Swimming upstream: struggling firms in corrupt cities*

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Abstract

We find that bankruptcy is regionally clustered, particularly following local spikes in financial misconduct. Part of this effect obtains through a banking channel: after an increase in fraudulent activity of local firms, credit becomes both more expensive and harder to obtain for nearby borrowers, even for those not guilty themselves. Struggling firms headquartered in high-fraud cities cut investment more sharply during industry downturns, experience lower stock returns, and declare bankruptcy more often. Our results indicate that a local corrupt environment amplifies the effects of financial distress.

Keywords: financial misconduct, corporate failure, bankruptcy, loan spread, security issuance, trust

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1 Introduction

Dallas and Minneapolis are fairly comparable cities in the central United States, each with a fast growing population, vibrant business center, and reputation for cultivating business-friendly climates. Over 100 public firms currently call the Minneapolis region home, placing it 5^{th} in ratio to population among large U.S. cities, with Dallas-Fort Worth (7^{th}) close behind. These cities, however, tend to be very different along one very important dimension. From 1970-2010, firms in the Dallas metropolitan area were over twice as likely to be prosecuted for financial misconduct as those headquartered in and around Minneapolis (2.21% versus 0.93%), a disparity peaking in the 1998-2002 time period, during which Dallas produced more cases of financial misconduct (14) than were produced in Minneapolis (10) over the entire four decades.

In this paper, we examine whether proximity to financial misconduct creates a unique set of challenges for financially distressed firms. Specifically, we ask whether regional proximity to financial misconduct increases a distressed firm's cost of debt, and in turn, whether this adversely impacts its investment and employment policy. Ultimately, we will be interested in whether a firm's very survival is influenced by the financial misconduct of its neighbors.

We are essentially telling a story about "trust," or the belief in one's counterparty to perform on obligation, formal or not.[1] Trust features prominently in many business decisions: CEOs are trusted to not abscond with signing bonuses, scientists to protect intellectual property, equity holders to repay their creditors, and executives to report financial performance honestly. In these and many other situations, higher levels of trust reduce deadweight costs (e.g., writing more complete contracts or enforcing them), and allowing resources to

[1]The theoretical contracting literature distinguishes between the concepts of *trust* and *reputation*; see Cabral (2012). Trust is typically invoked in moral hazard problems (involving hidden actions), whereas the concept of reputation arises in contexts involving adverse selection (involving hidden types). In a pure case of the former, "trusting" the agent is equivalent to understanding her payoffs given different actions, and thereby being able to predict her actions, e.g., trigger strategies in a repeated prisoner's dilemma. When both adverse selection and moral hazard are at work, agents can choose actions to build their reputations. This paper makes no distinction between pure trust (moral hazard) games and those where trust and reputation are mixed. What matters is that there exists regional and temporal variation in their determinants, e.g., social punishment being an especially effective deterrent in some cities compared to others.

be redirected to more productive activities.[2]

Our hypothesis is that the level of trust differs across regions, as well as over time, and that trust is particularly important for firms facing financial distress. Compared to their healthier counterparts, struggling firms face especially harsh incentive and information problems. Moreover, almost by definition, financially distressed firms rely on external capital markets, which directly expose them to the frictions that arise with incomplete contracting. As a result, a lack of trust may accentuate the already negative effects of distress, and hasten a struggling firm's demise.

Our empirical proxy for how much a firm can be trusted is the rates of financial misconduct recently committed by its geographic neighbors, as identified by Karpoff et al. (2013). In previous work (Parsons, Sulaeman, and Titman (2014)), we find that financial misconduct occurs in regionally concentrated waves, involving firms in a wide variety of sectors. Regardless of the mechanism causing this geographic clustering – innate differences in culture, common contextual factors, or peer influences between managers – the likelihood of a firm engaging in financial misconduct is strongly related to the behavior of neighboring firms. Thus, just as a parent might attempt to gauge her own child's behavior from observing his friends, banks and other stakeholders may use information from a firm's neighbors to shape their expectations of the firm's trustworthiness.

A cursory look at the data indicates that there is a cross-city correlation between rates of financial misconduct and rates of corporate failure. To illustrate this correlation, consider Figure 1. The vertical-axis graphs the average bankruptcy rate for firms headquartered in each of the 20 largest cities in the U.S. from 1970-2010, and the horizontal axis plots the average rates of financial misconduct for each city over the same horizon. The positive cross-sectional correlation (0.65) is clearly apparent, indicating that cities with high average rates of financial misconduct are strongly associated with high average failure rates.

[2]There is an extensive literature linking trust to financial development, including contributions by Arrow (1972), Putnam (1993), Fukuyama (1995), Knack and Keefer (1997), La Porta, Lopez-de-Silanes, Shleifer, and Vishny (1997), and Guiso, Sapienza, and Zingales (2004).

As we will show in our empirical tests, similar patterns can be seen in the time-series. That is, it is not simply that cities such as Dallas have higher than average bankruptcy rates, but rather that firms headquartered near Dallas are particularly likely to fail following spikes in financial misconduct, such as 1998-2002. Moving from the 25^{th} to 75^{th} percentile in the surrounding rate financial misconduct, or an increase of about 1.5 percentage points, increases by about 10% (0.15-0.20 percentage points) the likelihood that a firm will declare bankruptcy over the following year.

As mentioned above, the perception of mistrust can damage a firm for numerous reasons. In the next part of the paper, we examine the behavior of a particular group of stakeholders – creditors – not only because data are available, but also because debt contracts are especially sensitive to the lender(s)' trust that the borrower will repay as promised. This is essentially the same motivation underlying Guiso, Sapienza, and Zingales's (2013) study of strategic default in residential mortgages during the 2008-2010 housing crash.[3] Likewise, we find that when a region experiences a wave of financial misconduct, syndicated bank credit becomes temporarily more expensive for nearby firms, even those not directly implicated. Firms in regions above the median rate of financial misconduct pay, on average, about 13 basis points higher in interest costs. This effect is about twice as strong for out-of-state lenders (14 basis points, $t = 8.21$) compared to those more proximate (8 basis points, $t = 2.48$). One interpretation of this result is that non-local lenders are comparatively less informed about local trust and/or corruption, and so when forming expectations about the region, place substantial weight on recent waves of financial misconduct.

We also observe effects in the quantity of credit supplied, with firms in regions with high rates of financial misconduct borrowing less frequently and/or lower amounts. Though the results differ across specifications, firms above the median rate of financial misconduct are about 10-15% less likely to issue debt (defined as greater than 5% of total assets), indica-

[3] These authors document a strong role for borrower morality, with those believing that defaulting is "morally wrong" (which over 80% do on average) being substantially less likely to walk away from an underwater mortgage. They also find that strategic default is regionally clustered, with homeowners more likely to walk away from mortgages when their neighbors are doing the same.

tive of substantial credit rationing. It is worth reiterating that when predicting price and quantity effects in credit markets, none of the firms we consider were prosecuted for financial misconduct themselves; rather, the effects we document are generated purely *between* locally headquartered firms.

Given these effects in credit markets, a natural extension is to consider investment policy. Specifically, we consider whether cash-constrained firms headquartered in high-fraud areas tend to be more sensitive to industry downturns than their counterparts in lower fraud locations. The magnitude of this difference is remarkable. We find that cash-constrained firms located outside high fraud regions, cut investment by about 17%, on average, when stock returns in their industry are down -10% or more.[4] In contrast, the investment rates of cash-constrained firms in high-fraud areas (exceeding 2% in the previous year), decline over 32%.

Together, these results paint a coherent picture of the special obstacles a corrupt location poses for financially distressed companies: credit markets are tougher, investment expenditures are cut, and failure becomes more likely. We conclude by examining the extent to which the stock market recognizes that corrupt locations can magnify the effect of industry shocks. As we show, in industries exhibiting returns worse than -10%, the stock prices of cash-constrained firms in high-fraud areas decline about 17% more on average than their cash constrained counterparts in lower fraud areas.

To our knowledge, the geographic patterns in bankruptcy we document are new, and irrespective of the interpretation, suggest that regional information may be relevant in empirical models predicting firm failure. While much of our analysis focuses on the specific channel of credit rationing by fraud-averse lenders (often from distant states), other regional influences are at undoubtedly at work, potentially involving labor markets, city demographics, educational institutions, or even natural disasters. We leave a broader characterization of these factors to future research.

[4] Our definition of liquidity constrained is a cash burn rate sufficient to exhaust the firm's current assets in four years or less. Alternative definitions of cash constraints give similar results.

While previous research has studied the costs, both direct (e.g., SEC penalties) and indirect (e.g., increased cost of capital), of committing financial misconduct (Karpoff, Lee, and Martin (2008)), the effect of any spillovers to *uninvolved* nearby firms is less understood. In this respect, the most similar paper to ours is Giannetti and Wang (2014), which finds that following accounting scandals, local investors – think Houston investors after the Enron debacle – lose faith in the stock market generally, reducing their exposure to stocks, even those having nothing to do with the fraudulent event. Complementing their results for retail investors, our work suggests that even highly sophisticated financial institutions can be put off by financial misconduct; moreover, as we show, firm policies and even survival can be affected.

