper. We report the number of observations (Obs.), mean (Mean), standard deviation (Std. Dev), minimum value (Min.), 1st percentile (P1), 50th percentile (P50), and 99th percentile (P99), maximum value (Max.), skewness (Skew.), kurtosis (Kurt.). All variables are defined in Table A1 of Appendix A. All variables in this table are at the official/brokerage-year level.

Variables	Obs.	Mean	Std. Dev.	Min	P1	P50	P99	Max	Skew.	Kurt.
Official Promotion	2583	0.214	0.410	0	0	0	1	1	1.396	2.950
Kinship	3727	0.612	0.135	0.141	0.144	0.632	0.837	0.887	-0.877	3.980
Age	3727	49.831	6.936	29	35	50	66	75	0.169	2.918
Gender	3727	0.858	0.350	0	0	1	1	1	-2.046	5.185
Official Education	3727	0.798	0.401	0	0	1	1	1	-1.486	3.209
Certified	3727	0.464	0.499	0	0	0	1	1	0.144	1.021
Industry Knowledge	3727	24.329	18.701	1	3	19.263	114.600	116.167	2.715	12.149
Financial Knowledge	3727	44.716	8.865	18	21.25	44.138	64.792	64.987	-0.100	3.102
Report Length	3727	9.053	4.924	3	3	8.049	33	44.458	2.907	17.560
Plagiarism	3727	0.946	0.023	0.851	0.877	0.951	0.992	1	-1.152	4.959
Brokerage Revenue	3727	10363.700	10259.900	764.900	941.340	6086.570	43139.700	56013.400	1.660	5.475

Table 5

T-tests on analyst performance.

This table shows the variability in analyst performance. We first sort our sample analysts into quintiles based on their industry knowledge, and then conduct t tests on the other measures of their performance. Column "Top" contains the mean of the performance measure of the analysts who are in the top quintile in terms of industry knowledge; column "Bottom" contains the mean of the performance measure of the analysts who are in the bottom quintile in terms of industry knowledge. All variables are defined in Table A1 of Appendix A. The granularity of the t-tests is analyst-brokerage-year. Standard errors are in parentheses. *, **, and ***denote significance at the 10%, 5%, and 1% level, respectively.

	Top	Bottom	Diff-in-Mean
Financial Knowledge	45.196	37.595	7.601***
			(1.335)
Plagiarism	0.918	0.964	-0.046***
			(0.004)
Report Length	16.676	4.421	12.255***
			(0.743)
Piggyback	0.054	0.018	0.036
			(0.025)
AR_{1m} (Neutral)	0.526	0.306	0.221
			(0.380)
AR_{1m} (Recommend)	0.199	0.437	-0.238
			(0.408)
AR_{2m} (Neutral)	0.909	0.190	0.720
			(0.716)
AR_{2m} (Recommend)	0.598	0.487	0.111
			(0.707)
AR_{3m} (Neutral)	1.432	0.135	1.298
			(1.046)
AR_{3m} (Recommend)	0.910	0.579	0.331
			(1.026)

Table 6

Analyst performance and political connection: baseline regressions.

This table shows regression results of analyst performance on Kinship in Panel A and Post in Panel B. The dependent variable is analyst performance, measured by: (1) Industry Knowledge: the average number of occurrences of medical words by an analyst in a report written by the analyst in a particular year; (2) Financial Knowledge: the average number of occurrences of financial technical words in a report written by the analyst in a particular year; (3) Report Length: the average number of pages in a report written by the analyst in a particular year; (4) Plagiarism: the average of the highest cosine similarity between the reports, written by an analyst within a specific year, and other reports within the seven days preceding its publication (excluding the reports written by the same authors and those written by some of the same authors in the same brokerages); (5) Piggyback is cumulative abnormal return for seven days before analyst report issuance; (6) AR is calculated by multiplying the corresponding abnormal return of following analyst recommendation and holding for the respective periods as indicated in subscript (e.g. "1m" means one month), with a ternary variable, which takes the value 1 if the rating is better than the threshold, as indicated in the bracket in the header of the corresponding column; 0 if the rating equals the threshold; -1 if the rating is worse than the threshold. Kinship is a proxy of maximum kinship between an analyst and the members of CSRC management. Post equals 1 for observations after 2015, and 0 otherwise. All control variables are defined in Table A1 of Appendix A. The granularity of the regression is analyst-brokerage-year. Robust standard errors are in parentheses. *, **, and ***denote significance at the 10%, 5%, and 1% level, respectively.

