Contents lists available at ScienceDirect

The British Accounting Review

journal homepage: www.elsevier.com/locate/bar

Local creative culture and audit fees^{\star}

Mabel D. Costa^{a,*}, Ahsan Habib^b

^a Department of Accounting, Durham University Business School, Mill Hill Lane, Durham, DH1 3LB, United Kingdom
^b School of Accountancy, Massey University, Private Bag, 102904, Auckland, New Zealand

ARTICLE INFO

Keywords: Creative culture Audit fees Real earnings management Risk-taking Corporate governance

ABSTRACT

This paper examines the association between local creative culture and audit fees. Using a large, unbalanced panel data of listed US firms between 2004 and 2018, we find evidence that firms headquartered in US counties with high creative culture tend to pay higher audit fees than firms headquartered in counties with low creative culture. We also find that such firms tend to have longer audit report lag and are subject to more shareholder litigation. Cross-sectional tests show that real earnings management, managerial risk-taking propensity, and external corporate governance environment moderate the positive association between creative culture and audit fees. The positive association between local creative culture and audit fees remains robust to controlling for endogeneity concerns. Our study contributes to the emerging literature on local creative culture by providing evidence that local creative culture encourages managers and employees to undertake risky initiatives, thereby increasing audit risks.

1. Introduction

In recent decades, there has been an increase in literature on the effects of local socio-economic factors on accounting, finance and corporate governance outcomes (e.g., Jha, 2019; Jha & Chen, 2015; McGuire et al., 2012). This strand of research is important because people live in a society, and behave in a manner that is influenced by the socio-economic environment of the region in which they live and the people with whom they interact. Thus, business practices and policies are forged by local characteristics, and one such factor is local creative culture. In this paper, we examine the association between local creative culture, defined as the county-level proportion of the local creative class, ¹ and audit pricing.

Since Simunic's (1980) seminal paper on audit fees, a plethora of research has investigated the determinants of audit fees. However, the vast majority of these studies focus on client and/or auditor characteristics (Hay et al., 2006). The role of socio-economic factors in shaping organisation culture, decision-making and stakeholders' perception has not been extensively studied in the audit fee literature. Studies in social science document that individuals' socio-economic environment plays a crucial role in shaping their behaviour (Tong et al., 2022). Through social interaction within and outside their organisation, managers familiarise themselves with the locally accepted written or unwritten rules that guide behaviour. These written or unwritten values that guide local peoples' behaviour form informal institutions that play a significant role in society by complementing the formal institutions (Abdelsalam et al., 2021). Because organisational decisions are made by people, it is logical to expect that firms from dissimilar socio-economic environments will exhibit

* Corresponding author.

https://doi.org/10.1016/j.bar.2022.101151

Received 27 December 2021; Received in revised form 18 November 2022; Accepted 21 November 2022

Available online 23 November 2022







^{*} We highly appreciate the help and constructive comments from the Associate Editor (AE) and two anonymous reviewers.

E-mail addresses: mabel.d.costa@durham.ac.uk (M.D. Costa), a.habib@massey.ac.nz (A. Habib).

¹ Creative class is defined as the portion of the population engaging in occupations that require creative thinking (Ucar, 2018).

^{0890-8389/© 2022} The Author(s). Published by Elsevier Ltd on behalf of British Accounting Association. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

different behaviours. Following this notion, we examine how local creative culture, a type of social norm, is related to audit fees. Therefore, our study belongs to the extant literature that investigates the costs and benefits of local social norms (Jha et al., 2021; McGuire et al., 2012; Xu et al., 2019).

Creative classes are highly sought after in societies and organisations because of their ability to produce novel ideas and solutions for given problems, and their flexible nature, which allows them to adapt to dynamic environments (Runco, 2004). Florida (2002a,b) first explored the economic implications of local creative culture and argued that a creative class among the population plays a critical role in fostering economic growth and development because of their ability to think creatively (Florida, 2002a; McGranahan et al., 2011; Ucar, 2018). According to Leuenberger and Kluver (2005), creative classes promote creative culture, and such creative communities tend to generate creative solutions. Ucar (2018) shows that firms headquartered in US counties with high creative culture have more innovative outputs (i.e., as shown by the number of patents and patent citations). These firms enjoy a competitive advantage, have unique business processes and possess the ability to have higher risk-taking propensities (e.g., Amabile, 1983; Dewett, 2006; Gardner, 1993; Heilman, 2016). Aligned with this notion, Ucar (2019) shows a positive relation between local creative culture and firm risk-taking.

Prior research in psychology shows that creativity can also have negative consequences. An individual's ability to be creative in solving a problem or excelling at a task may also lead to unethical behaviour because creativity and dishonesty share the characteristic of 'thinking out of the box' or breaking the rules (Gino & Wiltermuth, 2014). Gino and Ariely (2012) show that individuals with the ability to think creatively often overstate their performance. Moreover, creative individuals tend to have a better ability to justify their unethical behaviour (Gino & Ariely, 2012). Guggenmos (2020) documents similar results for financial statement misreporting. Although undesirable, unethical behaviour is becoming increasingly common, resulting in financial losses worth millions of dollars per year (PricewaterhouseCoopers, 2016). However, financial losses are merely a small part of a much larger problem, since wider collateral damage associated with unethical behaviour manifests in business disruptions, regulatory and other investigations, and reputational harm, which may not be easy to quantify (PricewaterhouseCoopers, 2016). Guggenmos's (2020) findings suggest that creative culture leads to higher levels of real earnings management (REM), indicating poor financial reporting quality.

Audit risk is the product of inherent risk, control risk and detection risk. The Public Company Accounting Oversight Board (PCAOB) (2010, AS 2810) recommends that when evaluating the audit risk of a client's business, auditors should consider not only financial attributes but also qualitative ones. Prior studies have shown that auditors exert higher audit efforts to closely scrutinise clients deemed to be riskier in order to minimise the likelihood of financial statement misreporting (Davis et al., 1993; Hillegeist, 1999). According to Choi et al. (2022), REM increases clients' business risk, and therefore, auditors react to such client-specific risk by charging higher audit fees. As mentioned above, local creative culture tends to encourage REM activities and risk-taking propensities, thereby increasing clients' business risk. We therefore posit that such heightened risk will increase overall audit risk, resulting in higher audit fees. Simunic's (1980) seminal work on the drivers of audit fees suggests that audit fees consist of two factors: a resource cost factor and an expected loss factor. Thus, enhanced audit fees might come from enhanced effort or litigation risk or both. We therefore also examine the relation between creative culture and audit report lag (a proxy for audit efforts) and creative culture and shareholder litigation (a proxy for enhanced audit risk).

We test the association between county-level creative culture and audit fees with an unbalanced panel data of listed US firms between 2004 and 2018. Following prior literature (Ucar, 2018, 2019; Ucar & Staer, 2018), we calculate creative culture as the proportion of the creative class in a given county. According to the US Department of Agriculture's Economic Research Service (ERS), the county-level creative share data set comprises occupations that require a high level of creative thinking (Ucar, 2018). We find evidence that auditors charge higher fees for firms located in counties that have a higher proportion of the workforce employed in creative work than for firms located in counties with a lower proportion of the creative workforce. In terms of economic significance, a one standard deviation increase in creative culture increases audit fees by 5.28%. We also document a positive relationship between creative culture and audit report lag and shareholder litigation. Our findings remain robust after controlling for social capital, local corruption, religiosity, local economic and demographic factors, and firm-level internal corporate governance—variables that have been shown to be associated with audit fees.

Next, we perform three cross-sectional tests. We employ REM, risk-taking propensity and external corporate governance environment to test whether the relation between creative culture and audit fees is conditional on these three moderating variables. REM influences firm operations and cash flows and subsequently lowers firm value because of increased information opaqueness in capital markets (Badertscher, 2011; Cohen & Zarowin, 2010; Graham et al., 2005; Kothari et al., 2016). Therefore, REM increases auditor engagement risk and audit complexity, consequently increasing audit fees (Choi et al., 2022; Greiner et al., 2017). Since creative culture leads to higher levels of REM (Guggenmos, 2020), we expect the positive association between creative culture and audit fees to be more pronounced for firms with high REM. We then consider risk-taking as a moderating variable because firms vary considerably in their appetite for risk. A willingness to take risks is a crucial element of creative behaviour (Dewett, 2006). Risk-taking has potential benefits; for example, product development or research could result in successful patents or citations. Nevertheless, excessive risk-taking may be detrimental for shareholders and other stakeholders, such as auditors, who may have lower tolerance levels towards risk, particularly with respect to financial reporting. We therefore expect that higher risk-taking by firms headquartered in counties with high creative culture will increase audit fees. Finally, we examine the moderating effects of external corporate governance on the association between creative culture and audit fees. As discussed above, firms headquartered in counties with high creative culture are likely to engage in more REM and have more risk-taking propensities. Both REM and risk-taking incentives are embedded in strategic decision-making and executed through firms' operations. Weaker governance facilitates managers' engagement in opportunistic REM and value-destroying risk-taking activities. We therefore expect the positive association between creative culture and audit fees to be more pronounced for firms with weaker external governance. Our results suggest that REM, managerial risk-taking and external governance all play a moderating role in the positive association between creative culture and audit fees.

However, our results could be biased because of endogeneity concerns arising from several sources. First, the determinants of audit fees are numerous, and although we control for several determinants of audit fees, omitted variable bias, a source of endogeneity, remains a concern. We therefore use firm fixed effect to control for the effects of time-invariant firm characteristics. Second, it can be argued that the preference of a firm selecting the headquarter location in a county with high creative culture might be endogenous. If auditors charge higher fees for firms in counties with a higher proportion of the population engaged in creative work, then firms changing headquarters from low to high creative culture counties should pay higher audit fees. Our test results provide evidence supporting this conjecture. Third, we perform a entropy-balanced matching approach to control for endogeneity concerns arising from the observed differences in characteristics of firms located in high versus those in low creative culture regions and find evidence consistent with the baseline result. Finally, we perform a two-stage least squares (2SLS) regression to address the endogeneity concerns stemming from simultaneity bias. Our results remain robust under the 2SLS test.

Our research contributes to the literature in several ways. First, by examining the association between local creative culture and audit fees, our research enriches the emerging literature on the implications of informal institutions for accounting outcomes. Zattoni et al. (2020) note that although a plethora of research has investigated the relationship between formal institutions, agency problems and firm outcomes, little research exists on whether and how informal institutions alleviate agency problems and improve value for stakeholders. We respond to their call for additional research on the role of informal institutions. Our empirical findings provide evidence that local creative culture, as a local social norm, shapes clients behaviour and auditors' assessments of the client, consequently affecting the audit fees. This evidence is important because social norms act as potential substitutes for legal rules by influencing commitment and collaboration (Boytsun et al., 2011). To the best of our knowledge, this is the first study to examine the direct association between creative culture and auditors' pricing decisions. Second, our results complement the recent surge in studies that investigate how variations in socio-economic factors, such as social capital, influence managerial decision-making, business operations and stakeholders' assessment of the firm. Finally, although we acknowledge the bright side of creative culture that has been demonstrated in the literature, our empirical findings suggest that creative culture comes at some cost, namely, increased cost of monitoring agents as manifested in increased audit fees.

We proceed as follows. Section 2 discusses the literature and develops the hypothesis. Section 3 explains the research method and sample selection procedure. Sections 4 and 5 present the main regression results and endogeneity tests results, respectively. Section 6 concludes the paper.

2. Literature review and hypothesis development

Social norms are considered "common standards within a social group regarding socially acceptable or appropriate behaviour, the breach of which has social consequences. The strength of these norms varies from loose expectations to unwritten rules [with norms being] internalized in socialization" (Chandler & Munday, 2011, p. 178). Bicchieri (2006) develops a formal model that proposes that the decision to follow a social norm depends upon the belief of the existence of the norm, the belief that a large subset of people will honour the norm and the belief that people will expect others to honour such norms in similar situations. Local culture and norms affect individual beliefs because individuals often engage in social interactions in both formal and informal settings, and repeated interaction between individuals in the same locality creates social spillover. Thus, managers' actions are likely to be influenced by the socio-economic environment of the region in which they live or by the people with whom they interact. Marquis and Battilana (2009) note that even the "most cosmopolitan individuals and organisations are likely rooted in some home or headquarters location", which ensures that "local features remain salient" (p. 284).

Managers formulate corporate policies and support business practices, and are likely to be influenced by the socio-economic environment of the region in which they live and by the people with whom they interact. Thus, variation in corporate policies and business practices could be explained by the socio-economic environment of the region in which firms are located. Studies in recent decades have shown that regional socio-economic factors such as social capital, corruption, gambling norms and creative culture influence managerial decision-making and corporate policies. For instance, firms headquartered in regions with high social capital are unlikely to engage in fraudulent activities (Jha, 2019), and they pay less in audit fees (Jha & Chen, 2015). However, firms headquartered in regions with high levels of local gambling norms tend to pay higher audit fees (Callen & Fang, 2020). Firms located in counties with high creative culture pay lower dividends (Ucar & Staer, 2018) and engage in more innovative activities (Ucar, 2018).

Regions with a significant proportion of population working in professions that involve a high level of creative thinking are considered creative communities (Pitta et al., 2008; Ucar, 2018). When the population of a county comprises a large proportion of creative individuals, firms operating in that county will employ a large proportion of creative individuals at all levels of the organisation. Consequently, "managerial style, corporate culture, employees' preferences, [will be] generally aligned with the local environment of the firm" (Hilary & Hui, 2009, p. 458). Social interaction within and outside the organisation creates social spillover through which managers familiarise themselves with the locally accepted written or unwritten rules that guide behaviour. Therefore, such local norms become ingrained in both the conscious and the subconscious minds of managers, motivating them to behave according to social expectations (Dyreng et al., 2012).

The extant literature on the effects of local creative culture provides mixed evidence. Proponents of the 'bright side' of creative culture argue that the creative process involves two components: (i) divergent thinking, that is, developing original ideas and unearthing several potential solutions for a problem; and (ii) cognitive flexibility, that is, adapting knowledge based on dynamic situational needs (Gino & Ariely, 2012; Guilford, 1982; Spiro & Jehng, 1990). Because of divergent thinking and cognitive flexibility,

creative people create new knowledge and ideas that are vital for urban economic development (Florida, 2002a,b). Local creative culture supports both rural and urban growth (McGranahan & Wojan, 2007). Ucar (2018) documents that firms headquartered in counties with high creative culture tend to have more innovative outputs, as manifested by more patents and citations.

In contrast, proponents of the 'dark side' of creative culture argue that while divergent thinking and cognitive flexibility may facilitate more creative problem-solving or better performance, they may also facilitate immoral behaviour because creativity and dishonesty share the feature of 'thinking out of the box' or breaking the rules (Gino & Wiltermuth, 2014). When faced with ethical dilemmas, individuals weigh two divergent interests: the desire to maximise one's self-interest and the desire to view oneself in a positive light (Mead et al., 2009). To resolve this dilemma, individuals tend to 'behave dishonestly enough to profit from their unethical behaviour but honestly enough to maintain a positive self-concept as honest human beings' (Gino & Ariely, 2012, p.446). In a behavioural experiment by Gino and Ariely (2012), individuals with the ability to think creatively misreported their performance in a laboratory project, providing evidence to support the claim that creativity breeds dishonesty. This is exacerbated by creative individuals' ability to easily justify dishonest or unethical behaviour (Gino & Ariely, 2012; Gino & Wiltermuth, 2014). Therefore, it could be said that creative culture comes with costs.

Starting from the premise that creative culture encourages employees to engage in unethical activity or misreporting, Guggenmos (2020) finds that creative culture leads to higher risk-taking tendencies and self-seeking, myopic behaviour among managers by creating a corporate culture that encourages financial misreporting, such as REM. Prior studies (e.g., Dewett, 2004; Dewett, 2006; Ucar, 2019) have shown a connection between creativity and risk-taking because creativity involves a willingness to explore new avenues and undertake risky ventures. Therefore, the creative class of the population are generally considered to be risk-takers (e.g., Amabile, 1983; Dewett, 2006; Gardner, 1993; Heilman, 2016). Ucar (2019) shows that firms headquartered in high creative counties engage in more risk-taking activities and that such firms tend to hold more cash as a precautionary measure.

Audit risk is the product of (i) inherent risk, that is, the probability that environmental factors will lead to a material error; (ii) control risk, that is, the probability that the internal controls are ineffective at preventing or detecting material errors; and (iii) detection risk, that is, the probability that the audit procedures will be unsuccessful in detecting material errors (Gul & Goodwin, 2010). The determinants of audit fees can be broadly classified into three groups: (i) client characteristics, (ii) auditor characteristics and (iii) engagement characteristics (Hay et al., 2006). Firm size, operational complexity and firm risk are some of the client-specific characteristics that increase audit fees (Hay, 2013). Auditor firm size, auditor tenure and auditor industry specialisation are some of the auditor characteristics that increase audit fees (Hay, 2013; Mayhew & Wilkins, 2003). Audit report lag (Ho & Ng, 1996) and audit partner busyness (Hardies et al., 2015) are considered engagement characteristics that tend to push audit fees up.

Although creative culture may have positive implications for both organisations and society, creative culture may also encourage individuals to break the boundaries and act unethically, which is likely to increase overall audit risk and, consequently, audit fees. Various disciplines have studied the association between creativity and risk-taking. Mai et al. (2015) show that creativity leads to unethical behaviour. Beaussart et al. (2013) find a strong negative association between creativity and both observable integrity, and self-reported integrity. To reiterate the findings of Gino and Ariely (2012), creative individuals use their divergent thinking process to exhibit dishonest behaviour by misreporting performance. The possibility that clients might materially misstate their financial statements is considered to be a significant audit risk by auditors (Bedard & Johnstone, 2004; Gul et al., 2003). Therefore, auditors attempt to design audit procedures in ways that minimise audit risk (Gul, 2006; Lemon et al., 1993). The PCAOB (2010, AS 2810) encourages auditors to take a holistic view when assessing their clients' business environment by incorporating both non-financial or qualitative attributes and financial or quantitative characteristics. Thus, we posit that creative culture is pertinent to auditors' assessments of client risk. Local creative culture which is likely to increase the level of inherent risk associated with clients' business will demand auditors to engage in greater scrutiny during auditing and exert higher audit effort, including additional substantive testing to minimise the audit risk of clients in areas with high creative culture, all of which will require an additional audit fee premium. We therefore propose the following hypothesis:

H1. Firms headquartered in counties with higher creative culture pay higher audit fees, ceteris paribus.

Since the implementation of the Sarbanes-Oxley Act (SOX), the financial reporting environment and, consequently, auditor assessments of financial reporting risk have changed considerably. For example, Cohen et al. (2008) document a shift from accruals earnings management as the preferred earnings management technique to REM to avoid the increased regulatory scrutiny associated with accruals management under SOX. Because REM adversely affects future performance (Cohen & Zarowin, 2010; Kothari et al., 2016; Roychowdhury, 2006), firms with greater REM activity pose greater legal and reputational risks to auditors. Because auditors consider that REM increases clients' business risk, they charge higher audit fees (Choi et al., 2022).

Previous studies provide evidence that creativity increases unethical and dishonest behaviour (Mai et al., 2015), manipulation and misreporting performance (Gino & Ariely, 2012), and reduces integrity among individuals (Beaussart et al., 2013). Consistent with Gino and Ariely's (2012) experimental evidence that creative individuals demonstrate dishonest behaviour, Guggenmos (2020) documents that strong creative culture encourages firms to engage in earnings manipulation. The possibility that clients might materially misstate their financial statements is considered to be a significant audit risk by auditors (Bedard & Johnstone, 2004; Gul et al., 2003). Hence, when auditors assess the audit risk of clients based in areas with high creative culture, they are likely to consider the possibility of increased REM activities in their audit pricing decisions. We therefore hypothesise as follows:

H2. The positive association between creative culture and audit fees is more pronounced for firms with more REM, ceteris paribus.

Dishonest behaviour, manipulation and misstating financial performance also indicate the risk-taking nature of creative individuals. Creative culture encourages people to search for the unknown and deviate from norms, thereby supporting creative performance by encouraging risk-taking propensities (Ucar, 2018). Ucar (2019) finds that firms domiciled in high creative culture counties have higher risk-taking tendency measured by volatility of stock returns and return on assets. Although risk-taking may increase firm value through new product development or applied research resulting in successful patents or citations, excessive risk-taking may be detrimental for shareholders as well as for auditors. Given the litigation risk associated with audit failure, auditors may have lower tolerance levels towards risk, particularly the risk of financial misstatements. Previous studies (e.g., Bell et al., 2001; Davis et al., 1993; Johnstone & Bedard, 2001, 2003) have documented that auditors charge higher audit fees to riskier clients. Thus, we posit that the risk-taking nature of firms domiciled in high creative culture regions is pertinent to auditors' assessments of client risk and moderates the positive relation between creative culture and audit fees. We therefore hypothesise as follows:

H3. The positive association between creative culture and audit fees is more pronounced for firms with more risk-taking propensities, *ceteris paribus*.

Although risk-taking has potential benefits, excessive risk-taking may also be detrimental to the maximisation of shareholder value. Furthermore, REM adversely affects future performance and increases audit risk. Auditors consider their clients' control environment (PCAOB 2007, para. 25) and their external compliance control mechanisms (PCAOB 2007, para. 24) when assessing their clients' audit risk (Gul & Goodwin, 2010). Therefore, the external monitoring environment becomes part of auditors' risk assessment. An efficient set of corporate governance tools is expected to mitigate the agency conflicts stemming from the separation between ownership and control-conflicts that could motivate managers to misreport for maximising private control benefits. It is therefore important to investigate whether external governance can play a disciplining role for firms domiciled in counties with high creative culture, and whether auditors consider such monitoring in their pricing decisions. Owing to a larger stake of ownership in a firm and to fulfil fiduciary duties, institutional investors tend to monitor managerial activities and firm performance closely (Chung & Zhang, 2011) and therefore perform strong governance roles. Financial analysts likewise perform a monitoring role by producing and distributing information to the public that reduces information asymmetry and improves corporate transparency (Healy & Palepu, 2001; Jensen & Meckling, 1976). Lack of such external monitoring is likely to promote dishonest, unethical and risk-taking behaviour among managers domiciled in high creative counties thereby increasing overall audit risk leading to higher price charged by the auditor. Given the increased risks of misreporting and higher propensities for risk-taking by firms headquartered in high creative culture regions, we expect the positive association between creative culture and audit fees to be stronger for firms with poor governance. We therefore hypothesise as follows:

H4. The positive association between creative culture and audit fees is more pronounced for firms subject to weaker monitoring, *ceteris paribus*.