Finally, we note a general connection to the large literature on corruption and economic growth.[5] Most of this literature focuses on cross-country comparisons, finding that higher prevalence of corruption is associated with lower rates of investment and development. Acknowledging the considerable challenges in identification, many shared with our paper, our findings provide confirming evidence *within* the same (broad) legal environment, and thus mitigate at least one important confounding factor.

The paper is organized as follows. Following a description of the data in Section 2, we characterize (Section 3) the geographical distribution of corporate bankruptcies over the four decades 1970-2010, paying special attention to its relation to regional patterns in financial misconduct. As we will see, financial misconduct and corporate bankruptcies are strongly related in the cross-section of U.S. cities. Section 4 explores one potential mechanism: banks, wary of lending to potentially corrupt firms, charge higher interest rates to firms headquartered in areas with high fraud rates, even if they are not directly involved. In Section 5, we explore the implications for investment and stock returns, finding that firms in high-fraud areas are particularly sensitive to industry downturns. We conclude in Section 6.

[5] A necessarily incomplete list of prominent contributions include Knack and Keefer (1995), Mauro (1995), Kaufmann, Kray, and Zoido-Lobaton (1999), and Glaeser and Saks (2006).

2 Data

2.1 Firm location

Our dataset includes firms headquartered near any of the twenty largest metropolitan areas in the United States. The specific variable we use is ADDZIP listed in COMPUSTAT, corresponding to the current zip code each firm's headquarters or home office. Although this convention means that our dataset excludes firms once headquartered in one of our twenty areas but that now reside elsewhere, the fact that firms move so infrequently means that very few observations are lost.

The geographic unit we use is an "Economic Area," as defined by the U.S. Bureau of Labor Statistics. EAs are larger than metropolitan statistical areas (MSAs), and are designed to capture regions within which workers commute. Examples of economic areas are Dallas-Arlington-Fort Worth, Washington D.C.-Columbia-Baltimore, and San Francisco-Oakland-San Jose. We use the term "area" and "city" interchangeably throughout the paper.

2.2 Financial misconduct

The primary source for our financial misconduct data is Karpoff, Koester, Lee, and Martin (2012), hereafter KKLM, which details their hand-collection of over 10,000 events related to cases of corporate fraud and/or financial misconduct. KKLM aggregate information from four distinct but potentially correlated databases: 1) Government Accountability Office (GAO), 2) Audit Analytics (AA), 3) Securities Class Action Clearinghouse (SCAC), and 4) Securities and Exchange Commission's Accounting and Auditing Enforcement Releases (AAERs). As the first two databases contain (mostly) information on "restatement" of corporate financial statements, they provide good indicators of firms' attempts to manipulate earnings.[6] The SCAC maintains a registry of Federal class action securities lawsuits; com-

[6]KKLM's dataset distinguishes between intentional and unintentional errors by linking misstatements to subsequent SEC action. As KKLM describe in detail, up to roughly 80-90% of restatements are unintentional errors; therefore, they do not correspond to attempted financial fraud.

pared with the first GAO and AA datasets, this database reflects a wider variety of corporate misbehavior, which includes accounting fraud, fraudulent transfers in mergers and acquisition, misrepresentation, and insider trading. The AAER contains news releases announcing civil lawsuits brought by the SEC in federal court and other SEC's orders/notices concerning the settlement of administrative proceedings. There is substantial overlap between all four datasets in terms of events covered and timing (see KKLM, section 2.3). We refer the reader interested in further detail (e.g., regarding the data collection method itself, comparison with other measures of fraud) to their paper.

A significant advantage of the KKLM data is that it distinguishes between dates when a firm commits fraud (the "violation period") and the dates these actions became public (the "revelation period"). Most of our analysis will focus on the violation period, where we calculate the rate of fraud commission within a given geographic area. In particular, we calculate the *CityFMRate* for each firm-year as the fraction of firms within the same economic areas (as defined above) but outside the firm's Fama-French 48 industry classification that commit financial misconduct in that particular year.

Table 1 contains the summary statistics related to our regional fraud measure. Across all years and firms, the average value of $CityFMRate$ is 1.58%. However, there is a large variation around this average. The intraquartile range is between 0.64% to 2.17%, and more than 5% of firm-years have no financial misconduct in the surrounding area.

2.3 Corporate failures

Our analyses examine bankruptcy rates as a function of the financial misconduct of a firm's local neighbors. Accordingly, Table 1 also shows the average rate at which firms declare bankruptcy and/or are delisted from public exchanges for financial reasons. Following Campbell, Hilscher, and Szilagyi (2008), we use a broad definition of failure that includes financial-related delistings. In these cases, the firms' stocks underperform to the extent that they are delisted from the exchange. Typical financial reasons for delisting include bankruptcy, failures to pay exchange fees, or failures to maintain sufficient market capitalization or stock price. The average 1-year failure rate in our sample is 1.73%, which as we will discuss later, varies substantially over time and across cities and industries.

2.4 Other variables

Our tests also employ a number of standard control variables, all of which are obtained from standard sources. Stock returns are from CRSP and firm fundamentals from COMPUSTAT. These variables include size (total assets), market capitalization, market-to-book ratio, investment (CAPX/PPE), leverage (total liabilities over total assets), annual stock returns, standard deviation of returns, cash flow (EBITDA/PPE), and Tobin's q (market value of equity minus book value of equity plus PPE, divided by PPE). The summary statistics are shown in Table 1. When we predict firm failure, we augment the bankruptcy model developed by Campbell, Hilscher, and Szilagyi (2008), and so Table 1 also reports our sample average for the additional variables used in their model. We also report the sample averages of changes in investment and employment rates.

3 Regional effects in corporate bankruptcy

This section establishes two new facts about corporate bankruptcies: 1) they are clustered regionally, and 2) these regional clusters occur disproportionately following local waves of financial misconduct. The first sets of results are presented in subsections 3.1 and 3.2 where, respectively, we show that average bankruptcy rates differ between cities, and within cities over time. Subsection 3.3 shows the second result where, here too, we explore both cross-sectional and time series patterns. We find not only that cities with high average rates of financial misconduct also tend to have high rates of corporate failures, but also that the two series are correlated within specific cities. This second finding serves as the foundation for the rest of the paper, which considers in more detail the specific mechanism linking regional corruption and corporate failures.

3.1 Average difference in bankruptcy rates between cities

We begin by observing that failure rates differ considerably across U.S. cities, and that within these cities, tend to experience regional waves when an unusually high (low) rate of firms declare bankruptcy. Although most of the paper will focus on a specific regional factor – the breakdown of local trust – we start by establishing the more general relation between location and bankruptcy. To our knowledge, this has not been reported in the literature, and the magnitudes alone are worth noting, irrespective of the mechanism.

Figure 1 plots a heat map, where the diameter and shade of each circle is scaled to display the average bankruptcy rates for each of the twenty largest U.S. cities from 1970-2010. As the different sized circles show, average failure rates differ substantially between regions. Firms headquartered in cities such as Miami (3.26%) and Denver (3.01%) declare bankruptcy at much higher rates than average, with those in other regions (e.g., Indianapolis at 0.64% or Philadelphia at 0.74%) doing so much less often. Between cities, the standard deviation of average bankruptcy is 0.67%.

Given the magnitude of these differences, it is perhaps not surprising that city "fixed effects" are significant determinants of failure risk. In linear probability models predicting firm-level bankruptcy (not reported), city fixed effects are highly significant ($F = 8.81$).

3.2 Regional waves of bankruptcy

In addition to large cross-city differences in bankruptcy rates, we also observe geographic spikes in failure, variation that is not captured in standard predictors of firm-level bankruptcy. Table 2 shows this formally, where we present the results of hazard models of firm failure. The unit of observation is at the firm-year level, with the discrete dependent variable, $Bankrupt^{i,a}_{j,t}$, taking a value of one if firm j declares bankruptcy during year t, and zero otherwise.[7] Superscript a refers to one of the twenty areas included in our sample, and i refers to the firm's Fama-French 48 industry classification.

Firm-level predictors of bankruptcy are taken from Campbell, Hilscher, and Szilagyi's (2008) empirical study of the stock returns of financially distressed firms. These include the natural logarithm of market-to-book ratio, net income, book leverage, one-year lagged stock return, cash balance, stock price, one-year trailing stock return volatility, and the natural logarithm of total assets. With the exception of cash balance (which loads with the correct sign but is not statistically significant), all other variables enter significantly with the expected sign.

