The Walls Have Ears:
Local Information Environments and Corporate Fraud

Journal of Money, Credit, and Banking, forthcoming

Abstract

This paper shows that a firm's likelihood of committing corporate fraud is affected by the local information environment. We use the density of local bank branch networks as a proxy for the local information environment. We show that denser bank branch networks increase the likelihood of fraud detection, accelerate the detection of fraud, and decrease the fraud propensity of local firms. Our results cannot be explained by the clustering of firms in urban areas, geographic proximity to regulators, or other location effects. Overall, our study identifies a spatial dimension in the detection and prevention of corporate fraud.

"Fraud involves concealment while communication fosters openness"
Hooks, Kaplan, and Schultz (1994)

1. INTRODUCTION

The local information environment plays an important role in the detection and prevention of fraud. The Association of Certified Fraud Examiners (2014) reports that half of all corporate fraud cases are brought to light through information leakages. Similarly, the notion that the availability of high-quality information reduces fraudulent behavior by firms features prominently in the Securities and Exchange Commission's (SEC) rulemaking (Clayton 2017).

In this paper, we test two hypotheses on the link between the local information environment and fraud. Our first hypothesis posits that a local environment that is conducive to information flows is associated with a higher likelihood of fraud detection. Fraudulent firms often exhibit signs of suspicious behavior, such as accounting, operational, or management failings, several years prior to detection.[1] Whether (and how fast) these signs are noticed and pave the way for fraud detection should depend on the degree to which the local environment facilitates the circulation of local information. Recent analyses highlight the importance of local information flows for local corruption (Campante and Do 2014), international trade (Cohen, Gurun, and Malloy 2017), and corporate investment (Core, Lobanova, and Verdi 2016).

Our second hypothesis proposes that a firm's local information environment affects its incentives to commit fraud in the first place. According to Becker's (1968) economic theory of crime, individuals weigh the expected benefits of fraud against its costs when deciding whether to commit fraud. Thus, the probability of committing fraud decreases with the expected associated costs. If an enhanced information environment increases the likelihood of fraud detection (which is costly to firms), an informative environment should discourage firms from committing fraud in the first place.

Our proxy for the local information environment is the density of the local bank branch network. Banks play a unique role in gathering and processing information on local firms. Compelling evidence suggests that banks obtain information about their borrowers (Petersen and Rajan 2002, Roberts and Sufi 2009). For most firms, bank lending is the most frequent source of external finance (Hadlock and James 2002).[2] In the process of lending to firms, banks acquire firm-specific information (Schenone 2010, Sharpe 1990) that, over time, accumulates into substantial soft information (Berger and Udell 2002). As well as collecting borrower information at the point of loan origination, many banks continue to collect borrower information throughout the duration of a loan. Gustafson, Ivanov, and Meisenzahl (2020) report that banks regularly request information updates from corporate borrowers, and that many syndicated loans involve active monitoring with regular onsite visits between bank employees and borrower representatives. To maintain such active levels of monitoring, at least some of the monitoring and information-collection activities can be expected to be delegated to bankers at local branches (Levine et al. 2020). Therefore, branches are an important platform where borrower information is gathered and processed.

Besides obtaining information on clients, banks also have incentives to collect information on non-client firms. Garmaise and Natividad (2016) argue that banks generate hard-to-observe insights into neighborhood characteristics to tailor their monitoring efforts and product offerings to local firms. Therefore, the presence of bank branches in local neighborhoods may act as a conduit for the collection of local information and enhance the informativeness of the local business environment.[3]

In this paper, we exploit variation in the density of bank branches across the US: we calculate the number of branches located within a 10 km radius of each firm's headquarters.[4] We then link the branch density data to the propensity of firms to engage in fraud. Our fraud sample is an updated version of Dechow et al.'s (2011) sample of the Accounting and Auditing Enforcement Releases (AAERs) issued by the SEC. AAERs are issued against firms that are alleged to have been involved in accounting or auditing misconduct such as earnings inflation, material omissions, or record falsification.

One concern with our analysis is that we can only observe detected fraud (once an enforcement action has been issued) and not the population of all cases of fraud committed. To address the problem of partial observability, we follow Wang (2013) and employ a bivariate probit model that disentangles fraud commission from the detection of fraud conditional upon fraud having occurred.

Our baseline results indicate that an increase of one standard deviation in the number of bank branches within a 10 km radius reduces the likelihood that firms located within that area will commit fraud by 10.1% and increases the likelihood of detection (conditional upon fraud having been committed) by 8.3%. Our findings are robust to exclusion of the largest cities, using an alternative branch density measure that is uncorrelated to the local population size, and controlling for measures of the SEC's monitoring intensity. Further, we obtain similar results when matching fraud firms to non-fraud firms using one-to-one propensity score matching.

To address concerns that our baseline results are driven by unobserved characteristics that correlate with both branch density and the fraud propensity of local firms, we perform additional analyses that exploit reductions in branch density due to branch closures. We focus on the closures of duplicate branches where previously separate branch networks overlap after a merger. A merger-induced branch closure typically removes an entire bank from a local market. As local banking markets become less competitive, local banks gain greater pricing power over borrowers and have fewer incentives to invest in lending relationships by collecting and accumulating borrower information (see Garmaise and Moskowitz 2006, Presbitero and Zazzaro 2011). Further, branch consolidation programs are usually accompanied by staff layoffs and a loss of codified information on firms, thereby further impeding the information collection and dissemination role of local bank branch networks.

The results of our difference-in-differences analysis confirm that merger-induced branch consolidation is associated with fewer cases of detected fraud and more cases of committed fraud compared with a control group of matched firms located in counties unaffected by branch closures. Furthermore, the effects of branch consolidation on fraud are stronger for smaller firms and for closures of larger branches.

We construct additional tests to highlight the heterogeneous effects of bank branches on fraud. First, we use loan data from DealScan to show that our results become stronger in areas where local firms rely more on bank borrowing as a source of external finance. Importantly, our local bank density measures continue to have a significant fraud-reducing effect after controlling for the various local credit measures. This confirms that bank branches exert information effects even if some local firms do not have credit relationships with local banks. Second, the fraud-reducing effect of local bank branches is stronger for smaller and more opaque firms and when branches belong to smaller or local banks. Third, we show that the fraud-reducing effect of local bank branches is stronger when the firm has an insider-dominated board of directors or when it has an entrenched manager. The latter is consistent with the notion that the external information environment acts as a partial substitute for internal governance mechanisms.

In the final part of the paper, we show that an enhanced information environment is associated with firm behavior that makes the eventual commission of fraud less likely. That is, higher bank branch density means that nearby firms are less likely to manage their earnings, restate their financial statements, or have material internal control weaknesses. Also, fraud committed in an enhanced information environment is detected faster. A one standard deviation increase in the number of local bank branches shortens the time it takes to detect fraud by approximately 19% (the equivalent of six months).

Our paper contributes to several active research areas. First, we contribute to the literature on the impact of the local environment on agent behavior. Anselin, Varga, and Acs (1996) report evidence of positive externalities between university research and local innovation activities. Campante and Do (2014) find that geographic areas with more information sharing between citizens and the media are associated with lower levels of corruption-related crime. Core, Lobanova, and Verdi (2016) show that local information sharing causes geographically proximate firms to make similar and better decisions. Cohen, Gurun, and Malloy (2017) find that firms are more likely to trade with countries that have a large resident population near their headquarters. Our findings contribute to this line of research by highlighting the importance of a local environment that facilitates information flows for the detection and prevention of corporate fraud.

Second, our paper contributes to the literature on the determinants and economics of corporate fraud (e.g., Correia 2014, Kedia and Rajgopal 2011, Khanna, Kim, and Lu 2015, Yu and Yu 2011). Specifically, we identify bank branches as information agents that affect fraud propensity. Thus, our paper contributes to research on the role of other information agents such as the press (Miller 2006), the general public (Dyreng, Hoopes, and Wilde 2016), and employees (Call et al. 2017) in influencing financial reporting and fraud.

In contemporaneous work, Li, Makaew, and Winton (LMW) (2018) also address the role of banking presence in corporate fraud but focus on different underlying mechanisms. The authors focus on banking development and financial liberalization. In contrast, we focus on the information environment created by local branches. Because we demonstrate that lending to local firms is not a precondition for fraud-reducing branch effects, our information channel is distinct from LMW.'s (2018) channel of monitoring by banks.[5]

Finally, we contribute to the literature exploring the effects of banks on the real economy. Studies in this area focus on the role of banks in providing credit (Agarwal and Hauswald 2010, Nguyen 2019, Petersen and Rajan 2002) or in reducing information asymmetries between firms and credit markets (Erkens, Subramanyan, and Zhang 2014, Ferreira and Matos 2012). We show evidence of another benefit of banks: a hitherto undocumented positive externality linked to bank branches in the form of an improved information environment.

The remainder of the paper is organized as follows. Section 2 describes our data sources, empirical models, and variables. In Section 3, we present our baseline estimation results along with numerous robustness and identification tests. Section 4 presents additional analyses that link the fraud-reducing branch effects to banks' incentives to collect information on local firms. Section 5 sheds light on some of the mechanisms behind our results, and Section 6 concludes.

