Essays on malpractice in finance

Sakalauskaite, I.

Publication date
2018

Document Version
Other version

License
Other

Link to publication

Citation for published version (APA):
Sakalauskaite, I. (2018). *Essays on malpractice in finance*.

Chapter 3

Corruption and Failing Bank Resolution

3.1 Introduction

The idea that corruption harms financial sector health is not new. For example, a number of studies have demonstrated the prevalence of costly connected lending to politically favoured firms, and politically-motivated lending of state-owned banks.[1] However, the extent to which this translates to higher bank failure risk or costs is not well established. Meanwhile, understanding such effects is important: in the United States alone, the resolution of financial firms that failed during the financial crisis of 2007-2009 has cost the Federal Deposit Insurance Corporation (FDIC) around $90 billion, with only around 70% of failing bank asset value recovered through selling them.

This paper considers and provides empirical evidence on one potential channel through which corruption affects bank resolution. I argue that by depressing bank profitability, corruption not only heightens bank failure risk, but also diminishes the capacity of surviving banks to purchase the failing counterparts at their true value. Furthermore, lower prices that the deposit insurer can realise when selling failed bank franchises can in turn increase the likelihood of liquidations, especially in the presence of entry barriers. The importance of such concerns has been recently demonstrated by Granja et al. (2017) who show that during the financial crisis of 2007-2009, capital constraints as well as geographic or business model distance were important determinants in banks' decisions to purchase failing banks in the United States. These effects might also contribute to the other, potentially more direct, consequences of corruption whereby it reduces the charter values of banks operating in corrupt areas, or results in

[1] See, for example, Barry et al. (2016), Khwaja and Mian (2005), Sapienza (2004).

inefficient resolutions when some firms can lobby the regulators in failed bank auctions (as showed by Igan et al., 2017) or in order to receive financial assistance (Blau et al., 2013).

To analyse how these effects operate formally, the paper adapts the cash in the market pricing model used by Acharya and Yorulmazer (2008), who study the options available to the deposit insurer during financial crises. There, in cases of multiple bank failures, surviving banks do not have sufficient capacity to acquire failing bank assets at their true value, resulting in losses to the insurer and inefficient liquidations. In this paper I show that by reducing bank profitability, corruption results in similar constraints on the funds that the depositor insurer can raise through asset sales, even after accounting for the lower charter value of banks operating in corrupt areas.

The paper tests the model's predictions using data on resolution methods and costs for US banks that failed during 1976-2013. As a measure of corruption, I use variation in the number of public officials convicted for corrupt behaviour across US districts annually, reported by the US Department of Justice Public Integrity Section (PINS). The paper's empirical results indeed point to persistently strong effects that corruption has on resolution costs, 1 s.d. increase in the number of convictions being associated with an additional loss of 1% of failing bank assets. This result holds after controlling for failing bank characteristics, as well as economic conditions at the state and district level, and fixed state effects. Consistent with the model's predictions, I also find evidence that banks operating in corrupt areas are less likely to participate in purchase and assumption transactions of failing banks, local corruption in turn increasing the likelihood that a failing bank is liquidated rather than acquired.

Although the cash in the market pricing model introduced in this paper relies on the assumption that higher corruption reduces bank profitability, it does not focus on the exact channel through which corruption reduces bank returns. Several existing studies have investigated the multiple ways in which corruption can affect bank health, and provided evidence on their prevalence. For example, Chen et al. (2015) find that corruption encourages bank risk-taking. State-owned banks tend to engage in corrupt lending (Barry et al., 2016) and increase loan issuance around election periods (Dinç, 2005, and Sapienza, 2004). Meanwhile, Smith (2017) argues that corruption increases the risk of expropriation through bribes, leading firms to shield themselves by reducing cash holdings and increasing fragility though leverage.

The current paper rather attempts to identify how higher corruption leads to more liquidations and bigger losses to the deposit insurer, and is therefore closer to Igan et al. (2017) and Granja et al. (2017) who examine bank failures.

To that end, besides to the direct effect of cash in the market pricing where potential local acquirers might lack capacity to buy their failing counterparts, I study how corruption affects entry by outsiders. Namely, I consider two types of potential acquirers other than the local banks. First, the deposit insurance corporation can sell failing banks to financial institutions located in outside areas. The alternative to selling bank franchises to surviving local or foreign banks is costly liquidation as in Acharya and Yorulmazer (2008), where bank assets rather than charters are sold.

Implementing analysis similar to that in Granja et al. (2017) in which all US banks are treated as potential acquirers of each failing institution, I indeed find that higher corruption reduces the likelihood that banks participate in a successful acquisition. On the other hand, the probability of acquisitions increases if both target and potential acquirer banks are located in corrupt areas, possibly pointing to the role of learning effects in dealing with corrupt officials, or more efficient lobbying.[2] Furthermore, in line with the model's predictions, I show that higher corruption in target bank's area increases, rather than diminishes, entry from outside banks: when corruption is sufficiently high, depressed prices of failing banks outweigh the costs of entry to outsiders.

The other implication of the model arising from corruption reducing bank returns is that we might observe more bank failures in such areas. This paper finds that over the sample period, such effects have been mute. This can be explained by the analysis of bank failure risk being implemented after controlling for bank performance as well as local economic conditions, but also potentially the effects of forbearance by local supervisory agencies working in an opposite direction. Namely, although banks in corrupt areas can be expected to be weaker, corrupt public officials might be less willing to let such banks close. Evidence of such considerations has been provided by Brown and Dinç (2006) and Liu and Ngo (2014), who demonstrate that bank closures are less likely during the year before elections. Brown and Dinç (2011) also use international evidence of financial crises and show how rather than liquidating banks or accepting lower returns in cases of systematic crises, regulators might choose to forbear.

Overall, the evidence presented in this paper adds to the literature on the harmful effects that corruption has on the financial industry and broader economic outcomes. Numerous studies have focused on the relationship between corruption and economic growth and investment,[3] the number of public officials' convictions in the US being used to measure its effects of local borrowing costs (Butler et al., 2009), as well as firm-level outcomes working through liquidity and leverage (Smith, 2016), investment opportunities and transparency (Dass et al., 2016) or innovation (Brown et al., 2016). Meanwhile, studies of the channels working through the health of the financial sector have, besides to the previously discussed papers on related lending and lobbying, established that corruption increases the share of bad loans in the banking sector (Park,

[2] This evidence is also in line with the evidence in Kim (2016) for corporate mergers and acquisitions.
[3] see Mauro (1995), Wei (2000), Weill (2011), Mo (2001) for cross-country evidence, or Glaeser and Saks (2006), Johnson et al. (2010) or Aghion et al. (2016) for the US

2012) or reduce bank lending (Weill, 2011), but have not looked at the costs associated with bank failures.

The remainder of the paper is structured as follows: Section 3.3 introduces the model, and Section 3.4 empirical evidence for US banks. The last section concludes.

3.2 Model

In this part of the paper, I introduce a theoretical model which links political corruption to bank resolution methods and costs, and develop hypotheses to be tested empirically.

3.2.1 Model Setup

This model considers an economy in which a unit mass of banks operate for an infinite number of periods. Each period, there is 1 unit of funds available as insured deposits that banks can invest in a technology with returns R, which are uniformly distributed in $(\underline{R}, \bar{R})$. After the returns are realised, banks with funds sufficient to repay 1 to depositors continue to the next period, and banks with low return realisations are insolvent and taken over by the deposit insurance corporation.

The key objective of the deposit insurance corporation is to minimise its cost of insuring deposits, or the difference between the insured liabilities of failing banks and the funds raised in bank resolution. Each period, the deposit insurer makes the choice between selling failing banks to local or outside acquirers, or liquidating their assets in order to cover the shortfall in returns required to repay depositors in full.

The main variable of interest in this paper, corruption, is assumed to affect bank failures and resolution by reducing bank profitability. In the model, political corruption diminishes bank returns by proportion c, the cost being realised before payouts to depositors and shareholders. As noted in the previous section, there are multiple ways in which corrupt officials can have such effects on the financial firms: corruption has been shown to be related to bribes and extortion, as well as related lending to industries or firms which might have lower expected returns.

3.2.2 Results

Bank Failures and Cash in the Market

Corruption has a direct effect on the funds available to repay depositors. Consider period t after returns R in $(\underline{R}, \bar{R})$ are realised. Banks fail when their revenues after extortion by corrupt politicians are insufficient to repay 1 to depositors: $R(1-c) < 1$, or $R < \frac{1}{1-c}$. The proportion of such banks is then $\frac{\frac{1}{1-c} - \underline{R}}{\bar{R} - \underline{R}}$, and so the risk of bank failures in this system increases in corruption costs.

Assumption 3.1: I assume that $\underline{R} < 1 < \bar{R}(1-c)$ so that a proportion of banks always fails, but some banks are able to repay depositors even after a fraction c of their revenues is lost.

As banks with returns R from $\frac{1}{1-c}$ to $\bar{R}$ have sufficient funds to repay their depositors and survive, their total profits, or liquidity L, available for purchase of the failing banks is:

$$L = \int_{\frac{1}{1-c}}^{\bar{R}} [R(1-c)-1]\ f(R)dR = \frac{(\bar{R}(1-c)-1)^2}{2(1-c)(\bar{R}-\underline{R})}. \tag{3.1}$$

By reducing the share of surviving banks as well as their returns, extortion by corrupt officials also reduces the cash available to the surviving banks, and so liquidity L is decreasing in corruption costs:

$$\frac{\partial L}{\partial c} = \frac{1-\bar{R}^2(1-c)^2}{2(1-c)^2(\bar{R}-\underline{R})} < 0. \tag{3.2}$$

Acquisition of Failing Banks

The price at which failing banks or their assets are acquired by surviving firms firstly depends on their value. In the baseline model, I fix the fundamental bank charter value at v. It therefore disregards the effect that corruption directly has on it through reduction in profitability.[4] I furthermore make the assumption that the assets generated by failing banks at time t are reduced to 0, and so do not affect the value to acquirers and cannot be recovered by the deposit insurance corporation. This assumption can be justified by legal expenses or looting by failing bank managers in bankruptcy.

Whether the failing banks can be acquired by the local survivors at their fundamental value v depends both on surviving bank profitability and the share of failed banks. There is sufficient liquidity and bank charters are bought at full price $\bar{p} = v$ when:

$$\frac{(\bar{R}(1-c)-1)^2}{2(1-c)(\bar{R}-\underline{R})} \geq \int_{\underline{R}}^{\frac{1}{1-c}} v\ f(R)dR. \tag{3.3}$$

Assumption 3.2: I assume that when $c = 0$, there is sufficient cash in the market to purchase failing banks at their fundamental value v: $v < \frac{(\bar{R}-1)^2}{2(1-\underline{R})}$.

[4] Extension in Section 3.4.3 demonstrates that the results carry when the charter value is affected by corruption, as well.

At times when c is high and (3.3) does not hold, the cash held by the surviving banks is not sufficient to purchase all the failing banks at their fundamental value v. In that case, the maximum amount of funds that the deposit insurer can recover through purchase and assumption transactions is L, and the price p' at which the charter of each failing bank is purchased is the ratio of funds available L and the share of banks failing:

$$p' = \frac{\frac{(\bar{R}(1-c)-1)^2}{2(1-c)(\bar{R}-\underline{R})}}{\frac{\frac{1}{1-c}-\underline{R}}{\bar{R}-\underline{R}}} = \frac{(\bar{R}(1-c)-1)^2}{2(1-(1-c)\underline{R})}. \tag{3.4}$$

This implies that the deposit insurance corporation is able to recover only a fraction $\frac{(\bar{R}(1-c)-1)^2}{2v(1-(1-c)\underline{R})}$ of the true value of the failing banks' assets through selling them to the local surviving banks. This also leads to the first result:

Result 3.1: For a fixed charter value v, as $\frac{\partial p'}{\partial c} < 0$, the price at which failing banks can be acquired falls with corruption costs c.

This results both from the larger number of failing banks, and the lower returns of the surviving institutions.

Resolution Methods and Costs Without Outside Entry

In a model without outside acquirers, the resolution methods available to the deposit insurer are the sales of failing banks to surviving banks and liquidation. If the deposit insurer liquidates a failing bank, its assets are sold, and the charter value is not sustained. I assume that liquidation is costly, and buyers of bank assets can recover only a $(1-\Delta)$ fraction of the true asset value. This loss results from the limited familiarity by the buyers of such assets, as argued in Acharya and Yorulmazer (2008). If a bank is liquidated, its assets are sold to buyers that need not be banks, and so the amount of funds raised this way is not constrained by liquidity in the banking sector.

