Network Structure and Auditor Compensation: Evidence from a Bipartite Network

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ABSTRACT

This paper examines the relationship between the extent of knowledge flow during audit practice (measured by the local network clustering coefficient) and auditor compensation. We exploit a unique bipartite (i.e. two-mode) network composed of individual auditors assigned to different audit engagements from an audit firm for one full year to determine our local network clustering coefficient and auditor compensation data from this audit firm's personnel records. Informed by social networks theory and determinants of wage in labor economics, we find a positive association between local network clustering and auditor compensation, which is both statistically and economically significant. Our results are robust to alternative measures of local network clustering coefficient, alternative explanations of structural holes and centrality, alternative linear specification and endogeneity concern. Furthermore, we find that this positive association may be primarily driven by seniors working on audit engagements. Overall, our results suggest that embeddedness within knowledge networks plays an important role for auditor compensation.

Keywords: Auditor Compensation; Network Clustering; Audit Knowledge; Bipartite (two-mode) Network; Audit Engagement

JEL Codes: M41; M42; D83; J31; J44

I. INTRODUCTION

This paper examines whether the degree of tacit audit knowledge flow by auditors clustered in local professional networks is associated with auditor compensation[1]. Auditor compensation, both at partner and non-partner personnel level, has been scarcely empirically examined due to a difficulty to get access to reliable data (see for example Knechel, Niemi and Zerni 2013; Hoopes, Merkley, Pacelli and Schroeder 2018; Bianchi, Carrera and Trombetta 2019; Barrios 2019; Aobdia and Srivastava 2018; Vandenhaute, Hardies and Breesch 2020 for studies of estimated auditor compensation). Given that audits involve a series of judgmental procedure executed by audit engagement teams comprising partners, managers, seniors, and assistants,[2] the compensation auditors at various levels received is considered to be an important incentive for auditors to deliver high-quality outputs (e.g. Knechel et al. 2013; Hoopes et al. 2018; Vandenhaute et al. 2020). Given that audit personnel (i.e. non-partner) conducts most of the tasks during an audit and as audit personnel salaries are a significant determinant of audit quality (Hoopes et al. 2018), it is important to explore the determinants of audit personnel compensation.

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[1] In the auditing literature, there are different terms, such as auditor compensation, audit personnel salaries, wages, typically representing total income an auditor can receive that is available to researchers. In our context, auditor compensation consists of salaries and bonuses for assistants, seniors, managers, senior managers, directors. Here we use the terms audit personnel salaries (non-partner salaries), audit personnel compensation (i.e. non-partner compensation) and auditor compensation interchangeably.

[2] The importance of audit personnel has both attracted attention in both the academic arena and practitioners. For example, Persellin, Schmidt, Vandervelde and Wilkins (2019) have documented that the public accounting industry has undergone significant changes leading to the increased responsibilities, task complexities, and workload of auditors, which imply that loss of talented auditors may be critical if they are not sufficiently compensated. Moreover, American Institute of Certified Public Accountants (AICPA) also show that "While ranking may vary for [public accounting] firms of all sizes, a significant number of the challenges that firms cited above revolve around one core issue: finding and keeping talented people." (AICPA 2015).

In this stream of literature, there are several empirical studies that have explored the determinants of auditor compensation. Prior studies have majorly focused on the determinants of partner compensation (Knechel et al. 2013; Bianchi et al. 2019; Vandenhaute et al. 2020)[3]. One exception is Hoopes et al.'s (2018), which investigate non-partner auditors' salaries, by relying on the H-1B visa applications to proxy salaries in the United States. Complementing Hoopes et al.'s (2018) study which provides evidence that audit personnel salaries are a significant predictor of audit quality, we focus on the determinants of individual non-partner auditor compensation to further understand how audit firms can effectively incentivize audit personnel. This is important because previous empirical studies have largely documented that individual characteristics influence audit outcomes (Francis 2011; Gul, Wu and Yang 2013; DeFond and Zhang 2014; Bianchi 2018; Bianchi et al. 2019). To our knowledge, currently no study utilizes the true non-partner auditor compensation. Here we add an important effect of auditor work characteristic, embedded within audit practice, to the literature of auditor compensation, using social networks analysis[4].

[3] There are also studies related to auditor salaries in the U.S. setting, specially focused on the whole U.S. audit market. For example, relying on H-1B visa to obtain salaries of audit personnel at city and office level, Aobdia and Srivastava (2018) provide evidence that there is no wage depressing effect between immigrant and native auditors among Big N audit firms. Moreover, in testing whether the additional educational requirement increases auditor wages, Barrios (2019) uses Current Population Survey (CPS) to estimate the effect of this change.

[4] Network is a system composed of nodes and ties to link different nodes (e.g. Wasserman and Faust 1994). While one-mode network is consisted of a single type nodes and ties to link them together, a bipartite network is a system where there are two types of nodes and ties to link these two types of nodes. One example of one-mode network is auditors ask advice from other auditors. In this case, auditors are nodes and advice tie connects two auditors. One example of a bipartite network is the notion that auditors join specific engagements. In this setting, auditors are one type of node, engagements are the other type of node, and the tie is auditor-engagement linkage. See later section for more details.

Audits are conducted by engagement teams, typically consisting of assistants, seniors, managers, and partners[5] (e.g. Trotman, Bauer and Humpreys 2015). Auditors typically serve on multiple engagements and share engagement team memberships across different engagements. Due to the interdependence of auditors' work, auditing researchers have identified that auditor interactions and knowledge sharing can play an important role in explaining audit outcomes (Nelson and Tan 2005; Vera-Muñoz, Ho and Chow 2006; Bobek, Daugherty and Radtke 2012; Bianchi 2018; Bianchi et al. 2019). For instance, Bobek et al. (2012) show that auditor interactions and knowledge sharing within audit engagement teams are critical to resolve audit challenges. Recently, Bianchi (2018) provides empirical evidence that knowledge sharing during joint audits can improve audit quality. This study complements these prior studies on auditor interactions and knowledge sharing by examining how the knowledge flow originating from shared audit engagements influences auditor compensation, using a weighted bipartite (i.e. two-mode) network.

Although social networks analysis has been frequently used in organizational studies (see Borgatti and Foster 2003; Borgatti and Halgin 2011; Kilduff and Brass 2010 for a review), it is emerging in auditing research (see for example Horton, Tuna and Wood 2014; Causholli, Floyd, Jenkins and Soltis 2017; Bianchi 2018; Bianchi et al. 2019). Organizational network researchers have provided consistent evidence that network structures affect performance outcomes, both for individuals and organizations (e.g., Borgatti and Halgin 2011). Though different theories are used to explain how individuals within specific network structures in a network utilize information (cf. Burt 1992 for structural hole theory; Granovetter 1973 for the strength of weak ties; Granovetter

[5] Auditors' rank may vary from country to country. For example, in the Netherlands, the rank for auditors include assistant, senior, manager, senior manager, director, and partner.

1985 for network and embeddedness; Watts and Strogatz 1998 for small world network), social networks researchers agree that the specific empirical context of interest is key to choose the relevant theory (Ahuja 2000; Schilling and Phelps 2007; Opsahl and Panzarasa 2009; Opsahl, Agneessens and Skvoretz 2010; Opsahl 2013). For example, the structural hole theory and the theory of the 'strength of weak ties' emphasize that individuals linked to disconnected or weakly connected groups are likely to have access to novel information (i.e. Burt 1992; Granovetter 1973). In contrast, individuals tied to a strongly connected network can easily diffuse knowledge in this setting (the perspective of strong ties, Watts and Strongatz 1998; Coleman 1988; Granovetter 1985). In this study, we will therefore investigate unique features of the auditing context that may determine the network structure, which, in turn, affects auditor compensation.

Auditing literature provides evidence that audit knowledge is more likely to be tacit, knowledge that cannot be acquired via direct communication and requires intensive interactions (e.g. Vera-Muñoz et al. 2006; Bobek et al. 2012; Causholli et al. 2017; Bol, Estep, Moers, and Peecher 2018). Moreover, another characteristic of the auditing context is that audits are conducted by engagement teams, where auditors are assigned to different engagements during different periods. This process characterizes how tacit knowledge can be transmitted through sharing and changing audit engagements. Indeed, research in social networks indicates that *strong ties* can enable knowledge to be shared and transferred (cf. Gomes-Casseres, Hagedoom and Jaffe 2006). This is because strong ties can promote cooperation and coordination (Schilling and Phelps 2007; Uzzi and Spiro 2005; Phelps 2010), and enhance trust and reciprocity among each other (Coleman 1988; Hansen 1999), and are therefore necessary to transmit tacit knowledge (Causholli et al. 2017).

Combining the auditing context and the perspective of strong ties to transmit tacit audit knowledge in network theory, we identify *clustering* as our key measure to represent the extent of tacit knowledge diffusion among auditors across audit engagement teams. As clustering increases, auditor can possess more tacit audit knowledge, and therefore will increase their performance evaluations in audit firms by performing complex audit tasks well and signaling added values for audit firms. Through this way, we expect that there is a positive association between clustering and auditor compensation. Indeed, clustering has been found as a significant predictor of financial success of Broadway musical projects (e.g. Uzzi and Spiro 2005) and innovative outcomes such as patents (Schilling and Phelps 2007). Furthermore, economic literature indicates a positive association between network connectivity and individual wages (Ioannides and Soetevent 2006).

Our results yield a positive and significant association between auditor's network clustering and audit personnel compensation. That is, as auditor's network clustering increases one unit, we can observe an 10.52% increase in audit personnel compensation, which is also economically meaningful. Our results are robust to measuring clustering from the projected one-mode network from previous studies, alternative explanation using structural hole theory in one-mode network (constraint measure from Burt (1992)), alternative explanation using centrality measures (i.e. betweenness centrality measure), alternative linear specification and endogeneity concern.

We also run two additional analyses. First, we are interested in how network structure influences auditor at different ranks to explore which type of audit personnel may benefit more from network clustering. Our results reveal that the positive effect of clustering might majorly be driven by seniors. Second, in a similar notion with Uzzi and Spiro (2005), we use another measure, the ratio of clustering to average shortest path for each auditor, to assess whether this ratio is also a determinant to auditor compensation. This ratio can be interpreted as the amount of clustering (i.e. the extent of information and knowledge flow) by unit path. In an auditing setting, it represents how much of the tacit knowledge can be transmitted among different auditors within fixed steps. The higher the ratio, the easier an auditor can possess information and knowledge advantage. Our results also reveal a positive and significant association between this ratio and auditor compensation.

Our study contributes to the nascent stream of social networks studies in the auditing literature. We complement Horton et al. (2014), Causholli et al. (2017), Bianchi (2018), and Bianchi et al. (2019) in different ways. First, our focus is on a bipartite network utilizing how individual auditors are assigned to different audit engagement teams. This approach therefore more accurately represents the audit practice. Secondly, we consider booked hours for individual auditors linked to different engagement teams as weights. In fact, research in social networks analysis also emphasizes the critical role of weights for network measures (see Opsahl and Panzarasa 2009; Opsahl et al. 2010; Opsahl 2013 for more details). Finally, we focus on a clustering measure, as it has been argued to be a useful measure for information and knowledge diffusion (e.g., Watts and Strogatz 1998; Uzzi and Spiro 2005; Schilling and Phelps 2007; Phelps 2010). Indeed, this measure itself comes from the studies on information and disease diffusion (e.g. Watts and Strogatz 1998). Hence, this measure is more proper to capture the tacit audit knowledge flow in our auditing setting.