2. RESEARCH DESIGN

2.1 Accounting and Auditing Enforcement Releases

Our fraud dataset consists of quarterly Accounting and Auditing Enforcement Releases (AAERs) data from the USC Leventhal School of Accounting at the University of Southern California. AAERs are issued against firms that are alleged to have been involved in accounting or auditing misconduct, such as earnings inflation, material omission of expenses, or record falsification. Enforcement actions follow significant investigations by the SEC and involve material and economically significant violations as well as the allegation that investors were intentionally misled.[6] The initial dataset includes 4,012 AAERs issued by the SEC between May 17, 1982 and December 31, 2018.

AAERs data have been used extensively in prior work to study accounting misstatements and financial fraud (e.g., Black et al. 2018, Davidson, Dey, and Smith 2015, Dechow et al. 2011). The use of AAER data to identify fraud offers two major advantages. First, the misdetection rate (Type I error) is low in this dataset (Black et al. 2018, Dechow et al. 2011). Budgetary considerations mean that the SEC will select firms for enforcement actions where there is clear evidence of manipulation. Further, while the dataset does not contain cases of fraud not identified by the SEC (Type II error), the number of such cases among the type of large firms included in our sample should be low (Karpoff et al. 2017).

Our analyses are based on the years when the misconduct was committed rather than the year when the enforcement action was issued. Because there is a significant time lag between the years that the fraud was committed and those in which enforcement action was taken, many recent fraud cases are yet to be discovered. Thus, if we were to include the most recent years in our analysis, it would further aggravate the partial observability problem inherent in this type of research. Therefore, in line with the literature, we remove misstatement years from 2014 to avoid sample selection issues.

2.2 Bank branch data

We obtain information on bank branches from the Summary of Deposits database maintained by the Federal Deposit Insurance Corporation (FDIC). This includes detailed branch-level data (e.g., physical address, services offered, and deposits held) and bank-level data (e.g., type of bank and total assets). We limit our sample to the branch networks of large banks (> US$1 billion in assets) and branches that the FDIC classifies as a "full service, brick, and mortar office." Bank branch data are available from 1994.

2.3 Firm data

We include all firms with available accounting and market data from the Compustat/CRSP merged database. Information on the locations of firm headquarters is obtained from SEC filings. Analogous to the bank branch and fraud dataset, our firm data range from 1994 to 2013. We exclude firms with missing data for total assets, sales, earnings before interest, tax, and depreciation (EBITA), or headquarters locations. We also remove utility (SIC 4910 to 4939) and financial firms (SIC 6000 to 6999), because these firms are regulated and subject to different enforcement action processes. This procedure yields a sample of 58,158 firm-year observations.

[Table 1 around here]

Finally, we match the AAERs dataset and our CRSP/Compustat dataset and obtain a final sample of 250 fraud cases issued against 218 firms. The average duration over which fraud is committed in our sample is 2.4 years. This corresponds to 602 firm-year observations in which firms are alleged to engage in fraud. Table 1 provides descriptive statistics for our sample of corporate fraud cases.

2.4 Empirical design

Empirical research on corporate fraud faces an inherent challenge. To the econometrician, fraud remains unobserved until it has been detected. This means that our outcome variable is the product of two processes: the commission of fraud and the detection of fraud. Because detection is not perfect, we will not observe every instance of fraud that has been committed.

To address this partial observability problem, we follow Wang, Winton, and Yu (2010), Wang (2013), and Khanna, Kim, and Lu (2015) and employ a bivariate probit model that jointly estimates the probability of ex-ante fraud commitment (F_{it}) and ex-post fraud detection (D_{it}) using two equations:

$$F_{it}{*} = X_{F,\,it}\,\beta_F + \mu_{it} \tag{1}$$

$$D_{it}{*} = X_{D,\,it}\,\beta_D + \nu_{it} \tag{2}$$

where $X_{F,\,it}$ is a vector of variables that explain firm *i*'s incentives to commit fraud in year *t*, and $X_{D,\,it}$ is a vector of variables that explain firm *i*'s likelihood of getting caught. μ_{it} and ν_{it} are zero-mean disturbances with a bivariate normal distribution.

The two equations are estimated using the maximum-likelihood method. According to Poirier (1980), an important feature of this approach is that $X_{F,it}$ and $X_{D,it}$ do not contain the same set of variables, such that there is at least one vector that has one or more variables absent in the other vector (see also Wang 2013, Wang, Winton, and Yu 2010). We detail the variables included in both vectors in Section 2.5.2.

2.5 Variables

2.5.1 Main explanatory variable: local bank branch density

The main explanatory variable—local bank branch density—is the number of bank branches within a 10 km radius:

$$\text{Local bank density} = \ln(\text{\# bank branches in 10 km radius}) \tag{3}$$

To obtain the local bank density, we first calculate the distance from a firm's headquarters to each nearby bank branch using the Haversine formula. We obtain data on firm headquarters from Compustat and bank branch locations from the FDIC's Summary of Deposit. Geographic coordinates (longitude and latitude) are obtained from the US Census (2014) Gazetteer. We then sum up the number of bank branches that are located within a 10 km radius of a firm's headquarters. We use a 10 km radius because it ensures that branches and firms operate in a relatively homogeneous area with similar economic, social, and demographic conditions. Further, Rosenthal and Strange (2001) show that information spillovers occur mostly at the zip code level (which typically span a 16 km radius) and diminish significantly as the radius increases. Pool, Stoffman, and Yonker (2015) detect information flows at distances of up 10 miles.

2.5.2 Control variables

The bivariate model requires two sets of control variables: one to explain the commission of fraud and the other for the detection of fraud. The variables we include are based on existing theoretical and empirical work in the corporate fraud literature (Wang 2013, Wang, Winton, and Yu 2010).

Commission of fraud regressions:

Our baseline specification for the latent equation for firms committing fraud (F) is as follows:

$$F_{it}^* = X_{F,it}\,\beta_F + X_{FD,it}\,\gamma_{\mathrm{F}} + \mu_{it} \tag{4}$$

$X_{F,it}$ contains variables that previous studies have shown to influence a firm's incentive to commit fraud but not the likelihood that the fraud is detected. We include a firm's returns on assets (*ROA*), leverage, and external financing needs. Chief executive officers (CEOs) of poorly performing firms are more likely to inflate earnings or misstate other financial statement data. In contrast, highly leveraged firms are often cash cows with a large market share and steady profitability (Harford 1999). These firms have fewer incentives to engage in fraud. We control for firm profitability using the ratio of earnings before interest and tax divided by total assets (*ROA*) and leverage using the ratio of total liabilities to total assets. In addition, Dechow et al. (2011) show that firms subject to AAERs are actively seeking new financing. We capture a firm's projected outside financing needs using a firm's asset growth rate in excess of its maximum internally financeable growth rate, ROA/(1-ROA).

$X_{FD,it}$ contains variables that affect a firm's incentive to commit fraud as well as the likelihood of detection. We include firm-level measures such as size, age, growth prospects, real investments, and external monitoring mechanisms. Several studies have shown that securities fraud is more likely to be found in larger and more mature firms (Dechow et al. 2011, Khanna, Kim, and Lu 2015). In addition, Povel, Singh, and Winton (2007) argue that CEOs of high-growth firms that exhibit a downturn are more likely to commit wrongdoing. We control for a firm's growth potential using the market value of equity divided by the book value of equity (*Market-to-book*). Further, Wang (2013) argues that real investments such as research and development (R&D) or mergers and acquisitions (M&A) activities introduce noise to financial statements, making it difficult to detect misreporting. To control for a firm's real investments, we use its R&D and M&A expenditure. In addition, stock analysts and institutional investors also monitor management to deter and detect fraudulent activities (Dyck, Morse, and Zingales 2010). We control for the natural logarithm of the number of stock analysts that follow a firm and the fraction of ownership of all institutional investors.

Moreover, some industries display a higher propensity for detecting fraud. Following Wang (2013), we include dummies for technology firms (software and programming, computer and electronic parts, and biotech), services firms (financial services, business services, and telecommunication services), and the trade industry (wholesale and retail). Finally, we control for county measures of population size, income per capita, and unemployment.

Detection of fraud regressions:

$$D_{it}{*} = X_{FD,it}\ \delta_D + X_{D,it}\,\beta_D + \nu_{it} \tag{5}$$

As illustrated above, the vector $X_{FD,it}$ contains variables that influence of both the misconduct commission and detection processes. However, certain factors that trigger the detection of fraud are not related to fraud commission. This includes factors that are unpredictable at the time when fraud is committed. For example, a sudden change in performance, while difficult to predict by misstating managers, is likely to attract additional scrutiny by regulators and may thus increase the probability that misstatements are detected. Vector $X_{D,it}$ includes variables that affect detection but are plausibly exogenous to a firm's ex ante incentives to commit wrongdoing. Because fraud detection occurs after the commission of fraud, these variables are measured one year after fraud occurs. Following

Wang (2013), we include *Abnormal ROA*, *Adverse stock return*, *Abnormal return volatility*, and *Abnormal stock turnover* in this vector.

[Table 2 around here]

To capture *Abnormal ROA* performance relative to recent performance, we compute the residuals (ε_{it}) from the following model for each firm: $ROA_{it} = \beta_0 + \beta_1 ROA_{it\text{-}1} + \beta_2 ROA_{it\text{-}2} + \varepsilon_{it}$. *Adverse stock return* is a dummy variable that equals one if the bank's stock return is in the bottom 10% of all the firm-year return observations in the Compustat/CRSP database. In addition, a firm's stock return volatility and stock turnover could equally trigger detection by regulators. We measure *Abnormal return volatility* as the demeaned standard deviation of daily stock returns each year and *Abnormal stock turnover* as the demeaned daily stock turnover each year. Finally, we include year dummies in all regression specifications to control for the general economic environment.