With the objective to minimise the costs of insuring deposits, the insurer then prefers to sell banks to acquirers for a price p' when it is higher than the funds that can be raised through liquidation, $\underline{p} = v(1-\Delta)$. When there is sufficient liquidity in the market and condition (3.3) is satisfied, failing bank assets will be sold for their fundamental value $\bar{p} = v$, as $v > v(1-\Delta)$. As the share of failing bank rises and available liquidity decreases, depressing the price to p', sales to failing banks are preferred to liquidation when $p' > v(1-\Delta)$, or

$$\frac{(\bar{R}(1-c)-1)^2}{2(1-(1-c)\underline{R})} > v(1-\Delta). \tag{3.5}$$

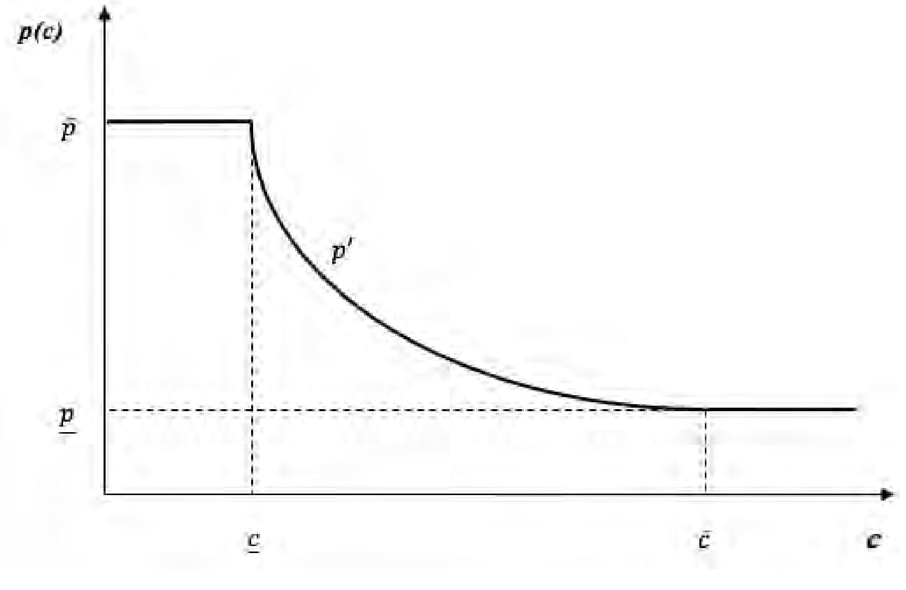
As the right-hand side of equation decreases with corruption, this leads to the following result:

Result 3.2: When banks from other areas cannot purchase failing banks, the probability that failing institutions are liquidated increases with corruption.

The resulting relationship between the price at which failing banks are sold and corruption levels is presented in Figure 3.1. When $c < \underline{c}$, (3.3) holds and bank assets are sold for their fundamental value $\bar{p} = v$. As corruption increases beyond $\underline{c}$, the price is determined by cash in the market, falling until $\bar{c}$ when liquidating failing banks results in higher revenues to the insurer.

Figure 3.1: Corruption and the Price of Failing Banks.

Notes: This figure illustrates how increasing corruption c reduces the price that the deposit insurer can realise from selling failing banks. It receives the true value $\bar{p}$ at low corruption levels, higher corruption reducing price $p^{'}$ through cash in the market pricing until liquidation value $\underline{p}$ exceeds the price that potential acquirers can pay.



The resulting resolution costs to the deposit insurer are equal to the difference between the size of insured deposits, 1, and the funds raised through the sales of failing banks. Assuming that v<1, or that bank failures are always costly to the insurer, her costs d per failed bank are $1 - v$ when potential acquirers have sufficient funds to buy failing banks at their fundamental value $\bar{p} = v$. For $\underline{c} < c < \bar{c}$, the insurer's loss is $1 - p'$, and it is $1 - v(1 - \Delta)$ for higher values of c. Figure 3.2 depicts how these costs are affected by corruption.

The total resulting costs to the regulator, D, are determined by the loss incurred in each bank as well as the share of banks failing. They are $\frac{\frac{1}{1-c}-\underline{R}}{\bar{R}-\underline{R}}(1-v)$ when $c < \underline{c}$. When liquidity in the market is not sufficient to recover the full fundamental value of failing banks v and $p' > v(1-\Delta)$, the cost to the deposit insurer is $D = \frac{\frac{1}{1-c}-\underline{R}}{\bar{R}-\underline{R}} - L$, as the funds she can raise by selling failed banks is limited by cash available to the surviving banks, L. When $c > \bar{c}$ and failing banks are liquidated, the insurer suffers the cost of $D = \frac{\frac{1}{1-c}-\underline{R}}{\bar{R}-\underline{R}}(1-v(1-\Delta))$, as shown in Figure 3.3.

Figure 3.2: Corruption and Deposit Insurance Costs.

Notes: This figure illustrates the loss to the deposit insurer arising as a result of corruption reducing the prices at which failing banks can be sold.

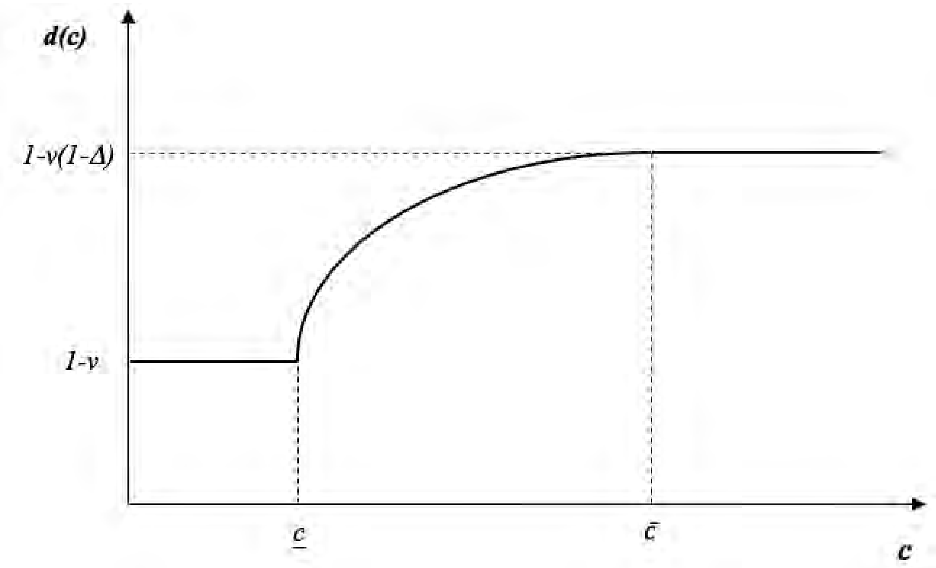
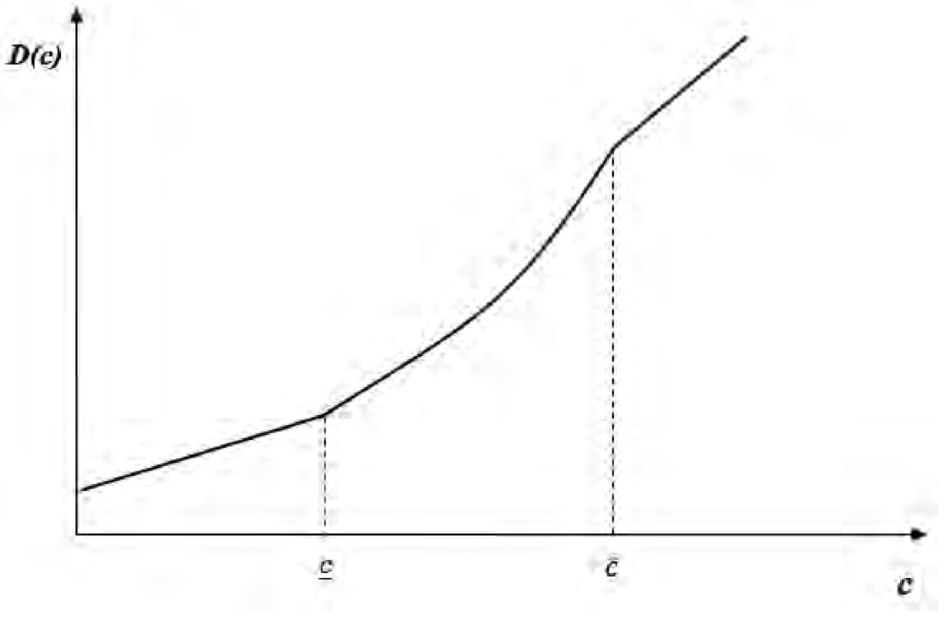


Figure 3.3: Corruption and Total Deposit Insurance Costs.

Notes: This figure plots the total loss to the deposit insurer, which depends on the number of banks failing and deposit insurance costs, for different levels of corruption.



Resolution Methods and Costs with Outside Entry

When outside investors can purchase the assets of failing local banks and have sufficient liquidity, the price at which these are sold depends on how non-local institutions value these assets. Often, the lack of familiarity with the local markets or asset-specific knowledge might reduce their value to outsiders. Empirical evidence on costs to the FDIC during the recent crisis in Granja et al. (2017) shows that such effects exist, as failing institutions are more likely to be acquired by proximate banks.

In the model, the price which outside investors are willing to pay for local banks is lower due to transaction costs, which in turn depend on local corruption. I assume that a fraction tc of a bank's value is lost due to the bureaucratic burdens and settling costs. $t>0$ represents entry and regulatory costs, and its effects rise in corruption as it increases the scope for public officials' extortion, or the power that they can exercise on bank business decisions.

The resulting maximum price p^* that outsiders a willing to pay for failing local banks is then $v(1-tc)$. Therefore, they will not be willing to pay the fundamental value $\bar{p}=v$ for such assets if transaction costs and corruption are present. Outside banks will be willing to purchase local financial institutions only when the price set by inside banks, p', is sufficiently low:

$$p^* = v(1 - tc) \geq \frac{(\bar{R}(1-c)-1)^2}{2(1-(1-c)\underline{R})} = p'. \tag{3.6}$$

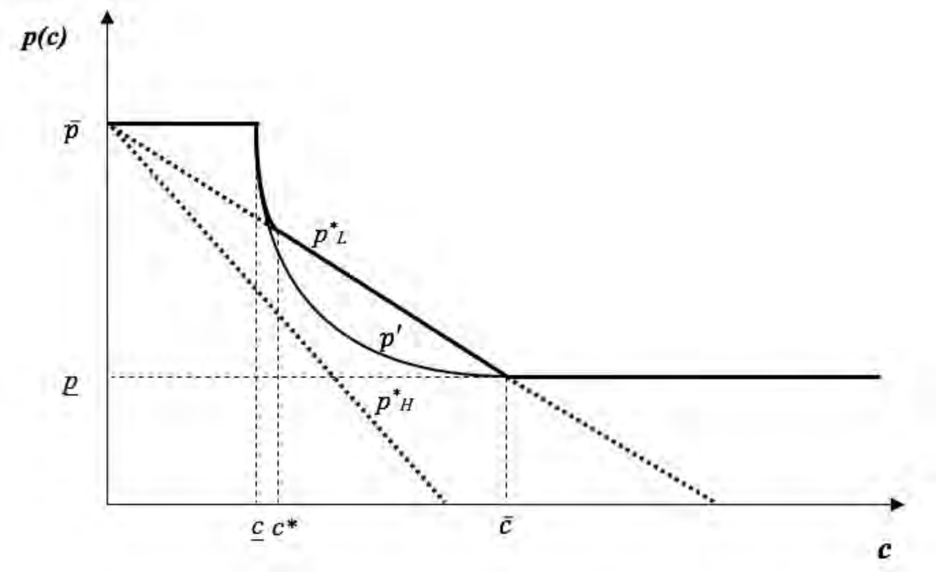
It can be seen that there are two effects that corruption has on the probability of entry of outsiders: first, on the left-hand side of (3.6), it reduces the price they are willing to pay by tv, making entry less likely. The second effect of corruption is the reduction in the price that inside banks can pay for failing banks through its direct effect on p' on the right-hand side, making it more likely that condition (3.6) is satisfied.

Result 3.3: The relationship between corruption and the propensity of outsiders to acquire failing banks depends on the interaction of its effects on entry costs tc and cash in the market pricing price p': if transaction costs t are sufficiently low, outsiders would be willing to enter when corruption in the target area is high as it reduces the prevailing price p' that insiders can pay. For very high values of c, the effect of transaction costs might outweigh the effects of cash in the market pricing.

Figure 3.4 illustrates two possible scenarios of outside entry, depending on transaction costs t, and the price $\underline{p}$ determined by the costs of bank asset liquidation. When t is high and the loss in the value to outsiders is high, local cash in the market price p' might be always above p^*_H, the price that outsiders are willing to pay, resulting in no entry. For sufficiently low values of t, their valuation is higher at p^*_L, and outsiders might enter when corruption is high (above some cutoff value c^*). For very high values of c, outsiders' valuation p^* might again fall below the cash in the market prices, or asset liquidation value $\underline{p}$.

Figure 3.4: Corruption and Outsider Entry.

Notes: This figure illustrates how entry by outside banks affects the price realised in bank resolution. When entry costs are sufficiently low, outside acquirers might purchase failing banks when their prices are depressed at intermediate corruption levels. As entry costs increase, outside institutions might be prevented from entering.



Result 3.4:the possibility of entry by outsiders can diminish the costs to the deposit insurer, and the likelihood of inefficient liquidations. Entry by outsiders increases the revenues that can be raised through the sales of failing bank assets for corruption levels c at which price p' might have prevailed otherwise, as well as in the region where liquidation would had been more profitable in the absence of outside entrants. Such effects are more likely to be observed when transaction costs t are low, and at intermediate corruption levels, as for high corruption, depressed prices through cash in the market pricing, and increased entry costs, might dominate.

Extension: Endogenous Charter Value

In this section I show that the results of cash in the market pricing can hold even when bank charter value is endogenously determined and diminishes with corruption. For simplicity, I consider the case in which banks operate for three periods and invest in a production technology with uncertain $\bar{R}$. $\bar{R}$ can take a high value $\bar{R^H}$ with probability p or a low value $\bar{R^L}$ corresponding to an economic downturn otherwise, with $\bar{R^H} > \bar{R^L}$.

In the model, banks take deposits at t=0 and realise their returns distributed in $(\underline{R}, \bar{R^H})$ if the economy is in a good state and $(\underline{R}, \bar{R^L})$ otherwise at $t = 1$. Banks with returns sufficient to repay the depositors continue their operations for one more period, while banks that do not have sufficient funds are taken into receivership by the deposit insurer.

