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Social network, corporate governance, and rent extraction in CEO compensation: Evidence from spatial econometric models[☆]

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1. Introduction

Among the controversies in corporate governance, perhaps none is more heated or widely debated across society than that of CEO pay (Larcker & Tayan, 2019). How CEO pay is determined, and the performance implications of CEO pay is an issue of first-order importance. Efficient contracting (Gabaix & Landier, 2008; Murphy, 1999) and managerial power (Bebchuk & Fried, 2004) have been advanced as the two main explanations for the high level of CEO compensation and the weak links between CEO compensation and firm performance. While both are widely accepted, neither explanation is fully consistent with the available evidence (Frydman & Jenter, 2010). Much remains to be known about the determinants of CEO pay (Core, Holthausen, & Larcker, 1999), and the precise channels by which executives and boards influence CEO pay (Engelberg, Gao, & Parsons, 2013).

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Recent studies have documented that geography has significant effects on corporate decisions and outcomes.[1] Kedia and Rajgopal (2009) find that geographically-proximate firms adopt similar policies in broad-based option grants. They argue that this arises because geographically-proximate firms are exposed to the same local market conditions and managers at neighbouring firms engage in social interactions. Dougal, Parsons, and Titman (2015) find a high correlation in the capital investment of neighbouring firms, even those in different industries. They suggest that one reason for correlated investment is that local social networks allow managers to share ideas. Parsons, Sulaeman, and Titman (2018) find that geographic variation in social norms accounts for a large proportion of the cross-sectional variation in financial misconduct across major US cities. The evidence from these and other studies on the role of geography suggests that CEO compensation may be correlated among neighbouring firms, over and beyond what economic fundamentals warrant. However, the existence of, reasons for, and consequences of spatial correlation in CEO compensation remain under-explored. Our paper aims to fill this gap.

An empirical challenge in investigating spatial effects in corporate decisions is that the interdependence in the cross section of neighbouring firms makes ordinary least squares (OLS) an inconsistent estimator.[2] Prior studies typically regress a firm-level outcome variable, such as CEO compensation (Bouwman, 2013) and corporate investment (Dougal et al., 2015), on the weighted average of that variable corresponding to the neighbouring firms. This approach is problematic, because it overlooks the “spatial lag” among neighbouring firms, and the autoregressive disturbance term (Anselin, 1988). We address such endogeneity concerns by using spatial econometric models, which are well suited for handling both types of interdependence (Kelejian & Prucha, 1998, 1999).[3] More importantly, by focusing on how spatial correlation in CEO pay is affected by CEOs' local social networks, corporate governance, as well as managerial power, and by examining the performance implications of spatial correlation in CEO pay, we shed light on the nature and consequences of spatial spillovers in CEO pay.

Using panel data for publicly traded US firms during 2010–2016, we find robust evidence of spatial correlation in CEO compensation. A 10% increase in the average CEO compensation of neighbouring firms (those headquartered within a 100-km radius) increases the focal firm CEO's total compensation by approximately 0.7% for the whole sample, rising to 2.21% if the CEOs belong to the same social network. This is after controlling other previously-documented determinants (e.g. firm characteristics, board attributes, ownership attributes, benchmark effects, local market competition for CEOs, cost of living, etc). Furthermore, we find the spatial effect to be concentrated among weak-governance firms, and for more powerful CEOs. However, irrespective of the presence of CEO social network connections, we find little evidence of spatial correlation in the firms' pay-performance sensitivity. Quite to the contrary, we find a negative association between predicted excess compensation (a proxy for agency problem) and subsequent firm performance, using the method of Core et al. (1999). The basic results are robust to a variety of checks. Taken together, the evidence suggests that spatial correlation in CEO compensation likely reflects some sort of rent extraction, which is facilitated by weak governance and information sharing through powerful CEOs' local social network connections.[4]

Our paper contributes to the executive compensation and corporate governance literatures. First, we apply spatial econometric methods, which are well-suited for handling spatial inter-dependencies, to investigate the role of geography in CEO compensation. Our finding of robust spatial effects in CEO compensation extends prior research on the role of geography in accounting and finance and suggests that geographical factor, by facilitating social interactions among locally-connected CEOs, is a hitherto unrecognized determinant of executive compensation, over and beyond governance and ownership variables documented in prior studies (Abernethy, Kuang, & Qin, 2015; Core et al., 1999). Given the increasing recognition that geography and social interactions have important impacts on corporate decisions and outcomes, future studies may benefit from applying spatial econometric models to account for spatial inter-dependencies in settings where agents are likely to influence one another.[5] To the best of our knowledge, ours is the first study in accounting and finance that applies spatial econometric models to examine spatial spillovers resulting from social interactions.

Second, by simultaneously considering the effects of social network connections and geography on CEO compensation as well as their implications for pay-performance sensitivity and future firm performance, we speak to the nature of spatial correlation in CEO compensation. We show that the spatial spillover effect in CEO compensation is distinct from previously-documented peer effects that emphasize positive externalities or learning. Bouwman (2013) documents spatial effects in CEO compensation. She concludes that her evidence is most consistent with relative status concerns, but she does not investigate the driving forces or performance consequences thereof. Our study takes one important step further to investigate the

[1] Another related literature examines the effects of geography and social interactions on investor decision-making (e.g. Coval & Moskowitz, 1999, 2001; Hong, Kubik, & Stein, 2005; Pool, Stoffman, & Yonker, 2015). See Gyimah, Machokoto, and Sikochi (2020) and references therein for evidence of peer effects on corporate financial policies.

[2] Interdependence refers to processes by which outcomes in some units affect outcomes in others. Such interdependence processes will induce spatial correlation (Franzese & Hays, 2007).

[3] For detailed discussions of identification issues in social interactions and spatial econometric specifications of social interactions, see Blume et al. (2011). We acknowledge that spatial econometric approaches do not solve all types of endogeneity issues. To aid inference, we provide some evidence on the underlying mechanisms to better understand the nature of spatial spillovers in CEO compensation.

[4] The recent experience of a colleague of one of the co-authors illustrates the importance of private information sharing when negotiating pay. Because she knew a senior colleague in the new employer, she got an insider's view of her perceived “market value”, and thus was able to push for the maximum possible pay (without fear of losing the job offer by asking for “too much”).

[5] Paige and Tate (2020), Denis, Jochem, and Rajamani (2020) and Manski (2000) discuss econometric challenges in studies of peer effects in finance and economics, and Blume et al. (2011) discuss spatial econometric approaches to social interactions.

underlying mechanisms and the performance implications of spatial correlation in CEO compensation. Shue (2013) also documents similarities in executive compensation arising from social interactions among business school classmates who become executives. However, she is unable to distinguish whether such similarities are reactions to peer fundamentals or reactions to peer outcomes.[6] We show that local social network connections lead to spatial correlation in CEO pay but not correlation in pay-performance sensitivity. Further, we find a negative association between predicted excess compensation (a proxy for agency cost) and future firm performance, which is stronger when the focal firm and the neighbouring firm CEOs belong to the same social network. Our findings thus suggest that the spatial effect in CEO compensation likely reflects an agency problem, as opposed to benign or positive peer effects whereby social interactions help CEOs become more productive–if similar levels of productivity led to similar compensation, one would expect a spatial correlation in pay-for performance and no spatial association between excess compensation and future performance, contrary to what we found.[7] Other than shedding empirical light on the nature and consequences of spatial spillovers in CEO compensation, our study adds to a small literature suggesting that social interactions may not improve investment quality (Hvide & Östberg, 2015), and, worse still, may lead to negative externalities (Dimmock, Gerken, & Graham, 2018).

Third, our paper contributes to the debate on the interrelationships among corporate governance, managerial power, social network and CEO compensation. We show that spatial correlation in CEO compensation is concentrated among firms with socially connected CEOs, weak governance, and powerful CEOs. The first piece of evidence is consistent with the finding in Engelberg et al. (2013) that local connections increase the value of CEOs' external networks (reflected in higher CEO compensation). However, our other findings contrast with Engelberg et al. (2013) who find that the effect of external networks on CEO pay is similar across firms with weak governance, strong governance, weak CEOs, and powerful CEOs, which they interpret as consistent with firms deriving informational benefits from the CEO's network. In contrast, our evidence suggests that spatial correlation in CEO compensation likely arises because powerful CEOs in weak-governance firms obtain information from local social networks that allows them to extract higher compensation in the pay-setting process but that does not improve firm performance– to the contrary, such rent-seeking negatively impacts firm performance. Thus, our evidence sheds new light on the drivers of CEO power in pay-setting and the adverse consequences of information sharing in CEO social networks when firms have weak corporate governance. The finding that powerful CEOs at weak-governance firms derive pecuniary benefits from social connections is consistent with research in social psychology and sociology which has long viewed power as a relationship (van Essen, Otten, & Carberry, 2015). It is also consistent with the view expressed by Jensen and Murphy (1990) and Bebchuk and Fried (2004) regarding the role of social and political forces in shaping executive compensation (for a summary, see van Essen et al., 2015).[8]

Overall, our evidence is supportive of the managerial power (rent extraction) hypothesis. The finding that weak governance leads to rent extraction by powerful, socially connected CEO in the form of excess compensation and subsequent poor firm performance has important policy implications. Among others, it lends support to increased executive compensation disclosure, an issue that has received significant regulatory attention around the world.[9]

Section 2 presents a highly selective literature review and the hypotheses. Section 3 discusses the research design, Section 4 presents the empirical results, and Section 5 concludes.

2. Literature review and hypotheses

Our paper builds on and extends prior research on the role of geography in CEO compensation. Bouwman (2013) is the most closely related to our study. Focusing on US listed firms during 1992–2006, she finds that firm's level of CEO pay is positively related to the average CEO pay at neighbouring firms. The association cannot be explained by the use of official peer groups or the use of neighbouring firms' CEO compensation in the benchmark exercise. She examines four explanations for the documented spatial effect: local firms hiring similar CEOs; a "leading firms" effect; local competition for CEOs; and relative status concerns ("envy") among geographically-close CEOs. Her tests lead her to conclude that the last explanation

[6] As Shue (2013, p. 1405) explains, "Reactions to peer fundamentals occur if the fundamental skills, beliefs, or information driving managerial decisions are transferred through networks. For example, compensation may be similar because executives transfer managerial skills to one another, leading to similar levels of productivity that then lead to similar compensation. In contrast, reactions to peer outcomes can occur if executives respond directly to the actions of peers, for example, if executives seek to match or exceed friends' compensation or acquisition levels or if a change in peers' compensation affects executives' outside options." The second scenario is similar to the "relative status concerns" explanation in Bouwman (2013).

[7] Our evidence also contrasts with and extends that in Francis et al. (2016), who attribute the CEO pay premium at large cities to local network spillovers and faster learning–while we are in agreement regarding local network spillovers, we differ from Francis et al. (2016) in that they suggest positive externalities/benefits from local network spillovers, whereas we document adverse consequences, especially under conditions of powerful CEOs and weak governance.

[8] Based on a meta-analysis of 219 US-based studies, van Essen et al. (2015) conclude that managerial power theory is well equipped for predicting total cash and total compensation but less so for predicting pay-performance sensitivity.

[9] In the US, the most important regulatory initiatives on executive compensation disclosure are the SEC's 1992 amendments requiring boards to provide more information on executive compensation, the 2006 introduction of the mandated Compensation Discussion and Analysis in the proxy statement of public firms, and the 2009 SEC requirement that firms disclose fees paid to compensation consultants for both consulting and other services (Chu, Faasse, & Rau, 2018). See Craighead, Magnan, and Thorne (2004), Bizjak, Lemmon, and Nguyen (2011), Faulkender and Yang (2013), Chung, Judge, and Li (2015), Rau (2017a), Ferri, Zheng, and Zou (2018), and Jiang, Liao, Lin, and Liu (2018) for more discussions of the theory and empirical evidence related to executive compensation disclosure worldwide.

seems to be the most consistent with the data. However, she (other than relying on OLS estimation) does not examine how spatial correlation in CEO pay is affected by CEO power and whether spatial correlation in CEO pay is accompanied by similar correlation in pay-performance sensitivity, nor does she examine the future performance implications of spatial correlation in CEO pay.

Yonker (2015) finds evidence of a geographical effect in US firms' hiring of CEOs: they hire same-state CEOs much more often than expected if geography were irrelevant. Such a local hiring bias exists even among the largest firms. He further finds that local CEOs get lower compensation than nonlocal CEOs, and that local CEOs' compensation depends on local market factors, unlike that of nonlocal CEOs. Although Yonker (2015) examines an agency theory explanation for the local hiring bias (finding that firms with boards with weaker incentives are more likely to hire locally), his evidence on compensation, turnover, and performance is inconsistent with this theory.

Francis, Hasan, John, and Waisman (2016) examine whether the clustering of firms around big cities affects CEO compensation. They find that the metropolitan size of a firm's headquarters positively affects CEO pay: all else equal, CEOs at firms in large urban cities on average receive 25% higher total compensation than their counterparts in rural-based firms. Using a sample of firms whose CEOs relocate from major metropolitan areas to smaller cities, they find that these CEOs earn a pay premium upon relocation, suggesting local network spillovers and faster learning.

Our paper differs from the above studies in several ways. First, unlike Yonker (2015) and Francis et al. (2016) we do not focus on comparing the level of compensation for local and nonlocal CEOs, or CEOs of firms in large (urban) versus small (rural) cities. Instead, our main objective is to examine the existence of spatial spillovers in CEO compensation, within well-defined geographical vicinities (ranging from a 100- to 400-KM radius). In doing so, we focus on neighbourhood effects in CEO compensation, not restricted to cities of any given metropolitan size.[10] Second, we adopt a spatial econometric approach to address the concern that OLS estimation, which the majority of prior studies used, is biased when there is spatial interdependence in the cross section. Third, we examine whether and how corporate governance, social network and CEO power jointly affect spatial correlation in CEO compensation, and the implications of spatial correlation in CEO compensation for future firm performance. Together, these tests speak to the nature (including underlying mechanisms) and consequences of spatial correlation in CEO pay. In doing so, we advance the literature in important ways.

