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Swimming upstream: Struggling firms in corrupt cities*

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Abstract

We find that a corrupt local environment amplifies the effects of financial distress. Following regional spikes in financial misconduct, credit becomes more difficult to obtain for local borrowers – even those not implicated themselves. This is particularly harmful for cash-constrained firms, which cut investment more sharply and lay off more workers during industry downturns. We also find that local clustering of financial misconduct are a risk factor for bankruptcy.

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

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I Introduction

Dallas and Minneapolis are fairly comparable cities in the central United States, each with a fast growing population, vibrant commerce center, and reputation for cultivating business-friendly climates. Over one hundred public firms currently call the Minneapolis region home, placing it 10^{th} relative to population among large U.S. cities, with Dallas-Fort Worth (8^{th}) ranking even higher. 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 ask whether proximity to regional spikes of financial misconduct – like Dallas in the late 1990s – creates a unique set of challenges for resident companies. Similar to foreign investors pulling out of countries following civil unrest or nationalization (Schneider and Frey (1985)), we hypothesize that local clustering of financial misconduct may taint an entire region, reducing financiers' willingness to provide capital to local firms at attractive terms. Among those most reliant on external finance, such frictions may carry through to real business decisions such as investment and employment, and in extreme cases, even survival.

That banks, or other suppliers of external financing, would be wary of financial misconduct is not a new idea. For one, when a firm's financial statements are not viewed as credible, it is difficult to estimate its ability to repay, or should it default, the value of its assets upon liquidation. Either may increase the cost of borrowing.[1] A second, more general consideration is that a history of financial misconduct reflects poorly on the *trustworthiness* of the firm's executives. A manager who does not respect explicit rules – think about misrepresenting earnings or trading on inside information – is unlikely to respect implicit agreements, which often play a role in debt financing.[2] At best, a lack of trust imposes additional costs (e.g., writing more complete contracts), and at worst, may preclude financing altogether.

What is new, and the subject of this paper, is whether a firm's financial misconduct imposes negative local spillovers on *nearby* firms that are not (perhaps yet) implicated themselves. Our analysis builds on Parsons, Sulaeman, and Titman (2018), which uses the financial misconduct data in Karpoff, Koester, Lee, and Martin (2017), and finds that financial misconduct exhibits a strong regional component, with fraud rates that differ by over a factor of three between cities. This paper examines whether such regional patterns are systematically related to the cost and availability of credit, and whether these frictions are large enough to impact real business decisions and outcomes.

We begin our analysis by exploring the link between regional rates of financial misconduct and credit supplied. Firms headquartered in cities with high rates of financial misconduct appear to borrow less frequently and/or lower amounts. Though the estimated magnitudes are relatively modest – an interquartile-sized increase in a city's rate of misconduct decreases the probability of a large (5% of assets) debt issuance by about one-half a percentage point, this is the average effect, which includes many large,

[1]See Francis, LaFond, Olsson, and Schipper (2004) and Hribar and Jenkins (2004) for evidence that concerns regarding earnings quality and restatements, respectively, increase the firm's cost of capital.

[2]See for example, Eaton and Gersovitz (1981), Gale and Hellwig (1985), Sharpe (1990), and Bharath, Dahiya, Sanders, and Srinivasan (2011) for discussions of implicit contracts in lending relationships.

financially healthy firms with considerable financial slack. As we will see, the cost of deteriorating local trust (or at least the perception thereof) is born primarily by the most vulnerable firms.

A less active credit market could, of course, also be driven by poor investment prospects, and thus, low demand for credit. Although our analysis features industry $\times$ year fixed effects, regional heterogeneity in economic conditions could, in theory, simultaneously influence local companies' investment prospects and incentives to engage in fraud. At least three factors point against this alternative. First, the results on credit provision not only survive, but are nearly unaffected by income, unemployment, and other local economic barometers, as well as city fixed effects. Second, if the local economy was driving the results, we would expect more substantial effects among small and/or service-based firms with more regionalized customer bases. Instead, when we exclude either group, the estimated impact of local misconduct rates grows, not shrinks. Finally, with a smaller sample restricted to borrowers from syndicated banks, we find that the *cost* of debt does not drop with a city's rate of financial misconduct, as we would expect if the latter simply proxies for weak credit demand.

For some firms these credit frictions may have real effects, influencing either the firm's investment or employment policies. Whereas cash rich firms and/or those with good prospects are less reliant on external debt, the business choices of more vulnerable firms may be significantly disrupted. Indeed, we find that the effects of negative industry shocks appear to be magnified for financially constrained firms headquartered in corrupt cities.

To hone in on these most vulnerable firms, we construct a composite index of measures developed by Hadlock and Pierce (2010) and Hoberg and Maksimovic (2015) to identify firms most likely to be financially constrained. Then, similar to Opler and Titman (1994), we form an indicator for distressed industries, identified as those experiencing substantial sector-wide negative investment growth over the prior year. The intuition is that firms unfortunate enough to find themselves in struggling industries, and who also lack the internal resources to self-finance their investment plans, are the most reliant on external capital markets. Our prediction is that among these especially fragile firms, investment expenditures will be the most sensitive to perceptions regarding the breakdown of trust.

The estimates provide strong support for this prediction. Although a city's rate of financial misconduct does not appear to depress investment in the entire cross-section of firms (consistent with the modest effects for debt-raising across the entire sample), we observe sharp declines among double-cursed firms in declining sectors with poor internal liquidity. Among these companies, a one percentage point increase in a city's rate of financial misconduct depresses capital expenditures scaled by lagged gross property, plant and equipment by between 1.7 and 2.3 percentage points, depending on the specification. As before, excluding small and/or service-sector firms makes little difference, providing further evidence against the ebbs and flows of regional economic conditions driving much, if any, of the results. Similar, albeit somewhat weaker, patterns are observed for employment changes.

Although our main focus is on the link between a location's fraud rate and investment and financing choices, we also recognize that a lack of trust can damage the ability of firms to operate along a number of dimensions, including its relationships with customers, suppliers, and even competitors. Hence, we might expect vulnerable firms in less trustworthy locations to suffer greater decreases in operating performance during

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downturns. To explore this, we run regressions similar to those previously estimated for investment and employment, but now consider return on assets (ROA). When the dependent variable is a dummy for being in the lowest ROA decile (defined at the industry-year level), the coefficient on the triple interaction is positive. This suggests that among already struggling firms, the likelihood of extreme poor performance is elevated by high rates of local financial misconduct.

In our final set of tests, we consider the ultimate consequence of local spikes of financial misconduct: bankruptcy. A cursory look at the data indicates a strong cross-city correlation between rates of financial misconduct and rates of corporate failure, as shown in Figure 2. The vertical-axis records 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 rate of financial misconduct for each city over the same horizon. The positive cross-city correlation ($\rho = 0.60$) is clearly apparent, indicating that cities with high rates of financial misconduct also tend to experience high corporate failure rates.

Similar patterns emerge in the time-series analysis of firm failure. It is not simply that cities such as Dallas have higher than average bankruptcy rates, but rather that firms headquartered in Dallas are particularly likely to fail following a rash of financial misconduct, such as 1998-2002. Being located in the top decile of regional financial misconduct increases by about 20% (0.40 percentage points) the likelihood that a resident firm will go bankrupt the following year. Thus, these results indicate that regional information on financial misconduct provides explanatory power in failure models even after controlling for other firm-specific and regional economic variables identified in prior studies.

Our main results indicate that following financial misconduct, nearby peer firms

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borrow less frequently, receive less attractive terms when they do, and ultimately invest less intensively. At a broad level, these findings complement comparable analyses of the offending firms' outcomes, where the linkage between misreporting and adverse capital market outcomes has been well documented. For example, Graham, Li, and Qiu (2008) and Chava, Huang, and Johnson (2017) find that firms experience impairments in credit terms and availability following misreporting, complementing earlier work by Hribar and Jenkins (2004) regarding the cost of equity capital. Another significant strand of this literature explores the implications for stock prices, with important contributions from Palmrose, Richardson, and Scholz (2004) and Karpoff, Lee, and Martin (2008a, 2008b).[3]

Importantly, as we find with geographical location, the adverse consequences of fraud often spill over to industry rivals, either through information or competitive effects.[4] Analyzed through the lens of securities prices, Gande and Lewis (2009) document negative abnormal returns for industry peers of firms having themselves been exposed as engaging in financial misconduct. Likewise, Choi, Karpoff, Lou, and Martin (2023) explore possible valuation spillovers during industry-level enforcement waves, finding the largest stock price effects among firms (and spillover firms) investigated early. In terms of operating performance, Wang and Zhang (2023) find contagion within industries; following the revelation of financial misconduct at one firm, industry peers face tighter financial constraints, and borrow less. Finally, Miao et al. (2023) and Cai, Cai, Wang, and Yang

[3]For a thorough review of the literature on the consequences of financial misconduct, see Karpoff's (2020) chapter 6 in the handbook of *Corruption and Fraud in Financial Markets: Malpractice, Misconduct, and Manipulation.*

[4]In the former, one firm's misconduct increases the market's subjective probability of a sector peer firm also committing misconduct. In the latter, the negative operating and valuation consequences following revelation of misconduct reduces competition, and hence benefits industry rivals. For more discussion of this issue, see Goldman, Peyer, and Stefanescu (2012) and Lel, Martin, and Qin (2023).

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(2023) document changes in the information environment at the sector level, following instances of financial fraud.

In this respect, one way to interpret our results is by recognizing headquarter cities as constituting quasi-industries, by virtue of co-located firms sharing labor markets, infrastructure, local regulation, and apparently, even ethical norms. On the investor side, Giannetti and Wang (2016) finds that following accounting scandals, local investors – think retail stockholders in Houston after the Enron debacle – lose faith in the stock market generally, reducing their exposure to equity, even for firms not in the region. Likewise, our work suggests that even highly sophisticated financial institutions, with potentially better access to information at their disposal, can be put off by financial misconduct. Moreover, as we show, firm policies and even survival are affected by these perceptions.

Our analysis is also relevant for the growing literature on trust and social capital, particularly as it relates to financial transactions. Important contributions here include Putnam (1993), Knack and Keefer (1995), La Porta, Lopez de Silanes, Shleifer, and Vishny (1997), and Guiso, Sapienza, and Zingales (2004).[5] Most of this literature focuses on cross-country comparisons, finding that a higher prevalence of corruption is associated with lower rates of investment and development. Our paper finds confirming evidence *within* the same (broad) legal environment and regulatory regime, and thus mitigates at least one of the important confounding factors that render identification difficult in existing studies.

[5] See also Mauro (1995), Kaufmann, Kraay, and Zoido-Lobaton (1999), and Glaeser and Saks (2006).

II Hypothesis Development

Our analysis connects themes from two strands of the finance literature. One emphasizes *geographic* heterogeneity in the characteristics and performance of public firms headquartered in different locations. An evolving literature shows that average investment rates, reliance on external capital, debt usage, executive compensation, valuation ratios, and stock returns differ significantly between firms headquartered in different cities.[6] This research documents co-movement in these and other measures, suggesting that the prospects of local firms are commonly exposed to one or more regional factors. Depending on the specific outcome measure, as well as how cities and industries are classified, these estimates suggest that a "location factor" is arguably one-third as important as a corresponding industry factor.