Disregarding time discounting, the charter value of such failing banks at $t = 1$ is equal to their expected profits at t=2:

$$v(c) = p\left(\frac{(\bar{R^H}(1-c)-1)^2}{2(1-c)(\bar{R^H}-\underline{R})}\right) + (1-p)\left(\frac{(\bar{R^L}(1-c)-1)^2}{2(1-c)(\bar{R^L}-\underline{R})}\right). \tag{3.7}$$

Although $v(c)$ is decreasing in c, cash in the market pricing can still result in this economy when liquidity available at $t = 1$ to purchase failing banks decreases in corruption at a higher rate than $v(c)$ during economic downturns. If the economy at $t = 1$ is in a downturn, or $\bar{R} = \bar{R^L}$, the share of banks failing is then $\frac{1-(1-c)\underline{R}}{(\bar{R^L}-\underline{R})}$. The profits of the surviving banks net of corruption costs and deposit repayments are:

$$L = \frac{(\bar{R^L}(1-c)-1)^2}{2(1-c)(\bar{R^L}-\underline{R})}. \tag{3.8}$$

There is sufficient liquidity to purchase the failing banks at their value $v(c)$ whenever the ratio of liquidity to the value of the failing banks is sufficiently high:

$$L > \underbrace{\frac{(1-\underline{R}(1-c))}{(\bar{R^L}-\underline{R})(1-c)}}_{\text{Share of banks failing}} \underbrace{\left[p\left(\frac{(\bar{R^H}(1-c)-1)^2}{2(1-c)(\bar{R^H}-\underline{R})}\right) + (1-p)\left(\frac{(\bar{R^L}(1-c)-1)^2}{2(1-c)(\bar{R^L}-\underline{R})}\right)\right]}_{\text{Their charter values}}. \tag{3.9}$$

When (3.9) does not hold for high values of c, the price at which a unit of failing assets is purchased is the ratio of liquidity and the total value of the assets that are available, depending on the share of banks failing and their charter values. The resulting price per unit of failing banks assets, p'', equals:

$$p'' = \frac{\frac{(\bar{R^L}(1-c)-1)^2}{2(1-c)(\bar{R^L}-\underline{R})}}{\frac{(1-\underline{R}(1-c))}{(\bar{R^L}-\underline{R})(1-c)}\left[p\left(\frac{(\bar{R^H}(1-c)-1)^2}{2(1-c)(\bar{R^H}-\underline{R})}\right) + (1-p)\left(\frac{(\bar{R^L}(1-c)-1)^2}{2(1-c)(\bar{R^L}-\underline{R})}\right)\right]} \tag{3.10}$$

Result 3.5: As $\frac{\partial p''}{\partial c} < 0$, political corruption increases the chances that the funds in the domestic banks are not sufficient to acquire the failing banks' assets at their true price, even accounting for the fact that the value of assets sold is also lower.

The results of the preceding section therefore also carry in this case, as corruption makes liquidations more likely, while the effects on the possibility of entry depend on the barriers which outsiders face when acquiring failing banks. These findings also illustrate the two channels in which bank resolution costs are affected by political corruption: by reducing bank profitability, corruption reduces both the price that potential acquirers are willing to pay for their charters, and the liquidity in the market that is available to purchase such assets. Such constraints can be especially severe during economic downturns, as it is then that the banks' charter values and current performance diverge.

Model Predictions

The cash in the market pricing model outlined relies on the assumption that corruption reduces bank profitability, and provides several empirical predictions with regards to the effects of corruption on bank resolution method and costs, and entry by banks from other areas.

Assumptions

Bank returns: The model assumes that corruption reduces bank profitability. This could result from political pressure to provide loans to subpar borrowers, as well as higher need to engage in bribing or lobbying.

Hypotheses

Resolution method: When corruption increases, the probability that a failing bank is liquidated is higher. Such effects can be expected to be stronger when entry from outside banks is curtailed through high entry barriers.

Acquisition by outside banks: The probability that a failing bank is acquired by an outside entrant rather than insider increases with corruption, as it depresses the capacity of surviving local institutions to purchase their failing counterparts. The relationship between acquisitions by outsiders and corruption is stronger when entry barriers are low, as for sufficiently high entry costs, even low values of corruption might make acquisitions unprofitable.

Resolution costs: Resolution costs are increasing in corruption levels through reducing failing bank charter values, the liquidity available in the local markets, as well as the willingness of outsiders to purchase them. Such effects can be expected to be stronger when outsiders cannot enter.

3.3 Corruption and Bank Resolution: Empirical Evidence

In this section, I use data on corruption and bank resolution in the US during 1976-2013 to test the model's predictions.

In what follows, I first review the institutional setting in which US banks operate, discussing their regulation, resolution, as well as entry restrictions. As the model predicts that banks are mainly affected through corruption reducing their returns, I also discuss the extent to which their resolution can be influenced by corruption directly through forbearance.

3.3.1 Institutional Setting

Bank Supervision

Commercial banks in the US are regulated and supervised by state and federal authorities. At the federal level, banks are supervised by the Office of Comptroller of the Currency (OCC), 12 members of the Federal Reserve System (Fed), and the Federal Deposit Insurance Corporation (FDIC). State-level supervision is carried out by designated authorities in each state (for example, the corresponding regulator in Texas is Texas Department of Banking, and in Florida, it is Florida Office for Financial Regulation).

Bank charters determine which institutions are involved in their supervision. National banks are chartered and mostly supervised by the OCC. For state banks, their supervision is carried out by the chartering state authority as well as the Fed or FDIC. Whether a bank is supervised by the FRS or the FDIC depends on whether they belong to the Federal Reserve System.[5]

Banks operating in the US are supervised through off-site as well as on-site inspections. Off-site supervision involves the analysis of bank balance sheets based on their quarterly reports (Call reporting), other data, and the context of developments in the economies in which they operate. On-site supervision is implemented by bank supervisors attending the banks physically, and gathering more information on their safety and soundness. Such inspections result in CAMELS ratings, which indicate the banks' sustainability, and affect the costs of deposit insurance or the need to take corrective actions. For small state banks, federal and state agencies alternate in their on-site inspections, while large state and national banks are continuously supervised by federal

[5] Meanwhile, thrifts have been historically supervised by the Office of Thrift Supervision, this role taken over by the OCC in 2011. As these firms have limited coverage in data and have different requirements, they are not included in the empirical analysis in this paper.

agencies.

For a more detailed description of bank supervision in the US, interesting and informative resources are Agarwal et al. (2014) who compare the stringency of state and federal agencies in evaluating bank soundness, and Walter (2004) on the processes guiding their resolution.

Resolution

In the US, the decision to close a failing commercial bank is typically made by the charter-granting agency, while the FDIC is then assigned as a receiver, responsible for conservatorship and resolution (Walter, 2004). Therefore, for national banks, the decision to close the institution is made by the OCC, and state agencies decide on the viability of state banks.[6]

Since the introduction of the Federal Deposit Insurance Corporation's Improvement Act (FDICIA) in 1991 following the costly savings and loans crisis, bank supervision and resolution is guided through the prompt corrective action rules (PCA). Their aim is to ensure that bank closures, or regulatory actions, are made on a timely basis to avoid costly forbearance.

More specifically, since 1993, US banks can be taken into conservatorship if they are insufficiently capitalised, or regulators foresee such risks because of certain exposures. Banks are deemed undercapitalised if their equity to assets ratio is below 4%, and critically undercapitalised if it is 2%. For critically undercapitalised institutions, the management is typically given a certain period of time to raise additional capital before the decision to close it is made.

When the charter granting authority deems a bank not viable, the FDIC is typically appointed as a receiver, responsible for resolving it and making insured depositors full. The FDICIA of 1991 assigns cost minimisation as the objective of FDIC, the least-cost resolution method to be preferred. When a bank is taken into FDIC receivership, it evaluates its assets and liabilities, and decides on a resolution method. The resolution methods available to the FDIC entail transactions in which failing banks keep or lose their charters. First, rather than selling the bank, the FDIC can provide financial assistance (assistance transaction) if it is believed to be cheaper than selling or liquidating it. The rules and conditions for assistance changed during the sample period, being restricted before 1982, and again after 1991.

If the bank does not receive public funds, the FDIC organises an auction in which potential acquirers bid for the bank's assets and franchise value. In a purchase and

[6] In a detailed analysis of bank resolution mechanisms in the US, Walter (2004) notes that in some instances, federal agencies can close a failing state-chartered bank: this occurs when state regulators' and federal authorities' views on bank viability diverge. Such instances have occurred in practice, FDIC closing several banks chartered by state agencies.

assumption transaction, an acquiring institution purchases (part of) the bank's assets, and assumes (part of) its liabilities. Typically, the bids for failing banks are lower than the value of their liabilities, leading to the FDIC compensating acquiring institutions for the difference. If the bids by potential acquirers are sufficiently low, the FDIC might find liquidating the bank and paying out its depositors directly to be cheaper.

While the role and responsibilities by state and federal regulators in ensuring efficient bank resolution were established in 1991, such strict guidelines were not present during the savings and loans crisis in the 1980's. A very interesting account of the challenges faced by US agencies in bank resolution during it is provided by Black (2006), while White and Yorulmazer (2014) provide an analysis of the trade-offs faced by the FDIC.

Bank Regulation, Resolution, and Corruption

In the model, the key channel through which corruption affects bank resolution is considered to be cash in the market pricing, resulting from lower profitability of local banks and entry barriers. However, several studies have demonstrated that pressure from politicians or firms can affect such outcomes directly. For example, Liu and Ngo (2014) have shown that banks have been significantly less likely to be closed in years of governor elections in US states, suggesting that politicians can affect the state officials in bank supervision.[7] If banks in corrupt areas are allowed to operate with insufficient capital levels, we would observe on average weaker banking sectors there, in turn leading to costlier failures.

Similarly, Inez et al. (2014) show that lobbying expenditures of banks directed at regulators affect the success of their bids for failing institutions, leading to costlier resolutions. Since some evidence exists that the successfulness of mergers and acquisitions in corrupt US areas is also affected by firm lobbying expenditure (Kim, 2016), one might argue that banks operating in such locations would be more willing in engage in lobbying towards agencies, as well.

On the other hand, there are several reasons for why these concerns can be limited, especially during the post-FDICIA period. First, if bank supervisors in corrupt areas are more likely to be affected by lobbying firms, or firms in such areas are more likely to lobby, we might observe more acquisitions from banks located in corrupt districts, rather than fewer. Furthermore, this channel need not translate into a higher risk of liquidations, as the model predicts.

In terms of forbearance, the results of Liu and Ngo (2014) on elections need not translate to variation in corruption across areas over time. There, while agencies forbear

[7] They also find that the FDICIA did not change this relationship, pointing to the persistence of the influence that politicians might have on regulators.

in the months before elections, bank failures increase in the after-election months, so the longer-term effect on bank closures is limited. Since this paper uses annual variation in the number of public officials' convictions as the corruption measure, and it tends to move slowly, it can be expected that on average, the effects on bank closure decisions will cancel out, and weak banks would have to fail at some point.

The involvement by federal authorities in supervising national banks, and rotation or supervision by multiple agencies in the case of state banks, also increase the risk that the decisions of potentially forbearing local agencies are overturned. For example, while Agarwal et al. (2014) indeed find that for small US state banks, state regulators are more lenient than their federal counterparts, the decisions of federal agencies to downgrade bank CAMELS ratings are not changed by state authorities subsequently following rotation in supervision, therefore having a lasting effect. Furthermore, the FDICIA allows for investigations into the conduct of supervisors when bank failure costs to the deposit insurer are high, increasing the accountability of state and federal agencies in ensuring timely resolution.

Bank Acquisitions

Several hypotheses in the theoretical model regard the willingness of outside banks to acquire failing firms. However, contrary to some other industries, mergers and acquisitions, as well as entry by new firms, in the financial sector are heavily regulated.

Historically, cross-state banking in the US has been restricted, implying that during some periods, potential acquirers might have not been able to purchase failing banks even if they found it profitable. Failing banks could not be acquired by out-of-state institutions until the early 1980's, when the 1982 Garn-St Germain act allowed such transactions in case of important bank failures, being specified to sufficiently large banks (assets exceeding 500m USD) later in 1987.

The lifting of interstate banking and branching restrictions over time has allowed banks from outside states to bid for failing firms more freely. Namely, interstate banking which allows banks to operate subsidiaries across different states (with own capital structure), was allowed in some states during 1970s-1980s on a reciprocity basis. In 1994, the Riegle-Neal Interstate Banking and Branching Efficiency act allowed state and national banks to have subsidiaries across states, and suggested a timeline for interstate branching restrictions to be lifted.

This implies that the period in which states lifted interbank banking restrictions, or the period post-1994 overall, might be the most suitable to study how corruption affects outside entry.

3.3.2 Key Variables and Descriptive Statistics

Corruption

As a measure of corruption, this paper uses information on the number of public officials convicted for corruption-related offences, provided by the US Department of Justice (DoJ) Public Integrity Section (PINS). The cases covered involve a wide range of crimes, including conflicts of interest, bribing, fraud, or election-related irregularities. As stated in Glaeser and Saks (2006), while the majority of corruption cases are handled by local Attorney General Offices, the PINS handles cases which concern public officials connected to the government, fall under multiple jurisdictions, or require more resources. The PINS publishes the statistics on the number of officials convicted at the judicial district level annually, which allows the measure of corruption to vary over time and locations. There are 93 judicial districts in total, 90 of which correspond to US states. I use data in 1976-2013 as this is the period on which the PINS data is available.

The use of PINS data in studying the effects of political corruption has several advantages. First, as some states contain more than one judicial district, it allows to identify the effects of corruption controlling for state-level factors. Furthermore, as the enforcement actions are initiated at the federal level, some concerns regarding differences in the strength of legal enforcement are also alleviated. Namely, if enforcement actions relied on local authorities, concerns could be raised that a higher number of convictions reflects better enforcement rather than a higher prevalence of corruption. Here, because of the involvement of federal authorities, more convictions are more likely to correspond to more corruption.