3. Research design

3.1. Data and sample selection

To investigate our research question, we retrieve audit-related data from Audit Analytics (AA), financial statement data from Compustat, stock return data from CRSP (Center for Research in Security Prices), corporate governance data from Board Analysts, analyst data from IBES (Institutional Brokers Estimates System), institutional ownership data from Thomson Reuters and demographic data from the US Census Bureau. We collect corporate headquarter addresses from a firm's 10-K filings in EDGAR (Electronic Data Gathering, Analysis, and Retrieval). We obtain data on local creative culture from the website of ERS. Because county-level creative culture data are available for 1990, 2000 and 2007, we use linear interpolation to fill in the values for the years without available data, which is consistent with Ucar's approach (2018, 2019).²

We begin with an initial sample of 69,344 firm-year observations for the period 2004–2018 with available audit fee data for nonfinancial and non-regulated industries. We begin with 2004 because the data on the internal control weakness (ICW) variable, one of the key determinants of audit fees, only became available in AA in 2004. We further delete 33,790 firm-year observations with missing control variables for the audit fee model, resulting in a sample size of 35,554 firm-year observations. We conduct our primary regression analysis on this sample. However, it is possible that the relation between local creative culture and audit fees may be affected by firm-level creativity. Since firms with more creativity may cluster in areas with a creative culture, the documented relationship between local creative culture and audit fees may be driven by the firm-level creativity rather than the local creative culture. To alleviate this concern, we include two firm-level culture variables that are available for a reduced sample of 24,238 firm-year observations.³ Furthermore, the inclusion of discretionary accruals (DAC), a proxy for financial reporting quality, resulted in a further loss of 1801 firm-year observations, thereby providing us with 22,437 firm-year observations for all our subsequent tests. From Table 1, it is evident that our sample observations come from a diverse range of industries, with two-digit Standard Industrial Classification (SIC) codes 35–39 (30.34%) and 70–79 (17.34%) commanding the largest industry representation.

² Use of linear interpolation to fill in the gaps in the data for the years without available data is a common practice in research related to social norms (e.g., Hasan et al., 2017; Jha, 2019; Jha & Chen, 2015).

³ We are grateful to Kai Li for providing us with the firm-level culture data.

Table 1

Industry distribution.

Code	Industry	Ν	%
1–14	Agriculture and mining	1032	4.60
15–17	Building construction	227	1.01
20-21	Food and kindred products	444	1.98
22-23	Textile mill products and apparels	162	0.72
24–27	Lumber, furniture, paper and printing	758	3.38
28-30	Chemical, petroleum, rubber and allied products	3357	14.96
31–34	Metal	779	3.47
35–39	Machinery, electrical, computer equipment	6808	30.34
40–47	Railroad and other transportation	646	2.88
50–52	Wholesale goods, building materials	1009	4.50
53–59	Store merchandise, auto dealers, home furniture stores	1908	8.50
70–79	Business services	3890	17.34
80–99	Other	1417	6.32
	Total	22,437	100.00

Note: This table reports the sample breakdown by industry.

3.2. Regression model

We develop the following ordinary least squares (OLS) regression model that includes commonly used control variables for audit fees to test H1 (Gul & Goodwin, 2010; Hay et al., 2006; Jha & Chen, 2015; Simunic, 1980).

$$LN_AF_{i,t} = \beta_0 + \beta_1 SHARE_{i,t} + \beta_2 LN_NAF_{i,t} + \beta_3 OPIN_{i,t} + \beta_4 ARL_{i,t} + \beta_5 BIG4_{i,t} + \beta_6 SPEC_{i,t} + \beta_7 BUSY_{i,t} + \beta_8 LN_TENURE_{i,t} + \beta_9 ICW_CNT_{i,t} + \beta_{10} SIZE_{i,t} + \beta_{11} LEV_{i,t} + \beta_{12} MTB_{i,t} + \beta_{13} ROA_{i,t} + \beta_{14} LOSS_{i,t} + \beta_{15} INVREC_{i,t} + \beta_{16} QUICK_R_{i,t} + \beta_{17} TANGIB_{i,t} + \beta_{18} FORSALE_{i,t} + \beta_{19} LN_SEG_{i,t} + \beta_{20} ACQ_{i,t} + \beta_{21} SPI_{i,t} + \beta_{22} CREATIVE_{i,t} + \beta_{23} CULTURE_{i,t} + \beta_{24} DAC_{i,t} + Fixed Effects + \varepsilon_{i,t}$$

$$(1)$$

where the dependent variable is the natural log of audit fees (LN_AF). Our main variable of interest is the share of creative culture (SHARE), defined as the proportion of the creative class in a given county. According to ERS, the county-level creative share data set comprises occupations that require a high level of creative thinking, such as architecture, arts, business and financial operations, computer and mathematical areas, design, engineering, entertainment, management and sports (Ucar, 2018).

We include several control variables as potential determinants of audit fees. We include LN_NAF, the natural log of non-audit fees, to control for the spillover effect of non-audit fees on audit fees. OPIN is a binary variable that takes the value of 1 for firms receiving a going concern audit opinion, and 0 otherwise. ARL is the natural logarithm of the number of days between the fiscal year end date and the audit report issue date. BIG4 is coded 1 for firms audited by one of the Big 4 audit firms, and 0 otherwise. SPEC is an indicator variable coded 1 if the audit firm is an industry specialist, and 0 otherwise. BUSY is a binary variable that takes the value 1 for firms having the fiscal year end in December, and 0 otherwise. LN_TENURE is defined as the natural logarithm of the number of years an incumbent auditor has audited a firm. ICW_CNT is the number of ICW-related disclosures. We expect that all the variables except LN_TENURE will increase audit fees. We do not have a prediction for the sign of LN_TENURE because long-tenured audit service could generate spillover benefits or impair auditor independence.

We control for firm-level variables that include the natural log of total assets (SIZE); firm leverage (LEV); growth opportunities (MTB); profitability, proxied by return on assets (ROA) and negative earnings (LOSS); inventories and receivables ratios defined as the sum of total inventories and accounts receivables divided by total assets (INVREC); the liquidity status of the firm proxied by quick ratio (QUICK_R); asset tangibility (TANGIB); foreign sale (FORSALE); number of business and geographic segments (LN_SEG); merger and acquisition activities (ACQ); and special items (SPI). We expect SIZE, LEV, MTB, LOSS, INVREC, FORSALE, LN_SEG, ACQ and SPI to have a positive association with LN_AF; and ROA, QUICK_R, and TANGIB to have a negative association with LN_AF. We also control for firm-level creative culture (CREATIVE), and firm-level integrity, quality, respect and teamwork (CULTURE). Given that CREATIVE captures firm's innovative culture and innovation is risky, we expect the coefficient on CREATIVE to be positive. The coefficient on CULTURE, however, is expected to be negative because firms with a culture of strong teamwork and respect among co-workers are perceived favourably by auditors from a business risk perspective. We include DAC to control for the effect of financial reporting quality on audit fees and expect the coefficient to be positive because high DAC implies greater financial reporting risk and hence higher audit fees (Choi et al., 2022). To avoid the undesirable influence of outliers, we winsorise all the continuous variables at the extreme 1% of their respective distributions. The appendix provides detailed variable definitions.

For moderation tests, we include two variants of REM, namely, REM_ABN and REM_TOT, to test the moderating effects of REM on the association between creative culture and audit fees (test of H2). REM_ABN is the sum of abnormal production cost and abnormal discretionary expenses. REM_TOT is the composite REM score and is calculated as the sum of abnormal production cost, abnormal discretionary expenses and abnormal cash flow. REM_ABN_D (REM_TOT_D) is a binary variable coded 1 if the value of REM_ABN (REM_TOT) is above median, and 0 otherwise. To test the moderating effects of risk-taking (test of H3), we again use two variants of risk-taking, namely, earnings volatility (EARN_VOL), defined as the standard deviation of the difference between firm-level earnings

M.D. Costa and A. Habib

before interest, taxes, depreciation and amortisation (EBITDA), scaled by total asset, and county-level average EBITDA scaled by total asset over the last five years. Our second proxy for risk-taking is asset volatility (AST_VOL), measured as the standard deviation of the stock return during the fiscal year times the market value of equity scaled by the market value of assets. EARN_VOL_D (AST_VOL_D) is a binary variable coded 1 if the value of EARN_VOL (AST_VOL) is above median, and 0 otherwise. Finally, to test the moderating effects of external governance (test of H4), we use institutional ownership (IOWN), defined as the percentage of common shares held by institutional investors, and analyst following (FOLLOW), defined as the number of analysts following a firm. IOWN_D (FOLLOW_D) is a binary variable coded 1 if the value of IOWN (FOLLOW) is below median, and 0 otherwise. We use the binary specification in our interactive model because the interpretation of the interaction term of the two continuous variables and its economic significance is challenging. Prior studies (Abdelsalam et al., 2021; Tong et al., 2022; Xu et al., 2022) have also used binary indicators in performing their cross-sectional tests.

Table 2

Descriptive statistics.

Variables	Ν	Mean	Std. Dev.	25%	Median	75%
Main test variables						
LN_AF	22,437	14.04	1.09	13.34	14.01	14.71
AFEE (million \$)	22,437	2.37	4.23	0.62	1.22	2.45
SHARE	22,437	0.31	0.07	0.26	0.31	0.36
LN_NAF	22,437	10.55	4.14	10.17	11.73	12.94
OPIN	22,437	0.03	0.16	0.00	0.00	0.00
ARL	22,437	64.06	22.60	55.00	60.00	72.00
BIG4	22,437	0.86	0.35	1.00	1.00	1.00
SPEC	22,437	0.45	0.50	0.00	0.00	1.00
BUSY	22,437	0.65	0.48	0.00	1.00	1.00
LN TENRURE	22,437	2.31	0.71	1.79	2.30	2.83
ICW CNT	22,437	0.14	0.74	0.00	0.00	0.00
SIZE	22.437	6.48	1.81	5.24	6.43	7.67
LEV	22,437	0.22	0.25	0.01	0.17	0.33
MTB	22,437	3.27	6.53	1.35	2.29	3.96
BOA	22,437	-0.04	0.30	-0.04	0.03	0.08
LOSS	22,437	0.34	0.47	0.00	0.00	1.00
INVRFC	22,137	0.24	0.17	0.11	0.00	0.34
OUICK B	22,437	0.24 2.37	2.58	1.04	1.58	0.34 2.71
TANGIB	22,437	0.22	0.22	0.06	0.14	0.31
FORSALE	22,437	0.22	0.22	0.00	0.00	1.00
INSEG	22,437	1.05	0.40	0.20	0.59	1.00
LIN_3EG	22,437	0.44	0.42	0.09	0.09	1.39
CDI	22,437	0.44	0.30	0.00	0.00	1.00
SPI ODEATRUE	22,437	0.15	0.34	0.00	0.00	0.00
CHITUDE	22,437	2.07	1.20	1.19	1.//	2.03 E 16
CULIURE	22,437	4.12	2.03	2.0/	3.71	5.10
DAC	22,437	-0.00	0.10	-0.04	0.00	0.04
LAWSUIT	22,437	0.01	0.11	0.00	0.00	0.00
LAWSUIT_TOT	22,437	0.06	0.25	0.00	0.00	0.00
Moderating variables						
REM_ABN	19,819	-0.04	0.42	-0.21	0.00	0.18
REM_TOT	19,819	-0.05	0.43	-0.25	-0.01	0.18
EARN_VOL	20,419	0.08	0.13	0.02	0.04	0.08
AST_VOL	22,188	0.08	0.06	0.05	0.07	0.11
IOWN	17,345	0.69	0.26	0.53	0.75	0.88
FOLLOW	17,592	10.91	8.58	5.00	8.00	15.00
Other control variables						
SC	22,437	-0.50	0.72	-1.03	-0.47	-0.05
CORRUP	22,437	0.35	0.42	0.13	0.27	0.45
RELIG	22,437	0.45	0.11	0.37	0.41	0.55
POPU	22,437	0.01	0.01	0.00	0.01	0.01
INCOME	22,437	11.06	0.27	10.85	11.04	11.25
AGE	22,437	3.61	0.09	3.55	3.60	3.66
EDU	22,228	0.40	0.11	0.31	0.39	0.48
MALE_FEMALE	22,437	0.98	0.03	0.96	0.98	0.99
DIVERSITY	22,437	0.18	0.09	0.13	0.17	0.22
URBAN	22,437	0.14	0.34	0.00	0.00	0.00
SJQ	22,362	22.08	13.14	11.00	21.00	30.00
POLITICAL	22,437	0.40	0.49	0.00	0.00	1.00
CEO_TENURE	10,292	10.14	4.78	7.00	9.00	13.00
CEO_DUAL	10,292	0.36	0.48	0.00	0.00	1.00
BDIND	10,470	0.71	0.16	0.63	0.75	0.83
GRANT_LAG	15,561	12.36	1.67	11.08	12.59	13.66

Note: This table presents the descriptive statistics for the regression variables. Refer to Appendix for variable definitions.

4. Empirical results

4.1. Descriptive statistics and correlation

The descriptive statistics for the variables used in our main analysis are presented in Table 2.⁴ The mean (median) value of LN_AF is 14.04 (14.01). The average audit fee (AFEE) in our sample is \$2.37 million. The average (median) proportion of SHARE is 0.31 (0.31), suggesting that an average of 31% of the county-level population engage in jobs requiring creative techniques. On average, 86% of sample firms are audited by BIG4 firms, and industry specialist auditors audit approximately 45% of the firm-year observations (SPEC). Three per cent of the sample firms receive a going concern audit opinion (OPIN). About 65% of our sample observations have their fiscal year end during the auditors' busy season (BUSY). The average firm size in our sample is large (SIZE = 6.48), with strong growth opportunities (MTB = 3.27), but negative mean profitability (ROA = -0.04, although the median ROA is 0.03). Approximately 34% of firms in our sample report negative income (LOSS). The leverage ratio is low (LEV = 0.22), and the short-term financial flexibility is quite strong (QUICK_R = 2.37).

Descriptive statistics of the moderating variables are also presented in Table 2. The mean (median) REM is -0.04 (0.00), while the composite REM_ABN (REM_TOT) is -0.05 (0.01). We further use risk-taking propensities as another moderating context and use two variants of risk measures. EARN_VOL has a mean (median) of 0.08 (0.04), while the AST_VOL has a mean (median) of 0.08 (0.07). Our final set of moderating variables are proxies of external governance. IOWN and FOLLOW have means (medians) of 0.69 (0.75) and 10.91 (8.00), respectively.

Correlations among key variables are presented in Table 3. A positive and significant correlation is found between LN_AF and SHARE (correlation coefficient 0.02, p < 0.01). This provides univariate support that auditors charge higher fees to firms head-quartered in counties with a more creative workforce. Audit fees are high for firms procuring non-audit services (LN_NAF; coefficient 0.47), firms audited by BIG4 (correlation 0.45) and firms audited by industry specialist auditors (SPEC, correlation 0.30). Audit fees are higher for larger firms (SIZE; coefficient 0.82) and more complex firms (coefficient are 0.40 for LN_SEG), but lower for firms with a higher proportion of foreign sales (FORSALE; coefficient -0.32) and a higher quick ratio (QUICK_R; coefficient -0.25).

4.2. Baseline regression results: local creative culture and audit fees

Table 4, Panel A, presents the regression results for the association between creative culture and audit fees. Column (1) reports results for the full sample of 35,554 firm-year observations excluding CREATIVE, CULTURE and DAC. Column (2) includes CREATIVE and CULTURE (sample size drops to 24,238 firm-year observations). Finally, column (3) reports the results for the full model including DAC (sample size is 22,437 firm-year observations). The coefficient on SHARE, our main variable of interest, is positive and significant in all three columns. The coefficients on SHARE are 0.874 (p < 0.01) in column (1), 0.738 (p < 0.01) in column (2), and 0.754 (p < 0.01) in column (3), thereby indicating that auditors charge higher fees for firms located in counties that have a higher proportion of the workforce employed in creative works. We therefore find support for H1. In terms of economic significance, the reported coefficient on SHARE for the full model (column 3) suggests that a one standard deviation increase in SHARE increases LN_AF by 5.28% [0.754 (the coefficient on SHARE) \times 0.07 (standard deviation of SHARE) \times 100]. Given that the mean audit fee in our sample is \$2.37 million, this implies an average increase in audit fees of approximately \$0.13 million—an economically significant increase.

The sign and significance of the control variables are generally consistent with the prior audit fee literature. Firms pay higher audit fees when they are audited by BIG4 and industry specialist auditors. In addition, non-audit fees (LN_NAF), audit opinion (OPIN) and audit tenure (LN_TENURE) show positive and significant relationships with audit fees. Audit fees are higher for large firms (SIZE), firms with more debt (LEV), firms incurring losses (LOSS), firms reporting complex operations (FORSALE and LN_SEG), firms involved in merger and acquisition activities (ACQ), and firms with more internal control weaknesses (ICW_CNT). Audit fees are lower for firms with operating profit (ROA), high asset tangibility (TANGIB) and liquidity (QUICK_R). Multicollinearity is not a serious concern because the highest variance inflation factor (VIF) is 3.91 for LN_SEG. This is well below the conventional threshold of 10.00 (Jha & Chen, 2015; Marquardt, 1970; Studenmund, 2016).

In developing H1 we have focused on whether the client firm is headquartered in counties with high as opposed to low creative culture. However, it is also important to consider whether the firm is audited by audit firms that are operating in the same county as that of the client or by audit firms from counties with a different creative culture. In the former case, it is expected that since the auditor and the client firm have a similar creative culture, the auditor will be familiar with the client's propensity towards risk and such familiarity will have minimal effects on audit fees. However, when the auditors are from counties with different creative cultures than their clients, the auditors may have to exert additional audit efforts to understand their clients' risk attitudes stemming from the variation in creative culture—a context that will likely affect audit fees differentially. To investigate this possibility, we rerun Equation (1) for the subsample of firms whose clients and auditors are located in counties with different creative cultures (SAME), and for the subsample of firms whose clients and auditors are located in counties with different creative cultures (DIFF). The untabulated results reveal the coefficient on SHARE to be positive and significant for both SAME (coefficient 0.98, p < 0.01) and DIFF (coefficient 0.96, p < 0.01) subgroups. The z-test for difference in coefficients on SHARE between the two groups is statistically insignificant. Thus, we conclude that local creative culture as a form of social norm is a priced audit risk factor that is not influenced by auditor location.

⁴ We provide descriptive statistics for the variables used in the comprehensive model, that is, the model that includes firm-level culture variables and DAC.

Variables	[1]	[2]	[3]	[4]	[5]	[6]	[7]		[8]		[9]	[10]		[11]	[12]
LN_AF [1]	1														
SHARE [2]	0.019**	1	1												
LIN_INAF [5]	0.408	-0.002	1	1											
API [5]	-0.132	0.020	-0.070	1 0 1 2 0 * * *	1										
RICA [6]	0.204	0.001	0.128	0.130	0 172***	1									
SPEC [7]	0.431	0.001	0.247	-0.108	-0.175	0.365***	1								
BUSV [8]	-0.001	0.003	_0.026***	0.055***	0.001	0.005	_0.00	7	1						
LN TENHRE [9]	0.330***	-0.060***	0.238***	-0.068***	-0.177***	0.005	0.163	***	_0 110**	*	1				
ICW CNT [10]	0.028***	0.012	-0.026***	0.078***	0.432***	-0.055**	** -0.04	1***	0.009		-0.104***	1			
SIZE [11]	0.822***	-0.090***	0 425***	-0.223***	-0.322***	0.423***	0 299	***	-0.027**	*	0.345***	-0.07	71***	1	
LEV [12]	0.181***	-0.095***	0.071***	0.141***	-0.013*	0.062***	0.049	***	0.091***		0.028***	0.031	***	0.217***	1
MTB [13]	0.014*	0.052***	0.022***	-0.028***	-0.057***	0.041***	0.020	**	0.037***		-0.001	-0.01	15*	0.001	-0.071***
ROA [14]	0.242***	-0.085***	0.142***	-0.446***	-0.156***	0.147***	0.095	***	-0.113**	*	0.132***	-0.05	57***	0.394***	-0.174***
LOSS [15]	-0.251***	0.113***	-0.166***	0.215***	0.182***	-0.144**	** -0.10	8***	0.125***		-0.184***	0.084	***	-0.387***	0.075***
INVREC [16]	-0.003	-0.132^{***}	0.016*	-0.035***	0.048***	-0.106**	** -0.02	1**	-0.179**	*	0.046***	0.040)***	-0.075***	-0.102^{***}
QUICK_R [17]	-0.248***	0.164***	-0.123^{***}	-0.044***	0.010	-0.037**	** -0.09	0***	0.075***		-0.096***	-0.03	36***	-0.256***	-0.233***
TANGIB [18]	0.031***	-0.288^{***}	-0.027***	-0.002	-0.050***	0.077***	0.073	***	0.056***		0.044***	-0.03	30***	0.254***	0.254***
FORSALE [19]	-0.317***	0.110***	-0.160***	0.064***	0.081***	-0.085**	** -0.10	0***	0.042***		-0.142^{***}	0.005	;	-0.301***	-0.069***
LN_SEG [20]	0.395***	-0.123^{***}	0.200***	-0.074***	-0.099***	0.103***	0.118	***	-0.022^{**}		0.178***	-0.00	09	0.368***	0.087***
ACQ [21]	0.348***	0.002	0.201***	-0.104***	-0.089***	0.133***	0.087	***	-0.027**	*	0.105***	-0.01	11	0.335***	0.044***
SPI [22]	0.019**	-0.016*	0.009	0.001	-0.005	0.008	-0.00	0	0.001		0.014*	-0.00	03	0.032***	0.007
CREATIVE [23]	0.030***	0.199***	0.022***	0.019**	-0.046***	-0.006	0.020	**	-0.081**	*	0.011	-0.02	20**	-0.030***	-0.092***
CULTURE [24]	-0.198***	0.182***	-0.083^{***}	0.085***	0.076***	-0.127**	** -0.09	5***	0.056***		-0.120^{***}	0.035	;*** ;	-0.294***	-0.134***
DAC [25]	-0.006	-0.022***	-0.003	-0.034***	-0.024***	-0.027**	** -0.01	0	0.000		0.025***	-0.02	25***	0.016*	-0.026***
Variables	[13]	[14]	[15]	[16]	[17]	[18]	[19]	[20]		[21]	[22]		[23]	[24]	[25]
MTB [13]	1														
ROA [14]	0.017*	1													
LOSS [15]	-0.007	-0.535^{***}	1												
INVREC [16]	-0.067***	0.132***	-0.132^{***}	1											
QUICK_R [17]	0.031***	-0.073***	0.133***	-0.265^{***}	1										
TANGIB [18]	-0.068***	0.087***	-0.077***	-0.220***	-0.277***	1									
FORSALE [19]	0.064***	-0.151***	0.175***	-0.119***	0.186***	-0.041***	1								
LN_SEG [20]	-0.069***	0.169***	-0.196^{***}	0.123***	-0.208***	0.046***	-0.845^{***}	1							
ACQ [21]	-0.003	0.187***	-0.223^{***}	0.031***	-0.154***	-0.133^{***}	-0.217^{***}	0.25	52***	1					
SPI [22]	-0.025^{***}	0.063***	-0.092***	-0.002	-0.007	0.040***	-0.030***	0.03	37***	0.004	1				
CREATIVE [23]	0.077***	-0.048***	0.077***	-0.081***	0.031***	-0.224***	0.078***	-0.0	091***	0.004	-0.0)29***	1		
CULTURE [24]	0.082***	-0.176***	0.200***	-0.087***	0.131***	-0.316***	0.155***	-0.1	189***	-0.035	-0.0)36***	0.457*	** 1	
DAC [25]	-0.020**	0.209***	-0.215^{***}	0.077***	0.046***	-0.009	-0.034***	0.03	39***	-0.027	*** 0.12	6***	-0.064	4*** -0.03	0*** 1

Note: This table presents the correlation coefficients of the main regression variables. *p < 0.05, **p < 0.01, ***p < 0.001. Refer to Appendix for variable definitions.