In general, we contribute to the auditing literature in terms of auditor compensation. For archival studies, there are several recent published studies on auditor salaries and compensation (e.g. Knechel et al. 2013; Hoopes et al. 2018; Bianchi et al. 2019; Vandenhaute et al. 2020). We extend these prior studies that made use of estimates of auditor compensation, by focusing on real compensation data for audit personnel. Furthermore, by finding that seniors benefit more from clustering, we contribute to the notion that the more hours allocated to seniors in an audit engagement may lead to better audit quality (Cameran et al. 2018). That is, the improved audit quality caused by more hours spent by seniors might be due to the beneficial effects from clustering, i.e. the extent of information and knowledge flow.

Furthermore, our study contributes to another archival audit study on how individual characteristics influence audit outcomes (Francis 2011; Gul et al. 2013; DeFond and Zhang 2014; Bianchi 2018; Bianchi et al. 2019). Different from previous studies, we further exploit the characteristic of auditors serving on multiple engagements to derive our network measure. Although our network is also based on archival records as in Bianchi (2018), we further provide suggestive survey evidence that auditors can learn from each other during multiple engagements and audit tacit knowledge is heterogeneous across engagements to validate our clustering measure. Therefore, we provide evidence that auditor working characteristic and environment can be a key determinant for auditor compensation.

The remainder of the paper is organized as follows. Section 2 will review the relevant literature and develop our main hypothesis. Section 3 will introduce our data and research design. While Section 4 will give the main results, Section 5 will give the additional analyses. Section 6 concludes and discusses.

II. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

Determinants of Auditor Compensation

Compensation is fundamental for organizations to incentivize individual employees to deliver high quality work (e.g. Baker, Jensen and Murphy 1988; Young, Beckman and Baker 2012). Thus, it is meaningful to investigate compensation to further understand employee's attitudes and behaviors (Young et al. 2012). To achieve firms' objectives, compensation schemes can play an important role (Jensen and Meckling 1976). Therefore, it is also important for audit firms to deliver high quality audits by incentivizing auditors through compensation (Knechel et al. 2013; Hoopes et al. 2018; Vandenhaute et al. 2020).

The current empirical studies on auditor compensation majorly focus on partner compensation. For example, Knechel et al. (2013) examine partner compensation in a Swedish context and provide evidence that client size, the number of clients, and the partner's ability to retain and attract new clients are significant determinants for partner compensation. Bianchi et al. (2019) provide evidence that auditors' network connectedness and industrial expertise are associated with their compensation in an Italian small audit market. One recent study is Vandenhaute et al. (2020), which examine the association between audit firm size and partner compensation. Though not strictly related to auditor compensation, Hoopes et al. (2018), focusing on non-partner salaries, find that factors such as auditor rank and education are significant determinants for audit personnel salaries. In this study, we extend the current literature to non-partner individual auditor compensation, and consider the important work characteristic based on social networks analysis.

Social Networks in an Auditing Setting

Network is a form of system where the nodes (i.e. different types of entities, such as human beings, firms, clubs, events, etc.) are connected by ties (e.g. Wasserman and Faust 1994; Borgatti, Mehra, Brass, and Labianca 2009). In fact, ever since Freeman developed the measures for centrality (e.g. Freeman 1978), social networks analysis has been popular in organizational research for decades (see for example Borgatti and Foster 2003; Borgatti and Halgin 2011; Kilduff and Brass 2010 for a review). Although social networks researchers have identified several competing mechanisms for explaining how network structure may influence outcomes, they have generally agreed that the choice of the relevant theory depends on the specific research context and research questions (Ahuja 2000; Schilling and Phelps 2007; Opsahl and Panzarasa 2009; Opsahl, Agneessens and Skvoretz 2010).

While the perspective of structural hole (Burt 1992, 2004) and the theory of 'the strength of weak ties' (Granovetter 1973) emphasizes the role of weak ties to acquire novel information, network embeddedness emphasizes social capital derived from strongly connected ties (Granovetter 1985; Coleman 1988, 1994; Putman 2000). Both perspectives have support from academic literature. For example, Hansen (1999) shows that while weak ties are helpful for innovative ideas, strong ties are required to transfer tacit information and knowledge (see also Krackhardt 1992). Ter Wal, Alexy, Block and Sandner (2016) show that while weak ties can provide diverse non-redundant information, strongly connected networks can provide information that is easy to interpret. To our research purpose, as auditors are assigned to different engagements, a phenomenon that is prevalent in audit practice (e.g. Bhattacharjee, Maletta and Moreno 2007), this comprises of a typical bipartite network, also referred to as a two-mode network (e.g. Borgatti and Everett 1997). One example of a bipartite network is given in Figure 1, which shows that two types of nodes (i.e. auditors and audit engagements) are linked together (i.e. the link between auditor and audit engagement). Under this situation, two features of the auditing context determine the nature and structure of our network, and therefore make us choose the network theory of strong ties to predict auditor compensation.

[INSERT FIGURE 1 ABOUT HERE]

Feature One: Auditor Interactions and Knowledge Sharing

To complete audits, auditors work together as a team, with different team members responsible for different tasks (e.g. Trotman et al. 2015). To achieve high audit quality, it is important for auditors to interact with each other (e.g. Nelson and Tan 2005; Vera-Muñoz et al. 2006; Bianchi 2018). As auditors have different level of knowledge and expertise due to different industries or different clients involved (Causholli et al. 2017; cf. Hayek 1945), knowledge sharing is necessary for auditors to deliver high quality audits because knowledge and expertise is unevenly distributed in audit engagements (Nelson and Tan 2005; Vera-Muñoz et al. 2006; Bobek et al. 2012; Causholli et al. 2017). Moreover, auditing literature also illustrates the important role of consultation from knowledge experts (Gold, Knechel and Wallage 2012), which indicates seeking knowledge is important for successful audits.

More importantly, auditing literature specifies that audit knowledge is more tacit than explicit (Vera-Muñoz et al. 2006; Causholli et al. 2017; Bol et al. 2018). Knowledge has been categorized as explicit and tacit (Polanyi 1966). Explicit knowledge is the knowledge that can be easily codified, transmitted and captured (Athanassiou and Nigh 1999; Vera-Muñoz et al. 2006; Causholli et al. 2017). One example in the auditing setting is the use of checklists, which informs auditors how to collect the relevant evidence from clients. In contrast, tacit knowledge is the deeper understanding, developed experientially, and it cannot be codified or communicated explicitly (Athanassiou and Nigh 1999). In essence, tacit knowledge requires strong interaction for transmission and can be understood by other team members only through personal contact over time (Winter 1987). In an auditing setting, tacit knowledge might be related to judgment on fair value accounting of complex financial instruments according to International Financial Reporting Standards (IFRS) (e.g. Laux and Leuz 2009). This judgment involves substantial insights and requires interactions with experts and clients. Therefore, to transmit tacit knowledge, strong ties are required, as it involves dense clusters for trust and reciprocity for a collective goal. This is consistent with Causholli et al.'s (2017) notion which argues that the network closure is beneficial for audit outcomes, as Causholli et al. (2017) find evidence that when auditors seek advice within densely connected knowledge-sharing networks, their performance is positively affected.

Feature 2: The Duality of Auditors and Audit Engagements

As indicated previously, bipartite network is composed of ties linked by auditor and audit engagement. Under such context, audit engagements display several important characteristics. First, shared team memberships augment the frequency of contact and by that develop familiarity and trust among team members (e.g. Nelson and Tan 2005; Vera-Muñoz et al. 2006; Causholli et al. 2017; Bianchi 2018). Second, collaborating on the same engagements means working towards a common goal, especially in an auditing setting with higher level of litigation risk (e.g. Schmidt 2012). Finally, increased trust and a common goal are both factors that can be expected to promote the development of a collective identity orientation (e.g. Brewer and Gardner 1996) among team members, facilitating the process of openly disclosed information and knowledge exchange

(Nahapiet and Ghoshal 1998; Agneessens and Wittek 2012). These perspectives are similar with the project teams in Brennecke and Rank (2016).

Furthermore, as auditors serve multiple engagements simultaneously, the individual auditors are assigned to different engagements with different experience in terms of the understanding of accounting and auditing standards, industry expertise, and the way of conducting audits (Causholli et al. 2017). Such contextual embeddedness in audit engagements is a significant determinant for auditors' advice seeking and giving (cf. Brennecke and Rank 2016). Molm, Collett and Schaefer (2007) show clear evidence that sharing a social focus, such as team memberships, and working toward a common goal seem to give rise to generalized exchange norms in project teams, which suggests that the tacit knowledge can be transmitted among engagements with the same members. This is a similar notion of embeddedness where the firms not only have to manage their relationships with their direct contacts, but they also have to accurately perceive and attempt to manage relationships among contacts of contacts (Uzzi 1997).

Hypothesis

Therefore, based on our specific auditing setting of tacit audit knowledge that is required to be shared and embedded network structure, strong ties are needed to transmit tacit audit knowledge. This perspective is consistent with studies in social networks. For example, Coleman (1988) argues that such strong ties in a dense cluster can promote mutual trust and reciprocity, an important condition to transfer tacit knowledge. To achieve goals, it is important for people in specific groups or organizations to have trust and reciprocity (e.g. Sykes, Venkatesh, and Johnson 2014). In fact, the idea of tacit knowledge and strong ties has been replicated in other settings (e.g., Tsai 2001; Reagans and McEvily 2003; Levin and Cross 2004; Smith, Collins and Clark 2005;

Schilling and Phelps 2007; Phelps 2010; Leonardi 2014; Argote and Fahrenkopf 2016; Ter Wal, Alexy, Block and Sandner 2016).

Moreover, importantly, auditing literature using social networks also emphasize that network structure can enable audit knowledge to be acquired and transmitted (e.g. Causholli et al. 2017; Bianchi 2018; Bianchi et al. 2019). For example, by examining the association between knowledge-seeking ties and individual auditor performance, Causholli et al. (2017) show that explicit knowledge plays a different role than tacit knowledge which is beneficial for manager performance when managers seek tacit knowledge. In investigating joint audits and audit quality in an Italian setting, Bianchi (2018) document that network connectedness may lead to more knowledge spillover which lead to better audit quality. Bianchi et al. (2019) document that social capital, represented by auditor network structure, can generate knowledge spillovers, and therefore is positively associated with audit partner compensation in a small Italian audit market.

In our study, we follow the previous studies to choose clustering as major focus of the network structure, manifested by the strong ties for tacit knowledge flow (e.g. Uzzi and Spiro 2005; Schilling and Phelps 2007; Phelps 2010). That is, as clustering increases, auditor can possess more tacit audit knowledge and can therefore perform well on complex audit tasks. In this way, auditors with higher clustering can receive better performance evaluations, and therefore increase their compensation. Moreover, another reason for such a positive association is that more knowledgeable auditors may be treated as valuable in audit firms and therefore audit firms compensate more to retain talents. Indeed, Clustering has been found as a significant predictor for Broadway musical's financial success (Uzzi and Spiro 2005), and firm's creative and innovative output (Schilling and Phelps 2007). Literature in economics also shows that individuals with a more connected network have higher wages (Ioannides and Soetevent 2006), suggesting a positive association between clustering and compensation. Thus, in sum, we come up with our main hypothesis in this study as follows:

HYPOTHESIS: All else equal, there is a positive association between network clustering and audit compensation.