Table 2 provides summary statistics for the variables that we use in our analysis. The median firm in our sample has US$ 239 million in total assets. This suggests that our sample includes many small and medium-sized firms for which bank credit is a frequent and predominant choice of external financing. We also report average values for firms that receive an enforcement action and firms that do not. Consistent with our main hypothesis, firms in the detected fraud sample are located in areas with a higher bank branch density. Further, and consistent with Wang (2013), we observe that firms in the detected fraud sample are larger, have greater financing needs, are followed by more analysts, and are more likely to engage in M&A activities. All regression specifications in the paper control for observable differences between fraud and non-fraud firms. Furthermore, we show in Section 3.2 that our results are robust to the use of a one-to-one propensity score matched sample of fraud firms to observationally similar non-fraud firms.

3. MAIN ANALYSIS: THE LOCAL INFORMATION ENVIRONMENT AND FIRM FRAUD

3.1 Baseline results

Table 3 reports the results of our bivariate probit estimation regression. Column (1) reports the prediction results for firms committing fraud [P(F=1)]; Column (2) shows the prediction results for firms that were detected to have committed fraud, conditional upon fraud having been committed [P(D=1|F=1)].

The coefficients on our key variable Ln*(#bank branches)* are statistically significant, indicating that a local information environment with more bank branches is associated with fewer cases of committed fraud and more cases of detected fraud. The marginal effects in Columns (1) and (2) indicate that a one standard deviation increase in the number of bank branches is associated with a 10.1% lower probability of fraud and 8.3% higher probability of detection. The effects are economically substantial and are comparable to those of other firm-level characteristics, such as external financing needs or market-to-book ratio.

[Table 3 around here]

The control variables have the expected signs. Highly leveraged firms and firms with greater external financing needs are more likely to commit fraud. Likewise, larger firms and firms in the technology industry experience a higher likelihood of detection conditional upon fraud having been committed. The variables excluded from the commission equation but included in the detection equation (*Abnormal ROA*, *Adverse stock return*, and *Abnormal stock volatility*) are jointly significant (F-stats = 31.33). Likewise, the variables excluded from the detection equation are also individually and jointly significant (F-stats = 63.69).

We perform various robustness tests of our baseline findings. The results of these tests are displayed in Internet Appendix IA1. We find that none of the following empirical variations has a material impact on our baseline results: (1) exclusion of firms in the 10 major metropolitan cities: New York City, Los Angeles, Chicago, Houston, Philadelphia, Phoenix, San Antonio, San Diego, Dallas, and Austin. This reduces our sample by almost 20%; (2) controlling for the SEC's monitoring intensity (Kedia and Rajgopal, 2011) by including an *SEC-city* dummy that equals one if the firm is located in the same city as an SEC regional office; (3) using an alternative bivariate probit model (e.g., Khanna, Kim, and Lu 2015) in which the control variables are excluded only in the fraud detection equation and not in the fraud commission equation; and (4) using alternative definitions of local bank density: *Residual* ln*(#bank branches)* , which is orthogonal to local population size. It is the residual of a regression of *Ln(#bank branches)* on the natural logarithm of the county's population, and *Ln(#main offices),* which is the natural logarithm of the number of bank main offices within a 10 km radius.

3.2 Addressing endogeneity

This section provides evidence in support of a causal relation between the local information environment and firm fraud using two empirical strategies. First, we match fraud firms to non-fraud firms using one-to-one propensity score matching. Second, we exploit branch consolidation programs in the aftermath of large bank mergers as a negative shock to the density of local bank branches.

3.2.1 Propensity score matching

Table 2 indicates that firms in the detected fraud sample differ from non-fraud firms in regard to various observable characteristics. While all regression specifications control for observable firm characteristics, we further address the concern that cross-sectional differences between fraud and non-fraud explain our results by constructing a propensity score matched sample of fraud firms to comparable non-fraud firms.[7]

[Table 4 around here]

We use a probit model to estimate the probability that a firm will receive an enforcement action. The probit model includes all covariates in the fraud commission and fraud detection equations. We then use the propensity scores from the probit estimation to perform a nearest-neighbor propensity score matching procedure (with no replacement). That is, we match each firm that receives an enforcement action to a similar firm without an enforcement action. Panel A of Table 4 confirms that our matching process removed observable differences between fraud and non-fraud firms.

Using the propensity score-matched sample, we re-estimate the baseline regressions and display the results in Panel B of Table 4. The coefficients on *Ln(#bank branches)* remain statistically significant, indicating that a local information environment with more bank branches is associated with fewer cases of committed fraud and more cases of detected fraud.

3.2.2 Evidence from merger-induced branch consolidation

While using a matched sample controls for differences in observable firm characteristics, it does not address the possibility that our results are driven by unobserved characteristics that are correlated with both local branch density and the fraud propensity of local firms. To further corroborate our baseline findings, we exploit reductions in the density of local bank branches that are generated by mergers involving large banks. We focus on large banks to ensure that the closed branches are sufficiently small for the merger decision to be plausibly unrelated to local factors.

Our empirical setting, also adopted in Garmaise and Moskowitz (2006) and Nguyen (2019), utilizes the closures of branches where once separate branch networks overlap after a bank merger. For instance, before SunTrust Banks acquired Crestar Financial Corporation in 1998, both banks had separate branches in Palm Beach County, Florida (among other locations). Following the acquisition, Crestar ceased to exist and, because maintaining two branches in the same county was superfluous, SunTrust closed the duplicate branches in Palm Beach.

Merger-induced consolidations of bank branches disrupt local banking markets in at least two ways. First, they remove an entire bank from the local market. As local banking markets become less competitive, local banks gain greater pricing power over borrowers and have fewer incentives to invest in lending relationships by collecting and accumulating borrower information (see Garmaise and Moskowitz 2006, Presbitero and Zazzaro 2011). Second, merger-induced branch consolidation causes a plausibly exogenous reduction in the density of local branch networks. This will typically be accompanied by staff layoffs and a loss of codified information on firms, thereby further impeding the information collection and dissemination role of local bank branch networks.

We identify US bank mergers between 1999 and 2013 from the Report of Changes to FDIC Financial Institution and Office Structure and compile a list of branch closures.[8] We restrict our sample to mergers between large non-failing banks with assets > $1 billion (in 2010 terms). In our sample, the deposits held in counties with post-M&A branch closures are 0.3% (1.4%) of the overall deposits of acquiring (target) banks. This suggests that the merger decision is plausibly exogenous to factors specific to the closed branches (e.g., unproductive employees) or the local county (e.g., resident wealth). The average number of closed branches is 22 and the average assets of closed branches are $4.7 million per county and consolidation event.

Further, we restrict our analysis to *duplicate* branch closures *within* counties. That is, we identify counties that meet the following two conditions: (i) one year prior to a merger, the target, and acquiring bank each maintain at least one branch in the same county; and (ii) one year after the merger's completion, one of the duplicate branches is closed. Focusing on duplicate branch closures within counties makes it more likely that the closures are indeed driven by consolidation and not by county characteristics (that would apply to all branches in a county).[9]

We adopt a difference-in-differences analysis and compare fraud cases by firms located in a county with merger-related branch closures (the treatment group) with fraud cases at a control group of firms without merger-related branch closures. To construct our control and treatment groups, we use data on non-financial Compustat firms and estimate a probit model of 3,118 treatment firm-year observations and 46,508 control group firm-year observations. In the probit model, we include all variables from Equation (4) plus dummy variables for industry (based on two-digit SIC codes), county income quintile, and years. We also include a variable that counts the number of fraud cases in the county three years prior to a branch closure. This is to ensure that a bank's decision to close branches is not driven by an area's historical fraud rate. We report the probit model in Column (1) of Internet Appendix IA2.

We then use the estimated propensity scores to perform a nearest-neighbor propensity score matching procedure (with no replacement). That is, we match each firm-year observation in the treatment group to a firm-year observation in the control group. This yields 2,436 pairs of matched firms. In Column (2) of Internet Appendix IA2, we re-run a probit model using the matched sample and find that all the independent variables become statistically indistinguishable from zero and the pseudo-R^2 becomes close to zero.

[Table 5 around here]

Panel A of Table 5 presents our bivariate probit results with the matched sample. We retain firm-year observations for both treatment and control firms for a seven-year window surrounding the branch closure and estimate the bivariate probit model. The key explanatory variable is *Branch closure*, a dummy that equals one after duplicate branches have been closed in a county. As shown in Panel A, *Branch closure* is associated with 11% fewer cases of detected fraud and 7% more cases of committed fraud.

Panel B explores whether the adverse effects of *Branch closure* vary according to firm size by dividing the sample into quartiles based on firm assets. We find that the effects of branch closures are most salient among the smallest firms in the sample. Specifically, the coefficients on *Branch closure* indicate that firms in the bottom size quartile experience 15% fewer cases of detected fraud and 12% more cases of committed fraud following merger-induced branch consolidation. The magnitude of the effects declines as we analyze progressively larger firms. For the largest firms in the sample, the effect of branch closures is indistinguishable from zero. Along the same lines, Panel C shows that the adverse effects of *Branch closure* are stronger for larger consolidation events (when the total assets of the closed branches are above the sample median). Overall, the results support a causal interpretation of the impact of local bank branch density on firm fraud.