Our main interest is in whether, after controlling for these known determinants of firm failure, bankruptcies tend to cluster regionally. To measure this, we include as a predictor of $Bankrupt_{j,t}^{i,a}$ the time t rate of bankruptcy in the firm's area (a), but outside its industry ($-i$). To model any non-linearity in this relationship, we allow for regional bankruptcy rates to enter through a series of dummy variables: an indicator for exactly zero bankruptcies in the year of interest, another indicator for area bankruptcy rates in the range (0%, 1.5%], one for (1.5%, 3%], and one if the local bankruptcy rate exceeds 3%. In all regressions, the omitted dummy is the first category, and to ensure that we are capturing time-series variation within regions, we include the average bankruptcy rate for each of the twenty cities in our sample (e.g., 3.26% for Miami).[8]

In the first column, we see that compared to the omitted category of zero regional bankruptcies in the year t, firms with at least one bankruptcy in the area are $e^{1.04} \approx 2.83$ times as likely to declare failure. Taking the failure probability of this omitted group of

[7]Because firms declare bankruptcy only once, the probability of failing in any year t is conditional upon survival (i.e., having not declared bankruptcy in year $t-1$, $t-2$, etc.). This induces serial correlation in the residuals, biasing the standard errors of the estimated coefficients. While hazard models are designed to take this serial dependence into account, alternative possibilities include either logit or linear probability models, with standard errors clustered at the firm level. See Shumway (2001) for more discussion of this issue. The results in Table 2 are very similar with either alternative.

[8]Due to the incidental parameters problem first described by Neyman and Scott (1948) –but see also Lancaster (2000) and Green (2004), city fixed effects will not be estimated consistently in non-linear models such as hazard or logit specifications. However, linear probability models (which are estimated consistently), give very similar results to those presented in Table 2.

0.44% as a baseline, having at least one local bankruptcy increases the chance of failure by 0.80% to 1.24%.

Columns 2 and 3 indicate a concave relation between a firm's failure probability and the failure rates of its local neighbors. In the second column, we split the space of positive local bankruptcy rates into two mutually exclusive regions: strictly positive but below 1.5%, and 1.5% or above. Comparing the coefficients indicates that the first few bankruptcies in a region have the biggest impact (more than doubling the baseline failure rate), with higher failure incidence mattering proportionately less (a further increase of about 50%). The final column continues this exercise, distinguishing between the regions (1.5%, 3.0%] and $> 3\%$. Progressing through each region, a higher failure rate of one's neighbors monotonically increases a firm's failure rate, although increases matter less and less. In the highest group, where at least 3% of a firm's neighbors have committed bankruptcy in a given year, the firm's probability of failing itself is $e^{.72+.34+.16} \approx 3.35$ times the baseline, or an increase in 103 percentage points.

3.3 Local financial misconduct as a bankruptcy risk factor

Table 2 indicates the presence of time-varying regional factors that influence the survival prospects of struggling companies, in addition to previously identified firm-level predictors like high leverage or poor profitability. Without additional analysis, which regional factor(s) are responsible for these patterns remain unspecified. For example, shocks to local labor markets might impact many firms within a region, simultaneously impacting their ability to hire or retain high quality workers. Or, perhaps unfavorable election outcomes, changes in local tax rates, or other governmental policies disproportionately harm firms in some regions, and during certain times. A third possibility is extreme weather events, like Hurricane Katrina which decimated New Orleans in 2005, or the Loma Prieta Earthquake, which caused almost $6 billion in damage to the San Francisco Bay Area in 1989.

Though numerous other possibilities exist, the remainder of this paper focuses on one particular mechanism: the breakdown of local trust, and its effect on financially vulnerable companies. The heart of our argument is that a lack of trust exacerbates information or incentive problems, which are particularly severe for struggling companies. Accordingly, the perception that a struggling firm cannot be trusted makes it especially costly for it to raise external finance, invest, and ultimately survive.

We present these results in reverse, showing first that regional misconduct is related to corporate failures, and then in subsequent sections (4 and 5), attempt to better flesh out the mechanism. Figure 2, already briefly discussed in the introduction, shows that measured over several decades (1970-2010), city with high average rates of financial misconduct also tend to have high average rates of corporate failure. The strength of this relation is remarkable, with only twenty data points (one for each city) generating a highly significant slope (0.85, $t = 3.61$) of the best fit line, shown in red.

One possible concern with the interpretation of Figure 1 is that it simply reflects the tendency of firms prosecuted for financial misconduct to subsequently declare bankruptcy, so that the averages shown on the $x-$ and y-axes are mechanically related.[9] Note that this issue is eliminated by how the averages in Figure 1 are calculated. The x-axis represents city-level average bankruptcy rates, ignoring any firms that, at any point in the sample period, declare bankruptcy.

In Table 3, we consider whether a relation between city-level financial misconduct and failure exists dynamically – i.e., whether firm bankruptcies are more likely following increases in regional measures of financial misconduct. In the first column, we take the failure model in Campbell et al. (2008), and add to it last year's $(t-1)$ average rate of financial misconduct in the city, $CityFMRate^{a,-i}_{p,t-1}$. As before superscript a refers to one of the twenty economic areas, and $-i$ specifies that financial misconduct is calculated outside the firm's Fama-French 48 industry classification. Subscript p stands for the "portfolio" of local firms which,

[9]As an extreme example of the concern, imagine that bankruptcy in year t occurs if, and only if, the firm is guilty of financial misconduct in year t. Here, city-level rates of financial misconduct and bankruptcy will be identical.

on average, contains roughly 130 companies. The estimated coefficient indicates that a one standard deviation increase in $CityFMRate$, about 1.35 percentage points, increases the odds ratio of a local firm declaring bankruptcy the following year by about $e^{11.4*.0135} = 1.17 - 1 = 17\%$. Given an overage average rate of bankruptcy of 1.58%, this translates to a marginal effect of 0.26 percentage points.

The second column presents the result when $HighCityFM^{a,-i}_{p,t-1}$ is parametrized discretely, taking a value of one if $CityFMRate^{a,-i}_{p,t-1}$ ranks in the top quartile (above 2.03% annually). The coefficient (0.298, $t = 5.12$) indicates that odds ratio is about $1 - e^{.298} \approx 35\%$ higher (about 0.55 percentage points) when $CityFMRate^{a,-i}_{p,t-1} = 1$, evaluated when all controls are at their sample means.

Given that we already know from Table 2 that bankruptcies tend to cluster regionally, it is natural to question whether the relation between city-level financial misconduct and bankruptcy shown in Table 3 represents a distinct finding. In column 3, we include as a predictor $HighCityFM^{-i,a}_{p,t-1}$, a dummy variable that takes a value of one if last year's $(t-1)$ rate of financial misconduct in firm j's area (a) was about the 75^{th} percentile. The portfolio (p) of these firms are calculated outside the firm's Fama-French 48 industry $(-i)$. Comparing columns 2 and 3 in Table 3, although accounting for a high rate of local firm failure ($> 3\%$) modestly reduces the effect of city-level financial misconduct, the coefficient on $HighCityFM$ remains highly significant (0.23, $t = 3.96$), maintaining about four-fifths of its magnitude. (A similar conclusion obtains when comparing the respective coefficients on a dummy variable for $> 3\%$ in city-level bankruptcy rates between Tables 2 and 3).

Our conclusion is that although local waves of misconduct appear to partly explain the regional clustering of corporate bankruptcy, the majority of the effect remains unexplained. We view the identification of these local factors as interesting avenues for future research, and in the remainder of the paper, focus specifically on the relation between financial misconduct and firm performance.

The final four columns account for time-series variation in bankruptcy rates for a number of relevant portfolios. Like we did for city-level bankruptcy in column 3, column 4 includes the same dummy variable, but for firms in the same Fama-French industry (i), but outside the area ($-a$). Likewise, column 5 considers firms in the same region (a) and industry (i). The second to last column accounts for spikes in market-wide bankruptcy not otherwise accounted for in these other portfolios. Our objective with all these controls is to ensure that our identification of any effect for city-level financial misconduct is distinct from any existing time-series trends in firm failure. The stability of the coefficient across all specifications suggests that this is the case.

4 Local corruption and access to credit

In the previous section, we saw that failure risk is regional, and also that an area's bankruptcies tend to spike following waves of financial misconduct. Here, we attempt to shed further light on the mechanism connecting declines in regional trust to corporate failures. Although trust is likely to influence many aspects of a firm's operations – strength of corporate governance, interaction with workers, credibility with customers, and ability to enter into long term agreements with suppliers are all plausibly impacted – we focus on a firm's relationship with potential creditors.

We explore this specific channel for two reasons. First, trust is especially important in debt contracts which, as their name suggests ("promissory" notes), represent a borrower's promise to repay lent funds at some future date. And, while debt contracts typically include a number of provisions either restricting or verifying the borrower's future actions – features intended to make default less likely or, should it occur, increase recovery – the inability to write complete contracts inevitably implies states where borrowers cannot be forced to repay, even if able. In these situations, repayment incentives will depend on other considerations, such as whether borrowers view it as unethical to default on a loan, or whether doing so will incur social penalties.

