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Full length article

Impact of social capital on tone ambiguity in banks’ 10-K filings

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ABSTRACT

We examine whether the social capital index of the county where the bank is headquartered is associated with the ambiguity of tone measures constructed from the textual analysis of banks’ 10-K filings. We hypothesize and find that banks located in high social capital areas exhibit lower ambiguous tone in their 10-K filings. Furthermore, the impact of social capital on management’s 10-K disclosure for banks located in high social capital areas is not mitigated during recessionary periods when management may have more unfavorable news to report. Unlike other studies that suggest that social norms can be forsaken when motive and opportunity exist, our results suggest that social capital is reasonably entrenched in banks’ reporting. In contrast, we find that banks located in low social capital areas report more ambiguously during recessionary periods when management may have to report unfavorable news.

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1. Introduction

Like other publicly traded firms, banks disclose in their annual reports their audited financial statements and their 10-K Reports, with the latter constituting almost 80% of the annual report in a typical bank. Management’s discretion in audited financial statements is limited due to measurement and reporting conventions imposed by Generally Accepted Accounting Principles (GAAP) and Generally Accepted Auditing Standards (GAAS), as well as bank-specific reporting requirements imposed by regulators (e.g., reporting requirements under Federal Deposit Insurance Corporation Improvement Act (FDICIA)). Principles like consistency, conservatism and materiality limit what management can report in their audited financial statements. However, management has significant discretion in what it can report in the 10-K reports without being limited by consistency, conservatism, materiality or even a historical focus.

While the subject matter and structure in the 10-K reports are mandated, the clarity (or ambiguity) of the content is left to management’s discretion. Stakeholders’ understanding of such information and their resulting interpretation and decisions — depend non-trivially on the ambiguity of management’s tone. The U.S. Securities and Exchange Commission (SEC) has appropriately called for narrative clarity and reduced ambiguity in 10-K filings, and has raised concern that firms may be deliberately ambiguous to protect themselves against potential claims (SEC, 2007). Such ambiguity may be heightened during recessionary periods when management may have to report unfavorable news. Ambiguity includes — but not restricted to — presenting both positive and negative outcomes as somewhat equally probable, but indifferent parts of the report. We therefore start with the premise that tone ambiguity is just as important as (or even more important than) the readability of the reports, in part because the former may be harder to detect.

Ambiguous 10-K Reports contribute to information risk and can reduce stakeholders’ ability to understand or assess firms’ investment and financing risks, and therefore valuation. Deliberate ambiguity that serves corporate or managerial interests at the expense of other stakeholders’ interests may undermine investor confidence. Loughran and McDonald (2011) show that firms that use ‘uncertain’ (in all its form such as approximate, contingent, indefinite and uncertainty) or weak modal words (e.g., possible, might, approximate and contingent) in their 10-K filings have greater stock return volatility in the following year.

We examine whether the tone ambiguity in the bank’s 10-K filings is associated with the social capital in the local county where the bank is headquartered. We refer to social capital as the (non-financial) factor that captures the extent to which individual managers — despite pursuing their self-interest in general — are influenced by the norms and values of their office headquarters’ regions. Some regions exhibit a high degree of community outlook, a high degree of altruism, a high degree of mutual trust and high propensity to honor obligations. These regions are considered to have high social capital, and which have (for example)
shown to have reported fewer cases of Covid-19 because citizens of such regions demonstrate greater willingness to incur personal costs (e.g., wearing masks) to contribute to social objectives (as reported in Ding et al. (2020)).

Since it is managers – and not corporations – that make decisions, studies have shown that the social capital of a region can impact its managers’ decisions and subsequent economic outcomes. For example, prior studies have shown that firms headquartered in high social-capital counties tend to have greater financial reporting transparency (Jha, 2019; Jin et al., 2017); engage in less tax avoidance (Hasan et al., 2017a,b); exhibit higher corporate social responsibility (Jha and Cox, 2015); and incur lower external audit fees (Jha and Chen, 2015). All these correlates with social capital arguably contribute to more pro-social and less opportunistic behavior.

We extend this line of reasoning by hypothesizing that such behavior by firms may also be augmented by less ambiguous disclosure in 10-K filings to make it easier for stakeholders to assess underlying firm performance. As Warren Buffet puts it, “a less-than-scrupulous issuer does not want us to understand a subject it feels legally obligated to touch upon” (SEC, 2007). Lo et al. (2017) argue that management has incentives in their disclosures to obscure the tools used to achieve earnings manipulations, if any.

As documented in Jin et al. (2017), we argue that banks headquartered in counties with high social capital will engage in less risk-taking and more accounting transparency and accounting conservatism, thereby necessitating less ambiguity in their 10-K filings. We further hypothesize that high social capital is entrenched in the DNA of the bank, thereby motivating them to report with a less ambiguous tone during periods of financial stability as well as during recessionary periods. This contrasts with Liu et al. (2014), 289) who find that “social norms can be crossed when motive and opportunity exist”. In other words, we find that social norms need not be contingent upon managerial incentives as suggested by Hechter (2008) in his analysis of the rise and fall of the Arthur Andersen accounting firm.

More recently, Horowitz (2019) emphasizes the importance of embedding the (social) norms and culture deep enough so that management behaves the right way even when no one is looking. When social norms are set sufficiently at the top, then management and employees will apply it consistently in all areas of reporting as well. Social capital can determine and reinforce mutual trust, as well as more pro-social and less opportunistic behavior. Such social capital can reduce informational and transactional risks, thereby reducing the scope for unethical, opportunistic or self-serving actions. It is in this sense that social capital is rightfully considered as a form of capital. Social capital can enhance economic returns to all sides of the transaction even in situations of information asymmetry and risk. Social capital can mitigate “the fear that one’s exchange partner will act opportunistically” (Bradach and Eccles, 1989), and allows both sides to an exchange transaction to anticipate the others’ actions with more certainty (Larcker and Tayan, 2013). The mutually accepted norms that constitute social capital can be beneficial to all parties to a long-run transaction, with mutual expectations that social contracts would be enforced fairly, ethically and unambiguously. In our specific context, readers of banks’ 10-K reports could trust management to take less opportunistic or self-serving actions and report outcomes truthfully, ethically and unambiguously if social capital levels are high. While tone ambiguity is not necessarily lying or manipulation of information, we argue that readers of 10-K filings prefer less ambiguity to more ambiguity and can at least qualitatively detect the relative extent of ambiguity in 10-K reports. Such a setting would incentivize managers to provide less ambiguous disclosure despite extant information asymmetry and despite not having a hard and defining boundary between ambiguous and unambiguous disclosures.

