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 both more expensive and harder to obtain for nearby 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. Moreover, we find that local waves of financial misconduct are a risk factor for bankruptcy.

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

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1 Introduction

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

In this paper, we ask whether proximity to a rash 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 city-level waves of financial misconduct may temporarily taint an entire region, reducing financiers' willingness to provide capital to local firms. Among those most reliant on external finance, such frictions may extend to influence real business decisions such as investment and employment, and in extreme cases, even survival.

That banks (and other providers of finance) 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 will increase the cost of borrowing.[1] A second consideration is that a history of financial misconduct reflects poorly on the 'trustworthiness' of the firm's executives.[2] A manager that does not respect explicit rules – think about misrepresenting

[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]The theoretical contracting literature distinguishes between the concepts of *trust* and *reputation*; see Cabral (2012). Trust is typically invoked in moral hazard problems (involving hidden actions), whereas the concept of reputation arises in contexts involving adverse selection (involving hidden types). In a pure case

earnings or trading on inside information – is unlikely to respect implicit agreements, which are often featured in debt financing.[3] At best, a lack of trust imposes additional costs (e.g., writing more complete contracts or enforcing them), and at worst, may prevent 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 not (perhaps yet) implicated themselves. In a recent paper, Parsons, Sulaeman, and Titman (2014) find that financial misconduct occurs in distinct, regionally-concentrated waves, involving firms in a wide variety of sectors. Regardless of the mechanism responsible for this geographic clustering – common environmental factors in the region, or peer effects between neighboring managers – these results suggest that the determinants of financial misconduct have a regional component, making it possible to predict a firm's likelihood of committing financial misconduct by observing the behavior of its regional peers. Moreover, as we show in this paper, evidence of financial fraud in a region has a material effect on the credit worthiness of its resident firms.

In our analysis, we will pay special attention to firms with already poor prospects. The reason is that although a corrupt environment may encourage misbehavior even by healthy companies (e.g., manipulating stock prices to maximize the value of option compensation), misrepresentation by struggling firms clearly imposes higher risk to creditors. Accordingly, following a rash of financial misconduct, we expect the weakest firms in the region to bear the brunt of lenders' skepticism.[4]

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of the former, "trusting" the agent is equivalent to understanding her payoffs given different actions, and thereby being able to predict her actions, e.g., trigger strategies in a repeated prisoner's dilemma. When both adverse selection and moral hazard are at work, agents can choose actions to build their reputations. This paper makes no distinction between pure trust (moral hazard) games and those where trust and reputation are mixed. What matters is that there exists regional and temporal variation in their determinants, e.g., social punishment being an especially effective deterrent in some cities compared to others.

[3]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.

[4]It may also be the case that financially distressed firms have higher incentives to commit financial misconduct, and that being surrounded by similarly misbehaving peers lowers the cost of doing so (e.g., via reduced social stigma or sharing of fraud-related information or techniques). Although the literature is ambiguous regarding the relationship between a firm's financial condition and its likelihood of engaging in financial misconduct (see Dechow, Ge, and Schrand (2010) for a review of this literature), a negative relation would further reinforce the hypothesis proposed above.

The source for our financial misconduct data is the hand-collected sample by Karpoff, Koester, Lee, and Martin (2013), hereafter KKLM. We describe the sample, and discuss the types of events identified as financial misconduct in Section 2.

We begin our analysis by exploring the link between regional rates of financial misconduct and the costs of syndicated bank loans in Section 3. When a region experiences a wave of financial misconduct, bank credit becomes temporarily more expensive for nearby firms. For regions in the top quartile of financial misconduct, resident firms pay, on average, about 14 basis points higher in interest costs. Consistent with our hypothesis that firms with poor prospects are most sensitive to spikes in local corruption, the effect is over twice as strong for borrowers with either low or no credit ratings (17 basis points, $t = 10.01$) versus those more creditworthy (8 basis points, t=2.08). Note also that because our regressions include city fixed effects (in addition to standard firm-specific controls), these estimates are identified by time-series variation in financial misconduct (i.e., local waves) within each area.

A second indication of lenders' collective wariness is that loan covenants become stricter following a rash of local financial misconduct. As with the cost of credit, the covenant effects are stronger for firms with either low or no credit ratings, for which information and monitoring concerns are likely the most severe.

We also observe effects in the quantity of credit supplied, with firms in cities that have higher fraud rates borrowing less frequently and/or lower amounts. Though the results differ across specifications, firms above the median rate of financial misconduct are about 10-15% less likely to issue significant amounts of debt (defined as greater than 5% of total assets). These reductions are not offset by additional equity issuance; consequently, regional waves of financial misconduct are associated with less overall inflow of external capital.

In summary, we find the following: (1) firms are less likely to obtain external financing following regional spikes in financial misconduct; (2) for those that are able to obtain financing, firms in cities that have higher fraud rates are less likely to issue debt; and (3) for those that are able to obtain loans, they face higher rates and/or stricter covenants. It is worth reiterating that when predicting these credit market effects, none of the firms we consider were prosecuted for financial misconduct themselves; rather, these are due to regional spillovers from firms (revealed to have) engaged in financial misconduct to those that have not.

The next part of the paper explores whether these elevated credit market frictions have real effects, influencing either the firm's investment (Section 4.1) or employment (4.2) policies. As before, we focus our attention on firms with poor prospects, but now measure these using industry-wide declines in performance.[5] Also, in an attempt to focus on firms most reliant on external capital markets, for which any type of credit market friction should have the largest real effects, we identify "financially constrained" firms as those in the top decile of the 'Kaplan-Zingales' index, as described by Lamont, Polk, and Saá-Requejo (2001). For these firms, we find dramatically elevated sensitivities to industry downturns. In response to a decline of at least 10% in industry-level investment, constrained firms headquartered in cities experiencing the top quartile of financial misconduct cut investment by almost twice as much compared to constrained firms in less corrupt locations.

We observe similar patterns when analyzing employment changes in response to negative industry shocks. Again focusing on firms in the top KZ-index decile, we find that constrained firms in areas ranking in the top quartile for financial misconduct reduce employment by about 50% more in downturns. Interestingly, we observe consistent effects using a different data set on city-level employment, collected by the Bureau of Labor Statistics. Following regional spikes in financial misconduct, we observe slower employment growth at the city level, even accounting for prior trends in the dependent variable. In addition to providing robustness to our earlier analysis, these latter results explicitly relate spikes in regional misconduct to *local* labor markets, a feat not possible using firm-level employment data from COMPUSTAT.

In our final analysis (Section 5), we consider the ultimate sequelae of local waves of

[5] Traditional models of investment include firm-level variables like Tobin's q and cash flows. This is less desirable in our setting, as the firm's own stock price might already capitalize the negative effects of being headquartered in a region with high rates of corporate fraud.

financial misconduct – bankruptcies in the region. 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 1. The vertical-axis graphs the average bankruptcy rate for firms headquartered in each of the 20 largest cities in the U.S. from 1970-2010, and the horizontal axis plots the average rates of financial misconduct for each city over the same horizon. The positive cross-city correlation (0.65) is clearly apparent, indicating that cities with high average rates of financial misconduct are strongly associated with high average failure rates.

Similar patterns emerge in the time-series. That is, it is not simply that cities such as Dallas have higher than average bankruptcy rates, but rather that firms headquartered in Dallas are particularly likely to fail following spikes in financial misconduct, such as 1998-2002. Moving from the 25^{th} to 75^{th} percentile in the regional rate of financial misconduct, or an increase of about 1.5 percentage points, increases by about 10% (0.15-0.20 percentage points) the likelihood that a resident firm will declare bankruptcy over the following year. Thus, in addition to firm-specific variables typically employed in failure models, these results indicate that regional information on financial misconduct provides additional explanatory power.

While previous research has studied the costs, both direct (e.g., SEC penalties) and indirect (e.g., increased cost of capital), of committing financial misconduct (Karpoff, Lee, and Martin (2008)), the effect of any spillovers to nearby firms is less understood. In this respect, the most similar paper to ours is Giannetti and Wang (2014), which finds that following accounting scandals, local investors – such as those in Houston after the Enron debacle – lose faith in the stock market, reducing their exposure to equity in general. Complementing their results for retail investors, our work suggests that even highly sophisticated financial institutions can be put off by financial misconduct; moreover, as we show, firm policies and even survival 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).[6] Most of this literature focuses on cross-country comparisons, finding that 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 thus mitigates at least one of the important confounding factors that render identification difficult in existing studies.