Table 3 Correlation.

9

M.D. Costa and A. Habib

Table 4

Baseline regression analysis.

	(1)	(2)	(3)
	LN_AF	LN_AF	LN_AF
HARE	0.874***	0.738***	0.754***
	[8.48]	[6.19]	[6.11]
N_NAF	0.025***	0.022***	0.022***
-	[17.01]	[12.49]	[11.87]
PIN	0.045**	0.135***	0.118***
	[1.98]	[4.71]	[3.92]
RI.	0.138***	0.002***	0.002***
	[5.93]	[4.50]	[4,17]
G4	0.481***	0.367***	0.351***
	[23,79]	[15.12]	[13.85]
FC	0.042***	0.048***	0.047***
	[3 27]	[3 61]	[3 45]
ICV	[3.27]	0.057***	[3.43]
/01	U.UOU"""	0.03/***	0.000
TENHIDE	[3.38] 0.042***	[3.13]	[3.1/]
I_IENUKE	0.042***	0.052***	0.052***
	[4./5]	[4.84]	[4.71]
W_CNT	0.055***	0.084***	0.085***
	[8.71]	[9.23]	[8.50]
ZE	0.480***	0.480***	0.480***
	[91.73]	[71.70]	[67.74]
.V	0.080***	0.033	0.034
	[6.64]	[1.30]	[1.14]
ГВ	-0.001	0.000	0.001
	[-1.51]	[0.65]	[0.86]
DA	-0.087***	-0.161^{***}	-0.235***
	[-13.46]	[-6.60]	[-9.05]
SS	0.152***	0.126***	0.117***
	[13.42]	[9.58]	[8,60]
VREC	0.222***	0.380***	0.377***
	[4 94]	[6 26]	[5.81]
IICK B	-0.028***	-0.028***	-0.028***
heit_it	[13 36]	[0 /1]	[0.020
NCIR	[-13.30]	[-9.41]	[-9.08]
INGIB	-0.493	-0.510	-0.304
DCALE	[-12.17]	[-10.27]	[-9.61]
JRSALE	0.052^^^	0.054	0.053
	[3.08]	[2.96]	[2./4]
I_SEG	0.21/***	0.229***	0.225***
	[10.04]	[9.51]	[9.03]
CQ	0.048***	0.031***	0.037***
	[4.41]	[2.76]	[3.19]
I	0.011	0.011	0.009
	[1.06]	[0.97]	[0.76]
REATIVE	-	0.017***	0.019***
		[3.19]	[3.42]
JLTURE	-	-0.009**	-0.010***
		[-2.52]	[-2.82]
AC	_		0.135***
			[2,94]
lustry	Yes	Yes	Yes
ar .	Yes	Yes	Ves
instant	9 085***	9.814***	0 977***
notailt	5.000	5.014	9.2// ***
	[51.30]	[32.34]	[98.03]
servations	35,554	24,238	22,437
dj. K-squared	0.85	0.79	0.79

Panel B: Creative culture, audit effort and litigation risk

	(1)	(2)	(3)
Dependent variables:	ARL	LAWSUIT	LAWSUIT_TOT
SHARE	5.883**	1.813*	0.895**
	[2.17]	[1.95]	[2.16]
LN_NAF	0.045	0.053**	0.003
	[1.19]	[2.41]	[0.52]
OPIN	4.233***	0.899***	0.602***
	[3.14]	[2.81]	[4.12]

(continued on next page)

Table 4 (continued)

ARL	_	0.003**	0.001
		[2.26]	[0.78]
BIG4	-2.298***	-0.179	-0.379***
	[-3.99]	[-0.80]	[-4.08]
SPEC	-0.603*	-0.059	0.090*
	[-1.82]	[-0.40]	[1.82]
BUSY	-0.749*	0.154	0.031
	[-1.75]	[0.97]	[0.48]
LN TENURE	-0.584**	-0.384***	-0.042
	[-2.04]	[-3.68]	[-1.16]
ICW CNT	11.924***	0.173***	0.090**
	[7.47]	[3.15]	[2.53]
SIZE	-3.272***	0.334***	0.568***
	[-20.81]	[5.93]	[23.33]
LEV	1.831**	0.073	-0.481***
	[2.41]	[0.26]	[-3.76]
МТВ	-0.132***	-0.005	0.001
	[-7.06]	[-0.42]	[0.45]
ROA	0.519	-0.296*	-0.404***
	[0.57]	[-1.93]	[-4,14]
LOSS	2.747***	0.559***	0.294***
	[6.57]	[3.32]	[5.23]
INVREC	1 092	0.786	-0.573***
	[0 69]	[1 60]	[-2,61]
OUICK B	-0.296***	0.028	-0.029***
forer w	[-3.63]	[0.72]	[-2,63]
TANGIB	0 333	0 115	-0.858***
mittib	[0.24]	[0 23]	[-4 49]
FORSALE	0.215	-0.250	_0 191**
I ONOTHER	[0.38]	[_0 00]	[-2 01]
IN SEC	0.310	_0.20]	0.395***
E1_9E0	[0 49]	[-1 52]	[-3.87]
400	0.571*	_0.074	_0.108**
ncy	[1.84]	[-0.50]	[-2 23]
SDI	0.249	_0.301	0.060
511	[0.60]	[1 28]	[1 08]
CDEATIVE	0.521***	0.116*	0.066***
CREATIVE	-0.321	-0.110	[2 60]
CULTUPE	[-4.08]	[-1./4]	[2.09]
COLIORE	0.014	0.087	[2 25]
DAC	[0.17]	1 125	[2:33]
DAC	-0.431	-1.123	-0.379
Inductor	[-0.20] Voc	[-1.30] Voc	[-2.30] Voc
Noor	res	res	res
I tal	1 es 07 1 6 0 * * *	1 es	1 es
Constant	0/.108^^^ [22 71]	-U.U44^^^ [0.02]	-3./04^^^
Observations	[32./1] 32.427	[-2.93]	[-/.33]
Observations	22,437	22,437	22,437
Auj. K-squared	0.30	0.09	0.12

Note: Panel A reports the results from OLS regressions of the association between creative culture and audit fees. Robust t-statistics are in brackets and are based on standard errors that are clustered by firm. Column (1) of Panel B reports the results from OLS regressions of the association between creative culture and audit effort proxied by ARL (audit report lag). Robust t-statistics are in brackets and are based on standard errors that are clustered by firm. Columns (2) and (3) of Panel B report the results from logistic regressions of the association between creative culture and litigation risk proxied by lawsuits. Robust z-statistics for columns (2) and (3) are in brackets and are based on standard errors that are clustered by firm. ***p < 0.01, **p < 0.05, *p < 0.10. Refer to Appendix for variable definitions.

4.2.1. Local creative culture, audit effort and litigation risk

Our argument thus far rests on prior studies showing that creative culture encourages employees to engage in misreporting (Guggenmos, 2020) and that creative individuals tend to exhibit heightened risk-taking tendencies (Dewett, 2006). Simunic's (1980) seminal work on the drivers of audit fees suggests that audit fees consist of a resource cost factor and an expected loss factor. Thus, the enhanced audit fees documented thus far may come from enhanced efforts or litigation risks or both. We therefore examine the relation between creative culture and audit report lag (a proxy for audit efforts) and creative culture and shareholder litigation (a proxy for enhanced audit risk). Panel B of Table 4 presents the results. Column (1) reveals that the coefficient on SHARE is positive and significant (coefficient 5.883, p < 0.05), suggesting that ARL is longer for firms headquartered in counties with high creative culture.

For the litigation test, we follow Callen and Fang (2020) and Jha and Chen (2015), and retrieve data on the litigations filed against the client firms from AA. We construct two binary variables, LAWSUIT and LAWSUIT_TOT, taking the value 1 for firm years with lawsuits against the firm, and 0 otherwise. Our approach is consistent with Jha and Chen (2015), who focus on the likelihood of the client being sued because it is a comprehensive measure of the client risk, both the financial reporting risk and the client business risk, that auditors face. We find a positive and significant coefficient on SHARE for LAWSUIT (coefficient 1.81, p < 0.10) (column 2) and for

Table 5

Creative	culture and	1 andit	tees.	Cross-sectional	tests

	(1)	(2)
	LN_AF	LN_AF
Ioderating variables:	REM_ABN_D	REM_TOT_D
HARE	0.842***	0.831***
	[5.43]	[5.36]
EM	0.099***	0.123***
	[3.66]	[4.59]
HARE x REM	0.141**	0.187***
	[2.29]	[3.14]
ther control variables	Yes	Yes
dustry	Yes	Yes
ear	Yes	Yes
onstant	9.173***	9.210***
	[75.94]	[76.14]
bservations	19,819	19,819
lj. R-squared	0.71	0.72

	(1)	(2)
	LN_AF	LN_AF
Moderating variables:	EARN_VOL_D	AST_VOL_D
SHARE	0.698***	0.693***
	[5.29]	[5.48]
RISK	0.009	0.012
	[0.17]	[1.00]
SHARE x RISK	0.110***	0.844***
	[2.67]	[3.09]
Other control variables	Yes	Yes
Industry	Yes	Yes
Year	Yes	Yes
Constant	9.215***	9.177***
	[90.66]	[97.09]
Observations	20,419	22,188
Adj. R-squared	0.79	0.79

Panel C: Moderating effect of external governance (GOVERN)

	(1)	(2)
	LN_AF	LN_AF
Moderating variables:	IOWN_D	FOLLOW_D
SHARE	0.633***	0.553***
	[3.57]	[3.11]
GOVERN	-0.075	-0.133^{*}
	[-1.11]	[-1.82]
SHARE x GOVERN	0.351*	0.576**
	[1.67]	[2.54]
Other control variables	Yes	Yes
Industry	Yes	Yes
Year	Yes	Yes
Constant	9.316***	9.291***
	[77.98]	[74.87]
Observations	17,345	17,592
Adj. R-squared	0.78	0.78

Note: Panel A reports the results from OLS regressions of the association between creative culture and audit fees moderated by real earnings management. Column (1) uses REM_ABN_D and column (2) uses REM_TOT_D as moderators. Panel B reports the results from OLS regressions of the association between creative culture and audit fees moderated by risk-taking. Column (1) uses EARN_VOL_D and column (2) uses AST_VOL_D as the proxies for managerial risk-taking. Panel C reports the results from OLS regressions of the association between creative culture and audit fees moderated by external governance. Column (1) uses IOWN_D and column (2) uses FOLLOW_D as the external governance variables. We use binary specification for the moderating variables for testing our hypotheses. Robust t-statistics are in brackets and are based on standard errors that are clustered by firm. ***p < 0.01, **p < 0.05, *p < 0.10. Refer to Appendix for variable definitions.

LAWSUIT_TOT (coefficient 0.895, p < 0.05) (column 3).

4.3. Local creative culture and audit fees: cross-sectional tests

In this section, we present the moderating effects of REM, risk-taking and external governance on the relationship between local creative culture and audit fees. Panel A of Table 5 reports the relationship between creative culture and audit fees conditional on firms' engagement in REM activities. Panel B tests whether the relation between creative culture and audit fees is moderated by risk-taking propensity. Finally, Panel C uses external governance as a cross-sectional context. We use binary specification of the moderating variables for ease of interpretation.

Column (1) in Panel A reports results using REM_ABN_D, and column (2) reports results using REM_TOT_D. We find that the coefficient on SHARE \times REM_ABN_D and SHARE \times REM_TOT_D positive and significant (coefficient 0.14, p < 0.05 and 0.19, p < 0.01, respectively). This finding supports the argument that firms located in counties with a high share of the population in creative jobs engage in more REM, which is priced by auditors; thus, H2 is supported., ⁵⁶

Panel B reports the results for the moderating effect of risk-taking (RISK). Columns (1) and (2) report results using EARN_VOL_D and AST_VOL_D, respectively. Column (1) shows that the coefficient on SHARE \times RISK is positive and significant (coefficient 0.11, p < 0.01). Column (2) shows that the coefficient on SHARE \times RISK is again positive and significant (coefficient 0.84, p < 0.01). In H3 we hypothesised that the positive association between creative culture and audit fees is likely to be more pronounced for firms with more risk-taking propensities. The results reported in Panel B provide evidence supporting H3.

Panel C in Table 5 presents the results for the moderating effect of external monitoring (GOVERN). It is evident from Panel C that the coefficient on SHARE \times GOVERN is positive and significant for IOWN_D (coefficient 0.351, p < 0.10, Column 1). This suggests that when external monitoring is *poor*, firms headquartered in counties with a high proportion of workers employed in creative works pay higher audit fees. We find similar evidence for analyst following (FOLLOW_D), whereby the coefficient is positive and significant for SHARE \times GOVERN (coefficient 0.576, p < 0.05, Column 2). This finding supports H4—the positive association between creative culture and audit fees is more pronounced for firms subject to weaker monitoring.

Taken together, the results reported in Table 5 provide empirical evidence that REM, managerial risk-taking and poor external monitoring play a moderating role in the positive relationship between creative culture and audit fees.

4.4. Local creative culture and audit fees: robustness tests

Prior research has found that US county-level social capital reduces audit fees (Jha & Chen, 2015). The findings support the notion that managers of firms headquartered in counties with high social capital report more credibly (Jha, 2019), and auditors factor this into their pricing decisions. In Table 6, column (1), we include county-level social capital (SC) in our baseline regression model and find the coefficient on SC to be negative and significant (coefficient -0.12, p < 0.01). Importantly, the coefficient on SHARE remains positive and significant (coefficient 1.133, p < 0.01).

Jha et al. (2021) and Xu et al. (2019) find a positive relationship between audit fees and US regional corruption levels. Thus, we control for state-level corruption conviction (CORRUP) in column (2). We find that the coefficient on CORRUP is insignificant; however, the coefficient on SHARE remains positive and significant (coefficient 0.754, p < 0.01). Gul and Ng (2018) and Leventis et al. (2018) show that auditee religiosity decreases audit fees. In column (3) of Table 6 we control for religious adherence (RELIG). The coefficient on RELIG is insignificant; however, the coefficient on SHARE is positive and significant (coefficient 0.744, p < 0.01).

Next, we control for various county-level and state-level demographic variables, including the population of the county (POPU), household income (INCOME), median age of the population (AGE), educational levels (EDU), male to female population ratio (MALE_FEMALE), racial diversity (DIVERSITY), urban location of firm headquarter (URBAN), state-level judicial quality (SJQ) and state-level political values (POLITICAL). We also control for firm-level internal governance variables, including CEO tenure (CEO_-TENURE), CEO duality (CEO_DUAL) and board independence (BDIND), across columns (4) to (7) in Table 6. The coefficients on SHARE

⁵ Roychowdhury (2006) restricts the sample to manufacturing firms in estimating REM because such firms tend to have a large amount of inventories and thus are more susceptible to conducting REM. Firms in service and high-tech industries, however, tend to have a large amount of intangible assets, and few inventories. Therefore, our documented results in Panel A may be driven by the nature of the firms rather than their REM activities. We therefore rerun Equation (1) for firms in the manufacturing industries (two-digit SIC codes 20–39) and for firms in other industries, including business and service industries. Untabulated regression results show that the coefficient on SHARE × REM_ABN_D and SHARE × REM_TOT_D remains positive and significant (coefficient 0.20, p < 0.05 and 0.23, p < 0.01, respectively) for manufacturing firms. The corresponding coefficients for other firms are 0.18 (p < 0.05) and 0.16 (p < 0.10), respectively. The results, therefore, suggest that the positive association between creative culture and audit fees is moderated by REM, instead of the nature of the firms.

⁶ Recent literature on earnings management suggests that in the post-SOX period, managers switched from accrual-based earnings management (DAC) to REM (Cohen et al., 2008; Graham et al., 2005). Despite this substitution effect, auditors are expected to consider DAC opportunistic and will incorporate the risk associated with DAC into their pricing decisions. Therefore, DAC could be more relevant than REM as a suitable proxy for testing H2 despite Choi et al. (2022) documenting that auditors, on average, charge a higher premium for REM than for DAC. We therefore test the following equation (we use the binarv specification as before): LN_AF_{it} = $\beta_0 + \beta_1$ SHARE_{it} + β_2 DAC_D_{it} + β_3 SHARE_{it} x DAC_D_{it} + β_4 REM_TOT_D_{it} + Other control variables + Fixed Effects + ε_{it} (2)The untabulated result shows that the coefficient on SHARE remains positive and significant (coefficient 0.879, p < 0.01); however, the coefficient on SHARE × DAC_D becomes insignificant (coefficient 0.083), thereby confirming our choice of REM as the relevant earnings management proxy.