These are precisely the types of considerations explored by Guiso, Sapienza, and Zingales (2013), who study *strategic default* in the residential mortgage market following the burst of the housing bubble after 2008. Using survey data, they find that views on fairness and morality were strongly related to the propensity to walk away from one's mortgage, despite having the ability to remain current. Interestingly, they also find geographical clustering in strategic default (as we do with corporate bankruptcies), suggesting regional diffusion in either the costs related to strategic default (e.g., social stigma), or knowledge related to it (e.g., banks' aggressiveness in recovery action).

It is debatable whether bankers explicitly consider strategic default as a meaningful risk factor, especially in light of management's strong incentives to preserve employment. Even so, the same types of factors that influence strategic default in mortgage markets, such as the belief that defaulting is unethical, may nevertheless influence repayment rates. For example, if exercising a valuable default option is considered morally wrong, perhaps risk shifting, whereby managers select high variance projects that enrich equity holders at the expense of debt holders, can likewise be considered unethical. Regardless of the specific mechanism, the analysis in this section explores whether spikes in local financial misconduct, our proxy for generalized trust in a region, are reflected in the supply and terms of debt contracts.

The second reason is the availability of data. We first investigate whether the price of credit is related to a region's financial misconduct (subsection 4.1). Note that this analysis is possible only for a particular kind of debt, syndicated bank loans, for which we can use DEALSCAN to infer deal terms. As we will see, credit spreads are higher when local rates of financial misconduct are higher. In subsection 4.2, we extend to consider the quantity of debt. Because we use COMPUSTAT to infer changes in total debt, this analysis is possible not only for syndicated loans, but also for other types of debt, e.g., bonds and non-syndicated bank credit.

4.1 Price

Table 4 presents the results of OLS regressions, in which the dependent variable is the spread (over LIBOR) a firm pays on syndicated bank credit, including any fees. In a syndicated loan, the debt contract is between a borrower and multiple banks, each of whom contribute a portion of the lent funds. Typically, a single "lead arranger" sets deal terms, and interacts directly with the borrower during the underwriting process. Occasionally, syndicated loans are originated using co-lead arrangers.

There are two reasons why the number of observations in Table 4 is so much smaller than that in Tables 2 and 3. First, the loan analysis includes only firm-years during which securities are issued. Second, the analysis includes only syndicated bank loans. Therefore, the analysis excludes firms that never receive syndicated bank loans as well as firm-years during which loan-issuing firms do not receive any loans.

The firm-level control variables in Table 4 include firm size (total asset), net income, leverage, cash holdings, stock returns, stock price, volatility, and market-to-book ratio. We also include several loan characteristics: the average maturity, the size of the loan, and two indicator variables capturing whether the lender is based in the U.S. and whether the lead arranger is a large commercial lender (i.e., Citigroup, JP Morgan, or Bank of America), respectively. To control for potential variation in loan spreads due to economic and industry conditions, we subtract the industry-year average from the dependent variable.

The main independent variable of interest in the loan spread regressions is the city-level financial misconduct. We ask the question of whether loan spread increases following increases in regional measures of financial misconduct. Similar to Table 3, we use both the raw city financial misconduct rate (in model 1) and a discrete measure for cities with high financial misconduct rate (in the remaining models). Models 1 and 2 report that increases in regional financial misconduct rate precede increasing loan spreads. In particular, the parameter estimate in model (2) indicates that being located in a high financial misconduct area increases the loan spread by 13.41 percent, which corresponds to about 23 basis points increase in loan spread from the average of around 175 basis points.

To gain further insights into the role of trust in loan pricing, we examine two potential proxies of higher levels of trust. First, we categorize loans into those issued by lenders in the firm's headquarter state vs. those issued by lenders outside that state. The hypothesis is that loan pricing by same-state lenders should be affected less by regional financial misconduct. This hypothesis is due to three related conjectures: (1) local lenders are better able to screen out borrowers with potential issues and therefore can offer better loan terms for those that they choose to lend to, and (2) the rationed firms may have to go to out-of-state lenders when the nearby lenders refuse them, and (3) the loan terms will be worse for these firms because of potential adverse selection. We find evidence consistent with this hypothesis in models (3) and (4). The marginal effect of financial misconduct on loan spread for loans issued by out-of-state lenders is almost twice that for loans issued by in-state lenders. The difference is statistically significant at 10% level.

Second, we categorize loans into those that represent the first time the lender provides the firm with a loan and those issued by repeat lenders to the firm. The hypothesis here is that loan pricing by repeat lenders should be affected less by regional financial misconduct, as these lenders have built a relationship with the firm. However, there is a confounding effect which is that repeat borrowers may be forced to go back to their previous lenders due to their (potentially unobserved) special characteristics and situations. Comparing models (5) and (6), we observe a very weak evidence that the marginal effect of financial misconduct on loan spread is reduced for loans issued by repeat lenders vs. those issued by first-time lenders. In an unreported analysis, we find that the positive effect of financial misconduct on loan spread is essentially eliminated for loans issued by same-state repeat lenders, consistent with the trust built through repeated interactions of proximate agents overcoming the negative effect of financial misconduct.

The positive effect of regional financial misconduct on loan spread may be due to either increases in loan demand by local firms or reductions in loan supply to these firms. In the next section, we examine the quantity of new debt issued by these firms following regional financial misconduct. Supply-driven increase in spread predicts a lower amount of debt issuance, while demand-driven increase predicts the opposite.

4.2 Quantity

Table 5 shows the results of logit regressions predicting security issuance. We measure net debt issuance as the change in debt liabilities in consecutive annual financial statements. Net equity issuance and net securities (debt plus equity) issuance are measured in similar fashion.

The dependent variable in the first column is an indicator variable that takes the value of 1 if the firm's net debt issuance is more than 5% of book asset and 0 otherwise. This column shows that firms in areas with high regional financial misconduct rate are less likely to issue debt, after controlling for potential determinants of demand for financing (e.g., firm size, net income, cash holdings) as well as measures of default risk (e.g., leverage, stock volatility). The point estimate for $HighCityFM$ in model (1) indicates that being located in a high fraud area reduces the probability of loan issuance by around 11 percent, which corresponds to about 4 percentage points increase in debt issuance probability from the unconditional probability of around 39 percentage points.

Model (2) shows that the reduction in debt issuance is not compensated by an increase in equity issuance. We find that being located in a 'corrupt' location reduces the probability of large securities issuance by around 9 percent. Moreover, when we focus on the subset of firms that issue a large amount of securities –for whom the benefits of obtaining external funding are presumably higher than the corresponding costs– in models (3) and (4), we continue to observe a lower propensity of debt issuance. As mentioned above, this is consistent with a supply-driven increase in loan pricing that we document in Table 4.

In summary, the results in Tables 4 and 5 are consistent with proximity to financial misconduct reducing the supply of credit –and indeed of overall external financing– to firms.

The results are therefore consistent with the positive role of trust in increasing access to credit and external financing in general.

5 Implications for firm policies and stock returns

In the preceding analysis, we found that regional misconduct appears to impact credit markets, influencing both the cost and quantity of debt supplied. This section extends to consider the uses of this capital, asking whether local waves of financial misconduct adversely impact the investment and employment policies of liquidity constrained companies. As we will see in subsection 5.1, proximity to financial misconduct significantly magnifies the impact of negative industry shocks, resulting in significantly lower investment rates for distressed firms in 'corrupt' locations. In subsection 5.2, we find the same results when examining layoffs following industry downturns. Finally, we explore the implications for stock prices in subsection 5.3. Mirroring the analysis of investment, we find that proximity to financial misconduct results in especially severe price declines during industry downturns.

5.1 Capital expenditures

In this section, we are interested in whether proximity to financial misconduct negatively impacts the investment plans of constrained companies – i.e., the types for which the negative effects on credit markets (Section 4) should have the largest impact. The specific question we ask: Upon experiencing a negative industry shock, do firms in areas having recently experienced high rates of financial misconduct cut investment more than their peers in less corrupt locations? And, are any differences between these groups magnified for firms more reliant on external capital markets?