4. HETEROGENOUS EFFECTS OF BRANCH DENSITY ON FRAUD

In this section, we present additional analyses to support our finding that bank branches affect corporate fraud by improving the local information environment. We demonstrate that the effectiveness of local bank branches can be linked to heterogeneity in the ability and ex-ante incentives of banks to collect information on local firms.

4.1 Bank branch effects when local firms borrow from local banks

An important implication of the information-gathering view of bank branches is that their effect on fraud should become stronger in local markets where local firms rely more on bank finance. In environments where lending is a primary source of external funds for firms, relationship lending is likely to flourish. A hallmark of relationship lending is the accumulation of soft information by banks over time (Berger and Udell 2002). Because the acquisition of this type of information is costly to banks, banks will be more likely to collect soft information in local markets where potential borrowers are abundant and information gathering is commercially viable (see Hauswald and Marquez 2006).

[Table 6 around here]

To test if the effects are more salient in local markets where firms rely more on bank finance, we obtain lending data from Thomson Reuters's DealScan, which collects loan-level data on private loans made by banks (and non-bank lenders) from SEC filings and industry sources. We interact our main measure of local bank branch density, *Ln(#bank branches)*, with three variables that capture the extent to which local firms rely on bank financing: (i) the importance of bank borrowing as a source of local firm financing (measured by the amount of loans local firms receive scaled by firms' total debt); and (ii) the dependence of local firms on external finance (as in Duchin, Ozbas, and Sensoy 2010), measured using the proportion of investment not financed by cash flow from operations).

Consistent with our expectation, Panel A of Table 6 shows that the fraud-reducing effect becomes stronger when firms rely more on bank borrowing. For instance, the marginal effects in Column (2) indicate that the fraud detection effect linked to local branches increases by nearly 10% in areas where firms rely more on bank borrowing as a source of financing. Importantly, Panel A also indicates that our local bank density measures continue to have a significant fraud-reducing effect after controlling for the various local credit measures such as local firms' reliance on bank financing and their external finance dependence. Consequently, bank branches enhance the local information environment above and beyond bank lending activities. Banks also improve the local information environment in their non-credit dealings with clients. This is consistent with Garmaise and Natividad's (2016) argument that banks have incentives to collect information on *non*-client firms in order to tailor their offerings towards local firms. Our results imply that lending to local firms is not the sole condition for the fraud-reducing effect of local bank branches.

4.2 Do bank branches produce financial spillovers?

Aside from collecting information on clients, bank branches may produce positive financial spillovers (Garmaise and Natividad 2016) that could reduce fraud propensity. For instance, if higher bank branch density facilitates local firms' access to financing, this could prevent local firms from being credit-constrained. Because credit constraints and financial distress generally trigger the commission of fraud (Dechow et al. 2011), enhanced access to financing could help to make local firms less likely to commit fraud ex ante.

We perform additional tests focusing on covariates that affect the ability of branches to provide financing. Large banks, as well as banks operating under a national charter, should be in a stronger position to alleviate financial constraints compared with smaller and local banks (Biswas, Gómez, and Zhai 2017). Similarly, transparent firms should have an advantage in terms of accessing capital. In contrast, under our preferred explanation of branches as information agents, the effect of branches on misconduct should be stronger for smaller banks (where decision-making is *less* likely to be automated), non-national banks (where local information is more likely to be utilized), and less transparent local firms (where soft information is more important).

We interact our main measure of local bank density *Ln(#bank branches)* with (i) *Small banks*, a dummy that equals one if the average bank size in a 10 km radius is below the sample median, and (ii) *Local banks*, a dummy that equals one if the fraction of banks with a national charter in a 10 km radius is below the sample median.[10] Following previous literature (e.g., Chen, Harford, and Lin 2017, He and Tian 2016), we use two proxies for firm transparency: (i) firm size and (ii) analyst following. Larger firms and firms followed by more stock analysts receive more investor attention, which makes these firms more transparent.

Consistent with our information hypothesis, Panel B of Table 6 shows that the fraud reduction rate of local bank branches becomes stronger when local bank branches belong to smaller or local banks. For instance, the marginal effects in Columns (4) suggest that the fraud detection effects of local branches are 8% stronger when local branches belong to smaller banks. Likewise, Panel C of Table 6 shows that local information environments are less likely to play a role among firms that are already transparent. The marginal effect in Column (2) indicates that a one standard deviation increase in firm size diminishes the detection effect of local branches by approximately 11%.

4.3 Are banks special?

The special role of banks as collectors of soft information is well documented in the literature (e.g., Agarwal and Hauswald, 2010, Petersen and Rajan, 2002). Therefore, the fraud-reducing effect that we link to the density of bank branches should not be observable for density measures in other local institutions.

To test this expectation, we construct local density measures for non-bank Compustat firms and hospitals (within a 10 km radius from a firm's headquarters).[11] We compare the fraud propensity of firms in the presence of bank branches versus other institutions. As shown in Panel D of Table 6, local bank density remains highly significant and is associated with a lower likelihood of corporate fraud. In contrast, the density of local firms or hospitals is not statistically associated with fraud propensity. This confirms our interpretation that bank branches play a special role in creating an informative environment over and above general urban density effects.

4.4 Local firm governance, CEO compensation, and fraud propensity

We focus on two indicators of weak internal governance mechanisms: (i) firms with insider-dominated boards of directors (i.e., a dummy that equals one if the percentage of inside directors is above the sample median), and (ii) firms with more entrenched managers (i.e., a dummy that equals one if the firm's entrenchment index is above the sample median) (Bebchuk, Cohen, and Ferrell 2009). Beasley (1986) shows that fraud firms have a significantly higher percentage of inside directors compared with non-fraud firms. Similarly, Khanna, Kim, and Lu (2015) show that entrenched managers are more likely to engage in misconduct. Consistent with this literature, Panel A of Table 7 indicates that the fraud-reducing effect of local bank branches is stronger when the firm has an insider-dominated board of directors or entrenched managers. For example, the result in column (4) indicates that the fraud detection effect of *Ln(#bank branches)* increases by 11% when the firm's entrenchment index is above the sample median. These results suggest that the external information environment could act as a partial substitute for internal governance mechanisms.

[Table 7 around here]

In Columns (5)–(6) of Panel A of Table 7, we examine how the baseline results vary with the equity-based compensation incentives of the CEO managing the firm. The prior literature links the use of high-powered CEO compensation incentives to more incidences of misreporting (e.g., Burns and Kedia 2006, Johnson, Ryan, and Tian, 2009). Following Nguyen, Hagendorff, and Eshraghi (2016), we define equity incentive-based compensation as the sensitivity of CEO wealth to stock return volatility (vega) scaled by the sensitivity of CEO wealth to stock price performance (delta). In line with our expectation, we find that the fraud-reducing effect of local bank branches is stronger for firms whose CEOs receive larger equity-based compensation. The marginal effects in column (4) indicate that the fraud deterrence effect of *Ln(#bank branches)* increases by 4% for firms whose CEO's fraction of equity-based compensation is above the sample median.

4.5. Innovation in information technology

Our sample period witnessed major advancements in information technology. Innovations in digitization and telecommunication tools, coupled with the widespread adoption of the Internet, have greatly facilitated information collection and sharing beyond organizational boundaries. This may have reduced the role of banks as information collectors. If so, we expect the effect of local bank branch density to be stronger in the earlier half of the sample than in more recent years. To examine this hypothesis, we interact *Ln(#bank branches)* with *Post2000*, a dummy that equals one for all years after 2000.

Panel B of Table 7 shows that the coefficient on the interaction term between *Ln(#bank branches)* and *Post2000* is positively significant in Column (1), suggesting that the fraud deterrence effect of local bank density becomes weaker after 2000. Nevertheless, the interaction coefficient is statistically insignificant in Column (2), indicating that local bank branches continue to play an equally important role in fraud detection after 2000. Further, the coefficients on *Ln(#bank branches)* are highly significant and similar in magnitude to those observed in Table 3 for our baseline regressions. This suggests that recent innovations in information technology have reduced (but not eliminated) the role of local bank branches in deterring fraud while maintaining their contribution to fraud detection.

5. HOW DOES AN ENHANCED INFORMATION ENVIRONMENT REDUCE FRAUD?

This final section shows that an enhanced information environment is linked to more transparent and reliable financial reporting as well as to faster fraud detection.

5.1 The information environment and financial reporting quality

A large body of literature studies the antecedents to fraud. Among the behaviors identified by researchers as paving the way for corporate misconduct are evasive financial reporting through earnings management and other means of undermining the accuracy of financial statements (e.g., Gonzalez, Schmid, and Yermack 2019; Kedia and Philippon 2009). Based on this literature, we link the local information environment to three indicators of low reporting quality: (i) earnings management, (ii) an ineffective internal control environment, and (iii) restatements following deliberate errors in a firm's financial statements.