Table 6

Robustness tests creative culture and audit fees - Additional control variables.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	LN_AF	LN_AF	LN_AF	LN_AF	LN_AF	LN_AF	LN_AF
SHARE	1.133***	0.754***	0.744***	1.022***	0.882***	1.169***	1.109**
	[8.94]	[6.10]	[6.01]	[2.89]	[4.30]	[2.84]	[1.99]
LN_NAF	0.022***	0.022***	0.022***	0.022***	0.030***	0.035***	0.028***
OPIN	[12.29]	[11.87]	[11.92]	[11.93]	[7.29]	[17.25]	[7.44]
OPIN	0.117***	0.118***	0.118***	0.119***	0.100	0.136***	0.133
ARI	[3.83] 0.002***	[3.92]	[3.91]	[3.93] 0.002***	[0.80]	[3.20]	[1.10]
ML	[4.01]	[4.17]	[4,16]	[4.00]	[1.86]	[3.53]	[1.70]
BIG4	0.367***	0.351***	0.353***	0.360***	0.195***	0.481***	0.235***
	[14.77]	[13.83]	[13.90]	[14.21]	[3.12]	[16.78]	[3.84]
SPEC	0.043***	0.047***	0.047***	0.043***	0.027	0.059***	0.027
	[3.18]	[3.45]	[3.46]	[3.15]	[1.28]	[3.63]	[1.32]
BUSY	0.054***	0.060***	0.061***	0.065***	0.067**	0.047**	0.061**
IN TENHDE	[2.96]	[3.17]	[3.22]	[3.44]	[2.31]	[2.07]	[2.13]
LN_IENUKE	[5 34]	0.052*** [4 71]	[4 63]	[4 64]	[2 08]	[5.83]	0.035"
ICW CNT	0.084***	0.085***	0.085***	0.084***	0.097***	0.101***	0.087***
1011_0111	[8.54]	[8.50]	[8.50]	[8.35]	[3.25]	[9.78]	[2.98]
SIZE	0.476***	0.480***	0.480***	0.473***	0.501***	0.351***	0.493***
	[67.43]	[67.74]	[67.82]	[66.02]	[40.59]	[44.88]	[42.43]
LEV	0.036	0.034	0.035	0.053*	0.034	0.402***	0.105
	[1.19]	[1.14]	[1.16]	[1.75]	[0.43]	[8.18]	[1.34]
MTB	0.001	0.001	0.001	0.000	-0.003*	-0.010***	-0.003**
POA	[1.08]	[0.87]	[0.83]	[0.50]	[-1./5] 0.40E***	[-9.99]	[-1.99]
KOA	-0.230 [-9.17]	-0.233	-0.233	-0.227	-0.493	0.029	-0.399 [-3.94]
LOSS	0.112***	0.117***	0.116***	0.103***	0.075***	0.225***	0.079***
	[8.38]	[8.60]	[8.53]	[7.62]	[3.07]	[14.00]	[3.48]
INVREC	0.391***	0.377***	0.380***	0.381***	0.825***	0.449***	0.866***
	[6.06]	[5.81]	[5.87]	[5.87]	[6.65]	[5.85]	[7.16]
QUICK_R	-0.029***	-0.028***	-0.028***	-0.029***	-0.022^{***}	-0.046***	-0.021***
TANOD	[-9.62]	[-9.08]	[-9.04]	[-9.53]	[-3.41]	[-12.93]	[-3.53]
TANGIB	-0.4/3***	-0.504***	-0.500***	-0.486***	-0.462***	-0.158***	-0.410***
FORSALE	[-9.29] 0.053***	[-9.01] 0.053***	[-9.51] 0.052***	[-9.09] 0.048**	0.068**	[-2.01] 0.067***	[-4.33] 0.049*
TOTOTILL	[2.80]	[2.73]	[2.72]	[2.46]	[2.32]	[2.94]	[1.75]
LN_SEG	0.239***	0.225***	0.225***	0.235***	0.260***	0.409***	0.255***
	[9.69]	[9.03]	[9.01]	[9.31]	[7.34]	[13.27]	[7.49]
ACQ	0.039***	0.037***	0.037***	0.038***	0.056***	0.123***	0.049***
	[3.41]	[3.19]	[3.20]	[3.30]	[3.23]	[8.79]	[2.87]
SPI	0.008	0.009	0.009	0.007	0.026	0.015	0.029*
CDEATIVE	[0.66]	[0.76]	[0.76]	[0.56]	[1.47]	[1.13]	[1.71]
CREATIVE	[3 66]	[3 42]	[3 33]	[3.06]	[2 79]	[1 63]	[2 51]
CULTURE	-0.010***	-0.010***	-0.010***	-0.010***	-0.013*	-0.027***	-0.013*
	[-2.87]	[-2.82]	[-2.78]	[-2.73]	[-1.69]	[-6.27]	[-1.72]
DAC	0.140***	0.135***	0.134***	0.127***	0.319***	0.191***	0.232**
	[3.12]	[2.94]	[2.92]	[2.82]	[2.90]	[3.56]	[2.16]
SC	-0.120***	-	-	-	-	-0.166***	-0.142***
CODDUD	[-10.51]	0.000				[-9.52]	[-5.79]
CORRUP	-	0.002	-	-	-	0.015	-0.042
RELIG	_		-0.098	_	_	-0.052	0.204
T(LLLIG			[-1.39]			[-0.46]	[1.29]
POPU	-	-	_	-3.203***	-	-4.640***	-4.013***
				[-3.87]		[-4.70]	[-3.13]
INCOME	-	-	-	0.182***	-	-0.029	-0.050
				[3.26]		[-0.43]	[-0.53]
AGE	_	-	-	0.074	-	0.406***	0.744***
FDU				[U.01] _0.440*		[2.70] 0.266	[3.07] 0.337
LDU	_	_	-	[-1.82]	-	[0.93]	[0.89]
MALE_FEMALE	_	_	_	-0.702*	_	-0.293	-0.091
-				[-1.82]		[-0.60]	[-0.15]
DIVERSITY	-	-	-	0.059	-	0.074	0.061
				[0.48]		[0.57]	[0.42]
URBAN	-	-	-	0.104***	-	0.123***	0.145***

(continued on next page)

Table 6 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	LN_AF	LN_AF	LN_AF	LN_AF	LN_AF	LN_AF	LN_AF
				[4.36]		[4.21]	[3.68]
SJQ	-	-	-	-0.003***	-	-0.002*	-0.002*
				[-3.36]		[-1.87]	[-1.81]
POLITICAL	-	-	-	-0.094***	-	-0.024	0.019
				[-5.21]		[-1.02]	[0.57]
CEO_TENURE	-	-	-	-	-0.004	-	-0.005*
					[-1.45]		[-1.77]
CEO_DUAL	-	-	-	-	-0.001	-	0.001
					[-0.05]		[0.03]
BDIND	-	-	-	-	0.161**	-	0.201***
					[2.29]		[2.97]
Industry	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	9.271***	9.276***	9.334***	7.916***	9.013***	8.300***	6.975***
	[99.17]	[98.35]	[90.03]	[10.91]	[45.44]	[9.50]	[6.63]
Observations	22,437	22,437	22,437	22,437	6508	22,437	6508
Adj. R-squared	0.79	0.79	0.79	0.79	0.80	0.72	0.82

Note: This table reports the results from OLS regressions of the association between creative culture and audit fees after incorporating additional county-level, state-level, and firm-level control variables. Robust t-statistics are in brackets and are based on standard errors that are clustered by firm. ***p < 0.01, **p < 0.05, *p < 0.10. Refer to Appendix for variable definitions.

continue to be positive and significant across all columns. For example, the coefficient on SHARE is positive and significant (coefficient 1.11, p < 0.05) in column (7), which includes all the additional control variables.

The results reported so far used linear interpolation to fill in the missing values for creative share for the years without available data: a procedure consistent with Ucar (2018, 2019) and other social norms research (Hasan et al., 2017; Jha, 2019; Jha & Chen, 2015). As a robustness test, we run Equation (1) using observations for 2007 alone, for which creative share data are available during our sample period. The untabulated result reveals a positive and significant coefficient on SHARE (coefficient 0.639, p < 0.01), which is consistent with our main findings.

5. Endogeneity tests

In this section, we conduct several tests to address endogeneity concerns. A common source of endogeneity is the omitted variable bias which can be addressed by including as many explanatory variables as possible. However, this is neither possible nor feasible since data availability of many of the potential variables to be included poses a challenge, and proxies for some of the variables are approximations of actual variables and thus subject to measurement errors. We control for several determinants of audit fees to bolster our finding of a positive relationship between creative culture and audit fees. However, given the concerns related to omitted variable bias mentioned above, we, perform a firm fixed-effect regression to control for firm-specific time-invariant unobservable factors. We report the results in Panel A of Table 7. The coefficient on SHARE remains positive and significant (coefficient 0.34, p < 0.05).⁷

Next, we test whether headquarter relocations affect the relationship between creative culture and audit fees. If auditors charge higher fees for firms in counties with a higher proportion of the population engaged in creative work, then firms changing headquarters from low to high creative culture counties should pay higher audit fees. We follow the approach of Hasan et al. (2017) and require that all relocated firms have data available for the two years immediately preceding and two years immediately following the year of relocation. For instance, if the firm relocated its headquarters in 2010, then we require pre-relocation data for 2008 and 2009 and post-relocation data for 2011 and 2012. We identify 225 headquarters relocations in our sample, which meets our data availability requirements.

To conduct this analysis, we replace the baseline SHARE variable with POST, INC_SHARE, and the interaction variable POST \times INC_SHARE in the regression model. POST is a binary variable that takes the value of 1 if the firm-year observation comes from the post headquarters relocation period and 0 otherwise. INC_SHARE is a binary variable that takes the value of 1 if a firm relocated its headquarters to a different county with a higher share of creative culture and 0 otherwise. We are interested in the coefficient of the interaction variable (POST \times INC_SHARE), which estimates the difference in the changes in audit fees over time between firms located in areas with high levels of creative culture and those in areas with little creative culture. Panel B of Table 7 reports the results. Column (1) does not include industry and year fixed effects, but column (2) does. We find that the coefficients on the interaction variable POST \times INC_SHARE positive and significant at p < 0.05 in both columns. This result therefore suggests that firms relocating their head-quarters to counties with a larger share of the creative population pay higher audit fees.

 $^{^{7}}$ We also include county fixed effects to control for county-level unobservable variables that could be correlated with both the dependent and the independent variables. We continue to find significant and positive coefficient on SHARE (coefficient 1.379, p < 0.05) (untabulated). However, a caveat is in order; given the limited variation in creative culture within a county, the inclusion of county-fixed effects in the regression models can remove a large part of the effect of creative culture on manager's behaviour (Jha, 2019).

-

Table 7

Accounting for endogeneity.

Pa

Panel A: Firm fixed effect regression			
	(1)		
	LN_AF		
SHARE	0.340**		
	[2.23]		
Other control variables	Yes		
Industry	No		
Year	Yes		
Firm	Yes		
Constant	10.678***		
	[124.35]		
Observations	22,437		
Adj. R-squared	0.92		

Panel B: Firms with creative culture changing headquarters relocations

	(1)	(2)
	LN_AF	LN_AF
POST	-0.151**	-0.182***
	[-2.58]	[-2.97]
INC_SHARE	-0.161***	-0.180***
	[-2.78]	[-3.03]
POST x INC_SHARE	0.158**	0.172**
	[2.41]	[2.59]
Other control variables	Yes	Yes
Industry	No	Yes
Year	No	Yes
Constant	9.903***	9.605***
	[36.12]	[28.32]
Observations	900	900
Adj. R-squared	0.80	0.82

Panel C: Entropy-balanced matching analysis

C.1. Covariates matching table

	Treatment variable: SHARE								
	Treatm	ent (SHARE	E_D = 1)	Control	l (SHARE_D	= 0) before matching	Control	(SHARE_D	= 0) after matching
Variables	Mean	Variance	Skewness	Mean	Variance	Skewness	Mean	Variance	Skewness
LN_NAF	10.44	17.35	-1.68	10.65	16.91	-1.78	10.44	17.35	-1.68
OPIN	0.03	0.03	5.53	0.02	0.02	6.73	0.03	0.03	5.53
ARL	64.53	648.80	13.88	63.58	372.80	13.78	64.53	648.80	13.88
BIG4	0.86	0.12	-2.06	0.86	0.12	-2.05	0.86	0.12	-2.06
SPEC	0.44	0.25	0.23	0.45	0.25	0.19	0.44	0.25	0.23
BUSY	0.66	0.23	-0.67	0.65	0.23	-0.63	0.66	0.23	-0.67
LN_TENURE	2.27	0.48	-0.23	2.35	0.52	-0.23	2.269	0.48	-0.23
ICW_CNT	0.14	0.60	11.66	0.14	0.50	7.59	0.14	0.60	11.66
SIZE	6.27	3.43	0.27	6.68	3.07	0.01	6.27	3.43	0.27
LEV	0.20	0.06	3.39	0.24	0.06	3.36	0.20	0.06	3.39
MTB	3.56	48.08	1.21	2.98	36.98	1.68	3.56	48.08	1.21
ROA	-0.07	0.12	-7.87	-0.01	0.06	-8.34	-0.07	0.12	-7.87
LOSS	0.40	0.24	0.40	0.28	0.20	1.01	0.40	0.24	0.40
INVREC	0.22	0.03	0.99	0.27	0.03	0.69	0.22	0.02	0.99
QUICK_R	2.81	8.55	3.53	1.95	4.39	5.01	2.81	8.55	3.53
TANGIB	0.17	0.03	1.92	0.28	0.06	1.06	0.17	0.03	1.92
FORSALE	0.73	0.15	-0.92	0.63	0.16	-0.43	0.73	0.15	-0.92
LN_SEG	0.99	0.17	0.88	1.11	0.19	0.40	0.99	0.17	0.88
ACQ	0.43	0.24	0.30	0.46	0.25	0.17	0.43	0.24	0.30
SPI	0.13	0.11	2.26	0.14	0.12	2.11	0.13	0.11	2.26
CREATIVE	2.26	1.70	1.56	1.88	1.39	1.74	2.26	1.70	1.56
CULTURE	4.44	4.22	1.14	3.81	3.82	1.38	4.44	4.22	1.14
DAC	-0.01	0.01	-0.67	0.00	0.01	-0.64	-0.01	0.01	-0.67
C.2. Entropy-	C.2. Entropy-balanced regression result								

(1)

LN_AF

0.805***

[6.10]

(continued on next page)

Table 7 (continued)

C.2. Entropy-balanced regression result	
	(1)
	LN_AF
Other control variables	Yes
Industry	Yes
Year	Yes
Constant	9.187***
	[90.56]
Observations	22,437
Adj. R-squared	0.78

Panel D: Two-stage-least-square (2SLS) regression analysis

Dependent Variables	(1)	(2)	
	SHARE	LN_AF	
	1st Stage	2nd Stage	
GRANT LAG	0.002***	_	
	[8.04]		
POPU	0.721***	_	
	[13.26]		
INCOME	0.044***	_	
	[13.33]		
AGE	-0.010	_	
	[-1.34]		
EDU	0.497***	_	
	[60.12]		
SHARE PREDICT	_	0.568***	
		[3,41]	
LN NAF	-0.000	0.020***	
	[-1 47]	[10.01]	
OPIN	-0.000	0.092***	
orm	[-0.18]	[2 67]	
ARI	0.000	0.002***	
	[1 16]	[2 78]	
BIG4	_0.003**	0 324***	
	[-1.96]	[10.68]	
SDEC	0.001	0.044***	
SFEC.	0.001	[2 80]	
DUCV	[0.97]	[2.80]	
6031	-0.002	0.002	
IN TENHIDE	[-1.//]	[2.67]	
LIN_TENORE	0.000	0.038	
ICMI CNIT	[0.49]	[4.40]	
ICW_CN1	-0.000	0.091	
CIZE.	[-0.33]	[7.03]	
SIZE	0.001	0.4/9***	
	[1.39]	[58.33]	
LEV	-0.003**	-0.001	
	[-2.08]	[-0.04]	
MIB	0.000	0.000	
	[0.38]	[0.14]	
ROA	-0.000	-0.242***	
	[-0.21]	[-8.55]	
LOSS	0.001	0.132***	
	[1.09]	[8.61]	
INVREC	-0.006**	0.424***	
	[-1.98]	[5.89]	
QUICK_R	-0.000	-0.030***	
	[-1.16]	[-8.17]	
TANGIB	-0.011^{***}	-0.485^{***}	
	[-3.97]	[-8.22]	
FORSALE	-0.002^{**}	0.065***	
	[-2.26]	[2.89]	
LN_SEG	-0.005***	0.227***	
	[-3.63]	[7.95]	
ACQ	-0.001	0.025*	
	[-0.92]	[1.84]	
SPI	0.000	0.004	
	[0.34]	[0.27]	
CREATIVE	0.000	0.014**	
		(continued on next name)	
		(communed on next page)	

Table 7 (continued)

Dependent Variables	(1)	(2)
	SHARE	LN_AF
	1st Stage	2nd Stage
	[1.46]	[2.24]
CULTURE	-0.000*	-0.007
	[-1.82]	[-1.61]
DAC	-0.002	0.097*
	[-1.11]	[1.82]
Industry	Yes	Yes
Year	Yes	Yes
Constant	-0.373^{***}	9.265***
	[-8.58]	[85.45]
Observations	15,377	15,377
Adj. R-squared	0.90	0.79

Notes: Panel A reports the result from firm fixed effect (FE) regressions of the association between creative culture and audit fees. Panel B reports the results of a difference-in-differences analysis based on the quasi-experiment. The model uses a reduced sample firms during the 2-year period before and the 2-year period after the relocation event. POST equals 1 if the observation is after the relocation event; it equals 0 if the observation is before the relocation event. INC_SHARE equals 1 if a firm relocates its headquarters to a county with a higher level of creative share; it equals 0 if a firm relocates to a county with a lower level of creative share. Panel C reports the results of the entropy-balanced matching test. Sub-Panel C.1 reports the covariates matching while C.2 reports the regression results. Panel D reports two-stage-least-square (2SLS) regression results. Robust t-statistics are in brackets and are based on standard errors that are clustered by firm. ***p < 0.01, **p < 0.05, *p < 0.10. Refer to Appendix for variable definitions.

Following Chahine et al. (2020), Glendening et al. (2019) and Madsen and McMullin (2020) we employ entropy balanced matching sample technique. This is to address the endogeneity problem stemming from observable differences in firm characteristics between firms located in high as opposed to low creative culture regions. Entropy balancing is used by specifying a set of covariates to be matched, the balance conditions and a tolerance threshold. The balance conditions are the mean, variance and skewness of covariate distributions that should be distributed evenly across treatment and control samples. Entropy-balancing uses "an iterative process to identify a weight for each observation in the control sample, such that the weighted control sample meets the balance conditions within the specified tolerance level" (McMullin & Schonberger, 2020, p. 92). According to McMullin and Schonberger (2020), the tolerance level sets the minimal degree of covariate balance required before the entropy balancing system stops altering control sample weights, similar to a caliper width for propensity score matching (PSM).⁸

For implementing the entropy balancing test, we proceed as follows. First, we divided our sample into two groups. SHARE_D is a binary variable coded 1 (treatment group) if the value of SHARE is above median, and 0 (control group) otherwise. Second, we employ entropy balancing to ensure that the mean, variance, and skewness of the observations in the two groups are similar. Panel C.1 of Table 7 shows that we achieve desirable covariate balance. Third, using the entropy-balanced sample, we combine the matched pairs into a pooled sample and, once again, perform our baseline regression analysis. We report entropy-balanced regression results in Panel C.2. It is evident that the coefficient on SHARE is positive and highly significant (coefficient 0.805, p < 0.01). These findings therefore suggest that our main results are robust to potential endogeneity concerns arising from observable, rather than unobservable, factors.

Our reported results could suffer from self-selection bias in that firms headquartered in counties with a larger proportion of creative population could be motivated to hire better auditors, thereby paying higher audit fees. We therefore use 2SLS to control for this endogeneity concern. Identifying an appropriate instrument that is correlated with the independent variable and non-correlated with the error term for social norms such as local creative culture is very difficult. Thus, we follow previous research (e.g., Callen & Fang, 2013; Chen et al., 2017; Xu et al., 2019) and develop the following first stage regression model to estimate the predicted value of SHARE (SHARE_PREDICT). In this model we include some macroeconomic factors that are likely to be correlated with local creative culture (SHARE):

$$SHARE_{i,t} = \beta_0 + \beta_1 GRANT_LAG + \beta_2 POPU + \beta_3 INCOME + \beta_4 AGE + \beta_5 EDU + Other control variables from Eq. (1) + Fixed Effects + \varepsilon_{i,t}$$

(3)

⁸ PSM method obtains propensity score, uses one of several matching techniques on the basis of estimated propensity score to check that covariates are balanced across treatment and comparison groups, and estimates regression based on new sample. However, in doing so PSM results in a significant loss of observations. The reweighting method used in entropy balancing, on the other hand, is more flexible. Entropy balancing reweights observations to achieve balance, and ensures that the weights are as close as possible to the base weights which prevents any form of loss of information (Hainmueller, 2012). This is why our analysis on entropy-balanced is performed on the full sample of 22,437 firm-year observations. Untabulated PSM results show that the coefficient on SHARE is positive and highly significant (coefficient 0.81, p < 0.01), however, the sample size shrinks to 14,967 firm-year observations.

Ucar (2019) documents a strong correlation between federal arts grants in a county (GRANT) and creative culture. He also controls for other local factors such as local population, education and demographic in conducting the 2SLS analysis. Following Ucar (2019) we include GRANT lagged by a year (GRANT_LAG), POPU, INCOME, AGE, EDU and other control variables from Equation (1) in estimating SHARE_PREDICT. In the second stage, we replace SHARE by SHARE_PREDICT, which is estimated using Equation (3). We report the first-stage regression results in column (1) of Panel D in Table 7. To assess the endogeneity of the first-stage model, we apply the Hausman test (Hausman, 1978) by regressing LN_AF on SHARE and on the residuals from the first-stage regressions. If SHARE is truly exogenous to the set of instruments, the coefficients on the residuals will be equal to 0. The results reject the exogeneity of SHARE at the 1% level (the coefficient on residual is 1.552, p < 0.001). Our main independent variable SHARE_PREDICT in the second-stage regression (column 2) has a positive and significant coefficient (0.568, p < 0.01), a result consistent with our main regression results. The Kleibergen-Paap Wald rk LM statistic of 863.07 is highly significant (p < 0.00) (untabulated) confirming that under-identification is not a concern for our estimates. The Cragg-Donald F-statistic of 20285.59 (untabulated) is significantly higher than the Stock and Yogo (2005) critical value of 26.87, implying that our analysis does not suffer from weak identification problem. Overall, our results remain robust to a battery of endogeneity tests.

6. Conclusion

Using a large sample of US listed firms for the period 2004–2018, we investigate the association between local creative culture and audit fees. Our study is motivated by the existing literature, which shows that managerial decisions and business practices are driven by the local culture (creative culture in our study) of the location of the firm's headquarter. Creative culture is considered beneficial and vital for generating new ideas and knowledge—a precursor for innovation and subsequent economic growth. However, a creative environment may also encourage undesirable outcomes, such as financial misreporting and excessive risk-taking. Our empirical results suggest that firms headquartered in US counties with high creative culture pay higher audit fees than others.

Further analyses provide evidence that REM, managerial risk-taking propensity and weak external monitoring moderate the positive relationship between creative culture and audit fees. The positive association between local creative culture and audit fees remains robust after controlling for known client-specific, auditor-specific, audit engagement-specific and county-specific attributes that affect audit pricing. We also find that firms relocating their headquarters from areas with low to high creative culture pay higher audit fees than others. Our finding that local creative culture increases audit fees remains robust after implementing county fixed effect, entropy-balanced technique and 2SLS regression to address endogeneity concerns. We acknowledge that our research may have some limitations, for instance, the weak instrument used in 2SLS analysis due to unavailability of an appropriate instrument.

Our research contributes to the emerging literature on local creative culture and the extant literature on audit fees. Our results complement the recent surge in studies that investigate how variations in socio-economic factors influence managerial decisionmaking and corporate policies. Auditors, a key stakeholder of a firm, consider that high levels of REM and excessive risk-taking propensities by firms located in counties with high creative culture increase audit risk; therefore, they charge higher audit fees. Taken together, our empirical findings provide evidence of the negative aspects of creative culture.

Data availability

Data will be made available on request.