Similar to Bouwman (2013), we expect CEO pay to exhibit spatial correlation, for a number of reasons. First, if firms prefer to hire CEOs from the geographic areas in which their headquarters are located (Yonker, 2015), then local competition for talent will link geography and CEO compensation. Second, firms in an area, for some reason, may prefer to hire CEOs with similar performance-relevant characteristics. Alternatively, CEOs with similar attributes/preferences (e.g. love for recreational amenities) may seek employment in the same locations (Branikas, Hong, & Xu, 2020). Both situations may lead to spatial correlation in CEO compensation. Third, physical proximity could create "neighbourhood effects" that cause firms in the vicinity to look to each other in their decision-making (Kedia & Rajgopal, 2009). Fourth, CEOs may care about their relative status (vis-a-vis their counterparts in neighbouring firms) when negotiating their pay. In addition, as we explain later, CEOs of neighbouring firms who are socially connected may share pay-related information with one another, which leads to similar pay levels in the neighbourhood. We propose our first hypothesis (in null form) as follows:

H1. There is no spatial correlation in the level of CEO pay.

The efficient contracting approach views executive pay as a means to mitigate an agency problem between shareholders and managers, with pay levels driven by market forces. On the other hand, the managerial power (rent extraction) approach views the pay-setting process as an agency problem on its own and suggests that weak boards tend to shift rents to the CEO at the cost of shareholders by implementing inefficient compensation arrangements featuring a poor link between pay and firm performance (Bebchuk & Fried, 2004). The core issue among the proponents of these two views is the question of whether executive pay represents arm's-length bargaining between managers and shareholders or rent seeking by powerful CEOs (Ferri & Göx, 2018).[11]

Building off the fact that social ties increase a director's dependence to the CEO, Hwang and Kim (2009) document that 87% of boards are conventionally independent but only 62% are conventionally and socially independent. Furthermore, they find that, compared to firms whose boards are only conventionally independent, firms whose boards are conventionally and socially dependent award a significantly higher level of total CEO compensation, exhibit weaker pay-performance sensitivity, and exhibit weaker turnover-performance sensitivity. Core et al. (1999) find that CEO compensation is higher when the CEO is also the board chair, there is a greater percentage of outside directors, and the outside directors are appointed by the CEO or are considered "gray" directors. They further find that predicted excess compensation (that portion over and above what is warranted by economic determinants of CEO pay in the absence of agency problem) leads to lower firm performance. The evidence from these studies suggests that a lack of independence between directors and CEOs weakens the monitory and disciplinary effectiveness of the board and has adverse consequences for shareholders.

[10] Note that neighbourhood effects exist both in rural areas and urban cities. Given the widely varying sizes/densities of different cities/areas, a more precise definition of neighbourhood (i.e. specific geographical distance) is advantageous in terms of interpretation.

[11] See Murphy (1999, 2013), Bertrand and Mullainathan (2001), Bebchuk and Fried (2004), Frydman and Jenter (2010), Frydman and Saks (2010), Core and Guay (2010), Edmans and Gabaix (2016), and Rau (2017a) for overviews of the literature on the controversy between the efficient contracting view and the managerial power approach.

Using MBA students at Harvard Business School, Shue (2013) documents greater similarity in executive compensation and acquisitions strategy when firms employ graduates from the same section as compared to the same class. Notably, peer similarities in compensation and acquisitions are more than twice as strong in the year immediately following reunions relative to other years. Her analyses suggest that the section peer effects arise from ongoing social interactions (as opposed to social ties formed in the past).

To the extent that ongoing social interaction is more likely to take place among executives who are socially connected, particularly when they work in the same geographical area (people are most likely to come in contact with those that live or work nearby–Engelberg et al., 2013), we expect that CEO compensation should demonstrate stronger spatial correlation when a focal firm CEO is socially connected with the neighbouring firm CEOs.

Based on the above, we propose our second hypothesis as follows:

H2. Spatial correlation in CEO compensation is stronger for socially connected CEOs.

Whereas social connection facilitates information exchange during the pay-setting process and induces spatial correlation among neighbouring firms' CEO pay, there is reason to expect stronger spatial effects in CEO pay when the focal firm CEO is more powerful, and when the focal firm has weak governance (Hwang & Kim, 2009). In fact, the two are interrelated as weak governance structures allow powerful CEOs to influence the board's decisions and thereby to take control of the pay-setting process (Engelberg et al., 2013; Ferri & Göx, 2018).[12] Bebchuk and Fried (2004) argue that weak boards tend to shift rents to the CEO at the cost of shareholders. Empirically, Abernethy et al. (2015) show that powerful CEOs adopt incentive contracts that are designed in their favour. Song and Wan (2019) find that more-powerful CEOs get a higher level of total compensation than less-powerful CEOs. Focusing on executive pay disparity and exploiting a quasi-natural experiment, Vo and Canil (2019) also find support for the managerial power hypothesis. To see how spatial correlation in CEO pay varies depending on the strength of corporate governance and CEO power, we propose our third and fourth hypotheses as follows:

H3. Spatial correlation in CEO pay is stronger in firms with more powerful CEOs.

H4. Spatial correlation in CEO pay is stronger among weak-governance firms.

Whereas CEOs' local social network connections enable them to extract higher pay, to the extent that this does not increase accountability or productivity (Lazear, 2000; Shue, 2013), one would not expect a spatial correlation in CEO pay-performance sensitivity. Worse still, to the extent that it reflects an agency problem, spatial correlation in CEO pay could be associated with poor future firm performance (Core et al., 1999). Our final two hypotheses are as follows:

H5. There is no spatial correlation in CEO pay-performance sensitivity.

H6. Predicted excess CEO compensation is not positively (and may be negatively) associated with future firm performance.

3. Research design

3.1. Sample and data

We begin by identifying all publicly traded companies that have a continuous listing on the NYSE, NASDAQ or AMEX during 2010–2016.,[13],[14] We get CEO compensation and CEO characteristics data from ExecuComp, and annual financial variables and industry codes from Compustat. The educational background, employment history, and social activities of all senior executives and directors are from BoardEx. All continuous firm variables are winsorized at the top and bottom 5

[12] There seems to be little consensus on the exact distinctions and links between corporate governance and managerial power. van Essen et al. (2015) argue that both CEO power and board power are indicators of managerial influence over the pay-setting process and its relationship with firm performance. They focus on two sets of mechanisms when analyzing managerial power: board structures and ownership characteristics. These characteristics have been used to measure corporate governance in some studies. In this paper we assume that CEO power and corporate governance are interrelated but not exactly the same constructs.

[13] Three considerations prevented us from extending the data to cover a longer period (for example, to compare the periods pre- and post the recent Global Financial Crisis, GFC). First, it is computationally complex and time-consuming to manipulate the spatial weighting matrix in spatial econometric models. Second, many companies suffered during GFC, and there are significant changes in compensation policies and practice following GFC. If we combined the observations from before and after the crisis, it might bias the results. Using a balanced panel in the post-GFC period helps to ensure that all the companies received the same macro-economic treatment. Third, as explained in the footnote immediately below, our balanced panel design precludes including firms that existed before GFC but were merged or went bankrupt after GFC. We acknowledge that the choice inevitably involves trade-offs.

[14] We have used a balanced panel dataset for testing the spatial correlation in CEO compensation (all companies must have a continuous listing during 2010–2016). The main reason for adopting a balanced panel in this study concerns estimation issues in econometrics. According to Wooldridge (2012), when we have a micro-dataset of individuals or companies, if observations are missing due to bankruptcies or mergers and acquisitions, it will cause a non-random sample in the subsequent years. This is a critical issue for estimation because if the missing data occurs systematically, it violates the assumption of exogeneity, causing the estimators to be biased or at least inconsistent. In addition, the spatial panel model is based on balanced panel dataset, and statistical software such as STATA and R (e.g. Millo & Piras, 2012), which we use for estimating spatial models, does not allow one to estimate the spatial auto-correlation based on an unbalanced dataset.

percentiles to mitigate the influence of outliers (the results are robust to commonly-used alternative thresholds). Per capita income data is from U.S. Bureau of Economic Analysis.[15]

We hand collect one-to-one CEO social network data and determine the relationship between any two CEOs based on existing studies of social network (e.g. Bouwman, 2013; El-Khatib, Fogel, & Jandik, 2015; Fracassi & Tate, 2012).[16] We first obtain the information about educational background, prior employment, and social memberships of CEOs from BoardEx. Then we identify connections between these CEOs. There are three types of connections: (1) Past professional connections are between individuals who used to work at the same company; (2) School connections are between individuals who attended the same university less than two years apart; (3) Other social connections are between individuals who were members at the same club or other social organizations. Based on the connections data, we construct matrices of CEO's social networks (year by year) to show if there are connections between any two CEOs. If two CEOs have any one of the aforesaid connections, the corresponding position in the matrix will be denoted as 1, otherwise 0.

We measure CEO power following Li, Gong, and Koh (2018), Engelberg et al. (2013) and Veprauskaite and Adams (2013).[17] We consider a CEO as powerful if she is also the board chair or plays a key executive role (Engelberg et al., 2013).

After merging the different databases, the final sample includes 6545 firm-year observations (935 unique firms). There are 24 firms having no neighbours within a 100 KM radius. And just 3408 firm-year observations have socially-connected neighbouring CEOs within a 100 KM radius. The mean (median) number of neighbouring firms (within a 100 KM radius) is 35 (24). The standard deviation is 33. In the primary analyses we focus on firms that have neighbouring firms.[18]

The level of CEO compensation is our main dependent variable. Following prior studies (Bebchuk & Grinstein, 2005; Bouwman, 2013; Francis et al., 2016; Garmaise, 2011), we use the natural logarithm of (1 plus) salary, and the natural logarithm of (1 plus) total compensation, respectively.[19] We simply refer to compensation (or pay) unless there is a need to distinguish between the two.

Our key independent variables vary in different regressions. In the first basic model, the key independent variable is average CEO compensation at neighbouring firms (headquartered within a 100 KM radius of the focal firm). We obtain firm's historical business address directly from 10-K filings (Kubick & Lockhart, 2016), and obtain the latitude and longitude data from Latlong.net.[20] There is no relocation of corporate headquarters in our sample during 2010–2016.

Neighbouring firms in the same industry may pay their CEOs according to the industry norm. To isolate the industry effect from the pure neighbourhood effect, we separately compute the average CEO compensation for neighbouring firms in the same industry, and for neighbouring firms in different industries.

To test for the social network effect, we divide the average compensation of neighbouring firm CEOs along the social network dimension, i.e. those sharing a social network and those not sharing a social network. These are computed in a way analogous to that used for computing average compensation along the industry dimension.

We include controls for factors that prior research suggests may affect CEO compensation (e.g. Bouwman, 2013; Core et al., 1999; Engelberg et al., 2013; Faulkender & Yang, 2010; Francis et al., 2016; Hwang & Kim, 2009; Taylor, 2013; Yonker, 2015). Since pay consultants and executive compensation committees benchmark CEO pay against that of similar-sized firms in the same industry (Bizjak, Lemmon, & Naveen, 2008; Faulkender & Yang, 2010), in all regressions we control for similar-sized industry-peer compensation. We control for firm size, growth opportunities and leverage (larger firms, firms with higher growth opportunities and firms with higher leverage pay high levels of CEO compensation because their firms are more complex and require greater efforts to manage), firm performance (firms with better stock performance/profitability and greater variance are associated with higher CEO pay), media coverage and analyst following (firms with more media coverage and analyst following may be more closely scrutinized); board characteristics (firms with more dependent boards and larger boards tend to pay higher CEO compensation), managerial attributes (older CEOs and more capable CEOs, reflected in higher managerial abilities, command higher pay),[21] ownership attributes (insider share ownership and external blockholder

[15] http://www.bea.gov/data/economic-accounts/regional.

[16] In this paper, a firm's CEO is considered as having a social network if she/he has a network connection (prior to her/his appointment at the focal firm) to another CEO covered in BoardEx. Connections to a director or non-CEO executive do not constitute social network for our research purpose, since our interest is in whether social network connections between CEOs affect spatial correlation in CEO compensation. Our focus on social network connections between CEOs contrasts with that of Engelberg et al. (2013), who measure a CEO's network connections to other executives (not limited to CEOs) and directors. Our basic results are robust to controlling for director interlocking (see the Robustness Check section).

[17] Song and Wan (2019) define powerful CEOs to be those who are also the board chair, company founder, or chair with a key executive role. Because we do not have data for the second attribute, we follow the approach in Engelberg et al. (2013). Veprauskaite and Adams (2013) measure CEO power using CEO-chair duality, tenure, and share ownership. We obtained qualitatively similar results using this alternative measure (we excluded CEO bonus and CEO remuneration that Veprauskaite and Adams also included in their definition of CEO power, because they appear as the dependent variable in our paper).

[18] The spatial model requires having at least one neighbour (hence the total number for firm-year observations in Tables 2 and 3 is 6377 rather than 6545). The number of firm-year observations varies from model to model depending on data availability for specific variables.

[19] In line with past studies, total compensation is taken to be the sum of salary, bonuses, options, restricted stocks and other compensation.

[20] https://www.latlong.net/.

[21] Custodio, Ferreira, and Matos (2013) show that CEOs with more general skills are paid more. However, their general skills index only covers the period 1993–2007. We get our data on CEO ability ("Manager_ability") from Demerjian et al. (2012), updated through 2016 and made available by Prof. Peter Demerjian at http://faculty.washington.edu/pdemerj/data.html. Because they use Data Envelopment Analysis (DEA) to measure the relative efficiency of the firm within its industry, the values of managerial ability can be negative (which occurs when the CEO has lower ability relative to industry peers).

ownership tend to reduce CEO pay), and local market conditions (areas with higher per capita income and stronger local competition for CEOs tend to pay more). Table 1 lists the variables and their definitions.

Year and industry fixed effects are also included.[22] Standard errors are robust for heteroscedasticity and are clustered by firm to allow for unobserved firm-level shocks to compensation to persist over time (Engelberg et al., 2013).

3.2. Spatial econometric model

It is well-known that when there exists spatial (or other kinds of) dependence among the observations in the cross-section, OLS estimation will no longer be unbiased (Anselin, 1988; Case, 1991). Spatial econometric models are well-suited to handle such interdependence (Anselin, 1988; Blume, Brock, Durlauf, & Ioannides, 2011; Franzese & Hays, 2007).