	(1) Industry Knowledge	(2) Financial Knowledge	(3) Report Length	(4) Plagiarism	(5) Piggyback	(6) AR_{1m} (Neutral)	(7) AR_{2m} (Neutral)	(8) AR_{3m} (Neutral)	(9) AR_{1m} (Recommend)	(10) AR_{2m} (Recommend)	(11) AR_{3m} (Recommend)
Panel A											
Kinship	-2.288	3.814*	0.975	-0.006	-0.024	0.112	0.794	1.011	0.788	1.410	1.589
	(4.357)	(2.187)	(1.239)	(0.006)	(0.050)	(0.793)	(1.342)	(1.935)	(0.664)	(1.166)	(1.707)
Analyst Experience	0.400	-0.002	0.121	0	-0.004**	-0.015	-0.007	-0.009	0.027	0.051	0.057
	(0.284)	(0.124)	(0.086)	(0)	(0.002)	(0.035)	(0.063)	(0.093)	(0.030)	(0.058)	(0.087)
Analyst Education	-7.547	-1.998	-2.428	0.008	-0.010	-0.547	-0.920	-0.962	-0.639	-1.052	-1.204
	(4.950)	(2.133)	(1.596)	(0.007)	(0.029)	(0.492)	(1.051)	(1.605)	(0.485)	(1.039)	(1.591)
Portfolio Complexity	0.039	0.035**	-0.030***	0***	0	0.005	0.013	0.022*	0	0.007	0.014
	(0.030)	0(.016)	(0.009)	(0)	(0)	(0.004)	(0.008)	(0.012)	(0.005)	(0.008)	(0.011)
Observations	678	678	678	678	536	536	536	536	536	536	536
R-squared	0.013	0.009	0.023	0.015	0.009	0.003	0.005	0.004	0.008	0.007	0.005
Panel B											
Post	2.015	3.107***	0.108	0.003	-0.132***	0.035	0.687	1.552*	0.307	1.177**	2.197***
	(1.891)	(0.911)	(0.581)	(0.003)	(0.014)	(0.312)	(0.570)	(0.828)	(0.282)	(0.527)	(0.770)
Analyst Experience	0.355	-0.037	0.123	0	-0.002	-0.015	-0.015	-0.030	0.025	0.037	0.027
	(0.290)	(0.121)	(0.086)	(0)	(0.002)	(0.034)	(0.063)	(0.092)	(0.030)	(0.058)	(0.087)
Analyst Education	-7.445	-1.951	-2.439	0.008	-0.008	-0.549	-0.939	-0.996	-0.653	-1.086	-1.254
	(4.993)	(2.206)	(1.604)	(0.007)	(0.025)	(0.494)	(1.053)	(1.599)	(0.490)	(1.043)	(1.584)
Portfolio Complexity	0.038	0.027*	-.031***	0***	0	0.004	0.012	0.019	-0.001	0.005	0.011
	(0.029)	(0.015)	(0.009)	(0)	(0)	(0.004)	(0.008)	(0.012)	(0.005)	(0.008)	(0.011)
Observations	678	678	678	678	536	536	536	536	536	536	536
R-squared	0.014	0.023	0.023	0.016	0.152	0.003	0.007	0.013	0.008	0.016	0.023

Table 7
Analyst performance and political connection: DID tests.

This table shows the difference-in-difference test results. The dependent variable is analyst performance, measured by: (1) Industry Knowledge: the average number of occurrences of medical words by an analyst in a report written by the analyst in a particular year; (2) Financial Knowledge: the average number of occurrences of financial technical words in a report written by the analyst in a particular year; (3) Report Length: the average number of pages in a report written by the analyst in a particular year; (4) Plagiarism: the average of the highest cosine similarity between the reports, written by an analyst within a specific year, and other reports within the seven days preceding its publication (excluding the reports written by the same authors and those written by some of the same authors in the same brokerages); (5) Piggyback is cumulative abnormal return for seven days before analyst report issuance. Kinship is a continuous measure that serves as a proxy of maximum kinship between an analyst and the members of China Securities Regulatory Commission (CSRC) management. Post equals 1 for observations after 2015, and 0 otherwise. All control variables are defined in Table A1 of Appendix A. The granularity of the regression is analyst-brokerage-year. Robust standard errors are in parentheses. *, **, and ***denote significance at the 10%, 5%, and 1% level, respectively.

	(1) Industry Knowledge	(2) Financial Knowledge	(3) Report Length	(4) Plagiarism	(5) Piggyback
Post	-6.198	2.167	-2.867*	0.013*	-0.185**
	(5.320)	(2.655)	(1.567)	(0.008)	(0.076)
Kinship	-6.587	1.371	-1.543	0.004	-0.079
	(6.353)	(3.136)	(1.878)	(0.010)	(0.099)
Post × Kinship	**15.756***	**2.873**	**5.702****	**-0.017**	**0.084**
	(9.244)	**(4.003)**	**(2.656)**	**(0.012)**	**(0.113)**
Analyst Experience	0.157	-0.202*	0.079	0	-0.002
	(0.307)	(0.111)	(0.088)	(0)	(0.002)
Analyst Education	-6.372	-1.924	-1.940	0.005	-0.006
	(4.222)	(1.810)	(1.403)	(0.006)	(0.026)
Portfolio Complexity	0.048*	0.019	-0.032***	0***	0
	(0.028)	(0.015)	(0.009)	(0)	(0)
Observations	956	956	956	956	536
R-squared	0.015	0.031	0.021	0.011	0.154

Table 8

Analyst recommendation profitability and political connection: DID tests.

This table shows the difference-in-difference test results. The dependent variable is calculated by multiplying the corresponding abnormal return of following analyst recommendation and holding for the respective periods as indicated in subscript (e.g. "1m" means one month), with a ternary variable, which takes the value 1 if the rating is better than the threshold, as indicated in the bracket in the header of the corresponding column; 0 if the rating equals the threshold; -1 if the rating is worse than the threshold. Kinship is a continuous measure that serves as a proxy of maximum kinship between an analyst and the members of China Securities Regulatory Commission (CSRC) management. Post equals 1 for observations after 2015, and 0 otherwise. All control variables are defined in Table A1 of Appendix A. The granularity of the regression is analyst-brokerage-year. Robust standard errors are in parentheses. *, **, and ***denote significance at the 10%, 5%, and 1% level, respectively.