2 Data

2.1 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. EAs are larger than metropolitan statistical areas (MSAs), and are designed to capture regions within which workers commute. Examples of economic areas are Dallas-Arlington-Fort Worth, Washington D.C.-Columbia-Baltimore, and San Francisco-Oakland-San Jose. We use the term "area" and "city" interchangeably throughout the paper.

2.2 Financial misconduct

The primary source for our financial misconduct data is Karpoff, Koester, Lee, and Martin (2012), hereafter KKLM, which details their hand-collection of over 10,000 events related to cases of corporate fraud and/or financial misconduct. KKLM aggregate information

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

from four distinct but potentially correlated databases: 1) Government Accountability Office (GAO), 2) Audit Analytics (AA), 3) Securities Class Action Clearinghouse (SCAC), and 4) Securities and Exchange Commission's Accounting and Auditing Enforcement Releases (AAERs). As the first two databases contain (mostly) information on "restatement" of corporate financial statements, they provide good indicators of firms' attempts to manipulate earnings.[7] The SCAC maintains a registry of Federal class action securities lawsuits; compared with the first GAO and AA datasets, this database reflects a wider variety of corporate misbehavior, which includes accounting fraud, fraudulent transfers in mergers and acquisition, misrepresentation, and insider trading. The AAER contains news releases announcing civil lawsuits brought by the SEC in federal court and other SEC's orders/notices concerning the settlement of administrative proceedings. There is substantial overlap between all four datasets in terms of events covered and timing (see KKLM, section 2.3). We refer the reader interested in further detail (e.g., regarding the data collection method itself, comparison with other measures of fraud) to their paper.

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

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

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

2.3 Corporate failures

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

2.4 Credit Spreads and Covenant Strictness

The first part of the 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 (and their locations), as well as syndicate members. Relative to the COMPUSTAT universe, the sample for our loan-level analysis is limited to firm-years during which we observe a syndicated bank loan.

We focus our attention to the price component of the cost of credit –i.e., the loan spread– as well as the non-price components, i.e., loan covenants. As each syndicated loan contract potentially includes multiple distinct as well as overlapping covenants, we employ the "strictness" measure proposed in Murfin (2012) to aggregate information from those covenants. This measure is conceptually intended to capture the (ex-ante) probability of covenant violations and therefore potential contract renegotiation between the borrower and its lenders.[8]

2.5 Other variables

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

3 Local corruption and access to credit

We begin by exploring the connection between regional waves of financial misconduct and the prices, terms, and availability 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 inevitably implies states where borrowers cannot be forced to repay, even if able. In these situations, repayment incentives will depend on other considerations, such as whether borrowers view defaulting on a loan as unethical, or whether doing so will incur social penalties.

[8]For more details regarding the construction of this strictness measure, please see Murfin (2012).

We investigate whether the price of credit is related to a region's financial misconduct (subsection 3.1). Note that this analysis is possible only for a particular kind of debt, syndicated bank loans, for which we can use DEALSCAN to infer deal terms. As we will see, credit spreads are higher when local rates of financial misconduct are higher, particularly when considering non-local banks. Subsection 3.2 considers whether local waves of financial misconduct influence non-priced deal terms, specifically, the strictness of covenants governing the borrower's behavior. Here too, we see an effect for regional misconduct. Finally, in subsection 3.3, we extend to consider the quantity of debt. Because we use COMPUSTAT to infer changes in total debt, this analysis includes bonds and non-syndicated bank credit as well as the syndicated loans considered in the initial analysis.

3.1 Credit spreads

Table 2 presents the results of OLS regressions, in which the dependent variable is the spread (over LIBOR) a firm pays on syndicated bank credit, including any fees. In a syndicated loan, the debt contract is between a borrower and multiple banks, each of whom contribute a portion of the lent funds. Typically, a single "lead arranger" sets deal terms, and interacts directly with the borrower during the underwriting process. Occasionally, syndicated loans are originated using co-lead arrangers.

Firm-level control variables in Table 2 include credit ratings, firm size (total asset), net income, leverage, cash holdings, stock returns, stock price, volatility, and market-to-book ratio. We also include several loan characteristics: the average maturity, the size of the loan, and two indicator variables capturing whether the lender is based in the U.S. and whether the lead arranger is a large commercial lender (i.e., Citigroup, JP Morgan, or Bank of America), respectively. To control for potential variation in loan spreads due to economic and industry conditions, we subtract the industry-year average from the dependent variable.

The main independent variable of interest is the rate of financial misconduct in the city where the firm is headquartered. In column 1, we use the raw rate of financial misconduct the year prior to the loan ($t-1$), finding that a one standard deviation increase in city-level misconduct (1.4%), increases the cost of syndicated credit by about 7 basis points. To capture non-linearities in this relation, the next column parametrizes city-level misconduct using a dummy variable, $High\ City\ FM$, which takes a value of one for city-years in the top quartile of average financial misconduct rates (2.17%). Here, we see that after controlling for other firm, industry, and loan-level determinants of credit spreads, being headquartered in a high-FM area is associated with a 14.5 basis point increase in interest rates. Against an average spread of 175 basis points, this represents an increase of about 8%.

It is worth noting that these effects are estimated after controlling for credit ratings. The evidence is thus consistent with rating agencies not fully incorporating the impact of local fraud waves into their credit models. Alternatively, it may be the case that lenders place extra emphasis on local fraud waves when they set borrowing rates.

Columns 3 and 4 break up the set of lenders into those from the same state, and those from different states. The thought is that if local lenders are better able to screen borrowers, they will rely less on relatively coarse signals (e.g., regional waves of financial misconduct), whereas non-local lenders should be more responsive. The results indicate exactly this. Although both sets of lenders charge higher rates following increases in financial misconduct, the increase is almost twice as large for out-of-state lenders (15 basis points versus 9). The difference is statistically significant at 5% level.

Second, we categorize loans into those that are issued to borrowers with low or no credit ratings and those that are issued to borrowers with stronger credit ratings. The hypothesis here is that loan pricing to high rated borrowers should be affected less by regional financial misconduct, as lenders are less likely to be worried about those borrowers' default probability and/or risk-shifting behavior that are likely to result in default. Comparing columns (5) and (6), we observe strong evidence that the marginal effect of financial misconduct on loan spread is reduced for loans issued to borrowers with high credit rating vs. those issued to low-rated/unrated borrowers. The marginal effect of financial misconduct on loan spread for low/unrated borrowers is twice that for high rated borrowers. The difference is statistically significant at 1% level.

To this point, we have explored only the short-run impact of local fraud waves on borrowing costs. Yet, there are at least two reasons to expect an effect when measured over longer horizons. First, financial misconduct hardly ever comes to light immediately, taking on average over three years to become public.[9] Second, to the extent that a local "climate" of misconduct is persistent, creditors may be wary of lending in a region, even several years after a spike in the fraud rates of local firms.

The second, third, and fourth columns of Table 3 allow, respectively, for the two, three, and four-year lagged rates of area-level financial misconduct to influence the (currently measured) cost of bank credit. Column 1 presents the benchmark one-year lagged fraud rate for comparison. Moving across the table, we see that lags at years $t-2$, $t-3$, and $t-4$ are all significant, although none exceed the influence of the fraud rate measured one year ago (column 1). The extent to which this represents delayed revelation versus the (perceived) persistence in the determinants of fraud is difficult to infer, but in any event, suggests that the impact of local misconduct has a long-lived influence on the cost of debt capital.

The final three columns present the results of placebo tests, where we model current borrowing costs as a function of either current (column 5) or *future* (columns 6 and 7) spikes in regional misconduct. These regressions provide falsification to a causal relation between fraud and credit spreads: events that have not yet occurred cannot engender a response from lenders. (Note that frauds occurring in the same year as the loan are also valid placebos, as fraud almost never becomes exposed – less than 5% of cases – in the same year it occurs.) Across columns 5-7, in no case do we observe a statistically significant coefficient, and the magnitudes are 5-10 times smaller than that observed in the previous four columns.