For measuring political corruption, one would ideally want to have data on the type of crimes committed. However, PINS provides only the overall number of convictions resulting from corrupt practices, which does not allow to distinguish extortion from other types of misbehaviour. Therefore, following Smith (2016), it is assumed that corruption across various levels and types of agencies is correlated, such that if relatively more corruption is observed in some areas, the other agencies are relatively more corrupt, as well. This assumption is in line with evidence in Parsons et al. (2018) who indeed show that across US cities, various types of misbehaviour (financial misconduct, political corruption, as well as more malpractice by doctors) are related even after accounting for enforcement quality and local- or firm- level characteristics.

To use the number of public officials' convictions as a measure of corruption, I match US counties to judicial districts by hand. To make the measure representative of corruption in the local population, I weigh the number of politicians by 100,000 inhabitants in the given district. I then use bank location at the county level as indicated to the Federal Reserve Board to match it to its district.

As disciplinary actions tend to follow corrupt behaviour with a time lag of several years because of the length of legal processes, the measure of PINS convictions reflects past corruption. In this paper, I follow Glaeser and Saks (2006) and as a measure of corruption use the trailing number of convictions, which is the ratio of average 5-year convictions to average 5-year district population.

Table 3.1 presents the descriptive statistics of the corruption variable at a judicial district level for the sample period 1976-2013. It can be seen that the number of convictions varies across districts even located within the same state, which is also reflected in Figure 3.5 which maps the intensity of convictions across US regions. Table 3.2 presents variation in the number of convictions over time, which also appears to be considerable.

Table 3.1: Corruption Across US Districts.

This table provides summary statistics of the number of convictions per 100,000 inhabitants across the judicial districts used in analysis during 1976-2013.

District	No. obs.	mean	median	s.d.	min.	max.
Alabama - Middle	9867	0.60	0.56	0.47	0	2.40
Alabama - North	15321	0.32	0.26	0.28	0	1.42
Alabama - South	6012	0.59	0.43	0.56	0	2.21
Alaska	1274	0.66	0.44	0.69	0	2.55
Arizona	5828	0.24	0.17	0.19	0	0.82
Arkansas - Eastern	18429	0.26	0.22	0.26	0	1.17
Arkansas- Western	13832	0.15	0.10	0.17	0	0.64
California - Central	24342	0.24	0.22	0.15	0.01	0.59
California - Northern	11230	0.13	0.09	0.14	0	0.63
California - Southern	3896	0.29	0.23	0.25	0	1.16
California- Eastern	8842	0.29	0.29	0.19	0	0.63
Colorado	39600	0.16	0.12	0.16	0	0.50
Connecticut	6367	0.22	0.22	0.14	0	0.68
Delaware	4281	0.30	0.17	0.31	0	1.13
Florida - Middle	28800	0.20	0.15	0.13	0.02	0.58
Florida - Northern	9471	0.35	0.32	0.29	0	1.56
Florida - Southern	11917	0.45	0.36	0.45	0	1.91
Georgia - Middle	20291	0.36	0.25	0.29	0	1.17
Georgia - Northern	21456	0.32	0.25	0.22	0.02	0.92
Georgia - Southern	12929	0.40	0.27	0.51	0	2.92
Hawaii	1134	0.26	0.19	0.25	0	1.10
Idaho	2891	0.18	0.10	0.18	0	0.61
Illinois - Central	53989	0.20	0.14	0.22	0	1.07
Illinois - Northern	54482	0.55	0.44	0.32	0.20	1.49
Illinois - Southern	25248	0.27	0.16	0.40	0	1.90
Indiana - Northern	14226	0.27	0.25	0.18	0	0.97
Indiana - Southern	22858	0.15	0.11	0.13	0	0.53
Iowa - Northern	44441	0.13	0.08	0.13	0	0.47
Iowa - Southern	31995	0.15	0.07	0.17	0	0.64
Kansas	71457	0.19	0.18	0.13	0	0.43
Kentucky - Eastern	21365	0.54	0.41	0.37	0	1.55
Kentucky - Western	20467	0.23	0.20	0.20	0	0.88
Louisiana - Eastern	6150	0.91	0.79	0.57	0.12	2.22
Louisiana - Middle	4223	0.63	0.49	0.57	0	2.24
Louisiana - Western	19819	0.29	0.25	0.26	0	1.17

District	No. obs.	mean	median	s.d.	min.	max.
Maine	3095	0.21	0.18	0.20	0	0.80
Maryland	12443	0.29	0.26	0.22	0	0.99
Massachusetts	11073	0.23	0.19	0.18	0.02	0.82
Michigan - Eastern	16884	0.20	0.17	0.15	0.02	0.69
Michigan - Western	18478	0.16	0.14	0.14	0	0.47
Minnesota	86560	0.11	0.09	0.10	0	0.48
Mississippi - Northern	8394	0.71	0.47	0.67	0	3.95
Mississippi - Southern	9969	0.47	0.43	0.37	0	1.30
Missouri - Eastern	30222	0.26	0.18	0.21	0.04	0.76
Missouri - Western	44336	0.22	0.23	0.18	0	0.66
Montana	17890	0.40	0.22	0.50	0	2.12
Nebraska	52378	0.15	0.06	0.17	0	0.57
Nevada	2971	0.19	0.18	0.17	0	0.95
New Hampshire	5049	0.13	0.09	0.18	0	0.74
New Jersey	15652	0.29	0.26	0.16	0.08	0.71
New Mexico	10614	0.27	0.21	0.19	0	0.75
New York - Eastern	3059	0.27	0.23	0.21	0.01	1.13
New York - Northern	7790	0.23	0.24	0.19	0	0.65
New York - Southern	9168	0.78	0.69	0.50	0	2.42
New York - Western	4488	0.26	0.21	0.19	0	0.73
North Carolina - Eastern	3640	0.20	0.12	0.18	0	0.68
North Carolina - Middle	4196	0.15	0.13	0.15	0	0.55
North Carolina - Western	2853	0.15	0.11	0.15	0	0.70
North Dakota	20330	0.44	0.31	0.52	0	2.50
Ohio - Northern	20151	0.35	0.33	0.28	0.03	1.52
Ohio - Southern	20540	0.28	0.25	0.16	0	0.58
Oklahoma -Northern	11269	0.25	0.20	0.30	0	1.19
Oklahoma - Eastern	12184	0.57	0.40	0.64	0	2.12
Oklahoma - Western	33293	0.50	0.23	0.77	0	3.09
Oregon	7561	0.08	0.05	0.09	0	0.30
Pennsylvania - Western	11134	0.21	0.17	0.17	0.03	0.92
Pennsylvania -Middle	17448	0.42	0.38	0.25	0	0.98
Pennsylvania- Eastern	8879	0.46	0.48	0.25	0.08	1.07
Rhode Island	1274	0.25	0.19	0.25	0	0.83
South Carolina	11447	0.32	0.25	0.24	0	0.87
South Dakota	17474	0.53	0.29	0.53	0	2.01
Tennessee - Eastern	14103	0.25	0.23	0.21	0	1.05
Tennessee - Middle	10953	0.26	0.20	0.27	0	1.51
Tennessee - Western	12620	1.04	0.76	1.14	0.16	6.45
Texas - Eastern	28760	0.25	0.16	0.26	0	1.21
Texas - Northern	55699	0.18	0.15	0.13	0	0.62
Texas - Southern	41499	0.23	0.21	0.18	0	0.91
Texas - Western	37031	0.21	0.19	0.16	0	0.79
Utah	6566	0.13	0.09	0.13	0	0.43
Vermont	2971	0.12	0	0.18	0	0.80
Virginia - Eastern	12623	0.45	0.36	0.37	0	1.30
Virginia - Western	11977	0.15	0.10	0.18	0	0.75
Washington - Eastern	3614	0.07	0	0.12	0	0.46
Washington - Western	8819	0.11	0.09	0.11	0	0.40
Washington D.C.	1421	4.75	3.83	2.97	1.29	13.58
West Virginia - Northern	10457	0.13	0.12	0.17	0	0.81
West Virginia - Southern	10486	0.45	0.30	0.37	0	1.41
Wisconsin - Eastern	27062	0.21	0.23	0.14	0	0.55
Wisconsin - Western	36704	0.08	0.05	0.10	0	0.32
Wyoming	9918	0.25	0.20	0.32	0	1.56
Total	1586199	0.28	0.19	0.37	0	13.58

Figure 3.5: Corruption in the United States.

Notes: This figure illustrates the distribution of corruption across US judicial districts. It is based on the median number of convictions per 100,000 inhabitants over the sample period of 1976-2013 in each district.

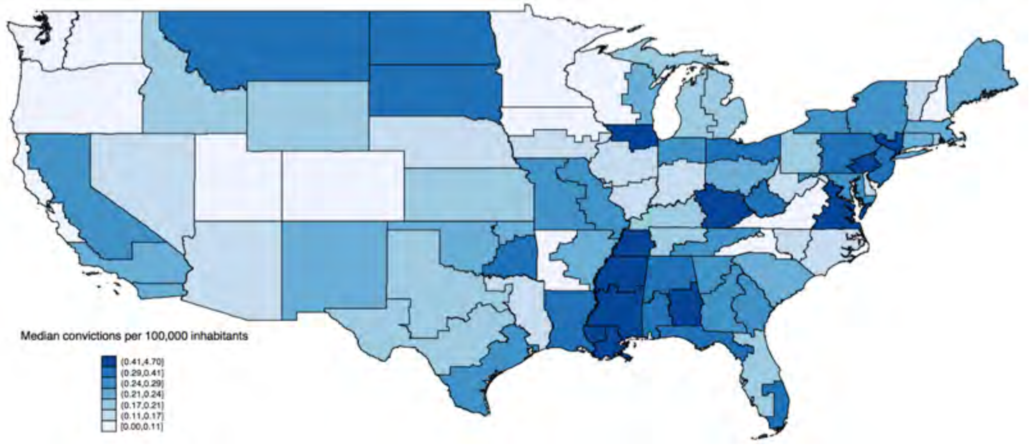


Table 3.2. Variation in Corruption Over Time.

This table provides summary statistics of the average number of convictions per 100,000 inhabitants across all US judicial districts during the sample period 1976-2013.

AVERAGE CONVICTIONS						
Year	No. obs.	mean	median	s.d.	min.	max.
1976	54,434	0.11	0.04	0.18	0	1.29
1977	54,565	0.12	0.06	0.18	0	1.47
1978	56,872	0.11	0.06	0.15	0	2.09
1979	56,831	0.14	0.09	0.17	0	1.37
1980	56,964	0.15	0.09	0.26	0	2.98
1981	57,079	0.22	0.07	0.49	0	3.09
1982	57,056	0.21	0.07	0.42	0	2.55
1983	57,139	0.34	0.19	0.63	0	6.45
1984	56,973	0.39	0.28	0.44	0	5.37
1985	56,803	0.25	0.20	0.29	0	2.52
1986	56,125	0.31	0.25	0.31	0	4.70
1987	54,586	0.30	0.28	0.24	0	2.04
1988	52,302	0.39	0.30	0.36	0	3.01
1989	50,489	0.43	0.33	0.37	0	4.01
1990	48,817	0.39	0.26	0.54	0	8.26
1991	47,333	0.21	0.18	0.26	0	3.83
1992	45,539	0.19	0.13	0.26	0	5.19
1993	43,602	0.32	0.25	0.33	0	6.55
1994	41,652	0.34	0.23	0.50	0	13.58
1995	39,455	0.35	0.25	0.46	0	10.08
1996	37,719	0.28	0.19	0.31	0	6.46
1997	36,236	0.30	0.18	0.38	0	5.64
1998	34,836	0.30	0.23	0.43	0	12.74
1999	33,892	0.30	0.22	0.44	0	10.52

Year	No. obs.	mean	median	s.d.	min.	max.
2000	33,016	0.28	0.19	0.35	0	8.04
2001	31,999	0.27	0.19	0.32	0	7.48
2002	31,193	0.29	0.21	0.31	0	7.68
2003	30,688	0.31	0.23	0.37	0	3.52
2004	30,089	0.31	0.21	0.32	0	5.81
2005	29,581	0.34	0.26	0.33	0	2.64
2006	29,192	0.32	0.25	0.34	0	4.38
2007	28,701	0.31	0.22	0.35	0	3.83
2008	28,102	0.36	0.28	0.39	0	11.37
2009	27,359	0.34	0.26	0.30	0	4.73
2010	26,228	0.34	0.24	0.35	0	6.77
2011	25,105	0.32	0.24	0.31	0	6.29
2012	24,291	0.33	0.28	0.31	0	7.40
2013	23,356	0.32	0.24	0.34	0	2.77
Total	1586199	0.28	0.19	0.37	0	13.58

Bank Data

The paper uses bank balance sheet data from Quarterly Call Reports provided by the Federal Reserve Bank of Chicago for the universe of commercial US banks during 1976-2013. I constrain the analysis to commercial banks because savings associations and other financial firms are not fully covered in the database and more importantly are subject to different regulations and constraints.[8]

To study the methods and costs of bank resolution, I further merge bank balance sheet data with the Federal Deposit Insurance Corporation database on historical US bank failures. The database provides information on the date of effective bank failures, resolution methods, and estimated cost to the insurer (the data on resolution costs is available starting in 1986). If the failing bank is resolved through a purchase and assumption transaction, the acquiring institution is identified, as well.