III. SAMPLE AND RESEARCH DESIGN

Sample

Our data were collected from an audit firm operating in the Netherlands. We collected both survey data and archival data from the personnel and hours registration systems of this audit firm. To begin with, one author randomly identified 80 engagement teams with different team size. For all of these engagements, employees working in assurance and provided that they booked a certain minimum number of hours on the engagement in a certain three-month time window were invited to participate in the survey. In total, 418 auditors received an invitation to participate. 240 auditors completed the survey, yielding a response rate of 57.4%. For those 240 auditors, there are 51 assistants, 97 seniors, 36 managers, 21 senior managers, 17 directors and 18 partners.

For each of the 418 invited auditors, the audit firm provided information from the personnel filings as well as information on all engagements these 418 auditors worked on during the 2018 fiscal year. In total, this involved 3450 unique engagements. Moreover, for the bipartite network, we had 9320 unique ties between individual auditors and specific engagements. Further, as booked hours were also available, this typically showed how many hours each auditor spent on a specific engagement, and we used this as weights to construct our final weighted bipartite network. The following figure shows a network graph of randomly selected 360 auditors and 770 engagements, composing of 900 unique ties.

[INSERT FIGURE 2 ABOUT HERE]

As our key interest is auditor clustering and auditor compensation, we focus our inference on these individual auditors. Combing information on the weighted bipartite network and auditor compensation further reduced our sample size. Specifically, as the audit firm did not have the required information for 19 individuals hired as temporary staff, we had to drop these 19 observations from our analyses. Moreover, we dropped the 8 auditors that left the audit firm before the time that could be eligible for bonus. As our focus is on auditor compensation, which typically consists of both salary and bonus, we decided to discard these 8 auditors as this may create outliers in our analysis[6]. Lastly, for similar reasons, we dropped one senior who according to the firm's records received 0 salary and 0 bonus. Finally, our sample consists of 390 auditors, including 97 assistants, 160 seniors, 50 managers, 37 senior managers, 21 directors and 25 partners.

Research Design

As we cannot observe partner compensation, we use the censoring method, that is, Tobit model (Tobin 1958; Cameron and Trivedi 2005; Wooldridge 2010) to estimate the effect of network clustering on auditor compensation[7]. Compared with OLS regression to delete all partners, Tobit model can still use the observed information of partners in our data and will have

[6] We also ran the same analyses including these 8 observations. Our results still hold when we included them.
[7] An important but reasonable assumption here is that partner compensation is higher than audit personnel compensation (i.e. non-partner compensation).

better inference. The Tobit model can be formulated as follows. Assume the true underlying model is:

$$y^* = \boldsymbol{x}'\boldsymbol{\beta} + \epsilon, \quad (1)$$

where linear regression assumptions apply. However, y^* can only be observed under some upper threshold, as follows:

$$y = \begin{cases} y^*, if\ y^* < U, \\ U, if\ y^* \geq U, \end{cases} \quad (2)$$

where y is the observed part of y^*, and U is the upper threshold where the value of y^* is not observed at or more than U. The model will be estimated in STATA 15, using maximum likelihood estimation routine.

We then introduce our variables under this model, and the definitions of variables are given in the Appendix 1. First, our dependent variable is auditor compensation, *AudCompen*, a transformed variable from the audit firm's HR system[8]. Our compensation includes two components: salary and bonus. As the transformed compensation is very large and skewed, we use natural logarithm transformation.

Our key independent variable is local network clustering[9]. The local clustering coefficient measures the density in a node's (i.e. one specific auditor's) local network around this node, and is the proportion of ties among a node's contacts over the possible number of ties between them

[8] Due to privacy reason, the audit firm did not provide the exact compensation data to us. They used the same formula to transform both salary and bonus to make sure the correspondence between the true compensation and the transformed compensation. So we can add them together without any distortion.

[9] Clustering can be measured for the whole network (i.e. global clustering) and for the node in the network (i.e. local clustering). See Opsahl (2013) for more details. As our analyses are majorly related to the individual auditor compensation, we use local network clustering for individual auditors.

(Watts and Strogatz 1998; Opsahl 2013). In network terminology, this coefficient is the fraction of the total number of triangles to the total number of potential triangles (i.e. two-paths); see Figure 3 below for a graphical depiction.

[INSERT FIGURE 3 ABOUT HERE]

However, the local clustering coefficient from Figure 3 ignores weights associated with ties and cannot be directly extended to the bipartite network. Barrat, Barthelemy, Pastor-Satorras and Vespignani (2004) incorporate the weights to the one-mode network, and Opsahl (2013) further develop the clustering coefficients for weighted bipartite network. The basic idea of Opsahl (2013) is based on network closure in a bipartite network, including the consideration of weights for different ties. Figure 4 provides one illustration for this configuration:

[INSERT FIGURE 4 ABOUT HERE]

Specifically, Opsahl (2013) exploits the idea of weighted one-mode network by using the proportion of the closed 4-path and open 4-path, similar with the concept in one-mode network. The relevant network measures are obtained from R packge "tnet" (Opsahl 2009; Opsahl 2013). This package provides the computation of local clustering coefficients for a bipartite network for each auditor, with five different types, including: clustering assuming no weights (*Clustering*), arithmetic mean of weights (*Clustering_am*), geometric mean for weights (*Clustering_gm*), the maximum among weights (*Clustering_ma*), and the minimum among weights (*Clustering_mi*). These five coefficients can provide a reasonable test for robustness to different methods for weighting.

We then control for the variables from archival records that could also impact auditor compensation[10]. We rely on the determinants of wage in labor economics to control for various auditor's work-related characteristics, following Mincer's (1974) specification[11]. Following this specification, we include human capital characteristic including age, *Age*, age squared, *Agesq*, gender, *Gender*, and education[12], *CPA_Dummy* (see also Hoopes et al. 2018; Barrios 2019; Bianchi et al. 2019). We then control for rank, *Rank*, the most important control for auditor compensation, as audit firms pay auditors based on rank differences (e.g. Hoopes et al. 2018). Related to rank, we also control for tenure, *Tenure*, to further reduce the concern of omitted variable bias.

As indicated, some work characteristics that may influence auditor compensation will also be controlled, as literature has identified factors such as office and city characteristics may influence auditor outcomes (e.g. Aobdia and Srivastava 2018; Beck, Francis, and Gunn 2018). We first control for the numbers of hours an individual is expected to work according to his or her labor contract in terms of full-time equivalent units, *FTE*. Full-time employees work for longer hours and therefore may earn more. So we predict a positive association between full time employees and auditor compensation. We also control for effective utilization rate, *Utilization*, as

[10] One important distinction from previous studies, such as Knechel et al. (2013), Vandenhaute et al. (2020), Bianchi et al. (2019) and Hoopes et al. (2018), is that we do not have information on clients' characteristics. Moreover, although we have office-level information, and can potentially include city characteristics (Beck, Francis, and Gunn 2018), to protect the privacy of all participants, all office-level (also city-level) information is anonymous. We complement the current literature by using the engagement and personal characteristics, as typically in the determinants of wages in labor economics (e.g. Becker 1962).

[11] The traditional Mincer equation regresses logarithm of earnings on a combination of independent variables, including age, gender, education, and a random term. As illustrated, consistent with our data collected from the firm's personnel records, we majorly consider the framework from labor economic literature to test the effect of network structure and auditor compensation.

[12] In an auditing setting, it is important for auditors to have the certification of Certified Public Accountant for auditing career progression (e.g. Barrios 2019).

higher utilization may lead to higher pay. We have information on the overtime records, and use *Logot*, the natural logarithm of overtime hours to predict compensation. Similarly, we control for total leave hours, *Logleave*, the natural logarithm of leave hours, as the longer hours of leave may lead to less pay. Moreover, we control for vacation hours, *Logvacation*, the natural logarithm of total vacation hours, as for total leave hours. Finally, we have the total engagement hour for full year for each auditor, *Logengfy*, the natural logarithm of total engagement hours for the full year, as the engagement hours may be a determinant of auditor performance, especially for assistants and seniors. Similarly, we also control for the total number of engagements for full year, *Lognumengfy*, the natural logarithm of total number of engagements for the full year for the same reason.

IV. RESULTS

Suggestive Evidence for Validation of Our Clustering Measure

Suggestive Evidence from Survey

Based on our assumption of strong ties to transmit tacit knowledge, it is necessary to investigate whether tacit knowledge has been transferred. To capture this process, we use survey instruments to examine how auditors' tasks vary across engagements and whether auditors can learn from each other when they are assigned to multiple engagements. If auditors' jobs vary across engagements, auditors need to interact with each other to deliver high quality audits, consistent with the notion of tacit audit knowledge (Vera-Muñoz et al. 2006; Bobek et al. 2012; Causholli et al. 2017; Bol et al. 2018). If auditors can learn a lot from each other, this is consistent with the notion that the tacit knowledge has been transferred. We use "task variety compared with other engagement teams" to capture the task variety across engagement and "job relational learning" to measure whether auditors can learn from each other. Due to the self-reporting nature, we interpret this evidence as suggestive.

For "task variety compared with other engagement teams", we have four items, also with the Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). The four items include: (1) "my work varies from engagement team to engagement team" (mean = 5.04, standard deviation = 1.25), (2) "in each engagement team I am part of, I work on different things" (mean = 4.88, standard deviation = 1.22), (3) "In each engagement team I am part of, I am required to do a wide range tasks I have not carried out before (mean = 3.97, standard deviation = 1.37), and (4) I perform a variety of unique tasks for each engagement team I work on (mean = 4.29, standard deviation = 1.33). The general mean is 4.54, with standard deviation 0.98. The average score suggests that auditors' tasks vary from engagement to engagement and sometimes they are even required to conduct tasks that they have not encountered before. This evidence suggests that the audit tasks are rather heterogeneous, a necessary condition for tacit knowledge to be transferred to complete audits.

For "job relational learning", we have six items, with the Likert scale ranging from 1 (strongly disagree) to 7 (strongly agree). The six items include: (1) "working in multiple engagements has offered me the opportunity to learn new things" (mean = 5.82, standard deviation = 1.07), (2) "working in multiple engagements has increased my knowledge as an auditor" (mean = 5.88, standard deviation = 1.02), (3) "working in multiple engagements has increased my understanding of complex audit issues and problems" (mean = 5.65, standard deviation = 1.06), (4) working in multiple engagements has helped me to better understand clients' perceptions about my job as an auditor" (mean = 5.36, standard deviation = 1.14), (5) working in multiple engagements has helped me understand how my work affects others' work within engagement teams" (mean = 5.48, standard deviation = 0.96), and (6) working in multiple engagements has improved my skills of project management (mean = 5.60, standard deviation = 1.09). The general mean for this instrument is 5.63 with standard deviation 0.85. This suggests that auditors perceive that their own work affects other team members' work and they can learn a lot during multiple engagements, which suggests that tacit audit knowledge has been transferred.

Suggestive Evidence from Simulation of Small World Network

To obtain a sense of how similar our network is with small world network, we conduct a simulation based on "sample_smallworld" function in R package "igraph" (Csardi and Nepusz 2006). Small world network is characterized by locally dense clusters with several non-occasional links among different clusters (e.g. Phelps 2010). If our network has similar local structures with small world network, it is justified that the clustering measure can be used. Figure 2 above using around 10% of total links shows that auditors are linked together by different engagements, and therefore our network displays the dense cluster of a small world network (Watts and Strogatz 1998). As typically this simulation is based on one-mode network, we obtain the weighted one-mode network through "tnet" package. Then we transfer this network to "igraph" object and conduct the simulation. According to the setup of small world, we find as we increase the rewiring probability (from 0 to 1, see Watts and Strogatz 1998 for more details) to around 0.2, the simulated small network and our network have similar global clustering coefficient and average shortest path. Despite this, we still interpret this evidence as suggestive, as in our setting we might not have the occasional long paths to link different local dense clusters, as in a typical small world network (e.g. Watts and Strogatz 1998; Uzzi and Spiro 2005). However, our use of clustering is well justified by such similar characteristics between our network and small world network, i.e. highly dense local cluster (e.g. Uzzi and Spiro 2005).