The second literature pertains to the importance of *trust* in financial transactions. Traditional definitions emphasize two key elements: an expectation that the trusted party (trustee) will take a specific action, and a risk of harm to another party (grantor) if such action is not taken. Rousseau, Sitkin, Burt, and Camerer (1998) define it as a "psychological state comprising the intention to accept vulnerability based upon the positive expectations of the intentions or behavior of another (p. 395)." It is straightforward to see why banks or public creditors, in particular, would be interested in assessing a borrower's trustworthiness. Although debt contracts feature covenants and provisions intended to limit, prevent, or provide advance notice of default, no contract can cover all relevant contingencies and types of misbehavior potentially harmful to lenders.

[6]See for example, Pirinksy and Wang (2006), Bouwman (2009), Dougal, Parsons, and Titman (2015), Adhikari, Cicero, and Sulaeman (2021), and Dougal, Parsons, and Titman (2022).

Trust can, of course, involve people or parties familiar with each other through experience. It can, however, become generalized and hence, extend to include a larger set of trustee-grantor pairs. Whereas trust in an individual might allow someone to claim, "I trust my plumber," high levels of generalized trust might permit him to say "I trust plumbers in my city." When this notion is shared by a large number of individuals, and spans a wide variety of action types, positive spillovers emerge. This broad family of externalities contributes to what has becomes known as "social capital" (Putnam (1993)), and in the development literature, has been credited with explaining part of the vast productivity gaps observed between nations. The foundation underpinning our analysis is that like countries, cities constitute units whereby social capital, or generalized trust, can vary considerably. If so, then economic activities most sensitive to trust may, in turn, mirror the ebbs and flows of regionalized trust.[7]

To fix these ideas, we find it convenient to characterize a manager's decision to commit financial misconduct using the following framework:

$$U(x, g) = b(x, g) – p[x, g] * [c(x, g)] \tag{1}$$

where $U()$ is the manager's utility, and x reflects the amount "stolen" by the manager. More generally of course, x is intended to represent fraudulent accounting, insider trading, or other types of financial misconduct. Low levels of x correspond to little theft, whereas high levels of x capture more serious violations.

The equation identifies three channels by which high trust – i.e., low x in equilibrium

[7] Guiso, Sapienza, and Zingales (2004) highlights that social capital can affect economic efficiency by "enhancing the prevailing level of trust" (p.526).

– can be maintained: b is the benefit of financial misconduct, p is the probability of being detected, and c is the cost conditional upon being detected. Each of these functions depends on x, under the intuition that stealing more would: 1) generate a bigger payoff, 2) probably leave more clues that increase the odds of being found out, 3) be more likely to be met with stiffer penalties, in the event the manager's misdeeds are discovered.

The second argument, g, captures anything that might affect b, p, or c, other than the amount stolen by the manager (x). For example, there is a literature on industry effects in corporate fraud,[8] implying that g could include sector characteristics, or possibly sector-time dynamics to capture business and industry cycles, and could be modeled as arguments of either $b()$ or $c()$. Likewise, both accounting and finance literature have studied various factors that influence detection probabilities, and might impact the manager's utility through $p()$. Our interest involves the regional factors that might go into g. One can imagine any of the three functions being impacted by geographical factors.

First, the benefit of financial misconduct might vary by location, for example, because of differences in compensation arrangements that vary geographically (e.g., more or less equity-based pay). One could also imagine relative consumption motives playing a role. For example, managers of nearby firms may compete in terms of the quality, size, or location of their houses, and this tendency may vary across cities.

Second, the probability of detection may also differ by location. Dyck, Morse, and Zingales (2010) point to industry regulators, the financial media, and a hodgepodge of other possible whistle blowers, any of which could exhibit spatial variation. Kedia and Rajgopal (2011) emphasize proximity to SEC regionaloffices.

[8]See Wang, Winton, and Yu (2010); Choi, Karpoff, Lou, and Martin (2023).

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Third and finally, the cost of fraud can exhibit geographical variation. Such costs can be imposed by legal authorities – fines, prison sentences, and so on – but generally, we expect such variation to be small in the US context. One of the central ideas in Parsons, Sulaeman, and Titman (2018) is that different cities, by virtue of having different cultures and/or social norms, could impose disparate cost on the violators of such norms. The strongest evidence, in our view, was that generalized misbehavior, involving a wide range of activities, tends to exhibit strong regional clustering. For example, Miami is associated with very high levels of marital infidelity, financial misconduct, and questionable relationships between doctors and drug companies; on the other hand, in Minneapolis, we see more prosocial behavior across these same activities.

Of course, how norms are maintained is itself multifaceted. *Reputation* is an important channel, often modeled as a multi-period prisoner's dilemma with tit-for-tat punishments maintaining good behavior. *Institutions* like the church or civic organizations likely play a role too, by both making norms public and serving an enforcement role (e.g., excommunication or censure). After a while, the maintenance of norms probably is perhaps best understood through *habits*: disposing of trash in a wastebasket rather than on the roadside is second nature to most of us, rather than being enforced by social or formal penalties.

Our empirical tests will regress instances of financial misconduct from one or more public firms to corporate behaviors and/or outcomes of nearby headquartered firms. For example, we will attempt to explain firm i's terms of financing or its investment choices as a function of financial misconduct perpetrated by nearby firms. Implicitly, we are testing a joint hypothesis: 1) trust is important for financial transactions, such as between a firm and a bank; and 2) trust has a regional component.

Framed in terms of Equation (1), imagine a bank considering a potential loan to firm i, attempting to forecast the likelihood of financial misconduct x by firm i's managers (which we take to be harmful to the bank). Whereas it may be difficult for the bank to infer, say, the idiosyncratic benefits (b) or costs (c) firm i's managers may derive from fraud, observing the behavior of nearby firms may be informative about any common (i.e., local) motivation for engaging in misbehavior. By observing the behavior of firm i's local peers, and inverting Equation (1), the bank is now equipped with a signal about the local component of b, p, or c, which in turn can be used to make a more informed forecast about the likelihood of firm i committing fraud and jeopardizing the bank.

We expect this inference to be especially important for financially distressed firms. Not only are such firms more likely to be reliant on external capital, but critically, also have elevated incentives to engage in financial misrepresentation. If so, then a bank will rationally place less weight on firm-specific signals about, say, b or c – perhaps inferred from conversations with the firm's management – and comparatively more weight on information that cannot be obfuscated by the firm. Provided that trust has a regional component, we would hence expect for potential lenders of struggling firms to be particularly attuned to instances of nearby fraud revelation.

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III Data

III.1 Firm location

Our dataset includes firms headquartered in 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, and described as follows:

> BEA's economic areas define the relevant regional markets surrounding metropolitan or micropolitan statistical areas. They consist of one or more economic nodes – metropolitan or micropolitan statistical areas that serve as regional centers of economic activity – and the surrounding counties that are economically related to the nodes. These economic areas represent the relevant regional markets for labor, products, and information. They are mainly determined by labor commuting patterns that delineate local labor markets and that also serve as proxies for local markets where businesses in the areas sell their products.[9]

Notably, whereas the boundaries defining EAs depend partly on commuting patterns, they are typically larger than "commuting zones (CZ)," the latter defined and maintained by

[9] https://apps.bea.gov/scb/pdf/2004/11November/1104Econ-areas.Pdf

the US Department of Agriculture.[10] For comparison, there are 179 economic areas, versus 709 commuting zones.[11] 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.

III.2 Financial misconduct

The primary source of our financial misconduct data, which covers the years 1970-2010, comes from the database developed and presented in Karpoff, Koester, Lee, and Martin (2017), hereafter KKLM.[12] These data contain information on 1,099 enforcement actions brought by the SEC and DOJ through 2011.[13] Included are charges described in Section 13(b) of the 1934 Exchange Act as amended in 1978. As discussed in Amiram et al. (2018), 13(b) infractions are instances of financial misrepresentation that are distinct from, say, 13(a) violations (i.e., financial misreporting) or violations of Section 17a of the 1933 Securities Act or Section 10b-5 of the 1934 Exchange Act (i.e., fraud). However, many 13(b) enforcement actions also include 13(a) or fraud charges, many are accompanied by one or more restatements, and many occur along with private securities class action lawsuits.

Enforcement actions typically occur over several months or years, during which the

[10] https://www.ers.usda.gov/data-products/commuting-zones-and-labor-market-areas/

[11] https://sites.psu.edu/psucz/files/2018/09/Labor-Markets-Paper-8.21-21-20kyd3a.pdf

[12] We thank an anonymous referee for guidance on accurately describing and characterizing the KKLM data. The data description in the first two paragraphs of this section are based almost entirely on this correspondence.

[13] The dataset shared by Professor Gerald Martin in 2012 is described in the working paper version of KKLM, posted on SSRN as https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2112569. This version is also archived: https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=f5ebab03b98c95366078a3d5ca46d15fade65b55.

SEC and/or DOJ usually issue more than one enforcement release. Any release issued by the SEC is designated as either an "Administrative Proceeding" or a "Litigation Release," and its header information identifies the corresponding law under with the SEC has authority to act. A sizable minority of SEC releases additionally receive a secondary designation as an "AAER (Accounting and Auditing Enforcement Releases)," given when the SEC's attorneys determine that the release is of particular interest to accountants or auditors.

The following types of activities are represented in the KKLM database: all SEC and DOJ releases, all code violations in addition to 13(b) charges, any associated financial restatements, any associated security class action lawsuits, and whether any of the SEC releases also have secondary AAER designations. The GAO and AA databases include some of these restatements, as well as restatements not associated with 13(b) enforcement actions; the SCAC database includes most of these associated securities class action lawsuits; and the Berkeley AAER database includes some (but not all) of the associated AAERs.

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 incidence within a given geographic area. In particular, we calculate the *City FM* rate 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. Our focus on the violation period rather than the revelation period reflects an assumption that local credit suppliers observe the city's culture in real time, rather than with a lag when the misconduct is revealed. The results that follow, which reveal stronger links between credit and misconduct in the violation period than in the revelation period, support this assumption.

Table 1 contains the summary statistics related to our regional fraud measure. Across all years and firms, the average value of $City\ FM$ rate is 1.58%. However, there is a large variation around this average. The intraquartile range is between 0.62% to 2.17%, and more than 5% of firm-years have no financial misconduct in the surrounding area.

III.3 Corporate failures

Our final set of 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 delistings due to performance issues, which are observations with the following delisting codes on CRSP: 552 (price fell below acceptable level), 560 (insufficient capital), 561 (insufficient float or assets), 574 (bankruptcy/insolvency), and 580 (delinquent in filing or payment of fees). Notably, these do not include delisting types in CRSP that do not seem related to bankruptcy, e.g., merger events. We augment these observations with observed bankruptcy events from UCLA-LoPucki Bankruptcy Research Database (BRD). The average 1-year failure rate in our sample is 1.81%, which as we will discuss later, varies substantially over time and across cities and industries.