To answer these questions, we estimate the following model of investment:

$$\begin{aligned} \mathit{\Delta Investment}_{j,t}^{i,a} = \alpha + \beta_1 \mathit{HighIndustryInvestment}_{p,t}^{i,-a} + \beta_2 \mathit{LowIndustryInvestment}_{p,t}^{i,-a} + \quad (1) \\ \beta_3 \mathit{LowIndustryInvestment}_{p,t}^{i,-a} \cdot \mathit{ConstrainedFirm} + \beta_4 \mathit{HighCityFM}_{p,t}^{-i,a} + \\ \beta_5 \mathit{HighCityFM}_{p,t}^{-i,a} \cdot \mathit{HighIndustryInvestment}_{p,t}^{i,-a} + \\ \beta_6 \mathit{HighCityFM}_{p,t}^{-i,a} \cdot \mathit{LowIndustryInvestment}_{p,t}^{i,-a} + \\ + \beta_7 \mathit{HighCityFM}_{p,t}^{-i,a} \cdot \mathit{LowIndustryInvestment}_{p,t}^{i,-a} \cdot \mathit{ConstrainedFirm} + \\ + \beta_8 \mathit{\Delta CashFlow}_{j,t}^{i,a} + \beta_9 \Delta q_{j,t}^{i,a} + \epsilon_{j,t}^{i,a}. \end{aligned}$$

The dependent variable, $\mathit{\Delta Investment}_{j,t}^{i,a}$, is the annual change in firm j's ratio of capital expenditures to lagged total assets, from $t-1$ to t. As before, i indicates industry and a geographic area.

Our focus is on the differential sensitivity to negative industry shocks, between firms headquartered in high versus low area-level rates of financial misconduct. We proxy for positive and negative industry shocks with dummy variables $\mathit{HighIndustryInvestment}_{p,t}^{i,-a}$ and $\mathit{LowIndustryInvestment}_{p,t}^{i,-a}$ respectively. The first takes a value of one if industry-level (i) investment, measured outside ($-a$) firm j's area is in the top quartile (above 1%; 5.4% on average), and the second if sector-wide investment is in the bottom quartile (below -7.5%; -14.1% on average). Coefficients β_1 and β_2, accordingly, measure the average sensitivity to industry-wide increases and decreases of this magnitude. The intercept, α, captures the effect of all other years, when investment growth (or shrinkage) in firm j's industry is fairly modest.

The next term in Equation (1) tells us whether financially constrained firms cut investment especially sharply during industry declines. Our measure for reliance on external capital markets, *ConstrainedFirm*, is a dummy variable taking a value of one if: 1) firm j's cash flows from operations, net of interest expenses is negative, and 2) the rate of burning cash will exhaust the firm's current assets within four years. Using COMPUSTAT variable definitions, this condition is $OANCF_t - XINT_t > \frac{-ACT_t}{4}$. (Our results are not sensitive to this particular choice of cutoff.) Coefficient β_3 thus captures the differential sensitivity of firms satisfying this condition to industry-level investment declines of 1% or more.

Our primary interest is whether being headquartered in an area with high rates of financial misconduct increases this sensitivity even further, i.e., whether the coefficient on the triple interaction, $HighCityFM_{p,t}^{-i,a} \cdot LowIndustryInvestment_{p,t}^{i,-a} \cdot ConstrainedFirm$, β_7, is negative and significant. To avoid confounding effects, Equation (1) also includes $HighCityFM_{p,t}^{-i,a}$ by itself (β_4), as well as its interaction with the high (β_5) and low (β_6) industry level investment variables.

Finally, in some specifications (for reasons we discuss below), we include as covariates changes in $Cashflow$ and q, traditionally identified determinants of corporate investment. Their effects are captured, respectively, by coefficients β_8 and β_9 in Equation (1).

Table 6 shows the results of estimating Equation (1). The first column includes only the high and low industry dummy variables, as well as an indicator for a high city-level rate of financial misconduct. As expected, both industry variables are highly significant, and with the expected sign. The coefficient on $HighCityFM_{p,t}^{-i,a}$ is not significant on its own, indicating that the typical firm's investment is not sensitive to local waves of financial misconduct.

The second column, however, paints a different picture. Here, we interact $HighCityFM_{p,t}^{-i,a}$ with both $HighIndustryInvestment_{p,t}^{i,-a}$ and $LowIndustryInvestment_{p,t}^{i,-a}$, thereby allowing for differential slopes between the three regions for industry-level investment. While neither the intermediate region (β_4) nor high (β_5) regions appear influenced by local financial misconduct, we estimate a negative and significant effect for β_6. This indicates that for firms in corrupt areas, industry-level declines in investment are associated with especially steep cuts in investment. The estimated coefficient is -6.83 ($t = -2.10$), so that the adverse impact on investment of a negative industry shock is more than doubled for firms in cities having recently experienced high rates of financial misconduct.

In the next column, we see that this effect is driven exclusively by firms consuming, rather than generating, cash. The coefficient on the triple interaction, β_7 is negative and significant, with a point estimate of -14.89 ($t = -2.69$). To put this magnitude in perspective, consider two financially constrained firms A and B, both of which have experienced a negative industry shock ($LowIndustryInvestment_{p,t}^{i,-a} = 1$). However, firm A is headquartered in a region with a high prevalence of financial misconduct ($HighCityFM_{p,t}^{-i,a} = 1$), whereas firm B is not ($HighCityFM_{p,t}^{-i,a} = 1$). Combining our estimates for coefficients β_2 and β_3, from Table 6, firm A can expect a decline in investment of about $-4 - 13 = -17\%$. Meanwhile, the predicted decline for firm B is almost twice as large at $-4 - 13 - 15 = -32\%$.

The final specification (column 4) includes changes in the firm's own q (lagged one year) and $CashFlow$, both traditional determinants of investment expenditures. Although each enters highly significantly and with the expected sign, we have heretofore postponed them in order to facilitate the interpretation of terms involving $HighCityFM_{p,t}^{-i,a}$. The specific concern is that either (particularly q) may already reflect any negative impact(s) of location on investment opportunities, thus removing some of the cross-sectional variation we hope to measure with our measure of regional misconduct. Yet, the similarity of the coefficients between the last and penultimate column suggests that this concern has little, if any, empirical merit.

5.2 Employment

In this section, we ask the same question, but apply it to changes in firm employment rather than capital expenditures. Relative to Equation (1), we make only two changes. First, the dependent variable, $\Delta Employment_{j,t}^{i,a}$, is now the percentage change in firm j's number of employees (COMPUSTAT variable EMP), from $t-1$ to t. Second, the industry-level dummy variables are defined using sector wide changes in employment. As before, *High* (*Low*) *Industry Employment* are dummy variables for the top (bottom) quartile of year-over-year employment growth at the industry level. These thresholds are, respectively, about 9% and 2%.

In the first column of Table 7, we see that, as expected, firms cut employees during industry declines and add them in industry booms. On average, firms add 5% to their workforce when industry-level employment growth is in the top quartile, and lay off 6% in response to industry downturns in the bottom quartile. Both results are highly significant. Column 1 also shows that unconditionally, spikes in regional financial misconduct are not associated with layoffs for nearby headquartered companies.

The next two columns allow for the effect of financial misconduct on employment to change with industry conditions, as well as with firm-level financial constraints. In columns 2, we estimate a negative point estimate for the interaction between $HighCityFM_{p,t}^{-i,a}$ and $LowIndustryEmployment_{p,t}^{i,-a}$, but it is not statistically significant ($t = -0.91$).

However, as shown in the third column, focusing specifically on liquidity-constrained firms paints a different picture. When $ConstrainedFirm$, defined as before, is interacted with the $HighCityFM_{p,t}^{-i,a} \cdot LowIndustryEmployment_{p,t}^{i,-a}$, we estimate a negative, and highly significant coefficient (-6.91, $t = -4.91$). Thus, compared to constrained firms headquartered in less corrupt areas, the effect of an industry downturn is magnified by about 50%, increasing from $-1.3 - 4.3 - 9.6 = -15\%$ to $-1.3 - 4.3 - 9.6 - 6.9 = -21.9\%$. The final column adds changes in q and $Cashflow$, both of which are highly significant. Though their inclusion reduces the magnitude on the triple interaction coefficient, the estimate remains economically and statistically significant, suggesting that in cities having recently experienced spikes in financial misconduct, industry downturns are particularly painful for employees of constrained companies.

5.3 Stock returns

Our final sets of results are presented in Table 8, which extends the same methodology outlined in the previous two subsections to stock returns. Now, the dependent variable, $Return_{j,t}^{i,a}$, is the stock return of firm j from $t-1$ to t. As we did for investment and employment, $LowIndustryReturn$ is dummy variable for the value-weighted return in firm j's industry (i) being in the bottom quartile, and *HighIndustryReturn* a corresponding dummy for the top quartile. All other variables are defined identically. Note also that Table 8 controls for firm size and market-to-book ratios, variables traditionally found to be related to stock returns.

Focusing on the main results shown in the third and fourth columns, we continued to see a dramatic difference between contained firms in high- versus low-financial misconduct cities. An industry return in the bottom quartile is associated with a roughly -13% drop in stock prices for unconstrained firms, and -39% for firms ones facing liquidity constraints. Though this is already a substantial drop, firms headquartered in regions with high rates of financial misconduct lose another 16%, a decline sufficient to destroy almost half the firm's equity value.

Together, the results in this section indicate that constrained firms headquartered in area characterized by high rates of corporate corruption fare especially poor during industry downturns. Tables 6 and 7 suggest that investment and employment suffers disproportionately, and in Table 8, we see evidence that these (and potentially other) regionally-based costs are reflected in equity prices.