Our first proxy of lower reporting quality is earnings management. Earnings management permits managers to misreport operating performance, hide unfavorable earnings realizations, and avoid general scrutiny from outside investors or market regulators (Lin, Officer, and Zhan 2015). We construct *EM_MJ* using the modified Jones' model (Dechow, Sloan, and Sweeney 1995) and *EM_J* following Jones (1991). Both earnings management variables are calculated using a two-step procedure. For each two-digit SIC industry and each year, we estimate discretionary accruals by regressing firms' total accruals on their property, plant, and equipment (PPE) and changes in sales (scaled by lagged total assets). Following Jones (1991), we calculate *EM_J* as the absolute value of the residual term obtained from the first-stage regression. To calculate *EM_MJ*, we follow Dechow, Sloan, and Sweeney (1995) by first estimating the 'normal' accrual level for each firm using the coefficients obtained from the first-stage regression. We then define *EM_MJ* as the absolute value of the difference between total accruals and the predicted firm-level accruals, scaled by lagged total assets. Both variables capture the discretionary component of a firm's total accruals.

[Table 8 around here]

Our second proxy of lower reporting quality is an indicator of whether the firm has material internal control weaknesses (*ICW*), defined as "a significant deficiency, or combination of significant deficiencies, that results in more than a remote likelihood that a material misstatement of the annual or interim financial statements will not be prevented or detected" (PCAOB, 2004). We rely on the Audit Analytics SOX 404 – Internal Controls database to identify firms that have material internal control weaknesses.[12]

Our third proxy of lower reporting quality is *Restatement*, defined as the revision of a company's previous financial statements because these contain material inaccuracies. Restatement data are obtained from the Audit Analytics "Audit Fees with Restatements" database. For all our proxies, we conjecture that a more informative information environment is associated with fewer incidences of any of the proxies of lower reporting quality.

Following the extant literature, we control for firm size, leverage, ROA, cash flow volatility, Ln(Analysts), market-to-book, and sales growth. As in Call et al. (2017), we also control for whether a firm is audited by one of the Big Four auditors (*Big*4 *auditor*). These auditors have high reputation incentives; hence, they may ensure that their clients adopt better financial reporting practices. Table 8 reports the results.

As shown in Table 8, the estimated coefficients on *Ln(#bank branches)* are statistically significant and negative across all specifications. For instance, a one standard deviation increase in *Ln(#bank branches)* is associated with a 1.6% reduction (= –0.016 × 1.005) in the probability of restatement. Relative to the average restatement rate of 13%, this estimate corresponds to an economically significant marginal effect of 12.3%. Thus, firms located in an enhanced information environment are less likely to manage earnings, are linked with more effective internal control environments, and are less likely issue restatements. Overall, this offers evidence that better quality information environments are associated with more transparent and reliable financial reporting behavior, which helps deter fraud.

5.2 The information environment and the speed of fraud detection

In a final step, we examine whether the information environment also expedites the uncovering of fraud. If managers believe they cannot conceal fraud for long, they may be less likely to engage in fraud. Black et al. (2018) and Dyck, Morse, and Zingales (2010) find results consistent with the notion that fraud committed in an enhanced information environment takes less time to detect.

We hypothesize that if an enhanced information environment facilitates the discovery and circulation of fraud-relevant information, this will increase the speed with which misconduct is detected. We obtain information on fraud duration from the AAERs dataset. We measure the number of quarters between the time when fraudulent activities are believed to have commenced and their detection. Our estimation is based on cross-sectional fraud case data and includes similar controls as in the fraud commission equation. Our sample includes 250 unique fraud cases with detection taking an average of 10 quarters, which is comparable to Black et al.'s (2018) sample. The results are displayed in Table 9.

[Table 9 around here]

Column (1) of Table 9 shows that local bank density decreases the number of quarters it takes to detect financial fraud cases. The estimated coefficient in Column (1) suggests that a one standard deviation increase in the number of bank branches in the local area shortens the time taken to detect fraud by approximately 17% (that is, by two quarters or 180 days). Column (2) estimates the duration model in which the dependent variable is the hazard ratio for the Cox regression (_*t*), which is the probability of detection in the next unit of time. Consistent with the OLS estimate, the hazard ratio is significantly and positively related to our measure of local bank density. Thus, the probability of fraud detection in the next quarter is higher in areas with a denser bank branch network.

6. CONCLUSIONS

Our paper explores how a firm's information environment impacts the likelihood that the firm engages in fraud. We propose a new proxy for the local information environment that is based on nearby bank branches as facilitators of an enhanced information environment. We exploit variation in the density of bank branches across the US to identify the effect of the local information environment on corporate fraud. We find that a higher local branch density is associated with fewer cases of committed fraud and more cases of detected fraud. The relationship is statistically significant and economically meaningful. To suggest a causal relationship between the local information environment and fraud committed by local firms, we rely on reductions in local branch density generated by branch closure programs in the aftermath of bank mergers. We also shed light on some of the mechanisms behind our findings. We show that besides facilitating the detection of corporate fraud, an improved information environment is linked to lower fraud propensity and faster fraud detection.

Taken together, our results indicate that bank branches are an important factor that affects fraud propensity. While policymakers are often concerned about the effect of bank branch closures on local credit supply, our findings highlight a hitherto undocumented externality linked to bank branches in the form of an improved information environment. Further, our results indicate that bank branches exert information effects beyond and independently of local credit provision. Therefore, our findings support calls that caution against the local impact of bank branch closure programs. This is an increasingly important issue given that the digital delivery of banking services, repeated merger waves, and general cost pressures in the industry raise questions over the viability of brick-and-mortar branches. In addition to the information flows we document in this paper, it is likely that there are other hitherto empirically undetected benefits linked to branch networks that affect the behavior of economic agents in their vicinity. Therefore, future research should further explore the information roles of local bank branches.

Appendix A1: Variable definitions

The order in which variables are listed follows the sequence they appear in the paper.

Variable	Definition	Source
Local density measures		
Ln(#bank branches)	Natural logarithm of the number of bank branches in a 10 km radius surrounding the firm.	FDIC
Residual Ln(#bank branches)	The residual from a regression of Ln(#bank branches) on the local county population.	
Ln(#main offices)	Natural logarithm of the number of main bank offices in a 10 km radius surrounding the firm.	FDIC
Small banks	Dummy which equals one if the average bank size in a 10 km radius is below the sample median.	FDIC
Local banks	Dummy which equals one if the fraction of banks with a national charter in a 10 km radius is below the sample median.	FDIC
Firm-specific characteristics		
ROA	Earnings before interest and taxes (EBIT) over total assets	Compustat
Financing need	A firm's asset growth rate in excess of the maximum internally financeable growth rate (ROA/(1-ROA)), as in Wang (2013)	Compustat
Leverage	Total debt divided by total assets.	Compustat
Ln(Assets)	Natural logarithm of total assets.	Compustat
Institutional investors	The fraction of ownership of all institutional investors.	13F Forms
Market-to-book	Market value of equity divided by book value of equity.	Compustat
R&D expenses	R&D expenditures divided by total assets.	Compustat
M&A expenses	M&A expenditures divided by total assets.	Compustat
Ln(Analysts)	Natural logarithm of the number of stock analysts following the firm	IBES
Ln(Firm age)	Natural logarithm of the number of years since the firm's IPO.	Compustat
Trade	Dummy which equals one for firms in Wholesale (5000–5190) or Retail (5200–5990).	
Technology	Dummy which equals one if the firm is in Pharmaceuticals (SIC 2833-2836), Computer-related hardware (SIC 3570-3577), Electronics (SIC 3600-3695) or Software and programming (SIC 7370-7377).	Classifications based on Wang (2013)
Service	Dummy which equals one for firms in Telecommunication (SIC 4812-4899), Services (SIC 7000–7361, 7380–7997, 8111–8744) or Healthcare Services (8000–8093).	
Bank borrowing	Dummy which equals one if the amount of bank loans local firms receive scaled by firms' total debt is above the sample median.	DealScan
External finance dependence	Dummy which equals one if local firms' external finance dependence is above the sample median. External financing dependence is calculated as (Compustat name): [Capital expenditures (capx) – funds from operations (fopt)]/capital expenditures (capx). If fopt is missing, funds from operations is defined as the sum of the following variables: Income before extraordinary items (ibc), depreciation and amortization (dpc), deferred taxes (txdc), equity in net loss/ earnings (esubc), sale of property, plant, and equipment and investments – gain/loss (sppiv), and funds from operations – other (fopo).	Compustat
Insider board	Dummy which equals one if the fraction of inside directors on the board is above the sample median and zero otherwise.	BoardEx
Entrenched management	Dummy which equals one if the firm's entrenchment index is above the sample median (i.e., greater than 3) and zero otherwise.	Riskmetrics
High Vega/delta	Dummy which equals one if the CEO's vega/delta is above the sample median and zero otherwise. Vega measures CEO wealth to stock return volatility and delta measures scaled by the sensitivity of CEO wealth to stock price performance.	Execucomp
Post2000	Dummy which equals one for all years after 2000 and 0 otherwise.	
Sales growth	The percentage of change in sales relative to prior year	Compustat
Cash flow volatility	The standard deviation of operating income before depreciation divided by total assets over ten years.	Compustat
Big4 auditor	A dummy which equals one when the firm is audited by a Big4 Auditor.	Audit Analytics
SEC-City	A dummy which equals one if the firm is located in a city with an SEC regional office.	SEC website