The influence of social environment on the quality of firms’ financial reporting has been documented by Kang et al. (2010), Kanagaretnam et al. (2011), and McGuire et al. (2012). Using a social capital index, Jha (2019) finds that firms headquartered in high social-capital counties report less accrual and real earnings management, while Jha and Chen (2015) find that firms headquartered in counties with higher social capital incur statistically and economically lower audit fees. If auditors can rely more on management in high social-capital counties, then arguably so can readers of 10-K filings. Therefore, if management conceals less about its performance in high social-capital counties, it will also be less ambiguous in their 10-K filings. And such lower ambiguity can be reasonably expected to extend in recessionary periods when management may have unfavorable news to report. Baxamusa et al. (2018) show that the cumulative abnormal return (CAR) around the announcement date of a strategic alliance is higher when the partner in the strategic alliance has a more readable 10-K report.

We focus on the banking industry given its unique nature of being highly regulated (at the federal, state, FDIC and SEC levels), and perhaps where informal influences or structures such as social capital may not matter as much. The banking sector also presents a setting where risk-taking incentives are high, the reporting of which may or may not be masked by management with ambiguity. Documenting the existence of social capital within the banking sector would allow us to illustrate that it is a strong and resilient form of capital. Examining the banking industry alone also provides an acid test for an association between social capital and tone ambiguity.

We construct our social capital index using principal component analysis (PCA) based on four different publicly available measures of civil society and social organizations at the county level following Rupasingha and Goetz (2008), as well as an alternate measure of social capital following Guiso et al. (2004) and Buonanno et al. (2009). Both these measures offer sufficient variation in social capital across counties.

Our findings are consistent with our hypotheses. After controlling for bank characteristics based on the prior literature, we find that the ambiguity of tone in 10-K filings is significantly lower in banks that are headquartered in high social-capital counties. In additional tests, we find that the impact of social capital on the ambiguity of tone was greater during recessionary periods of 2001 and 2007–2009. Ceteris paribus, firms headquartered in high social-capital counties reported less ambiguously in their 10-K filings compared to firms headquartered in low social-capital counties during recessionary periods (2001 and 2007–2009). This contrasts with Lo et al. (2017) who report that the social environment influences relationships with investors, and not just auditors (as shown by Jha and Chen, 2015). Our finding of a negative association between social capital and
Ambiguous disclosure is a link that can explain two strands of emerging literature: why firms headquartered in high-social-capital counties incur lower bank loan spreads (Hasan et al., 2017b); engage in less tax avoidance (Hasan et al., 2017a); enjoy lower audit fees (Jha and Chen, 2015); have greater financial reporting transparency (Jin et al., 2017), as well as why firms with lower ambiguity in annual reports enjoy lower borrowing costs (Ertugrul et al., 2017); and exhibit lower risk-taking (Kanagaretnam et al., 2017). The first four studies do not examine ambiguity while the last two studies do not consider social capital. Our results establishing the link between ambiguity and social capital can be relied upon to advance the hypotheses in all the above studies.

The rest of the paper proceeds as follows. The next section reviews the literature and develops our hypotheses. We present the research design and describe the data in Section 3, discuss the results in Section 4, offer robustness checks in Section 5 and conclude in Section 6.

2 Literature review and hypotheses development

Ambiguity of Disclosure

The seminal paper by Li (2008) examined the relationship between the readability of annual reports and financial performance of firms, and found that firms with lower reported earnings were more difficult to understand. Li estimated the complexity of disclosure with the Fog Index, where a higher reading of the index represents disclosure that is more difficult to understand. In their survey of the literature on textual analysis, Loughran and McDonald (2016) summarize the words selected by managers to describe their operations, and show how they are correlated with future stock returns, earnings, and even future fraudulent activities of management. A seminal study by Loughran and McDonald (2011) attempted to measure ambiguity of disclosure instead of the complexity of disclosure. They claimed that firms that used ‘uncertain’ (in all its form such as approximate, contingent, indefinite and uncertainty) or weak modal words (e.g., possible, might, approximate and contingent) in their 10-K filings (per 1000 words) arguably had greater ambiguity, and was associated with higher stock return volatility in the year following the disclosure. The common element of complexity and ambiguity is that higher scores on both measures make the disclosures harder to understand and therefore more difficult to interpret.

In the context of corporate culture, Audi et al. (2016) “hypothesize that a more frequent count of 21 unique “trust” words, like trust, character, and virtue, in the MD&A [Management Discussion and Analysis] section of a firm’s 10-K indicates a corporate culture that involves greater trust”, especially if such firms also use audit and control-type words. Balvers et al. (2016) document that “voluntary use by firms of monitoring and measurement of customer satisfaction is a credible signal that is associated with higher subsequent customer satisfaction”. Audited financial statements with notes that are an integral part of the financial reports have limited scope for complexity or ambiguity for sophisticated users. In contrast, the firm’s management has room to introduce complexity and ambiguity in their 10-K filings where rules dictate only the subject matter and structure, but not the scope and content. The challenge in determining complexity or ambiguity in corporate disclosures is not about discovering hidden facts, but about establishing the relevance of the fact to readers, or equivalently, management’s intent of what the disclosed fact may mean. Gladwell (2007) argues that everything that Jonathan Weil – a reported at the Wall Street Journal – uncovered about Enron was reported by Enron itself, but the tone of the disclosure was not unambiguous. In his legal analysis of the Enron case, Macey (2004) blamed the financial intermediaries for not processing and interpreting the financial information disclosed by Enron, even though he blames Enron for the engineered complexity and the tone ambiguity. With an abundance of information available via the internet, we have access to lots of facts but with limited knowledge of their relevance or the intent of parties disclosing the facts. This makes the examination of tone ambiguity just as important as readability.

With the increasing availability of online full-text information databases of SEC reports (including 10-K filings), many researchers are using textual analysis to investigate the link between language attributes and economic decisions or outcomes. For example, Li et al. (2013) conduct textual analysis on firms’ 10-K filings to uncover measures of competitiveness that reflect traditional measures such as the Herfindahl index. Lo et al. (2017) use textual analysis on MD&A reports to show that firms most likely to have managed earnings have MD&A’s that are more complex. Based on textual analysis of 10-K filings, Kanagaretnam et al. (2017) show that banks mask their risk-taking with ambiguity, while Ertugrul et al. (2017) show that firms with greater ambiguity face higher borrowing costs.

Complexity of disclosures has been shown to be associated with the accuracy of management forecasts (Guay et al., 2015), bond ratings (Bonsall and Miller, 2014), analyst coverage (Lehavy et al., 2011), investors’ stock holdings and trading behavior (Miller, 2010; Lawrence, 2013), and capital investment efficiency (Biddle et al., 2009).