As explained earlier in the text, the FDIC can use several methods for failing bank resolution. The FDIC distinguishes between the cases in which the failing bank loses its charter through purchase and assumption (PA) and payoff (PO) transactions. In PA transactions, the successor institution assumes target bank's deposits[9] and often a portion of other liabilities and assets. Meanwhile, in PO transactions, the FDIC compensates the insured depositors, and liquidates the failing bank's assets. Insured Deposit Transfer (IDT) transactions are in between purchase and assumption and liquidation transactions, as rather than paying depositors directly, the FDIC transfers depositors' accounts from the failing to an acquiring bank. The FDIC also provides

[8] To allow state-level clustering which is appropriate when measuring the effects of variables that vary at state or district level, I also drop banks that changed their location during the sample period.

[9] The FDIC distinguishes cases in which both insured and uninsured deposits or only insured deposits were assume by the acquiring institution (PA and PI transactions, respectively. The FDIC also characterises the P&A case in which it is not known whether all or just insured deposits were assumed by the acquirer.

information on assistance (A/A) transactions, in which failing banks receive financial assistance and do not lose their charters.

Following the savings and loans crisis, the FDIC has introduced the possibility to create bridge banks when resolving failed banks. When a bridge bank is created, the failing institutions stay under public ownership and control until resolved in an orderly manner rather than immediately. In these cases, the dataset uses the date at which a failing bank was taken into receivership as its closure date, and the resolution method indicates the manner in which the newly established bridge bank was resolved subsequently.

Table 3.3 presents the distribution of bank failure by type over the sample period, and Table 3.4 summarises the average cost of various types of bank liquidations. It can be seen that the majority of failures are concentrated around the savings and loan crisis of 1986-1992, and the financial crisis of 2008-2010. As expected, liquidations and insured deposit payouts are the costliest methods of bank resolution. On average, bank failures result in costs that are around 20% of failing banks' assets, being lower than the findings by James (1991) during late 1980's, and Granja (2017) for the recent crisis years, but the costs of liquidations are consistent with the ones that they report.

Table 3.3: Bank Resolution Methods Over the Sample Period.

Notes: this table provides information on the distribution of various bank failure types over years. "Assistance" transactions involve bank failures in which they received FDIC assistance and retained charters. "Ins Dep transfer" is a resolution method in which a failing bank's deposits are transferred to another bank. "P&A not specified" is a purchase and assumption transaction in which the FDIC does not specify whether all or only insured deposits and some/all assets have been transferred. In "P&A all dep", all deposits and some/all assets are sold. In "P&A ins dep", only insured deposits and all/some assets are transferred. "Liquidation" is a resolution method in which a failing bank is liquidated.

	Assistance	Ins. Dep. transfer	P&A not specified	P&A Ins/Unins. deposits	P&A Ins. deposits	Liquidation	Total
1976	0	0	8	0	0	3	11
1979	0	0	16	0	0	4	20
1980	1	0	7	0	0	3	11
1981	0	0	5	0	0	2	7
1982	2	0	24	0	0	7	33
1983	2	2	34	0	0	7	45
1984	1	12	60	0	0	4	77
1985	2	7	0	86	0	22	117
1986	7	19	0	95	0	20	141
1987	18	38	0	132	0	10	198
1988	80	27	0	161	0	6	274
1989	1	22	43	128	0	8	202
1990	1	9	0	137	0	8	155
1991	2	14	0	83	0	2	101
1992	2	14	0	41	30	8	95
1993	0	0	0	7	28	3	38
1994	0	2	0	2	7	0	11
1995	0	1	0	0	4	0	5
1996	0	0	0	2	2	0	4
1997	0	0	0	1	0	0	1
1998	0	0	0	1	2	0	3
1999	0	0	0	4	1	0	5
2000	0	0	0	1	5	0	6
2001	0	0	0	2	1	0	3
2002	0	0	0	0	6	3	9
2003	0	0	0	0	1	0	1
2004	0	0	0	2	1	0	3
2007	0	0	0	0	1	0	1
2008	3	0	0	12	6	0	21
2009	4	0	0	105	3	9	121
2010	0	0	0	125	0	3	128
2011	0	0	0	82	0	2	84
2012	0	0	0	38	0	2	40
2013	0	0	0	21	0	1	22
Total	126	167	197	1268	98	137	1993

Table 3.4: Resolution Costs.

Notes: This table summarises the ratio of FDIC estimated resolution costs to total failing bank assets by resolution type ($\frac{estimated\ loss}{assets_{t-1}}$) for each resolution method 1986-2013, as earlier estimates are not available. "Assistance" transactions involve bank failures in which they received FDIC assistance and retained charters. "Ins Dep transfer" is a resolution method in which a failing bank's deposits are transferred to another bank. "P&A not specified" is a purchase and assumption transaction in which the FDIC does not specify whether all or only insured deposits and some/all assets have been transferred. In "P&A all dep", all deposits and some/all assets are sold. In "P&A ins dep", only insured deposits and all/some assets are transferred. "Liquidation" is a resolution method in which a failing bank is liquidated.

Resolution method	No. obs.	mean	median	s.d.	min.	max.
Assistance	111	0.08	0.03	0.10	0	0.54
P&A insured and uninsured dep.	1180	0.23	0.22	0.13	0	0.76
P&A only insured dep.	97	0.20	0.15	0.17	0	0.94
P&A dep. not specified	43	0.16	0.13	0.16	0	0.80
Insured dep. transfer	146	0.28	0.29	0.15	0	0.73
Liquidation	85	0.29	0.27	0.13	0.01	0.57
Total	1662	0.22	0.21	0.14	0	0.94

In regression analysis, I control for state- and district-level economic conditions, as higher corruption is typically associated with lower income levels, or growth, which could also have a direct impact on bank profitability. Therefore, I control for state employment level, and district per capital income, income growth, and population. As corruption can affect public balances, which in turn might influence bank outcomes and resolution, I also control for state-level budget surplus to income ratio. Table 3.5 presents summary statistics of all variables used in empirical analysis.[10]

In Table 3.6, I compare low- and high- corruption districts in terms of bank outcomes and overall economic performance. Compared to the districts in the bottom quartile of median corruption, high corruption districts have larger banks who are on average more leveraged, and in line with the model's predictions, have lower returns on assets, and face costlier resolutions. Contrary to the findings in Smith (2016), they hold more cash on average, which could be attributed to regulation, and the existence of alternative channels through which corrupt officials can extract funds as compared to firms in other sectors. High-corruption states and districts also perform worse in terms of employment, fiscal positions, income levels and growth.

Table 3.5: Summary Statistics.

Notes: This table provides key statistics of the main variables used for the sample period 1976-2013, all winsorized at 1% and 99% of their distributions. All variables that are not ratio's are in real rather than nominal terms. A detailed description of variables and their sources is provided in Appendix 1.

	No. obs.	mean	median	s.d.	min.	max.
CORRUPTION: 5-year avg. $\frac{annual\ convictions}{district\ population}$*100,000	1576405	0.26	0.20	0.23	0	1.24
SIZE: ln(assets)	1587433	11.21	11.09	1.21	8.83	15.49
DEPOSITS: ln(deposits)	1586503	11.05	10.95	1.20	8.53	15.16
NONPERF: nonperforming/total loans	1171181	0.02	0.01	0.02	0	0.13
CAPITAL: equity/assets	1587433	0.10	0.09	0.04	0.04	0.31
CASH: cash/assets	1587430	0.07	0.06	0.06	0.01	0.32
LOANS: ln(total loans)	1587432	10.59	10.49	1.32	7.58	14.99
ROA: net income/total assets*100	1394201	0.57	0.58	0.73	-3	2.28
EMPL: state employment rate	1590959	0.55	0.54	0.06	0.42	0.68
SURPLUS: state surplus/state income	1534162	-0.06	-0.06	0.02	-0.13	-0.03
GROWTH: annual district income growth	1509874	2.20	2.22	2.68	-5.59	8.51
POPUL: ln(district population)	1590959	14.79	14.76	0.69	13.31	16.49
INCOME: ln(district income pc)	1590959	10.09	10.07	0.20	9.67	10.60

[10] The variables and their sources are described in more detail in Appendix 3.1.

Table 3.6: Comparing High- and Low- Corruption Districts.

Notes: this table compares key characteristics of firms operating in 1st and 4th quartiles of districts ordered by their median corruption. The statistics below use the median value of each variable within each bank in the sample and compute averages of those in 25% highest-corruption districts and 25% lowest-corruption districts. All variables are winsorized at 1% and 99% of their distributions.

	low corruption	high corruption	t-stat.	p-value
SIZE	10.94	11.50	-225	0.000
DEPOSITS	10.80	11.35	-225	0.000
CAPITAL	0.094	0.093	14.02	0.000
NONPERF	0.0138	0.0137	2.82	0.005
CASH	0.060	0.062	-33.74	0.000
LOANS	10.38	10.91	-202.95	0.000
ROA	0.61	0.60	7.28	0.000
EMPL	0.59	0.53	484.43	0.000
SURPLUS	-0.061	-0.064	94.47	0.000
GROWTH	2.23	2.16	32.52	0.000
INCOME	10.10	10.08	49.92	0.000
POPUL	14.66	14.73	-40.88	0.000
FDIC COST	0.198	0.219	-1.74	0.082

3.3.3 Results

Bank Returns and Failure Risk

As the model introduced in Section 3.2 makes the assumption that corruption reduces bank returns, in turn increasing their failure risk, I start the data analysis by investigating the extent to which bank profitability and corruption are related. I estimate a simple linear regression model:

$$ROA_{i,t} = \alpha + \beta Corruption_{d,y} + \gamma Bank\ Controls_{i,t} + \eta Controls_{s,y} + \theta_t + \theta_s + \epsilon_{i,t,s}. \quad (3.11)$$

I regress quarterly bank i returns on assets ROA on $CORRUPTION$ at the district level d, controlling for bank characteristics and state- or district- level conditions, as well as state and year fixed effects. At the bank level, I include its size, loans and deposits, as well as leverage as control variables, and also account for state employment and district income per capita, its growth, and population size. This implies that the relationship that is captured by regression analysis disregards the effects of corruption on bank performance that runs through reducing economic growth, investment, or bank loan issuance and deposits.

Regression estimates are presented in Table 3.7. In columns 1-3 which use the whole sample period, it appears that while corruption and bank profitability are negatively correlated, the effect is not statistically significant. Adding a quadratic term suggests that corruption is only associated with lower bank profitability in high-corruption districts. Columns 4-5 use only the post-FDICIA period, and corruption remains a significant explanatory variable for bank returns. However, the estimated relationship is economically small: a 1 s.d. increase in the number of average convictions reduces bank ROA by around 0.01p.p. in the post-1992 sample period, which can be explained by the number of control variables employed, potentially accounting for some of the negative effects directly. Splitting the sample to crisis and non-crisis years (following Liu and Ngo (2014), the crisis years are 1986-1992 for the savings and loans crisis, and 2007-2010 corresponding to the financial crisis), the relationship is on average stronger in normal times, only high corruption areas facing lower returns in crisis years.

Does corruption increase bank failure risk? The theoretical model predicts that by reducing bank profitability, corruption could increase the risk of bank failures, as they would be more likely to fall short in repaying their creditors. In Table 3.8, I estimate the following Cox proportional hazards model:

$$h(t) = exp(\beta Corruption_{d,t} + \gamma Bank\ Controls_{i,t-1} + \eta Controls_{s,t-1} + \theta_t + \theta_s). \quad (3.12)$$

This model estimates how corruption and control variables affect the relative risk of bank failures each quarter. I consider only FDIC resolution in which banks lose their charters as failures, and control for bank and state or district level characteristics in the quarter before bank failure, as well as state and quarter fixed effects.

The estimates reported in Table 3.8 show that corruption and bank failure risk are not significantly related, albeit positively correlated. However, here, similarly to Table 3.7, bank characteristics including returns are controlled for, and so the direct channel through which corruption is assumed to affect bank failures. Furthermore, as argued previously, increasing corruption might be associated with more forbearance, potentially counteracting the positive effect of extortion from corrupt officials. Estimation results on bank characteristics and economic conditions as expected show that more profitable, liquid, and capitalised banks are less likely to fail. Too many to fail concerns, or the share of banks failing in a district each given quarter, does not appear to be a strong consideration over the sample period.

In columns 5 and 6, similar to bank returns, the negative effects of political corruption are stronger during non-crisis years. This result is not surprising, as such relationship might be better identified in the absence of systemic banking crises where other factors might drive bank outcomes, also in line with findings by Liu and Ngo (2014) that electoral concerns affect bank closure decisions to a higher extent during non-crisis years.

Table 3.7: Corruption and Bank Returns.

Notes: This table presents estimates of a linear regression model using quarterly data for the sample of all commercial banks operating in the US during 1976-2013. The dependent variable is the ratio of bank's income to total assets (in percent). The independent variable of interest, CORRUPTION, is the ratio of average 5-year number of convictions to the average population in 100,000 in a given bank's district. SIZE is the natural logarithm of total bank assets; LOANS is the natural logarithm of total loans; CAPITAL is the ratio of bank shareholder equity to total assets, and DEPOSITS is the logarithm of the bank's deposits. EMPL is the employment ratio in the bank's state, while GROWTH, INCOME, and POPUL are district-level income growth, income per capita, and the natural logarithm of population. Post-FDICIA subsample includes years after 1992 when FDICIA became effective, and Crisis years are considered to be 1986-1992 and 2007-2010. Standard errors reported in parentheses are clustered at the state level, * $p<0.10$, **, $p<0.05$, *** $p<0.01$.