To use a spatial regression model, we must first identify neighbouring firms. We follow prior studies (e.g. Dougal et al., 2015; Engelberg et al., 2013; Francis et al., 2016; Kedia & Rajgopal, 2009) to define neighbours using a 100 KM radius (we also use a 400 KM radius and find mostly similar results). For a given focal firm, firms headquartered within the chosen radius are considered its neighbours. In contrast to studies that focus on differences in corporate outcomes between large economic (urban) areas and small (rural) areas, we adopt a method that defines neighbours based on the geographical distance between firms, irrespective of whether they belong to urban (big cities) or rural areas (small cities). Note that for different focal firms, there is a different group of neighbouring firms, though some of these will overlap.[23] An advantage of the spatial regression approach is that it accommodates such overlaps as well as spatial dependence.

After identifying neighbouring firms, we conduct a range of specification tests. The procedure is described in Appendix 1, and the test results are reported in Table A1. The specification tests indicate that the Spatial Lag Model (SLM) is preferred for analyzing CEO compensation.

Having selected the appropriate model specification, we perform the following baseline spatial regression model:

$$y_{it} = a_0 + \lambda \sum_{j=1}^{n} W_{ij} y_{jt} + \beta X_{it} + \gamma_i + \delta_i + \varepsilon_{it} \tag{1}$$

Where y_{it} denotes the level of CEO compensation (salary or total compensation) for CEO i in year t; X_{it} is a vector of control variables (economic, board, ownership and other attributes); γ_i denotes the year fixed effect; δ_i is the industry fixed effect; and ε_{it} denotes the (normally distributed) error term. $\sum_{j=1}^{n} W_{ij} y_{jt}$ is the spatially lagged dependent variable ('spatial lag'), reflecting the weighted average of the neighbouring firms' CEO compensation (excluding the focal firm CEO) according to the first-order spatial relationship between firm i and firm j. Thus, the coefficient λindicates the spatial effect (i.e. spatial correlation in CEO pay).

One can estimate the spatial model using Maximum Likelihood (ML); however, it is very computationally complex, especially for a large data set (Anselin, 1988). As an alternative, the Spatial Two-Stage Least Squares (2SLS) approach has been proposed (Anselin, 1990; Kelejian & Prucha, 1998; Kelejian & Robinson, 1993). Lee (2007) argues that the GMM estimator is asymptotically more efficient than the 2SLS estimator and asymptotically as efficient as the ML estimator. Also, GMM is computationally simpler than the ML estimator and also can correct for heteroscedasticity.[24] As a result, in this study we adopt the GMM method to estimate the spatial lag parameter λ. We use exogenous variables X to derive their spatial lag, WX, which is then used as a set of instruments to explain the spatial lag Wy (Anselin, 1999, 2017; Fingleton & Le Gallo, 2008; Franzese & Hays, 2007; Kelejian & Prucha, 1998, 1999; Kelejian, Prucha, & Yuzefovich, 2004; Lee, 2003).[25]

4. Results

4.1. Descriptive statistics

Table 2 reports the summary statistics for the variables used in the baseline regression. CEOs in our sample receive an average annual salary (total compensation) of \$879,820 (\$7,077,193). These figures are higher than those in earlier periods (e.g. Bouwman, 2013; Francis et al., 2016), consistent with a secular increase in CEO compensation. The sample firms are large, established and profitable firms (average log firm size = 22.167, average firm age = 30.46 years, average MB ratio = 1.278, average profitability = 5.5%) with seemingly independent boards (average board independence = 80%). The average CEO age and tenure is 57.099 and 7.679 years, with 96.4 percent of the CEOs being male. On average, CEOs own 1.435 percent, other

[22] Firms are assigned to their relevant Fama-French 12-Industry category. Because there is limited within-firm time-series variation in our key explanatory variable (social network connections), we do not use firm fixed effects, following Engelberg et al. (2013), Roberts and Whited (2013), and Coles and Li (2019).

[23] In other words, as we move from one focal firm to another in (initially) the same neighbourhood, a new (substantially overlapping) group of neighbours emerges.

[24] The Breusch-Pagan/Cook-Weisberg test for heteroscedasticity does not reject the null hypothesis of no heteroscedasticity.

[25] See Appendix 2 for a discussion of endogeneity issues and the instrument variable approach in spatial econometrics.

Table 1
Variable definitions.

Variable	Definition
Panel A. Dependent Variables	
Ln(Salary)	The natural log of (1 plus) salary.
Ln(Ttlcomp)	The natural log of (1 plus) total compensation, which includes salary, bonuses, options, restricted stocks, and other compensation.
Ela_SSR	The elasticity of salary to stock return.
Ela_TSR	The elasticity of total compensation to stock return.
Ela_SAR	The elasticity of salary to market-model abnormal stock return.
Ela_TAR	The elasticity of total compensation to abnormal stock return.
Panel B. Key Independent Variables	
Ln(NeighbourCEOsalary)	The natural log of (1 plus) the average CEO salary at firms headquartered within a 100 KM radius. Excludes focal CEO's own pay.
Ln(NeighbourCEOttlcomp)	The natural log of (1 plus) the average CEO total compensation at firms headquartered within a 100 KM radius. Excludes focal CEO's own pay.
Ln(NeighbourCEOsalary_ind)	The natural log of (1 plus) the average CEO salary at firms headquartered within a 100 KM radius and belonging to same industry. Excludes focal CEO's own pay.
Ln(NeighbourCEOttlcomp_ind)	The natural log of (1 plus) the average CEO total compensation at firms headquartered within a 100 KM radius and belonging to same industry. Excludes focal CEO's own pay.
Ln(NeighbourCEOsalary_Nind)	The natural log of (1 plus) the average CEO salary at firms headquartered within a 100 KM radius and belonging to different industry. Excludes focal CEO's own pay.
Ln(NeighbourCEOttlcomp_Nind)	The natural log of (1 plus) the average CEO total compensation at firms headquartered within a 100 KM radius and belonging to different industry. Excludes focal CEO's own pay.
Ln(NeighbourCEOsalary_C)	The natural log of (1 plus) the average CEO salary at firms headquartered within a 100 KM radius and with social network connection. Excludes focal CEO's own pay.
Ln(NeighbourCEOttlcomp_C)	The natural log of (1 plus) the average CEO total compensation at firms headquartered within a 100 KM radius and with social network connection. Excludes focal CEO's own pay.
Ln(NeighbourCEOsalary_NC)	The natural log of (1 plus) the average CEO salary at firms headquartered within a 100 KM radius and without social network connection. Excludes focal CEO's own pay.
Ln(NeighbourCEOttlcomp_NC)	The natural log of (1 plus) the average CEO total compensation at firms headquartered within a 100 KM radius and without social network connection. Excludes focal CEO's own pay.
Ln(NeighbourCEOsalary_C_ind)	The natural log of (1 plus) the average CEO salary at firms headquartered within a 100 KM radius and belonging to same industry, and with social network connection. Excludes focal CEO's own pay.
Ln(NeighbourCEOttlcomp_C_ind)	The natural log of (1 plus) the average CEO total compensation at firms headquartered within a 100 KM radius and belonging to same industry, and with social network connection. Excludes focal CEO's own pay.
Ln(NeighbourCEOsalary_NC_ind)	The natural log of (1 plus) the average CEO salary at firms headquartered within a 100 KM radius and belonging to same industry, and without social network connection. Excludes focal CEO's own pay.
Ln(NeighbourCEOttlcomp_NC_ind)	The natural log of (1 plus) the average CEO total compensation at firms headquartered within a 100 KM radius and belonging to same industry, and without social network connection. Excludes focal CEO's own pay.
Ln(NeighbourCEOsalary_C_Nind)	The natural log of (1 plus) the average CEO salary at firms headquartered within a 100 KM radius and belonging to different industry, and with social network connection. Excludes focal CEO's own pay.
Ln(NeighbourCEOttlcomp_C_Nind)	The natural log of (1 plus) the average CEO total compensation at firms headquartered within a 100 KM radius and belonging to different industry, and with social network connection. Excludes focal CEO's own pay.
Ln(NeighbourCEOsalary_NC_Nind)	The natural log of (1 plus) the average CEO salary at firms headquartered within a 100 KM radius and belonging to different industry, and without social network connection. Excludes focal CEO's own pay.
Ln(NeighbourCEOttlcomp_NC_Nind)	The natural log of (1 plus) the average CEO total compensation at firms headquartered within a 100 KM radius and belonging to different industry, and without social network connection. Excludes focal CEO's own pay.
Ave_NEla_SSR(SAR)	The average elasticity of salary to (abnormal) stock return at firms headquartered within a 100 KM radius. Excludes focal firm.
Ave_NEla_TSR(SAR)	The average elasticity of salary to (abnormal) stock return at firms headquartered within a 100 KM radius. Excludes focal firm.
Ave_NEla_SSR(SAR)_C	The average elasticity of salary to (abnormal) stock return at firms headquartered within a 100 KM radius and with social network connection. Excludes focal firm.
Ave_NEla_TSR(SAR)_C	The average elasticity of total compensation to (abnormal) stock return at firms headquartered within a 100 KM radius and with social network connection. Excludes focal firm.
Ave_NEla_SSR(SAR)_NC	The average elasticity of salary to (abnormal) stock return at firms headquartered within a 100 KM radius and without social network connection. Excludes focal firm.
Ave_NEla_TSR(SAR)_NC	The average elasticity of total compensation to (abnormal) stock return at firms headquartered within a 100 KM radius and without social network connection. Excludes focal firm.
Panel C. Control Variables	
Economic attributes	
Firm_size	The natural log of (1 plus) total assets.
Firm_age	Fiscal year minus founding year.
MB_ratio	Market value of equity divided by the book value of equity.
Profitability	Return on assets, measured as net income divided by total assets.
Leverage	The ratio of debt to total value of the firm.
Local_CEO_market	The number of same-industry firms within a 100 KM radius divided by the number of firms within a 100 KM radius.
Median CEO pay at benchmark firms	The natural log of (1 plus) median CEO pay at benchmark firms, i.e. those in the same industry (two-digit SIC) and same-size group (we classify firms as being in the large (small) firm group if they have sales above (below) the median sales in the year).
Stock return	The average monthly stock returns over the prior year.

Table 1 (*continued*)

Variable	Definition
Volatility of stock return	The standard deviation of stock returns over the prior year.
Media coverage	The natural log of (1 plus) the number of media reports which are relevant to the focal firm (source: RavenPack).
Analyst	The natural log of (1 plus) the number of analysts following a firm.
CEO-chair Duality	Dummy variable coded 1 if the CEO is also chair, and 0 otherwise.
Manager_ability	Managerial ability (Demerjian, Lev, & McVay, 2012).
CEO_Age	CEO's age.
Tenure	Number of years the executive has been the firm's CEO.
Gender	CEO's gender, coded 1 for male, and 0 otherwise.
Ownership attributes	
CEO_ownership	Percentage of total shares owned by CEO.
Insider_ownership	Percentage of total shares owned by insiders (excluding CEO).
Blockholding	Total institutional ownership, as a percent of shares outstanding.
Panel D. Other Variables	
E-index	Bebchuk et al.'s (2009) E-index (Entrenchment index) which is related to 6 corporate governance provisions tracked by the IRRC.
CEO Power	Dummy variable indicating CEO power, measured as the concentration of the CEO's titles. This is coded one if the CEO is the chairman of the board and also holds at least one of the following titles: president, chief operating officer, or chief finance officer.

insiders 3.121 percent, and outside institutional investors 0.829 percent of the firm's shares. In 63.2% of the firm-year observations the CEO may be considered powerful. The average E-index is 4.048. Untabulated analysis finds that the corporate governance and powerful CEO indicators are stable during the sample period.

We next present some additional descriptive statistics, which are tabulated in the Online Appendix in order to save space. Online Appendix Table 1, Panel A presents the industry distribution for our sample. Finance is the largest industry represented (20.11%), Business Equipment the second largest (15.8%), and Telephone and Television Transmission the smallest (1.07%).[26] In untabulated analyses, we find that our sample is representative of the universe of listed firms on NYSE, NASDAQ and AMEX.[27]

Online Appendix Table 1, Panel B presents the correlation between focal firm CEO pay and neighbouring firms' CEO pay. For every focal firm, we first find the average CEO pay at the neighbouring firms. We then group average CEO pay at neighbouring firms into ten decides (Column 1) and compute the average CEO pay at the focal firms corresponding to each decile (Column 2). It is apparent that when the neighbouring firm CEOs have higher pay, the focal firm CEOs also tend to have higher pay–the correlation coefficient is 0.7676 for salary and 0.6947 for total compensation (untabulated).

Our hypotheses center on the role of social network connection, CEO power and corporate governance on spatial correlation in CEO compensation and pay-performance sensitivity. Online Appendix Table 1, Panel C presents tests of difference in CEO pay conditioned on these variables. We start by comparing the focal firm CEO pay depending on whether it has neighbouring firms within a 100 KM radius. Panel C1 shows that when a focal firm has neighbours (the great majority of the cases), its CEO pay tends to be higher on average than when it has no neighbours. Panel C2 shows that while focal firm CEO salary does not differ depending on whether the neighbours are in the same industry, total compensation does. Moving on to Panel C3, when the focal firm and neighbouring firm CEOs are socially connected, the focal firm CEO enjoys higher pay (both salary and total compensation), compared to when they are not socially connected. Panel C4 shows that the higher pay for socially connected focal firm CEO does not depend on whether the focal firm and the neighbouring firms belong to the same industry. Panel C5 shows that, conditional on having neighbours, powerful CEOs on average get higher pay than less powerful CEOs. Panel C6 shows that, conditional on having neighbours, socially connected focal firm CEOs at weak-governance (high E-Index) firms enjoy higher pay than non-connected focal firm CEOs. The same however is also true for strong-governance firms, implying that social network connection may play a more important role in the pay-setting process than corporate governance does. A more definitive conclusion has to await a multivariate analysis that controls for other factors.

Online Appendix Table 1, Panel D roughly mirrors the analyses in Panel C, this time using pay-performance sensitivity in lieu of CEO pay. No statistically significant difference is found for pay-performance sensitivity, irrespective of the presence of neighbours and/or social network connections.

[26] In robustness checks, we exclude finance and utilities from our sample and obtain qualitatively similar results.

[27] In our primary sample, NYSE-listed firms represent 65.56% of the total firm-year observations, compared to 60.73% for the population of NYSE-listed firms as a proportion of all US-listed firms. The corresponding figures for AMEX- and NASDAQ-listed firms in our primary sample are respectively 0.32% and 34.12%, compared to 0.42% and 38.85% for the population. The total compensation levels for our sample firms are similar to the levels in their respective population.