Descriptive Statistics

Table 1 contains the descriptive statistics for this study. The mean of natural logarithm of auditor compensation (excluding partners) is 16.698 with a standard deviation of 0.387. We include five measures of clustering as mentioned in the previous section. The mean of clustering without taking weights is highest among five, 0.277, with standard deviation 0.108. We also observe that there is difference in these five measures of clustering. In terms of hierarchical positions, around 24.87% of all auditors are assistants, 41.03% are seniors, 12.82% are managers, 9.49% are senior managers, 5.38% are directors and 6.41% are partners. The average age of auditors is 31.033 with a standard deviation 8.357. The average tenure is 7.143 years with a standard deviation 8.507. In all auditors, female auditors cover 36.9%, and 32.8% of all auditors have obtained their CPA-degree. Most of the auditors are full time employees, with the average FTE-proportion being 93.5%. The average effective utilization for all auditors is 0.635, with a standard deviation 0.156. The average of natural logarithm of over-time hours for auditors is 4.409 with a standard deviation 1.289. Similarly, the mean of the natural logarithm of total leave hours is 4.639 with a standard deviation 3.497, indicating the leave hours is more various than over-time hours. The average of natural logarithm of vacation hours is higher, with a mean of 5.394 and a standard deviation of 0.696. The mean of natural logarithm of the total engagement hours for the whole year is 7.045, with a standard deviation 0.405. The average of the natural logarithm for total number of engagements for the full year is 3.010 with a standard deviation 0.494.

[INSERT TABLE 1 ABOUT HERE]

Table 2 shows Pearson correlation coefficients for the variables in the main analysis. Interestingly, the key independent variable, local clustering coefficients, and all other controls are significantly correlated with auditor compensation, which justifies the use of controls here. We can see the correlation between rank and auditor compensation is 0.969[13], which indicates the importance to control for rank. Besides rank, we also can see the important determinants of compensation based on age (0.854), tenure (0.809), and CPA (0.756). This is consistent with the evidence in labor economics in terms of human capital determinants of wage (Becker 1962; Hoopes et al. 2018; Beck et al. 2018; Barrios 2019; Aobdia and Srivastava 2018; Bianchi et al. 2019). We also observe positive and significant correlation coefficients between auditor compensation and all five types of clustering, which provides initial evidence that clustering might be positively associated with auditor compensation. There are also some other interesting observations between auditor compensation and other controls. First, gender (i.e. female) is negatively associated with audit personnel compensation. Second, effective utilization rate, over time hours, and the total number of engagement hours are also negatively correlated with auditor compensation. We need to be careful for interpreting such findings as these are correlation coefficients. Finally, full-time employee, leave hours, vacation hours, and the number of engagements for full year are positively correlated with auditor compensation.

[INSERT TABLE 2 ABOUT HERE]

[13] Note here Rank is an ordered categorical variable and auditor compensation is a continuous variable. Typically, Pearson correlation is computed based on two continuous variables. We use this coefficient as suggestive here. The same principle applies to dummy variables Gender and CPA_dummy as well.

Table 2 also shows that the correlations among five measures of clustering are very high, though there is still some variation. The correlations between clustering coefficients and other controls are small. We further notice that the intercorrelations among rank, age, tenure and CPA are very high, because these measures might be developed together. We observe that all other correlations are low to moderate (less than 0.6). To reduce the concern for multicollinearity, we exclude partner observations, and run OLS regression to check Variance Inflation Factor (VIF). We find that the value of VIF for all the variables under this analysis is less than 10, under the typical cutoff value[14]. Thus, multicollinearity may not be a critical issue in our study.

Main Results

Table 3 shows the main results based on Tobit regression with maximum likelihood estimation.

[INSERT TABLE 3 ABOUT HERE]

Each clustering coefficient produces a very similar coefficient. As pointed out by Opsahl et al. (2010), for considering weights, the most important issue is to consider what weight means in the specific research context. In our setting, the weight represents the booked hours for each engagement, which indicates that the larger the weight, the more possible for auditors to interact, communicate and coordinate. In essence, our setting requires strong ties rather than weak ties, therefore we stick to the interpretation of clustering coefficient under maximum weight (i.e. *Clustering_ma*). That is, our coefficient estimate for clustering value on auditor compensation is

[14]As we include a square term of age, and there will be very high correlations between Age and Agesq, we delete Agesq to detect the VIF coefficients. The maximum values of VIF for the five models using different clustering measures are 7.43, 7.42, 7.42, 7.43 and 7.42, while the average values of VIF for these five models are 3.11, 3.11, 3.11, 3.11, and 3.10.

0.100 (*t*-stat=2.95). Economically, one unit of increase in clustering can improve auditor compensation around 10.52%, which is meaningful.

We also notice that hierarchical positions in audit firms play a critical role in determining auditor compensation. As observed in correlation matrix, age, tenure and CPA are also significant determinants of auditor compensation, with coefficients 0.027 (*t*-stat=5.42), 0.006 (*t*-stat=4.17), and 0.056 (*t*-stat=4.18) respectively. We also find the age squared is negative and significant, which is the same finding suggesting that wages increase at a decreasing rate in the labor economic literature (e.g. Barrion 2019). All other controls are not significant at 5% level.

Robustness check 1: Alternative Measure of Clustering

Previous literature generally uses the projection method, i.e. projecting the two-mode network into one-mode network (e.g. Newman 2001; Uzzi and Spiro 2005; Schilling and Phelps 2007; Phelps 2010). However, as pointed by Opsahl (2013), the projection, even taking weights into account, might create problem as such projection may overstate the triangles in the one-mode network and increase the clustering coefficient. Thus, we would like to test whether there is a significant change when we use the clustering, *Clustering_pro*, obtained from the projected one-mode network from the original bipartite network. As the package "tnet" provides this measure, we obtain this measure from the projected two-mode network. We rerun the Tobit regression, and the results are provided in Table 4.

[INSERT TABLE 4 ABOUT HERE]

Similar with Opsahl's (2013) arguments, we can see the average value is higher than the average of all the five clustering coefficients from the original weighted two-mode network.

Despite this, the association between clustering and auditor compensation is stronger than in Table 3 (0.160, *t*-stat = 4.22), both statistically and economically. All the significant variables are the same as in the Table 3. Therefore, our main results are robust to the alternative use of projected clustering measure.

Robustness Check 2: Alternative Explanation Using Structural Hole

Structural hole theory is frequently used to explain job outcomes (Burt 1992, 2004). Structural hole theory indicates that egos with disconnected alters can manipulate and control information, and therefore can improve their own performance. The following Figure 5 shows the key tenet for this theoretical perspective:

[INSERT FIGURE 5 ABOUT HERE]

Consider the network structure for node 1, which connects nodes 2, 4, and 5. Typically, node 1 can serve as a broker between node 4 on one hand, and nodes 2 and 5 on the other hand, because there is no connection between node 4 and nodes 2 and 5. In this case, the communication between these two groups relies on node 1 who can access and manipulate information for himself or herself. In contrast, it is difficult for node 1 to obtain the similar information benefits from nodes 2 and 5, as nodes 2 and 5 are connected with each other. This is the one specific type of social capital derived from network structure supported by Burt (1992, 2004).

In an auditing setting, it is also possible for auditors not to share their information, afraid that other auditors may learn their own techniques. This section will empirically test this idea. As currently there is no solid measure of structural hole for a two-mode network, we obtain the projected one-mode network from "tnet" package, and then transport it to "igraph" package. The function "constraint" in "igraph" package provides the measure of structural hole for each auditor, according to Burt's formulation (Burt 2004). Therefore, we obtain the variable, *Constraint*, to measure each auditor's extent of structural hole. The higher the score of constraint for one auditor means the auditor has more redundant ties, and therefore it is more difficult for this auditor to control and manipulate information. Thus, we run two series of models: (1) we use constraint as the key independent variable without including the clustering coefficient; (2) we include the clustering coefficient (*Clustering_ma*) as we mention before as the key independent variable. Table 5 provides the results for the descriptive information of the constraint measure and the main results of Tobit regression.

[INSERT TABLE 5 ABOUT HERE]

Panel A in Table 5 shows the descriptive statistics for the measure of structural hole. Interestingly, under structural hole theory we would expect a negative association between constraint and auditor compensation. However, Model 1 of Panel B shows the opposite result: we find there is a positive and significant association between constraint and audit personnel compensation, suggesting that redundant (i.e., densely clustered) ties are positively associated with auditor compensation. Moreover, as we control for clustering, the association between constraint becomes not significant, but the positive and significant association between clustering under maximum weights and auditor compensation still holds, which gives more robustness of our main hypothesis.

Robustness Check 3: Alternative Explanation using Centrality Measures

Another competing measure is centrality measure. In the social networks literature, after Freeman (1978) developed the degree, betweenness and closeness centrality measures, they have been adapted and changed for organizational research for several decades (Borgatti 2005; Borgatti et al. 2006; Opsahl et al. 2010). Relevant to our setting, as one limitation of degree centrality is that this measure does not consider the global structure of the network, such as access to information or knowledge (e.g. Borgatti 2005), we choose betweenness as our major centrality measures as also did in robustness check in Bianchi (2018) and Bianchi et al. (2019)[15]. Betweenness assesses the degree to which a node lies on the shortest path between the other nodes, and work as a conduit of information (e.g. Wasserman and Faust 1994; Opsahl et al. 2010). To test this, we first use betweenness centrality as the key independent variable and then take it as a control when using clustering. We obtain this weighted betweenness centrality from “tnet” package, and also indicated by Opsahl et al. (2010), we choose the tunning parameter 1.5, as we need strong ties to enable the transfer of tacit knowledge. As betweenness measure is typically very large, we use log transformation[16]. Table 6 provides the results.

[INSERT TABLE 6 ABOUT HERE]

From Table 6, we can rule out that our results are driven by centrality measures, as in both models, betweenness is not significant. Therefore, our main hypothesis is still supported.

Robustness Check 4: Using Linear Model Excluding Partners

[15] To make it more robust, we also run models using degree centrality and closeness centrality. We find the same results as betweenness centrality.

[16] As indicated by Opsahl et al. (2010), one limitation for betweenness measure is it can contain 0. Therefore, here we use log(betweenness+1) to transform this variable.

As another robust test, we delete 25 observations of partners, and use OLS regression to run the same models. Table 7 provides the results.

[INSERT TABLE 7 ABOUT HERE]

Table 7 shows that the results are very close to Tobit output, and therefore provides clear evidence that there is a positive and significant relationship between clustering and auditor compensation. Hence, our main results are robust to this alternative linear specification.