These null results are helpful in two ways. First, they help rule out the impact of slow moving contextual (environmental) factors that might simultaneously influence fraud

[9]See Parsons, Sulaeman, and Titman (2014), section 4.2, for a more detailed discussion of the distribution of fraud revelation times in the Karpoff et. al (2014) data set.

propensity and credit risk. Examples might include trends in population, demographic shifts, improvements in education or worker training, and so on. Second, observing no result for future fraud spikes provides support for a causal interpretation: provided that it is fraud, per se, to which lenders are responding, it is impossible to observe a response to an event which has not yet occurred.

3.2 Covenant strictness

To complement our analysis of loan spread –i.e., the priced component of the cost of credit– this subsection examines the non-price components of deal terms. In particular, we consider whether local waves of financial misconduct affect loan covenants governing the borrower's behavior. As each loan potentially includes multiple distinct as well as overlapping covenants, we employ the "strictness" measure proposed in Murfin (2012) to aggregate information from those covenants. This measure is conceptually intended to capture the (ex-ante) probability of covenant violations and therefore potential contract renegotiation between the borrower and its lenders. In practice, the strictness measure reflects four characteristics of loan covenants: number, slackness (i.e., the firm's distance to tripping the covenants), scale, and covariance of covenants. As explained in detail in Murfin (2012), the addition of the last three covenant characteristics improve upon the extant literature that tends to focus on only the number of covenants or alternatively the slackness of individual covenants.

Similar to the loan spread analysis, we hypothesize that lenders would set stricter covenants when they are concerned that the borrower is more likely to take actions that will hurt its ability to repay the loan, i.e., when there is a local wave of financial misconduct. Our empirical evidence support this hypothesis. Table 4 reports the parameter estimate of regressions predicting loan strictness. With the exception of the dependent variable, the specifications in this table are identical to those in Table 2. We again use both the raw city financial misconduct rate (in model 1) and a discrete measure for cities with high financial misconduct rate (in the remaining models). Models 1 and 2 report that increases in regional financial misconduct rate precede stricter loan covenants. In particular, the parameter estimate in model (2) indicates that being located in a high financial misconduct area increases covenant strictness by 2.24 percentage points, which is about 10 percent of the unconditional mean of the strictness measure.

As we did in the spread analysis, we also cut the data cross-sectionally into (1) those issued by lenders in the firm's headquarter state vs. those issued by lenders outside that state, and (2) those issued to unrated or low rated borrowers vs. those issued to high rated borrowers. Again, the hypothesis is that the strictness of loan covenants put in place by same-state lenders and/or on high rated borrowers should be affected less by regional financial misconduct. We find evidence consistent with this hypothesis in models (3) to (6). The marginal effect of financial misconduct on covenant strictness for loans issued to unrated / low rated borrowers is positive and statistically significant, while the effect for loans issued to high rated borrowers is negative (albeit not statistically significant). The difference is statistically significant at 10% level.

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

3.3 Quantities

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

The dependent variable in the first column is an indicator variable that takes the value of

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

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

In summary, the results in Tables 2 through 5 are consistent with proximity to financial misconduct reducing the supply of credit –and indeed of overall external financing– to firms. The results are therefore consistent with the positive role of trust in increasing access to credit and external financing in general.

4 Implications for firm investment and hiring choices

This section takes as given that local waves of financial misconduct impose additional frictions to external finance, and considers whether these have implications for a firm's real decisions, such as employment or investment. Before describing our methodology and results, it is useful to explicitly state our hypothesis:

1. The possibility that a firm commits financial misconduct increases with the misconduct rate of its geographical peers.

2. Lenders would be more sensitive to potential misconduct among struggling firms with poor fundamentals due to their higher default risk.

3. Among the set of firms with poor fundamentals, some will be more or less reliant on external capital markets (e.g., due to differences in cash balances). Accordingly, the impact on investment or employment policy should be most pronounced for liquidity-constrained firms.

The first two steps are familiar, being the basis for the analysis in Section 3, where we found that the impact of local misconduct is most severe for the weakest firms in a region. What is new here is the third step, which distinguishes between a firm being financially distressed and financially constrained. Although related, these are distinct concepts. A firm financed mostly by equity has very little chance of defaulting, but may depend on regular capital infusions; likewise, a near-bankrupt firm may be investing at low levels relative to its cash balance, and thus, have little need to access capital markets. According to our hypothesis, it is the intersection – i.e., distressed *and* constrained firms – where we expect the impact of local misconduct to have the largest impact.

We operationalize each of the above steps as follows. For the first, we proxy for the risk of financial misconduct using the rate of a firm's neighbors, as we have in all previous analysis. For the second, we proxy for poor fundamentals using industry-level fluctuations in the dependent variable, e.g., drops in industry-level investment in our analysis of firm-level investment. We do this to avoid the problem of a firm's stock price already capitalizing the impact of negative regional spillovers; using only industry-level information subjects all firms within a given sector to homogenous shocks, allowing us to capture the marginal impact of location with our regional misconduct variables.

Finally, for the third, we use the Kaplan-Zingales (1997) index of financial constraints, as described by Lamont, Polk, and Saá-Requejo (2001). Intuitively, the KZ index maps firm attributes like dividend payout ratios and cash balances to management discussion indicating financial constraints. We focus on the top decile of firms in the KZ index, comprised mostly of firms categorized as "constrained" or "likely constrained." [10]

4.1 Capital expenditures

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

$$
\begin{aligned}
\mathit{\Delta Investment}_{j,t}^{i,a} = \alpha + \beta_1 \mathit{HighIndustryInvestment}_{p,t}^{i,-a} + \beta_2 \mathit{LowIndustryInvestment}_{p,t}^{i,-a} + \\
\beta_3 \mathit{ConstrainedFirm} + \beta_4 \mathit{LowIndustryInvestment}_{p,t}^{i,-a} \cdot \mathit{ConstrainedFirm} + \\
\beta_5 \mathit{HighCityFM}_{p,t}^{-i,a} + \\
\beta_6 \mathit{HighCityFM}_{p,t}^{-i,a} \cdot \mathit{HighIndustryInvestment}_{p,t}^{i,-a} + \\
\beta_7 \mathit{HighCityFM}_{p,t}^{-i,a} \cdot \mathit{LowIndustryInvestment}_{p,t}^{i,-a} + \\
+\beta_8 \mathit{HighCityFM}_{p,t}^{-i,a} \cdot \mathit{ConstrainedFirm} + \\
+\beta_9 \mathit{HighCityFM}_{p,t}^{-i,a} \cdot \mathit{LowIndustryInvestment}_{p,t}^{i,-a} \cdot \mathit{ConstrainedFirm} + \\
+\beta_{10} \mathit{\Delta CashFlow}_{j,t}^{i,a} + \beta_{11} \Delta q_{j,t}^{i,a} + \epsilon_{j,t}^{i,a}.
\end{aligned} \tag{1}
$$

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

[10] Studying low-dividend firms, Kaplan and Zingales (1997) classify "54.5 percent of firm-years as not (NFC) and 30.9 percent of firm-years as likely not financially constrained (LNFC) for *a total of 85.3 percent of firm-years in which [they] find no evidence of financing constraints that restrict investment*" (emphasis theirs). Out of the remaining 14.7 percent of low-dividend firm-years, they classify "7.3 percent as possibly constrained, 4.8 percent as likely constrained, and 2.6 percent as definitely constrained." Since our sample includes high-dividend firms (which are less likely to be constrained), we use a more stringent cutoff of the top decile.

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

The next terms in Equation (1) tell us whether financially constrained firms, defined as those in the top decile of the KZ index, cut investment more sharply during industry declines. To save space, we do not include the interaction between $HighIndustryInvestment_{p,t}^{i,-a}$ and $ConstrainedFirm$, but note that it is (as expected) insignificant in all specifications.