	(1) AR_{1m} (Neutral)	(2) AR_{2m} (Neutral)	(3) AR_{3m} (Neutral)	(4) AR_{1m} (Recommend)	(5) AR_{2m} (Recommend)	(6) AR_{3m} (Recommend)
Post	-3.514**	-5.691**	-6.571	-2.817*	-4.624*	-5.548
	(1.505)	(2.800)	(4.080)	(1.480)	(2.793)	(4.093)
Kinship	-3.654**	-6.096*	-7.645	-2.916	-4.803	-5.821
	(1.822)	(3.372)	(4.908)	(1.810)	(3.372)	(4.905)
Post × Kinship	**4.208****	**7.509****	**9.606***	**3.537***	**6.447***	**8.680**
	(1.930)	**(3.623)**	**(5.290)**	**(1.917)**	**(3.623)**	**(5.318)**
Analyst Experience	-0.007	0.007	0.013	0.008	0.025	0.027
	(0.027)	(0.050)	(0.074)	(0.025)	(0.048)	(0.073)
Analyst Education	-0.447	-0.702	-0.701	-0.569	-0.887	-1.018
	(0.496)	(0.987)	(1.463)	(0.494)	(0.980)	(1.452)
Portfolio Complexity	-0.004	-0.004	-0.005	-0.003	-0.004	-0.003
	(0.003)	(0.006)	(0.009)	(0.003)	(0.006)	(0.009)
Observations	658	658	658	658	658	658
R-squared	0.022	0.013	0.012	0.015	0.012	0.013

Table 9

Official promotion and analyst political connection: baseline tests.

This table shows the results of Cox proportional-hazards model for the full sample and the subsamples, respectively before 2015 and after 2015. The dependent variable is a dummy variable, which equals 1 if the brokerage official got promoted in the year. Kinship is a continuous measure that serves as a proxy of maximum kinship between an analyst and the members of China Securities Regulatory Commission (CSRC) management. Age is brokerage officials' age, and Age_{cat} is brokerage officials' age, which equals 1 if the Age of the official is between 50 and 60. All control variables are defined in Table A1 of Appendix A. The granularity of the regression is official/brokerage-year. Robust standard errors are in parentheses. *, **, and ***denote significance at the 10%, 5%, and 1% level, respectively.

	Full Sample		Before 2015		After 2015	
	(1)	(2)	(3)	(4)	(5)	(6)
Kinship	1.392**	1.398**	2.459**	2.336**	0.723	0.662
	(0.710)	(0.710)	(0.984)	(0.981)	(1.054)	(1.058)
Age	-0.005		0.021		-0.016	
	(0.009)		(0.015)		(0.011)	
Age_{cat}		0.225*		0.285		0.144
		(0.116)		(0.186)		(0.152)
Gender	-0.227	-0.274*	-0.34	-0.324	-0.247	-0.321
	(0.161)	(0.159)	(0.255)	(0.254)	(0.211)	(0.209)
Official Education	0.134	0.159	0.255	0.260	0.044	0.075
	(0.145)	(0.145)	(0.242)	(0.242)	(0.184)	(0.184)
Certified	0.080	0.038	0.222	0.241	-0.022	-0.084
	(0.117)	(0.115)	(0.188)	(0.185)	(0.155)	(0.152)
Brokerage Revenue	0***	0***	0	0	0***	0***
	(0)	(0)	(0)	(0)	(0)	(0)
Observations	2583	2583	1158	1158	1425	1425
Pseudo R^2	0.015	0.016	0.010	0.010	0.019	0.019

Table 10

Official promotion and analyst political connection: DID tests.

This table shows the difference-in-difference test results. The dependent variable is a dummy variable, which equals 1 if the brokerage official got promoted in the year. The explanatory variables are Kinship (a continuous measure that serves as a proxy of maximum kinship between an analyst and the members of China Securities Regulatory Commission (CSRC) management). Post equals 1 for observations after 2015, and 0 otherwise. Age is brokerage officials' current age. All control variables are defined in Table A1 of Appendix A. The granularity of the regression is official/brokerage-year. Robust standard errors are in parentheses. *, **, and ***denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)
Post	0.040**		0.371**
	(0.018)		(0.153)
Kinship		-0.056	0.221
		(0.104)	(0.141)
Post × Kinship			**-0.432****
			(0.201)
Age	-0.007***	-0.006***	-0.007***
	(0.001)	(0.001)	(0.001)
Gender	-0.002	-0.004	-0.011
	(0.023)	(0.023)	(0.023)
Official Education	0.012	0.012	0.008
	(0.020)	(0.020)	(0.02)
Certified	-0.009	-0.012	-0.011
	(0.016)	(0.016)	(0.016)
Brokerage Revenue	0**	0**	0**
	(0)	(0)	(0)
Observations	2583	2583	2583
R-squared	0.014	0.012	0.019

Table 11

Analyst political connection and Amihud illiquidity measure: subsample regressions.