Ambiguity of tone has been shown to be linked with the positive association between forward-looking information in the MD&A and future earnings (Li, 2010), with higher subsequent ROA (Davis et al., 2012; Davis and Tama-Sweet, 2012), with shareholder litigation (Rogers et al., 2011), and with stock return volatility (Kothari et al., 2009).

Social Capital

We build on the premise that social capital can reduce informational and transactional risks, and therefore reduce the scope for opportunistic or self-serving reporting by management. Social capital exerts its influence via norms of social peers surrounding corporate headquarters as well as via associational networks that make norm-consistent behavior an equilibrium point (or a self-fulfilling prophecy). Hasan et al. (2017a) refer to the combined influences as cooperative norms, and document that social capital does indeed constrain opportunistic behavior by firm management in reducing their level of tax avoidance. Hasan et al. (2017b) further show that the influence of high social capital can also enhance returns in the form of reduced borrowing costs. Examining proxies for social trust, Kanagaretnam et al. (2018) find both the levels of CEO compensation as well as the proportion of equity-based compensation to be lower in countries with higher levels of societal trust. This suggests that costly regulations on CEO compensation may not be as necessary for jurisdictions with higher levels of societal trust.

Using a large panel of companies from 52 countries, Ferris et al. (2017) find that managerial social capital with financiers reduces the cost of equity. Using a social capital index, Jha (2019) finds that firms headquartered in high social-capital counties have relatively less accrual and real earnings management, while Jha and Chen (2015) find that firms headquartered in counties...
with higher social capital incur statistically and economically lower audit fees, consistent with the notion that trustworthiness is priced. If auditors can rely more on management in high social-capital counties, then arguably so can readers of 10-K filings. Therefore, if management conceals less about its performance and risks in high social-capital counties, it can afford to be less ambiguous in their 10-K disclosures. This study extends Jha (2019) by documenting that more forthcoming disclosure in counties with higher social capital extends into both recessionary and non-recessionary periods. This study also motivates why the examination of tone ambiguity is just as important as (or even more important than) the analysis of readability conducted by Jha (2019).

We extend these two strands of emerging literature to examine whether social capital of the county in which the bank is headquartered is associated with the ambiguity of tone by banks in their 10-K filings. More specifically, our hypothesis is as follows:

**H1:** Banks headquartered in counties with higher social capital exhibit lower ambiguity of tone in their 10-K filings.

We further investigate whether the impact of social capital on the ambiguity of tone in 10-K filings is strengthened or mitigated during recessionary periods. An argument for the impact of social capital to remain influential during times of crisis when management has to report bad news is that social capital remains fairly constant or sticky across time, and the effect of social capital (like generosity or philanthropy) can be more pronounced during times of acute crisis when it is needed most. An alternate view is that managers accept the influence of their social environment and the social capital within their counties only when it is not too costly to be so influenced. If the cost of virtuous or unambiguous reporting during a financial crisis becomes too high, then perhaps management may transition to more ambiguous reporting in their 10-K filings. Our second hypothesis is therefore two-sided and specified as follows:

**H2:** The impact of social capital on banks’ ambiguity of tone in their 10-K filings during recessionary periods is different from the impact of social capital during non-recessionary periods.

Social capital may also be manifested in the importance managers attach to honoring one’s word that cannot be contractually obligated, and the value of such social capital may be underestimated. For example, Loughran et al. (2009) suggest that firms may incorrectly believe that the benefit of ambiguous reporting about business conduct may outweigh the cost of losing their long-term credibility (or social capital, in our terms). Liu et al. (2014), 305 document that if the relative price of obeying social norms becomes high, some market participants will “forego their adherence to social norms for financial rewards”. In the context of tax compliance, Blanthorne and Kaplan (2008) find that opportunities to evade income taxes influence the formation of taxpayers’ ethical beliefs, which in turn, affect intentions and decisions to evade taxes. Prentice and Miller (1996) describe such “compromises” as becoming part of acceptable future social norms. We therefore examine whether banks in high social capital areas report with a more consistent ambiguity tone during both recessionary and non-recessionary periods compared to banks in low social capital areas. This would be the case if behavior exhibited by high social capital banks is entrenched into the DNA of the banks, and therefore the less ambiguous tone of reporting is maintained even during bad times when management may have to report unfavorable news. Our third hypothesis is specified as follows:

**H3:** Ambiguity of tone in 10-K filings of banks located in high social capital areas will remain unchanged from periods of financial stability to periods of recessions, while the ambiguity of tone in 10-K filings of banks in low social capital areas will decline from periods of financial stability to periods of recessions.

### 3. Research design and data

We test our hypotheses using a multivariate regression model where the dependent variable is the measure of ambiguity tone in banks’ 10-K filings. Two alternate measures are used based on Loughran and McDonald (2011). The main test or independent variable is the social capital of the county (SC) where the bank is headquartered, and is constructed following Rupasingha and Goetz (2008). Most studies rely on Rupasingha and Goetz (2008) for their social capital construct, including Putnam (2007), Jha and Chen (2015), Hasan et al. (2017a, b), and Jin et al. (2017). Following Rupasingha and Goetz (2008), we use voter turnout in presidential elections and the census response rate as two measures of social norms. Higher values of these variables reflect higher social capital. We also use the number of social and civic associations and the number of nongovernmental organizations (NGOs) in the county as two measures of the network. We normalize both these measures by the population of the county. We then extract the first principal component of these four measures and use it to construct an index of social capital for each county for the years 1997, 2005, and 2009. We linearly interpolate the data to fill in the years 2000 to 2004 and 2005 to 2008.

An alternate measure of social capital based on Guiso et al. (2004) and Buonanno et al. (2009) is also used for our robustness checks. The formal regression model estimated is as follows:

\[
\text{Ambiguity}_{i,t} = \alpha + \beta \text{SC}_{i,t-1} + \gamma \text{BankLevel Controls}_{i,t-1} + \sum_{j=1}^{4} \text{BankType}_{j} + \text{Year}_{t} + \epsilon_{i,t}
\]

#### Table 1

**Sample selection and distribution.**

| Year | Total | Final sample |
|------|-------|-------------|
| 2001 | 380   | 6.76        |
| 2002 | 474   | 8.43        |
| 2003 | 503   | 8.95        |
| 2004 | 458   | 8.15        |
| 2005 | 434   | 7.72        |
| 2006 | 423   | 7.53        |
| 2007 | 404   | 7.19        |
| 2008 | 398   | 7.08        |
| 2009 | 352   | 6.26        |
| 2010 | 353   | 6.28        |
| 2011 | 348   | 6.19        |
| 2012 | 341   | 6.07        |
| 2013 | 298   | 5.30        |
| 2014 | 295   | 5.25        |
| 2015 | 160   | 2.85        |

Total 5621 100
Table 2
Descriptive statistics. This table presents the descriptive statistics of our sample. The sample is based on the Compustat Bank Fundamentals over the period 2001 to 2015. Panel A presents descriptive statistics for the sample. Panel B presents the results of Pearson correlations. Bold figures indicate significance levels at less than 5 percent. All variables are defined in the Appendix. The final sample consists of 5621 bank-year observations for 753 separate banks. All continuous variables are winsorized at the 1st and 99th percentiles.