Appendix. Variable definitions

Variables	Definition
Main test variables	
LN_AF	The natural logarithm of audit fees.
SHARE	The proportion of the creative class in a given county in percentage points.
LN_NAF	The natural logarithm of non-audit fees paid to the auditor.
OPIN	A binary variable coded 1 if the firms received a going concern opinion, and 0 otherwise.
ARL	The natural logarithm of the number of days between the fiscal year end and the audit report issue date.
BIG4	A binary variable coded 1 if the firm is audited by one of the Big4 auditors and 0 otherwise.
SPEC	A binary variable coded 1 if the firm's auditor is an industry specialist, and 0 otherwise. An industry specialist is an auditor with the largest
	market share according to client assets (AT) in the industry.
BUSY	A binary variable coded 1 if the fiscal year end is December, and 0 otherwise.
LN_TENURE	The natural logarithm of the number of years an incumbent auditor has audited a firm (Compustat AU).
ICW_CNT	The number of reported ineffective internal controls of the firm in a current year.
SIZE	The natural logarithm of total assets (AT).
LEV	Debt in current liabilities (DLC) divided by total assets (AT).
MTB	Market-to-book ratio defined as market value of equity (CSHO x PRCC_F) divided by common equity (CEQ).
ROA	Return-on-assets measured as net income (NI) divided by total assets (AT).
LOSS	An indicator variable coded 1 if ROA is less than zero, and 0 otherwise.
INVREC	Receivables and inventory ratios, defined as (accounts receivable (RECT) + inventory (INVT))/total assets (AT).
QUICK_R	Quick ratio defined as current assets (ACT) minus inventory (INVT) divided by current liabilities (LCT).

(continued on next page)

(continued)