This table shows the regression results for the subsamples, respectively before 2015 and after 2015, on market informational efficiency, which is measured as the change in Amihud illiquidity measure from previous year. The explanatory variable is Kinship (a continuous measure that serves as a proxy of maximum kinship between an analyst and the management-level members of China Securities Regulatory Commission (CSRC), Shanghai Stock Exchange and Shenzhen Stock Exchange). Post equals 1 for observations after 2015, and 0 otherwise. All control variables except number of analysts that covers the firm, volatility and momentum, are lagged by 1 year. All control variables are defined in Table A1 of Appendix A. The granularity of the regression is healthcare firm-year. Robust standard errors are in parentheses and are clustered at healthcare firm level. *, **, and ***denote significance at the 10%, 5%, and 1% level, respectively.

	Before 2015		After 2015	
	(1)	(2)	(3)	(4)
Kinship	1.761**	1.786**	0.094	0.108
	(0.774)	(0.775)	(0.760)	(0.766)
Market Cap.	-0.231***	-0.228**	-0.566***	-0.571***
	(0.088)	(0.089)	(0.147)	(0.148)
Price	-0.014	-0.018	-0.236**	-0.239**
	(0.062)	(0.060)	(0.106)	(0.106)
Volatility	-7.220	-7.310	-99.877***	-99.692***
	(11.055)	(10.830)	(16.395)	(16.394)
Momentum (3 months)	-0.007		0.015	
	(0.034)		(0.027)	
Momentum (6 months)		-0.005		0.003
		(0.014)		(0.015)
Local SOE	0.015	0.015	-0.140	-0.138
	(0.166)	(0.164)	(0.172)	(0.172)
Central SOE	0.076	0.078	0.184	0.183
	(0.201)	(0.201)	(0.160)	(0.160)

Trading Volume	0.244***	0.241***	0.554***	0.552***
	(0.087)	(0.089)	(0.122)	(0.122)
R & D Intensity	1.082	1.203	0.978	0.996
	(1.137)	(1.041)	(0.746)	(0.748)
Institutional Ownership	0.004	0.004	0.014***	0.014***
	(0.003)	(0.003)	(0.004)	(0.004)
Book-to-Market	-0.361	-0.340	-0.338	-0.327
	(0.377)	(0.375)	(0.348)	(0.347)
Leverage	-0.109	-0.091	0.114	0.118
	(0.264)	(0.260)	(0.374)	(0.375)
ROA	-0.812	-0.769	-3.702**	-3.646**
	(0.973)	(0.973)	(1.461)	(1.456)
Number of Covering Analysts	-0.012	-0.012	0.007	0.009
	(0.011)	(0.011)	(0.010)	(0.011)
Observations	184	184	480	480
R-squared	0.112	0.113	0.323	0.323

Table 12

Analyst political connection and Amihud illiquidity measure: DID tests.

This table presents difference-in-difference (DID) tests on market informational efficiency, which is measured as the change in Amihud illiquidity from the previous year. The explanatory variables are Kinship (a continuous measure that serves as a proxy of maximum kinship between an analyst and the management-level members of China Securities Regulatory Commission (CSRC), Shanghai Stock Exchange and Shenzhen Stock Exchange). Post equals 1 for observations after 2015, and 0 otherwise. All control variables except volatility and momentum are lagged by 1 year. All control variables are defined in Table A1 of Appendix A. The granularity of the regression is healthcare firm-year. Robust standard errors are in parentheses and are clustered at healthcare firm level. *, **, and ***denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Post	-0.245**	-0.240**			0.354	0.424
	(0.106)	(0.106)			(0.932)	(0.932)
Kinship			1.104*	1.131*	1.542**	1.633**
			(0.632)	(0.635)	(0.758)	(0.758)
Kinship × Post					-0.745	-0.829
					(1.218)	(1.219)
Market Cap.	-0.283***	-0.289***	-0.262**	-0.267**	-0.269**	-0.274**
	(0.106)	(0.107)	(0.107)	(0.108)	(0.108)	(0.108)
Price	-0.147*	-0.158*	-0.197***	-0.207***	-0.140*	-0.150*
	(0.079)	(0.080)	(0.073)	(0.074)	(0.080)	(0.081)
Volatility	-24.862***	-23.322***	-19.551***	-18.187***	-24.433***	-22.957***
	(5.647)	(5.434)	(4.629)	(4.459)	(5.607)	(5.399)
Momentum (3 months)	0.017		0.014		0.014	
	(0.020)		(0.019)		(0.020)	
Momentum (6 months)		-0.004		-0.006		-0.005
		(0.010)		(0.010)		(0.010)