County-level characteristics		
Ln(Personal income)	Natural logarithm of the average income from wages, investment enterprises and other ventures.	US Census Bureau
Unemployment rate	The number of unemployed people as a percentage of the labour force.	US Census Bureau
Ln(Population)	Natural logarithm of the county population.	US Census Bureau
Detection of fraud		
Abnormal ROA	Residual from the regression: $ROA_t = \alpha 0 + \alpha_1 ROA_{t-1} + \alpha_2 ROA_{t-2} + \varepsilon$	Compustat
Adverse stock return	Dummy which equals one if stock return is in the bottom 10% of all stocks in Compustat/CRSP sample	CRSP
Abnormal stock volatility	The demeaned standard deviation of daily stock volatility in a year	CRSP
Abnormal stock turnover	The demeaned average daily stock turnover in a year	CRSP
Measures of firm misconduct		
AAER	Dummy which equals one if firms receive an AAER in a given year	Leventhal School of Accounting
Fraud duration	The number of quarters from the commencement of fraudulent activities to the day they were detected.	Leventhal School of Accounting
EM_MJ	The discretionary component of a firm's total accruals, based on Dechow, Sloan and Sweeney (1995)	Compustat
EM_J	The discretionary component of a firm's total accruals, based on Jones (1991)	Compustat
Restatement	Dummy which equals one if firms restate accounting statements in a given year. We remove restatements arising from clerical errors.	Audit Analytics
Internal control weakness	Dummy which equals one if firms report an internal control weakness in a given year	Audit Analytics

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FOOTNOTES

[1] KPMG (2011) reports that, on average, it takes over four years to uncover fraud by US firms and 3% of fraud cases go undetected for 10 years or more. Consistent with that, Gonzalez, Schmid, and Yermack (2019) show that firms involved in cartel fixing engage in a series of evasive strategies to conceal their wrongdoing over a multi-year period. Kedia and Philippon (2009) show that firms often hire and invest excessively in the years prior to the detection of misreporting.

[2] The importance of bank lending is also evident from our sample. Only a small fraction of firms in our sample issue public debt as a means of debt financing (only 19% of sample firms have a long-term S&P credit rating at any point in time). This drops to 5% for firms below the sample's median asset size. Similarly, for equity financing, DeAngelo, DeAngelo, and Stulz (2010) show that 91% of firms in their 29-year sample period make three or fewer equity offerings.

[3] We do not propose that banks deliberately disclose material information on firms to other parties. Instead, social interaction effects within local areas or turnovers in local labor markets (as documented by Bayer, Ross, and Topa 2008; Cohen, Gurun, and Malloy 2017; Core, Lobanova, and Verdi 2016; Pool, Stoffman, and Yonker 2015) offer possible means by which local information can be shared beyond the boundaries of the bank. Based on mosaic theory (Pozen 2005), we argue that when employees interact and socialize, different pieces of information from various sources could be aggregated together to form a conclusion.

[4] A 10 km radius is consistent with the work of Rosenthal and Strange (2001), who show that information spillovers occur mostly at the zip code level and decrease significantly as the distance grows. More recent works (e.g., Bayer, Ross, and Topa 2008; Pool, Stoffman, and Yonker 2015) also report evidence of enhanced social interaction effects within similar distances.

[5] Because of differences between the two mechanisms under investigation, the measurement of banking presence also differs between LMW's work and ours. While LMW study foreign bank entry and financial liberalization at the level of Chinese provinces, we examine a microgeographic unit of 10 km and utilize the local penetration of branches.

[6] For a detailed description of the AAERs sample, see Dechow et al. (2011).

[7] In unreported analyses, we also use an industry-, age-, and size-matched control sample similar to that in Kedia and Philippon (2009) and obtain consistent results.

[8] 1999 is the first year in which data on bank mergers are available on the FDIC website.

[9]An additional advantage of this set-up is that it is based on multiple shocks (i.e., branch closures) affecting different firms at different points in time. This makes it unlikely that omitted variables that coincide with a single and common shock would affect a firm's fraud propensity.

[10] We obtain bank charter details from the FDIC Summary of Deposits.

[11] Data on the locations of hospitals are obtained from the US Census Bureau. For the period 1994–1997, we rely on the establishments' SIC codes to identify hospitals (SIC = 8060). From 1998 onwards, we use the NAICS code to identify hospitals (SIC = 622).

[12] The Sarbanes-Oxley Act (SOX) requires firms to evaluate the effectiveness of their internal controls and disclose any identified material weakness. Data on ICW are only available post-SOX and from 2003 onward. Therefore, the analysis of internal control deficiencies is based on a reduced subsample.

Table 1: Sample of corporate fraud cases

Panel A: Sample distribution by year			
Year	**# firms**	**# fraud firms**	**% fraud firms**
1994	3,079	13	0.42%
1995	3,236	21	0.65%
1996	3,420	21	0.61%
1997	3,580	29	0.81%
1998	3,470	36	1.04%
1999	3,543	50	1.41%
2000	3,403	63	1.85%
2001	3,199	74	2.31%
2002	3,188	61	1.91%
2003	3,127	60	1.92%
2004	3,039	45	1.48%
2005	2,883	32	1.11%
2006	2,715	20	0.74%
2007	2,554	13	0.51%
2008	2,465	10	0.41%
2009	2,407	13	0.54%
2010	2,361	10	0.42%
2011	2,263	9	0.40%
2012	2,186	14	0.64%
2013	2,040	8	0.39%
TOTAL	**58,158**	**602**	**0.98%**

Panel B: Top five industries by # of fraud cases		
	# fraud firms	**% fraud firms**
Software and programming (SIC 7370-7377)	127	21.10%
Industry manufacturing (SIC 3510–3569, 3578–3590, 3711–3873)	98	16.28%
Electronics (SIC 3600–3695)	63	10.47%
Services (SIC 7000–7361, 7380–7997, 8111–8744)	52	8.64%
Retail (SIC 5200–5990)	47	7.81%

Notes: Panel A reports the annual distribution of the total number of firms from the Compustat/CRSP merged database, the number of fraud firms, and the percentage of fraud firms (number of fraud firms/number of firms). Fraud firms are identified using Accounting and Auditing Enforcement Releases (AAERs). Panel B lists the top five industries by the number of fraud cases. % fraud firms is the number of fraud firms in a given industry/total number of fraud firms. Industry classifications are the same as in Wang (2013). We remove financial and utility firms from the sample.

Table 2: Summary statistics

	N	Mean	Std.	p.5	p.50	p.95	Fraud detected? Yes	No	diff
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Local bank density measure									
Ln(#bank branches)	58,158	4.120	1.005	2.197	4.248	5.537	4.201	4.119	**
Firm-specific characteristics									
Institutional investors	58,158	0.310	0.363	0.000	0.081	0.955	0.387	0.310	***
ROA	58,158	0.042	0.672	-0.409	0.108	0.273	0.097	0.041	**
Financing need	58,158	0.165	1.222	0.000	0.000	0.779	0.262	0.164	**
Leverage	58,158	0.177	0.275	0.000	0.114	0.558	0.184	0.177	
Ln(Assets)	58,158	5.569	2.061	2.400	5.477	9.179	6.769	5.557	***
Market-to-book	58,158	2.946	69.310	0.278	1.773	8.336	2.964	2.946	
R&D expenses	58,158	0.065	0.198	0.000	0.002	0.292	0.042	0.065	***
M&A expenses	58,158	0.023	0.066	0.000	0.000	0.145	0.034	0.023	***
Ln(Analysts)	58,158	1.170	1.192	0.000	1.099	3.219	1.508	1.166	***
Ln(Firm age)	58,158	2.785	0.667	1.792	2.708	3.912	2.700	2.786	***
Trade	58,158	0.124	0.330	0.000	0.000	1.000	0.135	0.124	
Technology	58,158	0.290	0.454	0.000	0.000	1.000	0.365	0.289	***
Service	58,158	0.146	0.353	0.000	0.000	1.000	0.146	0.146	
County-level characteristics									
Ln(Personal Income)	58,158	10.490	0.332	9.948	10.480	11.030	10.486	10.486	
Unemployment rate	58,158	5.528	2.317	2.800	5.100	9.900	5.177	5.532	***
Ln(Population)	58,158	13.270	1.364	10.640	13.450	15.470	13.263	13.267	
Detection of misconduct									
Abnormal ROA	58,158	0.010	0.221	-0.185	0.023	0.160	0.018	0.010	
Adverse stock return	58,158	0.085	0.279	0.000	0.000	1.000	0.050	0.086	***
Abnormal stock volatility	58,158	0.002	0.091	-0.098	-0.010	0.135	0.010	0.002	**
Abnormal stock turnover	58,158	0.010	1.449	-1.444	-0.114	1.868	0.062	0.009	

Notes: Definitions of all variables are included in Appendix A1. Columns (7) and (8) show average values by whether firms had fraud detected. Columns (9) shows the p-value of the difference between firms that receive an enforcement action and firms that do not are calculated. ***, **, and * indicate significance at the 1, 5, and 10% level, respectively.