Panel A: Descriptive statistics

| Variable          | N  | Mean  | Std. Dev. | 25th  | Median | 75th  |
|-------------------|----|-------|-----------|-------|--------|-------|
| Fin_Unc           | 5621| 1.294 | 0.308     | 1.153 | 1.324  | 1.486 |
| Fin Weak          | 5621| 0.478 | 0.157     | 0.380 | 0.481  | 0.586 |
| SCT   _t−1        | 5621| 0.118 | 0.828     | −0.637| −0.060 | 0.439 |
| SIZE   _t−1       | 5621| 5.161 | 1.679     | 3.962 | 4.901  | 6.143 |
| ROA   _t−1        | 5621| 0.007 | 0.009     | 0.005 | 0.008  | 0.011 |
| Deposits/Assets   | 5621| 0.749 | 0.095     | 0.693 | 0.767  | 0.820 |
| MTB   _t−1        | 5621| 1.426 | 0.704     | 0.936 | 1.302  | 1.801 |
| FIRM AGE   _t−1   | 5621| 12.139| 8.872     | 5.482 | 9.975  | 16.759|
| NIINT INC   _t−1  | 5621| 0.230 | 0.123     | 0.147 | 0.213  | 0.289 |
| MAs   _t−1        | 5621| 0.000 | 0.003     | 0.000 | 0.000  | 0.000 |
| RET VOL   _t−1    | 5621| 0.080 | 0.051     | 0.047 | 0.066  | 0.094 |
| DLW   _t−1        | 5621| 0.234 | 0.423     | 0.000 | 0.000  | 0.000 |
| Big5   _t−1       | 5621| 0.429 | 0.495     | 0.000 | 0.000  | 1.000 |
| Analysts   _t−1   | 5621| 2.843 | 4.623     | 0.000 | 1.000  | 4.000 |
| Population   _t−1 | 5621| 12.693| 1.421     | 11.632| 12.817 | 13.647|
| Income   _t−1     | 5621| 10.518| 0.286     | 10.317| 10.486 | 10.688|
| Education   _t−1  | 5621| 10.831| 1.430     | 9.762 | 10.984 | 11.770|

Panel B: Correlations among regression variables

| Variable          | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) | (17) |
|-------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|------|------|------|------|------|------|------|------|
| (1) Fin_Unc           | 1.000 |     |     |     |     |     |     |     |     |      |      |      |      |      |      |      |
| (2) Fin_Weak           | 0.790 |     |     |     |     |     |     |     |     |      |      |      |      |      |      |      |
| (3) SCT   _t−1        | −0.046 | −0.004 |     |     |     |     |     |     |     |      |      |      |      |      |      |      |
| (4) SIZE   _t−1       | 0.086 | −0.096 | −0.058 |     |     |     |     |     |     |      |      |      |      |      |      |      |
| (5) ROA   _t−1        | −0.110 | −0.193 | −0.138 | 0.331 |     |     |     |     |     |      |      |      |      |      |      |      |
| (6) Deposits/Assets   | 0.030 | 0.037 | 0.041 | −0.238 | −0.073 |     |     |     |     |      |      |      |      |      |      |      |
| (7) MTR   _t−1        | −0.038 | −0.143 | −0.222 | 0.483 | 0.484 | 0.026 |     |     |     |      |      |      |      |      |      |      |
| (8) FIRM AGE   _t−1   | 0.079 | −0.037 | 0.151 | 0.578 | 0.054 | −0.052 | 0.076 |     |     |      |      |      |      |      |      |      |
| (9) NIINT INC   _t−1  | 0.093 | −0.049 | 0.087 | 0.386 | 0.077 | −0.116 | 0.144 | 0.388 |     |      |      |      |      |      |      |      |
| (10) MAs   _t−1       | −0.054 | −0.062 | −0.059 | 0.001 | 0.509 | 0.010 | 0.118 | −0.031 | 0.019 |     |      |      |      |      |      |      |
| (11) RET VOL   _t−1    | 0.124 | 0.148 | 0.058 | −0.147 | 0.019 | 0.085 | −0.273 | 0.056 | 0.075 | −0.193 |     |      |      |      |      |      |
| (12) FIRM AGE   _t−1   | 0.114 | 0.081 | 0.032 | 0.216 | 0.043 | −0.062 | 0.065 | 0.125 | 0.170 | −0.032 | −0.069 |     |      |      |      |      |
| (13) DLW   _t−1        | −0.059 | −0.035 | −0.167 | 0.133 | −0.003 | −0.217 | −0.001 | 0.015 | −0.053 | −0.016 | 0.001 | 0.011 |     |      |      |      |
| (14) Big5   _t−1       | 0.009 | −0.126 | −0.130 | 0.533 | 0.181 | −0.151 | 0.278 | 0.325 | 0.243 | −0.004 | −0.036 | 0.106 | 0.202 |     |      |      |
| (15) Analysts   _t−1   | 0.100 | −0.055 | −0.043 | 0.758 | 0.149 | −0.193 | 0.221 | 0.576 | 0.322 | −0.020 | −0.035 | 0.155 | 0.174 | 0.442 |     |      |
| (16) Population   _t−1 | 0.025 | 0.090 | −0.338 | 0.329 | −0.002 | −0.102 | 0.161 | 0.154 | −0.013 | −0.022 | 0.070 | 0.037 | 0.246 | 0.301 | 0.312 |     |
| (17) Income   _t−1     | 0.020 | 0.101 | 0.231 | 0.204 | −0.109 | 0.015 | −0.027 | 0.195 | −0.019 | −0.056 | 0.070 | 0.084 | 0.056 | 0.081 | 0.200 | 0.486 |
| (18) Education   _t−1  | 0.028 | 0.000 | −0.372 | 0.320 | 0.000 | −0.098 | 0.163 | 0.140 | −0.018 | −0.018 | 0.069 | 0.028 | 0.248 | 0.294 | 0.299 | 0.993 | 0.445 |
Table 3
Ambiguous tone and social capital. This table presents the regression results of ambiguous tone in banks’ 10-K reports on social capital. Year fixed effects are included in the regressions but not reported. Standard errors are double-clustered by bank and year and t-values are presented in parentheses.