Local SOE	0.029	0.023	0.030	0.026	0.055	0.051
	(0.128)	(0.128)	(0.129)	(0.129)	(0.135)	(0.134)
Central SOE	0.277**	0.274**	0.273**	0.271**	0.302**	0.301**
	(0.137)	(0.137)	(0.136)	(0.136)	(0.146)	(0.145)
Trading Volume	0.253***	0.249***	0.232***	0.228***	0.248***	0.245***
	(0.083)	(0.083)	(0.082)	(0.082)	(0.083)	(0.083)
R & D Intensity	0.147	0.221	-0.016	0.065	0.157	0.236
	(0.618)	(0.621)	(0.630)	(0.636)	(0.616)	(0.618)
Institutional Ownership	0.011***	0.012***	0.012***	0.012***	0.011***	0.011***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Book-to-Market	0.700***	0.710***	0.614**	0.624**	0.682***	0.692***
	(0.257)	(0.257)	(0.244)	(0.244)	(0.254)	(0.254)
Leverage	0.075	0.086	0.152	0.163	0.106	0.118
	(0.270)	(0.271)	(0.270)	(0.271)	(0.273)	(0.274)
ROA	-2.554**	-2.463**	-2.300**	-2.208**	-2.447**	-2.352**
	(1.087)	(1.082)	(1.085)	(1.079)	(1.083)	(1.079)
Number of Covering Analysts	0.010	0.012	0.008	0.010	0.009	0.011
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Observations	664	664	664	664	664	664
R-squared	0.164	0.163	0.164	0.163	0.169	0.168

Table 13

Analyst political connection and brokerage profitability.

This table presents difference-in-difference (DID) tests on brokerage profitability, which is measured as respectively the brokerage profit, the change in the profit from the previous year, the return on assets (ROA), the return on equity (ROE), the change in the asset from the previous year, and the change in the equity from the previous year. The explanatory variable is Kinship (a continuous measure that serves as a proxy of maximum kinship between an analyst and the management-level members of China Securities Regulatory Commission (CSRC), Shanghai Stock Exchange and Shenzhen Stock Exchange). Post equals 1 for observations after 2015, and 0 otherwise. All control variables are defined in Table A1 of Appendix A. The granularity of the regression is healthcare firm-year. Robust standard errors are in parentheses and are clustered at brokerage level. *, **, and ***denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Profit	Profit Change	ROA	ROE	Asset Change	Equity Change
Post	-0.029	-0.620	-0.023	-0.037	1.207	-0.145
	(0.131)	(0.421)	(0.015)	(0.042)	(1.535)	(0.188)
Kinship	0.037	-0.497	-0.012	0.014	1.309	0.093
	(0.145)	(0.518)	(0.024)	(0.071)	(1.925)	(0.280)
Kinship × Post	-0.167	-0.409	0.019	-0.044	-2.181	-0.076
	(0.201)	(0.662)	(0.025)	(0.069)	(2.377)	(0.303)
Analyst Education	-0.063	0.440*	-0.001	0.011	0.144	0.131*
	(0.101)	(0.224)	(0.008)	(0.024)	(0.936)	(0.064)
Analyst Experience	-0.011	0.018	0	-0.002	0.057	-0.009
	(0.009)	(0.027)	(0.001)	(0.002)	(0.082)	(0.007)
Brokerage Asset	-0.032	-0.002	-0.004***	-0.003	0.687**	0.003
	(0.022)	(0.043)	(0.001)	(0.002)	(0.249)	(0.010)
Brokerage Revenue	0.519***	0.087***	0.007*	0.022***	0.026	0.056***
	(0.019)	(0.031)	(0.004)	(0.005)	(0.133)	(0.011)
Observations	154	152	154	154	151	153
R-squared	0.933	0.292	0.154	0.521	0.086	0.355

Table 14

Analyst political connection and brokerage wage.

This table presents difference-in-difference (DID) tests on wages in brokerage, respectively the wage of the managers and the subordinates. The explanatory variable is Kinship (a continuous measure that serves as a proxy of maximum kinship between an analyst and the management-level members of China Securities Regulatory Commission (CSRC), Shanghai Stock Exchange and Shenzhen Stock Exchange). Post equals 1 for observations after 2015, and 0 otherwise. All control variables are defined in Table A1 of Appendix A. The granularity of the regression is healthcare firm-year. Robust standard errors are in parentheses and are clustered at brokerage level. *, **, and ***denote significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)
	Subordinate Salary	Manager Salary
Post	277.922	-51.296
	(1415.819)	(46.541)
Kinship	-89.820	0.900
	(1207.105)	(60.189)
Kinship × Post	268.746	57.763
	(1769.215)	(56.007)
Analyst Education	682.350	26.620***
	(512.888)	(8.232)
Analyst Experience	-9.313	0.910
	(18.647)	(1.343)
Brokerage Asset	151.416	-1.253
	(96.964)	(0.946)
Brokerage Revenue	1268.101***	4.056***
	(121.996)	(1.314)
Observations	154	130
R-squared	0.769	0.194

Appendix A

Table A1
Definitions of variables.