Table 3: Bivariate probit model estimation for local bank density and corporate fraud

	P(F=1)	P(D=1|F=1)
	(1)	(2)
Ln(#bank branches)	-0.061***	0.068***
	[-3.019]	[3.413]
ROA	-0.130	
	[-0.820]	
Financing need	0.035***	
	[3.131]	
Leverage	-0.763***	
	[-4.920]	
Ln(Assets)	0.010	0.271***
	[0.601]	[15.187]
Institutional investors	0.116	0.123
	[1.504]	[1.617]
Market-to-book	0.012***	-0.006*
	[3.677]	[-1.755]
R&D expenses	-2.507***	0.846**
	[-6.711]	[2.500]
M&A expenses	1.418***	-0.098
	[5.042]	[-0.396]
Ln(Analysts)	-0.049*	-0.032
	[-1.726]	[-1.258]
Ln(Firm age)	0.023	-0.389***
	[0.519]	[-8.711]
Trade	0.046	0.049
	[0.791]	[0.883]
Technology	0.289***	0.222***
	[5.512]	[4.339]
Service	0.186***	-0.134**
	[2.944]	[-2.161]
Ln(Personal income)	-0.172*	0.303***
	[-1.947]	[3.380]
Unemployment rate	-0.017	0.042***
	[-1.320]	[2.645]
Ln(Population)	0.076***	-0.101***
	[4.118]	[-5.385]
Abnormal ROA		-0.004
		[-0.025]
Adverse stock return		-0.376***
		[-3.820]
Abnormal stock volatility		-0.562***
		[-2.868]
Abnormal stock turnover		0.018
		[0.844]
Observations	58,158	58,158
Log likelihood	-2978	-2978
Prob>Chi^2	0.000	0.000

Notes: This table presents the baseline results on the relationship between local bank density and corporate fraud. Column (1) shows the estimated relations between bank branch density within a radius of 10 km surrounding the firm and the commission of fraud (F=1), while column (2) shows the relations between local bank density and detection, given fraud (D=1|F=1). The sample covers the period 1994–2013. Definitions of all variables are provided in Appendix A1. *t-Statistics* are reported in parentheses; ***, **, and * indicate significance at the 1, 5, and 10% level, respectively.

Table 4: Propensity score-matched sample of fraud to non-fraud firms

Panel A: Univariate comparisons between fraud firms and matched non-fraud firms

	Detected fraud firms	**Matched non-fraud firms**	**p-value of difference**
	Mean	**Mean**	
ROA	0.099	0.097	0.902
Financing need	0.245	0.293	0.443
Leverage	0.184	0.191	0.543
Ln(Assets)	6.806	6.851	0.702
Institutional investors	0.394	0.376	0.449
Market-to-book	2.950	0.514	0.171
R&D expenses	0.041	0.044	0.655
M&A expenses	0.034	0.044	0.063
Ln(Analysts)	1.519	1.425	0.211
Ln(Firm age)	2.707	2.674	0.404
Trade	0.137	0.132	0.781
Technology	0.359	0.361	0.938
Service	0.149	0.132	0.390
Ln(Personal Income)	10.493	10.503	0.593
Unemployment rate	5.139	5.090	0.665
Ln(Population)	13.258	13.227	0.700
Abnormal ROA	0.018	0.026	0.195
Adverse stock return	0.051	0.059	0.533
Abnormal stock volatility	0.010	0.018	0.254
Abnormal stock turnover	0.064	0.228	0.059

Panel B: Bivariate probit estimates with matched firms

	P(F=1)	**P(D=1|F=1)**
	(1)	(2)
Ln(#bank branches)	-0.106**	0.611**
	[-2.274]	[2.471]
Control variables	Yes	Yes
Observations	1,184	1,184
Log likelihood	-721	-721
Prob>Chi2	0.000	0.000

Notes**:** This table shows analysis on a propensity score-matched sample of fraud firms to comparable non-fraud firms. Panel A compares the characteristics of firms in the detected fraud sample and comparable non-fraud firms. For each variable, the p-value of the difference between the two samples is calculated. Panel B reports bivariate probit results using a propensity score-matched sample. Column (1) reports the estimated relations between bank density and the commission of fraud (F=1), while column (2) reports the relations between local bank accessibility and detection, given fraud (D=1|F=1). The control variables are similar to those in Table 3 and are collapsed for brevity. The sample covers the period 1994–2013. Definitions of all variables are provided in Appendix A1. *t-Statistics* are reported in parentheses; ***, **, and * indicate significance at the 1, 5, and 10% level, respectively.

Table 5: Difference-in-differences analysis: duplicate branch closures and firm fraud

Panel A: Effects of branch closures on fraud

	P(F=1)	**P(D=1|F=1)**
	(1)	**(2)**
Branch closure	0.263**	-0.185*
	[2.421]	[-1.904]
Control variables	Yes	Yes
Observations	23,678	23,678
Log likelihood	-1322	-1322
Prob>Chi^2	0.000	0.000

Panel B: Effects of branch closures on fraud, by firm size quartile

	Smallest Q1		**Q2**		**Q3**		**Largest Q4**	
	P(F=1)	**P(D=1|F=1)**	**P(F=1)**	**P(D=1|F=1)**	**P(F=1)**	**P(D=1|F=1)**	**P(F=1)**	**P(D=1|F=1)**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Branch closure	1.534***	-2.269***	0.306	-4.412***	0.528	-0.314**	0.000	1.198
	[4.301]	[-4.620]	[1.315]	[-2.607]	[1.476]	[-2.311]	[-0.001]	[0.947]
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,919	5,919	5,920	5,920	5,857	5,857	5,982	5,982
Log likelihood	-60	-60	-189	-189	-417	-417	-406	-406
Prob>Chi^2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Panel C: Effects of branch closures on fraud, by total assets of closed branches

	Large closure		**Small closure**	
	P(F=1)	**P(D=1|F=1)**	**P(F=1)**	**P(D=1|F=1)**
	(1)	**(2)**	**(3)**	**(4)**
Branch closure	0.223**	-1.277***	0.031	-0.012
	[2.028]	[-3.823]	[0.176]	[-0.069]
Other controls	Yes	Yes	Yes	Yes
Observations	12,652	12,652	18,252	18,252
Log likelihood	-615	-615	-1005	-1005
Prob>Chi2	0.000	0.000	0.000	0.000

Notes**:** This table compares fraud at firms located in a county with merger-related branch closures (the treatment group) to fraud incidences at matched firms without merger-related branch closures (the control group). *Branch closure* is a dummy that equals one after duplicate branches have been closed in a county. Panel A reports the bivariate probit estimation results. Panel B shows the effects of *Branch Closure* by firm size (after dividing the sample into quartiles based on firm assets). Panel C examines the effects of *Branch Closure* by the size of the closed branch (relative to the sample median of the assets of branches). Odd-numbered columns show the estimated relations between local bank density and the commission of fraud (F=1), while even-numbered columns show the relations between local bank density and detection, given fraud (D=1|F=1). The control variables are similar to those in Table 3 and are collapsed for brevity. The sample covers the period 1994–2013. Definitions of all variables are provided in Appendix A1. *t-Statistics* are reported in parentheses; ***, **, and * indicate significance at the 1, 5, and 10% level, respectively.

Table 6: Heterogenous effects of bank branch density on fraud

Panel A: Do local firms borrow from local banks?

	P(F=1)	P(D=1|F=1)	P(F=1)	P(D=1|F=1)
	(1)	(2)	(3)	(4)
Ln(#bank branches)* Bank borrowing	0.030	0.086**		
	[0.526]	[2.197]		
Bank borrowing	0.074	-0.498***		
	[0.268]	[-2.893]		
Ln(#bank branches)* External finance dependence			-0.102**	-0.015
			[-2.276]	[-0.397]
External finance dependence			0.181	0.004
			[0.928]	[0.022]
Ln(#bank branches)	-0.088***	0.078***	-0.079***	0.058***
	[-2.673]	[3.418]	[-3.224]	[2.741]
Control variables	Yes	Yes	Yes	Yes
Observations	58,158	58,158	54,831	54,831
Log likelihood	2969	2969	-2820	-2820
Prob>Chi^2	0.000	0.000	0.000	0.000

Panel B: Branch incentives to collect soft information

	P(F=1)	P(D=1|F=1)	P(F=1)	P(D=1|F=1)
	(1)	(2)	(3)	(4)
Ln(#bank branches)* Local banks	-0.078**	0.021		
	[-2.202]	[0.585]		
Local banks	0.566***	-0.296*		
	[3.652]	[-1.875]		
Ln(#bank branches)* Small banks			-0.045	0.079**
			[-1.191]	[2.104]
Small banks			0.475***	-0.412***
			[2.915]	[-2.606]
Ln(#bank branches)	-0.025	0.051**	-0.029	0.037*
	[-1.263]	[2.529]	[-1.476]	[1.871]
Control variables	Yes	Yes	Yes	Yes
Observations	58,158	58,158	58,158	58,158
Log likelihood	2962	2962	2975	2975
Prob>Chi^2	0.000	0.000	0.000	0.000

Panel C: Local firm transparency

	P(F=1)	P(D=1|F=1)	P(F=1)	P(D=1|F=1)
	(1)	(2)	(3)	(4)
Ln(#bank branches)* Ln(Assets)	0.071*	-0.045**		
	[1.862]	[-2.385]		
Ln(Assets)	-0.054	0.165*		
	[-0.317]	[1.749]		
Ln(#bank branches)* Ln(Analysts)			0.140**	-0.078**
			[2.389]	[-2.329]
Ln(Analysts)			-0.489*	0.25
			[-1.853]	[1.613]
Ln(#bank branches)	-0.359	0.254*	-0.086	0.060
	[-1.447]	[1.832]	[-0.903]	[0.923]
Control variables	Yes	Yes	Yes	Yes
Observations	58,158	58,158	58,158	58,158
Log likelihood	-2988	-2988	-2986	-2986
Prob>Chi^2	0.000	0.000	0.000	0.000

Panel D: Are banks special?