III.4 Loan level data

One part of this paper focuses on loan terms, which we obtain from DEALSCAN. This dataset contains information regarding syndicated bank loans, in which one or several lead arrangers assess the borrower's credit quality, negotiate loan terms and conditions, and then attract additional syndicate members to provide portions of the loan financing under one set of contract. Dealscan reports various characteristics of each syndicated loan, including the loan spread (over LIBOR), various loan covenants that govern the terms for which default occurs or the contract is renegotiated between the borrower and its lenders, loan size, loan maturity, lead arrangers, as well as syndicate members. The sample for our loan-level analysis is limited to firm-years during which a syndicated bank loan is recorded on DEALSCAN.

III.5 Other variables

Our tests also employ a number of standard financial 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; COMPUSTAT item AT), market capitalization (shares outstanding; CSHO, multiplied by the closing price at the end of fiscal year; PRCC_F), market-to-book ratio (market capitalization, divided by shareholders' equity; SEQ), investment (capital expenditure; CAPX, divided by gross PP&E; PPEGT), book leverage (total liabilities; LT, divided by total assets; AT), annual stock returns, standard deviation of returns, cash flow (calculated as income before extraordinary items (IB) plus depreciation and amortization (DP), divided by gross PP&E (PPEGT)), and

Tobin's q, which is calculated following Fazzari, Hubbard, and Petersen (1988) and Erickson and Whited (2012) as market value of equity (CSHO×PRCC_F) plus debt (DLTT + DLC) minus current assets (ACT), divided by gross PP&E (PPEGT). The summary statistics of these variables are shown in Table 1.

[[Table 1 about here]]

In our analysis of firm failures, we closely follow the bankruptcy model developed by Campbell, Hilscher, and Szilagyi (2008) so that our results can be compared to the established bankruptcy literature. We use the functional forms of variables in their model in our analyses (e.g., log transformaton of (M/B) instead of M/B). Nevertheless, our inferences do not depend on the specific functional form of each variable (or the exclusion of some variables).

In our credit analysis, we also include several variables related to regional banking activities at the city level. These variables are designed to capture three important aspects of local banking activities highlighted in prior studies: (1) the competition intensity among local banks (Cetorelli and Strahan, 2006), (2) the availability of banking services and funding in the local economy (Kroszner and Strahan, 1999), and (3) the availability of deposits for local banks (Adhikari, Cicero, and Sulaeman, 2021). To capture local banking competition, we calculate the Herfindahl index of the number of branches of local banks and the Herfindahl index of the amount of deposits of local banks. To measure the availability of local banking services and funds, we include the number of local banks and the aggregate amount of local bank deposits. We divide both numbers by the number of resident firms in the city to capture the availability for each resident firm. To capture the availability of local supply of funds for the banks, we measure the per-capita (1) amount of bank deposit and (2) number of local banks. These variables are calculated using data obtained from FDIC Summary of Deposits database.

IV Local corruption and access to credit

We begin by exploring the connection between the regional incidence of financial misconduct and the availability and prices of credit. 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 and information asymmetries between borrowers and lenders inevitably lead to situations where borrowers have an incentive to mislead lenders. In these situations, the behavior of the borrowers may be governed by ethical considerations and social penalties, which may differ from region to region, in conjunction with purely economic considerations.

We investigate the hypothesis that credit is more difficult to obtain in those regions where borrowers are more likely to act opportunistically in unfavorable states. First, we consider the quantity of debt. Here, we see a significant effect of regional misconduct on debt issuance. Second, we examine the terms for a particular kind of debt, syndicated bank loans, for which the pricing data is available on DEALSCAN.

IV.1 Credit quantity

We start by examining the quantity of new debt issued by these firms following realizations of regional financial misconduct. We measure net debt issuance as the change in debt liabilities in consecutive annual financial statements, scaled by the one-year lagged value of book assets. Table 2 reports the results of linear probability model (LPM) regressions predicting debt issuance. The LPM specification allows us to accommodate a comprehensive set of fixed effects, which include those for industry × year and credit ratings, along with city dummies.

[[Table 2 about here]]

The dependent variable in the first column is an indicator variable that takes a value of 1 if the firm's net debt issuance is more than 5% of book assets and zero otherwise. This column shows that firms in areas with high regional financial misconduct rates 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) and measures of local banking activities. We also include various fixed effects in the linear probability model to control for potential heterogeneity across cities, industries, and firms. The coefficient indicates that a shift in the incidence of financial misconduct, the size of the interquartile range (.62% to 2.17%), reduces the probability of a debt issuance by $(-0.28) \times (0.0062 - 0.0217) \approx 0.42\%$. Relative to the unconditional probability of 36 percentage points, this represents a reduction of about 1.2%. Note that this marginal effect is estimated in the presence of city dummies, and so captures the average (across cities) time-series relation between financial misconduct and debt issuance.

As briefly described in the data section, the covariate of interest is regional financial misconduct during the violation period, *City FM*, for each firm-year, which is calculated as the fraction of firms within the same economic areas but outside the firm's Fama-French 48 industry classification that commit financial misconduct in that particular year. The implicit assumption is that the city's culture is known by credit suppliers, including local bankers, i.e., the incidence of financial fraud is a lagging indicator of culture. We think this is a reasonable assumption based on the literature on local banking relationships (e.g., Petersen and Rajan (1995)). Indeed, we find that our results are typically stronger when we use the violation period rather than the revelation period, consistent with this assumption.

The next two columns report the parameter estimates obtained using different thresholds to define net debt issuance. We observe a similar pattern using the threshold of either two percentage points lower (3% in column 2) or higher (7% in column 3). Higher rates of financial misconduct in a city are negatively associated with the use of credit. Although the differences are small, the point estimates are monotonic across size-of-issuance thresholds, providing some evidence that larger debt amounts may be particularly difficult to accommodate following local spikes in financial misconduct.

We perform three additional regressions to rule out potential explanations of our results that are based on variations of regional conditions related to banking and general economic activities. In column (4), we include measures of local banking activity to capture potential differences in local supply of bank loans. The point estimate of the City FM variable increases by about 25 percent relative to its estimate in column (1). In columns (5) and (6), we exclude small firms and those operating in service sectors, respectively. We observe larger point estimates, indicating that even for firms expected to be less sensitive to local economic conditions, higher rates of financial misconduct in a city are negatively associated with the use of credit.

IV.2 Credit pricing

We now consider how the pricing, i.e., the interest rates charged, on loans obtained by firms are influenced by regional financial misconduct. In addition to providing robustness to the results on debt quantities in Table 2, this analysis helps distinguish between demand- and supply-driven effects. More specifically, we hypothesize that the relation between regional increases in financial misconduct and credit is driven primarily by banks' collective concerns about accounting quality, and/or generalized trust, in a city – i.e., that financial misconduct creates a *negative credit supply shock*. The main alternative is that financial misconduct is correlated with *reduced demand for credit*, perhaps due to poor local economic conditions simultaneously driving both.

In addition to the discussion above regarding the effects of local economic conditions, examining loan pricing provides additional, albeit indirect, evidence that local shocks to demand for loans are unlikely to explain why firms obtain less bank debt when the incidence of financial misconduct increases in their cities. If the reduction in the quantity of loans was caused only by a reduction in local demand, one would expect to observe lower borrowing costs. However, as we show below, positive shocks to financial misconduct in a city is associated with negligible changes in interest rates, reflecting the role of the supply channel.

Table 3 presents the results of OLS regressions relating credit spreads across all

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bank-syndicated loans in DEALSCAN, within our sample of cities. The dependent variable is the log transformation of the spread (over LIBOR) a firm pays on syndicated bank credit, including any fees, and the independent variable of interest is the rate of financial misconduct in the firm's headquarter city. Firm-level control variables in Table 3 include credit ratings, firm size (total assets), net income, leverage, cash holdings, stock returns, stock price, volatility, and market-to-book ratios. 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 (e.g., Citigroup, JP Morgan, or Bank of America), respectively. To control for potential variation in loan spreads due to economic and industry conditions, we include industry $\times$ year fixed effects. Finally, we control for city-level economic condition variables – multiple lags of population and employment growth rates – in an attempt to account for the impact of the local economy on firms' demand for credit.

[[Table 3 about here]]

The results in the first column suggest that, after controlling for other firm, industry $\times$ year, and loan-level determinants of credit spreads, regional clustering of FM is not reliably related to interest costs. Although a non-result may arise from a underpowered test, and the number of observations in DEALSCAN is considerably smaller compared to the debt issuance sample obtained from COMPUSTAT, the most important control variables such as size, profitability, leverage, recent stock returns, and volatility all enter significantly, and with the expected signs. Neither the addition of credit ratings in column 2, and/or measures of local banking activity in columns 3 and 4, results in a meaningful

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change to the financial misconduct coefficient.

Although failing to find any effect on pricing cuts against large demand shifts being an important source of heterogeneity, it does not rule out demand-side considerations entirely. First, there is not a 1-for-1 correspondence between Table 3 (prices) and Table 2 (quantities), because DEALSCAN pertains only to syndicated bank loans, and only a small fraction of firms issuing debt (of any kind) in a given year borrow from a loan syndicate. Second, although we obtain similar magnitudes if we re-estimate Table 2 using only the sample that intersects with the DEALSCAN data, the fact that we lack spread data for 90% of the issuance observations is a clear limitation. A third issue is selection bias: pricing (spread) data is only available for firms that complete deals, leading us to not observe spreads for the most impacted firms that are not able to obtain debt. Fourth, the analysis here pertains to bank-syndicated loans which, because they are typically senior to the firm's general debt obligations, are likely to further understate any change in the firm's overall cost of debt. Fifth and finally, a null result on pricing could reflect *simultaneous* downward shifts in both supply and demand, reducing quantities but with little impact on interest costs.

To drill down deeper into demand shocks, we present several additional pieces of evidence. First, we note the cross-sectional results in the last two columns of Table 2. Columns (5) and (6), respectively, show the estimates when we exclude small firms and those operating in service sectors. The idea is to reduce the influence of firms who, by virtue of their size or sector, may be more sensitive to fluctuations in local economic conditions (a potential driver of demand). Among this subset of firms, we continue to observe no significant relation between city-level financial misconduct and loan pricing.[14]

As a second step in our exploration of the role demand shifts might play – and in particular, demand shifts related to fluctuations in local misconduct – we estimate two sets of models, presented in Internet Appendix (Tables IA.1 and IA.2). These regressions link a city's financial misconduct to prevailing economic conditions. Following Parsons, Sulaeman, and Titman (2018), we estimate negative binomial and Poisson model regressions of the incidence of a city's fraud on its local per-capita income, population, and wage growth rates, as well as the stock returns of locally headquartered firms in each city. These analyses indicate that measures of economic condition are not reliably related to the incidence rate of financial misconduct, at either the city or city-year levels.

Finally, we note that in both Tables 2 and 3, none of the local economic variables (coefficients not tabulated to save space) are significant. Further, the coefficient on city-level misconduct is virtually unchanged, whether or not they are included. We have also experimented with the volatilities of each economic measure – using either the full sample or last few years – but again finding no effect. Combining this with the non-result regarding loan spreads, we believe that fluctuations in local economic conditions are unlikely to represent an empirically relevant source of unobserved heterogeneity.