Variable	Definition
AR_{xm}	A variable constructed from the abnormal return of following analyst recommendation and hold for x months (x is a number). It is calculated by multiplying the abnormal return with a ternary variable, which takes the value 1 if the rating is better than a threshold; 0 if the rating equals a threshold; -1 if the rating is worse than a threshold. Threshold is indicated in the bracket following AR_{xm}, which can be e.g. "neutral".
Age	A dummy for brokerage officials' age, which equals 1 if the current age of the official is between 50 and 60.
Analyst Education	Dummy variable, which equals 1 if the analyst has a degree higher than bachelor and 0 otherwise.
Analyst Experience	The number of years of analysts working in security sector (not counting internship).
Book to Market	Book value of the firm's stockholder equity divided by market cap.
Brokerage Revenue	Standardized brokerage revenue
Certified	Dummy variable, which equals 1 if the brokerage official holds one or more professional certificates, 0 otherwise.
Central SOE	The brokerage is a central SOE.
Official Education	Dummy variable, which equals 1 if the brokerage official has a degree higher than bachelor and 0 otherwise.
Official Promotion	Dummy variable, which equals 1 if the brokerage official got promoted in the year.
Employment at Central SOE	Dummy variable, which equals 1 if the person is employed at central SOE.
Employment at Local SOE	Dummy variable, which equals 1 if the person is employed at local SOE.
Employment at SOE	Dummy variable, which equals 1 if the person is employed at SOE.
Firm Size	Revenue of healthcare firm in million CNY.
Gender	Brokerage official's gender.
Industry Knowledge	The average number of occurrences of medical words by an analyst in a report written by the analyst in a particular year.
Institutional Ownership	The percentage of a firm's shares owned by institutional investors.
Kinship	Continuous measure that serves as a proxy of maximum kinship between an analyst and the management-level members of China Securities Regulatory Commission (CSRC), Shanghai Stock Exchange and Shenzhen Stock Exchange. In a given year, the kinship variable of an analyst is determined by selecting the highest kinship score between the analyst and regulatory members holding influential positions during that period. Consequently, analysts holding the

	highest kinship scores with regulators who vacated their positions in a certain year will experience a negative impact on their political connections in the subsequent year, unless there is an incoming regulator holding a high kinship score with them.
Leverage	Book value of total liabilities divided by book value of equity.
Plagiarism	The average of maximum cosine similarity of a report with all the reports issued within seven days before its issuance written by the analyst in a particular year.
Post	Dummy variable, equals 1 for observations after 2015, and 0 otherwise.
Piggyback	Cumulative abnormal return in percentage points of the seven days before analyst report issuance.
Plagiarism	The average of the highest cosine similarity between the reports, written by an analyst within a specific year, and other reports within the seven days preceding its publication (excluding the reports written by the same authors and those written by some of the same authors in the same brokerages).
Portfolio Complexity	The number of companies the analyst covered in a specific year.
Report Length	The average number of pages in a report written by the analyst in a particular year.
Financial Knowledge	The average number of occurrences of financial technical words in a report written by the analyst in a particular year.
Number of Covering Analysts	The number of analysts covering a firm for a specific year.
$Post_{start}$	Dummy variable, which equals 1 if an analyst started to work in the security sector after 2015, and 0 otherwise.
Market Cap.	Daily market capitalization.
Price	Firm's average daily stock price in each year.
Volatility	Standard deviation of a firm's daily return in each year.

Table A2

CSRC official turnover

This table describes the CSRC management level replacement per year. Column (1) is the total number of people in the CSRC management team, including president, vice president, assistant of president, and leader of discipline inspection and supervision team. Information about assistants of president is not available after 2019. Column (2) is the number of people changed from the previous year. Those who left and those who entered CSRC management are both treated as changes. (For example, in year 2021, Jianjun Wang became vice president of CSRC for the first time, and Qingmin Yan and Zhengping Zhao were no longer vice president, so the number of people who changed in the previous year is 3). Column (3) is the number of personnel who left the position due to normal reasons, e.g. retirement. Column (4) is the number of personnel who left the position in that particular year due to abnormal reasons such as criminal investigation. Column (5) is the publication time of publication of the reports. Column (6) is the total number of position appointments at the management level indicated in the footnote. Column (7) is the number of personnel at the management level whose starting dates of the position were after the publication of the report.

Year	(1) Mng.	(2) Change	(3) Normal	(4) Abnormal	(5) Pub Time	(6) Footnotes	(7) After Pub.
2007	9	NA	NA	NA	04/2008	0	0
2008	9	3	3	0	05/2009	0	0
2009	9	0	0	0	05/2010	0	0
2010	9	0	0	0	07/2011	0	0
2011	9	2	2	0	05/2012	0	0
2012	8	5	4	1	06/2013	0	0
2013	8	1	1	0	06/2014	2	0
2014	7	1	1	0	04/2015	1	0
2015	8	10	6	4	08/2016	6	1
2016	8	0	0	0	06/2017	3	0
2017	8	0	0	0	05/2018	2	0
2018	10	2	2	0	05/2019	2	0
2019	6	3	2	1	05/2020	2	0
2020	6	0	0	0	05/2021	0	0
2021	5	3	3	0	06/2022	1	0
2022	5	0	0	0	08/2023	0	0
2023	5	0	0	0	NA	NA	NA

Appendix B

B1. Textual data cleaning

All the documents are in PDF format, which we use PDFMiner to parse. We remove tables, graphics, exhibits and other non-text items. We also remove the appendix section of analyst reports, as the standardized expressions in this section can affect the calculation of our plagiarism measure. Because most words in our corpora are in Chinese, which is not an inflected language, we do not lemmatize (remove the inflectional endings of words).[13] Because there are no white spaces between words in Chinese texts, we first segment our corpora (analyst reports and firm disclosures) into words using the PKUSEG toolkit developed by Luo et al. (2019).[14] By training the domain-specific model, we have identified the general and corpus-specific phrases in our corpora. After segmenting the texts, white spaces delimit all the words and phrases so that our algorithm treats them as single words. Then we process the words and phrases in our corpora into tokens.[15] After tokenization, we remove fillers, punctuations and other stop words (generally articles, auxiliary verbs, conjunctions, prepositions and pronouns).

