Essays on Contagion Effects of Corporate Frauds and Bond Defaults

by

Xin Cheng

A Dissertation submitted to the

Graduate School – Newark

Rutgers, The State University of New Jersey

in partial fulfillment of the requirements

for the degree of

Doctor of Management

Graduate Program in Finance

written under the direction of

Simi Kedia

and approved by

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Newark, New Jersey

May, 2017

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ABSTRACT OF THE DISSERTATION

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By Xin Cheng

Dissertation Director:

Simi Kedia

This dissertation is consisted of two essays to study contagion effect. The first essay investigates the role of supply chain links in spread and detection of corporate frauds. We examine and find that firms are more likely to begin misconduct if their current customers or suppliers are cheating. The effects are both statistically and economically significant. This higher likelihood of engaging in misconduct could be to preserve the value of their relationship specific investment that loses value if the cheating customer gets discovered. We find no support for this *Relationship Hypothesis*. We also examine if greater exposure to wrongful practices in the supply chain encourages the diffusion of these practices and find support for this *Exposure Hypothesis*. Lastly, we examine if discovery of a cheating customer increases the likelihood of firm's detection. We find that recent detected customer is associated with a higher likelihood of detection and a significantly lower time to detection providing strong support for the *Detection Hypothesis*.

In the second essay, we focus on state spillover effects of defaults in municipal bond market over 2000 to 2014. We document a significant price decline, -2.98% around the default. The price declines are greater for revenue bonds and bonds with no credit enhancement. We also find that on average, the abnormal price change for non-defaulted

bonds is about -1.1%. The reaction is bigger if the price change of defaulted bond is more negative or the portion of momentary defaults is higher. In addition, past defaults significantly raise the cost of new municipal borrowing from the same state. The evidence suggests that defaults are not rare, and have a significant negative effect on all municipal issuers from the same state.

ACKNOWLEDGEMENT

This dissertation was made possible with the help of many kind people. I would to give the special thanks to my advisor, Professor Simi Kedia. During my five years as a Ph.D. student, I learned from you how to be a serious and qualified researcher. I really appreciate your trust and your helps in my research. You are also my mentor to help me get my Ph.D. life on track. When I was stuck in research and thought about surrendering, you always encouraged and comforted me. Your academic spirits (Diligence, Modesty, Kindness, Passion etc.) will inspire and lead me in future career. Also, I'm grateful for the guide provided by Professor John Kose, Professor Yangru Wu, Professor Rose Liao and Professor Serdar Dinc who gave helpful suggestions and generous support.

I'm indebted to my parents for their unconditional love and support so that I can dedicate to research. Without their support, I'm not able to finish the degree.

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Chapter 1: Customer-Supplier Links: Spread and Detection of Corporate Misconduct

1. Introduction

The latest in the long list of corporate wrongdoing is Volkswagen's effort to circumvent U.S diesel emissions over several years. Though, Volkswagen was initially under investigation by the EPA its wrongdoings have sparked shareholder class action litigation for making misleading statements and omissions to investors regarding the company operations.[1] The investigation into Volkswagen has embroiled Bosch, a long time supplier of Volkswagen, that built key components in the diesel engines that Volkswagen has admitted were used to defeat emission tests. Federal prosecutors with the Department of Justice are examining whether Bosch knew of or participated in Volkswagen's rigging of emissions tests.[2] This case highlights the fact that the perpetuation, mitigation or detection of corporate misconduct is not an isolated firm decision but rather made amidst a nexus of linkages that span suppliers and customers. Another example is the case of Cardinal Health and three of its suppliers InterMune, Bradley Pharmaceuticals, and Medicis Pharmaceutical Corporation that were all subject to class action lawsuits for issuing false and misleading statements regarding their financial performance over the period from 2000 to 2008. In this paper, we examine the

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[1] For details see http://www.rgrdlaw.com/cases-volkswagen.html. Volkswagen is also subject to the first Bondholder class action lawsuit (See http://www.cnbc.com/2016/06/21/bondholders-file-proposed-class-action-against-volkswagen.html)

[2] "US probes Bosch in VW Cheating Scandal: Sources" – Friday, Nov 19, 2015 and available at http://www.reuters.com/article/us-volkswagen-emissions-probe-exclusive-idUSKCN0T82Q320151119

role of fraudulent customers and suppliers in the firm's propensity to also adopt wrongdoing and its possible detection.