	P(F=1)	P(D=1|F=1)	P(F=1)	P(D=1|F=1)
	(1)	**(2)**	**(3)**	**(4)**
Compustat firm density	0.001	0.000		
	[1.339]	[0.414]		
Hospital density			0.003	0.001
			[1.406]	[0.264]
Bank branch density	-0.121***	0.059*	-0.066***	0.063***
	[-3.755]	[1.892]	[-2.915]	[3.077]
Control variables	Yes	Yes	Yes	Yes
Observations	58,158	58,158	58,158	58,158
Log likelihood	-2971	-2971	-2979	-2979
Prob>Chi2	0.000	0.000	0.000	0.000

Notes: Panel A examines how the baseline results vary with local firms' bank borrowing intensity and likelihood of obtaining bank finance. *Bank borrowing* is a dummy which equals one if the amount of bank loans local firms receive scaled by firms' total debt is above the sample median. *External finance dependence* is a dummy which equals one if local firms' external finance dependence (measured as in Duchin, Ozbas and Sensoy (2010)) is above the sample median. Panel B examines how the baseline results vary by a branch's incentives to collect local information. *Local banks* is a dummy which equals one if the fraction of banks with a national charter in a 10 km radius is below the sample median. *Small banks* is a dummy which equals one if the average bank size in a 10 km radius is below the sample median. Panel C examines if the baseline results vary by the level of information asymmetry issues for outsiders. *Ln(Assets)* is the natural logarithm of the firm's total assets. *Ln(Analysts)* is the natural logarithm of the number of stock analysts that follow the firm. Panel D compares the effects of local bank density on fraud to the effects of density in other local institutions on fraud. *Compustat firm density* is the number of other Compustat firms located within a 10 km radius from the firm's headquarters. *Hospital density* is the number of hospitals located within a 10 km radius from the firm's headquarters. Odd-numbered columns report the estimated relations between local bank density and the commission of fraud (F=1) while even-numbered columns report the relations between local bank density and detection, given fraud (D=1|F=1). The control variables are similar to those in Table 3 and are collapsed for brevity. The sample covers the period 1994–2013. Definitions of all variables are provided in Appendix A1. *t-Statistics* are reported in parentheses. ***, **, and * indicate significance at the 1, 5, and 10% level, respectively.

Table 7: The role of CEO compensation incentives and corporate governance

Panel A: Corporate governance and executive compensation

	P(F=1)	P(D=1|F=1)	P(F=1)	P(D=1|F=1)	P(F=1)	P(D=1|F=1)
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(#bank branches)* Insider board	-0.204***	-0.021				
	[-3.191]	[-0.500]				
Insider board	1.273***	0.083				
	[4.406]	[0.474]				
Ln(#bank branches)* Entrenched management			-0.398***	0.311**		
			[-4.323]	[2.562]		
Entrenched management			1.985***	-1.946***		
			[5.001]	[-3.783]		
Ln(#bank branches)* High Vega/delta					-0.138**	-0.054
					[-2.496]	[-1.109]
High Vega/delta					0.317	0.252
					[1.289]	[1.201]
Ln(#bank branches)	-0.009	0.073***	-0.020	0.072*	-0.031	0.085**
	[-0.380]	[3.248]	[-0.592]	[1.828]	[-0.772]	[2.501]
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	58,157	58,157	19,761	19,761	22,535	22,535
Log likelihood	-2962	-2962	-1233	-1233	-1563	-1563
Prob>Chi^2	0.000	0.000	0.000	0.000	0.000	0.000

Panel B: Innovation in information technology

	P(F=1)	P(D=1|F=1)
	(1)	(2)
Ln (#bank branches)*Post2000	0.097***	0.001
	[2.676]	[0.023]
Post2000	-0.080	-1.079***
	[-0.333]	[-4.536]
Ln (#bank branches)	-0.121***	0.065**
	[-3.856]	[2.300]
Other controls	Yes	Yes
Observations	58,158	58,158
Log likelihood	-2978	-2978
Prob>Chi^2	0.000	0.000

Notes**:** Panel A examines how the baseline results vary with the firm's corporate governance quality and CEO compensation incentives. *Insider board* is a dummy which equals one if the fraction of inside directors on the board is above the sample median and zero otherwise. *Entrenched management* is a dummy which equals one if the firm's entrenchment index is above the sample median (based on the Bebchuk, Cohen, and Ferrell (2009) index) and zero otherwise. *High Vega/delta* is a dummy which equals one if the CEO's vega/delta is above the sample median and zero otherwise. Panel B examines how the baseline results vary with time. *Post2000* is a dummy that equals one for all years after 2000. Odd-numbered columns report the estimated relations between local bank density and the commission of fraud (F=1) while even-numbered columns report the relations between local bank density and detection, given fraud (D=1|F=1). The control variables are similar to those in Table 3 and are collapsed for brevity. The sample covers the period 1994–2013. Definitions of all variables are provided in Appendix A1. *t-Statistics* are reported in parentheses. ***, **, and * indicate significance at the 1, 5, and 10% level, respectively.

Table 8: Local bank density and firm reporting quality

	Earnings Management		Internal control weakness	Restatement
	EM_J	EM_MJ		
	(1)	**(2)**	**(3)**	**(4)**
Ln(#bank branches)	-0.002*	-0.003**	-0.015**	-0.016***
	[-1.926]	[-2.115]	[-2.298]	[-2.661]
Ln(Assets)	-0.006***	-0.006***	0.006	-0.026***
	[-7.632]	[-7.587]	[1.282]	[-6.025]
Market-to-book	0.000**	0.000**	0.000	0.000
	[2.204]	[2.248]	[0.013]	[-0.457]
Sales growth	0.014***	0.014***	0.000	0.003
	[18.460]	[18.794]	[-0.012]	[0.751]
ROA	-0.003*	-0.003*	-0.014*	0.004
	[-1.775]	[-1.766]	[-1.658]	[0.508]
Leverage	0.000	0.000	0.009	0.012
	[-0.125]	[-0.095]	[0.593]	[0.813]
Ln(Analysts)	-0.004***	-0.005***	-0.013***	-0.010**
	[-5.738]	[-5.801]	[-3.227]	[-2.516]
Cash flow volatility	0.030***	0.029***	0.06	0.007
	[3.824]	[3.628]	[1.463]	[0.164]
Big4 auditor	-0.001	-0.001	0.108***	0.063***
	[-0.903]	[-0.862]	[9.770]	[8.441]
R-Squared	0.362	0.362	0.375	0.162
Observations	33,938	33,834	21,936	36,704

Notes: This table reports firm fixed effect regression results on how local bank density affects three indicators of firm reporting quality. *EM_J* and *EM_MJ* are two measures of earnings management, *EM_J* is based on Jones (1991) and *EM_MJ* is based on Dechow, Sloan and Sweeney (1995). *Internal control weakness* is a dummy which equals one to any period in which management reports ineffective internal control in Audit Analytics "SOX 404 – Internal Controls" database. *Restatement* is a dummy which equals one to any period with a restatement classified as 'fraud' in Audit Analytics "Audit Fees with Restatements" database. We remove all financial and utility firms. The sample covers the period 1994–2013. All specifications include firm dummies. Definitions of all variables are provided in Appendix A1. *t-Statistics* are reported in parentheses. ***, **, and * indicate significance at the 1, 5, and 10% level, respectively.

Table 9: Local bank density and fraud detection speed

	Fraud Duration	_t
	(1)	(2)
Ln(#bank branches)	-1.706**	0.187*
	[-2.064]	[1.687]
ROA	5.787*	-1.578***
	[1.867]	[-3.769]
Financing need	-0.601	0.104
	[-0.648]	[0.833]
Leverage	-4.525	1.588***
	[-1.065]	[2.734]
Ln(Assets)	0.591	-0.119*
	[1.219]	[-1.784]
Institutional investors	7.486***	-0.970**
	[2.759]	[-2.557]
Market-to-book	-0.037	0.014
	[-0.201]	[0.604]
R&D expenses	8.59	-2.078*
	[0.954]	[-1.775]
M&A expenses	1.278	-0.943
	[0.164]	[-0.750]
Ln(Analysts)	-0.468	0.062
	[-0.601]	[0.569]
Ln(Firm age)	1.848*	-0.298*
	[1.655]	[-1.827]
Trade	4.448	-1.873
	[0.426]	[-1.425]
Technology	-0.292	-0.194
	[-0.112]	[-0.504]
Service	-1.429	-0.052
	[-0.328]	[-0.087]
Ln(Personal income)	6.492**	-0.950**
	[2.363]	[-2.444]
Unemployment rate	-0.034	-0.037
	[-0.101]	[-0.773]
Ln(Population)	0.904	-0.167*
	[1.302]	[-1.779]
R-squared	0.326	-
Log likelihood	-	-1075
Observations	250	250

Notes: This table relates local bank density to the speed of fraud detection and the hazard ratio. Column (1) reports the OLS regression while column (2) reports the Cox regression. The dependent variables are the number of quarters from the beginning of fraudulent activity to the detection date (Column (1)) and the hazard ratio for the Cox regression which measures the probability of fraud detection in the next quarter (Column (2)). We remove all financial and utility firms. The sample covers the period 1994–2013. Definitions of all variables are provided in Appendix A1. *t-Statistics* are reported in parentheses. ***, **, and * indicate significance at the 1, 5, and 10% level, respectively.