V Investment and hiring choices

This section examines how local rates of financial misconduct affect a firm's investment and employment choices. We are particularly interested in industries suffering

[14]We also note (unreported) that city-level rates of financial misconduct are not related to equity issuance, as we might expect if they were a proxy for the demand for external capital.

downturns, because firms in these industries are likely to be more closely evaluated by lenders. Our conjecture is that these firms are likely to be scrutinized more stringently in regions with higher rates of financial misconduct. As a result, firms in these regions, particularly those with insufficient internally generated funds (or cash on hand), will invest less and increase employment less than their counterparts in regions with lower rates of financial misconduct.

To be more specific, we will be examining whether firms most likely to be constrained – i.e., firms in declining industries with characteristics indicating financial constraints – are especially sensitive to financial misconduct by local peers. The basic idea is that the creditors of these vulnerable firms are likely to be most concerned about accounting and/or earnings quality, and thus, are more likely to shut off access to credit in locations where the level of trust is lower. In this way, increases in the rate of financial misconduct act as financial constraint amplifiers.

To test this idea, we build on the literature that examines how financial constraints influence how firms invest. As is well recognized, estimating the role of constraints presents a number of challenges. Most notably, the magnitude of cash flows, which is often used as a proxy for the tightening or loosening of constraints, is also likely to be correlated with investment opportunities (e.g., Alti (2003)). Moreover, Tobin's q provides, at best, a noisy a proxy for investment opportunities (Erickson and Whited (2000, 2002)). Our analysis does not directly speak to these issues, but rather takes as a starting point that financing constraints exist which, although not perfectly measured, are at least partly correlated with existing proxies developed by prior research.

More specifically, to identify the set of most vulnerable firms, we consider two criteria. First, we borrow from the prior literature, and rely on measures of financial constraints: 1) the size-and-age-based index developed by Hadlock and Pierce (2010, henceforth HP), and 2) the textual-based index developed by Hoberg and Maksimovic (2015, henceforth HM). As we will see, these measures are strongly, and negatively related to investment and employment growth. The second criteria is poor investment growth, defined at the industry (not firm) level, which captures unfavorable investment prospects. Our key coefficient is thus a triple interaction that includes: 1) a proxy for poor industry fundamentals (i.e., whether the industry is in a downturn), 2) financial constraints at the firm level, and 3) the rate of financial misconduct in the region.

V.1 Capital expenditures

We first consider whether a firm's capital expenditures are related to changes in local financial misconduct, estimating the following model of investment:

$$\begin{aligned} Investment_{j,t}^{i,a} = \alpha + \beta_1 LowIndustry\,Growth_{p,t}^{i,-a} + \beta_2 ConstrainedFirm + \\ \beta_3 LowIndustry\,Growth_{p,t}^{i,-a} \cdot ConstrainedFirm + \\ \beta_4 City\ \ FM_{p,t}^{-i,a} + \\ \beta_5 City\ \ FM_{p,t}^{-i,a} \cdot LowIndustry\,Growth_{p,t}^{i,-a} + \\ +\beta_6 City\ \ FM_{p,t}^{-i,a} \cdot ConstrainedFirm + \\ +\beta_7 City\ \ FM_{p,t}^{-i,a} \cdot LowIndustry\,Growth_{p,t}^{i,-a} \cdot ConstrainedFirm + \\ +\beta_8 CashFlow_{j,t}^{i,a} + \beta_9 q_{j,t}^{i,a} + \epsilon_{j,t}^{i,a}. \end{aligned} \tag{2}$$

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The dependent variable, $Investment^{i,a}_{j,t}$, is the annually measured ratio of capital expenditures (COMPUSTAT item CAPX) in year t to gross PP&E (property, plant, and equipment; COMPUSTAT item PPEGT) in year $t-1$, for firm j, which is in industry i and headquartered in city a. As described above, our focus is on how the sensitivity to negative industry shocks differ between firms headquartered in cities with high versus low rates of financial misconduct. We measure negative industry shocks with dummy variable $LowIndustryGrowth^{i,-a}_{p,t}$, which takes a value of one if sector-wide investment growth is in the bottom quartile. The coefficient β_1 thus captures the average sensitivity of firm investment to these industry-wide decreases. The intercept, α, captures the average effect in those other years when industry-level investment growth (or shrinkage) is fairly modest or positive. Nevertheless, our regression models include industry-year fixed effects to capture variation across industries, and therefore these parameters are not directly estimated.

Estimates of Equation (2) indicate the extent to which financially constrained firms reduce investment more sharply during industry declines. We employ two variants of financial constraint measures. The first is based on the HP index; we assign a value of 1 to *ConstrainedFirm* for firms that are in the top decile of the HP index and 0 otherwise. The second variant combines the HP index with the HM index; we assign annual percentile rankings to each firm based on each index, and then take the average of the two percentile rankings. We use the HP index exclusively when the HM index is not available for that year as the HM index is only populated for the latter part of our sample. We assign a value of 1 to *ConstrainedFirm* for firms that are in the top decile of the average percentile ranking, and 0 otherwise.

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Of primary interest is whether the rate of local financial misconduct, $City\ FM^{-i,a}_{p,t-1}$, amplifies the financial constraint effect, which is captured by the triple interaction, $City\ FM^{-i,a}_{p,t} \cdot LowIndustryGrowth^{i,-a}_{p,t} \cdot ConstrainedFirm$. The coefficient β_7 tells us whether financially constrained firms with poor industry fundamentals suffer disproportionately when headquartered in an area characterized by a high rate of financial misconduct. To avoid confounding effects, Equation (2) also includes $City\ FM^{-i,a}_{p,t}$ by itself (β_4), its interaction with the low industry level investment variable (β_5), and an interaction between $ConstrainedFirm$ and $City\ FM^{-i,a}$ (β_6).

We follow the existing literature and include $CashFlow$ and Tobin's q as covariates. Their effects are captured, respectively, by coefficients β_8 and β_9 in Equation (2).[15] Tobin's q is included in the analysis to capture investment opportunities. However, it provides, at best, a noisy proxy (Erickson and Whited (2000, 2002)); therefore, we also estimate regressions that adjust for measurement errors in Tobin's q using the Stata code from Erickson, Jiang, and Whited (2014).[16]

Table 4 reports our estimates. In the first two columns, we report the parameter estimates for the full samples with different definitions of financial constraints. In column (1), we use the HP index, whereas in column (2), we also incorporate the HM index. We observe a negative coefficient on the triple interaction, indicating a reduction in investment expenditures for struggling firms in corrupt cities.

[[Table 4 about here]]

[15]We control for financial constraints through the constraint indices, and for investment opportunities using industry-level investment growth. Tobin's q and cash flows provide further controls for firm-specific opportunities, but this makes little difference in the estimation of the coefficients of interest.

[16] `https://ideas.repec.org/c/boc/bocode/s457525.html`

The last two columns replicate the analysis on subsets of firms that should be less sensitive to fluctuations in local economic conditions. First, we exclude the quartile of the smallest firms, which are the most likely to have close ties to the local economy, and second, we exclude firms in the service sector. The estimates with these subsamples, reported in columns (3) and (4), are both negative and quantitatively similar to the corresponding coefficient in column (2), estimated on the entire sample. These subset analyses provide further evidence that local economic conditions are not driving the results.

V.2 Employment

Table 5 addresses the same question, but considers employment rather than capital expenditures. Accordingly, we make 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 item EMP), from $t-1$ to t, scaled by lagged assets. Second, the industry-level dummy variables are defined using sector wide changes in employment: *Low Industry Growth* is an indicator for the bottom quartile of year-over-year employment growth at the industry level.

[[Table 5 about here]]

Irrespective of how we measure financial constraints, the estimated coefficients on the triple interaction terms are negative; however, only the estimate in the regression involving the composite constraint measure in column (2) is statistically significant. The coefficient estimate indicates that all else equal, a shift in the interquartile range for financial misconduct is associated with a reduction in the growth rate of employment of

1.08% for financially constrained firms operating in low-growth industries. Columns (3) and (4) follow the structure of the prior table, and re-estimate the analysis for firms less likely to be impacted by local economic conditions. For both larger firms (column 3) as well as those in the non-service sector (column 4), the point estimates are negative, albeit with reduced statistical significance relative to the full sample.

V.3 Operating Performance

The prior two sets of tests link the adverse effects of a deterioration of local trust on credit to *firms'* investment and employment policies. However, it is possible that responses by *external stakeholders*, such as its suppliers and customers (Titman (1984), Maksimovic and Titman (1991)), or even its competitors (Chevalier (1995), Philipps (1997)) may further contribute to the decline of an already struggling firm. If so, then we would expect the combination of these indirect financial distress costs to eventually manifest in poor operating performance.

Accordingly, Table 6 shows the results of estimating regressions with a similar structure to Equation (1), but instead considering two measures of operating performance: 1) return on assets (ROA), defined as net income (COMPUSTAT item NI) divided by one-year lagged total assets (COMPUSTAT item AT), and 2) an indicator variable for firms in the bottom decile of ROA within each industry-year.

[[Table 6 about here]]

All right-hand-side variables are identical to those in Equation (1), except that the indicator variable capturing poor industry prospects, *Low Industry*, are now defined using sector-level average ROA. As with investment and employment, the *Low Industry* indicator corresponds to the bottom quartile of industries, but ranked by ROA. As before, our main interest is in the triple interaction involving distressed industries, firm-level financial constraints, and the rate of financial misconduct prevailing in the firm's headquarter city.

The first pair of columns show the estimates when the dependent variable is firm-year level ROA, both without (column 1) and with (column 2) the corrections for measurement errors of q described above in the analysis of investment and employment. Although the point estimates for the triple interaction terms are negative – weakly suggestive of lower operating performance for struggling firms following local increases in financial misconduct – neither are statistically significant at conventional levels.

However, given that the relation may be non-linear, the second pair of columns present results when the dependent variable is an indicator for a firm being in the bottom decile of its corresponding industry-year dyad. Here, the results are somewhat stronger, with p-values of 6.4% and 3.5%, for columns 3 (no measurement error correction) and 4 (corrected), respectively. The results regarding operating performance hence echo a similar theme: it is the most vulnerable firms, on the precipice of failure, for which collapses in local trust appear most costly. Moreover, to the extent that operating performance reflects the strategic responses of customers, suppliers, or competitors, the reach of trust breakdowns may extend to virtually all the firm's stakeholders.

VI Do financial misconduct rates predict bankruptcy?

In the analyses above, we established that being located in a corrupt city affects a firm's ability to raise capital. We show that this, in turn, affects its ability to grow, as evidenced by its capital expenditures, employment, and operating performance. Critically, the disadvantages associated with being in a corrupt location are especially severe during industry downturns. Our conjecture is that this inability to raise capital in downturns can ultimately increase the prevalence of bankruptcy in these cities. Thus, in this final section, we extend our analysis to explicitly consider the geographic clustering of corporate failures, and its link to clustering of financial misconduct.

VI.1 Average differences in bankruptcy risk between cities

Before we explore the connection between financial misconduct and the ability of its most fragile firms to survive, we begin by characterizing some basic geographical patterns of bankruptcy. These have not, to our knowledge, been documented in the existing literature.