The main variable of interest is an indicator for a high rate of local financial misconduct in the preceding year ($t = 1$), $HighCityFM_{p,t-1}^{-i,a}$, measured in the firm's headquarter area (a), but outside its industry ($-i$). As in prior specifications, this variable takes a value of one for city-year observations ranking in the top quartile, in the distribution of all city years. Among these variables, our primary interest is the triple interaction, $HighCityFM_{p,t}^{-i,a} \cdot LowIndustryInvestment_{p,t}^{i,-a} \cdot ConstrainedFirm$. The coefficient β_9 tells us whether constrained firms with poor industry fundamentals suffer disproportionately when headquartered in an area characterized by high rates of financial misconduct. To avoid confounding effects, Equation (1) also includes $HighCityFM_{p,t}^{-i,a}$ by itself (β_5), its interaction with the high (β_6) and low (β_7) industry level investment variables, and an interaction between $ConstrainedFirm$ and $HighCityFM^{-i,a}$ (β_8).

Finally, in some specifications (for reasons we discuss below), we follow the existing literature and include as covariates changes in $Cashflow$ and q, traditionally identified determinants of corporate investment. Their effects are captured, respectively, by coefficients $\beta_1 0$ and β_{11} in Equation (1).

Table 6 shows the results. The first column includes only the high and low industry dummy variables, as well as an indicator for a high city-level rate of financial misconduct. As expected, both industry variables are highly significant, and with the expected signs. The coefficient on $HighCityFM_{p,t}^{-i,a}$ is not significant on its own, indicating that local waves of financial misconduct do not have a material impact on investment growth for the typical firm. The second columns adds *ConstrainedFirm*, where we see that firms likely to be liquidity constrained are associated with investment cuts of around 2% per annum ($t = -3.90$).

The next two columns incorporate interaction terms involving $HighCityFM_{p,t}^{-i,a}$. In column three, we see that neither interaction with $HighIndustryInvestment_{p,t}^{i,-a}$ or $LowIndustryInvestment_{p,t}^{i,-a}$ is statistically significant. However, when we distinguish between constrained and unconstrained firms in column 4, a different picture emerges. The coefficient on the triple interaction, β_8 is negative and significant, with a point estimate of -9.16 ($t = -2.71$). To put this magnitude in perspective, note that it is roughly equivalent to the coefficient on the $LowIndustry$ dummy, so that financially constrained firms in high-FM regions cut investment by almost twice as much in response to downturns.

The final specification (column 5) includes changes in the firm's own q (lagged one year) and $CashFlow$. Although each enters highly significantly and with the expected sign, we have heretofore postponed them in order to facilitate the interpretation of terms involving $HighCityFM_{p,t}^{-i,a}$. As discussed above, the concern here is that either (particularly q) may already reflect any negative impact(s) of being located in a corrupt city on the ability to raise capital, thus removing some of the cross-sectional variation we hope to measure with our measure of regional misconduct. Yet, the similarity of the coefficients between the last and penultimate column suggests that this is not a major concern.

4.2 Employment

Table 7 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 variable EMP), from $t-1$ to t, scaled by lagged assets. Second, the industry-level dummy variables are defined using sector wide changes in employment. As before, *High* (*Low*) *Industry Employment* are dummy variables for the top (bottom) quartile of year-over-year employment growth at the industry level. These thresholds are, respectively, about 9% and 2%.

In the first column, we see that, as expected, firms cut employees during industry declines and add them in industry booms. On average, during industry-level employment booms, employment growth is about nine percent higher than average; in contrast, employment growth shrinks by five percent during industry slowdowns. Both results are highly significant. Column 1 also shows that unconditionally, spikes in regional financial misconduct are not associated with layoffs for nearby headquartered companies. The next column mirrors the analysis of capital expenditures, indicating that constrained firms, regardless of headquarter location, experience slower employment growth (-4.99%, $t = -9.50$), relative to their unconstrained peers.

As before, neither interaction between $HighCityFM_{p,t}^{-i,a}$ and the industry dummies is significant on average (column three), but when we focus specifically on constrained firms in column four, we find significant results, both economically and statistically. We estimate a coefficient on the triple interaction of -6.91, with a t-statistic of almost five in absolute value. Thus, compared to constrained firms headquartered in less corrupt areas, the effect of an industry downturn is magnified by about 50%, increasing from $-1.3-4.3-9.6 \approx -15\%$ to $-1.3-4.3-9.6-6.9 \approx -22\%$. Adding q and $Cashflow$ (both of which are high significant) in column five has almost no impact on any of the estimated coefficients.

It is tempting to use these results to make causal inferences between regional corruption and its implication for the local economy. However, recall that because we are using

COMPUSTAT to measure employment, it is impossible to distinguish between a firm laying off workers (or at least hiring at a lower rate) at headquarters versus other locations where it may have operations. To see the issue, consider the example of Detroit-based retailer Kmart's admission of financial fraud in 2001. Table 7 examines employment growth for nearby-headquartered firms in different sectors, such as Ann Arbor's Domino's Pizza. However, because the vast majority of Domino's employees are based elsewhere, it is unclear whether Kmart's financial misconduct matters much for the local Detroit economy.

To gain insight into this issue, in Table 8, we measure *local* employment using data from the U.S. Bureau of Economic Anlaysis, and link this to waves of local financial misconduct.[11] Because data are aggregated at the area-year level, this analysis has much less power ($20\times39 = 780$ observations) versus previous tests. However, the advantage is that it allows us to isolate the local impact of financial misconduct; moreover, it accounts for the impact on privately held, local companies.

The key covariate of interest is $Fraud^{a}_{t-1}$, the average one-year lagged fraud rates in each city, aggregated across all industries. As in previous analysis, we parametrize this both with the continuous rate of financial misconduct, as well as with a dummy indicator for ranking in the top quartile, *HighCityFM* (subscripts suppressed).

The first column indicates a negative, statistically significant relation between last year's $(t-1)$ city-level financial misconduct and this year's (t) city-level employment growth. The coefficient is -0.22 ($t = 3.23$), indicating that a one standard deviation increase in city-level FM rates, about 1.3 percent, is associated with a decrease in future employment growth of about 29 basis points. Against a baseline average of 1.65 percent for employment growth, this represents a change on the order of 17%.

In the next several columns, the financial misconduct variate enters discretely. Column two indicates a decrease in employment growth of around 72 basis points ($t = -4.78$), strengthening to 88 basis points ($t = -4.25$) when city fixed effects are included. This latter

[11] Data are recorded at the zip code level, and aggregated to the "Economic Area" unit used for all of our analysis.

specification ensures that we are identifying the impact on local employment of local fraud waves, rather than persistent cross-city differences in average rates of financial misconduct. The coefficient settles to -42 basis points with year fixed effects (column 4), suggesting that a fraud wave is associated with reductions in local employment growth by about 25% relative to its baseline average.

Given that employment growth is highly persistent, and that local waves of corporate fraud may span multiple years, one potential concern with the estimates in Table 8 is that employment growth leads, rather than lags, city-level FM rates. Accordingly, in column 5, we include the one-year lag of each city's employment growth as a predictor. Perhaps unsurprisingly, last year's employment growth rate has a very strong impact on this rate in the current year. However, the impact of city-level FM rates remains significant, with a point estimate of -27 basis points ($t = -2.22$), a percentage reduction of about 13%.

Another question is what is the proper horizon – i.e., how quickly we might expect local spikes in misconduct to reduce local employment. For the firms directly involved, this should be relatively quick; for neighboring firms, however, one might imagine the negative spillovers to take some time. Accordingly, in the last two columns, we analyze the predictive ability of further lags of city-level fraud rates. This leads to similar results. Relative to column one, the percentage impact is slightly smaller, with a one standard deviation increase in local fraud waves reducing the growth rate in local employment by about 22 basis points ($t = -2.25$). Column six shows the results of the discrete specification, which also gives similar, through slightly larger results, compared to using only recent occurrences of financial misconduct.

Together, the results in this section indicate that constrained firms headquartered in areas characterized by high rates of corporate corruption fare especially poorly during industry downturns. Tables 6 and 7 suggest that investment and employment suffers disproportionately during industry downturns, and in Table 8, we see a direct impact on the local economy. The next section extends this analysis even further, testing for a link between local misconduct waves and corporate failures.