varianceLemmanTANOIBLemmanPORSLAPForeign sales, defined as net property, plant, and equipment (PENT) divided by total assets (AT).PORSLAPForeign sales, defined as the properties of alse by foreign segments (Computed segment (Computed segment (Computed Segment Computed Segment (Computed Segment Computed Segment Segment Computed Segment Comp	(communed)	
TANGEAxet tageluing, defined a net property, plant, and equipment (DPENT) divided by footal assets (AT).PONSULEProfest soles, defined a net by properts of a sole by foreign assets (Compared Equipment Compared Equipment Compare	Variables	
PORSALEForeign sine, defined as the properties of sales by foreign segments (Compared segment IR).LV SEGThe natural logarithm of the number of business and goographic segments (Compared segment IR).LV SEGA binary variable coded 1 if the frm has non-zero, non-missing pecial terms (SP), and 0 otherwise.SPIThe provides frame of the other of the non-zero, non-missing pecial terms (SP), and 0 otherwise.CULTUREIt provides framework of control of control of the other o	TANGIB	Asset tangibility, defined as net property, plant, and equipment (PPENT) divided by total assets (AT).
$ A_{2} \otimes A_{1} = 0 \ the matrix of the number of homes model in engreen (Comparise) segment (Compa$	FORSALE	Foreign sales, defined as the proportion of sales by foreign segments (Computat segment file).
Aug A many variable code 1 is near the variable of a dimension of a dimension a driving unity of any dimension. Any of any dimension of the sector of the s	LN_SEG	The natural logarithm of the number of business and geographic segments (Compustal segment file).
An analy virtual control in the first and and the state a	ACQ	A binary variable coded 1 if the firm was involved in mergers or acquisitions activity during the year, and 0 otherwise.
Cut Turker of the second energy of even a system vindom. Duta developed by $[1 \neq a \leq (2021)$ and provided by Real II. CUT TURE IF provides for Imave of even even cultures. It is measures and a second even of integrity, quality, repect, and teramwork-related works in the QA section of enrings calls averaged over a 3-year window. Duta developed by 11 et al. (2021) and provided by Kai IJ. DAC Discretionary accurate calculated using the Modified Jones model controlling for Imm performance (Nechow et al., 1998) Storate (et al., 2022) and provided by Kai IJ. DAC We entrance the following equation for all firms in the same industry with at least eight otherwittons for an industry in a particular year: $\frac{ACC_{int}}{(1 + a_{int})} = f_{int} (\frac{1 + a_{int}}{(1 + a_{int})} + p_{int} (\frac{PR_{int}}{(PR_{int})} + p_{int} (RP_{int}) + p_{int} $	CREATIVE	A binary variable coded 1 if the firm has non-zero, non-missing spectral nems (SPI), and 0 onerwise.
CULTUREIt provides for firm-level overall culture. It is measured as the summation of weighted-frequency count of integrity, and provided by Ko II.DACDiscritionary accruate calculated using the Modified Jones model controlling for firm performance (beckwert al., 1998; Rothard et al., 2005). We estimate the following equation for all firms in the same lendestry with at least eight observations for an industry in a particulary year. $T_{N_{cl,1}} = n_{cl}(\frac{-1}{N_{cl,1}}, -1) = \frac{1}{N_{cl}(\frac{-1}{N_{cl,1}}, -1)} = \frac{1}{N_{cl}(\frac{-1}{N_{cl}}, -1)} = \frac{1}{N_{$	GREATIVE	calls averaged over a 3-year window. Data developed by Li et al. (2021) and provided by Kai Li.
reamwork-related words in the QA section of examples of the averaged over a 3-year window. Data developed by Let al. (2022) and provided by Kai L. DAC Uscertinary accruits calculated using the Modified Jones model controlling for firm performance (Dechover al.), 176 app. 2005). We estimate the following equation for all firms in the scale clipt observations for an induction for an intrudue year interval of the section of	CULTURE	It provides for firm-level overall culture. It is measured as the summation of weighted-frequency count of integrity, quality, respect, and
Keil LiExercitionary accruais calculated using the Modified Jones model controlling for firm performance (Dechow et al., 1995; Kolland et al., 2005). We estimate the following equation for all firms in the same industry with at least eight observations for an industry in a particular year: $\frac{AC_{C1}}{T_{A_{L-1}}} = \eta_{A} \left[\frac{AS_{L1}T_{A}}{T_{A_{L-1}}} \right] + r_{A} \left[\frac{(P_{PL})}{T_{A_{L-1}}} \right] + r_{A} ((P_{PL})) + r_{A} (AAD) where ACC is total accruats calculated asemingibule for examples in the same industry inter and discontinued operations (BD minus operating cash flow (OANCP); TA is total asset in year 1; Is SALESis the change in sales from year 1 is year 1; BACLES is the change in accounts receivable from year 1; Is year 1; BACLESis the change in sale from year 1; Is year 1; BACLES is the change in accounts receivable from year 1; Is year 1; Ib year 1; Is $		teamwork-related words in the QA section of earnings calls averaged over a 3-year window. Data developed by Li et al. (2021) and provided by
DAC Uncertainary accruate calculated using the Modified Jones model controlling for firm performance (Dechov et al., 1995; Rohand et al., 2005). We estimate the Bollowing equation for all firms in the same industry with a least eight observations for an industry in a particular year in the change in a control line of the same industry with a particular year. $\frac{ACC_{1,1}}{AC_{1,-1}} = f_{1}\left(\frac{1}{AC_{1,-1}}\right) + r_{1}\left[\frac{SALES_{1,-1}}{ACL_{1,-1}}\right] + r_{1}\left(\frac{RPE_{1,1}}{ACL_{1,-1}}\right) + r_{1}$		Kai Li.
We estimate the following equation for all firms in the same industry with at least eight observations for an industry in a particular year: $\frac{AC_{c1}}{T_{A_{c1}-1}} + \pi_{c1} \left[\frac{A_{c1}}{T_{A_{c1}-1}} + \pi_{$	DAC	Discretionary accruals calculated using the Modified Jones model controlling for firm performance (Dechow et al., 1995; Kothari et al., 2005).
$\frac{AC_{1}}{A_{1-1}} = n_{1} \left(\frac{1}{A_{1-1}}\right) + n_{1} \left[\frac{SALES_{1-1}}{A_{1-1}} + n_{2} \left(\frac{PT_{1}}{A_{1-1}}\right) + r_{2} \left($		We estimate the following equation for all firms in the same industry with at least eight observations for an industry in a particular year:
$\begin{aligned} & \text{Tr}_{A_{k-1}} & (\neg T_{A_{k-1}}) & (\neg T_{$		$\frac{ACC_{i,l}}{ACC_{i,l}} = \gamma_0 \left(\frac{1}{1}\right) + \gamma_1 \left[\frac{\Delta SALES_{i,l} - \Delta RECEIV_{i,l}}{1}\right] + \gamma_2 \left(\frac{PPE_{i,l}}{1}\right) + \gamma_3 (ROA_{i,l-1}) + \epsilon_{i,l} (A.1) \text{ where ACC is total accruals calculated as}$
earning before extraordinate operations (U) minus operating cash 100% (DACL) for a start 1, SALSA is the change in a loss from year 1: to year 1, 2PRC2H is the change in accounts receivable form year 1: to year 1; PRC his the gross property plant & equipment; ROA is the return on assets measured as earnings before extraordinary tiens and discontinued operations for the gross property plant & equipment; ROA is the return on assets measured as earnings before extraordinary tiens and discontinued operations for the gross property plant & equipment; ROA is the return on assets in measured as earnings before extraordinary tiens and discontinued operations (A) 1, Le., DAC – ACC-NAC. LAWSUTT TOT A binary variable coded 1 if avoing the intraorded in the return of the following AA classoptics (Ayoe 2), Financial Reporting (type 49) or Accounting and Auding Enforcement Release (type 54), and 0 otherwise. LAWSUTT TOT A binary variable coded 1 if avoing the intraorded in a code the following AA classoptics. Class Action (type 1), Accounting Malepractic (type 2), antituma (type 6), Margaru (type 30), Financial Reporting (type 40), Bankruptery - Ca 11 (type 30), Accounting and valuing Enforcement Release (type 4), Stock Options backdoning (type 55), Stockholaters Suite (type 52), or Derivative (type 57), and 0 otherwise. Moderating variable REM.ANN The sum of abnormal production (REM PROD); and abnormal discretionary expenses (REM DISX). To measure REM PROD, we first estimate the normal of or production costs during equivalin (A 1) below according to the model developed by Roychowdany (2000). $\frac{PROD}{A_{11}} = q_{11} + a_{11} + a_{12} + a_$		$TA_{i,t-1} TA_{i,t-1} TA_{i,t-1$
Is the change in state many year 1 or year 1 ache. Lin y the change in accounts reconvertione trong year 1 or year 1 prices the gross property paint of wide by total searchs for the same year. The coefficient estimates from Equation (A.1) are used to estimate the non-discretionary component of wide by total accruals (MAC) for our same firms. The directionary accruate are then the restates from equation (A.1), Lo, C = ACC-NDAC. A property the ADAC for our same firms. The directionary accruate are then the restates from equation (A.1), Lo, C = ACC-NDAC. A property the ADAC for our same firms. The directionary accruate are then the restates from equation (A.1), Lo, C = ACC-NDAC. A property the ADAC for our same firms. The directionary accruate are then the restates from equation (A.1), Loy (Pq. 1). Accounting Malpacetic (type 2), Antitust (type 6). Mergens (type 33), Tax (type 43), Financial Reporting (type 48), Bankruptcy - Ch. 11 (type 53), Accounting and Addining Enformment Release (type 44), Stock Options Backdating (type 55), Stockholders Suits (type 62), Initial Public Offering (type 93) or Derivative (type 97), and 0 otherwise. Moderating variable: NEM (ABN The sum of abnormal production (NEM PHOD); and abnormal discretionary expenses (NEM DISX). To measure REM PROD, we first estimate the normal level of ord production costs using equation (A.1) below, according to the model developed by Roychowdhary (2006). <i>PROD_</i> = a_0 + a_1 \frac{1}{A_{-1}} + a_2 \frac{SALES}{A_{-1}} + a_2 \frac{SSALES}{A_{-1}} + a_2 \frac{SSALES}{A_{-1}		earnings before extraordinary items and discontinued operations (IB) minus operating cash flows (OANCF); TA is total assets in year t-1; ASALES
A equipment, Norks in electron of assess instance is sensitively from Equivality infers and usofficient estimates the moment of total accruatio (NDAC) for our sample time. The discretionary accruate are then the residuates from equipation (A.1), i.e., DIC - ACCNDAC.LAWSUITA hanny variable of a fill answer is initiated that is included it and on the 565 mig A comparing Maprecites (type 2), Fanaccial TA hanny variable of a fill answer is initiated that is included it and the 565 mig A comparing Maprecites (Type 2), Fanaccial TA hanny variable of a fill answer is initiated that is included it and the 565 mig A comparing (type 40) Apprecise (Type 3), Accounting Malprecise (type 2), Antracut (type 6). Megress (type 33), Tax (type 43), Fanaccial Happrecise (Type 2), Antracut (type 53), Accounting and Auditing Enforcement Release (type 33), Tax (type 43), Fanaccial Happrecise (type 2), and the type 3), Accounting and Auditing Enforcement Release (type 33), Tax (type 43), Fanaccial Happrecise (type 2), and the type 3), Accounting the formation of the fidulation of the fidulat		is the change in sales from year r-1 to year t; ARELED vis the change in accounts receivable from year r-1 to year t; PPE is the gross property plant from the provide the providet the provide the provide the p
Introduction from our sample firms. The discretionary securals are then the residuals from expansion. (A.1), Le. DAG. ACX.NDAG.LAWSUITAbinary variable codel 11 flowards in builded in our of the following AA categories. Accounting Malpretice (type 2), Enancial Reporting (type 48) or Accounting and Audiling Enforcement Release (type 53), and 0 otherwise.LAWSUIT.TOTA binary variable codel 11 flowards is inducted in one of the following AA categories: Class Action (type 1), Accounting Malpretice (type 2), antitian (type 60), the second of the following AA categories: Class Action (type 1), Accounting and Auditing Enforcement Release (type 54), stock Options Backdating (type 55), stockholders Suits (type 62), linital Public Offering (type 93) or Derivative (type 97), and 0 otherwise.Moderating variablesThe sum of abnormal production (RBM_PROD); and abnormal discretionary expenses (REM_DISX). To measure REM_PROD, we first estimate the normal level of production costs using equation (A.1) leiow, according to the model developed by fixed-workworking (2006).PROD $\frac{PROD}{A_{1-1}} = a_{1-1} + a_{1-1} $		a equipment, NOA is use return to assets measured as earnings before extraordinary items and uscontinued operations for the preceding year divided by total assets for the component of the configured terminate from Equation (A 1) are used to estimate the non-discretionary component of
LANSUITA hinary variable coded 11 lawsuit is initiated that is included in one of the following AA categories. Class Action (type 1), Accounting Malpractice (type 2), Financial Reporting (type 40) of Accounting and Auditing Enforcement Release (type 50), and O otherwise.LANSUIT_TOTA binary variable coded 11 flawsuit is initiated that is included in one of the following AA categories. Class Action (type 1), Accounting Malpractice (type 2), antitiated that is included in one of the following AA categories. Class Action (type 1), Accounting and Auditing Enforcement Release (type 54), Stock Options Backdating (type 55), Stockholders Statis (type 62), Initial Public Offering (type 53) or Derivative (type 97), and 0 otherwise.Moderating variablesThe sum of abnormal production (IREM PROD); and abnormal discretionary expenses (REM DISX). To measure REM PROD, we first estimate the normal level of production costs using equation (A.1) below, according to the model developed by lixychowchury (2006).PROD, $\frac{PROD}{A_{-1}} = a_0 + a_{1-1} + a_{2-1} + a_{2$		unded by total assets for the same sense that the control of the sense is a sense of the sense of the same sense of the same sense of the sense of
Reporting (type 44) or Accounting and Auditing Enforcement Release (type 54), and 0 otherwise.LAWSUIT TOTA binary variable codd 1 if alwayti is initized than or of the following Ac careports: Class Action (type 1), Accounting Malpractice (type 2), antitius (type 63), track (type 33), Tax (type 43), Francial Reporting (type 48), Bankrupty - Ch 11 (type 53), Accounting and Auditing Enforcement Release (type 54), Stock Options Backdating (type 55), Stockholders Suits (type 62), Initial Public Offering (type 93) or Derivative (type 97), and 0 otherwise.Moderating variablesThe sum of abnormal production (RBM PROD); and abnormal discretionary expenses (REM DISX). To measure REM PROD, we first estimate the mormal level of production costs using equation (A.1) below, according to the model developed by Keychowedinary (2006).PDD: $p_{en} = n_{en} + n_{en}^{-1} + q_{en}^{SMLS} + q_{en}^{SML$	LAWSUIT	A binary variable coded 1 if lawsuit is initiated that is included in one of the following AA categories: Accounting Malpractice (type 2). Financial
LAWSUT_TOT A binary variable coded 1 if lawsiit is initiated that is included in one of the following AA categories: Class Action (type 1), Accounting Malprecise (type 2), Antitust (type 5), Stock Dyptons Backdating (type 55), Stockholders Suits (type 62), Initial Public Offering (type 93) or Derivative (type 97), and 0 otherwise. Moderning variable REM ABN The sum of abnormal production (REM PROD); and abnormal discretionary expenses (REM DISC). To measure REM PROD, we first estimate the normal level of production costs using equation (A.1) below, according to the model developed by Roychowdhury (2006). PROD, $= a_{1} + a_{1} + a_{1} + a_{2} \frac{SALS}{A_{1}} + a_{2} \frac{SALAS}{A_{1}} + a_{2} \frac$		Reporting (type 48) or Accounting and Auditing Enforcement Release (type 54), and 0 otherwise.
Malpractice (type 23), Anitrust (type 6), Mergers (type 33), Tax (type 43), Enancial Reporting (type 48), Enankrupty - Ch 11 (type 52), Accounting and Auditing Edirochement Release (type 54), Stock Options Backdating (type 55), Stockholders Suits (type 62), Initial Public Offering (type 93) or Derivative (type 97), and 0 otherwise.Moderating variablesREM_AINThe sum of abnormal production (REM_PROD); and abnormal discretionary expenses (REM_DISX). To measure REM_PROD, we first estimate the normal level of production (osts Suits); equation (A.1) below, according to the model developed by Ricychowdhury (2006). $\frac{PROD}{A_{i-1}} = a_0 + a_{i}\frac{1}{A_{i-1}} + a_{i}\frac{SALES}{A_{i-1}} + a_{i-1}\frac{A_{i-1}}{A_{i-1}} + a_{i}\frac{SALES}{A_{i-1}} = A_{i-i}\frac{A_{i-1}}{A_{i-1}} + a_{i-i}\frac{SALES}{A_{i-1}} = A_{i-i}\frac{A_{i-i}}{A_{i-1}} + a_{i-i}\frac{SALES}{A_{i-1}} = A_{i-i}\frac{A_{i-i}}{A_{i-1}} + a_{i-i}\frac{SALES}{A_{i-1}} = A_{i-i}\frac{A_{i-i}}{A_{i-i}} + a_{i-i}\frac{SALES}{A_{i-i}} = A_{i-i}A_{i-i} + a_{i-i}\frac{SALES}{A_{i-i}} = A_{i-i}A_{i-i} + a_{i-i}\frac{SALES}{A_{i-i}} = A_{i-i}A_{i-i} + a_{i-i}\frac{SALES}{A_{i-i}} + a_{i-i}A_{i-i} + a_{i-i}A$	LAWSUIT_TOT	A binary variable coded 1 if lawsuit is initiated that is included in one of the following AA categories: Class Action (type 1), Accounting
Accounting and Auditing Enforcement Release (type 54), Stock Options Backdating (type 55), Stockholders Suits (type 62), Initial Public Offering (type 93) or Derivative (type 97), and 0 otherwise.Moderning variablesREM ABNThe sum of ahnormal production (REM PROD); and abnormal discretionary expenses (REM DISX). To measure REM PROD, we first estimate the normal level of production costs using equation (A.1) below, according to the model developed by Roychowdhury (2006). $\frac{PROD}{A_{A_1}} = a_b + a_1 \frac{A_{A_1}}{A_{A_1}} + a_b \frac{SSLES^{-1}}{A_{A_1}} (A_2)$ where PROD, is the sum of the cost of goods sold in year t and the change in inventory from t 1 to (A, A, and A_{A_1}) + a_b (SALES^{-1}) (A_2) where PROD, is the sum of the cost of goods sold in year t and the change in inventory from t 1 to (A, A, and A_{A_1}) + a_b (SALES^{-1}) (A_2) where PROD, is the sum of the cost of goods sold in year t and the change in inventory from t 1 to (A, A, and A_{A_1}) + a_b (SALES^{-1}) (A_2) where PROD, is the sum of the cost of goods sold in year t and the change in inventory from t 1 to (A, A, and A_{A_1}) + a_b (SALES^{-1}) (A_2) where PROD, we first measure the normal level of discretionary expenses (REM DISX) using equation (A.3) below. DEXES = a_b + a_{A_1} + a_b (SALE^{-1}) (A_3) where DISX, are the discretionary expenses (Le, the sum to RAD, Advertising, and SGA expenditure) In year. If we hands expection within the value of REM. REM ABD A binary variable coded 1 if the value of REM. ABD A binary variable coded 1 if the value of REM. DEXES = a_b + a_{A_1} + a_b (SALE^{-1}) (A_2) + A(A) where CPO, is the cash flow from operations in year t. The ACFO is the residual from the abver regression. We multiply the residual by -1 so that the higher values indicate greater annount of discretionary expenses cont down and, hence, higher REM.REM_TOTComposite REM score accluat		Malpractice (type 2), Antitrust (type 6), Mergers (type 33), Tax (type 43), Financial Reporting (type 48), Bankruptcy - Ch 11 (type 53),
Offering (type 93) or Derivative (type 97), and 0 otherwise.Moderating variablesREM_ABNThe sum of abnormal production (REM_PROD): and abnormal discretionary expenses (REM_DISX). To measure REM_PROD, we first estimate the normal level of production costs using equation (A.1) below, according to the model developed by Rychowdhury (2006). $ROD_{A_{1-1}} = a_0 + a_1 \frac{1}{A_{1-1}} + a_0 \frac{SMLS}{A_{1-2}} + a_0 \frac{SSMLS}{A_{1-2}} + a_0 \frac{SMLS}{A_{1-1}} + (A_{2-1}) where PROD, is the sum of the cost of goods sold in year r and the changein lineatory or m e1 to c. A1-1 is the total access in year e1. Soles, is the net sales in year r, Sales, is the change in net sales from year r 1 to r.Equation (A.2) is estimated rous-sectionally for each industry year with a least 15 observations. The abnormal level of discretionary production(REM_PROD) is measured as the estimated residual from the regression.Similarly, following (loc)chowdhury (2006), we first measure the normal level of discretionary expenses (I.e., the sum of R&D, advertising, and SGAA expenditure)in year r. Iv estimate equation (A.3) below.\frac{DISX_{i-1}}{A_{i-1}} = a_0 + a_{i-1} + a_{$		Accounting and Auditing Enforcement Release (type 54), Stock Options Backdating (type 55), Stockholders Suits (type 62), Initial Public
Moderating variablesREM ABNThe sum of abnormal production (REM, PROD); and abnormal discretionary expenses (REM, DISX). To measure REM, PROD, we first estimate the normal level of production cests using equation (A.1) below, according to the model developed by Roychowdhury (2006). $PROD_{A_{1-1}} = a_0 + a_{1-1} + a_2 \frac{SALES}{A_{1-1}} + a_2 \frac{SALES}{$		Offering (type 93) or Derivative (type 97), and 0 otherwise.
Moderating variablesREM, ABNThe sum of abnormal production (REM, PROD); and abnormal discretionary expenses (REM, DISX). To measure REM, PROD, we first estimate the normal level of production costs using equation (A.1) below, according to the model developed by Bychowdhury (2006). $PROD_{A_{-1}} = a_0 + a_1 \frac{1}{A_{0-1}} + a_2 \frac{SALES}{A_{1-1}} + a_3 \frac{SALES}{A_{1-1}} + a_4 \frac{SALES}{A_{1-1}} + (A_2, A) where PROD, is the sum of the cost of goods sold in year t and the change in inventory from 6-1 to t, A_{-1} is the total assets in year t, 15 abse, is the net sales in year t, 25 adse, is the change in net sales from year t-1 to t.Equation (A.2) is estimated cross-sectionally for each industry-year with at least 15 observations. The abnormal level of discretionary production (REM, PROD) is measured as the estimated residual from the regression.Similarly, following itorychowdhury (2006), we first measure the normal level of discretionary expenses (IEM, DISX) using equation (A.3) below.\frac{DISX}{A_{1-1}} = a_0 + a_{1-1} + a_{1-1}^{SALES} + (A_{1-1}) where DISX, are the discretionary expenses (IEM, DISX). The abnormal level of DISX is the estimated residual from the regression. We multiply the residuals by -1 so that the higher values indicate greater amounts of discretionary expenses (IEM, DISX).REM, ABN DA binary variable coded 1 if the value of REM ADIS A ACDFO to calculate abnormal ICO, we first measure the normal levels of CFO, using the following cross-sectional regression for each industry and year with at least 15 observations.REM_TOTComposite REM score calculated as APDOD + ADISX + ACDFO to calculate abnormal ICO, we first measure the normal levels of CFO, using the following cross-sectional regression. We multiply the residuals by -1 so that higher values at REM.REM_TOTA binary variable coded 1 if the value of RE$		
Moderating variablesREM ABNThe sum of abnormal production (REM PROD); and abnormal discretionary expenses (REM DISX). To measure REM PROD, we first estimate the normal level of production costs using equation (A.1) below, according to the model developed by Roychowdhury (2006). $PROD_{ra,-1} = a_0 + a_1 A_{ca} + a_0 \frac{SALES}{A_{ca,-1}} + a_0 \frac{SALES}{A_{ca,-1}} + a_1 A_{ca} + a_{ca} (A.2) where PROD, is the sum of the cost of goods sold in year t and the change in inventory from t-1 to t. A.1, a is the total assets in year t-1, Sales, is the net sales in our t, A.2) is estimated cross-sectionally for each industry-year with at least 15 observations. The abnormal level of discretionary production (REM PROD) is measured as the estimated residual from the regression.Nimilarly, following Roychowdhury (2006), we first measure the normal level of discretionary expenses (REM DISX) using equation (A.3) below.\frac{DISX}{A_A} = a_0 + a_{1,\frac{1}{A_A}} + a_0 \frac{SALES + 1}{A_A} (A.3) where DISX, are the discretionary expenses (REM DISX) using equation (A.3) below.\frac{DISX}{A_A} = a_0 + a_{1,\frac{1}{A_A}} + a_0 \frac{SALES + 1}{A_{A_A}} (A.3) where DISX, are the discretionary expenses (REM DISX) observations. The abnormal level of DISX is the estimated residual from the regression.NEM ABN DA binary variable coded 11 fit wavalue of REM ABN is above median, and 0 otherwise.REM_TOTComposite REM score calculated as APROD + ADISX + ACFO. To calculate abnormal level, we have normal levels of CPO, using the following cross-sectional regression free action HOT to above regression.REM TOTA binary variable coded 11 fit wavalue of REM TOT is above median, and 0 otherwise.ARN, VOLB hinary variable coded 11 fit wavalue of REM TOT is above median, and 0 otherwise.EARN, VOL, DA binary variable coded 11 fit$	M. 1	
The model developed by Roychow that Section 2 (200), where the section 2 (200), the section	Moderating varia	Jes The sum of abnormal production (PEM DPOD): and abnormal discretionary expenses (PEM DISY). To measure PEM DPOD, we first estimate the
PROD: PROD: At-1 = $a_0 + a_1 + a_2 + a_2 + a_1 + a_2 + a_2 + a_1 + a_2 + a_1 + a_1 + a_2 + a_1 + a_2 + a_1 + a_1$	REW_ADN	normal level of production (using rOO), and ability according to the model developed by Roychowdbury (2006)
$\frac{1}{A_{k-1}} = a_0 + a_1 \frac{1}{A_{k-1}} + a_2 \frac{1}{A_{k-1}} + a_3 - \frac{1}{A_{k-1}} + a_4 - \frac{1}{A_{k-1}} + a_4 - \frac{1}{A_{k-1}} + a_{k-1} + a_{k-1$		PROD 1 SALES ASSALES ASALES ASALES - ASALES - 1
in inventory from i 1 to 1, A, is the total assets in year t-1, Sales, is the net sales in year t, Asles, is the net sales the summary expenses (i.e., the summary expenses (i.e., the sum of R&D, Dis) is measured as the estimated residual from the regression.Similarly, following Roychowdhury (2006), we first measure the normal level of discretionary expenses (I.e., the sum of R&D, Dis) is measured as the estimated residual from the regression.Similarly, following Roychowdhury (2006), we first measure the normal level of discretionary expenses (I.e., the sum of R&D, advertising, and S&A expenditure)in year, t. We estimate equation (A.3) cross-sectionally for industry-years with at least 15 observations. The abnormal level of DISX is the estimated residual from the regression. We multiply the residuals by -1 so that the higher values indicate greater amounts of discretionary expenses cut down and, hence, higher REM.REM, ABN, DA binary variable coded 1 if the value of REM, ABN is above median, and 0 otherwise.Composite REM score calculated as APROD + ADISX + ACFO. To calculate abnormal ICO, we first measure the normal levels of CFO, using the following cross-sectional argeression for each industry and year with at least 15 observations:CFO ₁ A ₁₋₁ = a ₀ + a ₁ A ₁₋₁ + a ₂ SALES ₁₋₁ + a ₂ SALES ₁₋₁ (A.4) where CFO, is the cash flow from operations in year t. The ACFO is the residual from the above regression. We multiply the residual by -1 so that higher values imply greater REM.REM, TOT, DA binary variable coded 1 if the value of REM, TOT is above median, and 0 otherwise.EARN, VOLEarnings volatility, another proxy for risk-taking of firm in year t. The calculation involves two steps (Gupta & Krishnamurti, 2018). First, we calculate difference between firm-level EBITDA scaled by total asset and country-le		$\frac{1}{A_{t-1}} = a_0 + a_1 \frac{1}{A_{t-1}} + a_2 \frac{1}{A_{t-1}} + a_3 \frac{1}{A_{t-1}} + a_4 \frac{1}{A_{t-1}} + a_$
Equation (A.2) is estimated cross-sectionally for each industry-year with at least 15 observations. The abnormal level of discretionary production (REM PROD) is measure das the estimated residual from the regression. Similarly, following Roy-howdhury (2006), we first measure the normal level of discretionary expenses (REM_DISX) using equation (A.3) below. $\frac{DISX}{A_{c}} = a_{0} + a_{1}^{-1} + a_{c} \frac{SALBE_{c-1}}{A_{c-1}} (A.3)$ where DISX, are the discretionary expenses (i.e., the sum of R&D, advertising, and SG&A expenditure) in year t. We estimate equation (A.3) cross-sectionally for industry-years with at least 15 observations. The abnormal level of DISX is the estimated residual from the regression. We multiply the residuals by -1 so that the higher values indicate greater amounts of discretionary expenses cut down and, hence, higher REM. REM, ABN, D A binary variable coded 1 if the value of REM_ABN is above median, and 0 otherwise. Group cite REM score calculated as APROD + ADISX + ACPO. To calculate abnormal CPO, we first measure the normal levels of CPO, using the following cross-sectional regression for each industry and year with at least 15 observations: $\frac{CPO_{t}}{A_{t-1}} = a_{t} + a_{t}\frac{3}{A_{t-1}} + a_{2}\frac{3ALES}{A_{t-1}} + a_{2}\frac{3A_{t-1}}{A_{t-1}} + a_{2}\frac{3ALES}{A_{t-1}} + a_{2}\frac{3A_{t-1}}{A_{t-1}} + a_{2}\frac{3A_{t-1}}{A_{t-1}} + a_{2}\frac{3A_{t-1}}{A_{t-1}} + a_{2}\frac{3A_{t-1}}{A_{t-1}} + a_{2}\frac{3A_{t-1}}{A_{t-1}} + a_{2}\frac{3A_{t-1}}{A_{t-1}} + a$		in inventory from t-1 to t, At-1 is the total assets in year t-1, Sales, is the net sales in year t, Δ Sales, is the change in net sales from year t-1 to t.
(REM PROD) is measured as the estimated residual from the regression.Similarly, following Roychowdhury (2006), we first measure the normal level of discretionary expenses (REM,DISX) using equation (A.3) below. $\frac{DISX}{Dist}_{i} = a_0 + a_1 \frac{1}{A_{i-1}} + a_2 \frac{SALES_{i-1}}{A_{i-1}}$ (A.3) where DISX, are the discretionary expenses (i.e., the sum of RAD, advertising, and SG&A expenditure)in year t. We estimate equation (A.3) cross-sectionally for industry-years with at least 15 observations. The abnormal level of DISX is the estimated residual from the regression. We multiply the residuals by -1 so that the higher values indicate greater amounts of discretionary expenses cut down and, hence, higher REM.REM,ABN,DA binary variable coded 1 if the value of REM,ABN is above median, and 0 otherwise.REM_TOTComposite REM score calculated as APROD + ADISX + AFCO. To calculate abnormal CFO, we first measure the normal levels of CFO, using the following cross-sectional regression for each industry and year with at least 15 observations: $\frac{CFD}{A_{i-1}} = a_0 + a_i \frac{1}{A_{i-1}} + a_2 \frac{SALES_i}{A_{i-1}} + a_{i-1} (A.4) where CFO, is the cash flow from operations in year t. The ACFO is the residual from the above regression. We multiply the residual by -1 so that higher values imply greater REM.REM TOT D.A binary variable coded 1 if the value of REM TOT is above median, and 0 otherwise.EARN,VOLEarnings volatility, a proxy for risk-taking of firm in year t. The calculation involverage EBITDA scaled by total asset. Next, we take the standard deviation of this difference over the last five years.EARN,VOL,DA binary variable coded 1 if the value of EANN VOL is above median, and 0 otherwise.EARN,VOL,DA binary variable coded 1 if the value of EANN VOL is above median, and 0 otherwise$		Equation (A.2) is estimated cross-sectionally for each industry-year with at least 15 observations. The abnormal level of discretionary production
Similarly, following hoychowdhury (2006), we first measure the normal level of discretionary expenses (REM_DISX) using equation (A.3) below. $\frac{DSX_{1}}{A_{1}} = a_{0} + a_{1} \frac{1}{A_{1-1}} + a_{2} \frac{SALES_{1-1}}{A_{1-1}} (A.3) where DISX, are the discretionary expenses (i.e., the sum of R&D, advertising, and SG&A expenditure) in year t. We estimate equation (A.3) cross-sectionally for industry-years with at least 15 observations. The abnormal level of DISX is the estimated residual from the regression. We multiply the residuals by -1 so that the higher values indicate greater amounts of discretionary expenses cut down and, hence, higher REM. REM ABN D A binary variable coded 1 if the value of REM_ABN is above median, and 0 otherwise. REM TOT Composite REM score calculated as APROD + ADISX + ACFO. To calculate abnormal CFO, we first measure the normal levels of CFO, using the following cross-sectional regression for each industry and year with at least 15 observations: \frac{CPO_{1}}{A_{r-1}} = a_{0} + a_{1} \frac{A_{r-1}}{A_{r-1}} + a_{r} \frac{\Delta SALES_{1}}{A_{r-1}} - (A_{r}) + a_{r} \frac{\Delta SALES_{1}}{A_{r-1}} - a_{r} \frac{\Delta SALES_{1}}{A_{r-1}} + a_{r} \frac{\Delta SALES_{1}}{A_{$		(REM_PROD) is measured as the estimated residual from the regression.
$\frac{DDSA_{t}}{A_{t}} = a_{0} + a_{1}\frac{1}{A_{t-1}} + a_{2}\frac{SAL2S-1}{A_{t-1}} (A.3) where DISXt are the discretionary expenses (i.e., the sum of R&D, advertising, and SG&A expenditure) in year t. We estimate equation (A.3) cross-sectionally for industry-years with at least 15 observations. The abnormal level of DISX is the estimated residual from the regression. We multiply the residuals by -1 so that the higher values indicate greater amounts of discretionary expenses cut down and, hence, higher REM. REM_ABN_D A binary variable codel 1 if the value of REM_ABN is above median, and 0 otherwise. REM_TOT Composite REM score calculated as APROD + ADISX + ACCO. To calculate abnormal CPO, we first measure the normal levels of CFO, using the following cross-sectional regression for each industry and year with at least 15 observations: \frac{CFO_{i}}{A_{i-1}} = a_{0} + a_{1}\frac{1}{A_{i-1}} + a_{2}\frac{SALES}{A_{i-1}} - (A.4) where CFO, is the cash flow from operations in year t. The ACFO is the residual from the above regression. We multiply the residual by -1 so that higher values imply greater REM. REM_TOT_D A binary variable coded 1 if the value of REM_TOT is above median, and 0 otherwise. EARN_VOL Earnings volatility, a proxy for risk-taking of firm in year t. The calculation involves two steps (Gupta & Krishnamurti, 2018). First, we calculate difference between firm-level EBITDA scaled by total asset and county-level average EBITDA scaled by total asset. Next, we take the standard deviation of this difference over the last five years. EARN_VOL_D A binary variable coded 1 if the value of EARN_VOL is above median, and 0 otherwise. AST_VOL Asset volatility, another proxy for risk-taking of firm in year t. AST_VOL is measured as the standard deviation of the stock return during the fiscal year times the market value of OXN NFCC, F). All divided by the market value of assets (CSHO x PRCC, F + AT - CEQ). AST_VOL_D A binary variable coded 1 if the value of AST_VOL is above median, and 0 otherwise. IOWN The perc$		Similarly, following Roychwdhury (2006), we first measure the normal level of discretionary expenses (REM_DISX) using equation (A.3) below.
 At. At. At. At. At. At. At. At. At. At.		$\frac{DISX_t}{\Delta t} = \alpha_0 + \alpha_1 \frac{1}{4} + \alpha_2 \frac{\Delta ALES_{t-1}}{4}$ (A.3) where DISX _t are the discretionary expenses (i.e., the sum of R&D, advertising, and SG&A expenditure)
estimated residual from the regression. We multiply the residuals by -1 so that the higher values indicate greater amounts of discretionary expenses cut down and, hence, higher REM. REM_ABN A binary variable coded 1 if the value of REM_ABN is above median, and 0 otherwise. REM_TOT Composite REM score calculated as APROD + ADISX + ACFO. To calculate abnormal CFO, we first measure the normal levels of CFO, using the following cross-sectional regression for each industry and year with at least 15 observations: $\frac{CFO}{A_{t-1}} = a_0 + a_1 \frac{1}{A_{t-1}} + a_2 \frac{SALES}{A_{t-1}} + (A_2 \frac{SALES}{A_{t-1}}) + (A_2$		$A_t = A_{t-1} = A_{t-1}$ in year t We estimate equation (A 3) cross-sectionally for industry-years with at least 15 observations. The abnormal level of DISX is the
expenses cut down and, hence, higher REM.The transformation of the second of the transformation of the second of the		estimated residual from the regression. We multiply the residuals by -1 so that the higher values indicate greater amounts of discretionary
REM_ABN_DA binary variable coded 1 if the value of REM_ABN is above median, and 0 otherwise.REM_TOTComposite REM score calculated as APROD + ADISX + ACFO. To calculate abnormal CFO, we first measure the normal levels of CFO, using the following cross-sectional regression for each industry and year with at least 15 observations: $\frac{CFO_t}{A_{t-1}} = a_0 + a_t \frac{1}{A_{t-1}} + a_2 \frac{SALES_t}{A_{t-1}} + a_2 \frac{SALES_t}{A_{t-1}} (A.4) where CFO, is the cash flow from operations in year t. The ACFO is the residual from theabove regression. We multiply the residual by -1 so that higher values imply greater REM.REM_TOT_DA binary variable coded 1 if the value of REM_TOT is above median, and 0 otherwise.EARN_VOLEarnings volatility, a proxy for risk-taking of firm i ny eart t. The calculation involves two steps (Gupta & Krishnamurti, 2018). First, we calculatedifference between firm-level EBITDA scaled by total asset and county-level average EBITDA scaled by total asset. Next, we take the standarddeviation of this difference over the last five years.EARN_VOLA binary variable coded 1 if the value of EARN_VOL is above median, and 0 otherwise.AST_VOLA binary variable coded 1 if the value of AST_VOL is above median, and 0 otherwise.IOWNThe percentage of common shares held by institutional investors. Data retrieved from Thomson Reuter's F13 File.IOWN_DA binary variable coded 1 if the value of FOLLOW is below median, and 0 otherwise.FOLLOWThe number of analysts following a firm. Data retrieved from Themson Reuter's F13 File.IOWN_DA binary variable coded 1 if the value of FOLLOW is below median, and 0 otherwise.FOLLOW_DA binary variable coded 1 if the value of FOLLOW is below median, and 0 otherwise.$		expenses cut down and, hence, higher REM.