	Bank ROA								
SAMPLE	Whole sample			Post-FDICIA		Non-crisis years		Crisis years	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CORRUPTION_t	-0.0379	-0.0163	0.115	-0.0467*	0.0116	-0.0379*	0.0265	-0.0202	0.288**
	(0.0504)	(0.0276)	(0.0825)	(0.0259)	(0.0713)	(0.0202)	(0.0625)	(0.0424)	(0.139)
SIZE_t	0.113***	0.128***	0.129***	0.122***	0.122***	0.0793***	0.0797***	0.215***	0.218***
	(0.0389)	(0.0260)	(0.0259)	(0.0343)	(0.0343)	(0.0279)	(0.0279)	(0.0394)	(0.0399)
LOANS_t	-0.0949***	-0.0808***	-0.0809***	0.00846	0.00847	-0.0302**	-0.0303**	-0.150***	-0.151***
	(0.0306)	(0.0226)	(0.0228)	(0.0172)	(0.0171)	(0.0125)	(0.0125)	(0.0440)	(0.0444)
CAPITAL_t	0.932*	4.406***	4.404***	2.430***	2.429***	3.882***	3.881***	5.319***	5.310***
	(0.466)	(0.283)	(0.281)	(0.228)	(0.227)	(0.186)	(0.186)	(0.561)	(0.555)
DEPOSITS_t	0.0779**	0.0453*	0.0444*	-0.0398	-0.0400	0.0327	0.0324	0.0455	0.0427
	(0.0388)	(0.0239)	(0.0238)	(0.0250)	(0.0250)	(0.0216)	(0.0216)	(0.0334)	(0.0329)
EMPL_t		3.042***	3.050***	4.994***	4.972***	1.600**	1.606***	6.943***	6.927***
		(0.641)	(0.639)	(1.081)	(1.070)	(0.599)	(0.597)	(1.167)	(1.130)
GROWTH_t		0.0333***	0.0330***	0.0186***	0.0186***	0.0160***	0.0158***	0.0411***	0.0403***
		(0.00554)	(0.00540)	(0.00471)	(0.00475)	(0.00299)	(0.00293)	(0.00772)	(0.00740)
INCOME_t		-0.332***	-0.323***	-0.229***	-0.222***	-0.252***	-0.249***	-0.459**	-0.431*
		(0.114)	(0.112)	(0.0754)	(0.0730)	(0.0679)	(0.0670)	(0.226)	(0.222)
POPUL_t		-0.0374*	-0.0406*	-0.0933***	-0.0951***	-0.0407**	-0.0419***	-0.0244	-0.0363
		(0.0222)	(0.0217)	(0.0202)	(0.0203)	(0.0152)	(0.0151)	(0.0394)	(0.0384)
CORRUPTION_t^2			-0.123*		-0.0569		-0.0619		-0.278**
			(0.0692)		(0.0536)		(0.0546)		(0.118)
State effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. obs.	1385805	1336281	1336281	655007	655007	879899	879899	456382	456382
Adj. R^2	0.181	0.249	0.249	0.293	0.293	0.263	0.263	0.216	0.216

Table 3.8: Corruption and Failure Risk.

Notes: This table presents estimates of a Cox proportional hazards model, measuring how corruption affects the relative risk of bank failures. The sample includes all commercial banks in the US during 1976-2013 and uses quarterly data. Only bank failures involving charter loss are considered (assistance transactions as defined by the FDIC are not considered as failure). The independent variable of interest, CORRUPTION, is the ratio of average 5-year number of convictions to the average population in 100,000 in a given bank's district. DEPOSITS is the logarithm of the bank's deposits; CASH is the natural logarithm of the bank's cash holdings, ROA is the ratio of bank's net income to total assets; NONPERF is the ratio of bank's nonperforming and non-accruing loans to total loans; CAPITAL is the ratio of bank shareholder equity to total assets. EMPL is the employment ratio in the bank's state, and SURPLUS is the ratio of state budget surplus to total income. GROWTH, INCOME, and POPUL are district-level income growth, income per capita, and the natural logarithm of population. SHAREFAILED is the ratio of failing banks' assets to total bank assets in a given district each quarter, disregarding the assets of a bank if it fails. For variables other than corruption, lagged values of control variables are used. Post-FDICIA subsample includes years after 1992 when FDICIA became effective, and Crisis years are considered to be 1986-1992 and 2007-2010. Standard errors reported in parentheses are clustered at the state level, * p<0.10, **, p<0.05, *** p<0.01.

	BANK FAILURE					
SAMPLE	Whole sample			Post-FDICIA	Non-crisis years	Crisis years
	(1)	(2)	(3)	(4)	(5)	(6)
CORRUPTION$_t$	0.0176	0.0814	0.0941	0.332	0.606*	0.0399
	(0.123)	(0.158)	(0.164)	(0.353)	(0.356)	(0.207)
DEPOSITS$_{t-1}$	-0.195***	-0.197***	-0.292***	-0.198***	-0.382***	-0.163***
	(0.0493)	(0.0486)	(0.0632)	(0.0677)	(0.0747)	(0.0433)
CASH$_{t-1}$	-2.880***	-2.785***	-2.923***	-0.726	-3.740***	-2.671***
	(0.503)	(0.517)	(0.531)	(0.673)	(1.298)	(0.585)
ROA$_{t-1}$	-58.43***	-58.38***	-58.20***	-56.63***	-53.56***	-58.83***
	(3.261)	(3.289)	(3.336)	(6.552)	(8.513)	(3.420)
NONPERF$_{t-1}$	17.37***	16.95***	16.90***	18.74***	22.28***	15.18***
	(1.595)	(1.523)	(1.611)	(1.723)	(2.025)	(1.607)
CAPITAL$_{t-1}$	-102.5***	-102.2***	-100.6***	-104.8***	-91.27***	-108.0***
	(5.479)	(5.499)	(5.455)	(9.564)	(8.216)	(9.211)
EMPL$_{t-1}$		-9.176***	-7.763**	14.70*	3.055	-11.85***
		(3.475)	(3.572)	(8.834)	(4.973)	(3.668)
SURPLUS$_{t-1}$		-20.48***	-17.91**	-12.27	-26.89**	-18.57**
		(6.979)	(7.157)	(15.84)	(11.33)	(8.063)
GROWTH$_{t-1}$		0.0245	0.0150	-0.00136	0.00508	0.0440**
		(0.0169)	(0.0172)	(0.0500)	(0.0431)	(0.0214)
POPUL$_{t-1}$		0.0692	0.189**	0.203	0.317***	0.0143
		(0.0554)	(0.0937)	(0.152)	(0.110)	(0.0460)
INCOME$_{t-1}$		0.476	0.402	-0.839	-0.955	0.924**
		(0.422)	(0.426)	(0.802)	(0.780)	(0.401)
SHAREFAILED$_t$			15.23	11.54		
			(10.28)	(7.486)		
State effects	Yes	Yes	Yes	Yes	Yes	Yes
Date effects	Yes	Yes	Yes	Yes	Yes	Yes
No. Obs.	1153889	1135381	1135094	650814	680390	454991

Who Acquires the Failing Banks?

The channel through which corruption is argued to affect bank failure costs in the model works through reducing the funds available to the potential acquirers. In this section, I start testing the model's predictions by first examining whether banks located in corrupt areas are less likely to acquire their failing counterparts.

I estimate a model similar to that in Granja et al. (2017), where for each bank j failing every quarter during the sample period 1976-2013, all non-failing institutions are treated as potential acquirers. Since the analysis is focused on bank acquisitions, I drop cases in which failing banks received financial assistance or were liquidated. Bridge banks are excluded from this analysis as the conditions under which they are resolved differ from the ones during their closure.[11] In the baseline analysis, I also disregard cases in which multiple subsidiaries belonging to the same BHC fail at the same time, as these are most often resolved together, and would result in over-weighing of some instances (For example, in July 1989, the FDIC reports failures of 24 subsidiaries of the Texas American Bank, all acquired by the same institution subsequently. A year earlier, 40 subsidiaries of the First Republican Bank were resolved.).

For each failing bank-potential acquirer pair I then create a dummy variable equal to 1 if a potential acquirer i actually buys the failing institution j. I use the FDIC bank failures dataset which identifies the acquirers of banks resolved through purchase and assumption transactions: out of the total of 1563 purchase and assumption transactions in the sample, 1449 did not involve bridge banks, of which 1129 could be matched to acquiring commercial bank data (additional 128 matches were made in insured deposit transfer transactions).

I then estimate how corruption in the potential acquirer's district affects the likelihood of a successful acquisition, controlling for both potential acquirer's and target bank's characteristics, and fixed quarter and state effects, in a logit model

$$\begin{split} Pr(acquisition) = F(\beta corruption_{di,t} + \gamma Acquirer\ Controls_{i,t-1} + \\ + \gamma Target\ Controls_{j,t-1} + \theta_t + \theta_{si} + \theta_{sj}). \end{split} \tag{3.13}$$

The estimates are presented in Table 3.9, and provide some support to the model's prediction. While in columns 1-3 when the whole sample period is used, $CORRUPTION$ does not reduce the probability of a bank acquiring its failing counterpart significantly, the effects are stronger in the years during which interstate banking restrictions were lifted, and during the crisis years. As expected, potential acquirers' balance sheet strength is also an important determinant of successful acquisitions: larger banks with higher income, liquidity, and capitalisation are more likely to purchase their failing counterparts. Being located in a different district, as expected, reduces the likelihood of entry, which is line with findings in Granja et al. (2017).

The stronger relationship between corruption and probability of successful acquisitions during the years in which banks can acquire institutions in other states can be potentially attributed to better identification when entry constraints are lower. Also, from columns 9-12, it appears that while the negative effects of corruption on bank failure risk or returns might be better identified in years with a few bank failures, financial

[11] I also drop instances in which the FDIC does not indicate a bridge bank, but the acquiring institution is established during the quarter the bank's failure.

crises seem to be the periods in which corruption affects their resolution more.

In the estimated models, all target banks are acquired, and therefore studying how their characteristics affect the likelihood of acquisitions is not informative. However, it is possible to measure how it interacts with the potential acquiring banks' features. In columns 4, 6, 8 and 10, I estimate linear regression models to study how potential acquirers' and target bank exposures to corruption interact. Interestingly, regression results show that while corruption in itself reduces the probability of an acquisition, this is not the case when both banks operate in corrupt regions, even if they are located in different districts.

Such findings might be in line with similar evidence on the success of mergers and acquisitions in other industries found by Kim (2016). It could be attributed to firms learning how to deal with corrupt officials, creating synergy effects, or result from firms' lobbying effort. Namely, if banks operating in corrupt areas are more active in lobbying banking agencies, they might be more likely to successfully acquire institutions in environments that are more corrupt.

Table 3.9: Corruption and Bank Acquisitions.

Notes: This table presents estimates of a probit model and linear regressions. The dependent variable SUCCESS takes the value of 1 if a potential acquirer i acquires failing institution j, and zero otherwise. The sample of potential acquirers includes all commercial banks in the US during 1976-2013. Only banks eventually resolved in a purchase and assumption transaction, and for which data on the acquiring institution were available, are treated as targets. It excludes banks resolved through bridge banks, acquired by institutions established at the time of acquisition, and cases of multiple bank failures. The control variables reported are at the potential acquirer's i level. The independent variable of interest, CORRUPTION^i, is the ratio of average 5-year number of convictions to the average population in 100,000 in a given bank i's district, corruption^j measuring corruption in the target bank's district. SIZE is the natural logarithm of total bank assets; CASH is the natural logarithm of the bank's cash holdings, ROA is the ratio of bank's net income to total assets; CAPITAL is the ratio of bank shareholder equity to total assets. Target and potential acquirer state- and district-level controls are state employment, and district income, income growth, and population size in the preceding quarter. Target-bank controls include variables CORRUPTION, SIZE, CASH, CAPITAL and ROA for the quarter before failure. Post-interstate subsample includes years after which interstate banking restrictions in acquiring bank states were lifted, and Crisis years are considered to be 1986-1992 and 2007-2010. Standard errors reported in parentheses are clustered at the target state level, * p<0.10, ** p<0.05, *** p<0.01.

	Pr(Acquisition)											
SAMPLE	Whole sample				Outside acquirers		Post-interstate		Non-crisis		Crisis	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
CORRUPTION$^i{}_t$	-0.182	-0.0679	-0.261	-0.000108***	-0.396	-0.0000345**	-0.710*	-0.000160***	0.444	-0.00000912	-0.673*	-0.000144***
	(0.271)	(0.210)	(0.388)	(0.0000330)	(0.572)	(0.0000165)	(0.372)	(0.0000393)	(0.783)	(0.0000467)	(0.347)	(0.0000454)
CORRUPTION$^i{}_t$				0.000340*		0.0000793*		0.000496***		0.000105		0.000415*
x CORRUPTION$^j{}_t$				(0.000188)		(0.0000450)		(0.000181)		(0.000172)		(0.000221)
SIZE$^i_{t-1}$	0.772***	0.809***	0.819***	0.000107***	1.217***	0.0000452***	0.852***	0.000120***	0.847***	0.000133***	0.810***	0.0000996***
	(0.0431)	(0.0430)	(0.0462)	(0.0000150)	(0.0698)	(0.0000114)	(0.0505)	(0.0000208)	(0.0775)	(0.0000187)	(0.0447)	(0.0000153)
CASH$^i_{t-1}$	0.966**	0.877*	0.961	0.000226***	0.235	0.0000350	0.855	0.000239***	-0.0762	0.000139	1.370**	0.000251***
	(0.394)	(0.496)	(0.593)	(0.0000487)	(1.093)	(0.0000314)	(0.698)	(0.0000610)	(1.145)	(0.000101)	(0.557)	(0.0000528)
ROA$^i_{t-1}$	34.13***	47.57***	49.03***	0.00336***	39.60***	0.000195	47.06***	0.00365***	65.32***	0.00451***	46.04***	0.00318***
	(6.424)	(6.462)	(6.689)	(0.000399)	(11.86)	(0.000205)	(7.067)	(0.000435)	(17.09)	(0.00126)	(6.747)	(0.000470)
CAPITAL$^i_{t-1}$	6.132***	6.478***	7.306***	0.00122***	5.780**	0.000430**	7.138***	0.00129***	8.405**	0.00170***	6.996***	0.00108***
	(1.180)	(1.165)	(1.166)	(0.000212)	(2.579)	(0.000165)	(1.266)	(0.000268)	(3.362)	(0.000596)	(0.880)	(0.000175)
DISTRICTCHANGE		-5.491***	-5.444***	-0.00309***			-5.161***	-0.00317***	-5.364***	-0.00402***	-5.437***	-0.00287***
		(0.184)	(0.185)	(0.000477)			(0.197)	(0.000581)	(0.252)	(0.000540)	(0.224)	(0.000438)
Model	Probit	Probit	Probit	Linear	Probit	Linear	Probit	Linear	Probit	Linear	Probit	Linear
State/district controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Date effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Target state effects	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Target controls	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Target st./distr. controls	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. Obs.	13046984	13046984	10692310	10708507	6823777	10467691	8031901	8261160	2406037	2489521	7905633	8218986
Pseudo-R^2/Adj. R^2	0.0995	0.324	0.321	0.00246	0.231	0.000177	0.314	0.00243	0.330	0.00300	0.320	0.00233

Another implication of the cash in the market pricing model is that in areas of high political corruption, we might observe more, rather than fewer, acquisitions from outside institutions, even in the presence of entry costs. There, if the price that the local banks can pay for failing bank assets is sufficiently low, it might increase the attractiveness of such targets to outsiders.