5 Local financial misconduct as a bankruptcy risk

In sections 3 and 4, we established that being located in a corrupt city affects a firm's ability to raise capital, which can in turn affect its ability to grow, as evidenced by its capital expenditures and the growth in employment. In this final section, we extend our analysis to consider the geographic clustering of corporate bankruptcies, and their link to waves of financial misconduct. We begin by documenting that bankruptcies have a strong regional component in section 5.1, finding that average failure rates differ substantially between cities, and over time within these cities. Section 5.2 then considers one particularly regional factor – spikes in financial misconduct – that partly explain these regional differences in bankruptcy.

5.1 Regional patterns in corporate bankruptcy

Although we are primarily interested in the relation between regional misconduct and failure risk, we are unaware of evidence of geographical patterns in bankruptcy. Therefore, before exploring the impact of local misconduct, we take a brief step back and characterize some basic cross-sectional and time series patterns in corporate failures over the past four decades.

To start, consider Figure 2, which plots as a heat map the average bankruptcy rates for firms in each of our twenty cities. Darker and/or larger circles represent higher average failure rates, with firms headquartered in cities such as Denver (3.01%), Dallas (2.01%), and Miami (3.26%) declaring bankruptcy more often than average, and those in Indianapolis (1.21%), Philadelphia (1.09%), and Cleveland (0.88%) doing so much less often.[12] To save space, we do not tabulate the results, but in linear probability models of firm failure, city fixed effects are (jointly) highly significant.

In addition to these average cross-sectional differences, cities tend to experience waves of corporate failures, much in the same way that financial misconduct exhibits regional ebbs and flows. In Table 9, we show this formally, adapting the logit model of firm failure developed by

[12]Some of the cross-sectional variation shown in Figure 2 may capture differences in failure rates combined with industry clustering; however, the figure is remarkably similar if we instead use industry adjusted averages.

Campbell, Hilscher, and Szilagyi (2008), adding to their list of predictors the rate of financial misconduct of a firm's geographic neighbors.[13] These predictors are the natural logarithm of the firm's market-to-book ratio, net income, book leverage, one-year lagged stock return, cash balance, stock price, one-year trailing stock return volatility, and the natural logarithm of total assets.

Our main interest is in whether, after controlling for these known determinants of firm failure, bankruptcies tend to cluster regionally. To allow for a potentially non-linear relation, we allow for the bankruptcy rates of a firm's non-industry, regional peers to enter through a series of dummy variables: an indicator for exactly zero bankruptcies in the year of interest, another indicator for area bankruptcy rates in the range (0%, 1.5%], one for (1.5%, 3%], and one if the local bankruptcy rate exceeds 3%. In all regressions, the omitted dummy is the first category, and to ensure that we are capturing time-series variation within regions, we include the average bankruptcy rate for each of the twenty cities in our sample (e.g., 3.26% for Miami).[14]

In the first column, we see that compared to the omitted category of zero regional bankruptcies in the year t, firms with at least one bankruptcy in the area are $e^{1.04} \approx 2.83$ times as likely to declare failure. Taking the failure probability of this omitted group of 0.44% as a baseline, having at least one local bankruptcy increases the chance of failure by 0.80% to 1.24%.

Columns 2 and 3 indicate a concave relation between a firm's failure probability and the failure rates of its local neighbors. In the second column, we split the space of positive local bankruptcy rates into two mutually exclusive regions: strictly positive but below 1.5%,

[13] Because firms declare bankruptcy only once, the probability of failing in any year t is conditional upon survival (i.e., having not declared bankruptcy in year $t-1$, $t-2$, etc.). This induces serial correlation in the residuals, biasing the standard errors of the estimated coefficients. While hazard models are designed to take this serial dependence into account, alternative possibilities include either logit or linear probability models, with standard errors clustered at the firm level. See Shumway (2001) for more discussion of this issue. The results in Table 9 are very similar with either alternative.

[14] Due to the incidental parameters problem first described by Neyman and Scott (1948) –but see also Lancaster (2000) and Greene (2002), city fixed effects will not be estimated consistently in non-linear models such as hazard or logit specifications. However, linear probability models (which are estimated consistently), give very similar results to those presented in Table 9.

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

5.2 Local financial misconduct and corporate bankruptcy

While evidence of regional bankruptcy clustering can arise for a number of reasons, we focus on regional waves of financial misconduct as a potential risk factor for firm failure. The heart of our argument is simply an extension of the results documented in Sections 3 and 4: proximity to financial misconduct decreases the availability of external finance, elevating the bankruptcy risk for the most financially vulnerable firms.

As we showed earlier in Figure 1, cities with high average rates of financial misconduct (measured from 1970-2010) tend to tend to have high average rates of corporate failure. The three cities that we mention in the previous subsection as examples of cities with low bankruptcy rates (i.e., Cleveland, Philadelphia, and Indianapolis) are in the bottom five of financial misconduct rates, while the three cities with high bankruptcy rates (i.e., Dallas, Denver, and Miami) are in the top five of financial misconduct rates. The strength of this relation is remarkable, with only twenty data points (one for each city) generating a highly significant relation (slope=0.85, $t = 3.61$).

One potential objection to Figure 1 is that it simply reflects the tendency of firms prosecuted for financial misconduct to subsequently declare bankruptcy, so that the averages shown on the $x-$ and y-axes are mechanically related.[15] However, this issue is eliminated by how the averages in Figure 1 are calculated. The x-axis represents city-level average financial misconduct rates, ignoring any firms that, at any point in the sample period, declare bankruptcy.

Another concern pertaining to the interpretation of Figure 1 is that bankruptcy and financial misconduct rates are co-determined by longstanding local factors, such as differences in the strength of local institutions (e.g., courts). While we cannot eliminate this concern entirely, examination of the time series mitigates the impact of relatively static influences, such as long-lived differences in demographics, "culture," tolerance of corruption, and so on. We present the results of this analysis in Table 10, where we relate the probability of a firm declaring bankruptcy to local measures of recent financial misconduct. Importantly, this analysis controls for the average probability of financial misconduct within each city, so that the estimates presented are identified from time series variation in financial misconduct and corporate failure within cities.

In the first column, we again start with Campbell, Hilscher, and Szilagyi's (2008) failure model, and add to it last year's $(t-1)$ average rate of financial misconduct in the city, $CityFMRate^{a,-i}_{p,t-1}$. As before superscript a refers to one of the twenty economic areas, and $-i$ specifies that financial misconduct is calculated outside the firm's Fama-French 48 industry classification. Subscript p stands for the "portfolio" of local firms which, on average, contains roughly 130 companies. The estimated coefficient indicates that a one standard deviation increase in $CityFMRate$, about 1.35 percentage points, increases the odds ratio of a local firm declaring bankruptcy the following year by about $e^{11.4*.0135} = 1.17 - 1 = 17\%$. Given an average rate of bankruptcy of 1.58%, this implies a marginal effect of 0.26 percentage points.

The second column presents the result when $HighCityFM^{a,-i}_{p,t-1}$ is parameterized discretely, taking a value of one if $CityFMRate^{a,-i}_{p,t-1}$ ranks in the top quartile (above 2.03%

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

annually). The coefficient (0.298, $t = 5.12$) indicates an odds ratio of about $1 - e^{.298} \approx 35\%$ higher (about 0.55 percentage points) when $CityFMRate^{a,-i}_{p,t-1} = 1$, evaluated when all controls are at their sample means.

Given that we already know from Table 9 that bankruptcies tend to cluster regionally, it is natural to question whether the relation between city-level financial misconduct and bankruptcy shown in Table 10 represents a distinct finding. In column 3, we include as a predictor $HighCityFM^{-i,a}_{p,t-1}$, a dummy variable that takes a value of one if last year's $(t-1)$ rate of financial misconduct in firm j's area (a) was above the 75^{th} percentile. The portfolio (p) of these firms are constructed outside the firm's Fama-French 48 industry $(-i)$. A comparison of columns 2 and 3 in Table 10 indicates that although accounting for a high rate of local firm failure ($> 3\%$) modestly reduces the effect of city-level financial misconduct, the coefficient on $HighCityFM$ remains highly significant (0.23, $t = 3.96$), maintaining about four-fifths of its magnitude. (A similar conclusion obtains when comparing the respective coefficients on a dummy variable for $> 3\%$ in city-level bankruptcy rates between Tables 9 and 10.)