Table 2
Summary statistics.

variable	N	mean	stdev	min	p10	p50	p90	max
Salary ($000s)	6377	879.820	305.500	347.234	497.701	861.779	1328.758	1536.096
Ttlcomp ($000s)	6377	7077.193	5260.964	809.972	1579.715	5552.480	15599.591	21461.158
Ln(Salary)	6377	6.716	0.369	5.85	6.21	6.759	7.192	7.337
Ln(Ttlcomp)	6377	8.561	0.827	6.697	7.365	8.622	9.655	9.974
Ln(NeighbourCEOsalary)	6377	6.716	0.147	5.85	6.547	6.732	6.868	7.337
Ln(NeighbourCEOttlcomp)	6377	8.561	0.317	6.697	8.240	8.601	8.858	9.881
Firm_size	6377	22.167	15.39	19.396	20.076	22.067	24.500	25.195
Firm_age	6377	30.46	19.75	5	11	24	60	82
MB_ratio	6377	1.278	0.953	0.124	0.265	1.024	2.776	4.055
Profitability	6377	0.055	0.052	−0.103	0.003	0.049	0.132	0.172
Leverage	6377	0.212	0.158	0.000	0.000	0.200	0.448	0.611
Local_CEO_market	6377	0.171	0.168	0.000	0.000	0.121	0.439	1.000
Median CEO pay at benchmark firms (Ln(Salary))	6377	6.735	0.216	6.397	6.467	6.908	6.980	6.996
Median CEO pay at benchmark firms (Ln(Ttlcomp))	6377	8.608	0.524	7.897	7.993	9.018	9.177	9.242
Stock return	6377	0.016	0.027	−0.121	−0.012	0.015	0.045	0.259
Volatility of stock return	6377	0.088	0.051	0.017	0.043	0.076	0.143	0.877
Media coverage	6377	5.369	1.761	0	4.078	5.545	6.948	12.059
Analyst	6377	2.338	0.757	0	1.386	2.398	3.219	4.025
Ln(Percapitaincome)	6377	10.746	0.160	10.328	10.543	10.734	10.954	11.240
Board_size	6377	9.547	1.995	6	7	9	12	14
Independence	6377	0.800	0.101	0.571	0.636	0.818	0.909	0.917
CEO-chair duality	6377	0.509	0.500	0	0	1	1	1
CEO_age	6377	57.099	6.252	41	49	57	66	79
Tenure	6377	7.679	6.263	1	1	6	18	24
Gender	6377	0.964	0.186	0	1	1	1	1
Manager_ability	6377	0.020	0.137	−0.272	−0.107	0.008	0.187	0.681
CEO_ownership	6377	1.435	2.353	0.031	0.064	0.481	4.016	11.342
Insider_ownership	6377	3.121	5.387	0.030	0.12	0.935	9.904	25.192
Blockholding	6377	0.829	0.152	0.386	0.630	0.846	0.994	1.134
E-index	6377	4.048	0.928	1	3	4	5	6
Powerful CEO	6377	0.632	0.482	0	0	1	1	1

This table presents the summary statistics for the variables used in the basic regression analyses (where the included firms have a neighbour within a 100 KM radius). Additional summary statistics are presented in the Online Appendix. See Table 1 for variable definitions.

4.2. Spatial correlation in CEO compensation: Preliminary evidence

Bouwman (2013) is a study most closely related to ours. However, she (other than using a much earlier period 1992–2006) estimated the impact of neighbouring firm CEO pay on focal firm CEO pay using OLS.[28] When spatial dependence exists in the cross section of firms, OLS is a biased and inefficient estimator (Anseline, 1988; Case, 1991; Kalenkoski & Lacombe, 2013; LeSage & Pace, 2009; Ward & Gleditsch, 2008). Empirical studies (e.g. Keller & Shiue, 2007) show that accounting for spatial structure can qualitatively change the inferences. To check if, and to what extent accounting for spatial dependence alters the inferences in our specific context, we estimate the CEO pay impact of neighbouring CEO pay using both OLS and the Spatial Lag Model. Results are reported in Table 3.

We first use the same control variables as in Bouwman's (2013) main results (her Table 2, Panel A).[29] The variables of interest are LN(NeighbourCEOsalary) and LN(NeighbourCEOttlcomp). In the OLS model (Columns 1–2), a focal firm's CEO salary (total compensation) is estimated to increase by about 0.153% (0.158%) if the average salary (total compensation) of neighbouring firm CEOs increases by 1%. In Bouwman (2013), the focal firm CEO's total compensation is estimated to increase by 0.122% for a 1% increase in the neighbouring firm CEOs' total compensation. These coefficients (elasticity) are roughly comparable despite the different samples used. When the same control variables are used in the Spatial Lag Model (Column 3), the coefficient on LN(NeighbourCEOsalary) changes only slightly from 0.153 to 0.135. However, when we look at total compensation (Column 4), which prior studies usually focus on, the difference between the OLS estimate and the Spatial Lag Model estimate is much bigger: the coefficient on LN(NeighbourCEOttlcomp) has dropped from 0.158 in the OLS model to just 0.074 in the Spatial Lag Model. While the estimates are all statistically significant, considering the spatial dependence in the cross section of firms considerably reduces the magnitude of the spatial effect (when using the same sample and variables). This indicates that it is important to take into consideration the spatial structure in the data, and justifies our use of the spatial model. As seen in Columns 5–8, adding more control variables (used in other related studies) does not change the above conclusion.

[28] Her neighbouring CEOs' average pay was lagged relative to focal CEO pay (she asks, "by how much does a focal firm CEO's pay this year change if the average CEO pay at neighbouring firms last year increased by 1%?"). In our spatial model, we allow neighbouring firm CEOs' pay to influence the focal firm CEO pay contemporaneously–arguably, this specification better captures the spatial spillover effects. In untabulated robustness tests, we obtain qualitatively similar results if we add the (lagged by one year) % pay-gap between focal CEO pay and neigbouring CEOs' average pay used in Bouwman (2013).

[29] We do not have data for external CEO and state income tax rate which Bouwman (2013) included. The latter variable was insignificant in her results while the first one is. According to Bouwman (2013, Footnote 7), "the use of the external hire variable causes a significant reduction in sample size. Importantly, however, when I rerun the regressions in the paper without this variable, I obtain comparable results."

Table 3
Baseline results: Comparing the OLS and spatial lag models.

	OLS		GMM		OLS		GMM	
	Ln(Salary)	Ln(Ttlcomp)	Ln(Salary)	Ln(Ttlcomp)	Ln(Salary)	Ln(Ttlcomp)	Ln(Salary)	Ln(Ttlcomp)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ln(NeighbourCEOsalary)[a]	0.153***		0.135***		0.131***		0.115***	
	(0.024)		(0.033)		(0.023)		(0.028)	
Ln(NeighbourCEOttlcomp)[a]		0.158***		0.074**		0.120***		0.069**
		(0.023)		(0.037)		(0.023)		(0.029)
CEO_age	0.003***	0.002	0.004***	0.001	0.003***	0.001	0.003***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Tenure	0.003***	0.002	0.003***	0.002	0.004***	0.002	0.005***	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.0015)
Firm_size	0.137***	0.345***	0.141***	0.350***	0.110***	0.261***	0.115***	0.270***
	(0.004)	(0.009)	(0.004)	(0.009)	(0.006)	(0.012)	(0.006)	(0.012)
MB_ratio	−0.021***	0.118***	−0.014**	0.126***	−0.021**	0.100***	−0.012*	0.109***
	(0.007)	(0.013)	(0.007)	(0.013)	(0.007)	(0.014)	(0.007)	(0.013)
Stock return	0.341**	1.673***	0.321**	1.744***	0.068	1.250***	0.025	1.196***
	(0.142)	(0.303)	(0.141)	(0.302)	(0.155)	(0.329)	(0.154)	(0.326)
Profitability	0.299***	0.190	0.274**	0.167	0.366***	0.310	0.302**	0.273
	(0.112)	(0.229)	(0.111)	(0.228)	(0.116)	(0.238)	(0.114)	(0.235)
Ln(Percapitaincome)	0.023	0.188***	0.029	0.211***	0.052**	0.225***	0.052**	0.224***
	(0.021)	(0.049)	(0.021)	(0.050)	(0.022)	(0.049)	(0.021)	(0.049)
Median CEO pay at benchmark firm	0.286***	0.703***	0.284***	0.687***	0.271***	0.664***	0.273***	0.640***
	(0.024)	(0.052)	(0.024)	(0.052)	(0.024)	(0.050)	(0.024)	(0.049)
Gender					−0.069***	−0.158***	−0.079***	−0.180***
					(0.017)	(0.034)	(0.017)	(0.034)
Manager_ability					0.006	0.065**	0.009	0.075**
					(0.014)	(0.029)	(0.014)	(0.029)
Firm_age					0.001***	0.001**	0.001***	0.001**
					(0.000)	(0.000)	(0.000)	(0.000)
Leverage					0.130***	0.382***	0.096***	0.359***
					(0.023)	(0.050)	(0.023)	(0.049)
Board_size					0.009***	0.004	0.009***	0.004
					(0.002)	(0.005)	(0.002)	(0.005)
Independence					0.140**	0.659***	0.142***	0.725***
					(0.043)	(0.087)	(0.042)	(0.084)
CEO-chair duality					0.050***	0.101***	0.050***	0.092***
					(0.007)	(0.016)	(0.007)	(0.015)
Local_CEO_market					−0.001	0.037	0.023	0.042
					(0.021)	(0.046)	(0.020)	(0.045)
CEO_ownership					−0.010***	−0.034***	−0.008**	−0.031***
					(0.003)	(0.006)	(0.003)	(0.006)
Insider_ownership					0.001	0.005*	0.000	0.006**
					(0.001)	(0.002)	(0.001)	(0.002)
Blockholding					0.249***	0.714***	0.266***	0.739***
					(0.026)	(0.059)	(0.026)	(0.058)
Volatility of stock return					0.308***	0.009	0.287***	0.021
					(0.085)	(0.172)	(0.084)	(0.170)
Analyst					0.032***	0.051**	0.023**	0.043**
					(0.008)	(0.018)	(0.008)	(0.017)
Media coverage					−0.004	0.063***	−0.005	0.082***
					(0.006)	(0.012)	(0.006)	(0.011)
Cons	2.296***	−2.382***	2.307***	−1.908**	1.976***	−3.147***	1.974***	−2.805***
	(0.299)	(0.596)	(0.325)	(0.601)	(0.306)	(0.609)	(0.311)	(0.595)
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	6377	6377	6377	6377	5981	5981	5981	5981
R-squared	0.53	0.58	0.53	0.58	0.56	0.63	0.56	0.62
Number of Instruments	/	/	8	8	/	/	22	22
Kleibergen-Paap rk LM Statistic (for Underidentification Test)	/	/	183.51***	139.61***	/	/	308.12***	235.54***
Cragg-Donald Wald F Statistic (for Weak identification Test)	/	/	71.45**	45.17**	/	/	44.12**	34.09**
Sargan-Hansen's J Statistic (for Overidentification Test)	/	/	11.77	10.99	/	/	26.83	26.47

This table reports the results of estimating the CEO pay impact of neighbouring CEO pay using both OLS and the Spatial Lag Model. Regressions include control variables as indicated, plus industry and year fixed effects. Robust standard errors are in parentheses. Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. See Table 1 for variable definitions.

[a] Ln(NeighbourCEOsalary), Ln(NeighbourCEOttlcomp) are treated as endogenous variables. The instrumental variables used for explaining the endogenous variables are all of the spatial weighted exogenous explanatory variables, WX. Please refer to Appendix 2 for detailed explanations. These instruments

pass the weak instrument and diagnostic tests. For underidentification test, we use Kleibergen-Paap rk statistic to test for the rank condition. A rejection of the null hypothesis implies the model is identified. For weak identification test, we test if the IV estimator generates a maximal bias relative to OLS of 5%, the lowest level of maximal IV relative bias listed in Table 1 of Stock and Yogo (2005). The critical value for the Cragg–Donald statistic for a 5% maximal IV relative bias at the 5% significance level is 20.25 for models (3) and (4) with 1 endogenous regressor, and 21.40 for models (7) and (8) with 1 endogenous regressor. For overidentification test, the null hypothesis is that all excluded instruments are exogenous, so failure to reject the null hypothesis implies that all instruments are valid.

Table 4
Pure local versus industry effects.

	Ln(Salary)	Ln(Ttlcomp)
	(1)	(2)
Ln(NeighbourCEOsalary_ind)[a]	0.022*	
	(0.012)	
Ln(NeighbourCEOsalary_Nind)[a]	0.086**	
	(0.024)	
Ln(NeighbourCEOttlcomp_ind)[a]		0.062***
		(0.024)
Ln(NeighbourCEOttlcomp_Nind)[a]		0.080*
		(0.042)
Economic attributes	Yes	Yes
Board attributes	Yes	Yes
Ownership attributes	Yes	Yes
Year	Yes	Yes
Industry	Yes	Yes
N	5981	5981
R-squared	0.51	0.58
Number of Instruments	22	22
Kleibergen-Paap rk LM Statistic (for Underidentification Test)	306.44***	225.35***
Cragg-Donald Wald F Statistic (for Weak identification Test)	36.21**	24.14**
Sargan-Hansen's J Statistic (for Overidentification Test)	25.44	23.89

This table reports the results to distinguish the "pure" local (neighbourhood) effect from the industry effect. Regressions include control variables as indicated, plus industry and year fixed effects and a constant term (untabulated). Robust standard errors are in parentheses. Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. See Table 1 for variable definitions and Table 3 for the control variables.

[a] Ln(NeighbourCEOsalary_ind), Ln(NeighbourCEOsalary_Nind), Ln(NeighbourCEOttlcomp_ind) and Ln(NeighbourCEOttlcomp_Nind) are treated as endogenous variables. The instrumental variables used for explaining the endogenous variables are of the spatial weighted exogenous explanatory variables, WX. Please refer to Appendix 2 for detailed explanations. These instruments pass the weak instrument and diagnostic tests. For underidentification test, we use Kleibergen-Paap rk statistic to test for the rank condition. A rejection of the null hypothesis implies the model is identified. For weak identification test, we test if the IV estimator generates a maximal bias relative to OLS of 5%, the lowest level of maximal IV relative bias listed in Table 1 of Stock and Yogo (2005). The critical value for the Cragg–Donald statistic for a 5% maximal IV relative bias at the 5% significance level is 20.60 with 2 endogenous regressors. For overidentification test, the null hypothesis is that all excluded instruments are exogenous, so failure to reject the null hypothesis implies that all instruments are valid.