REM_TOTComposite REM score calculated as APROD + ADISX + ACFO. To calculate abnormal CFO, we first measure the normal levels of CFO, using the following cross-sectional regression for each industry and year with at least 15 observations: $\frac{CFO_1}{A_{t-1}} = a_0 + a_1 \frac{1}{A_{t-1}} + a_2 \frac{\Delta SALES_t}{A_{t-1}}$ $(A.4)$ where CFO _t is the cash flow from operations in year t. The ACFO is the residual from the above regression. We multiply the residual by -1 so that higher values imply greater REM.REM_TOT_DA binary variable coded 1 if the value of REM_TOT is above median, and 0 otherwise.EARN_VOLEarnings volatility, a proxy for risk-taking of firm <i>i</i> in year t. The calculation involves two steps (Gupta & Krishnamurti, 2018). First, we calculate deviation of this difference over the last five years.EARN_VOL_DA binary variable coded 1 if the value of EARN_VOL is above median, and 0 otherwise.AST_VOLAsset volatility, another proxy for risk-taking of firm <i>i</i> in year t. ATS_VOL is measured as the standard deviation of the stock return during the fiscal year times the market value of equity (CSHO x PRCC_F), all divided by the market value of assets (CSHO x PRCC_F + AT - CEQ).AST_VOL_DA binary variable coded 1 if the value of AST_VOL is above median, and 0 otherwise.IOWNThe percentage of common shares held by institutional investors. Data retrieved from Thomson Reuter's F13 File.IOWNA binary variable coded 1 if the value of FOLLOW is below median, and 0 otherwise.FOLLOW_DA binary variable coded 1 if the value of FOLLOW is below median, and 0 otherwise.FOLLOW_DA binary variable coded 1 if the value of FOLLOW is below median, and 0 otherwise.FOLLOW_DA binary variable coded 1 if the value of	REM_ABN_D	A binary variable coded 1 if the value of REM_ABN is above median, and 0 otherwise.
following cross-sectional regression for each industry and year with at least 15 observations: $\frac{CPO_t}{A_{t-1}} = a_0 + a_t \frac{1}{A_{t-1}} + a_2 \frac{\Delta SALES_t}{A_{t-1}} + a_2 \frac{\Delta SALES_t}{A_{t-1}}} + a_2 \frac{\Delta SALES_t}{A_{t-1}} + a_2 \frac{\Delta SALES_t}{A_{t-1}}} + a_2 \frac{\Delta SALES_t}{A_{t-1}} + a_2 \frac{\Delta SALES_t}{A_{t-1}}} + a_2 \frac{\Delta SALES_t}{A_{t-1}} + a_2 \frac{\Delta SALES_t}{A_$	REM_TOT	Composite REM score calculated as APROD + ADISX + ACFO. To calculate abnormal CFO, we first measure the normal levels of CFO, using the
$\frac{CPO_t}{A_{t-1}} = a_0 + a_1 \frac{1}{A_{t-1}} + a_2 \frac{SALES_t}{A_{t-1}} + a_2 \frac{SALES_t}{A_{t-1}} (A.4) where CFO_t is the cash flow from operations in year t. The ACFO is the residual from the above regression. We multiply the residual by -1 so that higher values imply greater REM. REM_TOT_D A binary variable coded 1 if the value of REM_TOT is above median, and 0 otherwise. EARN_VOL Earnings volatility, a proxy for risk-taking of firm i in year t. The calculation involves two steps (Gupta & Krishnamurti, 2018). First, we calculate difference between firm-level EBITDA scaled by total asset and county-level average EBITDA scaled by total asset. Next, we take the standard deviation of this difference over the last five years. EARN_VOL,D A binary variable coded 1 if the value of EARN_VOL is above median, and 0 otherwise. AST_VOL Asset volatility, another proxy for risk-taking of firm i in year t. AST_VOL is measured as the standard deviation of the stock return during the fiscal year times the market value of equity (CSHO x PRCC_F), all divided by the market value of assets (CSHO x PRCC_F + AT – CEQ). AST_VOL_D A binary variable coded 1 if the value of XD_VOL is above median, and 0 otherwise. IOWN The percentage of common shares held by institutional investors. Data retrieved from Thomson Reuter's F13 File. IOWN The number of analysts following a firm. Data retrieved from IBES. FOLLOW A binary variable coded 1 if the value of FOLLOW is below median, and 0 otherwise. Additional control variables SC Social capital index using two variants of social norms and two measures of networks for each county for the years 1997, 2005, 2009 and 2014. The two measures of social norms are voter turnout in presidential elections and the census response rate. Higher values for these variables represent higher social capital. The two measures of networks are the number of social and civic associations and the massing years 1998–2004; and 2006 to 2008, 2010 to 2013; and 2015 to 2019 (Rupasingha et al., 2000; Rupasing$		following cross-sectional regression for each industry and year with at least 15 observations:
 A_{t-1} A_{t-1} A_{t-1} A_{t-1} A_{t-1} above regression. We multiply the residual by -1 so that higher values imply greater REM. REM_TOT_D A binary variable coded 1 if the value of REM_TOT is above median, and 0 otherwise. EARN_VOL Earnings volatility, a proxy for risk-taking of firm <i>i</i> in year <i>t</i>. The calculation involves two steps (Gupta & Krishnamurti, 2018). First, we calculate difference between firm-level EBITDA scaled by total asset and county-level average EBITDA scaled by total asset. Next, we take the standard deviation of this difference over the last five years. EARN_VOL_D A binary variable coded 1 if the value of EARN_VOL is above median, and 0 otherwise. AST_VOL Asset volatility, another proxy for risk-taking of firm <i>i</i> in year <i>t</i>. AST_VOL is measured as the standard deviation of the stock return during the fiscal year times the market value of AST_VOL is above median, and 0 otherwise. AST_VOL_D A binary variable coded 1 if the value of AST_VOL is above median, and 0 otherwise. IOWN The percentage of common shares held by institutional investors. Data retrieved from Thomson Reuter's F13 File. IOWN_D A binary variable coded 1 if the value of FOLLOW is below median, and 0 otherwise. FOLLOW The number of analysts following a firm. Data retrieved from IBES. FOLLOW J A binary variable coded 1 if the value of FOLLOW is below median, and 0 otherwise. Additional control variables SC Social capital index using two variants of social norms and two measures of networks for each county for the years 1997, 2005, 2009 and 2014. The two measures of social norms are voter turnout in presidential elections and the census response rate. Higher values for these variables represent higher social capital for each county for the years 1997, 2005, 2009 and 2014. A linear interpolation fills the missing years 1998–2004; and 2006 to 2008, 2010 to 2013; and		$\frac{CFO_t}{t} = a_0 + a_1 \frac{1}{t} + a_2 \frac{SALES_t}{t} + a_2 \frac{ASALES_t}{t}$ (A.4) where CFO _t is the cash flow from operations in year t. The ACFO is the residual from the
 A binary variable coded 1 if the value of FARN_TOL is above median, and 0 otherwise. EARN_VOL Earnings volatility, a proxy for risk-taking of firm <i>i</i> in year <i>t</i>. The calculation involves two steps (Gupta & Krishnamurti, 2018). First, we calculate difference between firm-level EBITDA scaled by total asset and county-level average EBITDA scaled by total asset. Next, we take the standard deviation of this difference over the last five years. EARN_VOL_D A binary variable coded 1 if the value of EARN_VOL is above median, and 0 otherwise. AST_VOL Asset volatility, another proxy for risk-taking of firm <i>i</i> in year <i>t</i>. AST_VOL is measured as the standard deviation of the stock return during the fiscal year times the market value of equity (CSHO x PRCC_P), all divided by the market value of assets (CSHO x PRCC_F + AT – CEQ). A binary variable coded 1 if the value of AST_VOL is above median, and 0 otherwise. IOWN The percentage of common shares held by institutional investors. Data retrieved from Thomson Reuter's F13 File. IOWN D A binary variable coded 1 if the value of FOLLOW is below median, and 0 otherwise. FOLLOW A binary variable coded 1 if the value of FOLLOW is below median, and 0 otherwise. SC Social capital index using two variants of social norms and two measures of networks for each county for the years 1997, 2005, 2009 and 2014. The two measures of social norms are voter turnout in presidential elections and the census response rate. Higher values for these variables represent higher social capital. The two measures of networks are the number of social and civic associations and the missing years 1998–2004; and 2006 to 2008, 2010 to 2013; and 2015 to 2019 (Rupasingha et al., 2000; Rupasingha & Goetz, 2008). CORRUP Corruption measured as state-level adherents divided by state-level population. Data collected from the Association of Religious Data Archives (ARDA) (https://www.the		$A_{t-1} = A_{t-1} = A_{t-1} = A_{t-1} = A_{t-1}$
 EARN_VOL Earnings volatility, a proxy for risk-taking of firm i in year t. The calculation involves two steps (Gupta & Krishnamurti, 2018). First, we calculate difference between firm-level EBITDA scaled by total asset and county-level average EBITDA scaled by total asset. Next, we take the standard deviation of this difference over the last five years. EARN_VOL_D A binary variable coded 1 if the value of EARN_VOL is above median, and 0 otherwise. AST_VOL Asset volatility, another proxy for risk-taking of firm i in year t. AST_VOL is measured as the standard deviation of the stock return during the fiscal year times the market value of equity (CSHO x PRCC_F), all divided by the market value of assets (CSHO x PRCC_F + AT – CEQ). AST_VOL_D A binary variable coded 1 if the value of AST_VOL is above median, and 0 otherwise. IOWN The percentage of common shares held by institutional investors. Data retrieved from Thomson Reuter's F13 File. IOWN D A binary variable coded 1 if the value of FOLLOW is below median, and 0 otherwise. FOLLOW D A binary variable coded 1 if the value of FOLLOW is below median, and 0 otherwise. FOLLOW D A binary variable coded 1 if the value of FOLLOW is below median, and 0 otherwise. Additional control variables SC Social capital index using two variants of social norms and two measures of networks for each county for the years 1997, 2005, 2009 and 2014. The two measures of networks are the number of social and civic associations and the number of nongovernment organisations in counties. Both of these measures are normalized by the population in the county. A principal component analysis is used to construct an index of social capital for each county for the years 1997, 2005, 2008). CORRUP CORRUP Corruption mea	REM TOT D	above regression, we multiply the restorated by -1 so that matter values many greater rest.
difference between firm-level EBITDA scaled by total asset and county-level average EBITDA scaled by total asset. Next, we take the standard deviation of this difference over the last five years.EARN_VOL_DA binary variable coded 1 if the value of EARN_VOL is above median, and 0 otherwise.AST_VOLAsset volatility, another proxy for risk-taking of firm i in year t. AST_VOL is measured as the standard deviation of the stock return during the fiscal year times the market value of equity (CSHO x PRCC_F), all divided by the market value of assets (CSHO x PRCC_F + AT – CEQ).AST_VOL_DA binary variable coded 1 if the value of AST_VOL is above median, and 0 otherwise.IOWNThe percentage of common shares held by institutional investors. Data retrieved from Thomson Reuter's F13 File.IOWN DA binary variable coded 1 if the value of FOLLOW is below median, and 0 otherwise.FOLLOW The number of analysts following a firm. Data retrieved from IBES.FOLLOW DA binary variable coded 1 if the value of FOLLOW is below median, and 0 otherwise.Additional control variablesSCSocial capital index using two variants of social norms and two measures of networks for each county for the years 1997, 2005, 2009 and 2014. The two measures of social capital. The two measures of networks are the number of social and civic associations and the number of nongovernment organisations in counties. Both of these measures are normalized by the population in the county. A principal component analysis is used to construct an index of social capital for each county for the years 1997, 2005, 2008).CORRUPCorruption measured as state-level corruption conviction scaled by state-level population itimes 100,000. Data obtained from Report to Congress on the activities a	EARN VOL	Earning's volatility, a proxy for risk-taking of firm in year t. The calculation involves two steps (Gupta & Krishnamurti, 2018). First, we calculate
deviation of this difference over the last five years.EARN_VOL_DA binary variable coded 1 if the value of EARN_VOL is above median, and 0 otherwise.AST_VOLAsset volatility, another proxy for risk-taking of firm i in year t. AST_VOL is measured as the standard deviation of the stock return during the fiscal year times the market value of equity (CSHO x PRCC_F), all divided by the market value of assets (CSHO x PRCC_F + AT – CEQ).AST_VOL_DA binary variable coded 1 if the value of AST_VOL is above median, and 0 otherwise.IOWNThe percentage of common shares held by institutional investors. Data retrieved from Thomson Reuter's F13 File.IOWN_DA binary variable coded 1 if the value of IOWN is below median, and 0 otherwise.FOLLOWThe number of analysts following a firm. Data retrieved from IBES.FOLLOW DA binary variable coded 1 if the value of FOLLOW is below median, and 0 otherwise.Additional control variablesSCSocial capital index using two variants of social norms and two measures of networks for each county for the years 1997, 2005, 2009 and 2014. The two measures of social norms are voter turnout in presidential elections and the census response rate. Higher values for these variables represent higher social capital. The two measures of networks are the number of social and civic associations and the number of nongovernment organisations in counties. Both of these measures are normalized by the population in the county. A principal component analysis is used to construct an index of social capital for each county for the years 1997, 2005, 2009 and 2014. A linear interpolation fills the missing years 1998–2004; and 2006 to 2008, 2010 to 2013; and 2015 to 2019 (Rupasingha et al., 2000; Rupasingha & Goetz, 2008).CORRUPCorr	-	difference between firm-level EBITDA scaled by total asset and county-level average EBITDA scaled by total asset. Next, we take the standard
 EARN_VOL_D A binary variable coded 1 if the value of EARN_VOL is above median, and 0 otherwise. AST_VOL Asset volatility, another proxy for risk-taking of firm <i>i</i> in year <i>t</i>. AST_VOL is measured as the standard deviation of the stock return during the fiscal year times the market value of equity (CSHO x PRCC_F), all divided by the market value of assets (CSHO x PRCC_F + AT – CEQ). AST_VOL_D A binary variable coded 1 if the value of AST_VOL is above median, and 0 otherwise. IOWN The percentage of common shares held by institutional investors. Data retrieved from Thomson Reuter's F13 File. IOWN_D A binary variable coded 1 if the value of IOWN is below median, and 0 otherwise. FOLLOW The number of analysts following a firm. Data retrieved from IBES. FOLLOW A binary variable coded 1 if the value of FOLLOW is below median, and 0 otherwise. Additional control variables SC Social capital index using two variants of social norms and two measures of networks for each county for the years 1997, 2005, 2009 and 2014. The two measures of social norms are voter turnout in presidential elections and the census response rate. Higher values for these variables represent higher social capital. The two measures or networks are the number of social and civic associations and the number of nongovernment organisations in counties. Both of these measures are normalized by the population in the county. A principal component analysis is used to construct an index of social capital for each county for the years 1997, 2005, 2008. CORRUP Corruption measured as state-level corruption conviction scaled by state-level population times 100,000. Data obtained from Report to Congress on the activities and operations of the public integrity settion (https://www.justice.gov/crimial-pin/annual-reports). ReLIG Religious adherence calculated as state-level adherents divided by state-level population. Data c		deviation of this difference over the last five years.
AST_VOLAsset volatility, another proxy for risk-taking of firm i in year t. AST_VOL is measured as the standard deviation of the stock return during the fiscal year times the market value of equity (CSHO x PRCC_F), all divided by the market value of assets (CSHO x PRCC_F + AT - CEQ).AST_VOL_DA binary variable coded 1 if the value of AST_VOL is above median, and 0 otherwise.IOWNThe percentage of common shares held by institutional investors. Data retrieved from Thomson Reuter's F13 File.IOWN_DA binary variable coded 1 if the value of IOWN is below median, and 0 otherwise.FOLLOWThe number of analysts following a firm. Data retrieved from IBES.FOLLOW_DA binary variable coded 1 if the value of FOLLOW is below median, and 0 otherwise.Additional control variablesSCSCSocial capital index using two variants of social norms and two measures of networks for each county for the years 1997, 2005, 2009 and 2014. The two measures of social anorms are voter turnout in presidential elections and the census response rate. Higher values for these variables represent higher social capital. The two measures of networks are the number of social and civic associations and the number of nongovernment organisations in counties. Both of these measures are normalized by the population in the county. A principal component analysis is used to construct an index of social capital for each county for the years 1997, 2005, 2009.CORRUPCorruption measured as state-level corruption conviction scaled by state-level population times 100,000. Data obtained from Report to Congress on the activities and operations of the public integrity section (https://www.justice.gov/criminal-pin/annual-reports).Religious adherence calculated as state-level adherents divided by state-l	EARN_VOL_D	A binary variable coded 1 if the value of EARN_VOL is above median, and 0 otherwise.
fiscal year times the market value of equity (CSHO x PRCC_F), all divided by the market value of assets (CSHO x PRCC_F + AT - CEQ).AST_VOL_DA binary variable coded 1 if the value of AST_VOL is above median, and 0 otherwise.IOWNThe percentage of common shares held by institutional investors. Data retrieved from Thomson Reuter's F13 File.IOWN_DA binary variable coded 1 if the value of IOWN is below median, and 0 otherwise.FOLLOWThe number of analysts following a firm. Data retrieved from IBES.FOLLOW_DA binary variable coded 1 if the value of FOLLOW is below median, and 0 otherwise.Additional control variablesSCSCSocial capital index using two variants of social norms and two measures of networks for each county for the years 1997, 2005, 2009 and 2014. The two measures of social norms are voter turnout in presidential elections and the census response rate. Higher values for these variables represent higher social capital. The two measures of networks are the number of social and civic associations and the number of nongovernment organisations in counties. Both of these measures are normalized by the population in the county. A principal component analysis is used to construct an index of social capital for each county for the years 1997, 2005, 2009.CORRUPCorruption measured as state-level corruption conviction scaled by state-level population times 100,000. Data obtained from Report to Congress on the activities and operations of the public integrity section (https://www.justice.gov/criminal-pin/annual-reports).Religious adherence calculated as state-level adherents divided by state-level population. Data collected from the Association of Religious Data Archives (ARDA) (https://www.thearda.com/rcms2010/index.asp).	AST_VOL	Asset volatility, another proxy for risk-taking of firm i in year t. AST_VOL is measured as the standard deviation of the stock return during the
AST_VOL_D A binary variable coded 1 if the value of AST_VOL is above median, and 0 otherwise. IOWN The percentage of common shares held by institutional investors. Data retrieved from Thomson Reuter's F13 File. IOWN_D A binary variable coded 1 if the value of IOWN is below median, and 0 otherwise. FOLLOW The number of analysts following a firm. Data retrieved from IBES. FOLLOW_D A binary variable coded 1 if the value of FOLLOW is below median, and 0 otherwise. Additional control variables SC SC Social capital index using two variants of social norms and two measures of networks for each county for the years 1997, 2005, 2009 and 2014. The two measures of social norms are voter turnout in presidential elections and the census response rate. Higher values for these variables represent higher social capital. The two measures of networks are the number of social and civic associations and the number of nongovernment organisations in counties. Both of these measures are normalized by the population in the county. A principal component analysis is used to construct an index of social capital for each county for the years 1997, 2005, 2009 and 2014. A linear interpolation fills the missing years 1998–2004; and 2006 to 2008, 2010 to 2013; and 2015 to 2019 (Rupasingha et al., 2000; Rupasingha & Goetz, 2008). CORRUP Corruption measured as state-level corruption conviction scaled by state-level population times 100,000. Data obtained from Report to Congress on the activities and operations of the public integrity section (https://www.justice.gov/crimial-pin/annual-reports). R		fiscal year times the market value of equity (CSHO x PRCC_F), all divided by the market value of assets (CSHO x PRCC_F + AT – CEQ).
IOWN The percentage of common shares held by institutional investors. Data retrieved from Inomson Retter's F13 File. IOWN_D A binary variable coded 1 if the value of IOWN is below median, and 0 otherwise. FOLLOW The number of analysts following a firm. Data retrieved from IBES. FOLLOW_D A binary variable coded 1 if the value of FOLLOW is below median, and 0 otherwise. Additional control variables SC SC Social capital index using two variants of social norms and two measures of networks for each county for the years 1997, 2005, 2009 and 2014. The two measures of social norms are voter turnout in presidential elections and the census response rate. Higher values for these variables represent higher social capital. The two measures of networks are the number of social and civic associations and the number of nongovernment organisations in counties. Both of these measures are normalized by the population in the county. A principal component analysis is used to construct an index of social capital for each county for the years 1997, 2005, 2009 and 2014. A linear interpolation fills the missing years 1998–2004; and 2006 to 2008, 2010 to 2013; and 2015 to 2019 (Rupasingha et al., 2000; Rupasingha & Goetz, 2008). CORRUP Corruption measured as state-level corruption conviction scaled by state-level population times 100,000. Data obtained from Report to Congress on the activities and operations of the public integrity section (https://www.justice.gov/criminal-pin/annual-reports). Religious adherence calculated as state-level adherents divided by state-level population. Data collected from the Association of Religious Dat	AST_VOL_D	A binary variable coded 1 if the value of AST VOL is above median, and 0 otherwise.
FOUND A binary variable coded 1 in the value of FOWN is below inclusing, and 0 otherwise. FOLLOW The number of analysts following a firm. Data retrieved from IBES. FOLLOW_D A binary variable coded 1 if the value of FOLLOW is below median, and 0 otherwise. Additional control variables SC SC Social capital index using two variants of social norms and two measures of networks for each county for the years 1997, 2005, 2009 and 2014. The two measures of social norms are voter turnout in presidential elections and the census response rate. Higher values for these variables represent higher social capital. The two measures of networks are the number of social and civic associations and the number of nongovernment organisations in counties. Both of these measures are normalized by the population in the county. A principal component analysis is used to construct an index of social capital for each county for the years 1997, 2005, 2009 and 2014. A linear interpolation fills the missing years 1998–2004; and 2006 to 2008, 2010 to 2013; and 2015 to 2019 (Rupasingha et al., 2000; Rupasingha & Goetz, 2008). CORRUP Corruption measured as state-level corruption conviction scaled by state-level population times 100,000. Data obtained from Report to Congress on the activities and operations of the public integrity section (https://www.justice.gov/criminal-pin/annual-reports). Religious adherence calculated as state-level adherents divided by state-level population. Data collected from the Association of Religious Data Archives (ARDA) (https://www.thearda.com/rcms2010/index.asn).	IOWN IOWN D	The percentage of common shares held by institutional investors. Data fertileved information nominon ketter s F13 File.
FOLLOW_D A binary variable coded 1 if the value of FOLLOW is below median, and 0 otherwise. Additional control variables Social capital index using two variants of social norms and two measures of networks for each county for the years 1997, 2005, 2009 and 2014. SC Social capital index using two variants of social norms and two measures of networks for each county for the years 1997, 2005, 2009 and 2014. The two measures of social norms are voter turnout in presidential elections and the census response rate. Higher values for these variables represent higher social capital. The two measures of networks are the number of social and civic associations and the number of nongovernment organisations in counties. Both of these measures are normalized by the population in the county. A principal component analysis is used to construct an index of social capital for each county for the years 1997, 2005, 2009 and 2014. A linear interpolation fills the missing years 1998–2004; and 2006 to 2008, 2010 to 2013; and 2015 to 2019 (Rupasingha et al., 2000; Rupasingha & Goetz, 2008). CORRUP Corruption measured as state-level corruption conviction scaled by state-level population times 100,000. Data obtained from Report to Congress on the activities and operations of the public integrity section (https://www.justice.gov/criminal-pin/annual-reports). Religious adherence calculated as state-level adherents divided by state-level population. Data collected from the Association of Religious Data Archives (ARDA) (https://www.thearda.com/rcms2010/index.asn).	FOLLOW	A billed y validation council in the value of forwing in terms including, and o council wise. The number of anglests following a firm Data retrieved from IRES
Additional control variables SC Social capital index using two variants of social norms and two measures of networks for each county for the years 1997, 2005, 2009 and 2014. The two measures of social norms are voter turnout in presidential elections and the census response rate. Higher values for these variables represent higher social capital. The two measures of networks are the number of social and civic associations and the number of nongovernment organisations in counties. Both of these measures are normalized by the population in the county. A principal component analysis is used to construct an index of social capital for each county for the years 1997, 2005, 2009 and 2014. A linear interpolation fills the missing years 1998–2004; and 2006 to 2008, 2010 to 2013; and 2015 to 2019 (Rupasingha et al., 2000; Rupasingha & Goetz, 2008). CORRUP Corruption measured as state-level corruption conviction scaled by state-level population times 100,000. Data obtained from Report to Congress on the activities and operations of the public integrity section (https://www.justice.gov/criminal-pin/annual-reports). RELIG Religious adherence calculated as state-level adherents divided by state-level population. Data collected from the Association of Religious Data Archives (ARDA) (https://www.thearda.com/rcms2010/index.asp.).	FOLLOW D	A binary variable coded 1 if the value of FOLLOW is below median and 0 otherwise
SCSocial capital index using two variants of social norms and two measures of networks for each county for the years 1997, 2005, 2009 and 2014. The two measures of social norms are voter turnout in presidential elections and the census response rate. Higher values for these variables represent higher social capital. The two measures of networks are the number of social and civic associations and the number of nongovernment organisations in counties. Both of these measures are normalized by the population in the county. A principal component analysis is used to construct an index of social capital for each county for the years 1997, 2005, 2009 and 2014. A linear interpolation fills the missing years 1998–2004; and 2006 to 2008, 2010 to 2013; and 2015 to 2019 (Rupasingha et al., 2000; Rupasingha & Goetz, 2008).CORRUPCorruption measured as state-level corruption conviction scaled by state-level population times 100,000. Data obtained from Report to Congress on the activities and operations of the public integrity section (https://www.justice.gov/criminal-pin/annual-reports).RELIGReligious adherence calculated as state-level adherents divided by state-level population. Data collected from the Association of Religious Data Archives (ARDA) (https://www.thearda.com/rcms2010/index.asp.).	Additional contro	l variables
The two measures of social norms are voter turnout in presidential elections and the census response rate. Higher values for these variables represent higher social capital. The two measures of networks are the number of social and civic associations and the number of nongovernment organisations in counties. Both of these measures are normalized by the population in the county. A principal component analysis is used to construct an index of social capital for each county for the years 1997, 2005, 2009 and 2014. A linear interpolation fills the missing years 1998–2004; and 2006 to 2008, 2010 to 2013; and 2015 to 2019 (Rupasingha et al., 2000; Rupasingha & Goetz, 2008). Corruption measured as state-level corruption conviction scaled by state-level population times 100,000. Data obtained from Report to Congress on the activities and operations of the public integrity section (https://www.justice.gov/criminal-pin/annual-reports). Religious adherence calculated as state-level adherents divided by state-level population. Data collected from the Association of Religious Data Archives (ARDA) (https://www.thearda.com/rcms2010/index.asp).	SC	Social capital index using two variants of social norms and two measures of networks for each county for the years 1997, 2005, 2009 and 2014.
 represent higher social capital. The two measures of networks are the number of social and civic associations and the number of nongovernment organisations in counties. Both of these measures are normalized by the population in the county. A principal component analysis is used to construct an index of social capital for each county for the years 1997, 2005, 2009 and 2014. A linear interpolation fills the missing years 1998–2004; and 2006 to 2008, 2010 to 2013; and 2015 to 2019 (Rupasingha et al., 2000; Rupasingha & Goetz, 2008). CORRUP CORRUP Corruption measured as state-level corruption conviction scaled by state-level population times 100,000. Data obtained from Report to Congress on the activities and operations of the public integrity section (https://www.justice.gov/criminal-pin/annual-reports). RELIG RELIG RELIG Religious adherence calculated as state-level adherents divided by state-level population. Data collected from the Association of Religious Data Archives (ARDA) (https://www.thearda.com/rcms2010/index.asp.). 		The two measures of social norms are voter turnout in presidential elections and the census response rate. Higher values for these variables
organisations in counties. Both of these measures are normalized by the population in the county. A principal component analysis is used to construct an index of social capital for each county for the years 1997, 2005, 2009 and 2014. A linear interpolation fills the missing years 1998–2004; and 2006 to 2008, 2010 to 2013; and 2015 to 2019 (Rupasingha et al., 2000; Rupasingha & Goetz, 2008). CORRUP Corruption measured as state-level corruption conviction scaled by state-level population times 100,000. Data obtained from Report to Congress on the activities and operations of the public integrity section (https://www.justice.gov/criminal-pin/annual-reports). RELIG Religious adherence calculated as state-level adherents divided by state-level population. Data collected from the Association of Religious Data Archives (ARDA) (https://www.thearda.com/rcms2010/index.asp.).		represent higher social capital. The two measures of networks are the number of social and civic associations and the number of nongovernment
construct an index of social capital for each county for the years 1997, 2005, 2009 and 2014. A linear interpolation fills the missing years 1998–2004; and 2006 to 2008, 2010 to 2013; and 2015 to 2019 (Rupasingha et al., 2000; Rupasingha & Goetz, 2008). CORRUP Corruption measured as state-level corruption conviction scaled by state-level population times 100,000. Data obtained from Report to Congress on the activities and operations of the public integrity section (https://www.justice.gov/criminal-pin/annual-reports). RELIG Religious adherence calculated as state-level adherents divided by state-level population. Data collected from the Association of Religious Data Archives (ARDA) (https://www.thearda.com/rcms2010/index.asp.).		organisations in counties. Both of these measures are normalized by the population in the county. A principal component analysis is used to
1998–2004; and 2006 to 2008, 2010 to 2013; and 2015 to 2019 (Rupasingha et al., 2000; Rupasingha & Goetz, 2008). CORRUP Corruption measured as state-level corruption conviction scaled by state-level population times 100,000. Data obtained from Report to Congress on the activities and operations of the public integrity section (https://www.justice.gov/criminal-pin/annual-reports). RELIG Religious adherence calculated as state-level adherents divided by state-level population. Data collected from the Association of Religious Data Archives (ARDA) (https://www.thearda.com/rcms2010/index.asp.).		construct an index of social capital for each county for the years 1997, 2005, 2009 and 2014. A linear interpolation fills the missing years
CORRUP Corruption measured as state-level corruption conviction scaled by state-level population times 100,000. Data obtained from Report to Congress on the activities and operations of the public integrity section (https://www.justice.gov/criminal-pin/annual-reports). RELIG Religious adherence calculated as state-level adherents divided by state-level population. Data collected from the Association of Religious Data Archives (ARDA) (https://www.thearda.com/rcms2010/index.asp.).	CODDUT	1998–2004; and 2006 to 2008, 2010 to 2013; and 2015 to 2019 (Rupasingha et al., 2000; Rupasingha & Goetz, 2008).
RELIG Religious adherence calculated as state-level adherents divided by state-level population. Data collected from the Association of Religious Data Archives (ARDA) (https://www.thearda.com/rcms2010/index.asp.).	CORRUP	corruption measured as state-level corruption conviction scaled by state-level population times 100,000. Data obtained from Report to Congress on the activities and constrained of the multi-anterim scale (https://comput.gov/co
Archives (ARDA) (https://www.thearda.com/rcms2010/index.asp).	RELIG	on the activities and operations of the public integrity section (https://www.jusice.gov/criminal-pin/antual-reports). Beligious adherence calculated as state.lawal adherents divided by state lawal population. Data calculated from the Association of Baligious Data
	ILLIO	Archives (ARDA) (https://www.thearda.com/rcms2010/index.asp).