I test this prediction in Table 3.10. I generate a dummy variable that equals 1 if the acquiring institution is not located in the failing bank's district, and use the same set of bank failures as previously (focusing on banks resolved through purchase and assumption transactions, and dropping bridge banks or cases of multiple bank failures), and estimate the following probit model:

$$Pr(outside\ entry) = \Phi(\beta corruption_{dj,t} + \gamma Target\ controls_{j,t-1} + \theta_t + \theta_{sj}). \quad (3.14)$$

In (3.14), I measure how corruption in the failing bank j location and its characteristics before failure affect the likelihood of acquisition by an outside rather than a neighbouring bank.

The results reported in Table 3.10 are by and large supportive to the existence of such effects. In columns 1-4, I use the whole sample period which also includes the years in which entry constraints were present, and show that as the corruption in target bank locations increased, it became more likely that a failing institution would be acquired by a bank from another district. This could indicate that as corruption reduces the capacity of local institutions, it makes such targets more attractive to purchasers from outside. In column 4, I estimate a linear regression model and show that as expected, such effects have become most visible since the relief of interbank banking restrictions in the failing banks' states.

Therefore, in columns 5-8, I focus in the period during which interstate banking restrictions in target banks were relieved, as expected showing stronger effects. Only in column 6 where I add fixed state-year effects, the identification relying on annual variation of corruption levels within states, corruption retains its sign, but loses significance. In the last two columns, I split the sample to non-crisis and crisis years, and find that the effects are present in both periods. This finding is interesting, as it suggests that even in periods of a few bank failures, corruption might be related to the propensity of local institutions to acquire failing banks, in line with the effects on bank returns presented in Table 3.7.

Table 3.10: Corruption and Outsider Entry.

Notes: This table presents estimates of a probit model in columns 1-3 and 5-8, and results from a linear regression model in column 4. The dependent variable DISTRICTCHANGE takes the value of 1 if the acquiring and target banks are located in different districts, and zero otherwise. The sample includes all cases of bank failures during 1976-2013 in which banks were resolved through a purchase and assumption transaction, and for which data on the acquiring institution is available. The sample of target banks excludes banks resolved through bridge banks, acquired by institutions established at the time of acquisition, and cases of multiple bank failures. The independent variable of interest, corruption, is the ratio of average 5-year number of convictions to the average population in 100,000 in a given failing bank's district. SIZE is the natural logarithm of total bank assets; DEPOSITS is the logarithm of its deposits; ROA is the ratio of bank's net income to total assets; CAPITAL is the ratio of bank shareholder equity to total assets. SHAREFAILED is the ratio of failing banks' assets to total bank assets in a given district each quarter, disregarding the assets of a bank if it fails. For variables other than corruption, lagged values of control variables are used. INTERBANK is a variable which takes value 1 after each state lifts restrictions on interstate banking. Post-interstate subsample includes years after which interstate banking restrictions in target bank states were lifted, and Crisis years are considered to be 1986-1992 and 2007-2010. Columns 2-8 control for employment ratio in the bank's state, the ratio of state budget surplus to total income, and district-level income growth, income per capita, and the natural logarithm of population. Robust standard errors are reported in parentheses, * p<0.10, ** p<0.05, *** p<0.01.

	Pr(outside acquirer)							
SAMPLE	Whole period				Post-interstate			
							Non-crisis	Crisis
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CORRUPTION_t	0.762*	0.901**	0.873*	-0.0840	1.933***	1.439	4.649**	2.125***
	(0.444)	(0.450)	(0.457)	(0.0896)	(0.581)	(1.072)	(2.139)	(0.669)
DEPOSITS_{t-1}	0.251	0.329	0.467	0.00663	0.876	1.940*	6.677**	0.223
	(0.920)	(0.941)	(0.954)	(0.202)	(0.998)	(1.107)	(2.920)	(1.139)
SIZE_{t-1}	0.257	0.192	-0.0853	0.0950	-0.456	-1.529	-6.015**	0.320
	(0.903)	(0.924)	(0.940)	(0.201)	(0.985)	(1.092)	(2.858)	(1.114)
ROA_{t-1}	-14.33*	-13.71*	-13.51*	-2.534*	-15.54*	-12.76*	-29.31	-19.72*
	(7.951)	(8.036)	(8.003)	(1.348)	(8.744)	(7.627)	(23.84)	(10.88)
CAPITAL_{t-1}	6.057	6.525	5.817	1.631	10.72	42.33***	284.1	10.79
	(10.01)	(9.759)	(9.911)	(1.703)	(11.33)	(13.96)	(174.6)	(10.93)
SHAREFAILED_t			21.91**	0.764	18.99**	24.94*		
			(10.98)	(0.586)	(9.508)	(14.73)		
CORRUPTION_t x INTERSTATE				0.366***				
				(0.134)				
INTERSTATE				-0.0883				
				(0.0729)				
Model	Probit	Probit	Probit	Linear	Probit	Probit	Probit	Probit
State/district controls	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State effects	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes
Date effects	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes
State-year effects	No	No	No	No	No	Yes	No	No
No. Obs.	670	670	670	864	594	476	98	471
Pseudo-R^2/Adj. R^2	0.346	0.355	0.360	0.340	0.362	0.281	0.350	0.369

Resolution Method

Another prediction of the model is that by reducing the cash available to potential local acquirers, corruption can make liquidations more profitable to the deposit insurer as compared to the price that can be realized through purchase and assumption transactions. This result can be expected to hold even when outside entry is possible if outside entrants are also willing to pay a fraction of the bank's charter value because of entry costs or own capacity constraints.

To that end, I again estimate a probit model over the sample of failed US commercial banks during 1976-2013, the dependent variable being a dummy that equals 0 if a failing bank is purchased, and 1 if it is liquidated. Namely, for each failing bank j, I assign a value of 0 if its resolution method identified by the FDIC is "PA" or "PI" and 1 if it is "IDT" or "PO". Similar to the preceding analysis, I disregard the cases in which multiple subsidiaries in a BHC failed during the sample period, as these provide multiple observations with typically the same result, but keep bridge banks.[12]

The regression results are presented in Table 3.11 and indeed show that banks in more corrupt regions are more likely to be liquidated rather than acquired, even after controlling for their size, profitability, nonperforming loans, capitalization before failure, and local economic conditions.

In line with the model's predictions, the relationship between corruption and the risk of liquidation becomes considerably weaker when only the period in which target bank states allow outside entry is used (column 6), which can be also inferred from the interaction term in column 5. According to the cash in the market pricing model, this could be attributed to outside entry resulting in outside banks purchasing institutions in corrupt areas that would have been liquidated otherwise.

Interestingly, column 7 in which only the post-1992 period is used with FDIC's mandate to minimise costs being formalised shows a reversal of results, higher corruption reducing the risk of liquidation, although the relationship is not statistically significant.[13] Overall, this is in contrast to the model's predictions, as corruption can be expected to reduce both local and outside institutions' willingness to bid for failing banks. As in the post-1992 period, the majority of bank failures happened during the financial crisis, this suggests that liquidations were less prevalent in the more corrupt areas. When the sample is split according to crisis versus non-crisis years, in line with other findings on corruption affecting bank resolution, such effects are more visible when multiple banks fail.

[12] The results are robust to dropping them.

[13] This regression uses fixed year rather than quarterly effects because of the limited number of observations.

Table 3.11: Resolution Methods.

Notes: This table presents estimates of a probit model in which the dependent variable, LIQUIDATION, takes value 1 if a failing bank is liquidated, and 0 if it is resolved through a purchase and assumption transaction. The sample includes all banks that failed during 1976-2013 except for institutions receiving financial assistance and not losing their charters. The sample includes bridge banks, and excludes cases in which multiple banks belonging to the same holding company failed together. The independent variable of interest, corruption, is the ratio of average 5-year number of convictions to the average population in 100,000 in a given bank's district. SIZE is the natural logarithm of total bank assets; LOANS is the natural logarithm of total loans; NONPERF is the ratio of bank's nonperforming and non-accruing loans to total loans; CAPITAL is the ratio of bank shareholder equity to total assets, and DEPOSITS is the logarithm of the bank's deposits. SHAREFAILED is the ratio of failing banks' assets to total bank assets in a given district each quarter, disregarding the assets of each bank itself. FDICIA is a dummy variable that takes value 1 in years during which FDICIA was in force, starting in 1993, and INTERBANK is a variable which takes value 1 after each state lifts restrictions on interstate banking. Post-interstate subsample includes years after which interstate banking restrictions in target bank states were lifted, Post-FDICIA period is post-1993, and Crisis years are considered to be 1986-1992 and 2007-2010. All regressions control for employment ratio in the failing bank's state, the ratio of state budget surplus to total income, and district-level income growth, income per capita, and the natural logarithm of population. Robust standard errors are reported in parentheses, * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

	Pr(liquidation)								
SAMPLE	Whole sample					Post-interstate	Post-FDICIA	Non-crisis	Crisis
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CORRUPTION_t	0.884***	0.869***	1.953*	0.251***	0.254**	0.775*	-3.993	-0.569	1.406***
	(0.306)	(0.307)	(1.060)	(0.0704)	(0.116)	(0.466)	(3.409)	(1.372)	(0.386)
DEPOSITS_{t-1}	-0.888	-1.031	-1.537	-0.194	-0.200	-0.441	0.438	-0.0425	-1.391
	(0.738)	(0.773)	(0.999)	(0.181)	(0.181)	(0.952)	(2.348)	(1.869)	(0.890)
SIZE_{t-1}	0.844	1.018	1.533	0.181	0.188	0.456	-0.376	0.215	1.337
	(0.725)	(0.772)	(0.991)	(0.177)	(0.177)	(0.948)	(2.352)	(1.838)	(0.875)
ROA_{t-1}	-2.443	-2.877	-7.987	-0.121	-0.114	-9.796	-9.914	13.58	-7.655
	(5.087)	(5.081)	(5.509)	(1.039)	(1.046)	(6.759)	(21.52)	(12.85)	(6.115)
CAPITAL_{t-1}	15.77***	15.90***	27.91***	3.266**	3.197**	27.33***	-55.68	6.755	28.11***
	(5.918)	(5.919)	(7.712)	(1.399)	(1.403)	(9.814)	(40.85)	(10.70)	(8.933)
NONPERF_{t-1}	0.276	0.262	-0.496	0.0325	0.0176	2.188	-11.89**	1.080	0.844
	(1.414)	(1.413)	(1.690)	(0.316)	(0.317)	(1.901)	(5.863)	(3.030)	(1.697)
SHAREFAILED_t		-5.076	-5.600	0.376	0.340	-5.089	3.481		
		(5.913)	(8.180)	(0.351)	(0.343)	(6.217)	(19.56)		
CORRUPTION_t x FDICIA				-0.202**					
				(0.0931)					
FDICIA				0.000647					
				(0.138)					
CORRUPTION_t x INTERBANK					-0.0723				
					(0.130)				
INTERBANK					0.0500				
					(0.0808)				
Model	Probit	Probit	Probit	Linear	Linear	Probit	Probit	Probit	Probit
State/district level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State effects	Yes	Yes	Np	Yes	Yes	Yes	Yes	Yes	Yes
Date effects	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes
State-year effects	No	No	Yes	No	No	No	No	No	No
No. Obs.	1021	1021	724	1342	1342	733	208	163	797
Pseudo-R^2/Adj. R^2	0.346	0.355	0.360	0.126	0.124	0.362	0.281	0.350	0.369

Resolution Costs

Finally, Table 3.12 examines whether higher corruption results in costlier bank resolutions. As a measure of bank resolution costs, I use the ratio of costs estimated by the FDIC to failing bank's total assets in the preceding quarter. The estimated costs incurred by the FDIC indicate the size of assistance in a purchase and assumption transaction, or the difference between the value of insured deposits and the funds recovered as assets mature or are sold in cases when the bank is liquidated. As the FDIC provides data on resolution costs starting only in 1986, the analysis does not include years 1976 to 1985.