6 Conclusion

This paper studies the relation between a region's financial misconduct, and the prospects of financially distressed firms headquartered nearby. Following spikes in local financial misconduct, credit becomes more expensive and harder to obtain for resident companies. This suggests that regional ebbs and flows financial misconduct imposes an externality on neighboring firms – indeed, virtually none of the impacted firms were guilty of misbehavior themselves.

It is worth re-emphasizing that local financial misconduct has virtually no impact on the investment or employment policies of financially healthy companies, but rather is concentrated among firms more dependent on credit markets. Thus, although many of a firm's relationships are based on trust, those with external suppliers of finance appear particularly sensitive to it.

Figure 1: Heat Map of Corporate Failure Rate

This figure reports the geographical distribution of city-level corporate failure rates over our entire sample.

Figure 2: Corporate Fraud and Failure Rates

This figure reports the scatterplot of city-level financial misconduct and corporate failure rates over our entire sample. The straight line depicts the best-fit line.

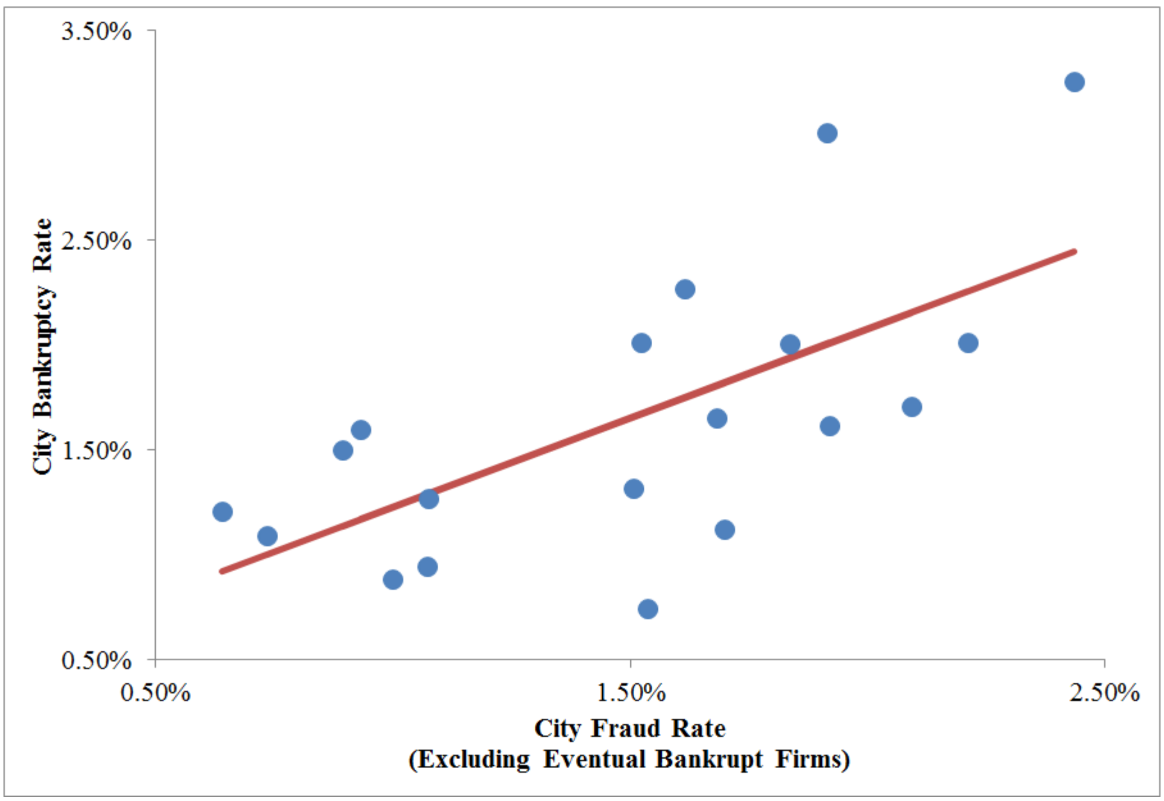

Table 1: Summary Statistics

This table contains summary statistics of firms in our sample. City-Level Fraud Rate is the average fraud rate for the city, i.e., the number of non-industry firms in the city committing financial misconduct, divided by the number of non-industry firms headquartered in the city. Political Corruption is the count of prosecutions of elected and appointed public officials at all levels of government and/or of election crimes (per million of population) in the city. Bankrupt (Next Year) is a dummy variable which takes a value of one if the firm experience default or delisting due to performance issues in the following year, and zero otherwise. Bankrupt (in 3 Years) is a dummy variable which takes a value of one if the firm experience default or delisting due to performance issues in the following 3 years, and zero otherwise. We report summary statistics of the panel data.

Variable	N/Year	5th Pctl	25th Pctl	Median	75th Pctl	95th Pctl	Mean	Std Dev
City-Level Fraud Rate (Fraud/# Firm)	2,904.76	0	0.62%	1.37%	2.17%	4.20%	1.58%	1.36%
Bankrupt (Next Year)	2,904.76	0	0	0	0	0	1.74%	13.08%
Bankrupt (in 3 Years)	2,904.76	0	0	0	0	1	5.44%	22.67%
Asset (in M)	2,904.76	4.88	30.86	137.95	709.23	8,316.66	1,877.06	6,820.07
Market Cap (in M)	2,904.76	3.95	24.07	101.13	509.46	5,149.90	1,130.25	3,701.27
M/B	2,904.76	0.50	1.06	1.74	3.09	9.02	2.86	3.60
Investment / PPE	2,904.76	3.55%	12.67%	23.97%	45.43%	132.83%	39.92%	50.46%
Book Leverage	2,904.76	3.95%	17.05%	37.38%	62.52%	89.93%	41.16%	27.44%
Annual Return (Last Year)	2,904.76	-62.11%	-22.73%	5.86%	38.56%	137.34%	16.70%	64.67%
Annual Return (This Year)	2,904.76	-67.81%	-26.92%	3.66%	36.84%	133.33%	13.59%	65.17%
Std. Deviation of Daily Return	2,904.76	1.21%	2.12%	3.17%	4.70%	8.27%	3.71%	2.27%
Cash Flow / PPE	2,904.76	-538.69%	1.76%	30.03%	79.06%	339.73%	-12.61%	394.23%
Lagged Q	2,904.76	0.00	1.07	2.78	10.30	74.83	11.16	19.15
Net Income / Asset	2,904.76	-28.28%	-2.63%	1.73%	4.18%	8.04%	-3.00%	27.36%
Cash Holdings / Asset	2,904.76	0.29%	1.87%	5.53%	13.59%	39.77%	11.07%	16.61%
Log(Price)	2,904.76	-0.29	1.39	2.40	2.71	2.71	1.91	1.07
Change in Investment Rate	2,904.76	-79.45%	-12.10%	-0.62%	7.90%	54.42%	-4.33%	55.02%
Change in Employment	2,904.76	-64.70%	-8.48%	2.03%	15.15%	63.70%	2.06%	29.66%

Table 2: Regional Clustering of Corporate Bankruptcy

This table contains the parameter estimates of hazard model regressions predicting corporate failures. The dependent variable is *Bankruptcy*, a dummy variable which takes a value of one if the firm experience default or delisting due to performance issues during the year, and zero otherwise. The main independent variables of interest are indicator variables capturing the level of corporate failure in the city (calculated using firms outside of the FF48 industry of the firm of interest). All firm-level control variables are calculated at the end of the previous year. The t-stats in parentheses are calculated by clustering errors at the firm level.