(continued)

Variables	Definition
POPU	County-level population growth. Data collected from US Census Bureau.
INCOME	Natural log of the median household income per capita in a county in a given year. Data collected from US Census Bureau.
AGE	Natural logarithm of the median age of residents in a county during a year. Data collected from US Census Bureau.
EDU	Percentage of persons at least 25 years old with at least one year of college education in the county in a given year. Data collected from US Census
	Bureau.
MALE_FEMALE	Male to female ratio calculated as state-level male population divided by state-level female population. Data collected from US Census Bureau.
DIVERSITY	Racial diversity ratio measured as state-level total population minus state-level white population scaled by state-level total population. Data
	collected from US Census Bureau.
URBAN	A binary variable coded 1 if the county of the firm's headquarters resides within the ten largest metropolitan areas, which are Houston, Dallas,
	Detroit, Boston, Philadelphia, San Francisco, Baltimore, Chicago, Los Angeles and New York, and 0 otherwise.
SJQ	State judicial quality using the overall state ranking reported in the 2001 State Liabilities Rankings Study which was conducted for the US
	Chamber of Commerce. Score of 1 indicates best and 50 indicates worst judicial quality.
POLITICAL	State-level political values. A binary variable coded 1 if democratic presidential candidate won the state in the most recent presidential election,
	and 0 otherwise.
CEO_TENURE	Number of years the CEO has held this position.
CEO_DUAL	An indicator variable for a CEO who is also the Chairperson of the board.
BDIND	Number of independent directors on the board divided by the board size.
GRANT_LAG	The natural logarithm of annual total federal arts grants in a county lagged by one year. Data obtained from https://apps.nea.gov/grantsearch/.

References

Abdelsalam, O., Chantziaras, A., Ibrahim, M., & Omoteso, K. (2021). The impact of religiosity on earnings quality: International evidence from the banking sector. The British Accounting Review, 53(6), Article 100957.

Amabile, T. M. (1983). The social psychology of creativity: A componential conceptualization. Journal of Personality and Social Psychology, 45(2), 357.

Badertscher, B. A. (2011). Overvaluation and the choice of alternative earnings management mechanisms. The Accounting Review, 86(5), 1491–1518.

Beaussart, M. L., Andrews, C. J., & Kaufman, J. C. (2013). Creative liars: The relationship between creativity and integrity. Thinking Skills and Creativity, 9, 129–134. Bedard, J. C., & Johnstone, K. M. (2004). Earnings manipulation risk, corporate governance risk, and auditors' planning and pricing decisions. The Accounting Review, 79(2), 277–304.

Bell, T. B., Landsman, W. R., & Shackelford, D. A. (2001). Auditors' perceived business risk and audit fees: Analysis and evidence. Journal of Accounting Research, 39 (1), 35-43

Bicchieri, C. (2006). The grammar of society: The nature and dynamics of social norms. New York: Cambridge University Press.

Boytsun, A., Deloof, M., & Matthyssens, P. (2011). Social norms, social cohesion, and corporate governance. Corporate Governance: An International Review, 19(1), 41-60.

Callen, J. L., & Fang, X. (2013). Institutional investor stability and crash risk: Monitoring versus short- termism? Journal of Banking & Finance, 37, 3047–3063. Callen, J. L., & Fang, X. (2020). Local gambling norms and audit pricing. Journal of Business Ethics, 164(1), 151-173.

Chahine, S., Colak, G., Hasan, I., & Mazboudi, M. (2020). Investor relations and IPO performance. Review of Accounting Studies, 25(2), 474-512.

Chandler, D., & Munday, R. (2011). In A dictionary of media and communication (1st ed.). Oxford University Press.

Chen, Y., Knechel, W. R., Marisetty, V. B., Truong, C., & Veeraraghavan, M. (2017). Board independence and internal control weakness: Evidence from SOX 404 disclosures. Auditing: A Journal of Practice & Theory, 36, 45-67.

Choi, A., Lee, E. Y., Park, S., & Sohn, B. C. (2022). The differential effect of accrual-based and real earnings management on audit fees: International evidence. Accounting and Business Research, 52(3), 254–290.

Chung, K. H., & Zhang, H. (2011). Corporate governance and institutional ownership. Journal of Financial and Quantitative Analysis, 46(1), 247-273.

Cohen, D. A., Dey, A., & Lys, T. Z. (2008). Real and accrual-based earnings management in the pre-and post-Sarbanes-Oxley periods. The Accounting Review, 83(3), 757-787

Cohen, D. A., & Zarowin, P. (2010). Accrual-based and real earnings management activities around seasoned equity offerings. Journal of Accounting and Economics, 50 (1), 2-19,

Davis, L. R., Ricchiute, D. N., & Trompeter, G. (1993). Audit effort, audit fees, and the provision of non-audit services to audit clients. The Accounting Review, 135–150. Dechow, P. M., Sloan, R. G., & Sweeney, A. P. (1995). Detecting earnings management. The Accounting Review, 70(2), 193-225.

Dewett, T. (2004). Employee creativity and the role of risk. European Journal of Innovation Management, 7, 257-266.

Dewett, T. (2006). Exploring the role of risk in employee creativity. Journal of Creative Behavior, 40(1), 27-45.

Dyreng, S. D., Mayew, W. J., & Williams, C. D. (2012). Religious social norms and corporate financial reporting. Journal of Business Finance & Accounting, 39(7-8), 845-875.

Florida, R. (2002a). The rise of the creative class: And how it's transforming work, leisure, community and everyday life. New York: Basic Books.

Florida, R. (2002b). Bohemia and economic geography. Journal of Economic Geography, 2(1), 55-71.

Gardner, H. (1993). Creating minds: An anatomy of creativity seen through the lives of freud, einstein, picasso, stravinsky, eliot, Graham, and gandhi. New York: Basic Books. Gino, F., & Ariely, D. (2012). The dark side of creativity: Original thinkers can be more dishonest. Journal of Personality and Social Psychology, 102(3), 445.

Gino, F., & Wiltermuth, S. S. (2014). Evil genius? How dishonesty can lead to greater creativity. Psychological Science, 25(4), 973-981.

Glendening, M., Mauldin, E. G., & Shaw, K. W. (2019). Determinants and consequences of quantitative critical accounting estimate disclosures. The Accounting Review, 94(5), 189–218.

Graham, J. R., Harvey, C. R., & Rajgopal, S. (2005). The economic implications of corporate financial reporting. Journal of Accounting and Economics, 40(1-3), 3–73. Greiner, A., Kohlbeck, M. J., & Smith, T. J. (2017). The relationship between aggressive real earnings management and current and future audit fees, Auditing: A

Journal of Practice & Theory, 36(1), 85-107. Guggenmos, R. D. (2020). The effects of creative culture on real earnings management. Contemporary Accounting Research, 37(4), 2319-2356.

Guilford, J. P. (1982). Cognitive psychology's ambiguities: Some suggested remedies. Psychological Review, 89, 48-59.

Gul, F. A. (2006). Auditors' response to political connections and cronvism in Malaysia. Journal of Accounting Research, 44(5), 931-963.

Gul, F. A., Chen, C. J., & Tsui, J. S. (2003). Discretionary accounting accruals, managers' incentives, and audit fees. Contemporary Accounting Research, 20(3), 441-464. Gul, F. A., & Goodwin, J. (2010). Short-term debt maturity structures, credit ratings, and the pricing of audit services. The Accounting Review, 85(3), 877-909. Gul, F. A., & Ng, A. C. (2018). Auditee religiosity, external monitoring, and the pricing of audit services. Journal of Business Ethics, 152(2), 409-436.

Gupta, K., & Krishnamurti, C. (2018). Do macroeconomic conditions and oil prices influence corporate risk-taking? Journal of Corporate Finance, 53, 65-86.

Hainmueller, J. (2012). Entropy balancing for causal effects: A multivariate reweighting method to produce balanced samples in observational studies. Political Analysis, 20(1), 25-46.

Hardies, K., Breesch, D., & Branson, J. (2015). The female audit fee premium. Auditing: A Journal of Practice & Theory, 34(4), 171-195.

Hasan, I., Hoi, C. K., Wu, Q., & Zhang, H. (2017). Social capital and debt contracting: Evidence from bank loans and public bonds. Journal of Financial and Quantitative Analysis, 52(3), 1017–1047.

Hausman, J. (1978). Specification tests in econometrics. Econometrica, 46, 1251-1273.

Hay, D. (2013). Further evidence from meta-analysis of audit fee research. International Journal of Auditing, 17(2), 162–176.

Hay, D. C., Knechel, W. R., & Wong, N. (2006). Audit fees: A meta-analysis of the effect of supply and demand attributes. *Contemporary Accounting Research*, 23(1), 141–191.

Healy, P., & Palepu, K. (2001). Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature. Journal of Accounting and Economics, 31, 405–440.

Heilman, K. M. (2016). Possible brain mechanisms of creativity. Archives of Clinical Neuropsychology, 31(4), 285-296.

Hilary, G., & Hui, K. W. (2009). Does religion matter in corporate decision making in America? Journal of Financial Economics, 93(3), 455-473.

Hillegeist, S. A. (1999). Financial reporting and auditing under alternative damage apportionment rules. The Accounting Review, 74(3), 347-369.

Ho, S. W. M., & Ng, P. P. H. (1996). The determinants of audit fees in Hong Kong: An empirical study. Asian Review of Accounting, 4(2), 32-50.

Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behaviour, agency costs and ownership structure. Journal of Financial Economics, 3(4), 305–360.

Jha, A. (2019). Financial reports and social capital. Journal of Business Ethics, 155(2), 567–596.

Jha, A., & Chen, Y. (2015). Audit fees and social capital. The Accounting Review, 90(2), 611-639.

Jha, A., Kulchania, M., & Smith, J. (2021). U.S. political corruption and audit fees. The Accounting Review, 96(1), 299-324.

Johnstone, K. M., & Bedard, J. C. (2001). Engagement planning, bid pricing, and client response in the market for initial attest engagements. *The Accounting Review*, 76 (2), 199–220.

Johnstone, K. M., & Bedard, J. C. (2003). Risk management in client acceptance decisions. The Accounting Review, 78(4), 1003–1025.

Kothari, S. P., Leone, A. J., & Wasley, C. E. (2005). Performance matched discretionary accrual measures. Journal of Accounting and Economics, 39(1), 163–197.
Kothari, S. P., Mizik, N., & Roychowdhury, S. (2016). Managing for the moment: The role of real activity versus accruals earnings management in SEO valuation. The Accounting Review, 91(2), 559–586.

Lemon, W. M., Arens, A. A., & Loebbecke, J. K. (1993). Auditing: An integrated approach. Englewood Cliffs, NJ: Prentice Hall.

Leuenberger, D. Z., & Kluver, J. D. (2005). Changing culture: Generational collision and creativity. Public Manager, 34(4), 16.

Leventis, S., Dedoulis, E., & Abdelsalam, O. (2018). The impact of religiosity on audit pricing. Journal of Business Ethics, 148(1), 53-78.

Li, K., Mai, F., Shen, R., & Yan, X. (2021). Measuring corporate culture using machine learning. *Review of Financial Studies*, 34(7), 3265–3315.

Madsen, J. M., & McMullin, J. L. (2020). Economic consequences of risk disclosures: Evidence from crowdfunding. *The Accounting Review*, 95(4), 331–363.

Mai, K. M., Ellis, A. P., & Welsh, D. T. (2015). The gray side of reativity: Exploring the role of activation in the link between creative personality and unethical behavior. *Journal of Experimental Social Psychology*, 60, 76–85.

Marquardt, D. W. (1970), Generalized inverses, ridge regression, biased linear estimation, and nonlinear estimation. Technometrics, 12(3), 591-612.

Marquis, C., & Battilana, J. (2009). Acting globally but thinking locally? The enduring influence of local communities on organizations. Research in Organizational Behavior, 29, 283–302.

Mayhew, B. W., & Wilkins, M. S. (2003). Audit firm industry specialization as a differentiation strategy: Evidence from fees charged to firms going public. Auditing: A Journal of Practice & Theory, 22(2), 33–52.

McGranahan, D., & Wojan, T. (2007). Recasting the creative class to examine growth processes in rural and urban counties. Regional Studies, 41(2), 197-216.

McGranahan, D. A., Wojan, T. R., & Lambert, D. M. (2011). The rural growth trifecta: Outdoor amenities, creative class and entrepreneurial context. Journal of Economic Geography, 11(3), 529–557.

McGuire, S. T., Omer, T. C., & Sharp, N. Y. (2012). The impact of religion on financial reporting irregularities. The Accounting Review, 87(2), 645-673.

McMullin, J. L., & Schonberger, B. (2020). Entropy-balanced accruals. Review of Accounting Studies, 25(1), 84-119.

Mead, N. L., Baumeister, R. F., Gino, F., Schweitzer, M. E., & Ariely, D. (2009). Too tired to tell the truth: Self-control resource depletion and dishonesty. Journal of Experimental Social Psychology, 45, 594–597.

Pitta, D. A., Wood, V. R., & Franzak, F. J. (2008). Nurturing an effective creative culture within a marketing organization. Journal of Consumer Marketing, 25, 137–148. PricewaterhouseCoopers. (2016). Adjusting the lens on economic crime (global economic crime survey). Retrieved from https://www.pwc.ch/en/publications/2017/ global-economic-crime-survey-2016-pwc-en.pdf.

Public Company Accounting Oversight Board (PCAOB). (2007). An audit of internal control over financial reporting that is integrated with an audit of financial statements. Auditing Standard No. 5. Washington, D.C.: PCAOB.

Public Company Accounting Oversight Board (PCAOB). (2010). Auditing standard No. 2810: Evaluating audit results. Retrieved from https://pcaobus.org/Standards/ Auditing/Pages/AS2810.aspx#_AppB.

Roychowdhury, S. (2006). Earnings management through real activities manipulation. Journal of Accounting and Economics, 42(3), 335-370.

Runco, M. A. (2004). Creativity. Annual Review of Psychology, 55, 657-687.

Rupasingha, A., & Goetz, S. J. (2008). US county-level social capital data, 1990-2005. PA: The Northeast Regional Center for Rural Development, Penn State University, University Park.

Rupasingha, A., Goetz, S. J., & Freshwater, D. (2000). Social capital and economic growth: A county-level analysis. Journal of Agricultural & Applied Economics, 32(3), 565–572.

Simunic, D. A. (1980). The pricing of audit services: Theory and evidence. Journal of Accounting Research, 161–190.

Spiro, R. J., & Jehng, J. (1990). Cognitive flexibility and hypertext: Theory and technology for the non-linear and multidimensional traversal of complex subject matter. In D. Nix, & R. Spiro (Eds.), Cognition, education, and multimedia (pp. 163–205). Hillsdale, NJ: Erlbaum.

Stock, J. H., & Yogo, M. (2005). Testing for weak instruments in linear IV regression. In D. W. K. Andrews, & J. H. Stock (Eds.), Identification and inference for econometric models: Essays in honor of Thomas Rothenberg (pp. 80–108). New York: Cambridge University Press.

Studenmund, A. H. (2016). In Using econometrics: A practical guide (7th ed.). Boston, MA: Pearson.

Tong, L., Wu, B., & Zhang, M. (2022). Do auditors' early-life socioeconomic opportunities improve audit quality? Evidence from China. *The British Accounting Review*, 54(2), Article 101040.

Ucar, E. (2018). Local creative culture and corporate innovation. Journal of Business Research, 91, 60-70.

Ucar, E. (2019). Creative culture, risk-taking, and corporate financial decisions. European Financial Management, 25(3), 684–717.

Ucar, E., & Staer, A. (2018). Local creative culture and dividend policy. Financial Services Review, 27(4).

Xu, H., Dao, M., & Petkevich, A. (2019). Political corruption and auditor behavior: Evidence from US firms. European Accounting Review, 28(3), 513-540.

Xu, H., Dao, M., Wu, J., & Sun, H. (2022). Political corruption and annual report readability: Evidence from the United States. Accounting and Business Research, 52(2), 166–200

Zattoni, A., Dedoulis, E., Leventis, S., & Ees, H. V. (2020). Corporate governance and institutions—a review and research agenda. Corporate Governance: An International Review, 28(6), 465–487.