The results for the control variables appear sensible. Consistent with prior research, focal firm CEO pay is significantly and positively associated with median CEO pay at similar-size industry peers.[30] Larger and more profitable firms pay higher CEO compensation, older firms and older CEOs are associated with higher pay, and longer-serving and more capable CEOs receive greater total compensation. CEOs also acting as board chair earn higher compensation. CEOs of firms in higher-income regions receive greater total compensation. CEO share ownership and female CEOs are negatively associated with CEO compensation. Given the focus of this study and for brevity, in the remainder of the paper we do not tabulate or discuss results for the control variables.

[30] The fact that we find a significant spatial effect over and beyond the benchmark firms effect indicates that this effect is distinct from the benchmark effect documented in prior studies. The coefficient is approximately 0.27 for salary and 0.70 for total compensation (for both the OLS model and Spatial Lag Model). Using a sample of relatively large S&P 900 firms during 2006–2007, Faulkender and Yang (2010) report a coefficient of approximately 0.58 for CEO total compensation at benchmark firms, while Bouwman (2013) reports a coefficient on CEO total compensation of only approximately 0.07 for all firms included in ExecuComp during 1994–2006. The differences in results (in terms of magnitude) may be due to different sample composition/period, the inclusion of different variables, and/or different modelling approaches.

Table 5
Effect of social network on spatial correlation in CEO compensation.

	Ln(Salary)	Ln(Ttlcomp)
	(1)	(2)
Ln(NeighbourCEOsalary_C)[a]	0.181***	
	(0.040)	
Ln(NeighbourCEOsalary_NC)[a]	−0.025	
	(0.029)	
Ln(NeighbourCEOttlcomp_C)[a]		0.221***
		(0.038)
Ln(NeighbourCEOttlcomp_NC)[a]		−0.084
		(0.058)
Economic attributes	Yes	Yes
Board attributes	Yes	Yes
Ownership attributes	Yes	Yes
Year	Yes	Yes
Industry	Yes	Yes
N	3227	3227
R-squared	0.57	0.53
Number of Instruments	22	22
Kleibergen-Paap rk LM Statistic (for Underidentification Test)	226.46***	239.81***
Cragg-Donald Wald F Statistic (for Weak identification Test)	21.83**	35.47**
Sargan-Hansen's J Statistic (for Overidentification Test)	25.22	16.46

This table reports the results to examine the effect of social network on neighbouring firms' CEO compensation. Regressions include control variables as indicated, plus industry and year fixed effects and a constant term (untabulated). Robust standard errors are in parentheses. Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. See Table 1 for variable definitions and Table 3 for the control variables.

[a] Ln(NeighbourCEOsalary_C), Ln(NeighbourCEOsalary_NC), Ln(NeighbourCEOttlcomp_C) and Ln(NeighbourCEOttlcomp_NC) are treated as endogenous variables. The instrumental variables used for explaining the endogenous variables are all of the spatial weighted exogenous explanatory variables, WX. Please refer to Appendix 2 for detailed explanations. These instruments pass the weak instrument and diagnostic tests. For underidentification test, we use Kleibergen-Paap rk statistic to test for the rank condition. A rejection of the null hypothesis implies the model is identified. For weak identification test, we test if the IV estimator generates a maximal bias relative to OLS of 5%, the lowest level of maximal IV relative bias listed in Table 1 of Stock and Yogo (2005). The critical value for the Cragg−Donald statistic for a 5% maximal IV relative bias at the 5% significance level is 20.60 with 2 endogenous regressors. For overidentification test, the null hypothesis is that all excluded instruments are exogenous, so failure to reject the null hypothesis implies that all instruments are valid.

To distinguish the "pure" local (neighbourhood) effect from the industry effect, we include among the explanatory variables the average CEO pay of local non-industry firms and the average CEO pay of local industry firms.[31] Table 4 reports the results.

The coefficients on NeighbourCEOsalary_ind and NeighbourCEOttlcomp_ind (i.e. average CEO salary and total compensation, respectively, at same-industry neighbouring firms) are positive and statistically significant, ranging from about 0.022 (for salary) to 0.062 (for total compensation). The coefficients on NeighbourCEOsalary_Nind and NeighbourCEOttlcomp_Nind (i.e. average CEO salary and total compensation, respectively, at neighbouring firms in different industries) are also positive and statistically significant, at about 0.08. Thus, after controlling for economic, board and ownership attributes, a focal firm's CEO compensation is positively and significantly associated with neighbouring firms' CEO compensation, irrespective of the industry affiliation of the neighbouring firms.

The results so far support the presence of spatial correlation in CEO pay. As discussed in the Literature Review, social network/interactions, CEO power, and corporate governance are likely to influence the spatial correlation in CEO compensation. We next test these predictions.

4.3. *Effects of social network on spatial correlation in CEO compensation*

Bouwman (2013) tested four possible explanations for spatial correlation in CEO compensation and concluded that relative status concern among geographically-close CEOs seems to be the most consistent with the data. However, she did not explicitly test for the influence of CEO power or the performance consequences of spatial correlation in CEO pay, nor did she

[31] The results for similar-size industry peers in Table 3 show that industry affiliation affects CEO pay. However, the peers were selected based on both industry and size (irrespective of location). In this additional analysis, we include all the other control variables (including similar-size industry peers) but further divide the local firms into industry and non-industry firms. Doing so allows us to more closely examine the relative importance of the same-industry vs different-industry effects within the spatial (neighbourhood) effects we have documented.

Table 6
Interactive effect of industry and social network on CEO compensation.

	Ln(Salary)	Ln(Ttlcomp)
	(1)	(2)
Ln(NeighbourCEOsalary_C_ind)[a]	0.022**	
	(0.010)	
Ln(NeighbourCEOsalary_NC_ind)[a]	0.028	
	(0.034)	
Ln(NeighbourCEOsalary_C_Nind)[a]	0.019***	
	(0.007)	
Ln(NeighbourCEOsalary_NC_Nind)[a]	−0.016	
	(0.011)	
Ln(NeighbourCEOttlcomp_C_ind)[a]		0.062***
		(0.016)
Ln(NeighbourCEOttlcomp_NC_ind)[a]		0.011
		(0.056)
Ln(NeighbourCEOttlcomp_C_Nind)[a]		0.048***
		(0.013)
Ln(NeighbourCEOttlcomp_NC_Nind)[a]		−0.028
		(0.021)
Year	Yes	Yes
Industry	Yes	Yes
N	3227	3227
R-squared	0.48	0.48
Number of Instruments	22	22
Kleibergen-Paap rk LM Statistic (for Underidentification Test)	243.5***	242.86***
Cragg-Donald Wald F Statistic (for Weak identification Test)	49.87**	49.65**
Sargan-Hansen's J Statistic (for Overidentification Test)	21.49	15.95

This table reports the results to gauge the interactive effect of industry and social network on spatial correlation in CEO pay. Regressions include control variables as indicated, plus industry and year fixed effects and a constant term (untabulated). Robust standard errors are in parentheses. Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. See Table 1 for variable definitions and Table 3 for the control variables.

[a] Ln(NeighbourCEOsalary_C_ind), Ln(NeighbourCEOsalary_NC_ind), Ln(NeighbourCEOsalary_C_Nind), Ln(NeighbourCEOsalary_NC_Nind), Ln(NeighbourCEOttlcomp_C_ind), Ln(NeighbourCEOttlcomp_NC_ind), Ln(NeighbourCEOttlcomp_C_Nind) and Ln(NeighbourCEOttlcomp_NC_Nind) are treated as endogenous variables. The instrumental variables used for explaining the endogenous variables are all of the spatial weighted exogenous explanatory variables, WX. Please refer to Appendix 2 for detailed explanations. These instruments pass the weak instrument and diagnostic tests. For underidentification test, we use Kleibergen-Paap rk statistic to test for the rank condition. A rejection of the null hypothesis implies the model is identified. For weak identification test, we test if the IV estimator generates a maximal bias relative to OLS of 5%, the lowest level of maximal IV relative bias listed in Table 1 of Stock and Yogo (2005). The critical value for the Cragg−Donald statistic for a 5% maximal IV relative bias at the 5% significance level is 19.77 with 4 endogenous regressors. For overidentification test, the null hypothesis is that all excluded instruments are exogenous, so failure to reject the null hypothesis implies that all instruments are valid.

examine the interactive effects of industry affiliation and social networks on spatial correlation in CEO pay. We have argued that information exchange through social interactions is a plausible mechanism driving the spatial correlation in CEO compensation. We now test this hypothesis by examining whether and how CEO social networks and CEO power affect spatial correlation in CEO compensation.

Table 5 presents the results for the influence of CEO social networks. We focus on the coefficients on NeighbourCEOsalary_C and NeighbourCEOttlcomp_C, which represent respectively the average CEO salary and total compensation at neighbouring firms where the CEOs are socially connected to the focal firm CEO. The coefficients are positive and (both statistically and economically) significant, ranging from 0.181 to 0.221. Thus, *ceteris paribus* a focal firm's CEO pay increases by roughly 20% if its CEO is connected to the neighbouring firm CEOs (given an average total compensation equal to $7,077,193 per year, this corresponds to a "social connection premium" of approximately $1.41 million per year). By contrast, the coefficients on NeighbourCEOsalary_NC and NeighbourCEOttlcomp_NC (average CEO salary and total compensation at non-connected neighbouring firms) is indistinguishable from zero, suggesting that neighbouring firms' CEO compensation does not significantly affect the focal firm's CEO pay if the CEOs do not belong to the same social network. The evidence suggests that spatial correlation in CEO pay is driven by the presence of social network, consistent with H2. It appears that when the

Table 7
Effect of CEO power on spatial correlation in CEO compensation.

	More-powerful CEO		Less-powerful CEO	
	Ln(Salary)	Ln(Ttlcomp)	Ln(Salary)	Ln(Ttlcomp)
	(1)	(2)	(3)	(4)
Ln(NeighbourCEOsalary)[a]	0.204*** (0.034)		−0.014 (0.048)	
Ln(NeighbourCEOttlcomp)[a]		0.134*** (0.034)		−0.072 (0.056)
Economic attributes	Yes	Yes	Yes	Yes
Board attributes	Yes	Yes	Yes	Yes
Ownership attributes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
N	3824	2157	3824	2157
R-squared	0.59	0.52	0.65	0.60
Number of Instruments	22	22	22	22
Kleibergen-Paap rk LM Statistic (for Underidentification Test)	207.05***	113.18***	118.83***	112.76***
Cragg-Donald Wald F Statistic (for Weak identification Test)	27.35**	24.92**	29.83**	24.69**
Sargan-Hansen's J Statistic (for Overidentification Test)	27.51	18.92	24.54	26.92

This table reports the results to gauge the effect of CEO power on spatial correlation in CEO pay. Regressions include control variables as indicated, plus industry and year fixed effects and a constant term (untabulated). Robust standard errors are in parentheses. Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. See Table 1 for variable definitions and Table 3 for the control variables.

[a] Ln(NeighbourCEOsalary) and Ln(NeighbourCEOttlcomp) are treated as endogenous variables. The instrumental variables used for explaining the endogenous variables are all of the spatial weighted exogenous explanatory variables, WX. Please refer to Appendix 2 for detailed explanations. These instruments pass the weak instrument and diagnostic tests. For underidentification test, we use Kleibergen-Paap rk statistic to test for the rank condition. A rejection of the null hypothesis implies the model is identified. For weak identification test, we test if the IV estimator generates a maximal bias relative to OLS of 5%, the lowest level of maximal IV relative bias listed in Table 1 of Stock and Yogo (2005). The critical value for the Cragg−Donald statistic for a 5% maximal IV relative bias at the 5% significance level is 21.40 with 1 endogenous regressor. For overidentification test, the null hypothesis is that all excluded instruments are exogenous, so failure to reject the null hypothesis implies that all instruments are valid.

focal firm and neighbouring firm CEOs belong to the same social network, this facilitates information exchange through social interactions, which helps the focal firm CEO extract a higher compensation.[32]

To gauge the interactive effect of industry and social network on spatial correlation in CEO pay, we further divide local firms into four types: same-industry firms whose CEOs belong to the same social network, same-industry firms whose CEOs do not belong to the same social network, non-industry firms whose CEOs belong to the same social network, and non-industry firms whose CEOs do not belong to the same social network. Table 6 reports the results.

The coefficients on NeighbourCEOsalary_C_ind (average CEO salary at connected same-industry neighbouring firms) and NeighbourCEOsalary_C_Nind (average CEO salary at connected non-industry neighbouring firms) are both positive and statistically significant, whereas the coefficients on NeighbourCEOsalary_NC_ind (average CEO salary at non-connected same-industry neighbouring firms) and NeighbourCEOsalary_NC_Nind (average CEO salary at non-connected non-industry neighbouring firms) are indistinguishable from zero. Qualitatively similar (and quantitatively stronger) results are obtained for total compensation. Thus, it is primarily the presence of social network (as opposed to industry affiliation) among local firms that induces spatial correlation in CEO pay, again consistent with H2.

4.4. Effects of CEO power on spatial correlation in CEO compensation

To the extent that social connections facilitate information exchange among locally connected CEOs, we expect more-powerful CEOs to extract a compensation premium, by using managerial power to their own advantage (Abernethy et al., 2015; Bebchuk et al., 2002; Brown, Gao, Lee, & Stathopoulos, 2012; Vo & Canil, 2019). To test this conjecture, we group the sample firms into those with more-powerful CEOs and those with less-powerful CEOs and re-run the basic regression. Table 7 reports the results.

In firms with more-powerful CEOs, the coefficients on average CEO compensation of neighbouring firms are positive and statistically significant, for both salary (Model 1) and total compensation (Model 2). The coefficient of 0.134 suggests that all else equal, a more powerful CEO would get an extra "power premium" of about $1.27 million per year). A similar phenomenon

[32] An alternative (and related) explanation is that the focal firm CEO uses socially connected CEOs at neighbouring firms as actual or psychological benchmarks to negotiate higher pay. DiPrete, Eirich, and Pittinsky (2010) show that benchmarking against peers in one's social network potentially explains a considerable fraction of the overall upward movement of executive compensation since the early 1990s. However, evidence from our other tests tends to support the rent extraction hypothesis.