To start, consider Figure 1, which plots as a heat map the average bankruptcy rates for firms in each of our twenty cities, measured over the entire sample period. Darker and/or larger circles represent higher average failure rates, with firms headquartered in cities such as Denver (3.58%), Dallas (2.10%), and Miami (3.77%) experiencing bankruptcy more often than average, and those in Indianapolis (1.25%), Philadelphia (1.39%), and Cleveland (0.98%) doing so less often. Although some of the cross-sectional variation shown in Figure 1 may capture differences in failure rates that arise because of industry differences, the figure is virtually identical if we adjust for cross-industry variation.[17]

[[Figure 1 about here]]

We next plot each city's average rate of financial misconduct against its average rate of bankruptcy in Figure 2. In this plot, we consider a potential mechanical relation between bankruptcy and financial misconduct due to firms committing misconduct being more likely to end up in bankruptcy. In our sample, firms identified as having committed financial misconduct over the past three years (about 1.5% of firm-years), the annual probability of bankruptcy is 4.09%, which is about 2.5 times the corresponding probability (1.67%) for firms that were not identified as having committed financial misconduct over the past three years. Similarly, the probability of a bankrupt firm having committed financial misconduct in any of the 3 years preceding its bankruptcy is 3.94%, which is about 2.4 times the corresponding probability (1.60%) for non-bankrupt firms.

[[Figure 2 about here]]

In consideration of this potential mechanical relation between bankruptcy and financial misconduct, the x-axis in Figure 2 reflects city-level average financial misconduct rates, excluding any firms that, at any point in the sample period, declare bankruptcy. The y-axis represents city-level bankruptcy rates, excluding bankrupt firms that were detected to have committed misconduct in the 3 years preceding the bankruptcy. We observe a clear

[17] We also perform an untabulated analysis examining whether there is "excess clustering" of bankruptcy in certain cities. We employ count regression models estimated via maximum likelihood to estimate whether the variation in (residual) bankruptcies between, say, Seattle and Cleveland falls within the range predicted from random sampling variation once we account for the variation in the number of firms, local economic conditions, and firm characteristics. We consistently observe that the difference in average bankruptcy rates across cities is more than we would expect from chance alone.

relation between a city's rate of financial misconduct and the rate of bankruptcy of resident firms, with a correlation of 0.60.[18]

VI.2 Firm-level bankruptcy estimates

We continue our analysis of bankruptcy by estimating failure (i.e., bankruptcy) models at the level of the individual firm. Two sets of hazard models are estimated in Table 7. The first is a dynamic, firm-level hazard model following Campbell, Hilscher, and Szilagyi's (2008) failure model, which is extended to allow the bankruptcy rates of a firm's regional peers operating in different industries to enter through a series of dummy variables: an indicator for 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., 3.77% for Miami). The same set of firm-level controls are included in all regressions.

[[Table 7 about here]]

In the first column, relative to the omitted category of zero regional bankruptcies in the year t, firms with at least one (other) bankruptcy in the area are $e^{0.89} \approx 2.43$ times as likely to declare failure. Taking the failure probability of the omitted group of 0.44% as a baseline, having at least one local bankruptcy increases the chance of failure by 0.63

[18]The figures in Figure 2 are not sensitive to including bankrupt firms and/or firms that commit financial misconduct, which may give rise to a mechanical relation. Including these firms, the correlation is 0.62, very similar to the 0.60 reported in Figure 2, with the slope of the best-fit line of 0.93 (vs. 0.91 used in Figure 2).

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percentage points to 1.07%. The estimates in Columns 2 and 3 reveal 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. A comparison of these coefficients reveal that the first few bankruptcies in a region have the biggest impact (almost doubling the baseline failure rate), with higher failure incidence mattering proportionately less (a further increase of about 47%).

The third column continues this exercise, distinguishing between the regions having bankruptcy rates between 1.5% and 3%, and those with rates above 3%. Progressing through each region, a higher failure rate of one's neighbors monotonically increases a firm's failure rate. In the highest group, where at least 3% of a firm's neighbors have entered bankruptcy in a given year, the firm's probability of failing itself is $e^{.59+.30+.17} \approx 2.88$ times the baseline, or an increase of 0.83 percentage points. The last column in this table includes additional variables to control for variations in economic conditions (i.e., per capita income, wage, and population growth rates). In addition to addressing the possible relation between local economic conditions and firm performance, these controls also address the correlation between business conditions and corporate fraud (Wang, Winton, and Yu (2010)), as well as enforcement that may be counter-cyclical. As a further, more direct control for regional differences in enforcement, we follow Kedia and Rajgopal (2011), and use the location of SEC regional enforcement offices as a proxy for authoritative scrutiny faced by local firms.[19] The parameter estimates are affected very

[19]In unreported results, we also address regional differences in enforcement using the natural experiment studied by Dyck, Morse, and Zingales (DMZ, 2010). Following the collapse of Enron in 2001, firms that had used Enron's auditor, Arthur Andersen (AA), scrambled for new representation after AA's license to practice accounting was revoked. Using DMZ's assumption that new auditors would have had little incentive

little by these additional control variables.

Table 8 extends the analysis by asking whether some, and if so how much, of the dynamic clustering of bankruptcy can be explained by prevailing rates of financial misconduct at the city level. In the first column, we again start with Campbell, Hilscher, and Szilagyi's (2008) failure model, and add four variables related to geography: (1) city-clustering: *HighCityBankruptcy*, a dummy variable that takes a value of 1 if last year's rate of bankruptcy for a firm's regional peers, but outside its FF-48 industry ($-i$), was above 3%; (2) industry-clustering: *HighIndustryBankruptcy*, a dummy variable that takes a value of one if last year's rate of bankruptcy for a firm's industry peers, but with headquarters outside the area ($-a$), was above 3%; (3) city-industry-clustering: $HighCity - IndustryBankruptcy$, a dummy variable that takes a value of one if last year's rate of bankruptcy of other firms in the same region (a) and industry (i) was above 3%; and (4) time clustering beyond the three variables above: *HighMarketBankruptcy*, a dummy variable that takes a value of one if last year's rate of bankruptcy of all firms in the sample was above 3%.

[[Table 8 about here]]

In addition to the firm-level characteristics and various indicator variables aimed at capturing potential clustering, all models also include the time-series average of each city's financial misconduct rate, along with time-varying city-level economic condition measures.

to overlook existing fraud initiated by AA, we take the city-level misconduct using only firms switching from AA to new auditors as reflecting the true rate of underlying fraud. The correlation between the city rank using AA-switchers to al other firms (i.e., firms that did not switch auditors from AA) is approximately 60%. Because these rankings would be uncorrelated if differences in enforcement alone were responsible for the overall dispersion in observed FM, we take this as evidence that unobserved heterogeneity in enforcement is unlikely to drive our results.

The last three columns also include the SEC regional office indicator variable. By employing these additional variables, we aim to control for the effect(s) of regional, industry, regional-industry, and overall secular trends in bankruptcy rates, and hence, separately identify the effects of local financial misconduct on the risk of firm failure.

Table 8 indicates that even in the presence of these control variables, the estimated coefficient on $City\ FM$ is highly significant. As in prior tables, this is also true for the two subsets of firms least likely to be impacted by local economic conditions. Column 3 shows the results when small firms are excluded, whereas column 4 pertains to non-sector service firms.

In unreported extensions of both Tables 7 and 8, we have estimated additional regressions that control for both the firm's own credit rating, and/or the average credit rating of the headquarter city. Neither has a meaningful impact on our reported results, suggesting that rating agencies do not fully incorporate the impact of local financial misconduct into their credit models. We have verified this conjecture by engaging in private conversation with an economist at a large, reputable credit rating agency. The economist acknowledged that there are likely regional elements of credit risk, but also cited political and liability concerns as reasons why this information is not explicitly accounted for this in ratings.

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VII Conclusion

There is now a substantial literature that links both firm values[20] and financing and investment choices to firm locations.[21] It is likely that differences in weather and the historical locations of universities, as well as other institutions, play a role in a region's demographics. These factors ultimately affect characteristics of firm employees, which may in turn influence the success and direction of corporate policies.

Cultural differences may also play a role in how, and how well, a firm operates. While culture tends to be multi-faceted, this study focuses on how one specific aspect, general perceptions of *trust*, may influence the availability and terms of financing. We hypothesize that ebbs and flows of local corporate fraud influence investors' beliefs regarding their counterparties' willingness to fulfill obligations. Hence, fraud realizations impose a negative externality, casting a shadow over an entire geographic area, making it difficult or even impossible for resident firms – even those not implicated themselves – to access credit. For the most financially vulnerable, this can adversely influence investment and employment policy and, in extreme cases, even survival.

Our primary findings are as follows:

1. Following regional increases in financial misconduct, local firms raise less debt (as a percentage of assets).

2. The effects of financial misconduct on financial market conditions has real effects on investment and employment. This is especially the case for financially constrained

[20] See Dougal, Parsons, and Titman (2022).
[21] See Dougal, Parsons, and Titman (2015).

firms in declining industries, which tend to exhibit declines in investment and employment relative to their counterparts in regions with less financial misconduct.

3. Firms are more likely to go bankrupt, following a spike in regional misconduct.

Taken together, this evidence suggests that because a firm's location can affect how it is perceived by lenders, its location can have a profound effect on its real decisions, performance, and ultimately its survival.

More generally, our evidence speaks to the importance of trust for firms reliant on external capital. As discussed in the theoretical contracting literature (see Cabral (2012)), trust is crucial for games involving moral hazard. Debt contracts offer a prime example, especially for loans that must be evaluated based on soft information conveyed by the borrower. Viewed through this lens, the evidence in this paper directly indicates "trust spillovers," in the sense that one firm's default reduces creditors' subjective probabilities of the reliability of its local neighbors.

A number of mechanisms can potentially generate these regional trust spillovers and can explain why trust may ebb and flow over time. To see this, note that the decision to engage in financial misconduct results from a cost and benefit analysis, implying that localized variation in either can generate spatial patterns in white collar crime. We acknowledge the possibility of geographic differences in the marginal benefit of financial misconduct. However, the benefits mainly reflect compensation arrangements – which do vary regionally – but since benefits are largely observable, it is less likely that observed financial misconduct convey information about the benefits of misconduct by neighboring firms. For this reason, the largely unobservable expected costs of misconduct are likely to

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be more important.

In addition to the direct costs of being caught, e.g., fines and possible jail time, the individuals may suffer career as well as social consequences for their involvement with corporate malfeasance. Given that these consequences and their costs are largely unobservable, it is reasonable to assume that observed rates of financial misconduct in a community are an indicator of the perceived cost of misconduct in the community, and in this way, they may influence the level of regional trust. In other words, when a lender observes financial misconduct by one borrower, it affects the lender's priors about the trustworthiness of other lenders.

While our focus has been on the perceptions and corresponding responses of lenders, one might expect regional spikes in financial misconduct to illicit similar responses from a firm's non-financial stakeholders. For example, workers asked to develop firm-specific human capital are entering into an implicit contract with the firm, and like creditors, are potentially exposed to losses to the value of their human capital should the firm deviate from a promised strategy. Indeed, while we attribute the observed link between regional employment growth and financial misconduct to the financial challenges facing local firms, it could also be caused, at least in part, by the reluctance of workers to join firms they perceive as less credible and/or trustworthy, as discussed in Maksimovic and Titman (1991).