The results are by and large supportive of corruption increasing resolution costs. The baseline regression model over the whole sample period indicates that when corruption increases by 1 conviction per 100,000 inhabitants, the resolution cost to the FDIC increases by around 5% of the failing bank's assets in the previous quarter (or around 1% of the failing bank's assets for a 1 s.d. increase). The result remains strong when I control for bank characteristics before assumption by the FDIC, or state- and district- level economic conditions.

In column 3, I also control for the bank's resolution method, the proportion of banks failing in a given district other than the bank in question, and whether the bank is acquired by an entity from another area. It can be seen that as expected, liquidations are associated with higher costs to the FDIC, but the corruption variable remains significant. Meanwhile, it does not appear that the share of banks failing, or being acquired from an outside institution, affects resolution costs considerably once the other factors are controlled for.

I also test for how easier entry by outsiders, and the introduction of the least-cost criterion for the FDIC when resolving failing banks, affected the relationship between corruption and resolution costs. The theoretical model predicts that outside entry might make bank resolution less costly, as it allows for a larger number of outside acquirers. In column 5, the interaction term does not indicate the existence of such effects, and using only the period in which entry restrictions were eased in column 6 provides somewhat stronger effects when compared to the whole sample, which is in contrast to the model's predictions. At the same time, the regressions also already control for the resolution method and acquirer location. Meanwhile, during the post-1992 period in which bank supervision is guided by prompt corrective action and least cost resolution, the effects of corruption have been stronger. This finding can potentially be attributed to the clearer definition of the FDIC mandate of cost minimisation, which allows the effects of corruption to be better identified.

When the sample is split to crisis and non-crisis years, the significance of the corruption variable disappears in the non-crisis subsample. This finding is in line with the other results of corruption becoming more relevant for bank resolution in crisis times. For the crisis years, the relationship also appears to be weaker when bank resolution method is controlled for. However, as political corruption has been shown to be related to a higher risk of bank liquidations and assumptions from outside banks, it also controls for the direct effects that corruption has on bank failure costs.

Overall, these findings together with the other results presented in Section 3.3 provide a broad picture on how corruption is related to bank resolution methods and costs. It appears that in areas with a higher number of public officials' convictions, banks are less likely to participate in auctions for failing bank assets by the FDIC, failing banks being more likely to be acquired by outsiders. However, outside entry does not eliminate the higher risk of costly liquidations.

Table 3.12: Corruption and Bank Resolution Costs.

Notes: This table presents estimates of a linear regression model in which the dependent variable is the ratio of resolution costs reported by the FDIC to the failing bank's assets in the quarter before closure. The sample includes all banks that failed during 1976-2013 except for institutions getting financial assistance and not losing their charter The sample includes bridge banks, and excludes cases in which multiple banks belonging to the same holding company failed together. The independent variable of interest, corruption, is the ratio of average 5-year number of convictions to the average population in 100,000 in a given bank's district. SIZE is the natural logarithm of total bank assets; LOANS is the natural logarithm of total loans; NONPERF is the ratio of bank's nonperforming and non-accruing loans to total loans; CAPITAL is the ratio of bank shareholder equity to total assets, and DEPOSITS is the logarithm of the bank's deposits. SHAREFAILED is the ratio of failing banks' assets to total bank assets in a given district each quarter, disregarding the assets of each bank itself. LIQUIDATION is a dummy variable which takes value 1 if a failing bank is liquidated, and 0 if it is resolved through a purchase and assumption transaction. DISTRICTCHANGE takes the value of 1 if in the case of resolution through a purchase and assumption transaction, the acquiring and target banks are located in different districts, and zero otherwise. FDICIA is a dummy variable that takes value 1 in years during which FDICIA was in force, starting in 1993, and INTERBANK is a variable which takes value 1 after each state lifts restrictions on interstate banking. Post-interstate subsample includes years after which interstate banking restrictions in target bank states were lifted, Post-FDICIA period is post-1993, and Crisis years are considered to be 1986-1992 and 2007-2010. All regressions control for employment ratio in the failing bank's state, the ratio of state budget surplus to total income, and district-level income growth, income per capita, and the natural logarithm of population. Robust standard errors are reported in parentheses, * p<0.10, ** p<0.05, *** p<0.01.

	FDIC COSTS/BANK ASSETS										
SAMPLE	Whole sample					Post-interstate	Post-FDICIA	Non-crisis		Crisis	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$CORRUPTION_t$	0.0564**	0.0564**	0.0434*	0.0219	0.0261	0.0568**	0.121**	0.0151	-0.0168	0.0463**	0.0295
	(0.0234)	(0.0234)	(0.0233)	(0.0253)	(0.0392)	(0.0286)	(0.0482)	(0.0926)	(0.0969)	(0.0232)	(0.0230)
$DEPOSITS_{t-1}$	0.440***	0.443***	0.456***	0.456***	0.454***	0.502***	0.332***	0.333*	0.295	0.447***	0.476***
	(0.0632)	(0.0642)	(0.0631)	(0.0627)	(0.0630)	(0.0666)	(0.0985)	(0.193)	(0.199)	(0.0665)	(0.0662)
$SIZE_{t-1}$	-0.448***	-0.452***	-0.464***	-0.463***	-0.462***	-0.510***	-0.361***	-0.364*	-0.334*	-0.452***	-0.482***
	(0.0622)	(0.0636)	(0.0624)	(0.0621)	(0.0624)	(0.0658)	(0.0962)	(0.189)	(0.196)	(0.0654)	(0.0656)
ROA_{t-1}	0.198	0.204	0.244	0.229	0.225	0.178	1.350	-0.327	-0.290	0.0674	0.137
	(0.441)	(0.441)	(0.433)	(0.432)	(0.433)	(0.475)	(0.838)	(1.202)	(1.194)	(0.465)	(0.456)
$CAPITAL_{t-1}$	0.403	0.409	0.232	0.206	0.209	-0.0589	-0.188	6.925***	6.889***	-0.390	-0.642
	(0.523)	(0.524)	(0.523)	(0.523)	(0.525)	(0.606)	(0.739)	(2.414)	(2.285)	(0.528)	(0.519)
$NONPERF_{t-1}$	0.433***	0.434***	0.437***	0.433***	0.437***	0.432***	0.699***	0.504	0.531	0.430***	0.428***
	(0.111)	(0.111)	(0.110)	(0.110)	(0.111)	(0.118)	(0.200)	(0.353)	(0.345)	(0.116)	(0.115)
$SHAREFAILED_t$		0.0703	0.0534	0.0391	0.0538	0.0767	0.155		0.534		0.193
		(0.169)	(0.164)	(0.162)	(0.164)	(0.162)	(0.133)		(2.152)		(0.159)
RESOLUTION			0.0539***	0.0555***	0.0544***	0.0583***	0.0380		0.0296		0.0599***
			(0.0115)	(0.0116)	(0.0116)	(0.0130)	(0.0287)		(0.0489)		(0.0118)
DISTRICTCAHNGE			-0.00170	-0.00244	-0.00190	-0.000767	-0.00119		0.0332		-0.000272
			(0.00846)	(0.00846)	(0.00847)	(0.00892)	(0.0124)		(0.0202)		(0.00935)
$CORRUPTION_t$ x FDICIA				0.0796*							
				(0.0458)							
FDICIA				-0.124							
				(0.0815)							
$CORRUPTION_t$ x INTERBANK					0.0264						
					(0.0459)						
INTERBANK					0.00639						
					(0.0313)						
State/district level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed state effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed date effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. Obs.	1180	1180	1180	1180	1180	1043	457	204	204	976	976
Adj. R^2	0.257	0.256	0.273	0.275	0.272	0.283	0.379	0.404	0.411	0.275	0.298

3.4 Conclusions

Empirical results presented in this paper demonstrate that even in highly-regulated industries, and countries with strong institutions, perverse effects of corruption can still be observed. Studying the methods and costs of failing bank resolutions in the US shows that the FDIC suffers higher losses in bank failures in more corrupt areas, such banks also running a higher risk of being liquidated.

As several studies have shown that areas with higher corruption levels suffer weaker development, pointing mostly to its effects on investment, these findings suggest one more channel through which corruption might hurt growth. Although FDIC losses need not affect local economies directly, higher risk that failing banks are liquidated, or assumed by outsiders, could potentially have such consequences. Furthermore, if these effects are present in countries with arguably strong institutions, it can be expected that the repercussions might be even worse in states with higher corruption levels.

The findings in the paper also provide several directions for future research. It is important to understand how supervisory agencies, as well as bank creditors or depositors, incorporate the expected costs of corruption in their decisions from the ex-ante perspective. For example, existing studies suggest that firms react to the risk of political expropriation by increasing their leverage, and investors require higher return for bonds issued by corrupt municipalities. In the financial sector, this could lead to lower stickiness in banks' funding structures if creditors react to the higher liquidation risk, and costlier capital. Another potential research direction concerns the extent to which corruption and regulatory forbearance are related. The reluctance by supervisory agencies to discipline or close weak banks could also explain worse outcomes in resolution, the effects potentially varying with electoral or other political pressures.

Appendix 3.1. Data Sources

Notes: this table presents the definitions and data sources of the variables used in analysis.

Variable	Description	Data source
CORRUPTION	Annual frequency data. It is the number of politicians' convictions per 100,000 inhabitants at judicial district level averaged over 5 years, divided by 5-year average district population. The data on public officials' convictions comes from the Public Integrity Section (PINS) at the US DoJ. PINS oversees enforcement actions against elected and appoinnted federal, state, and local officials who participate in criminal misconduct and election crimes.	Data on the number of convictions at the judicial district levels comes from DoJ PINS publications "Reports to Congress on the Activities and Operations of PIN", population data comes from Bureau of Economic Analysis/Census Bureau.
SIZE	Quarterly data. It is the natural logarithm of a bank's total assets (rcfd2170) in real terms (2000 price level=1).	Bank Call report data obtained from Bank Regulatory Database on Wharton. Price level information is from CPI Detailed Report for December 2015 produced by the Bureau of Labour Statistics.
DEPOSITS	Quarterly data. It is the natural logarithm of a bank's total deposits (rcfd2200) in real terms (2000 price level=1).	Bank Call report data obtained from Bank Regulatory Database on Wharton. Price level information is from CPI Detailed Report for December 2015 produced by the Bureau of Labour Statistics.
NONPERF	Quarterly data. It is the ratio of a bank's loans that are 90+days late and still accruing (rcfd1407) and nonaccruing loans (1403) to gross total loans and leases (rcfd1400) in nominal terms.	Bank Call report data obtained from Bank Regulatory Database on Wharton.

Variable	Description	Data source
CAPITAL	Quarterly data. It is a measure of a bank's leverage/capitalisation. It is the ratio of a bank's equity equity/assets$_{t-1}$ (rcfd2200) to total assets (rcfd2170) in nominal terms.	Bank Call report data obtained from Bank Regulatory Database on Wharton.
CASH	Quarterly data. It is a measure of a bank's liquidity. It is the ratio of a bank's holdings of cash and equivalent (rcfd0010) to total assets (rcfd2170) in nominal terms.	Bank Call report data obtained from Bank Regulatory Database on Wharton.
LOANS	Quarterly data. It is the natural logarithm of a bank's gross total loans and leases (rcfd1400) in real terms (2000 price level=1).	Bank Call report data obtained from Bank Regulatory Database on Wharton. Price level information is from CPI Detailed Report for December 2015 produced by the Bureau of Labour Statistics.
ROA	Quarterly data. It is a bank's ROA calculated as the ratio of net income (riad4340) to total assets (rcfd2170) in nominal terms, and multiplied by 100.	Bank Call report data obtained from Bank Regulatory Database on Wharton.
EMPL	State-level annual data. It is calculated as the ratio of employment (number of jobs) at the state level to the state's population. I use it over unemployment because for the latter, data before 1980 is scarce.	Data for employment and population were obtained from the Bureau of Economic Analysis website.
SURPLUS	State-level annual data. It is calculated as the ratio of state's budget surplus to total income: (tax revenues-state expenditures)/state income at nominal level.	Data were obtained from the Bureau of Economic Analysis.
POPUL	District-level annual data. It is the natural logarithm of total district-level population. District-level data generated by using county-level information and aggregating to the district level.	Data on aggregate income comes from U.S. Department of Commerce Bureau of Economic Analysis Regional Income Division.

Variable	Description	Data source
INCOME	District-level annual data. It is the natural logarithm of per capital personal income (thousands of dollars) at the district level, expressed in real terms (2000 price level=1). The variable is generated by dividing total district income by total district population. District-level data for total income and population are generated by using county-level information and aggregating to the district level.	Data on aggregate income and population comes from U.S. Department of Commerce Bureau of Economic Analysis Regional Income Division, and Price level information is from CPI Detailed Report for December 2015 produced by the Bureau of Labour Statistics.
GROWTH	District-level annual data. It is the growth in total per capita district income in real terms, using INCOME.	Data on aggregate income comes from U.S. Department of Commerce Bureau of Economic Analysis Regional Income Division, and Price level information is from CPI Detailed Report for December 2015 produced by the Bureau of Labour Statistics.
SHAREFAILED	District-level quarterly data. The variable is generated by dividing the total assets of banks failing by total assets of banks operating in the district (rcfd2170). For failing banks, information for the quarter before closure is used. Total district banking assets do not include the assets of failing banks. For failing banks, the SAHREFAILED variable does not incorporate their value.	Total bank assets comes from Bank Call report data obtained from Bank Regulatory Database on Wharton. Data on bank failures comes from the FDIC "Failures and Assistance Transactions - Historical Statistics on Banking" database.
FAILCOST	Bank-level data. The variable is generated by dividing the FDIC reported losses for failing banks by their assets the previous quarter (rcfd2170).	Total bank assets comes from Bank Call report data obtained from Bank Regulatory Database on Wharton. Data on bank failures comes from the FDIC "Failures and Assistance Transactions - Historical Statistics on Banking" database.