Robustness Check 5: Instrumental Variable Estimation

As our network clustering originates from individual auditors assigned to audit engagements for the whole year, we might have endogenous issue, because this measure can represent a choice variable. For individual auditors, especially senior managers, directors, and partners, they may choose the auditors they like to work with. To address this issue, we use instrumental variable approach according to the data we have. To choose a potential instrument, because our network measure is derived from ties between individuals and engagements, location can be a determinant for this clustering measure. On the other hand, within the same firm, the compensation may not be very likely to be driven by location as audit firms tend to have firm-wide compensation policies in the Netherlands. Therefore, we choose office location as our instrument[17]. Moreover, a falsification test of regressing auditor compensation on location shows

[17] It is typical to choose physical or biological characteristics as instruments (Roberts and Whited 2013). As in the Netherlands, audit firms' office locations generally are not very far away from each other, joint engagement regularly happens. Therefore, the location of individual auditors may be strongly related to the engagements they will have, and therefore will influence the clustering for each auditor. On the other hand, the data coordinator of the audit firm indicated that the bonus policy is the same across all offices in the country. The data coordinator also suggested that auditor salary is similar based on the sub-rank. Thus, although audit firms may compensate auditors according the living standards of cities, the office location might be justified the use of instrument in our case.

that office location is not significant for auditor compensation. Thus, we argue that office location could theoretically be a valid instrument. Running this analysis with conditional maximum likelihood estimation, Table 8 shows the results.

[INSERT TABLE 8 ABOUT HERE]

Table 8 shows that the significant association between clustering and audit personnel compensation does not hold. However, the Wald test of exogeneity fails to reject the null hypothesis of no endogeneity. Thus, according to this test statistics, we do not have sufficient information to reject this null hypothesis (STATA 2015). We need to interpret this evidence with some caution. Larker and Rusticus (2010) show clear evidence that it is extremely difficult to choose the valid instruments in an accounting setting. Our results may suggest that we do not have a valid instrument to address this as office location may be an individual choice variable due to the location to home or city related reasons. Moreover, Angrist and Pischke (2008) show that bad choice of instrument, or even the choice of a moderately valid instrument may lead to worse results than regular regression. Thus, in our setting, a regular Tobit model may be equally appropriate for our analyses. Thus, the interpretation of the main analysis is still appropriate.

V. ADDITIONAL ANALYSES

Additional Analysis 1: Splitting the Sample Based on Ranks

In this section, we explore which group of auditors could benefit more from the network clustering. As we are aware that network clustering is related to tacit knowledge transfer which typically will benefit assistants and seniors, we first run the analyses based on each rank in our sample, i.e., assistant, senior, manager, senior manager and director. Note here we do not include age squared because within each rank the age variation is not that high, but including this variable does not change the results. Results show that only the senior sample shows a positive and significant association. Table 9 shows the OLS results for the senior sample. Then we combine the senior group with any other group(s), untabulated results show that there are positive and significant associations between network clustering and auditor compensation. Moreover, any combination without the group of seniors is not significant. Therefore, we interpret this evidence as suggestive that our results might be majorly driven by seniors, in a similar notion that more allocated hours of seniors are positively associated with better audit quality (Camarra et al. 2018).

[INSERT TABLE 9 ABOUT HERE]

From Table 9, it is also interesting to see the similarities and differences with the main results. Age and tenure are still the significant determinants for auditor compensation for seniors. CPA is also significant, but the coefficient is smaller than that in the main analysis, indicating CPA is important for seniors, but generally less important for all auditors. Here effective utilization becomes significant. Effective utilization is more important for seniors than the whole sample, as effective utilization may be an important performance evaluation measure for lower-ranking auditors. Gender is marginally significant and female seniors tend to earn more than their male counterparts, although there is no such relationship for the whole sample.

Untabulated results about each group reveal several interesting findings as well. For assistants, the most important determinant is tenure[18]. For managers, the two significant predictors include CPA (0.068, *p*-value=0.004), and age (0.005, *p*-value =0.042). For managers, they are in

[18] This is the same with the point by the data coordinator from this audit firm. The firm gives the same salary and bonus to assistants, but according to the timing of entry, bonus tends to be different.

the middle level, and CPA can be important differentiation between seniors and managers. For senior managers, the most important determinants are age (0.013, *p*-value =0.000) and CPA (0.072, *p*-value =0.034). As auditors become promoted, experience will play a major role. Finally, for directors, the only significant predictor is age (0.030, *p*-value =0.028). This evidence suggests that as auditors successfully progress their career, experience becomes more important. One limitation for such analyses is that the sample size of senior managers and directors is small, 37 and 21 respectively.

Additional Analysis 2: Additional Measure of Clustering

When the embedded network expands and evolves, the small world network may emerge (Watts and Strogatz 1998; Uzzi and Spiro 2005). In small world network, the local dense clusters help facilitate the information flow, while at the same time, such information or knowledge can be transferred to other clusters. One illustration of the small world network is illustrated in Figure 6:

[INSERT FIGURE 6 ABOUT HERE]

It is easy to see, for example, the dense cluster association with node 42, can be linked to the dense cluster associated with node 27. Therefore, the distance to transmit information become much shorter than before. In this type of network, information and knowledge can be spread quickly.

Our network displays some similar features with a small network: rather dense cluster but with fewer non-occasional long links to each cluster (see Figure 2 and Figure 6 for an illustrative comparison). Thus, we further assess the ratio of clustering and average shortest path for each auditor to measure the clustering by unit path, *Ratio*, *Ratioam*, *Ratiogm*, *Ratioma*, and *Ratiomi*, corresponding to *Clustering*, *Clusteringam*, *Clusteringgm*, *Clusteringma*, and *Clusteringmi*, similar with measure adopted by Uzzi and Spiro (2005). The measure means that for each auditor the network clustering by the average shortest path, with high values representing that auditor can access tacit knowledge within smallest steps. We rerun all the analyses, and the results are similar with the main analyses[19]. Table 10 provides the results.

[INSERT TABLE 10 ABOUT HERE]

Table 10 provides very similar results with Table 3, and therefore provide more evidence of the robustness of clustering measure. Further untabluated results based on sample splitting shows similar results as in the clustering.

VI. CONCLUSIONS AND DISCUSSIONS

This study provides another social networks study in an auditing setting, using the novel measure of *clustering*, which represents the extent of tacit audit knowledge flow around individual auditor. We provide evidence that local network clustering is positively associated with auditor compensation, both statistically and economically. Specifically, one-unit increase of clustering can lead to 10.52% increase in auditor compensation. This result is robust to alternative measure of local network clustering, structural hole, centrality measures, alternative linear specification and endogeneity concern. Furthermore, additional analyses show that this effect may be driven by seniors. This is similar to the notion that allocated hours of seniors in audit engagements play a critical role in determining audit quality (Cameran et al. 2018). The primary reason might be

[19] We also run models based on average shortest path alone, and have failed to find similar significant results. These results suggest that the shorter average paths may be one distinction between the network we have and small world network, because auditors assigned to different engagements may lack of long links to connect two far groups.

related to the division of labor in an audit engagement: partners tend to manage the client relationships, directors and managers manage the whole team, seniors execute the auditing tasks and assitants may collect evidence according to seniors' requests (see Cameran et al. 2018; Maister 1982). Therefore, the tacit knowledge is more relevant to seniors as they are more directly exposed to different settings when they execute audits and therefore require more tacit knowledge to make accurate judgement.

Moreover, our results are important for audit firms and regulators as well. To begin with, it is important to emphasize the staffing decision for audit engagements. As shown, local network structure is important for tacit audit knowledge to transfer, and therefore it is important for audit firms and regulators to design audit engagements based on auditor expertise, knowledge base, and how to facilitate auditor interactions and knowledge sharing. For example, audit firms can use formal and informal training or social programs to make auditors know more about each other. Secondly, both audit firms and regulators should pay more attention to the development of seniors, as they are the key to execute the audits. In this respect, how to make knowledge flow through tacit knowledge should be an important consideration when staffing audit engagements.

Though promising, our study still suffers several limitations. To begin with, we collect our data from an audit firm in the Netherlands. This may make our results difficult to generalize to other audit firms and to other countries. Therefore, more research should be conducted with respect to more representative samples. Secondly, our network measure is based on the 418 auditors who were invited to participate in survey. Therefore, we do not have information on the experts (e.g. tax consultants, IT professionals etc.). We do not have other assurance members who were not invited for this survey either. More efforts should be made to collect complete individual-engagement data. Moreover, we do not have information related to audit engagement information to capture audit quality, e.g. audited financial statements. We also do not have more specific client information either. Future research should collect more engagement-level information, such as client characteristics that can influence both auditor compensation and audit quality. Furthermore, based on our instrument, it is still difficult to make causal inferences. Our research may be benefited if we can make use of exogenous shocks or more disclosure of the anonymized information (e.g. Angrist and Pischke 2008). Related to this perspective, longitudinal data may be collected to distinguish between cause and effect. One final limitation is, as we do not have detailed performance evaluations[20], we cannot directly verify the tacit audit knowledge flow directly affects performance evaluation of each auditor, which in turn affects auditor compensation. More detailed performance evaluations may be collected to verify this process in the future.

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[20] Although the audit firm provides the performance evaluations, including annual performance evaluations and annual engagement evaluations. There are several limitations. To begin with, there are no performance ratings on directors and partners, and a large amount of performance ratings on assistants are missing. In sum, 30.51% of the performance ratings and 36.41% of the engagement ratings are missing. Secondly, for each rank available, all performance ratings and engagement ratings tend to cluster on the same score, covering 63.49% for performance rating and 63.31% for engagement rating. The analyses using linear regression, logit and ordered logit cannot find any meaningful results.

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FIGURES AND TABLES

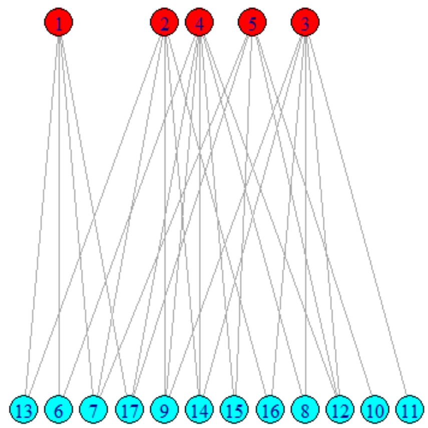

Fig. 1. This figure illustrates a typical bipartite (i.e. two mode) network. In our setting, it means auditors (i.e. blue nodes) join engagements (i.e. red nodes). The links among the same nodes are not allowed. This network is simulated from R package "igraph".