Finally, it should be noted that while we have identified an important component of regional culture, as measured by the rate of financial misconduct, our measure probably captures only a small part of what makes regions distinct. Indeed, although trust is likely to be extremely relevant for the financially constrained and distressed firms that we focus on, our measure of financial misconduct only partially explains the observed geographical clustering of bankruptcies. This could be because financial misconduct is a relatively weak proxy for trust, or it might also be the case that there are other important urban characteristics that also contribute to the success and failure of its resident firms. Identifying these other characteristics is likely to be a promising area for future research.

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Figure 1: Heat Map of Corporate Failure Rate

This figure reports the geographical distribution of city-level corporate failure rates over our entire sample. The sample period is 1970-2010.

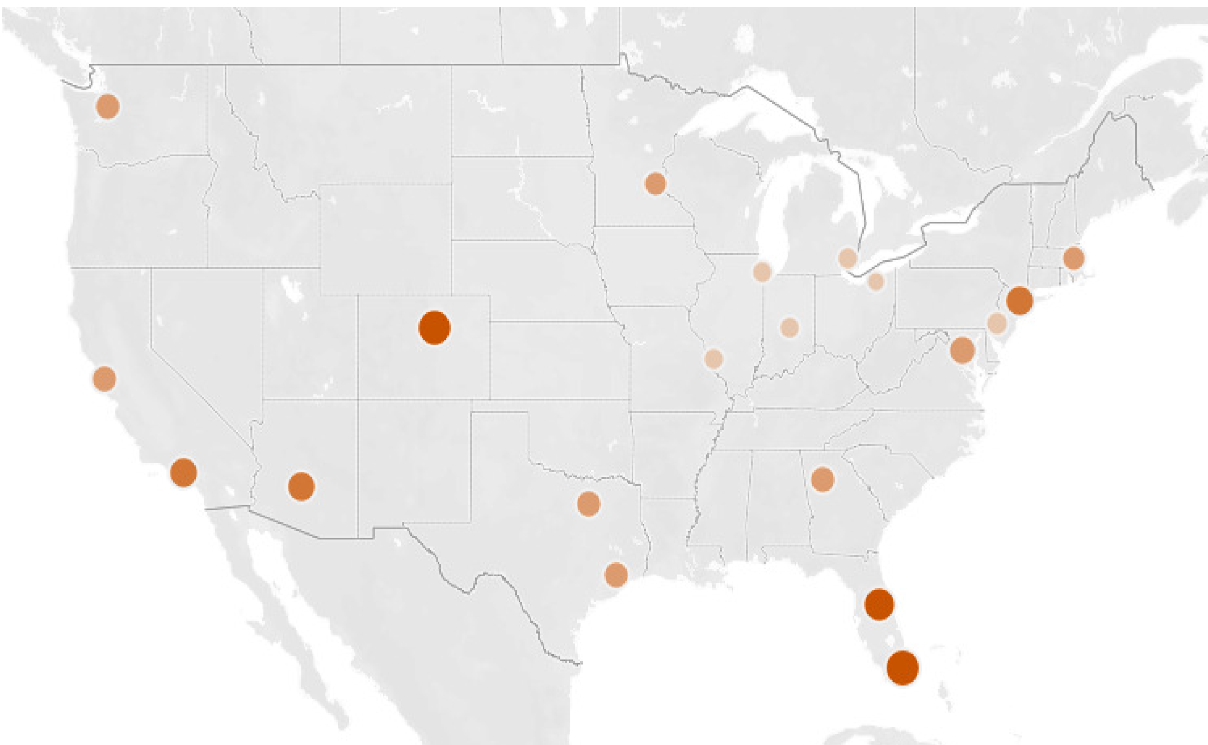

Figure 2: Corporate Financial Misconduct and Failure Rates

This figure reports the scatterplot of city-level financial misconduct and corporate failure rates in each of the 20 major US cities in our sample, calculated over our entire sample period of 1970-2010. The correlation coefficient of the two rates is 0.60. The straight line depicts the best-fit line with a slope of 0.91 (t-stat = 3.15).

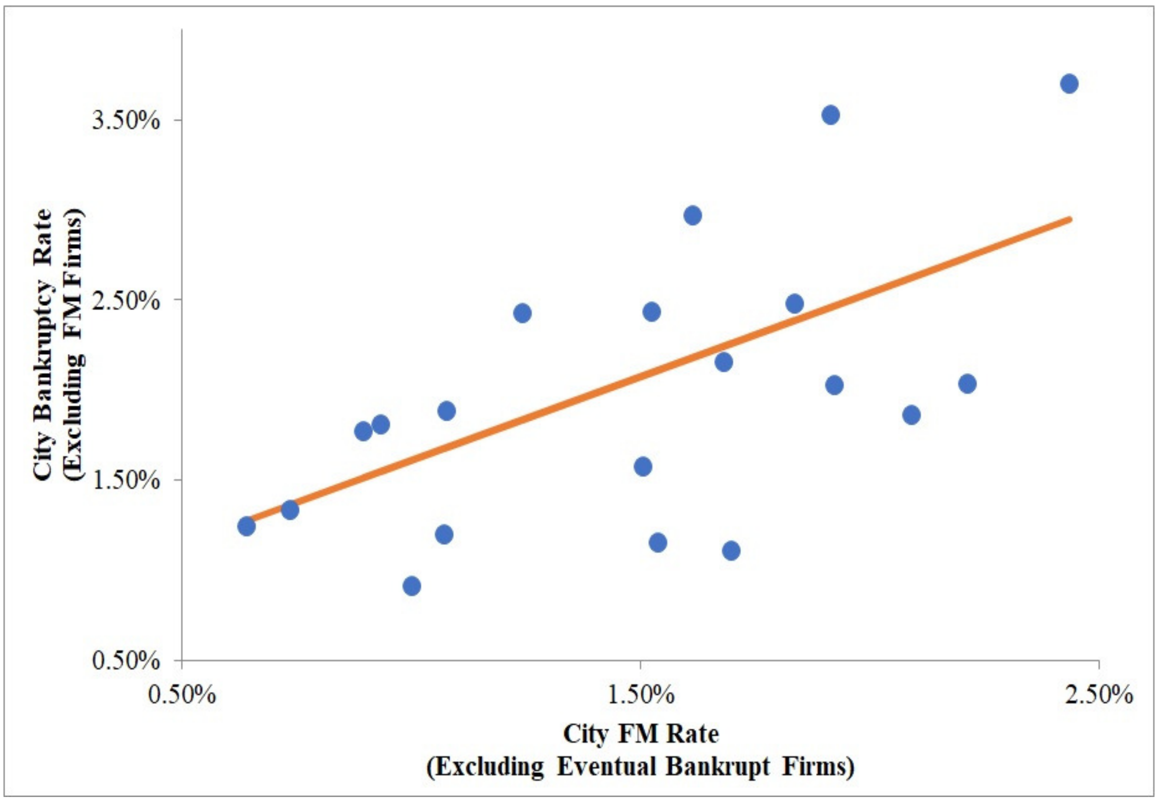

Table 1: Summary Statistics

This table contains summary statistics of firms in our sample. City-Level FM 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. Bankrupt 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. Compustat item names are listed in uppercase inside parentheses. We report summary statistics of the panel data. Panel A reports the statistics for the full-sample analysis, while Panel B reports the statistics for the sample of loan issuers. The sample period is 1970-2010.

Panel A – Full Sample								
Variable	N/Year	5th Pctl	25th Pctl	Median	75th Pctl	95th Pctl	Mean	Std Dev
City-Level FM Rate (Fraud/# Firm)	2,904.76	0	0.62%	1.37%	2.17%	4.20%	1.58%	1.36%
Net Debt Issuance (divided by book asset)	2,904.76	-22.64%	-3.32%	2.24%	9.55%	33.41%	2.45%	44.97%
Net Debt Issuance >5%	2,904.76	0	0	0	1	1	36.07%	48.02%
Investment (CAPX/PPEGT)	2,904.76	1.67%	6.24%	11.49%	21.55%	66.59%	19.87%	27.26%
Change in Employment (EMP; in bp)	2,904.76	-36.80	-2.16	0.38	9.25	73.11	5.70	23.52
Bankrupt	2,904.76	0	0	0	0	0	1.81%	13.35%
Asset (AT, in M)	2,904.76	4.88	30.86	137.95	709.23	8,316.66	1,877.06	6,820.07
Cash Flow (IB+DP / PPEGT)	2,904.76	-202.78%	3.42%	14.50%	31.85%	127.81%	-3.20%	154.94%
Tobin's q								
(CSHO×PRCC_F+DLTT+DLC-ACT / PPEGT)	2,904.76	0.00	0.38	1.06	3.65	27.23	4.01	6.94
Market Cap (CSHO×PRCC_F, in M)	2,904.76	3.95	24.07	101.13	509.46	5,149.90	1,130.25	3,701.27
Annual Stock Return	2,904.76	-62.11%	-22.73%	5.86%	38.56%	137.34%	16.70%	64.67%
M/B (Market Cap / SEQ)	2,904.76	0.50	1.06	1.74	3.09	9.02	2.86	3.60
Net Income (NI/AT)	2,904.76	-28.28%	-2.63%	1.73%	4.18%	8.04%	-3.00%	27.36%
Book Leverage (LT/AT)	2,904.76	3.95%	17.05%	37.38%	62.52%	89.93%	41.16%	27.44%
Cash Holdings (CHE/AT)	2,904.76	0.29%	1.87%	5.53%	13.59%	39.77%	11.07%	16.61%
Return Volatility	2,904.76	1.21%	2.12%	3.17%	4.70%	8.27%	3.71%	2.27%
Log (Price)	2,904.76	-0.29	1.39	2.40	2.71	2.71	1.91	1.07

Table 1: Summary Statistics

Panel B – Loan Issuers								
Variable	N/Year	5th Pctl	25th Pctl	Median	75th Pctl	95th Pctl	Mean	Std Dev
Spread (in bps)	292.91	25	75	150	255	405	178.09	128.49
Loan Maturity	292.91	11	23	36	60	81	41.59	77.94
Log (Loan Size)	292.91	15.42	17.22	18.66	20.03	21.73	18.62	1.96
US Lender Dummy	292.91	0	1	1	1	1	94.37%	23.05%
Large Lender Dummy (Citi/JP/BoA)	292.91	0	0	0	1	1	34.56%	47.56%
Log (Asset)	292.91	9.37	11.27	12.82	14.42	16.50	12.87	2.20
Annual Stock Return	292.91	-63.64%	-20.16%	8.12%	40.00%	135.14%	18.69%	72.78%
Log (M/B)	292.91	-0.53	0.24	0.69	1.21	2.08	0.73	0.82
Net Income (NI/AT)	292.91	-17.29%	-0.38%	2.47%	3.97%	6.98%	-0.72%	16.47%
Book Leverage (LT/AT)	292.91	8.56%	25.01%	40.97%	59.52%	82.41%	42.74%	22.59%
Cash Holdings (CHE/AT)	292.91	0.18%	0.98%	2.88%	7.31%	21.82%	5.94%	9.07%
Return Volatility	292.91	1.32%	2.08%	2.96%	4.27%	7.06%	3.46%	2.24%
Log (Price)	292.91	0.50	1.96	2.71	2.71	2.71	2.22	0.80
Bond Rating Available	292.91	0	0	0	1	1	31.34%	46.39%
Bond Rating (1-22)	92.22	5	7	10	13	15	9.97	3.53