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

Our conclusion is that although local waves of misconduct appear to partly explain the regional clustering of corporate bankruptcy, the majority of the effect remains unexplained. We view the identification of these local factors as interesting avenues for future research.

6 Conclusion

As any traveler knows, urban areas have distinct cultures that describe the behavior of their residents. New Yorkers are stereotypically aggressive and impatient, Bostonians smart and educated, Minnesotans wholesome and family-oriented, and Seattleites bookish and melancholy. In some cases, even proper identities have emerged: residents of Missouri (the "show me" state) are notoriously skeptical, whereas Texas's monicker, the Lone Star State, reflects its fiercely independent nature. Although the reasons for these differences are complex and multifaceted – explanations often invoke geography, institutions, genetics, and even serendipity – the result is a heterogenous distribution that provides a useful laboratory for studying the relation between cultural attributes and other outcomes of interest.

In this study, we are interested in extent to which general perceptions of trust – the belief in one's counter party to fulfill an obligation, formal or not – influences the availability and terms of financing. Whereas the average trustworthiness of residents and/or corporate managers likely differs appreciably across cities, and presumably permits cross-sectional comparisons, the presence of other slow-moving regional factors renders this source of variation less than ideal from an identification standpoint. Therefore, this paper exploits time-series variation in financial misconduct within cities. Specifically, we examine whether such regional fraud "waves" cast a shadow over an entire region, making it difficult for resident firms – even those not implicated themselves – to access credit. For the most financially vulnerable, this can adversely influence firm policy and, in extreme cases, even survival.

Our primary findings are as follows:

1. Following regional increases in financial misconduct, credit market conditions tighten for borrowers headquartered in the region. Spreads for syndicated loans are 15-20 basis points higher, and covenants are stricter. The magnitude of these effects is higher for lower rated firms.

2. Following regional increases in financial misconduct, local firms raise less debt (as a

percentage of assets) and less external capital in general.

3. The effects of financial misconduct on financial market conditions has real effects on investment and employment. This is especially the case for financially constrained firms in declining industries, which tend to raise less capital, and exhibit declines in investment and employment relative to their counterparts in regions with less financial misconduct.

4. Firms are more likely to go bankrupt, in the three years 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 and ultimately its survival. Our evidence also provides support for the more general idea that trust and reputation considerations play important roles for firms that need to raise external capital. In these and many other situations, higher levels of trust reduce deadweight costs (e.g., writing more complete contracts or enforcing them), and allow resources to be directed to more productive activities.

While our focus has been on the perceptions and the 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 implicitly entering into an implicit contract, and like creditors, are potentially exposed to losses should the firm deviate from a promised strategy. Indeed, while we attributed 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 Titman (1984)).

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 financial misconduct is likely to be most important for the financially constrained and distressed firms that we focus on, it only partially explains the observed geographical clustering of bankruptcies. Identifying other urban characteristics that can contribute to the success and failure of its residents is likely to be a promising area for future research.

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Figure 1: Corporate Fraud and Failure Rates