Table 8
Role of corporate governance in spatial effects of CEO compensation.

	High E-index		Low E-index	
	Ln(Salary)	Ln(Ttlcomp)	Ln(Salary)	Ln(Ttlcomp)
	(1)	(2)	(3)	(4)
Ln(NeighbourCEOsalary_C)[a]	0.245***		0.029	
	(0.070)		(0.046)	
Ln(NeighbourCEOsalary_NC)[a]	0.050		0.014	
	(0.035)		(0.101)	
Ln(NeighbourCEOttlcomp_C)[a]		0.171***		0.102
		(0.042)		(0.063)
Ln(NeighbourCEOttlcomp_NC)[a]		0.028		0.056
		(0.071)		(0.515)
Economic attributes	Yes	Yes	Yes	Yes
Board attributes	Yes	Yes	Yes	Yes
Ownership attributes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
N	2422	2422	805	805
R-squared	0.36	0.54	0.54	0.67
Number of Instruments	22	22	22	22
Kleibergen-Paap rk LM Statistic (for Underidentification Test)	28.77*	53.75***	55.01***	43.63***
Cragg-Donald Wald F Statistic (for Weak identification Test)	21.25**	41.47**	21.49**	26.88**
Sargan-Hansen's J Statistic (for Overidentification Test)	17.44	11.86	34.04**	15

This table reports the results of testing the role of corporate governance in spatial effects of CEO compensation. Regressions include control variables as indicated, plus industry and year fixed effects and a constant term (untabulated). Robust standard errors are in parentheses. Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. See Table 1 for variable definitions and Table 3 for the control variables.

[a] Ln(NeighbourCEOsalary_C), Ln(NeighbourCEOsalary_NC), Ln(NeighbourCEOttlcomp_C) and Ln(NeighbourCEOttlcomp_NC) are treated as endogenous variables. The instrumental variables used for explaining the endogenous variables are all of the spatial weighted exogenous explanatory variables, WX. Please refer to Appendix 2 for detailed explanations. These instruments pass the weak instrument and diagnostic tests. For underidentification test, we use Kleibergen-Paap rk statistic to test for the rank condition. A rejection of the null hypothesis implies the model is identified. For weak identification test, we test if the IV estimator generates a maximal bias relative to OLS of 5%, the lowest level of maximal IV relative bias listed in Table 1 of Stock and Yogo (2005). The critical value for the Cragg–Donald statistic for a 5% maximal IV relative bias at the 5% significance level is 20.60 with 2 endogenous regressors. For overidentification test, the null hypothesis is that all excluded instruments are exogenous, so failure to reject the null hypothesis implies that all instruments are valid.

is not found for less-powerful CEOs (Models 3–4). These results, which are consistent with H3, suggest that powerful CEOs are able to influence the pay-setting process by leveraging their local social network connections (Brown et al., 2012; Engelberg et al., 2013; Ferri & Göx, 2018). The increased bargaining power may arise because they hold greater sway over the board, have more outside options, and/or have pay-related information obtained from their locally connected counterparts.

4.5. Effect of corporate governance on spatial correlation in CEO compensation

So far, we have found significant spatial correlation in CEO compensation that is primarily driven by social network connections and powerful CEOs. This raises the possibility that spatial correlation in CEO compensation reflects CEOs' ability to extract higher compensation by taking advantage of their local social networks. If strong corporate governance mitigates agency problems and enhances managerial accountability, we would expect well-governed firms to exhibit less spatial correlation in CEO pay, all else equal. To test this hypothesis, we use the E-index (Bebchuk, Cohen, & Ferrell, 2009) to measure the strength of corporate governance (a high E-index score indicates weaker corporate governance). Results are reported in Table 8.

A comparison of the results for the weak-governance firms (left panel) and the strong-governance firms (right panel) indicates that spatial correlation in CEO compensation is found for the weak-governance firms only.[33] Consistent with our previous results, the spatial correlation is most discernible when the neighbouring firm CEOs and the focal firm's CEO belong to the same social network. Thus, the evidence suggests that in weak-governance firms, socially connected CEOs are able to extract higher compensation, by taking advantage of information obtained from connected CEOs at neighbouring firms, or by using connected neighbouring CEOs as the benchmark to negotiate for higher pay–leading to spatial spillovers in CEO pay beyond what is warranted by economic determinants. By contrast, well-governed firms seem better able to resist such rent extraction. The evidence is supportive of H4.

[33] Faulkender and Yang (2010) find that the gaming of compensation peer groups (i.e. selection bias toward highly paid peers) is more prevalent at firms with weak corporate governance.

Table 9
Spatial correlation in pay-performance sensitivity.

Panel A. The whole sample	Ela_SSR	Ela_TSR	Ela_SAR	Ela_TAR
	(1)	(2)	(3)	(4)
Ave_NEla_SSR[a]	0.302 (0.253)			
Ave_NEla_TSR[a]		0.476 (0.313)		
Ave_NEla_SAR[a]			0.431 (0.302)	
Ave_NEla_TAR[a]				0.206 (0.278)
Economic attributes	Yes	Yes	Yes	Yes
Board attributes	Yes	Yes	Yes	Yes
Ownership attributes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
N	5981	5981	5981	5981
R- squared	0.11	0.02	0.10	0.06
Number of Instruments	22	22	22	22
Kleibergen-Paap rk LM Statistic (for Underidentification Test)	65.01***	53.91***	68.75***	50.31***
Cragg-Donald Wald F Statistic (for Weak identification Test)	21.75**	28.66**	22.98**	26.24**
Sargan-Hansen's J Statistic (for Overidentification Test)	11.20	14.85	9.79	11.04

Panel B. Accounting for social network	Ela_SSR	Ela_TSR	Ela_SAR	Ela_TAR
	(1)	(2)	(3)	(4)
Ave_NEla_SSR_C[a]	−0.160 (0.139)			
Ave_NEla_SSR_NC[a]	−0.224 (1.457)			
Ave_NEla_TSR_C[a]		0.116 (0.915)		
Ave_NEla_TSR_NC[a]		0.275 (1.012)		
Ave_NEla_SAR_C[a]			0.068 (0.162)	
Ave_NEla_SAR_NC[a]			−0.199 (1.634)	
Ave_NEla_TAR_C[a]				0.262 (0.198)
Ave_NEla_TAR_NC[a]				0.210 (0.208)
Economic attributes	Yes	Yes	Yes	Yes
Board attributes	Yes	Yes	Yes	Yes
Ownership attributes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
N	3227	3227	3227	3227
R-squared	0.08	0.02	0.09	0.03
Number of Instruments	22	22	22	22
Kleibergen-Paap rk LM Statistic (for Underidentification Test)	65.82***	54.57***	54.90***	55.24***
Cragg-Donald Wald F Statistic (for Weak identification Test)	23.71**	29.97**	29.23**	29.56**
Sargan-Hansen's J Statistic (for Overidentification Test)	9.93	10.60	9.34	14.27

This table reports the results of estimating the CEO pay-performance sensitivity impact of neighbouring CEO pay-performance sensitivity. Regressions include control variables as indicated, plus industry and year fixed effects and a constant term (untabulated). Robust standard errors are in parentheses. Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. See Table 1 for variable definitions and Table 3 for the control variables.

[a] Ave_NEla_SSR, Ave_NEla_TSR, Ave_NEla_SAR, Ave_NEla_TAR, Ave_NEla_SSR_C, Ave_NEla_SSR_NC, Ave_NEla_TSR_C, Ave_NEla_TSR_NC, Ave_NEla_SAR_C, Ave_NEla_SAR_NC, Ave_NEla_TAR_C, Ave_NEla_TAR_NC are treated as endogenous variables. The instrumental variables used for explaining the endogenous variables are all of the spatial weighted exogenous explanatory variables, WX. Please refer to Appendix 2 for detailed explanations. These instruments pass the weak instrument and diagnostic tests. For underidentification test, we use Kleibergen-Paap rk statistic to test for the rank condition. A rejection of the null hypothesis implies the model is identified. For weak identification test, we test if the IV estimator generates a maximal bias relative to OLS of 5%, the lowest level of maximal IV relative bias listed in Table 1 of Stock and Yogo (2005). The critical value for the Cragg−Donald statistic for a 5% maximal IV relative bias at the 5% significance level for Panel A is 21.40 with 1 endogenous regressor; for Panel B it is 20.60 with 2 endogenous regressors. For overidentification test, the null hypothesis is that all excluded instruments are exogenous, so failure to reject the null hypothesis implies that all instruments are valid.

Table 10
Predicted excess compensation and subsequent firm performance.

	(1) Pooled	(2) With neighbours within 100 KM radius	(3) With socially connected neighbours within 100 KM radius	(4) Without socially connected neighbours within 100 KM radius	(5) No social network, irrespective of geographical proximity
Sales	0.004***	0.004***	0.002**	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Pred_Excess_Comp	−0.146**	−0.101*	−0.300***	−0.012	0.082
	(0.058)	(0.056)	(0.076)	(0.083)	(0.081)
S.D. of ROA	0.267***	0.247***	0.164	0.366***	0.336***
	(0.061)	(0.062)	(0.103)	(0.075)	(0.074)
Year	Yes	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes	Yes
N	5610	5466	3029	2581	2437
R-squared	0.187	0.182	0.190	0.194	0.182

This table reports the results of testing the relationship between predicted excess compensation and subsequent firm performance (ROA). Predicted excess compensation (Pred_Excess_Comp) is the amount of total compensation attributable to the board and ownership variables (estimated with coefficients from the total compensation regression in Table 3), scaled by total compensation. The standard deviation of ROA is the standard deviation of annual percentage return on assets for the five years ending with the year prior to the year in which compensation is awarded. Sales are for the year prior to the year in which compensation is awarded. Robust standard errors are in parentheses. Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively.

4.6. Is there spatial correlation in pay-performance sensitivity?

CEO compensation may be used for incentivizing executives and aligning managers' interests with those of shareholders (Ferri & Göx, 2018; Jensen & Meckling, 1976). To the extent that compensation incentivizes CEOs and reduces the agency problem, one should expect firm performance to be positively correlated with pay-performance sensitivity (PPS). And to the extent that pay consultants, compensation committees and/or CEOs benchmark their compensation against that of neighbouring firms' CEOs, efficient contracting suggests that one should expect the spatial correlation in CEO compensation to be accompanied by spatial correlation in PPS. On the other hand, if high CEO pay reflects an agency problem (Core et al., 1999), one might expect a negative association between measures of managerial power and PPS (Hwang & Kim, 2009). Indeed, Brown et al. (2012) find that the size of the CEO network (a measure of CEO power) is positively related to the level of CEO compensation and inversely related to its PPS. Renneboog and Zhao (2011) find that companies with strong director networks (which lead to more managerial influence) have higher CEO compensation and less PPS.

In line with prior studies, we use elasticity of CEO pay to stock return (alternately, abnormal stock return) to measure PPS, following Frydman and Jenter (2010).[34] Table 9 reports the results. Irrespective of the proxy used, and irrespective of the existence of a social network, we find little evidence of spatial correlation in PPS–all the coefficients on neighbouring firm CEOs' PPS are statistically insignificant. Thus, the correlation in focal firm and neighbouring firm CEOs' compensation is not accompanied by a similar spatial correlation in their accountability towards shareholders, as measured by PPS. The evidence is inconsistent with spatial correlation in CEO compensation reflecting manager-shareholder interest-alignment (the "efficient contracting" view), under which a positive correlation between firm performance and PPS would be expected to exist and spill over between the focal firm and neighbouring firms. H5 cannot be rejected.

4.7. CEO compensation and firm performance

Efficient contracting and managerial power have been advanced as the main explanations for high executive compensation (Bebchuk et al., 2002; Bebchuk & Fried, 2004; Hall & Murphy, 2003; Murphy, 1999). The empirical evidence is mixed (Frydman & Jenter, 2010). To discriminate between these competing explanations, Core et al. (1999) propose a method to compute an expected level of excess CEO compensation.[35] The idea is that CEO compensation regressions that include the economic determinants capture the "equilibrium level of CEO compensation in the absence of any agency problems". We follow their method to compute the predicted excess compensation for each CEO (with subscripts suppressed):

$$\boldsymbol{\mathit{Predicted\ excess\ compensation}} = \sum \hat{\beta}\ \text{board attributes} + \sum \hat{\gamma}\ \text{ownership attributes} \tag{2}$$

where the estimated coefficients on the board and ownership variables are those from the spatial model in our Table 3. The excess compensation computed this way captures the predicted level of compensation due to the board and ownership variables, over and beyond what is warranted by economic determinants (Core et al., 1999).

[34] Similar results are obtained using the Core and Guay (2002) method.
[35] The same method is adopted in Chalmers et al. (2006) and Albuquerque, De Franco, and Verdi (2013) among others.

We examine the association between this measure of predicted excess compensation and subsequent operating performance, including the same control variable as in Core et al. (1999).[36] According to Core et al., if the managerial power hypothesis is true, a negative association between compensation and board/governance attributes is expected. However, if the CEO compensation and board/governance variables reflect firm's demand for CEO talent (the efficient contracting view), then no association (maybe even a positive association) could be expected. To isolate the effects of geography and social connection on the predicted excess compensation-subsequent performance relation, we also perform the regressions on subsamples partitioned by geographical proximity and social connection. Table 10 reports the results.

Mode (1) reports results for the pooled sample. Sales are positively associated with subsequent (one-year-ahead) operating performance. Of more relevance, predicted excess compensation and subsequent performance are significantly and negatively related. Both results are consistent with Chalmers, Koh, and Stapledon (2006) and Core et al. (1999).

To see if the results vary depending on geographical proximity and social network, we next re-run the test for subsamples partitioned based on the presence/absence of neighbours within a 100 KM radius and/or social network connections. As reported in Model (2), when the focal firm has neighbours (irrespective of the presence of CEO social network), the coefficient on predicted excess compensation is statistically significant and negative.

Model (3) is the equivalent of Model (2), with the additional requirement that the focal and neighbouring firms' CEOs belong to the same social network. The coefficient on predicted excess compensation is negative and statistically significant, and larger in magnitude than in Model (2). Thus, when the focal firm CEO is socially connected with neighbouring firm CEOs, rent extraction is more likely to occur and lead to poorer subsequent performance. Model (4) presents results when the focal firm CEO and neighbouring firm CEOs do not belong to the same social network. The coefficient on predicted excess compensation now becomes indistinguishable from zero. Comparing the results from Model (3) and Model (4), it seems that the presence of local social network connections is a key driving force behind the negative relation between predicted excess compensation and subsequent performance. This point is reinforced when we re-run the analysis for the subsample of firms with no social connections between CEOs (irrespective of whether the firms have neighbours within a 100 KM radius). The result, reported in Model (5), indicates no statistically significant relation between excess compensation and subsequent performance.