	(1)	(2)	(3)	(4)
	Hazard model predicting bankruptcy			
City Bankruptcy > 3% Dummy			0.1636***	0.3766***
			(2.67)	(6.54)
City Bankruptcy > 1.5% Dummy		0.4167***	0.3371***	
		(5.31)	(4.00)	
City Bankruptcy > 0 Dummy	1.0408***	0.7227***	0.7237***	
	(8.07)	(5.04)	(5.03)	
Average Bankruptcy Rate in the City	0.9346	-5.0514	-8.0386	-3.9647
	(0.20)	(-1.03)	(-1.60)	(-0.80)
Log(MV)	-0.2691***	-0.2691***	-0.2704***	-0.2644***
	(-11.28)	(-11.26)	(-11.34)	(-11.15)
Net Income	-0.1969***	-0.1980***	-0.1960***	-0.1920***
	(-6.10)	(-6.23)	(-6.21)	(-5.98)
Leverage	0.9410***	0.9094***	0.9032***	0.9163***
	(7.31)	(7.07)	(7.04)	(7.06)
Lagged Return	-1.5461***	-1.5179***	-1.5122***	-1.5459***
	(-8.79)	(-8.69)	(-8.69)	(-8.82)
Cash	-0.2168	-0.2308	-0.2291	-0.2103
	(-1.20)	(-1.29)	(-1.29)	(-1.20)
Price	-0.5805***	-0.5795***	-0.5763***	-0.5873***
	(-17.09)	(-17.06)	(-17.04)	(-17.43)
Volatility	3.4973***	3.3686***	3.4400***	3.5590***
	(5.57)	(5.38)	(5.51)	(5.86)
Log(M/B)	0.4257***	0.4255***	0.4273***	0.4377***
	(18.40)	(18.18)	(18.28)	(18.72)
Observations	90,096	90,096	90,096	90,096
R^2	0.049	0.049	0.049	0.048

Table 3: Regional Financial Misconduct and Bankruptcy

This table contains the parameter estimates of hazard model regressions predicting corporate failures. The dependent variable is *Bankruptcy*, a dummy variable which takes a value of one if the firm experience default or delisting due to performance issues during the year, and zero otherwise. The main independent variables of interest include city-level financial misconduct rate (in Model 1) and an indicator variable (*High City FM*) that takes the value of 1 if the city-level fraud rate (calculated outside the firm's FF48 industry) is in the top quartile (in Models 2-6). The control variables include indicator variables capturing the level of corporate failure of more than 3% in the firm's city (model 3 onwards), in the firm's industry (model 4 onwards), in the firm's city and industry (model 5 onwards) and in the economy as whole (model 6). All firm-level control variables are calculated following Campbell, Hilsher, and Szilagyi (2008) at the end of the previous year. All models include the average bankruptcy rate in the city throughout the whole sample. The *t*-stats in parentheses are calculated by clustering errors at the firm level.

	(1)	(2)	(3)	(4)	(5)	(6)
	Hazard model predicting bankruptcy					
City FM Rate	11.2009***					
	(6.06)					
High City FM		0.2897***	0.2416***	0.2344***	0.2301***	0.2278***
		(4.95)	(4.09)	(3.97)	(3.91)	(3.86)
High City Bankruptcy			0.3506***	0.2905***	0.2449***	0.2348***
			(5.84)	(4.74)	(3.88)	(3.44)
High Industry Bankruptcy				0.3178***	0.2872***	0.2822***
				(5.43)	(4.89)	(4.71)
High City-Industry Bankruptcy					0.2692***	0.2683***
					(4.21)	(4.19)
High Market Bankruptcy						0.0274
						(0.42)
Average Bankruptcy Rate in the City	3.0084	3.5878	-4.8786	-2.8452	-4.2266	-3.8195
	(0.61)	(0.73)	(-0.96)	(-0.56)	(-0.81)	(-0.72)
Log(MV)	-0.2588***	-0.2572***	-0.2598***	-0.2535***	-0.2535***	-0.2531***
	(-10.53)	(-10.46)	(-10.59)	(-10.27)	(-10.26)	(-10.24)
Net Income	-0.1794***	-0.1825***	-0.1804***	-0.1706***	-0.1758***	-0.1753***
	(-5.38)	(-5.59)	(-5.65)	(-5.36)	(-5.78)	(-5.76)
Leverage	0.9213***	0.9343***	0.9090***	0.9194***	0.9266***	0.9252***
	(6.98)	(7.04)	(6.88)	(6.94)	(6.98)	(6.97)
Lagged Return	-1.5579***	-1.5550***	-1.5251***	-1.4862***	-1.4764***	-1.4749***
	(-8.38)	(-8.35)	(-8.29)	(-8.15)	(-8.12)	(-8.11)
Cash	-0.1682	-0.1886	-0.1917	-0.1739	-0.2104	-0.2081
	(-0.96)	(-1.06)	(-1.09)	(-1.01)	(-1.20)	(-1.19)
Price	-0.6035***	-0.6020***	-0.5918***	-0.5880***	-0.5805***	-0.5801***
	(-16.87)	(-16.82)	(-16.69)	(-16.72)	(-16.55)	(-16.55)
Volatility	3.2044***	3.2056***	3.3324***	3.4711***	3.5313***	3.5458***
	(5.25)	(5.16)	(5.38)	(5.63)	(5.77)	(5.79)
Log(M/B)	0.4249***	0.4230***	0.4239***	0.4236***	0.4204***	0.4209***
	(17.48)	(17.37)	(17.33)	(17.30)	(16.95)	(17.02)
Observations	90,096	90,096	90,096	90,096	90,096	90,096
R^2	0.048	0.048	0.048	0.049	0.049	0.049

Table 4: Regional Financial Misconduct and Credit Spreads

This table contains the parameter estimates of regressions predicting loan spread. The dependent variable is the log of loan spread, adjusted by the average of other loans taken by firms in the same FF48 industry in the same calendar year. The main independent variable of interest is *City Fraud Rate*, which is the rate at which non-industry firms in the city commit financial fraud in the previous year. Models 2-6 use an indicator variable, *High City FM*, that takes the value of 1 for years in which the city financial misconduct rate is in the top quartile, and 0 otherwise. All firm-level control variables are calculated at the end of the previous year. The first two models include all loans with available data in the sample. Models (3) and (4) separate the sample into loans issued by same-state lenders and those issued by out-of-state lenders, respectively. Models (5) and (6) separate the loan sample into loans issued by a lender who had lent to the firm before and those issued by a first-time lender to the firm, respectively. The *t*-stats are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	All Loans	All Loans	Same-State	Out-of-State	Repeat	First-Time
Dependent Variable:	Industry-adjusted Log(Spread)					
City FM Rate	4.1367***					
	(8.18)					
High City FM		0.1341***	0.0798**	0.1443***	0.1298***	0.1368***
		(8.77)	(2.48)	(8.21)	(5.55)	(6.77)
Log (Size)	-0.1338***	-0.1366***	-0.1580***	-0.1339***	-0.1784***	-0.1173***
	(-18.90)	(-19.22)	(-10.10)	(-16.65)	(-16.00)	(-12.54)
Net Income/Asset	-0.2087***	-0.1996***	-0.1803**	-0.1997***	-0.3381**	-0.1543***
	(-4.02)	(-3.85)	(-2.18)	(-3.00)	(-2.35)	(-2.74)
Debt/Asset	0.5134***	0.5267***	0.4067***	0.5635***	0.6187***	0.4812***
	(12.14)	(12.45)	(4.71)	(11.61)	(9.25)	(8.82)
Stock Return	-0.0003	-0.0027	-0.0087	-0.0057	-0.0328	0.0056
	(-0.02)	(-0.24)	(-0.43)	(-0.41)	(-1.51)	(0.41)
Cash/Asset	0.2250***	0.2168***	0.1109	0.2744***	0.4489***	0.1120
	(2.77)	(2.67)	(0.75)	(2.82)	(2.80)	(1.18)
Price	-0.0024	0.0010	0.0201	-0.0029	0.0947***	-0.0277
	(-0.16)	(0.07)	(0.70)	(-0.16)	(3.27)	(-1.55)
Volatility	3.2113***	3.1378***	3.4072***	2.8382***	4.1367***	2.5941***
	(6.76)	(6.60)	(3.62)	(5.16)	(5.05)	(4.44)
Log (M/B)	0.0585***	0.0593***	0.0704***	0.0578***	0.0303	0.0773***
	(5.00)	(5.07)	(3.04)	(4.25)	(1.55)	(5.30)
Loan Maturity	-0.0000	-0.0000	-0.0032***	0.0000	0.0000	-0.0013***
	(-0.34)	(-0.40)	(-4.71)	(0.18)	(0.42)	(-3.13)
Log (Loan Size)	-0.0380***	-0.0385***	-0.0393***	-0.0339***	0.0080	-0.0607***
	(-5.77)	(-5.85)	(-2.62)	(-4.58)	(0.77)	(-6.83)
US Lender Dummy	0.0538*	0.0552*		0.0675**	0.0144	0.0798**
	(1.72)	(1.76)		(2.11)	(0.30)	(1.96)
Large Lender Dummy (Citi/JP/BoA)	-0.1033***	-0.0987***	-0.0850*	-0.1115***	-0.0583**	-0.1486***
	(-6.15)	(-5.88)	(-1.69)	(-6.05)	(-2.37)	(-6.36)
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,844	6,844	1,570	5,274	2,787	4,057
R^2	0.475	0.476	0.524	0.473	0.524	0.435

Table 5: Regional Financial Misconduct and Supply of Credit

This table contains the parameter estimates of logit regressions predicting security issuance. The dependent variables are the following indicator variables: *Debt* $> 5\%$, which takes the value of 1 if the firm's net debt issuance is more than 5% of book asset and 0 otherwise; or $(D + E) > 5\%$, which takes the value of 1 if the firm's combined net debt and equity issuance is more than 5% of book asset, and 0 otherwise. In model (3), we limit the sample to firms whose net debt issuance *or* net equity issuance is more than 5% of book asset. In model (4), we limit the sample to firms whose net security (i.e., debt *plus* equity) issuance is more than 5% of book asset, i.e., if the indicator variable $(D + E) > 5\%$ equals to 1. *High City FM* takes the value of 1 if the city-level financial misconduct rate (calculated outside the firm's FF48 industry) is in the top quartile. The t-stats in parentheses are calculated by clustering errors at the firm level.