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

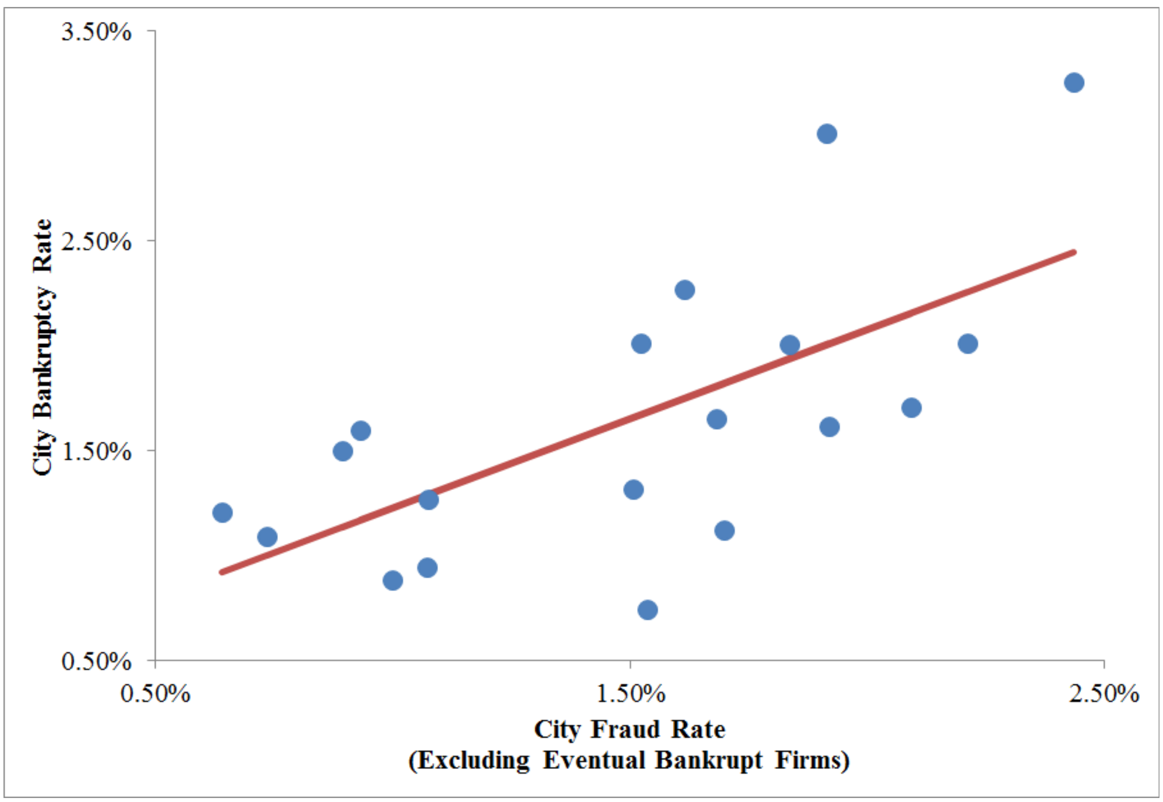

Figure 2: Heat Map of Corporate Failure Rate

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

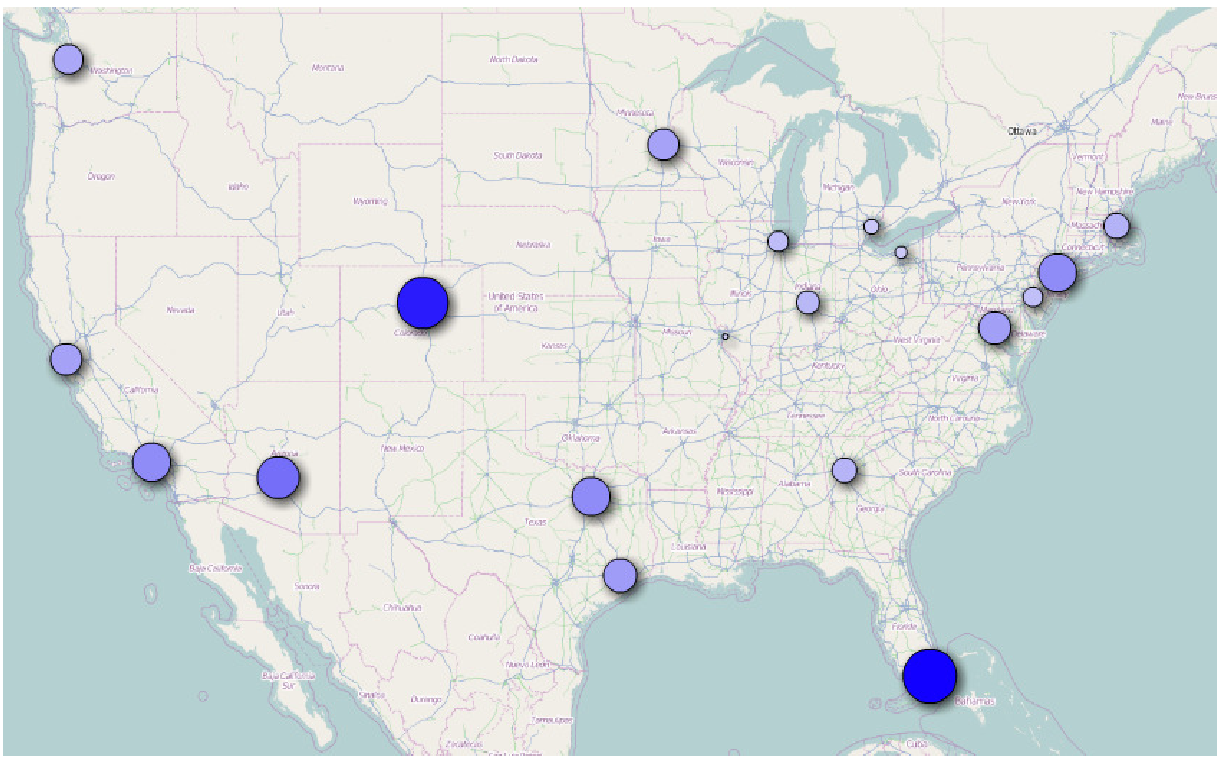

Table 1: Summary Statistics

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 (Next Year) is a dummy variable which takes a value of one if the firm experience default or delisting due to performance issues in the following year, and zero otherwise. Bankrupt (in 3 Years) is a dummy variable which takes a value of one if the firm experience default or delisting due to performance issues in the following 3 years, and zero otherwise. We report summary statistics of the panel data.

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

Table 2: Regional Financial Misconduct and Credit Spreads

This table contains the parameter estimates of regressions predicting loan spread. The dependent variable is the log of loan spread, adjusted by the average of other loans taken by firms in the same FF48 industry in the same calendar year. The main independent variable of interest is *City FM Rate*, which is the rate at which non-industry firms in the city commit financial fraud in the previous year. Models 2-6 use an indicator variable, *High City FM*, that takes the value of 1 for years in which the city financial misconduct rate is in the top quartile, and 0 otherwise. All firm-level control variables are calculated at the end of the previous year. The first two models include all loans with available data in the sample. Models (3) and (4) separate the sample into loans issued by same-state lenders and those issued by out-of-state lenders, respectively. Models (5) and (6) separate the loan sample into loans issued to firms with low or no credit rating, and those issued to firms with high credit rating (BBB or above), respectively. The t-stats are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	All Loans	All Loans	Same-State	Out-of-State	Low/Unrated	High Rated
Dependent Variable:	Industry-adjusted Log(Spread)					
City FM Rate	4.4961***					
	(8.99)					
High City FM Dummy		0.1449***	0.0925***	0.1538***	0.1658***	0.0798**
		(9.58)	(2.90)	(8.85)	(10.01)	(2.08)
Log (Size)	-0.1352***	-0.1382***	-0.1564***	-0.1365***	-0.1571***	-0.0134
	(-19.34)	(-19.69)	(-10.07)	(-17.18)	(-20.82)	(-0.70)
Net Income/Asset	-0.2088***	-0.1991***	-0.1676**	-0.2047***	-0.2191***	0.9306
	(-4.03)	(-3.85)	(-2.02)	(-3.09)	(-4.21)	(1.61)
Debt/Asset	0.4972***	0.5114***	0.3839***	0.5478***	0.4758***	0.7226***
	(11.91)	(12.25)	(4.49)	(11.43)	(10.31)	(6.45)
Stock Return	0.0015	-0.0011	-0.0065	-0.0038	-0.0161	0.1299**
	(0.13)	(-0.10)	(-0.32)	(-0.28)	(-1.38)	(2.45)
Cash/Asset	0.2620***	0.2548***	0.1465	0.3093***	0.2326***	0.6896**
	(3.25)	(3.16)	(0.99)	(3.21)	(2.78)	(2.18)
Price	-0.0011	0.0029	0.0174	0.0003	0.0179	-0.4616*
	(-0.07)	(0.19)	(0.61)	(0.02)	(1.17)	(-1.93)
Volatility	3.3464***	3.2769***	3.4896***	3.0126***	3.3408***	-4.4647*
	(7.06)	(6.91)	(3.71)	(5.50)	(6.89)	(-1.85)
Log (M/B)	0.0532***	0.0540***	0.0647***	0.0521***	0.0653***	-0.0207
	(4.61)	(4.68)	(2.81)	(3.89)	(5.35)	(-0.58)
Loan Maturity	-0.0000	-0.0000	-0.0033***	0.0000	-0.0001	0.0002
	(-0.26)	(-0.34)	(-4.91)	(0.28)	(-0.55)	(0.24)
Log (Loan Size)	-0.0360***	-0.0365***	-0.0414***	-0.0309***	-0.0287***	-0.0724***
	(-5.50)	(-5.58)	(-2.76)	(-4.20)	(-4.01)	(-4.41)
US Lender Dummy	0.0667**	0.0679**	0.0000	0.0827***	0.0746**	-0.0142
	(2.13)	(2.17)	(.)	(2.59)	(2.20)	(-0.18)
Large Lender (Citi/JP/BoA)	-0.1022***	-0.0971***	-0.0594	-0.1145***	-0.0970***	-0.0322
	(-6.17)	(-5.86)	(-1.20)	(-6.29)	(-5.28)	(-0.85)
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,050	7,050	1,619	5,431	5,869	1,181
R^2	0.482	0.483	0.535	0.478	0.351	0.343

Table 3: Lags and Leads of Regional Financial Misconduct and Credit Spreads

This table contains the parameter estimates of regressions predicting loan spread. The dependent variable is the log of loan spread, adjusted by the average of other loans taken by firms in the same FF48 industry in the same calendar year. The main independent variable of interest is *City FM Rate*, which is the rate at which non-industry firms in the city commit financial fraud in the previous year. More specifically, we use an indicator variable, *High City FM*, that takes the value of 1 for years in which the city financial misconduct rate is in the top quartile, and 0 otherwise. In each model we include both *City FM Rate* and one of the lag or lead versions of this variable. All firm-level control variables are calculated at the end of the previous year; their estimates are suppressed to conserve space. The t-stats are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable:	Industry-adjusted Log(Spread)$_t$						
High City FM Dummy$_{t-1}$	0.1449***	0.1178***	0.0984***	0.0929***	0.1348***	0.1390***	0.1438***
	(9.58)	(7.48)	(6.00)	(5.04)	(7.53)	(8.74)	(9.25)
Lags:							
High City FM Dummy$_{t-4}$		0.1353***					
		(8.40)					
High City FM Dummy$_{t-3}$			0.1286***				
			(7.85)				
High City FM Dummy$_{t-2}$				0.0873***			
				(4.73)			
Leads:							
High City FM Dummy$_t$					0.0197		
					(1.11)		
High City FM Dummy$_{t+1}$						0.0278*	
						(1.77)	
High City FM Dummy$_{t+2}$							0.0187
							(1.20)
Constant	1.9972***	2.0324***	2.0253***	1.9973***	1.9523***	1.9493***	1.9463***
	(19.95)	(19.45)	(19.38)	(19.04)	(18.95)	(18.93)	(18.89)
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,050	6,616	6,619	6,615	6,732	6,739	6,736
R^2	0.482	0.495	0.494	0.491	0.484	0.484	0.484