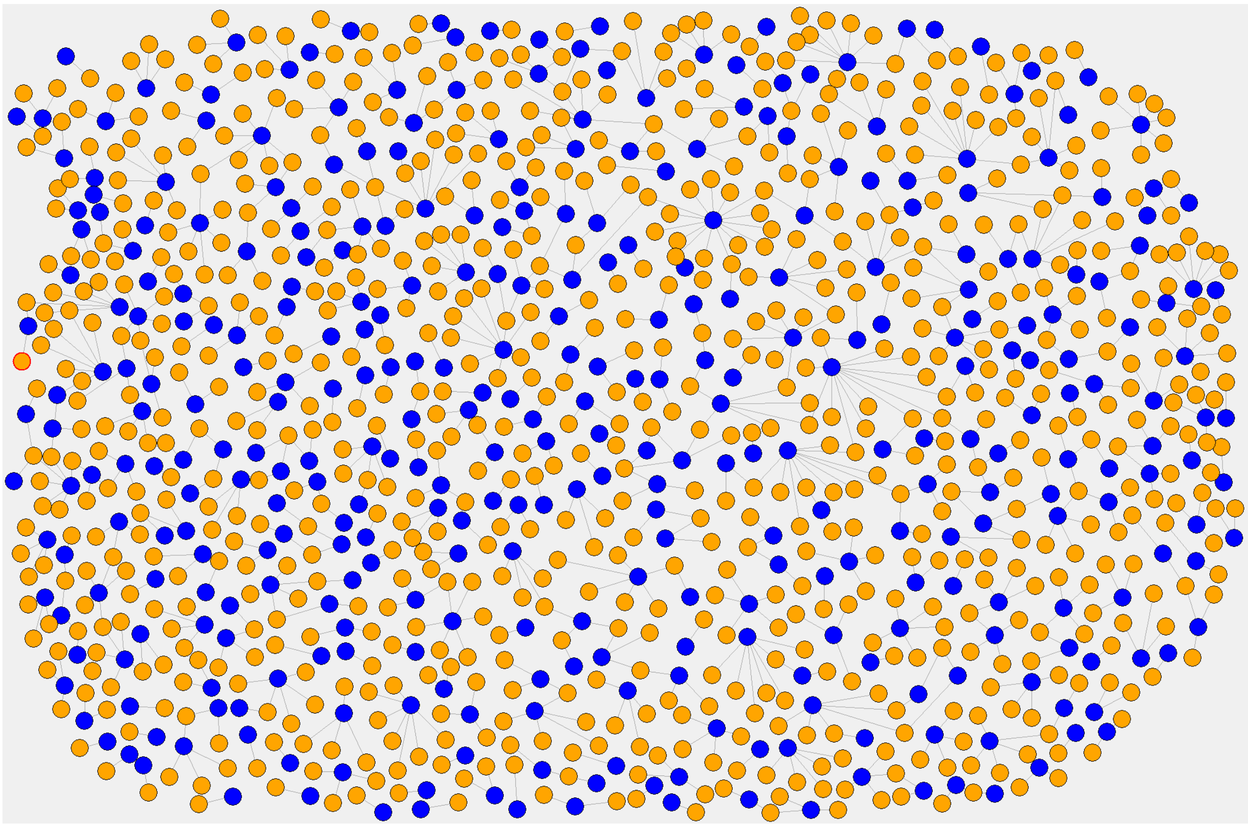

Fig. 2. This figure shows a network illustration from our data. For illustrative reason, we randomly select 900 auditor-engagement links, around 10% of the total links. We can see from this graph that auditors are embedded within audit engagements, and tacit audit knowledge may be transmitted through auditors sharing and changing audit engagements. However, compared with small world network, our network may lack of non-occasional links to connect two long-distance clusters. This graph is obtained from R package "igraph".

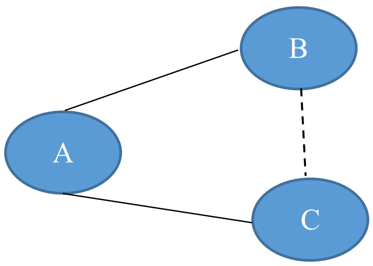

Fig. 3. This figure provides an illustration for network closure (i.e. clustering) around node A. In an auditing setting, nodes A, B and C are auditors. The local clustering around node A measures the proportion of the number of triangles (A-B-C) around node A to the number of two path (A-B, A-C).

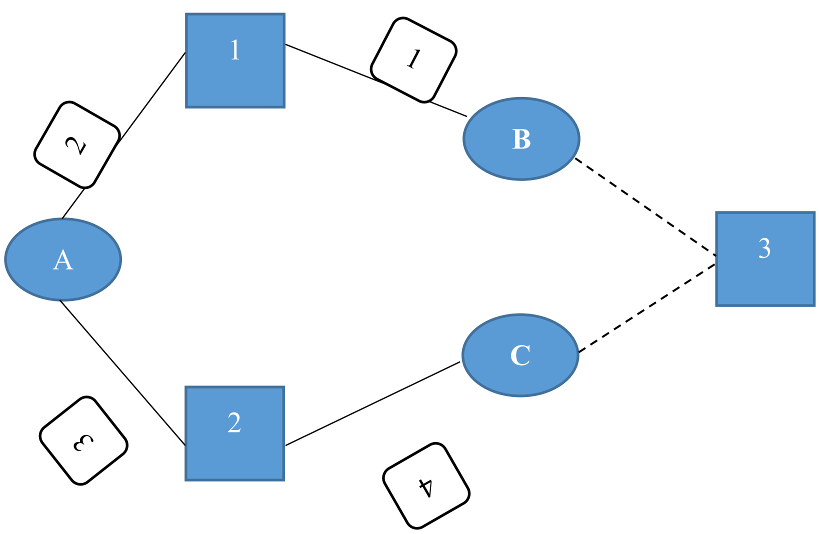

Fig. 4. This figure provides an illustration of local network closure (i.e. local clustering) for a bipartite network around focal node A. The squares and circles represent two different types of nodes. In an auditing setting, the circle represents auditor while the square represent engagement. Weights are also included in the black squares along the ties.

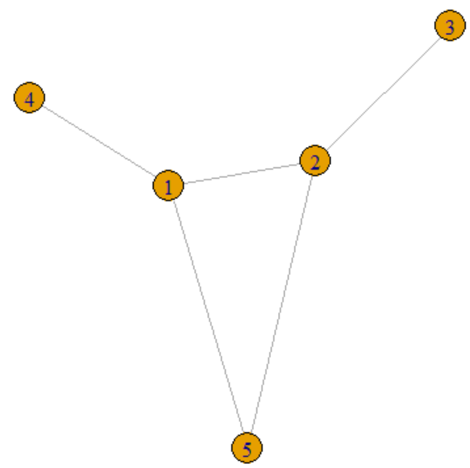

Fig. 5. This figure illustrates the key idea underlying structural hole theory. Consider the network structure of node 1, which connects nodes 2, 4, and 5. Typically, node 1 can serve as a broker between node 4 on one hand, and nodes 2, and 5 on the other hand, because there is no connection between node 4 and nodes 2, and 5. The network is simulated from R package "igraph".

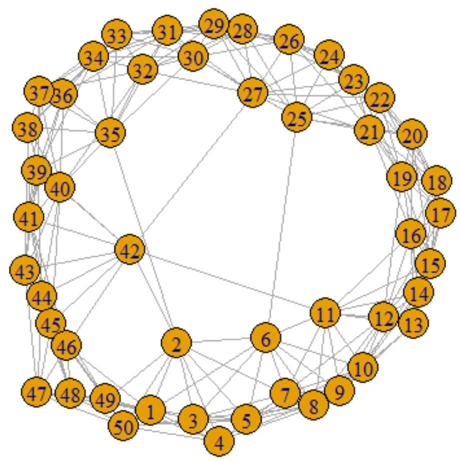

Fig. 6. This figure illustrates one example of small world network with 50 nodes. This graph is simulated from R package "igraph".

Table 1:

Descriptive statistics of key variables (N=390)

Variables	**Mean**	**SD**	**Min**	**Q1**	**Median**	**Q3**	**Max**
AudCompen	16.698	0.387	16.188	16.369	16.574	16.911	17.885
Clustering	0.296	0.108	0.124	0.224	0.272	0.345	0.630
Clustering_am	0.277	0.108	0.111	0.205	0.252	0.321	0.628
Clustering_gm	0.271	0.114	0.105	0.197	0.240	0.318	0.680
Clustering_ma	0.281	0.108	0.118	0.209	0.258	0.324	0.627
Clustering_mi	0.269	0.127	0.082	0.182	0.242	0.323	0.704
Rank	2.487	1.426	1.000	2.000	2.000	3.000	6.000
Age	31.033	8.357	22.000	26.000	28.000	33.000	59.000
Tenure	7.143	8.507	0.397	1.797	3.792	8.833	37.852
Gender	0.369	0.483	0.000	0.000	0.000	1.000	1.000
CPA_Dummy	0.328	0.470	0.000	0.000	0.000	1.000	1.000
FTE	0.935	0.131	0.400	0.750	0.910	1.000	1.000
Utilization	0.653	0.156	0.131	0.587	0.678	0.758	0.940
Logot	4.409	1.289	0.000	3.998	4.737	5.212	6.343
Logleave	4.639	3.497	4.159	4.425	4.836	4.836	6.909
Logvacation	5.394	0.696	2.197	5.242	5.593	5.801	6.109
Logengfy	7.045	0.405	5.142	6.918	7.137	7.295	7.522
Lognumengfy	3.010	0.494	1.792	2.708	2.996	3.258	4.443

Notes: This table reports summary descriptive statistics for 390 auditors. For auditor compensation variable, as we do not have data on partner, all the descriptive statistics are based on 365 observations excluding partners. All continuous variables are winzorized at 1 percentile and 99 percentile. All variable definitions can be found in Appendix 1.

Table 2:

Correlation matrix (N=390)

Variables	1	2	3	4	5	6	7	8	9
1. AudCompen									
2. Clustering	**0.229**								
3. Clustering_am	**0.162**	**0.959**							
4. Clustering_gm	**0.165**	**0.938**	**0.981**						
5. Clustering_ma	**0.166**	**0.960**	**0.996**	**0.962**					
6. Clustering_mi	**0.174**	**0.858**	**0.900**	**0.963**	**0.867**				
7. Rank	**0.969**	**0.165**	0.087	0.090	0.088	0.091			
8. Age	**0.854**	0.092	0.018	0.024	0.018	0.034	**0.861**		
9. Tenure	**0.809**	0.080	0.005	0.009	0.004	0.027	**0.805**	**0.916**	
10. Gender	**-0.182**	-0.063	-0.053	-0.055	-0.050	-0.071	**-0.172**	**-0.208**	**-0.248**
11. CPA_Dummy	**0.756**	**0.173**	**0.106**	**0.109**	**0.109**	**0.120**	**0.735**	**0.642**	**0.641**
12. FTE	**0.262**	0.098	**0.105**	**0.104**	**0.106**	**0.112**	**0.256**	**0.189**	**0.207**
13. Utilization	**-0.461**	-0.019	0.072	0.046	0.077	-0.004	**-0.564**	**-0.561**	**-0.534**
14. Logot	**-0.283**	-0.037	0.015	0.015	0.014	0.005	**-0.301**	**-0.290**	**-0.254**
15. Logleave	**0.132**	0.074	0.057	0.072	0.053	0.084	0.058	0.082	**0.103**
16. Logvacation	**0.164**	0.059	0.067	0.072	0.067	0.089	**0.115**	**0.123**	**0.162**
17. Logengfy	**-0.291**	0.023	**0.118**	0.096	**0.121**	0.055	**-0.381**	**-0.426**	**-0.387**
18. Lognumengfy	**0.353**	0.028	-0.088	-0.048	-0.098	0.006	**0.392**	**0.405**	**0.463**

Variables	10	11	12	13	14	15	16	17	18
1. AudCompen									
2. Clustering									
3. Clustering_am									
4. Clustering_gm									
5. Clustering_ma									
6. Clustering_mi									
7. Rank									
8. Age									
9. Tenure									
10. Gender									
11. CPA_Dummy	**-0.127**								
12. FTE	-0.029	**0.226**							
13. Utilization	0.083	**-0.454**	**-0.226**						
14. Logot	**0.100**	**-0.245**	**0.101**	**0.331**					
15. Logleave	**0.177**	0.066	0.094	**-0.368**	**-0.175**				
16. Logvacation	-0.009	0.051	**0.767**	**-0.209**	**0.150**	**0.196**			
17. Logengfy	0.011	**-0.319**	**0.309**	**0.696**	**0.328**	**-0.215**	**0.250**		
18. Lognumengfy	**-0.199**	**0.329**	**0.220**	**-0.306**	**-0.159**	-0.016	**0.168**	-0.063	

Notes: This table reports the Pearson correlation coefficients of the variables for the main analysis. The bold coefficients are those significant at 5 percent. The correlation between AudCompen and all other variables are based on the 365 observations excluding partners. The definition of all variables is available in Appendix 1.