We parse analyst reports to identify the issue dates, recommendations, brokerages, and the number of pages of the reports. We use Named Entity Recognition (NER) to identify and tag named entities, such as places, companies, persons and dates in the downloaded analyst reports. The NER we use follows an optimized BERT pretraining approach (Devlin et al., 2018; Liu et al., 2019).[16] Because Hexun.com lists the issue date, brokerage, rating, target firm, and analyst, we directly scrape these variables for reports downloaded from Hexun. For reports downloaded from Wind and Huibo, we manually extract the issue date. We use the NER algorithm to extract target firms, brokerages and analysts. To increase the accuracy, we set a

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[13] The non-Chinese words in analyst reports and firm disclosures are financial or medical jargons, such as EPS or English acronyms for cancer drug targets, so we do not lemmatize them.

[14] This segmentation method is based on Sun et al. (2012). PKUSEG provides domain-specific pretrained models, and allows users to add additional training data. We use the pretrained model for medicine and use the products in the healthcare industry as our user-defined dictionary. We keep punctuations to identify sentence boundaries before segmenting phrases.

[15] After cleaning, we use “words” to refer to both words and phrases in our corpora, which our algorithms regard as single words.

[16] The package we use comes from this website: https://huggingface.co/uer/roberta-base-finetuned-cluener2020-chinese. Our loss function is binary cross entropy.

condition that analyst names appear next to their registration number at SAC before extracting analysts. We extract the ratings by searching keywords related to investment recommendations on the first page of analyst reports. Then we manually check the company names, brokerages, recommendations, and analysts to minimize the possibility for errors.

B2. Construction of industry knowledge dictionary

B2.1. Precompiled word list

We first compile a word list for the healthcare industry using a top-down approach. The Global Industry Classification Standard (GICS) divides the healthcare industry into two industry groups- healthcare equipment & services, pharmaceuticals & biotechnology & life sciences, which are further divided into 10 sub-industries. Out of the 10 segments, managed healthcare and healthcare technology are more closely related to the insurance and IT industry, respectively, so we remove them from our segment list. For each of the eight remaining segments, we search for relevant jargons and terms.

Most healthcare products require regulatory approval and are registered online, so from China's National Medical Products Administration (NMPA), we download the product names for four industry segments- healthcare equipment, healthcare supplies, biotechnology and pharmaceuticals. For the healthcare distributors segment, we obtain words related to the wholesale and retail of healthcare products. For the healthcare facilities segment, we obtain words related to hospitals and clinical centers. Finally, we gather words related to clinical, manufacturing, or other outsourcing for the last two segments: healthcare services, life sciences tools & services.

The words related to each category are from the following websites:

Drugs, medical equipment and supplies: National Medical Products Administration

https://www.nmpa.gov.cn/datasearch/home-index.html#category=hzp

Drug and treatment categories: Drug.com and DXY.cn

https://www.drugs.com/

https://portal.dxy.cn/

CRO, CDMO and other outsourcing: Websites of large Contract Research Organizations (CROs), Contract Development and Manufacturing Organization (CDMO), and other healthcare service firms.

IQVIA：https://www.iqvia.com/

Labcorp：https://drugdevelopment.labcorp.com/

PPD：https://www.ppd.com/

Parexel：https://www.parexel.com/

WuXi AppTec：https://www.wuxiapptec.com/

Hangzhou Tigermed：https://www.tigermed.net/

AmerisourceBergen Corp. (ABC): https://www.amerisourcebergen.com/

Cardinal Health Inc. (CAH): https://www.cardinalhealth.com/en.html

KingMed: http://www.kingmed.com.cn/

Dian Diagnostics Group: http://www.dazd.cn/

Hospitals and clinical centers: a-hospital.com

http://www.a-hospital.com/

Wholesale and retail of healthcare products: The Ministry of Commerce of China

https://yplt.mofcom.gov.cn/stat/page/auth/DrugWall.html

After collecting all the words from the sources above, we manually inspect and remove ambiguous words that have meanings in other fields. For example, EPS may stand for both Epstein–Barr virus in medical context or earnings per share in financial contexts, which may bias our industry knowledge measure, so we remove it from the dictionary. As many companies manufacture the same products, we only keep unique product names. For example, there are 149,402 domestic drugs listed on the NMPA by the end of 2021, but there are only 17,856 unique domestic drug names. After removing duplicates, we have 19,185 drugs and 42,333 medical devices / equipments from the NMPA. The precompiled list contains a total number of 73651 unique specialized terms in the healthcare industry words. Most of these words are in Chinese, exceptions include imported products and cancer drug targets such as PD-1 (Programmed cell death protein 1).