| 1 | Fin_Unc | 2 | Fin_Weak |
|---|---------|---|---------|
| OLS | OLS | OLS | OLS |
| SC1<sup>−1</sup> | −0.024** | −0.015*** | (−2.445) | (−2.894) |
| SIZE<sup>−1</sup> | 0.021*** | −0.006 | (2.764) | (−0.968) |
| ROA<sup>−1</sup> | −0.588 | −0.259 | (−0.915) | (−0.627) |
| Deposits/Assets<sup>−1</sup> | 0.089 | −0.006 | (1.400) | (−0.190) |
| MTB<sup>−1</sup> | −0.021* | 0.005 | (−1.771) | (0.768) |
| FIRM_AGE<sup>−1</sup> | −0.001 | −0.001* | (−1.032) | (−1.769) |
| NCENT<sup>−1</sup> | 0.131*** | 0.001 | (2.796) | (0.025) |
| DLW<sup>−1</sup> | −1.549 | −0.820 | (−0.858) | (−0.780) |
| RET_VOL<sup>−1</sup> | 0.129 | 0.103* | (1.518) | (1.872) |
| MA<sup>−1</sup> | 0.011 | 0.008 | (0.958) | (0.943) |
| Big5<sup>−1</sup> | −0.018 | 0.001 | (−1.158) | (0.869) |
| Analysts<sup>−1</sup> | 0.004 | −0.004 | (0.269) | (−0.428) |
| Population<sup>−1</sup> | 0.001 | 0.000 | (0.619) | (−0.033) |
| Income<sup>−1</sup> | 0.001 | −0.002 | (0.040) | (−0.093) |
| Education<sup>−1</sup> | −0.004 | 0.023 | (−1.512) | (1.389) |
| Intercept | 1.775** | 0.479*** | (7.044) | (3.192) |

Bank Type fixed effect Yes Yes
Year fixed effect Yes Yes
Observations 5621 5621
Adj.R<sup>2</sup> / Pseudo R<sup>2</sup> 0.637 0.502

Notes:
Fin_Unc is the proportion of occurrences for uncertainty words for each year for every 10 words in a 10-K report.
Fin_Weak is the proportion of occurrences for weak words for each year for every 10 words in a 10-K report.
The independent variables are defined in the Appendix.
*Statistical significance at the 10% level.
**Statistical significance at the 5% level.
***Statistical significance at the 1% level.

where subscripts i and t refer to bank and year, respectively, making our unit of analysis a bank-year. BankLevelControls is a vector of bank-specific control variables adapted from Li (2008), and include size, market-to-book ratio, age of the firm, the proportion of total income that is made up of non-interest income, special items (scaled by the book value of total assets), return volatility, an indicator variable for acquisitions, an indicator variable for incorporation in Delaware, an indicator variable for audit by Big 5, an indicator variable for financial crisis period (2007–2009), county-level demographic variables (population, income and education from Hasan et al. (2017), and bank type (commercial, state commercial, federally chartered savings institutions, and non-federally chartered savings institutions).

In our robustness checks, we also include the following independent variables: Fog Index based on Li (2008), scaled length of the annual report in words, scaled size of the 10-K report, natural log of the population in the county, the ratio of male-to-female population in the county, the ratio of married-to-total households in the county, the ratio of population over age 25 who have at least an undergraduate degree, the natural log of per capita personal income of the county, the proportion of the population that self-identifies as being religious, and the Herfindahl index for ethnic heterogeneity in the county during a year. The variables are defined in the Appendix.

We do not control for country, institutions and legal origin since our entire sample is from the U.S. We cluster the standard errors at the county level since social capital is sticky and may not change over time. We automatically allows us to control for clustering at the firm level (Cameron and Miller, 2011; Bertrand and Mullainathan, 2001).

5 The correlations between social capital in 1997, 2005, 2009 and 2014 are all in the range of 0.81 and 0.95, suggesting that social capital is sticky and does not change over time. As a result, we do not include county-level fixed effects.
Table 4 (continued).

Panel B The effect of High and low social capital

| 1 | 2 | 3 |
|---|---|---|
| **Fin_Unct** | **Fin_Weak** | **OLS** | **OLS** | **OLS** |
| Dummy for 75th percentile of SC1\_t−1 | −0.006 | −0.009 |
| Dummy for 75th percentile of SC1\_t−1, Recession | (−0.505) | (−1.189) |
| Dummy for 25th percentile of SC1\_t−1 | 0.027* | 0.001 |
| Dummy for 25th percentile of SC1\_t−1, Recession | (1.875) | (2.699) |
| SIZE\_t−1 | 0.029** | 0.000*** |
| ROA\_t−1 | −0.095 | −0.227 |
| Deposits/Assets\_t−1 | −0.009 | −0.008 |
| MTB\_t−1 | (1.893) | (1.215) |
| FIRM\_AGE\_t−1 | −0.021* | 0.005 |
| NIINT\_INC\_t−1 | −0.595 | (0.721) |
| RET\_VOL\_t−1 | −0.001 | (−0.010) |
| SI\_t−1 | 0.120* | 0.000 |
| MA\_t−1 | −5.145 | −0.820 |
| DLW\_t−1 | 0.126 | 0.103 |
| Big\_t−1 | 0.010 | 0.008 |
| Analysts\_t−1 | (1.861) | (1.842) |
| Population\_t−1 | −0.019 | −0.001 |
| Income\_t−1 | −0.001 | (−0.000) |
| Education\_t−1 | 0.000 | 0.000 |
| Intercept | 1.778** | 4.666*** |
| Bank Type fixed effect | Yes | Yes |
| Year fixed effect | Yes | Yes |
| Observations | 5621 | 5621 |
| Adj.R\(^2\) | 0.537 | 0.503 |

Notes:
Fin_Unct is the proportion of occurrences for uncertainty words for each year for every 10 words in a 10-K report.
Fin_Weak is the proportion of occurrences for weak words for each year for every 10 words in a 10-K report.
The independent variables are defined in the Appendix.
*Statistical significance at the 10% level.
**Statistical significance at the 5% level.
***Statistical significance at the 1% level.

et al. 2004). We estimate Model (1) using both Ordinary Least Squares (OLS) and Ordered Logistic Regression.

Sample and Descriptive Statistics
Our sample starts with 8216 bank-years spanning the years 2001–2015. Missing data for various independent variables reduces the final sample to 5621 bank-years as described in Panel A of Table 1. Panel B documents the distribution of our final sample across years.
Panel A of Table 2 presents the descriptive statistics of the dependent and independent variables. There is sufficient variation in our measure of the ambiguity of tone in banks’ 10-K reports.