Table 3:

Main Results for Tobit Regression (N=390)

Dependent Variable: Auditor Compensation										
	Model 1		**Model 2**		**Model 3**		**Model 4**		**Model 5**	
	Coef.	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**
Clustering	0.095	2.82**								
Clustering_am			0.099	2.95***						
Clustering_gm					0.096	3.06**				
Clustering_ma							0.100	2.95**		
Clustering_mi									0.086	3.06**
Rank (ref. Assistant)										
Senior	0.192	16.83***	0.193	16.93***	0.192	16.88***	0.193	16.96***	0.192	16.83***
Manager	0.431	22.63***	0.432	22.78***	0.432	22.76***	0.432	22.79***	0.431	22.75***
Senior Manager	0.629	26.03***	0.630	26.18***	0.629	26.14***	0.630	26.19***	0.630	26.17***
Director	1.041	34.79***	1.042	34.86***	1.042	34.88***	1.042	34.86***	1.043	34.94***
Partner	2.775		2.777		2.791		2.776		2.799	
Age	0.028	5.48***	0.027	5.45***	0.028	5.53***	0.027	5.42***	0.028	5.60***
Agesq	-0.000	-3.84***	-0.000	-3.83***	-0.000	-3.91***	-0.000	-3.79***	-0.000	-4.00***
Tenure	0.006	4.21***	0.006	4.21***	0.006	4.31***	0.006	4.17***	0.007	4.38***
Gender	0.002	0.29	0.003	0.35	0.003	0.36	0.003	0.34	0.003	0.37
CPA_Dummy	0.056	4.19***	0.069	5.32***	0.055	4.14***	0.056	4.18***	0.054	4.09***
FTE	0.077	1.51	0.076	1.49	0.075	1.47	0.077	1.50	0.073	1.44
Utilization	0.060	1.24	0.059	1.23	0.060	1.24	0.059	1.22	0.064	1.33
Logot	0.002	0.66	0.002	0.63	0.002	0.57	0.002	0.64	0.002	0.54
Logleave	-0.004	-0.61	-0.004	-0.64	-0.004	-0.68	-0.004	-0.63	-0.004	-0.64
Logvacation	0.006	0.75	0.005	0.76	0.007	0.76	0.006	0.74	0.007	0.76
Logengfy	-0.019	-1.05	-0.021	-1.18	-0.020	-1.12	-0.021	-1.19	-0.018	-1.04
Lognumengfy	-0.006	-0.73	-0.004	-0.42	-0.005	-0.55	-0.003	-0.38	-0.006	-0.70
Loglikelihood Ratio Statistic	1831.69***		1832.42***		1833.08***		1832.40***		1833.08***	

Notes: This table reports the Tobit output under different measures of local clustering coefficients from the bipartite network. As we have 25 partners, we have 25 upper censored observations. Due to censoring on partner observations, we also do not have inference information at partner level. The coefficients of constant is 15.775 (t-stat=123.20) for Model 1, 15.788 (t-stat=123.17) for Model 2, 15.782 (t-stat=123.39) for Model 3, 15.790 (t-stat=123.13) for Model 4, and 15.771 (t-stat=123.46). The Pseudo R-Square is 2.080 for Model 1, 2.081 for

Model 2, 2.082 for Model 3, 2.081 for Model 4, and 2.082 for Model 5. As STATA utilizes MacFadden's method to compute pseudo R square for Tobit regression, pseudo R-Square under such specification cannot indicate model fit. Hence, we do not report it in the table. All variables are listed in Appendix 1. $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table 4:

Results Using Alternative Clustering

Panel A: Descriptive Statistics for Clustering_pro							
	Mean	**SD**	**Min**	**Q1**	**Median**	**Q3**	**Max**
Clustering_pro	0.345	0.110	0.160	0.269	0.327	0.404	0.688
Panel B: Results of Tobit Regressing (Dependent Variable = AudCompen)							
	Coef.	**t-stat**					
Clustering_pro	0.160	4.22***					
Rank (ref. Assistant)							
Senior	0.190	16.86***					
Manager	0.428	22.77***					
Senior Manager	0.628	26.43***					
Director	1.040	35.20***					
Partner	2.785						
Age	0.026	5.20***					
Agesq	-0.000	-3.55***					
Tenure	0.006	4.07***					
Gender	0.002	0.23					
CPA_Dummy	0.055	4.17***					
FTE	0.068	1.35					
Utilization	0.059	1.24					
Logot	0.002	0.65					
Logleave	-0.003	-0.50					
Logvacation	0.007	0.86					
Logengfy	-0.024	-1.35					
Lognumengfy	0.013	1.29					
Loglikehood Ratio Test	1827.97***						

Note: This table reports the descriptive information for the alternative measure of clustering (Panel A) as in Table 1, and Tobit output using this alternative clustering measure (Panel B) as in Table 3. The constant for this model is 15.759 (t-stat = 124.81). The pseudo R-Square is 2.091. All variables are listed in Appendix 1. $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table 5:

Results for Structural Hole Theory

Panel A: Descriptive Statistics for *Constraint*							
	Mean	**SD**	**Min**	**Q1**	**Median**	**Q3**	**Max**
Constraint	0.097	0.053	0.030	0.067	0.083	0.110	0.309

Panel B: Results of Tobit Regressing (Dependent Variable = AudCompen)				
	Model 1		**Model 2**	
	Coef.	**t-stat**	**Coef.**	**t-stat**
Constraint	0.150	2.05*	0.106	1.42
Clustering_ma			0.089	2.55*
Rank (ref. Assistant)				
Senior	0.194	16.93***	0.192	16.91***
Manager	0.438	23.08***	0.433	22.88***
Senior Manager	0.638	26.51***	0.632	26.30***
Director	1.045	34.75***	1.043	34.97***
Partner	2.823		2.791	
Age	0.028	5.55***	0.027	5.40***
Agesq	-0.000	-3.96***	-0.000	-3.76***
Tenure	0.006	4.26***	0.006	4.14***
Gender	0.002	0.27	0.003	0.40
CPA_Dummy	0.056	4.15***	0.056	4.19***
FTE	0.069	1.34	0.074	1.46
Utilization	0.066	1.37	0.059	1.23
Logot	0.003	0.78	0.003	0.73
Logleave	-0.002	-0.34	-0.003	-0.57
Logvacation	0.007	0.85	0.007	0.79
Logengfy	-0.018	-1.15	-0.021	-1.20
Lognumengfy	0.004	0.36	0.002	0.22
Loglikelihood Ratio Test	1827.97***		1834.41***	

Notes: This table reports the descriptive information of constraint (Panel A) as in Table 1 and Tobit output using structural hole as key independent variable and control (Panel B) as in Table 3. The constant is 15.734 (t-stat=121.82) for Model 1 and 15.769 (t-stat=122.47) for Model 2. The Pseudo R square is 2.076 for Model 1 and 2.083 for Model 2. All variables are listed in Appendix 1. $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table 6:

Results for Betweenness Centrality

Panel A: Descriptive Statistics for *Betweenness*							
	Mean	**SD**	**Min**	**Q1**	**Median**	**Q3**	**Max**
Betweenness	5.527	1.549	0.000	4.836	5.848	6.569	7.983

Panel B: Results of Tobit Regressing (Dependent Variable = AudCompen)				
	Model 1		**Model 2**	
	Coef.	**t-stat**	**Coef.**	**t-stat**
Betweenness	-0.003	-1.16	-0.002	-0.60
Clustering_ma			0.099	2.77**
Rank (ref. Assistant)				
Senior	0.196	17.05***	0.193	16.98***
Manager	0.437	22.92***	0.432	22.78***
Senior Manager	0.636	26.28***	0.630	26.18***
Director	1.044	34.59***	1.042	34.88***
Partner	2.808		2.777	
Age	0.028	5.59***	0.027	5.42***
Agesq	-0.000	-4.00***	-0.000	-3.78***
Tenure	0.007	4.34***	0.006	4.18***
Gender	0.001	0.18	0.002	0.34
CPA_Dummy	0.056	4.19***	0.056	4.20***
FTE	0.077	1.49	0.079	1.55
Utilization	0.071	1.46	0.062	1.26
Logot	0.002	0.62	0.002	0.73
Logleave	-0.003	-0.51	-0.004	-0.69
Logvacation	0.007	0.77	0.006	0.73
Logengfy	-0.013	-0.72	-0.019	-1.05
Lognumengfy	-0.002	-0.24	-0.001	-0.20
Loglikelihood Ratio Test	1825.15***		1832.76***	

Notes: This table reports the descriptive information of betweenness centrality (Panel A) as in Table 1 and Tobit output betweenness centrality as the key independent variable and control (Panel B) as in Table 3. The constant is 15.742 (t-stat=121.24) for Model 1 and 15.780 (t-stat=122.12) for Model 2. The pseudo R square is 2.073 for Model 1 and 2.081 for Model 2. All variables are listed in Appendix 1. $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table 7:

Results for OLS Regression (N=365)

Dependent Variable: Auditor Compensation										
	Model 1		Model 2		Model 3		Model 4		Model 5	
	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat	Coef.	t-stat
Clustering	0.095	2.75**								
Clustering_am			0.099	2.88**						
Clustering_gm					0.096	2.99**				
Clustering_ma							0.100	2.87**		
Clustering_mi									0.086	2.99**
Rank (ref. Assistant)										
Senior	0.192	16.41***	0.193	16.50***	0.192	16.46***	0.193	16.54***	0.192	16.41***
Manager	0.431	22.06***	0.432	22.21***	0.432	22.20***	0.432	22.22***	0.431	22.18***
Senior Manager	0.629	25.38***	0.630	25.53***	0.629	25.49***	0.630	25.54***	0.630	25.51***
Director	1.041	33.92***	1.042	33.99***	1.042	34.01***	1.042	33.99***	1.043	34.07***
Age	0.028	5.34***	0.027	5.31***	0.028	5.39***	0.027	5.28***	0.028	5.46***
Agesq	-0.002	-3.75***	-0.000	-3.73***	-0.000	-3.81***	-0.000	-3.70***	-0.000	-3.90***
Tenure	0.006	4.11***	0.006	4.10***	0.006	4.20***	0.006	4.07***	0.007	4.27***
Gender	0.002	0.28	0.003	0.34	0.003	0.35	0.003	0.33	0.003	0.36
CPA_Dummy	0.056	4.08***	0.056	4.06***	0.055	4.04***	0.056	4.07***	0.054	3.99***
FTE	0.077	1.47	0.076	1.46	0.075	1.43	0.077	1.46	0.073	1.40
Utilization	0.060	1.21	0.059	1.20	0.060	1.21	0.059	1.19	0.062	1.24
Logot	0.002	0.64	0.002	0.61	0.002	0.56	0.002	0.62	0.002	0.52
Logleave	-0.004	-0.59	-0.004	-0.63	-0.004	-0.66	-0.004	-0.62	-0.004	-0.62
Logvacation	0.006	0.73	0.006	0.74	0.007	0.74	0.006	0.73	0.007	0.74
Logengfy	-0.019	-1.02	-0.021	-1.15	-0.020	-1.09	-0.021	-1.16	-0.018	-1.01
Lognumengfy	-0.006	-0.71	-0.003	-0.41	-0.005	-0.53	-0.003	-0.37	-0.006	-0.68
R-Sqaured	0.97		0.97		0.97		0.97		0.97	