Overall, the evidence supports a negative association between predicted excess CEO compensation and subsequent operating performance, consistent with H6. The negative relationship is stronger when the focal firm CEO and the neighbouring firm CEOs belong to the same social network. In line with Core et al. (1999), we interpreter these results as supportive of the rent extraction hypothesis.

4.8. Alternative explanations

We have documented significant spatial effects in CEO pay, especially when the focal firm CEO and neighbouring firm CEOs belong to the same social network, when the focal firm CEO is more powerful, and when the focal firm has weaker corporate governance. We have interpreted the evidence as most consistent with rent extraction. However, other explanations are possible. For example, it may be argued that spatial correlation in CEO compensation results from pay consultants using neighbouring firms' CEO pay as the benchmark for the focal firm's CEO pay. However, our results are obtained after controlling for this benchmark effect. Using a small sample of hand-collected data on benchmark firms that were actually used in fixing CEO pay, Bouwman (2013) also found no evidence that the use of neighbouring firms' CEO compensation in the benchmark exercise accounts for spatial correlation in CEO compensation. Even if neighbouring firms' CEO compensation is used as the benchmark, there is little economic rationale for the spatial effect to be concentrated among weak governance firms, and among firms whose CEOs are socially connected or are powerful (contrary to what we find), nor any reason to expect spatial correlation in CEO compensation to be associated with poor future firm performance (again, contrary to what we find).

Prior studies find that CEO pay is higher when CEOs are reciprocally interlocked—the current CEO of firm A serves as a director of firm B and the current CEO of firm B serves as a director of firm A (Hallock, 1997; Renneboog & Zhao, 2011). To check if accounting for director interlocking alters our results, we added a variable indicating whether the focal firm CEO serves as a director in any of the neighbouring firms (alternatively, the fraction of such instances). We also tried including the average CEO pay at neighbouring firms with interlocked directors. The coefficient on these variables is never statistically significant, but more importantly, all of our key results remain qualitatively the same.

Social networks and interactions allow not only information exchange among individuals, but also mutual influence of their preferences and biases. For instance, it is possible that overconfidence (e.g. beliefs about one's abilities and hence labour market competitiveness) may spread from one member of a social network to another through social interactions (Shue, 2013).[37] To the extent that these CEO-level behavioural biases are unobserved but are correlated with CEO pay, our results may be biased or inconsistent.

We have considered the possibility of unobserved biases spreading through CEO social networks by explicitly testing for this using the Spatial Error Model (SEM). In the Spatial Error Model (SEM): $y = X\beta + u$ where $u = \rho Wu + \varepsilon$, the spatial auto-

[36] Core et al. (1999) argue and find that operating performance is more appropriate in this research setting than stock market returns.

[37] See Rau (2017b) on the link between social networks and financial outcomes, and Subrahmanyam (2008) on the link between social networks and corporate governance.

Table 11
Robust check using spatial durbin model.

	Ln(Salary)	Ln(Ttlcomp)	Ln(Salary)	Ln(Ttlcomp)
	(1)	(2)	(3)	(4)
Ln(NeighbourCEOsalary)[a]	0.115***		0.113***	
	(0.028)		(0.043)	
Ln(NeighbourCEOttlcomp)[a]		0.069**		0.064**
		(0.029)		(0.032)
Economic attributes	Yes	Yes	Yes	Yes
Board attributes	Yes	Yes	Yes	Yes
Ownership attributes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
Rho			−0.044	0.061
			(0.037)	(0.220)
N	5981	5981	5981	5981
R-squared	0.56	0.62	0.57	0.62
Number of Instruments	22	22	22	22
Kleibergen-Paap rk LM Statistic (for Underidentification Test)	308.12***	235.54***	90.714***	78.58***
Cragg-Donald Wald F Statistic (for Weak identification Test)	44.12**	34.09**	42.26**	48.56**
Sargan-Hansen's J Statistic (for Overidentification Test)	26.83	26.47	8.09	7.54

This table reports the results of Spatial Durbin model with spatial dependence in the error term. Regressions include control variables as indicated, plus industry and year fixed effects and a constant term (untabulated). Robust standard errors are in parentheses. Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. See Table 1 for variable definitions and Table 3 for the control variables.

[a] Ln(NeighbourCEOsalary) and Ln(NeighbourCEOttlcomp) are treated as endogenous variables. The instrumental variables used for explaining the endogenous variables are all of the spatial weighted exogenous explanatory variables, WX. Please refer to Appendix 2 for detailed explanations. These instruments pass the weak instrument and diagnostic tests. For underidentification test, we use Kleibergen-Paap rk statistic to test for the rank condition. A rejection of the null hypothesis implies the model is identified. For weak identification test, we test if the IV estimator generates a maximal bias relative to OLS of 5%, the lowest level of maximal IV relative bias listed in Table 1 of Stock and Yogo (2005). The critical value for the Cragg−Donald statistic for a 5% maximal IV relative bias at the 5% significance level is 21.40 with 1 endogenous regressor. For overidentification test, the null hypothesis is that all excluded instruments are exogenous, so failure to reject the null hypothesis implies that all instruments are valid.

correlation is supposed to be observed in the error term u. Untabulated regression result shows that the value of rho (the coefficient on the spatial lagged error 'Wu') is 0.039 but its p-value is 0.575, so rho is not statistically significant. In addition, as reported in Panel B of Table A1, based on the test result of the LM-Error test (Anselin, 2005), we can reject the null hypothesis of the presence of spatial auto-correlation in the error term (capturing unobserved variables) as the p-value is 0.372. These results provide little evidence that unobserved biases spread through the social network to influence spatial correlation in CEO compensation.

Furthermore, if one assumes that these biases are time-invariant (within the 7 years of our sample period), then these biases could be treated as a time-invariant fixed effect. The first-difference model could help remove this fixed effect (Wooldridge, 2012). We estimated a first-difference model using data in 2010 and 2016.[38] The untabulated regression result of this model still suggests a positive and significant spatial correlation in CEO compensation (for example, for salary, the coefficient is 0.112 with a p-value of 0.034).

Therefore, while we cannot definitively rule out biases spreading through social networks, there is little evidence in our data to suggest that this could be driving the effect of social network on spatial correlation in CEO compensation. An alternative, behavioural explanation must not only document significant spatial spillovers in CEO compensation, but the omitted behavioural biases must also account for the rich patterns we have documented regarding the systematic influences of social connections, managerial power, and corporate governance.[39]

4.9. Robustness tests

4.9.1. Model selection

As part of the robustness checks, we redo the spatial model tests by adopting Bramoulle, Djebbari and Fortin's (2009) approach by extending our Spatial Lag Model (SLM) to control for the weighted average of economic, board and

[38] Since these biases are assumed to be time-invariant, if we take the difference between two years' CEO compensation equations, this time-invariant component will be offset.

[39] One limitation in our paper (as well as many related studies) is that we do not directly observe social interactions and information exchange among socially connected executives, nor do we have direct access to the CEO pay negotiation process. Nevertheless, the rich patterns we document strongly suggest managerial influence over pay-setting aided by local social connections, CEO power, and weak governance.

Table 12
Robust check using spatial dynamic panel data model.

	Ln(Salary)	Ln(Ttlcomp)	Ln(Salary)	Ln(Ttlcomp)
	(1)	(2)	(3)	(4)
Ln(NeighbourCEOsalary)[a]	0.024*		0.202**	
	(0.013)		(0.098)	
Lag of Ln(Salary)	0.778***		0.194***	
	(0.019)		(0.041)	
Ln(NeighbourCEOttlcomp)[a]		0.038**		0.137*
		(0.019)		(0.081)
Lag of Ln(Ttlcomp)		0.668***		0.026*
		(0.023)		(0.014)
Economic attributes	Yes	Yes	Yes	Yes
Board attributes	Yes	Yes	Yes	Yes
Ownership attributes	Yes	Yes	Yes	Yes
Economic attributes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Industry Fixed Effect	Yes	Yes		
Firm Fixed Effect			Yes	Yes
N	2864	2864	2864	2864
R-squared	0.82	0.77	0.83	0.80
Number of Instruments	22	22	22	22
Kleibergen-Paap rk LM Statistic (for Underidentification Test)	54.37***	60.17***	59.682***	38.28**
Cragg-Donald Wald F Statistic (for Weak identification Test)	24.22**	34.64**	27.65**	22.57**
Sargan-Hansen's J Statistic (for Overidentification Test)	19.71	12.78	22.08	26.02

This table reports the results of estimating the CEO pay impact of neighbouring CEO pay using Spatial Dynamic Panel Data Model. Regressions include control variables as indicated, plus year and industry or firm fixed effects. Robust standard errors are in parentheses. Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. See Table 1 for variable definitions and Table 3 for the control variables.

[a] Ln(NeighbourCEOsalary_C) and Ln(NeighbourCEOttlcomp_C) are treated as endogenous variables. The instrumental variables used for explaining the endogenous variables are all of the spatial weighted exogenous explanatory variables, WX. Please refer to Appendix 2 for detailed explanations. These instruments pass the weak instrument and diagnostic tests. For underidentification test, we use Kleibergen-Paap rk statistic to test for the rank condition. A rejection of the null hypothesis implies the model is identified. For weak identification test, we test if the IV estimator generates a maximal bias relative to OLS of 5%, the lowest level of maximal IV relative bias listed in Table 1 of Stock and Yogo (2005). The critical value for the Cragg–Donald statistic for a 5% maximal IV relative bias at the 5% significance level is 21.40 with 2 endogenous regressors. For overidentification test, the null hypothesis is that all excluded instruments are exogenous, so failure to reject the null hypothesis implies that all instruments are valid.

ownership attributes. Table 11 reports results from this extended model (Spatial Durbin Model). A significant spatial correlation in CEO compensation is reaffirmed. In addition, the coefficient of Rho is insignificant in column (3) and (4), indicating that the auto-correlation is not caused by an error process. These results again support the use of the SLM and the robustness of the SLM results.

4.9.2. Dynamic spatial panel data model

Given the panel structure of our data, it is worth using spatial panel data models, which can allow cross-sectional dependence as well as state dependence, and can also control for unknown heterogeneity (Lee & Yu, 2010). We estimate the following dynamic spatial panel data model:

$$y_{it} = a_0 + y_{it-1} + \lambda \sum_{j=1}^{n} W_{ij} y_{jt} + \beta X_{it} + \gamma_i + \delta_i (or\ \zeta_i) + \varepsilon_{it} \quad (3)$$

All the variables are as defined in Equation (1). Results are reported in Table 12. In Columns 1–2, we control for industry fixed effects ($\boldsymbol{\delta_i}$), as done in most prior studies. It is noted that focal firm CEO pay displays a fair degree of stickiness–current year CEO pay is significantly positively related to preceding year CEO pay (more so for salary than total compensation). Our variable of interest, average neighbouring CEO pay, now becomes statistically indistinguishable from zero. However, when we control for firm fixed effects ($\boldsymbol{\zeta_i}$) instead of industry fixed effects, this variable becomes positive and statistically significant (for both salary and total compensation). In addition, the coefficient on preceding year CEO salary remains positive and

Table 13
Robustness check using different samples.

Panel A. 100 KM to 400 KM

	100 KM Full Sample		400 KM Sub Sample	
	Ln(Salary)	Ln(Ttlcomp)	Ln(Salary)	Ln(Ttlcomp)
	(1)	(2)	(3)	(4)
Ln(NeighbourCEOsalary_C)[a]	0.008***		0.231***	
	(0.002)		(0.037)	
Ln(NeighbourCEOsalary_NC)[a]	0.002		−0.021	
	(0.056)		(0.031)	
Ln(NeighbourCEOttlcomp_C)[a]		0.020***		0.292***
		(0.005)		(0.046)
Ln(NeighbourCEOttlcomp_NC)[a]		0.053		−0.128*
		(0.111)		(0.069)
Economic attributes	Yes	Yes	Yes	Yes
Board attributes	Yes	Yes	Yes	Yes
Ownership attributes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
N	6545	6545	4387	4387
R-squared	0.351	0.352	0.345	0.241
Number of Instruments	22	22	22	22
Kleibergen-Paap rk LM Statistic (for Underidentification Test)	31.89*	38.99***	54.35***	29.68*
Sargan-Hansen's J Statistic (for Overidentification Test)	23.61	15.84	23.46	15.04

Panel B. 20 Largest Economic Areas (LEAs)

	20 LEAs (100 km)		Out of 20 LEAs (400 km)	
	Ln(Salary)	Ln(Ttlcomp)	Ln(Salary)	Ln(Ttlcomp)
	(1)	(2)	(3)	(4)
Ln(NeighbourCEOsalary_C)[a]	0.167***		0.286***	
	(0.063)		(0.059)	
Ln(NeighbourCEOsalary_NC)[a]	0.482		0.006	
	(0.336)		(0.018)	
Ln(NeighbourCEOttlcomp_C)[a]		0.245***		0.351***
		(0.060)		(0.061)
Ln(NeighbourCEOttlcomp_NC)[a]		−0.424		0.054
		(0.489)		(0.035)
Economic attributes	Yes	Yes	Yes	Yes
Board attributes	Yes	Yes	Yes	Yes
Ownership attributes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Industry	Yes	Yes	Yes	Yes
N	2633	2633	1342	1342
R-squared	0.351	0.363	0.372	0.382
Number of Instruments	22	22	22	22
Kleibergen-Paap rk LM Statistic (for Underidentification Test)	81.45***	46.79***	79.35***	40.56***
Cragg-Donald Wald F Statistic (for Weak identification Test)	25.40**	22.87**	25.01**	22.13**
Sargan-Hansen's J Statistic (for Overidentification Test)	25.12	14.80	29.50	19.64

This table reports the results of using different samples. Regressions include control variables as indicated, plus industry and year fixed effects and a constant term (untabulated). Robust standard errors are in parentheses. Superscripts ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. See Table 1 for variable definitions and Table 3 for the control variables.