Raw values of Fin_Weak ranging from 0.380 at the 25th percentile to 0.586 at the 75th percentile, with a median (mean) of 0.481 (0.478). Similarly, there is considerable variation in our measure of social capital in the county where the bank is headquartered, ranging from −0.637 at the 25th percentile to 0.439 at the 75th percentile, with a median (mean) of −0.060 (−0.118). Panel B of Table 2 presents the Pearson correlations. As expected, the correlation between ambiguity and social capital is negative and significant (p < 0.01).

4. Results
Our main multivariate results presented in Table 3 – are consistent with our first hypothesis. Ceteris paribus, banks located in counties with high social capital exhibit lower ambiguous tone in their 10-K filings under both our measures of ambiguity. Because of the ordinal nature of the dependent variable Financial
Robustness checks. This table presents the regression results of robustness checks. Year fixed effects are included in the regressions but not reported. Standard errors are double-clustered by bank and year and t-values are presented in parentheses.

### Panel A: Independent variable is SC2

|  | 1 | 2 |
|---|---|---|
| SC2i,t−1 | −0.549*** | −0.499** |
| Controlsi,t−1 | Yes | Yes |
| Bank Type fixed effect | Yes | Yes |
| Year fixed effect | Yes | Yes |
| Observations | 5621 | 5621 |
| Adj.R² | 0.636* | 0.500 |

### Panel B: Dependent variable is the original unscaled value

|  | 1 | 2 |
|---|---|---|
| SC1i,t−1 | −0.032** | −0.046*** |
| Controlsi,t−1 | Yes | Yes |
| Bank Type fixed effect | Yes | Yes |
| Year fixed effect | Yes | Yes |
| Observations | 5621 | 5621 |
| Adj.R² | 0.117 | 0.029 |

### Panel C: Controlling for local religiosity

|  | 1 | 2 |
|---|---|---|
| SC1i,t−1 | −0.027*** | −0.016*** |
| Local religiosity−1 | −2.738 | −2.919 |
| Controlsi,t−1 | Yes | Yes |
| Bank Type fixed effect | Yes | Yes |
| Year fixed effect | Yes | Yes |
| Observations | 4527 | 4527 |
| Adj.R² | 0.303 | 0.300 |

### Panel D: Subsample of banks subject to FDICIA internal control provisions (i.e., if bank assets > $500 million before 2005 or > $1 billion after 2005)

|  | 1 | 2 |
|---|---|---|
| SC1i,t−1 | −0.025** | −0.016*** |
| Controlsi,t−1 | Yes | Yes |
| Bank Type fixed effect | Yes | Yes |
| Year fixed effect | Yes | Yes |
| Observations | 3504 | 3504 |
| Adj.R² | 0.669 | 0.589 |

### Panel E: Subsample of banks not in the FDICIA subsample or not otherwise subject to FDICIA internal control provisions

|  | 1 | 2 |
|---|---|---|
| SC1i,t−1 | −0.025* | −0.013 |
| Controlsi,t−1 | Yes | Yes |
| Bank Type fixed effect | Yes | Yes |
| Year fixed effect | Yes | Yes |
| Observations | 2117 | 2117 |
| Adj.R² | 0.595 | 0.407 |

(continued on next page)

Uncertainty and Financial Weakness — we also estimate ordered logistic regressions (not reported) and obtain similar results to OLS regressions (in columns 1 and 2 of Table 3).

Size of the bank is found to be positively associated with ambiguity when ambiguity is measured by Financial Uncertainty, but not statistically associated when ambiguity is measured by Financial Weakness. The positive association may be justified because larger banks have more transactions as well as more complex interactions that naturally lead to more ambiguous reporting. The lack of association with Financial Weakness may be justified on the grounds that larger banks have more stable operations that can withstand variations or shocks, and financially stronger (including perhaps “too big to fail”). Similarly, age is marginally negatively associated with ambiguity for arguably the same reason.

On the grounds that norms and values may matter less for more dispersed firms, we decompose our sample into small banks (total assets < $1 billion) and large banks (≥ $1 billion), and find the coefficients of the two sub-groups are not statistically different (results not presented).

Growth – as proxied by market-to-book ratio – is found to be marginally negatively associated with ambiguity when ambiguity is measured by Financial Uncertainty, but not significantly associated when ambiguity is measured by Financial Weakness. The proportion of income not related to interest is positively associated with ambiguity as measured by Financial Uncertainty, suggesting that banks may have a harder time communicating about operations outside their natural deposit-taking and loan granting line-of-businesses. Finally, the volatility of monthly stock returns is positively associated with ambiguity, suggesting that management may find it difficult to convey the higher levels of operational risk in their 10-K filings.

Table 4 presents the results of our second hypothesis. We find that the mitigating impact of social capital on the ambiguity of tone in 10-K filings is maintained at a statistically significant level (when ambiguity is measured by Financial Uncertainty it is in fact enhanced) during the recessionary periods (2001 and 2007–2009) compared to the non-crisis period (2002–2006 and 2007–2009).
Table 7
Two-stage regression using instrumental variable. This table presents the results of a two-stage regression based on an instrumental-variable. The instrumental-variable is Ethnicity homogeneity, which is a Herfindahl index calculated across four basic Census tract ethnic categories that include Hispanic, non-Hispanic black, non-Hispanic white, and Asian in a county during a year. Year fixed effects are included in the regressions but not reported. Standard errors are double-clustered by bank and year and t-values are presented in parentheses.