Notes: This table reports the OLS results when excluding partners. The coefficients of constant are 15.775 (t-stat=120.12) for Model 1, 15.788 (t-stat=120.09) for Model 2, 15.782 (t-stat=120.30), 15.790 (t-stat=120.06) for Model 4, and 15.771 (t-stat=120.38). All variables are listed in Appendix 1. $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table 8:

Results for Instrumental Variable Estimation (N=365)

Dependent Variable: Auditor Compensation

	Model 1		**Model 2**		**Model 3**		**Model 4**		**Model 5**	
	Coef.	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**
Clustering	0.005	0.08								
Clustering_am			0.005	0.08						
Clustering_gm					-0.001	0.993				
Clustering_ma							0.009	0.14		
Clustering_mi									-0.005	-0.08
Rank (ref. Assistant)										
Senior	0.196	16.65***	0.196	16.80***	0.196	16.75***	0.196	16.83***	0.196	16.66***
Manager	0.439	22.09***	0.439	22.43***	0.439	22.41***	0.438	22.41***	0.439	22.33***
Senior Manager	0.639	25.38***	0.638	25.72***	0.639	25.56***	0.638	25.71***	0.639	25.64***
Director	1.046	34.45***	1.046	34.54***	1.046	34.51***	1.046	34.56***	1.046	34.53***
Partner	2.735	0.06	2.736	0.06	2.736	0.06	2.919		2.747	0.006
Age	0.028	5.53***	0.028	5.53***	0.028	5.58***	0.028	5.50***	0.029	5.63***
Agesq	-0.000	-3.92***	-0.000	-3.93***	-0.000	-3.99***	-0.000	-3.90***	-0.000	-4.06***
Tenure	0.006	4.16***	0.006	4.17***	0.006	4.23***	0.006	4.14***	0.006	4.31***
Gender	0.001	0.18	0.002	0.19	0.001	0.18	0.002	0.20	0.001	0.16
CPA_Dummy	0.056	4.19***	0.056	4.19***	0.056	4.16***	0.056	4.19***	0.055	4.11***
FTE	0.078	1.52	0.078	1.50	0.076	1.47	0.078	1.51	0.074	1.53
Utilization	0.066	1.35	0.066	1.34	0.066	1.35	0.065	1.33	0.067	1.37
Logot	0.003	0.80	0.003	0.76	0.003	0.74	0.003	0.76	0.002	0.71
Logleave	-0.003	-0.43	-0.003	-0.44	-0.003	-0.42	-0.003	-0.45	-0.002	-0.40
Logvacation	0.006	0.70	0.006	0.71	0.006	0.72	0.006	0.71	0.006	0.75
Logengfy	-0.019	-1.05	-0.018	-1.03	-0.018	-0.99	-0.019	-1.05	-0.017	-0.97
Lognumengfy	-0.006	-0.64	-0.005	-0.61	-0.005	-0.61	-0.005	-0.60	-0.005	-0.59
Wald Test of Exogeneity	2.46 (0.1168)		2.72 (0.0989)		3.45 (0.0634)		2.37 (0.1238)		3.27 (0.0706)	

Notes: This table reports results for Instrumental Variable estimation. The coefficients of constants are 15.777 (t-stat=122.32), 15.776 (t-stat=121.91), 15.769 (t-stat=121.98), 15.778 (t-stat=121.95), 15.762 (t-stat=122.06). All variables are listed in Appendix 1. $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table 9:

Results for OLS Regression for Seniors (N=160)

Dependent Variable: Auditor Compensation										
	Model 1		**Model 2**		**Model 3**		**Model 4**		**Model 5**	
	Coef.	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**
Clustering	0.088	1.99*								
Clustering_am			0.093	2.14*						
Clustering_gm					0.089	2.21*				
Clustering_ma							0.094	2.10*		
Clustering_mi									0.084	2.37*
Age	0.017	6.04***	0.017	6.03***	0.017	6.01***	0.017	6.03***	0.017	5.98***
Tenure	0.024	8.13***	0.024	8.16***	0.025	8.32***	0.024	8.10***	0.025	8.50***
Gender	0.022	1.90	0.022	1.95	0.022	1.94	0.022	1.96	0.022	1.95
CPA_Dummy	0.039	2.11*	0.038	2.11*	0.038	2.07*	0.038	2.11*	0.036	2.00*
FTE	0.001	0.01	0.005	0.119	0.008	0.07	0.004	0.03	0.011	0.09
Utilization	0.265	1.99*	0.271	2.04*	0.276	2.08*	0.268	2.01*	0.281	2.13*
Logot	0.005	0.56	0.005	0.64	0.005	0.65	0.005	0.63	0.006	0.65
Logleave	-0.014	-1.47	-0.014	-1.43	-0.014	-1.45	-0.014	-1.42	-0.014	-1.44
Logvacation	0.026	1.77	0.025	1.75	0.025	1.71	0.026	1.76	0.024	1.66
Logengfy	-0.120	-1.66	-0.125	-1.73	-0.127	-1.75	-0.124	-1.71	-0.128	-1.78
Lognumengfy	-0.003	-0.24	-0.001	-0.05	-0.001	-0.08	-0.001	-0.04	-0.001	-0.07
R-Sqaured	0.61		0.61		0.61		0.61		0.62	

Notes: This table reports the OLS results for the effect of local network clustering for auditor compensation based on seniors. The coefficient of constant is 16.557 (t-stat=45.82) for Model 1, 16.574 (t-stat=45.99) for Model 2, 15.688 (t-stat=46.09) for Model 3, 16.568 (t-stat=45.95) for model 4, and 16.599 (t-stat=46.22). All variables are listed in Appendix 1. $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

Table 10:

Main Results for Tobit Regression using Alternative Measures (N=390)

Dependent Variable: Auditor Compensation										
	Model 1		**Model 2**		**Model 3**		**Model 4**		**Model 5**	
	Coef.	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**	**Coef.**	**t-stat**
Ratio	0.081	2.54*								
Ratioam			0.088	2.75**						
Ratiogm					0.090	2.95**				
Ratioma							0.087	2.70**		
Ratiomi									0.083	3.03**
Rank (ref. Assistant)										
Senior	0.193	16.83***	0.193	16.92***	0.192	16.87***	0.193	16.94***	0.192	16.82***
Manager	0.431	22.59***	0.432	22.73***	0.431	22.71***	0.432	22.73***	0.431	22.70***
Senior Manager	0.629	25.94***	0.630	26.09***	0.628	26.04***	0.630	26.10***	0.629	26.07***
Director	1.042	34.73***	1.042	34.81***	1.042	34.84***	1.042	34.80***	1.043	34.92***
Partner	2.781		2.784		2.783		2.783		2.799	
Age	0.027	5.42***	0.027	5.40***	0.027	5.47***	0.027	5.38***	0.028	5.54***
Agesq	-0.000	-3.83***	-0.000	-3.82***	-0.000	-3.89***	-0.000	-3.79***	-0.000	-3.96***
Tenure	0.006	4.28***	0.006	4.28***	0.007	4.37***	0.006	4.24***	0.007	4.43***
Gender	0.002	0.20	0.002	0.27	0.002	0.28	0.002	0.26	0.002	0.31
CPA_Dummy	0.056	4.20***	0.056	4.19***	0.055	4.17***	0.056	4.19***	0.055	4.13***
FTE	0.077	1.50	0.076	1.49	0.076	1.49	0.076	1.49	0.075	1.48
Utilization	0.065	1.34	0.063	1.31	0.063	1.31	0.063	1.30	0.067	1.38
Logot	0.002	0.58	0.002	0.55	0.002	0.50	0.002	0.57	0.002	0.46
Logleave	-0.003	-0.52	-0.003	-0.56	-0.004	-0.61	-0.003	-0.55	-0.003	-0.57
Logvacation	0.007	0.78	0.007	0.78	0.007	0.78	0.007	0.77	0.007	0.78
Logengfy	-0.021	-1.19	-0.023	-1.30	-0.022	-1.26	-0.023	-1.30	-0.021	-1.18
Lognumengfy	-0.007	-0.79	-0.005	-0.52	-0.006	-0.64	-0.004	-0.49	-0.007	-0.80
Loglikelihood Ratio Test	1830.20***		1831.30***		1832.43***		1831.03***		1832.86***	

Notes: This table reports the Tobit results using the measure of the ratio between local clustering and average shortest path as in Table 3. The coefficients of constant are 15.798 (t-stat=122.35) for Model 1, 15.810 (t-stat=122.25) for Model 2, 15.806 (t-stat=122.74) for Model 3, 15.810 (t-stat=122.12) for Model 4, and 15.794 (t-stat=123.15) for Model 5. The values of pseudo R-squared are 2.078 for Model 1, 2.080 for Model 2, 2.081 for Model 3, 2.079 for Model 4, and 2.081 for Model 5. All variables are listed in Appendix 1. $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

APPENDIX 1: DEFINITION OF VARIABLES

Variable Name	Definition
AudCompen	Auditor compensation for each auditor
Clustering	Local clustering coefficient for focal auditor without taking weights in the bipartite (i.e. two-mode) network, obtained in "tnet" package
Clustering_am	Local clustering coefficient for focal auditor by taking arithmetic weights in the bipartite (i.e. two-mode) network, obtained in "tnet" package
Clustering_gm	Local clustering coefficient for focal auditor by taking geometric weights in the bipartite (i.e. two-mode) network, obtained in "tnet" package
Clustering_ma	Local clustering coefficient for focal auditor by taking the maximum of weights in the bipartite (i.e. two-mode) network, obtained in "tnet" package
Clustering_mi	Local clustering coefficient for focal auditor by taking the minimum of weights in the bipartite (i.e. two-mode) network, obtained in "tnet" package
Rank	Categorical variable for auditor's rank: 1. Assistant, 2. Senior, 3. Manager, 4. Senior manager, 5. Director, 6. Partner
Age	Auditor's age
Agesq	The squared value of auditor's age
Tenure	The tenure of auditor when entering into the audit firm
Gender	Dummy variable: 1. Female, 2. Male
CPA_Dummy	Dummy variable for whether auditor has been a Certified Public Accountant: 1. Yes, 2. No
FTE	The proportion of full time employee in terms of working hours
Utilization	The effective utilization for each auditor
Logot	The natural logarithm of total overtime hours for each auditor
Logleave	The natural logarithm of total leave hours for each auditor
Logvacation	The natural logarithm of total vacation hours for each auditor
Logengfy	The natural logarithm of total engagement hours for the full fiscal year for each auditor
Lognumengfy	The natural logarithm of total number of engagement for the full fiscal year for each auditor
Clustering_pro	The local clustering coefficient for focal auditor from the projected weighted one-mode network using Newman's (2001) method, obtained from "tnet" package
Constraint	The local constraint coefficient for each focal auditor from the projected weighted one-mode network using Burt's (2004) method, obtained from "igraph" package
Betweenness	The natural logarithm of betweenness centrality for each auditor from the projected weighted one-mode network using "tnet" package
Closeness	Closeness centrality for each auditor from the projected weighted one-mode network using "tnet" package
Ratio	The ratio of local clustering coefficient and average shortest paths for the focal auditor without taking the weights from the weighted bipartite network

Ratioam	The ratio of local clustering coefficient and average shortest paths for the focal auditor using the anthemic weights from the weighted bipartite network
Ratiogm	The ratio of local clustering coefficient and average shortest paths for the focal auditor using the geometric weights from the weighted bipartite network
Ratioma	The ratio of local clustering coefficient and average shortest paths for the focal auditor using the maximum of weights from the weighted bipartite network
Ratiomi	The ratio of local clustering coefficient and average shortest paths for the focal auditor using the minimum of weights from the weighted bipartite network