	(1)	(2)	(3)	(4)
Dependent Variable:	Debt > 5%	(D+E) > 5%	Debt > 5%	Debt> 5%
Sample:	All Firms	All Firms	Debt > 5% or Equity > 5%	(D+E) > 5%
High Fraud Dummy	-0.12***	-0.10***	-0.17***	-0.10***
	(-6.70)	(-5.21)	(-6.10)	(-3.55)
Log(MV)	-0.05***	-0.07***	-0.03***	-0.08***
	(-9.99)	(-11.37)	(-3.39)	(-8.82)
Lagged Return	0.13***	0.30***	-0.00	0.01
	(11.79)	(21.53)	(-0.05)	(0.54)
Log(M/B)	0.54***	0.64***	0.09***	0.22***
	(36.30)	(34.88)	(4.55)	(10.69)
Net Income	-0.25***	-0.87***	0.26***	0.29***
	(-6.52)	(-10.77)	(2.79)	(3.74)
Leverage	1.99***	0.88***	3.58***	3.87***
	(38.16)	(14.81)	(41.74)	(41.72)
Cash	-1.00***	-0.83***	-1.09***	-0.91***
	(-13.10)	(-11.42)	(-9.89)	(-8.13)
Volatility	-0.47	2.92***	-7.34***	-3.21***
	(-1.26)	(6.62)	(-11.73)	(-5.34)
Price	0.15***	0.15***	0.23***	0.13***
	(12.62)	(11.00)	(12.37)	(7.35)
Constant	-1.08***	-0.19***	0.24**	0.49***
	(-16.82)	(-2.65)	(2.27)	(4.62)
Observations	82,881	82,881	43,964	41,815
Pseudo R^2	0.050	0.063	0.134	0.116

Table 6: Investment Plans of Constrained Firms in High Financial Misconduct Regions

This table contains the parameter estimates of regressions predicting the change in investment rates. The dependent variable is the change in investment rate, calculated as the ratio of CAPX to lagged PPE. The independent variables include indicator variables capturing the level of the dependent variable at the industry level: *High Industry* takes the value of 1 if the industry-average change in investment rate is in the top quartile; and *Low Industry* takes the value of 1 if the industry-average change in investment rate is in the bottom quartile. *High City FM* takes the value of 1 if the city-level fraud rate (calculated outside the firm's FF48 industry) is in the top quartile. *Low CF* takes the value of 1 if the firm's cash flow is negative and the magnitude is larger than a quarter of the firm's current asset, and 0 otherwise. The t-stats in parentheses are calculated by clustering errors in two dimensions: firm level and year level.

	(1)	(2)	(3)	(4)
Dependent Variable:	Change in Investment Rate			
High Industry Investment	5.12***	4.82***	4.80***	4.61***
	(4.62)	(5.24)	(5.20)	(5.43)
Low Industry Investment	-7.79***	-5.76***	-3.48***	-3.85***
	(-4.60)	(-4.77)	(-3.18)	(-3.14)
Low Industry * Constrained			-11.98***	-13.60***
			(-5.74)	(-5.60)
High City FM	-0.49	1.15*	1.17*	0.24
	(-0.35)	(1.73)	(1.76)	(0.32)
High City FM * High Industry Investment		0.80	0.83	0.30
		(0.47)	(0.49)	(0.20)
High City FM * Low Industry Investment		-6.83**	-0.26	-0.14
		(-2.10)	(-0.19)	(-0.09)
High City FM * Low Industry Investment * Constrained			-14.89***	-14.58***
			(-2.69)	(-2.73)
Constrained			-1.17*	-1.08
			(-1.71)	(-1.57)
Laq Q				0.21***
				(12.82)
CF				0.39***
				(3.68)
Constant	-2.98***	-3.45***	-3.23***	-5.45***
	(-4.91)	(-6.84)	(-6.17)	(-8.85)
Observations	86,634	86,634	86,634	81,717
R^2	0.008	0.009	0.014	0.033

Table 7: Employment Plans of Constrained Firms in High Financial Misconduct Regions

This table contains the parameter estimates of regressions predicting the growth in firm employment. The dependent variable is the rate of change of employment, calculated as the ratio of change in the number of employees to lagged number of employees. The independent variables include indicator variables capturing the level of the dependent variable at the industry level: *High Industry Employment* takes the value of 1 if the industry-average change in employment is in the top quartile; and *Low Industry Employment* takes the value of 1 if the industry-average change in employment is in the bottom quartile. *High City FM* takes the value of 1 if the city-level financial misconduct rate (calculated outside the firm's FF48 industry) is in the top quartile. *Low CF* takes the value of 1 if the firm's cash flow is negative and the magnitude is larger than a quarter of the firm's current asset, and 0 otherwise. The *t*-stats in parentheses are calculated by clustering errors in two dimensions: firm level and year level.

	(1)	(2)	(3)	(4)
Dependent Variable:	Change in Employment Rate			
High Industry Employment	5.40***	5.22***	5.08***	4.53***
	(13.10)	(11.74)	(11.84)	(11.58)
Low Industry Employment	-6.01***	-5.57***	-4.26***	-3.84***
	(-9.27)	(-10.70)	(-8.00)	(-6.99)
Low Industry * Constrained			-9.61***	-8.85***
			(-12.82)	(-10.61)
High City FM	0.17	0.35	0.13	-0.19
	(0.37)	(0.61)	(0.21)	(-0.36)
High City FM * High Industry Employment		0.63	0.97	0.53
		(0.93)	(1.39)	(0.77)
High City FM * Low Industry Employment		-1.35	1.75*	1.27
		(-0.91)	(1.69)	(1.24)
High City FM * Low Industry Employment * Constrained			-6.91***	-4.91***
			(-4.91)	(-3.42)
Constrained			-1.28***	-1.00**
			(-3.07)	(-2.42)
Laq Q				0.12***
				(14.18)
CF				0.77***
				(11.77)
Constant	4.87***	4.81***	4.94***	3.57***
	(17.58)	(18.67)	(20.12)	(13.31)
Observations	91,438	91,438	84,072	79,321
R^2	0.029	0.029	0.040	0.072

Table 8: Stock Returns of Firms in High Financial Misconduct Regions

This table contains the parameter estimates of regressions predicting annual stock return. The dependent variable is annual stock returns (including delisting returns). The independent variables include indicator variables capturing the level of the dependent variable at the industry level: *High Industry Return* takes the value of 1 if the industry-average return is in the top quartile; and *Low Industry Return* takes the value of 1 if the industry-average return is in the bottom quartile. *High City FM* takes the value of 1 if the city-level financial misconduct rate (calculated outside the firm's FF48 industry) is in the top quartile. *Low CF* takes the value of 1 if the firm's cash flow is negative and the magnitude is larger than a quarter of the firm's current asset, and 0 otherwise. The *t*-stats in parentheses are calculated by clustering errors in two dimensions: firm level and year level.

	(1)	(2)	(3)	(4)
Dependent Variable:	Annual Stock Return			
High Industry Ret.	0.1418***	0.1329***	0.1331***	0.1227***
	(5.37)	(4.53)	(4.52)	(6.05)
Low Industry Ret.	-0.1413***	-0.1337***	-0.1263***	-0.1033***
	(-6.89)	(-6.76)	(-6.46)	(-8.03)
Low Industry Ret. * Constrained			-0.2801***	-0.1777***
			(-4.68)	(-3.92)
High City FM	-0.0103	-0.0095	-0.0071	-0.0125
	(-0.67)	(-0.53)	(-0.38)	(-0.73)
High City FM * High Industry Ret.		0.0324	0.0177	-0.0205
		(1.06)	(0.63)	(-0.63)
High City FM * Low Industry Ret.		-0.0315	-0.0171	0.0100
		(-1.13)	(-0.64)	(0.41)
High City FM * Low Industry Ret. * Constrained			-0.1597**	-0.1048**
			(-2.42)	(-2.02)
Constrained			-0.1214***	-0.1431***
			(-6.82)	(-8.83)
Lag Size	-0.0217***	-0.0217***	-0.0265***	-0.0235***
	(-2.72)	(-2.72)	(-3.54)	(-3.75)
Lag M/B	-0.0568***	-0.0565***	-0.0550***	-0.0472***
	(-3.29)	(-3.29)	(-3.25)	(-3.51)
Constant	0.4662***	0.4657***	0.5450***	0.4867***
	(5.05)	(5.08)	(6.46)	(4.52)
Year FE	Yes	Yes	Yes	
Regression Model	Panel	Panel	Panel	Fama-MacBeth
Observations	92,672	92,672	92,672	92,672
R^2	0.099	0.099	0.104	0.072