[a] Ln(NeighbourCEOsalary_C), Ln(NeighbourCEOsalary_NC), Ln(NeighbourCEOttlcomp_C) and Ln(NeighbourCEOttlcomp_NC) are treated as endogenous variables. The instrumental variables used for explaining the endogenous variables are all of the spatial weighted exogenous explanatory variables, WX. Please refer to Appendix 2 for detailed explanations. These instruments pass the weak instrument and diagnostic tests. For underidentification test, we use Kleibergen-Paap rk statistic to test for the rank condition. A rejection of the null hypothesis implies the model is identified. For weak identification test, we test if the IV estimator generates a maximal bias relative to OLS of 5%, the lowest level of maximal IV relative bias listed in Table 1 of Stock and Yogo (2005). The critical value for the Cragg−Donald statistic for a 5% maximal IV relative bias at the 5% significance level is 20.60 with 2 endogenous regressors. For overidentification test, the null hypothesis is that all excluded instruments are exogenous, so failure to reject the null hypothesis implies that all instruments are valid.

statistically significant, though its magnitude has dropped relative to when we control for industry fixed effects. The coefficient on preceding year total compensation, though still positive, becomes statistically insignificant.[40] To the extent that including firm fixed effects better controls for unknown firm heterogeneity, we place greater emphasis on these latter results.

[40] The serial correlation coefficient for salary (total compensation) is 0.835 (0.825). When we break down total compensation into salary and "others" (including bonuses, options, restricted stocks, and other compensation), we find that the "others" component has a serial correlation of only 0.149. This is reasonable as the latter types of compensation are more variable from year to year (depending, in part, on the firm performance and the timing of option/stock grants). This may also explain the generally weaker spatial spillover effects for total compensation than that for salary, as well as the lower degree of "stickiness" in total compensation than salary.

It is re-assuring that our basic conclusion regarding the positive spatial effects in CEO pay is fairly robust to the use of dynamic spatial panel data models.

4.9.3. Sample selection

In the main tests our sample firms are restricted to those that have at least one neighbour within the specified radius, in line with existing studies. Here, we redo our tests using several sample sets to demonstrate the robustness of our results to sample selection.

First, we apply the tests to the full sample (6545 firm-year observations), including firms with no neighbouring firms within a 100 KM radius. Second, we re-run the tests for another subsample comprising 4387 firm-year observations which have at least 1 socially connected neighbouring firm within a 400 KM radius. As reported in Panel A of Table 13, irrespective of whether the sample firms have neighbours within a 100 KM radius, and when expanding the radius to 400 KM, the spatial correlation in CEO compensation is still concentrated among firms whose CEOs belong to the same social network.

Some past studies focus on differences in corporate outcomes between large economic (urban) areas and rural areas. To see if our results are affected by the big city-small city (urban-rural) distinction, we divide the sample into firms headquartered in the 20 largest economic areas (LEAs) (Dougal et al., 2015) and those outside of the 20 LEAs, and then test for correlation in CEO compensation separately. Table 13, Panel B shows that our basic results still hold for the 20 LEAs. By contrast, the correlation disappears for firms outside the 20 LEAs.[41] However, when we expand the radius to 400 KM, the correlation re-emerges for those firms outside the 20 LEAs. One possible explanation for this is that the density of firms outside of the 20 LEAs is much lower than that in the 20 LEAs, and so applying the 100 KM radius to such firms would miss out their neighbours and lead to low power in the tests.

Our primary sample includes all industries in the Fama-French 12-industry category, including financial firms and regulated firms. There is little consensus in the literature as to whether firms in the financial and regulated industries should be included in studies of CEO compensation. Bouwman (2013, p. 13) states that “While studies on corporate policies such as capital structure and dividend policy typically exclude financials and utilities, there is no fundamental reason to exclude them from a study that focuses on compensation. In line with the compensation literature (e.g., Bizjak, Lemmon, & Naveen, 2008; Faulkender & Yang, 2010; Kedia & Rajgopal, 2009), I therefore include these firms.” However, some other studies have excluded these industry firms. One might argue that this is the right thing to do, especially since the executive compensation in large financial institutions is intensely scrutinized after the Global Financial Crisis. To check the robustness of our results to the inclusion/exclusion of these two industries, we re-run our baseline analysis after excluding these industries (approximately 25% of our primary sample). The (untabulated) results are qualitatively similar.

5. Summary and conclusion

Despite the continuing heated debate on determinants and consequences of CEO compensation and a growing body of research documenting the effect of geography on various corporate decisions, few studies have considered the effect of geography on CEO compensation and related performance implications. The limited extant research on this issue has not adequately addressed econometric concerns arising from spatial dependence in the cross section of neighbouring firms. We apply a spatial model, which is well suited to handle this type of econometric problem, to investigate this under-explored issue. We find that focal firm CEO compensation is significantly and positively associated with neighbouring firm CEO compensation. The spatial effect is particularly strong when the focal firm and neighbouring firm CEOs are socially connected, when the focal firm CEO is more powerful, and when the focal firm has weak governance, suggesting that in these situations the focal firm CEO are able to extract higher compensation, presumably by taking advantage of information obtained through their locally connected CEO friends or by using them as benchmarks to negotiate for higher pay. Interestingly, the spatial correlation in CEO compensation is not accompanied by a corresponding spatial correlation in pay-performance sensitivity. Quite to the contrary, we find predicted excess compensation (a proxy for an agency problem in CEO pay) to be negatively associated with subsequent operating performance. The negative association is stronger when the focal firm and neighbouring firm CEOs belong to the same social network.

Our findings suggest that geography proximity, by facilitating social interactions in a local network of CEOs, is a hitherto unrecognized determinant in CEO compensation. To the extent that spatial correlation in CEO compensation reflects rent extraction by powerful CEOs in weak-governance firms and that such rent extraction leads to lower subsequent firm performance, it behooves stakeholders (including board of directors, investors and regulators) to consider the need for requiring CEOs to disclose any social connections with local CEOs as part of their Compensation Discussion and Analysis. Future research may examine potential correlation in the quality (e.g. innovation) of locally connected executives. We also call for further evidence from other (non-US) market settings to corroborate our findings.

[41] The coefficient on Local_CEO_market is positive and statistically significant for firms in the 20 LEAs only. To the extent that this reflects the extent of (within-industry) local competition for CEOs, this corroborates the finding in Yonker (2015) that local CEOs with more outside options are paid more.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.bar.2021.100987.

Appendix 1. Spatial model specification tests

We first test for spatial auto-correlation for CEO salary and total compensation by the Moran's I test (Appendix Table A1, Panel A). The test statistics reject the null and suggest that the conventional OLS regression model of CEO compensation is misspecified (by overlooking the spatial error term). The tests reveal a significant positive spatial auto-correlation in CEO compensation.

Although the Moran's I test is a powerful test for misspecification of spatial dependence/auto-correlation, it fails to indicate whether the auto-correlation is caused by an error process or omitted spatially lagged dependent variable, or both (Anselin & Kelejian, 1997).[42] The Lagrange Multiplier (LM) tests are used to select the appropriate spatial model specifications (Anselin, 2005; Anselin & Hudak, 1992; Burridge, 1980).[43]

When we use CEO salary as the dependent variable (Appendix Table A1, Panel B), the null was rejected by the LM-Lag test but not the LM-Error test. This suggests that the SLM model is preferred. In the case of total compensation, both the LM test for Spatial Lag Model and the LM test for Spatial Error Model reject the null. We thus follow Anselin's (2005) rule to check the Robust LM test results. The Robust LM test does not reject the null, so the Spatial Lag Model (SLM) is preferred for analyzing CEO's salary and total compensation.

Appendix Table A1
Model Specification Tests

Panel A. Moran's I Test for spatial auto-correlation					
Variables	I	E(I)	sd(I)	z	p-value*
Ln(Salary)	0.047	0.000	0.006	8.220	0.000
Ln(Ttlcomp)	0.043	0.000	0.006	7.464	0.000

Panel B. Spatial model specification tests	Ln(Salary) Value	P-value	Ln(Ttlcomp) Value	P-value
Lagrange Multiplier (lag)	15.771	0.000	50.659	0.000
Robust LM (lag)	17.167	0.000	45.934	0.000
Lagrange Multiplier (error)	0.797	0.372	4.930	0.026
Robust LM (error)	2.193	0.139	0.205	0.651

Appendix 2. Endogeneity and the Instrumental Variables Approach in Spatial Econometrics

1. Endogeneity and Instruments

The Spatial Lag Model (SLM) used in our paper takes the following basic form:

$$y = \lambda Wy + X\beta + \varepsilon$$

We derive the reduced form as follows:

$$y = (I - \lambda W)^{-1} X\beta + (I - \lambda W)^{-1}\varepsilon$$

As a result, $E[(Wy)^T\varepsilon] = E[y^T W^T \varepsilon] \neq 0$, therefore, the term Wy is correlated with the error term. So, Wy is endogenous (known as simultaneous equation bias).

[42] There are three spatial model specifications: (1) The general spatial model (SARAR) - this model accounts for both spatial lag and autoregressive errors: y = λWy + Xβ+u, where u = ρWu+ε with ε~N(0,σ^2 I_n). (2) The Spatial Autoregressive Model (SAR), aka. Spatial Lag Model: y = λWy + Xβ+ε. This model includes a spatial lagged dependent variable as an endogenous explanatory variable but excludes the spatial auto-correlation in the error term. (3) Spatial Error Model (SEM): y = Xβ+u where u = ρWu+ε. In this model the spatial auto-correlation is only observed in the error term.

[43] Anselin (2005) offered a rule for spatial regression model selection decision: (1) when neither the LM-Lag test nor the LM-Error test rejects the null hypothesis of the presence of spatial auto-correlation, the conventional model without spatial component is preferred. (2) When one test rejects the null while the other doesn't, then one may just go with the spatial regression model suggested by the test statistic (i.e. rejecting the null). (3) In case both tests reject the null, then one checks the Robust forms of the test statistics.

One of the solutions for solving the endogeneity problem in Wy is using instrumental variables to explain Wy (Lee, 2003; Kelejian & Prucha, 1998, 1999; Kelejian, Prucha & Yuzefovich, 2004).

According to Chamberlain (1987), the optimal instrumental variables are the conditional means, so the ideal instruments for endogenous variable, Wy, are $E(Wy|X)$ where X is a vector of exogenous variables.

$$E(Wy|X) = WE(y|X)$$

$$= W(I_n - \lambda W)^{-1} X\beta$$

$$= W\left[I_n + \lambda W + \lambda^2 W^2 + \lambda^3 W^3 + \ldots\right] X\beta_0$$

$$= WX\beta + W^2 X(\lambda\beta) + W^3 X\left(\lambda^2\beta\right) + \ldots$$

As a result, the instruments are spatially weighted X, which are known as WX, W^2X, and higher orders. Kelejian and Robinson (1993), Kelejian and Prucha (1998) and Anselin (2017) suggest only choosing a subset of the instruments to estimate the coefficient of the spatial lag, as it could avoid possible multicollinearity. Indeed, WX, W^2X, and higher orders are simply the estimates of the mean of X which may have linear dependence and so little independent variation. Therefore, Anselin (2017) suggests that researchers may just use WX or WX and W^2X as instruments in practice. In addition, many studies (e.g. Fingleton & Le Gallo, 2008; Franzese & Hays, 2007) only used WX as the instruments. Our selection of instrumental variables are guided by previous literature in spatial econometrics, and in our case, we find a degree of linear dependence between WX and W^2X which lead to the concern of multicollinearity. As a result, we have used WX as our instruments as suggested by the literature (e.g. Anselin, 2017; Fingleton & Le Gallo, 2008; Franzese & Hays, 2007).

2. The Relevance and Exclusion Criteria

We next show that the instruments in a spatial model setting meet the two criteria for defining instruments.

Relevance

The change in WX is associated with the variation in Wy, as Wy could be written as a function of WX, because, according to Chamberlain (1987), $E(Wy|X) = WX\beta + W^2X(\lambda\beta) + W^3X(\lambda^2\beta) + \ldots$, so they are correlated. This means that the change in average pay of neighbouring CEOs (Wy) is associated with the change in average level of these neighbouring CEOs and firms' attributes (WX). For example, when the average of neighbouring firms' profitability or CEOs' tenure is higher, we may expect an increase in the average pay of these neighbouring firms' CEOs. Thus the relevance criterion is satisfied.

Exclusion

These instruments, WX, are the mean of X (weighted by spatial matrix W). Since X is a vector of exogenous variables by definition (that is $E(y - \lambda Wy - X\beta|X) = 0$), X is not correlated with the disturbance of the outcome equation. As a result, the mean of X, WX, is not correlated with y. Although WX do not directly impact the outcome variable y, they could be used to predict the endogenous variable Wy. For example, when the average level of neighbouring firm CEOs' tenure is higher, it could cause these neighbouring firm CEOs' pay to change, but it does not directly impact the pay of the focal firm CEO (which means the focal firm CEOs' pay can be higher or lower).

3. List of Instrumental Variables

We indicate the endogenous variables in each Table with [a]; for instance, in Table 3, Ln(NeighbourCEOsalary)[a].

As explained above, the instrumental variables for Wy are the products of the spatial weight matrix and all the exogenous variables, i.e. WX. To illustrate, in Table 3 we have a total of 23 explanatory variables (X). Except for the endogenous variable Wy (e.g. Ln(NeighbourCEOsalary)[a]), all the remaining (exogenous) X are used to derive the instrumental variable WX. Thus, in Table 3, since we have 22 exogenous variables, the instrument variables are the products of these 22 variables and W.

It is important to note that in each Table, W is defined differently. For instance, in Table 3, W is defined by neighbours within the 100 KM radius. In Table 4, W is defined by same-industry neighbours. In Table 5, W is defined by neighbours in the same social network.

4. Weak instrument and diagnostic tests

In each Table where IVGMM is used, we report a battery of weak instrument and diagnostic tests. These instruments pass the weak instrument and diagnostic tests. Take salary (Column (7)) in Table 3 as an example: The p-value for the Sargan-Hansen's J statistic is 0.177, which indicates that the instruments are valid and that the model is correctly specified. The p-value for Kleibergen-Paap rk LM statistic is 0.00, which is highly significant and indicates that the model is identified and so under-identification is not an issue. The Cragg-Donald Wald F statistic for the weak identification test is 44.12, which is greater than the critical value of Stock and Yogo's (2005) weak instrument test based on 2SLS bias at the 5% significance level. As a result, these instruments are not weak.

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