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Table 2: Regional Financial Misconduct and Supply of Credit

This table contains the parameter estimates of linear probability models predicting debt issuance. The dependent variable in each regression is an indicator variable: *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 *Debt* > 3% and *Debt* > 7% , which are similarly defined using 3% and 7% of book asset threshold, respectively. *City FM* is the city-level financial misconduct rate (calculated outside the firm's FF48 industry) in the previous year. All models include city fixed effects, industry-year fixed effects, and ratings fixed effects, as well as time-varying city-level economic condition variables (employment, population, and wage growth rates). Models (4)-(6) include banking variables described in Section 2.5. The t-stats in parentheses are calculated by clustering errors at the city level. The sample period is 1970-2010.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Debt> 5%	Debt> 3%	Debt> 7%	Debt> 5%	Debt> 5%	Debt> 5%
Sample:					Excluding Small Firms	Excluding Service Sector
City FM	-0.28**	-0.26*	-0.33*	-0.36**	-0.40**	-0.42**
	(-2.18)	(-1.97)	(-1.80)	(-2.75)	(-2.24)	(-2.06)
Log (Market Cap)	-0.01**	0.00	-0.01***	-0.01**	-0.01***	-0.01***
	(-2.67)	(0.55)	(-5.61)	(-2.65)	(-4.16)	(-6.40)
Lagged Stock Return	0.02***	0.02***	0.02***	0.02***	0.04***	0.03***
	(9.89)	(7.47)	(7.88)	(9.95)	(9.43)	(7.12)
Log (M/B)	0.12***	0.10***	0.12***	0.12***	0.12***	0.11***
	(25.97)	(21.89)	(27.22)	(25.80)	(27.89)	(31.95)
Net Income	-0.05***	-0.04***	-0.05***	-0.05***	-0.07***	-0.06***
	(-4.85)	(-4.47)	(-4.71)	(-4.82)	(-3.32)	(-3.88)
Book Leverage	0.46***	0.40***	0.50***	0.46***	0.46***	0.47***
	(28.12)	(30.40)	(26.74)	(27.98)	(23.00)	(36.29)
Cash Holdings	-0.13***	-0.15***	-0.10***	-0.13***	-0.19***	-0.13***
	(-11.07)	(-14.28)	(-8.19)	(-10.98)	(-10.59)	(-10.03)
Return Volatility	-0.06	-0.19	0.00	-0.06	0.59***	-0.07
	(-0.46)	(-1.60)	(0.00)	(-0.51)	(3.53)	(-0.55)
Log(Price)	0.03***	0.04***	0.02***	0.03***	0.04***	0.03***
	(10.61)	(12.28)	(7.50)	(10.77)	(12.14)	(10.38)
HHI (bank deposits)				-0.18	-0.24	-0.08
				(-1.14)	(-1.43)	(-0.50)
HHI (bank branches)				0.15	0.19	0.14
				(1.08)	(1.33)	(1.00)
Bank deposit / firm				-0.00	-0.00	-0.00**
				(-1.30)	(-0.99)	(-2.09)
Banks / firm				0.07**	0.09**	0.10***
				(2.78)	(2.85)	(3.16)
Bank dep. / resident				0.00	0.00	0.00**
				(1.39)	(1.09)	(2.52)
Banks / resident				-0.05	-0.04	-0.07**
				(-1.59)	(-1.09)	(-2.38)
City FE	✓	✓	✓	✓	✓	✓
City Econ. Cond. Vars.	✓	✓	✓	✓	✓	✓
Year*Industry FE	✓	✓	✓	✓	✓	✓
Rating FE	✓	✓	✓	✓	✓	✓
Observations	72,764	72,764	72,764	72,764	51,513	52,773
R^2	0.0904	0.0827	0.0989	0.0904	0.0945	0.0952

Table 3: Regional Financial Misconduct and Credit Spreads

This table contains the parameter estimates of regressions predicting loan spread. The dependent variable is the log transformation of the loan spread (over LIBOR) a firm pays on syndicated bank credit, including any fees. *City FM* is the city-level financial misconduct rate (calculated outside the firm's FF48 industry) in the previous year. All firm-level control variables are calculated at the end of the previous year. All models include city fixed effects, industry-year fixed effects, and ratings fixed effects, as well as time-varying city-level economic condition variables (employment, population, and wage growth rates). Models (3)-(6) include banking variables described in Section 2.5. The *t*-stats in parentheses are calculated by clustering errors at the city level. The sample period is 1970-2010.

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable:	Log(Spread)					
Sample:					Excluding Small Firms	Excluding Service Sector
City FM	0.0238	-0.0741	-0.1041	-0.1587	-0.2789	-0.4998
	(0.04)	(-0.12)	(-0.16)	(-0.26)	(-0.37)	(-0.68)
Log (Market Cap)	-0.2230***	-0.1698***	-0.2228***	-0.1695***	-0.2510***	-0.2263***
	(-25.93)	(-19.78)	(-25.87)	(-19.75)	(-23.64)	(-21.92)
Lagged Stock Return	-0.0395***	-0.0191	-0.0394***	-0.0188	-0.0204	-0.0363**
	(-3.18)	(-1.61)	(-3.18)	(-1.59)	(-1.10)	(-2.47)
Log (M/B)	0.0759***	0.0558***	0.0756***	0.0555***	0.0649***	0.0822***
	(6.27)	(4.62)	(6.27)	(4.60)	(4.32)	(6.04)
Net Income	-0.2354***	-0.1912***	-0.2343***	-0.1899***	-0.4985***	-0.4339***
	(-2.95)	(-2.68)	(-2.93)	(-2.66)	(-2.85)	(-4.43)
Book Leverage	0.6351***	0.4788***	0.6331***	0.4756***	0.6033***	0.5979***
	(12.33)	(9.74)	(12.32)	(9.70)	(9.86)	(9.75)
Cash Holdings	0.3357***	0.2210***	0.3346***	0.2199***	0.5604***	0.3901***
	(3.70)	(2.66)	(3.70)	(2.65)	(4.26)	(3.49)
Return Volatility	5.0131***	4.3689***	5.0132***	4.3584***	9.7870***	5.0104***
	(7.63)	(7.54)	(7.64)	(7.53)	(7.54)	(6.68)
Log (Price)	0.0711***	0.0042	0.0713***	0.0041	-0.0071	0.0675***
	(3.83)	(0.27)	(3.85)	(0.26)	(-0.27)	(3.24)
Loan Maturity	0.0000	-0.0000	0.0000	-0.0000	0.0001	0.0000
	(0.87)	(-0.45)	(0.85)	(-0.45)	(1.03)	(0.17)
Log (Loan Size)	-0.0433***	-0.0589***	-0.0432***	-0.0589***	-0.0142	-0.0402***
	(-4.61)	(-6.54)	(-4.60)	(-6.54)	(-1.25)	(-3.48)
Large Lender	-0.0875***	-0.0697***	-0.0888***	-0.0713***	-0.0698***	-0.0826***
	(-4.91)	(-4.05)	(-4.97)	(-4.15)	(-3.66)	(-4.37)
HHI (bank deposits)			-0.6120	-0.3336	-0.3383	-0.4690
			(-1.32)	(-0.84)	(-0.63)	(-0.85)
HHI (bank branches)			0.3166	0.3091	0.2841	0.3124
			(0.72)	(0.81)	(0.56)	(0.62)
Bank deposit per firm			-0.0003**	-0.0003***	-0.0002	-0.0002*
			(-2.28)	(-2.61)	(-1.62)	(-1.65)
Banks per firm			0.1312	0.2157	0.0823	-0.0366
			(0.90)	(1.48)	(0.44)	(-0.21)
Bank deposit per resident			0.0107	0.0134*	0.0078	0.0082
			(1.26)	(1.68)	(0.81)	(0.84)
Banks per resident			-0.2023*	-0.3016***	-0.0865	-0.0626
			(-1.85)	(-2.97)	(-0.63)	(-0.47)
City FE	✓	✓	✓	✓	✓	✓
City Econ. Cond. Vars.	✓	✓	✓	✓	✓	✓
Industry*Year FE	✓	✓	✓	✓	✓	✓
Rating FE		✓		✓	✓	✓
Observations	7,079	7,079	7,079	7,079	5,229	5,234
R^2	0.519	0.569	0.520	0.570	0.514	0.519

Table 4: Investment Plans of Constrained Firms in Regions with Financial Misconduct

This table contains the parameter estimates of regressions predicting corporate investment rates. The dependent variable is investment rate, calculated as the ratio of CAPX to lagged Gross PPE. The independent variables include indicator variables: (1) *Low Industry Investment Growth* takes the value of 1 if the industry-average change in investment rate is in the bottom quartile and (2) *Constrained* takes the value of 1 if the firm is in the top decile of either: the Hodrick-Pierce (HP) index (columns 1) or the composite percentile ranking of the Hodrick-Pierce (HP) index and the Hoberg-Maksimovic (HM) index (columns 2 to 4), and 0 otherwise. *City FM* is the city-level financial misconduct rate (calculated outside the firm's FF48 industry) over the previous year. Column 3 excludes firms whose asset sizes are in the bottom quartile, while column 4 excludes firms in the service sectors. All models include industry*year fixed effects, city fixed effects, and city-level economic condition variables. All regressions are adjusted for potential mismeasurement of q. The t-stats in parentheses are calculated by clustering errors at the city level. The sample period is 1970-2010.

	(1)	(2)	(3)	(4)
Dependent Variable:	Investment rate (CAPX/lag Gross PPE), in percent			
Constrained Measure:	High HP	High (HP, HM)		
Sample:	All firm-years		Excluding Small Firms	Excluding Service Sectors
ConstrainedFirm	-0.16***	-0.03***	0.09***	-0.13***
	(-10.80)	(-6.08)	(14.40)	(-8.14)
City FM	-0.05	-0.20*	-0.35***	-0.34**
	(-0.37)	(-1.77)	(-3.03)	(-2.25)
City FM * Low Ind. Growth	-0.09	0.02	0.04	0.36
	(-0.44)	(0.09)	(0.20)	(1.37)
ConstrainedFirm * Low Ind. Growth	0.03	0.01	-0.01	0.01
	(1.63)	(1.58)	(-1.51)	(0.91)
City FM * ConstrainedFirm	1.18**	0.43*	-0.13	1.52***
	(2.12)	(1.82)	(-0.47)	(2.74)
City FM * ConstrainedFirm * Low Ind. Growth	-1.74**	-2.29***	-3.79***	-3.03***
	(-2.27)	(-7.81)	(-6.35)	(-4.67)
Laq q	0.07***	0.03***	0.03***	0.06***
	(44.10)	(28.64)	(27.37)	(26.17)
CF	-0.00	-0.00	0.00	0.00
	(-0.78)	(-0.45)	(0.92)	(1.38)
Adjusted for Mismeasured Q	✓	✓	✓	✓
City Economic Conditions Variables	✓	✓	✓	✓
City Fixed Effects	✓	✓	✓	✓
Industry*Year Fixed Effects	✓	✓	✓	✓
Observations	86,779	86,779	60,700	63,416
Within R^2	0.1152	0.1144	0.1585	0.1021

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Table 5: Employment Plans of Constrained Firms in Regions with Financial Misconduct

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 percentage change in the firm's number of employees (COMPUSTAT item EMP), scaled by lagged assets. The independent variables include indicator variables: (1) *Low Industry Employment Growth* takes the value of 1 if the industry-average change in employment rate is in the bottom quartile and (2) *Constrained* takes the value of 1 if the firm is in the top decile of either: the Hodrick-Pierce (HP) index (column 1) or the composite percentile ranking of the Hodrick-Pierce (HP) index and the Hoberg-Maksimovic (HM) index (columns 2 to 4), and 0 otherwise. *City FM* is the city-level financial misconduct rate (calculated outside the firm's FF48 industry) over the previous year. Column 3 excludes firms whose asset sizes are in the bottom quartile, while column 4 excludes firms in the service sectors. All models include industry*year fixed effects, city fixed effects, and city-level economic condition variables. All regressions are adjusted for potential mismeasurement of q. The t-stats in parentheses are calculated by clustering errors at the city level. The sample period is 1970-2010.