| Ethnicity homogeneity | Fin_Unc_{−1} | Fin_Weak_{−1} | Fitted social capital_{−1} | OLS | OLS | OLS |
|-----------------------|--------------|---------------|-----------------------------|-----|-----|-----|
|                       |              |               |                             |     |     |     |
| 1.956                 | −0.058***    | −0.034***     | −0.334***                   |     |     |     |
| (10.707)              | (−2.650)     | (−2.643)      | (−2.643)                    |     |     |     |
| SIZE_{−1}             | 0.034        | 0.021***      | −0.005                      |     |     |     |
| (1.304)               | (2.883)      | (−0.873)      | (−0.873)                    |     |     |     |
| ROA_{−1}              | −5.544***    | −0.742        | −0.342                      |     |     |     |
| (−2.607)              | (−1.189)     | (−0.831)      | (−0.831)                    |     |     |     |
| Deposits/Assets_{−1}  | −0.068       | 0.077         | −0.013                      |     |     |     |
| (−0.247)              | (1.220)      | (−0.361)      | (−0.361)                    |     |     |     |
| MTB_{−1}              | −0.127***    | −0.026***     | 0.003                       |     |     |     |
| (−3.742)              | (−2.138)     | (0.388)       | (0.388)                     |     |     |     |
| FIRM_AGE_{−1}         | 0.007*       | 0.000         | −0.001                      |     |     |     |
| (1.942)               | (−0.562)     | (−1.321)      | (−1.321)                    |     |     |     |
| NIINT_INC_{−1}        | 0.426***     | 0.141***      | 0.007                       |     |     |     |
| (2.153)               | (3.000)      | (0.264)       | (0.264)                     |     |     |     |
| Si_{−1}               | 1.187        | −1.610        | −0.852                      |     |     |     |
| (0.369)               | (−0.908)     | (−0.835)      | (−0.835)                    |     |     |     |
| RET_VOL_{−1}          | 0.448        | 0.144         | 0.111*                      |     |     |     |
| (1.233)               | (1.616)      | (1.948)       | (1.948)                     |     |     |     |
| MA_{−1}               | −0.044       | 0.010         | 0.007                       |     |     |     |
| (−1.087)              | (0.852)      | (0.863)       | (0.863)                     |     |     |     |
| DLW_{−1}              | −0.063       | −0.021        | −0.001                      |     |     |     |
| (−1.013)              | (−1.349)     | (−0.128)      | (−0.128)                    |     |     |     |
| BigSi_{−1}            | −0.037       | 0.003         | −0.004                      |     |     |     |
| (−0.709)              | (0.237)      | (−0.460)      | (−0.460)                    |     |     |     |
| Analysts_{−1}         | −0.005       | 0.001         | 0.000                       |     |     |     |
| (−0.657)              | (0.379)      | (−0.208)      | (−0.208)                    |     |     |     |
| Population_{−1}       | 0.457***     | 0.017         | 0.007                       |     |     |     |
| (3.287)               | (0.527)      | (0.341)       | (0.341)                     |     |     |     |
| Income_{−1}           | 1.126***     | 0.543***      | 0.043*                      |     |     |     |
| (11.700)              | (−1.100)     | (1.991)       | (1.991)                     |     |     |     |
| Education_{−1}        | −0.582***    | −0.028        | −0.015                      |     |     |     |
| (−4.252)              | (−0.816)     | (−0.744)      | (−0.744)                    |     |     |     |
| Intercept             | −11.159      | 1.523***      | 0.344*                      |     |     |     |
| (−10.011)             | (5.384)      | (1.982)       | (1.982)                     |     |     |     |
| Bank Type fixed effect | Yes          | Yes           | Yes                         |     |     |     |
| Year fixed effect     | Yes          | Yes           | Yes                         |     |     |     |
| Observations          | 5621         | 5621          | 5621                        |     |     |     |
| Adj.R²                | 0.496        | 0.638         | 0.502                        |     |     |     |
| F-value               | 384.85       |               |                             |     |     |     |

Notes:
SC1 is the measure of Social Capital at the county level. Fin_Unc is the proportion of occurrences for uncertainty words for each year for every 10 words in a 10-K report. Fin_Weak is the proportion of occurrences for weak words for each year for every 10 words in a 10-K report.

The independent variables are defined in the Appendix.

*Statistical significance at the 10% level.
**Statistical significance at the 5% level.
***Statistical significance at the 1% level.

2010–2015). This suggests that the impact of social capital is reasonably consistent over time, and continues to be exhibited (like generosity or philanthropy) during times of financial crisis when it may be most necessary to readers of 10-K filings.6

Table 5 further shows that social capital has a mitigating effect on the Fog index of a bank (Column 1) and on the size of the 10-K computer file (Column 3), but not on the length of the 10-K report (Column 2).

5. Robustness checks

Table 6 reports our sensitivity tests using alternate measures of our variables of interest. Panel A reports that ambiguity of tone continues to be marginally lower for banks headquartered in counties with higher social capital when the latter is measured by state-level, per capita organ donation. Panel B shows that the results hold when we do summarize the ambiguity measures by their decile rank instead of using the original values of the proportion of occurrences of words from the uncertainty word list per 1000 words in 10-K reports (Fin_Unc) or the proportion of occurrences for words from the list of weak words for each 1000 words in 10-K reports (Fin_Weak). Panel C includes control for religiosity at the county level, and our main hypothesis continues to hold. Interestingly, religiosity contributes to additional reduction of ambiguity when ambiguity is measured by the prevalence of weak words. Panel D shows that the results continue to hold in a subsample of banks subject to FDICIA internal control provisions, while Panel E shows that the results hold (but less strongly) for the subsample of banks not subject to FDICIA internal control provisions. Panel F shows that the results hold when the social capital measure is coded as 1 if above median and 0 otherwise, while Panel G shows that results hold after controlling for Earnings Before Taxes and Provision (EBTP).

Table 7 presents our results based on a two-stage regression using an instrumental variable. Our instrumental variable is Ethnicity homogeneity – a Herfindahl index calculated across four census tract ethnic categories (Hispanic, non-Hispanic black, non-Hispanic white, and Asian) in a county during a year. We first regress social capital on Ethnicity Homogeneity plus all other control variables from Table 3 to derive fitted values of social capital. We then estimate model (1) using fitted values of social capital instead of the constructed values of social capital (based on Rupasingha and Goetz, 2008). Our results remain consistent: higher fitted values of social capital are associated with lower levels of ambiguity tone in banks’ 10-K reports. In summary, our key results continue to hold after all sensitivity tests.

6. Conclusion

While management’s discretion on how and what to report is limited to audited financial statements, it has significant discretion in what it can report in the 10-K filings without being too limited by consistency, conservatism, materiality or even a historical focus. While the subject matter and structure in the 10-K reports are mandated, the clarity or ambiguity of the content is left to management’s discretion. Stakeholders’ understanding of such information and their resulting interpretation and decisions — depend non-trivially on the ambiguity of management’s tone.

Ambiguous 10-K Reports contribute to information risk and can reduce stakeholders’ ability to understand or assess firms’ investment and financing risks, and therefore valuation. Deliberate ambiguity that serves corporate or managerial interests at the expense of other stakeholders’ interests can lead to a decline in investor confidence. We examine whether the ambiguity of the tone in the bank’s 10-K filings is associated with the social capital in the local county where the bank is headquartered. We argue that textual reporting is consistently less ambiguous in banks headquartered in counties with high social capital since such

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6 When we run two separate tests for recessionary and non-recessionary periods and compare the p-value (not reported), we find the results consistent to those reported in Table 4 for the interaction term Social Capital * Recession.