Table 4: Regional Financial Misconduct and Loan Covenants

This table contains the parameter estimates of regressions predicting the strictness of loan covenants. The dependent variable is the strictness of loan covenants as proposed in Murfin (2012). The main independent variable of interest is *City FM Rate*, which is the rate at which non-industry firms in the city commit financial fraud in the previous year. Models 2-6 use an indicator variable, *High City FM*, that takes the value of 1 for years in which the city financial misconduct rate is in the top quartile, and 0 otherwise. All firm-level control variables are calculated at the end of the previous year. The first two models include all loans with available data in the sample. Models (3) and (4) separate the sample into loans issued by same-state lenders and those issued by out-of-state lenders, respectively. Models (5) and (6) separate the loan sample into loans issued to firms with low or no credit rating, and those issued to firms with high credit rating (BBB or above), respectively. The t-stats are reported in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)
Sample:	All Loans	All Loans	Same-State	Out-of-State	Low/Unrated	High Rated
Dependent Variable:	Covenant Strictness					
City FM Rate	80.8612***					
	(2.61)					
High City FM Dummy		2.2378**	1.2864	2.0108*	2.5646**	-1.7247
		(2.33)	(0.58)	(1.82)	(2.39)	(-0.77)
Log (Size)	-3.2695***	-3.3146***	-3.0487***	-3.2132***	-3.6594***	0.8149
	(-6.93)	(-6.99)	(-3.00)	(-5.91)	(-7.07)	(0.65)
Net Income/Asset	1.2619	1.3800	1.2557	4.0940	1.4524	-29.0540
	(0.50)	(0.55)	(0.34)	(1.06)	(0.55)	(-0.97)
Debt/Asset	13.0255***	13.4060***	16.8298***	12.7732***	14.4674***	14.8209**
	(4.65)	(4.78)	(2.67)	(3.99)	(4.43)	(2.34)
Stock Return	-1.7633***	-1.8412***	-1.4600	-1.7593**	-1.7929**	-2.9311
	(-2.65)	(-2.76)	(-1.25)	(-2.12)	(-2.54)	(-1.00)
Cash/Asset	-3.3321	-3.6688	-9.7270	-4.3947	-1.5451	-21.3012
	(-0.71)	(-0.78)	(-1.04)	(-0.80)	(-0.31)	(-1.26)
Price	2.6453**	2.7427***	-2.5331	4.1984***	2.9646***	8.2694
	(2.54)	(2.64)	(-1.18)	(3.46)	(2.70)	(0.70)
Volatility	67.0974**	68.1607**	-49.3831	104.2987***	60.4044*	343.6092**
	(2.13)	(2.16)	(-0.69)	(2.93)	(1.81)	(2.33)
Log (M/B)	1.7209**	1.7393**	1.8584	1.2894	1.8266**	1.9261
	(2.27)	(2.29)	(1.11)	(1.47)	(2.12)	(1.17)
Loan Maturity	-0.0039	-0.0040	-0.0339	-0.0039	-0.0039	0.0039
	(-1.33)	(-1.35)	(-0.62)	(-1.33)	(-1.28)	(0.10)
Log (Loan Size)	2.6614***	2.6604***	1.5378	2.7451***	2.9438***	-0.3540
	(6.07)	(6.06)	(1.55)	(5.51)	(5.98)	(-0.37)
US Lender Dummy	0.8850	0.8734	0.0000	0.5863	0.4575	0.1493
	(0.40)	(0.39)	(.)	(0.26)	(0.19)	(0.03)
Large Lender (Citi/JP/BoA)	1.2530	1.3933	3.4965	1.7569	1.0671	2.1008
	(1.21)	(1.35)	(0.92)	(1.57)	(0.90)	(1.11)
Rating FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,770	1,770	350	1,420	1,516	254
R^2	0.160924	0.160242	0.303443	0.162367	0.131073	0.276789

Table 5: Regional Financial Misconduct and Supply of Credit

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

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

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

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

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	Change in Investment Rate				
High Industry Investment	9.55***	9.43***	9.04***	9.04***	8.76***
	(16.64)	(15.90)	(15.60)	(15.58)	(17.70)
Low Industry Investment	-12.21***	-11.82***	-10.70***	-10.79***	-11.40***
	(-9.81)	(-10.11)	(-15.00)	(-14.99)	(-16.47)
Constrained		-2.14***	-2.15***	-2.49***	-2.99***
		(-3.90)	(-3.93)	(-2.85)	(-3.22)
Low Industry * Constrained				0.85	1.72
				(0.53)	(1.04)
High City FM	-0.75	-0.92	-0.09	-0.46	-0.97
	(-0.74)	(-0.92)	(-0.15)	(-0.86)	(-1.38)
High City FM * High Industry Inv.			1.43	1.46	0.70
			(1.44)	(1.48)	(0.64)
High City FM * Low Industry Inv.			-4.15	-2.95	-2.92
			(-1.45)	(-0.97)	(-0.99)
High City FM * Constrained				3.26*	3.82**
				(1.91)	(2.27)
High City FM * Low Ind. Inv. * Constrained				-9.16***	-9.11***
				(-2.71)	(-2.77)
Laq Q					0.21***
					(12.85)
CF					0.63***
					(4.37)
Constant	-2.97***	-2.53***	-2.73***	-2.70***	-4.87***
	(-9.56)	(-8.35)	(-12.15)	(-11.57)	(-12.67)
Observations	84,932	79,348	79,348	79,348	78,545
R^2	0.021	0.020	0.021	0.021	0.039

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

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

	(1)	(2)	(3)	(4)	(5)
Dependent Variable:	Change in Employment Rate				
High Industry Employment	9.17***	8.06***	8.12***	8.12***	8.20***
	(13.87)	(10.96)	(10.70)	(10.72)	(10.43)
Low Industry Employment	-5.24***	-5.25***	-5.35***	-5.43***	-5.19***
	(-12.00)	(-10.52)	(-10.10)	(-10.36)	(-9.93)
Constrained		-4.99***	-4.99***	-5.58***	-5.28***
		(-9.50)	(-9.50)	(-9.09)	(-9.12)
Low Industry * Constrained				1.61	2.28**
				(1.47)	(2.17)
High City FM	-0.12	0.19	0.17	-0.12	-0.12
	(-0.34)	(0.50)	(0.34)	(-0.26)	(-0.27)
High City FM * High Ind. Emp.			-1.20	-1.19	-1.14
			(-0.68)	(-0.68)	(-0.66)
High City FM * Low Ind. Emp.			0.61	1.00	1.08
			(0.66)	(1.20)	(1.41)
High City FM * Constrained				4.48***	4.47***
				(3.37)	(3.37)
High City FM * Low Ind. Emp. * Constrained				-6.50***	-6.90***
				(-2.68)	(-2.65)
Laq Q					0.06***
					(7.30)
CF					0.45***
					(7.01)
Constant	4.67***	4.41***	4.41***	4.45***	3.72***
	(17.08)	(15.96)	(16.16)	(16.43)	(13.79)
Observations	95,824	78,580	78,580	78,580	77,561
R^2	0.047	0.041	0.041	0.041	0.048

Table 8: City Level Employment Effects of Financial Misconduct

This table contains parameter estimates from pooled regressions predicting area-level employment growth rates. The dependent variable in all regressions is $EmploymentGrowth^a_{t-1\to t}$, which is the employment growth of area a in year t. The independent variable of interest is either $City\ FM^a_{t-1}$, the fraud rate of local firms in year $t-1$, $City\ FM^a_{Avg.\ t-3\ to\ t-1}$, the three-year moving average of fraud rate of local firms, calculated in years $t-3$ to $t-1$, or their respective indicator variables which indicate when the city-level FM rates are above 2%. Models include various variations of fixed effects as well as the lagged dependent variable measured at the same horizon as the lagged fraud rates: $EmploymentGrowth^a_{t-2\to t-1}$ or $EmploymentGrowth^a_{t-4\to t-1}$. The t-stats reported in parentheses are adjusted for clustering at the area level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Employment Growth $_{t-1\to t}$						
City FM $_{t-1}$	-0.2168***						
	(-3.23)						
High City FM Dummy $_{t-1}$		-0.0072***	-0.0088***	-0.0042***	-0.0027**		
		(-4.78)	(-4.25)	(-2.78)	(-2.22)		
City FM $_{Avg.\ t-3\ to\ t-1}$						-0.1657**	
						(-2.25)	
High City FM Dummy $_{Avg.\ t-3\ to\ t-1}$							-0.0054***
							(-2.58)
Emp. Growth$_{t-2\to t-1}$					0.6287***		
					(24.86)		
Emp. Growth$_{t-4\to t-1}$						0.1331***	0.1338***
						(7.59)	(7.97)
Constant	0.0193***	0.0183***					
	(7.36)	(7.42)					
City FE			yes	yes	yes	yes	yes
Year FE				yes	yes	yes	yes
Observations	780	780	780	780	780	740	740
R^2	0.013	0.011	0.153	0.725	0.834	0.768	0.770

Table 9: Regional Clustering of Corporate Bankruptcy

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

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

Table 10: Regional Financial Misconduct and Bankruptcy

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

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