	(1)	(2)	(3)	(4)
Dependent Variable:	Change in Employment), in percent			
Constrained Measure:	High HP	High (HP, HM)		
Sample:	All firm-years		Excluding Small Firms	Excluding Service Sectors
ConstrainedFirm	-0.04***	-0.05***	0.04***	-0.04***
	(-8.68)	(-9.34)	(6.98)	(-5.48)
City FM	(0.78)	(0.70)	(0.44)	(3.24)
	(-0.30)	(-0.43)	(-0.27)	(-0.71)
City FM * Low Ind. Growth	0.32*	0.36**	0.17	0.44***
	(1.84)	(2.09)	(0.93)	(2.63)
ConstrainedFirm * Low Ind. Growth	0.03**	0.03***	-0.02*	0.03***
	(2.43)	(4.12)	(-1.72)	(3.08)
City FM * ConstrainedFirm	0.21	0.37*	0.01	0.21
	(0.88)	(1.68)	(0.05)	(0.84)
City FM * ConstrainedFirm * Low Ind. Growth	-0.39	-0.70**	-0.91	-0.86*
	(-0.86)	(-2.37)	(-1.22)	(-1.71)
Laq q	0.01***	0.01***	0.01***	0.00***
	(28.17)	(28.14)	(20.90)	(12.46)
CF	0.00***	0.00***	0.01***	0.00***
	(18.04)	(18.39)	(15.42)	(12.29)
Adjusted for Mismeasured Q	✓	✓	✓	✓
City Economic Conditions Variables	✓	✓	✓	✓
City Fixed Effects	✓	✓	✓	✓
Industry*Year Fixed Effects	✓	✓	✓	✓
Observations	84,967	84,967	60,069	62,087
Within R^2	0.0161	0.0159	0.0182	0.0124

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Table 6: Performance of Constrained Firms in Regions with Financial Misconduct

This table contains the parameter estimates of regressions predicting firm performance. The dependent variable in the first two models is the return on assets (ROA), defined as net income (NI), divided by the firm's total asset (AT) at the end of the previous fiscal year. The dependent variable in the last two models is an indicator variable for firms in the bottom decile of ROA within each year. The independent variables include indicator variables: (1) *Low Industry* takes the value of 1 if the industry-average ROA is in the bottom quartile and (2) *Constrained* takes the value of 1 if the firm is in the top decile of the composite percentile ranking of the Hodrick-Pierce (HP) index and the Hoberg-Maksimovic (HM) index, and 0 otherwise. *City FM* is the city-level financial misconduct rate (calculated outside the firm's FF48 industry) over the previous year. Columns 2 and 4 are adjusted for potential mismeasurement of q. All models include industry*year fixed effects, city fixed effects, and city-level economic condition variables. The t-stats in parentheses are calculated by clustering errors at the city level. The sample period is 1970-2010.

	(1)	(2)	(3)	(4)
Dependent Variable:	ROA		Bottom ROA Decile	
Constrained Measure:	High (HP, HM)			
ConstrainedFirm	-0.19***	-0.13***	0.39***	0.33***
	(-22.68)	(-15.91)	(20.97)	(25.41)
City FM	-0.04	-0.18**	-0.13	0.02
	(-0.28)	(-2.19)	(-0.67)	(0.16)
City FM * Low Industry	-0.16	0.08	0.23	-0.02
	(-1.08)	(0.60)	(1.02)	(-0.10)
City FM * ConstrainedFirm	0.49	0.17	-1.64*	-1.30**
	(1.46)	(0.60)	(-2.05)	(-2.18)
ConstrainedFirm * Low Industry	0.05***	0.04***	-0.11***	-0.10***
	(3.89)	(2.84)	(-3.08)	(-3.52)
City FM * ConstrainedFirm * Low Industry	-0.85	-0.80	2.30*	2.24**
	(-1.49)	(-1.52)	(1.97)	(2.11)
Laq q	-0.00***	-0.00***	0.00***	0.00***
	(-5.96)	(-10.29)	(8.93)	(20.36)
Adjusted for Mismeasured q		✓		✓
City Economic Conditions Variables	✓	✓	✓	✓
City Fixed Effect	✓	✓	✓	✓
Industry*Year Fixed Effects	✓	✓	✓	✓
Observations	89,055		89,055	
Within R^2	0.144		0.145	

Table 7: Regional Clustering of Corporate Bankruptcy

This table contains the parameter estimates of hazard model regressions predicting corporate failures following Campbell, Hilsher, and Szilagyi (2008). 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 defined following Campbell, Hilsher, and Szilagyi (2008) and calculated at the end of the previous year. All models include the average bankruptcy rate in the city throughout the whole sample. Model 4 adds an indicator variable for SEC regional office in the city, and time-varying city-level economic condition variables (employment, population, and wage growth rates). The t-stats in parentheses are calculated by clustering errors at the city level. The sample period is 1970-2010.

	(1)	(2)	(3)	(4)
	Hazard model predicting bankruptcy			
City Bankruptcy > 3% Dummy			0.1751*	0.1914*
			(1.65)	(1.85)
City Bankruptcy > 1.5% Dummy		0.3904***	0.3018**	0.2901**
		(3.09)	(2.21)	(2.16)
City Bankruptcy > 0 Dummy	0.8881***	0.5864***	0.5910***	0.5653**
	(4.75)	(2.67)	(2.69)	(2.57)
Average Bankruptcy Rate in the City	3.1276	-1.8824	-5.0399	-15.9625**
	(0.57)	(-0.33)	(-0.89)	(-2.48)
Log(Market Cap)	-0.2532***	-0.2516***	-0.2529***	-0.2523***
	(-8.53)	(-8.52)	(-8.62)	(-8.83)
Lagged Stock Return	-1.5564***	-1.5254***	-1.5190***	-1.5123***
	(-6.60)	(-6.54)	(-6.58)	(-6.52)
Log(M/B)	0.4076***	0.4064***	0.4080***	0.4086***
	(16.13)	(16.04)	(16.22)	(15.65)
Net Income	-0.1911***	-0.1923***	-0.1902***	-0.1910***
	(-5.82)	(-5.91)	(-5.84)	(-6.09)
Book Leverage	1.0636***	1.0301***	1.0210***	1.0418***
	(8.23)	(7.92)	(7.86)	(7.94)
Cash Holdings	-0.1784	-0.1922	-0.1913	-0.1722
	(-1.03)	(-1.11)	(-1.09)	(-1.01)
Return Volatility	3.4155***	3.3175***	3.3923***	3.3225***
	(5.03)	(4.86)	(5.03)	(4.81)
Log(Price)	-0.5742***	-0.5735***	-0.5707***	-0.5713***
	(-12.89)	(-12.92)	(-13.04)	(-12.92)
City Economic Conditions Variables				✓
SEC Regional Office Indicator				✓
Observations	80,057	80,057	80,057	80,057
R^2	0.054	0.054	0.054	0.054

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Table 8: Regional Financial Misconduct and Bankruptcy

This table contains the parameter estimates of hazard model regressions predicting corporate failures following Campbell, Hilsher, and Szilagyi (2008). 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 variable of interest is *City FM*, which is the city-level financial misconduct rate (calculated outside the firm's FF48 industry) over the previous year. The control variables include indicator variables capturing the rate of corporate failure of more than 3% in the firm's city, in the firm's industry, in the firm's city and industry, and in the economy as whole. All models include the average bankruptcy rate in the city throughout the whole sample, and time-varying city-level economic condition variables (employment, population, and wage growth rates). Models 2 to 4 also include an indicator variable for SEC regional office in the city. All firm-level control variables are defined following Campbell, Hilsher, and Szilagyi (2008) and calculated at the end of the previous year. The t-stats in parentheses are calculated by clustering errors at the city level. The sample period is 1970-2010.

	(1)	(2)	(3)	(4)
	Hazard model predicting bankruptcy			
Sample:	All firm-years		Excluding Small Firms	Excluding Service Sector
City FM Rate	7.5785***	7.5742***	13.7759***	6.9332**
	(3.04)	(3.05)	(3.66)	(2.57)
High City Bankruptcy	0.2164**	0.2158**	0.1174	0.2869**
	(2.13)	(2.12)	(0.86)	(2.50)
High Industry Bankruptcy	0.2516***	0.2517***	0.3062***	0.1819**
	(4.42)	(4.42)	(3.30)	(2.49)
High City-Industry Bankruptcy	0.2405***	0.2410***	0.2772**	0.1136
	(2.99)	(2.99)	(2.45)	(1.07)
High Market Bankruptcy	0.0197	0.0198	-0.2134*	0.0983
	(0.22)	(0.23)	(-1.71)	(0.94)
Average Bankruptcy Rate in the City	-9.1585	-9.0000	-9.0674	-17.0201*
	(-1.29)	(-1.26)	(-0.77)	(-1.92)
Log(Market Cap)	-0.2506***	-0.2506***	-0.2658***	-0.3042***
	(-8.68)	(-8.69)	(-6.23)	(-10.06)
Lagged Stock Return	-1.4929***	-1.4931***	-3.5687***	-1.6135***
	(-6.59)	(-6.59)	(-11.96)	(-6.39)
Log(M/B)	0.4137***	0.4139***	0.3815***	0.4411***
	(15.55)	(15.55)	(9.29)	(13.92)
Net Income	-0.1782***	-0.1784***	-0.1504***	-0.3857***
	(-5.92)	(-5.92)	(-3.22)	(-6.29)
Book Leverage	1.0697***	1.0700***	2.0222***	1.0074***
	(8.06)	(8.07)	(10.54)	(5.96)
Cash Holdings	-0.1762	-0.1754	-0.3050	-0.2601
	(-1.06)	(-1.06)	(-1.12)	(-1.16)
Return Volatility	3.3817***	3.3860***	5.7059***	3.1646***
	(5.28)	(5.29)	(5.85)	(4.65)
Log(Price)	-0.5672***	-0.5670***	-0.3661***	-0.5202***
	(-13.37)	(-13.37)	(-7.30)	(-11.05)
City Average FM Rate	✓	✓	✓	✓
City Economic Conditions Variables	✓	✓	✓	✓
SEC Regional Office Indicator		✓	✓	✓
Observations	80,057	80,057	59,393	59,009
R^2	0.054	0.054	0.035	0.051