7 FDICIA (Federal Deposit Insurance Corporation Improvement Act) internal control provisions apply to banks with total assets exceeding $500 million before 2005 and exceeding $1 billion during or after 2005.
banks are more forthcoming and therefore have fewer reasons for opportunistically or self-serving reporting. Social capital can enhance economic returns to all sides of the transaction in situations of information asymmetry and risk, and can mitigate the fear that one’s exchange partner will act opportunistically. In our context of 10-K reports, investors could trust management to look after their long-run interests and report

### Table A.1

| Variable definitions | Definitions |
|----------------------|-------------|
| **Dependent variables** | Fin_Unc denotes the proportion of occurrences for uncertainty words for each year for every 10 words in a 10-K report. Uncertainty word list includes words denoting uncertainty, focusing on the general notion of imprecision rather than exclusively focusing on risk, such as approximate, contingency, depend, fluctuate, uncertain, variability. Word list is from Loughran and McDonald (2011). Fin_Weak denotes the proportion of occurrences for weak words for each year for every 10 words in a 10-K report. The list of weak words expresses low level of confidence, such as could, might, depending, possibly. The word list is from Loughran and McDonald (2011). |
| **Independent variables** | ProvOT, RespN, Nccs97, SC1 denote the percentage of voters who voted in presidential elections, response rate to the Census Bureau’s decennial census, number of tax-exempt non-profit organizations per 10,000 of population, and social capital defined as the first principal component of a principal component analysis (PCA) based on the above four NERCID variables at the county level. This variable is the measure of social capital at the county level. It is constructed following Rupasingha and Goetz (2008). Specifically, the variable is constructed by using the first component from a principal component analysis that uses four different measures. For example, we use the following four measures: assn97, nccs97, provote96, respnn00 for 1997, where assn97 is the sum of the religious organizations, civic and social associations, business associations, political organizations, professional organizations, labor organizations, bowling centers, physical fitness facilities, public golf courses, sport clubs, and recreation clubs, and membership organizations not elsewhere classified in 1997. We divide the total by 10 because there are 10 different categories. Further, we also divide it by the population of the county. We then multiply it by 10,000. The measure nccs97 is the total number of nongovernment organizations excluding the ones with an international focus in 1997 divided by the population multiplied by 10,000. The measure provote96 is the number of votes cast divided by the population above 18 times 100. The measure respnn00 is the census response rate. Then we use a principal component analysis and use the first component to construct the social capital index for each county. We use an analogous approach for 2005 and 2009. For each of these years, we use the presidential elections and census response closest to 2005 and 2009, respectively. We then linearly interpolate and fill the social capital data for the in-between years. SC2 reflects the state-level per capita organ donor, which is the total number of organ donors in a state in a given year divided by total state population in that year multiplied by 1,000. Donor is a person from whom at least one organ or tissue is recovered for the purpose of transplantation. Organ donation data can be obtained from the OPTN via the link: http://optn.transplant.hrsa.gov/latestData/stateData.asp?type=state. We follow Guiso et al. (2004) and Buonanno et al. (2009) to construct this variable. |
| **Control variables** | SIZE reflects the natural log of market value of common equity (log(PRCC_F*CASHO)). Source: Compustat Bank Fundamentals. MTB denotes market-to-book ratio at year-end (PRCC_F*CASHO)/ eq. Source: Compustat Bank Fundamentals. ROA denotes net income divided by book assets (N/AT) in fiscal year t-1. Source: Compustat Bank Fundamentals. Deposits/Assets denotes total deposits divided by book assets (DPTC/AT) in fiscal year t-1. Source: Compustat Bank Fundamentals. FIRM_AGE denotes number of years that a firm has been in CRSP monthly stock return files. NIINT_INC denotes the ratio of non-interest income to the sum of interest and non-interest incomes (TNII/(NIINT+TNII)). Source: Compustat Bank Fundamentals. Sh denotes special items scaled by book value of assets. RET_VOL denotes standard deviation of the monthly stock returns. MA denotes indicator variable coded 1 for non-zero spending on acquisitions (AQC). Source: Compustat Bank Fundamentals. DLW denotes indicator variable coded 1 if a company is incorporated in Delaware and 0 otherwise. Big5 denotes an indicator variable coded 1 if audited by a big 5 firm and 0 otherwise. Analysts denotes number of analysts for the latest consensus forecast (numest). If this number is not available for a firm, then the number of analysts following is assumed to be zero. Bank Type includes (1) Commercial Banks; (2) State Commercial Banks (3) Federally Chartered Savings Institutions; and (4) Non-Federally Chartered Savings Institutions. |
| **Robustness Checks variables** | Fog denotes the Fog Index of the firm’s annual report. Fog index of the firm’s annual report, defined as 0.4 multiplied by the sum of the average number of words per sentence and the percentage of complex words. Complex words are those with more than two syllables. Length denotes the number of words in the firm’s annual report. File size refers to the file size of 10-K. The file size of 10-K is in megabytes of the SEC EDGAR “complete submission text file” for the 10-K filing. Financial Crisis denotes an indicator variable that equals 1 for fiscal years 2007, 2008 and 2009, and 0 otherwise. Population reflects the natural logarithm of total resident population in the county. Source: Bureau of Economic Analysis. Income reflects the natural logarithm of median household income in the county. Source: Bureau of Economic Analysis. |

(continued on next page)
outcomes truthfully, consistently and unambiguously if social capital levels are high.

Our findings are consistent with our hypothesis. After controlling for bank characteristics, we find that banks’ ambiguity of tone in their 10-K filings is significantly lower in banks that are headquartered in high social-capital counties.

In further tests, we find that the impact of social capital on ambiguity of tone was not altered during recessionary periods of 2001 and 2007–2009. Ceteris paribus, banks headquartered in high social-capital counties reported less ambiguously in their 10-K filings compared to banks headquartered in low social-capital counties during recessionary periods (2001 and 2007–2009).

Our findings contribute to the literature on the impact of social capital on management’s disclosures and transparent reporting. Our finding of a negative association between social capital and ambiguous disclosure contributes to the separate sub-literatures on social capital and ambiguity. The literature on social capital includes studies that addressed why firms headquartered in high social-capital counties incur lower bank loan spreads (Hasan et al., 2017b); engage in less tax avoidance (Hasan et al., 2017a); enjoy lower audit fees (Jha and Chen, 2015); and have greater financial reporting transparency (Jin et al., 2017). The literature on disclosure ambiguity has explored why firms with lower ambiguity in annual reports enjoy lower borrowing costs (Ertugrul et al., 2017) and exhibit lower risk-taking (Kanagaretnam et al., 2017). Our results establishing the link between ambiguity and social capital can be relied upon to advance the hypotheses in all the above studies spanning the social capital and ambiguity sub-literatures.

Declaration of competing interest

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Appendix

See Table A.1.

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