B2.2. Word embedding for identifying additional words

To supplement our precompiled words above, we extract additional words from firm disclosures, as managers are likely to list the relatively important products, services, ingredients, and innovations in disclosures such as the annual reports. From firm disclosures, we look for words that are contextually similar to those in our precompiled word list through word embedding, a method that maps words and phrases into vectors of real numbers through their likelihood of cooccurrence with neighboring words. Vector values capture the semantic similarity of words in the corpus. We do not set a minimum requirement for word frequency so that we can capture medical and pharmaceutical jargons that are relatively rare. We use the word2vec method developed by Mikolov et al. (2013a and 2013b), and we use the Gensim library to train the model. We use continuous bag-of-words (CBOW) approach with 2 layers of neural network[17] to learn the embeddings, and our training algorithm is hierarchical softmax. Our context window size is seven, meaning that we use the three neighboring words before and after each target word for prediction. The size of the word vectors is 100.

After we obtain the word vector for each word in our corpus, we compare the vector values of our seed words (those that appear in both our precompiled word list and firm disclosures) with those of all the other words. We calculate the cosine similarity between the vector of each seed word and that of each word in our corpus, and extract words whose vectors have cosine similarities[18] of at least 0.7 with that of one or more seed words. We have culled 6523 words from firm disclosures in this way.

Then, two coauthors manually sift out irrelevant words and phrases, and we Google their definitions for cross reference. We make sure that each word extracted by our algorithm belongs to a category in our precompiled word list, and we also remove ambiguous acronyms with multiple meanings. We compare our chosen words to ensure that our interpretations of web definitions are consistent. Human inspection removed 58% of the words identified by the algorithm above, so we add 2744 words to our healthcare word list. After removing duplicate words, we have a total of 75848 words in our healthcare industry dictionary.

B3. Plagiarism measure

We define the likelihood of plagiarism as the similarity between a report and all reports

[17] The training algorithm for the neural network is stochastic gradient descent with backpropagation.
[18] See the definition of cosine similarity in Section B3 of the Appendix.

issued in the previous 7 days. We measure the similarity between two reports as the cosine similarity between their word vectors, or the dot product of the word vectors normalized by their vector lengths (Kwon and Lee, 2003). The angle between the two vectors is inversely related to their closeness, as shown in the formula below. This measure is in the interval of [0,1] and the closer to one, the more similar two reports are. We define the variable Plagiarism as the maximum cosine similarity between a report and all the reports issued in the previous seven days.

$$\text{Report similarity} = \frac{\text{Vector}_i \cdot \text{Vector}_j}{|\text{Vector}_i||\text{Vector}_j|} \tag{5}$$

B4. Kinship measure

B4.1. Photo collection and preprocessing

We collect the photos of analysts who are still working in brokerages from the website of the Securities Association of China (SAC). As the SAC removes the profiles of the analyst who no longer work in the security sector, we collect their photos from various Internet sources, including news sites and social media platforms, where we use screenshots to extract their photos from videos. We use the corresponding official websites and annual reports to collect the photos of the current and past officials of the CSRC, and those of the current officials of the Shanghai Stock Exchange and the Shenzhen Stock Exchange. We collect photos of the past regulators of the Shanghai Stock Exchange and the Shenzhen Stock Exchange from other Internet sources, such as news sites and social media platforms.

Where possible, we use photos of the following characteristics. The person in the photos should face the camera as much as possible, with the face clear in view, neutral facial expression, and appropriate lighting. We find photos of 74 financial regulators and 418 analysts.

We remove the watermarks on some analysts' photos using an online tool WatermarkRemover.io.[19] In some photos, objects such as microphones cover part of the faces, and we removed them with an online tool Cleanup.Picture.[20] We manually crop the collected photos so that they have equal width and length as the photos in the training set. In the

[19] https://www.watermarkremover.io/

[20] https://cleanup.pictures/

standardization process, we keep the relevant facial features unchanged.

B4.2. Algorithm and training data description

Our goal is to use an analyst's and a financial regulator's photos to compute their kinship score, ranging from 0 to 1, where higher values signify a higher probability of a blood relationship between the two. Our kinship prediction algorithm is based on one of the best-performing algorithms from the competition "Northeastern SMILE Lab - Recognizing Faces in the Wild" (Howard et al., 2019).

We use a ResNet architecture, the deep residual learning pioneered by He et al. (2016), which balances maintaining granularity with preventing overfitting. For our loss function, we follow Lin et al. (2017) and use focal loss. More specifically, we follow Xie et al. (2017) and use some of the procedures and methods in Oxford VGGFace project (Parkhi et al., 2015; Cao et al., 2018), including the Keras Functional Framework v2+ and ResNet-50 architecture. This architecture employs a 50-layer convolutional neural network (CNN) that includes 48 convolutional layers, one MaxPool layer, and one average pool layer. The convolutional layers in the network select relevant features from facial images, which enhances the accuracy of kinship assessment by focusing on the most discriminative aspects of the faces. The MaxPool layer emphasizes the most prominent features, while the Average Pool layer computes the average of features, making the kinship scoring mechanism more robust. We use the rectifier activation function in the hidden layers and sigmoid activation function.

Our training dataset for the machine learning algorithm comprises the frontal face photos of 310 Chinese parent-child pairs from the KinFaceW Dataset (Lu et al., 2012, 2014).[21] We do not use the complete KinFaceW Dataset, because we may overestimate the kinship between Chinese analysts and financial regulators using photos of people from different ethnicities in the training set.

[21] We manually filter the dataset to obtain parent-child pairs of Chinese ethnicities. The training dataset is from https://www.kinfacew.com/download.html