There are several channels through which a firm's decision to engage in wrongdoing can be impacted by the presence of fraudulent customers and suppliers. First, economic linkages through the supply chain usually involve investment in relationship specific assets. As these investments are specific to the customer or the supplier, their value depends on the future prospects of this business relation. Negative financial shocks like financial distress or misconduct by the customer or the supplier are likely to significantly reduce the value of a firm's relationship specific investment. When faced with a customer or supplier that is engaged in wrongdoing, the firm is more likely to stay silent, and possibly facilitate the continuation of the misconduct if the relationship is important and the relationship specific investment at stake is large. This *Relationship Hypothesis* predicts that the stronger the economic relationship of the firm to its fraudulent customer or supplier the more likely it is to engage in wrongdoing.

Supply chain linkages not only involve economic dependence but also provide an opportunity for firms to interact with their suppliers and customers and to learn about each other's practices. Prior research has shown that green activities and adoption of organization practices spread down the supply chain.[3] Firms are likely to learn about questionable practices or aggressive accounting strategies that others in the supply chain follow and may be influenced into adopting these. A recent literature documents that corporate misconduct spreads through industry, geography, and common board of

[3] Vachon and Klassen (2006) find evidence of environmental collaboration with primary suppliers. Corbett (2006) reports that ISO 9000 series of quality management systems standards is widely diffused through global supply chains.

directors.[4] This *Exposure Hypothesis* suggests that the nexus of economic linkages in the product market are an important conduit through which firms learn and adopt negative corporate practices. The greater the exposure of the firm to wrongful practices in the supply chain the greater is the likelihood that a firm also adopts these practices.

Lastly, the discovery of misconduct by a firm might put its customers and suppliers in the spotlight with the regulators and capital market participants. This is illustrated in the Volkswagen scandal where it was the discovery of fraud at Volkswagen that generated the investigation into Bosch, its supplier. This implies that firms with extensive supply chain connections face the risk that if any firm in the supply chain were to be discovered in misconduct it would significantly increase regulatory attention over the supply chain. The *Detection Hypothesis* suggests higher likelihood of detection, conditional on having engaged in misconduct, when customers and suppliers are discovered as engaging in misconduct.

This study of the effect of fraudulent customers and suppliers on the propensity to engage in misconduct complements prior work that has examined earnings management in the supply chain. Raman and Shahrur (2009) document that firms are more likely to manage accruals and report higher earnings to encourage suppliers to invest in relationship specific assets. This management of accruals is not seen in the presence of important customers possibly because reporting higher earnings may encourage customers to ask for concessions. We control for these incentives for managing earnings

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[4] See for example Kedia, Koh and Rajgopal (2015) for industry and geographic diffusion, Bizjak , Lemmon and Whitby (2009) and Chiu, Teoh and Tian (2013) for the role of board connections and Francis and Michas (2013) for the role of auditors in the spread of earning management practices.

that arise in supply chain networks and focus on how the presence of wrongful practices impacts hitherto clean firms in the supply chain.

We begin by examining the role of fraudulent customers and suppliers on the firm's propensity to engage in wrongdoing. We then examine whether this effect can be explained by the *Relationship Hypothesis*, the *Exposure Hypothesis* or *the Detection Hypothesis*. Our sample consists of all firms in COMPUSTAT with required data over the period 1998 to 2013. We collect data on the key customers, i.e., those that account for at least 10% of firm sales. Over this time period, on average, 45% of firm years report having a public or private corporate customer. As we know the important customers, we can use this to construct a dataset of suppliers. However, this does not give us a list of important suppliers only those that listed a public firm as a customer. Consequently, the list of suppliers is small and on average only 8% of the firms have suppliers in our sample. Due to the paucity of the supplier coverage, and further because the suppliers that are identified need not be the more important suppliers, we examine and report the results on suppliers in the end.

We proxy misreporting by class action litigation obtained from the Securities Class Action Clearinghouse. As we examine the decision to engage in wrongdoing we keep only the first identifiable lawsuit for the firm. The final sample consists of 956 lawsuits with non-missing controls from 1998 to 2013. We find that the presence of fraudulent customer or supplier is significantly positively associated with the likelihood of engaging in wrongdoing. The effects are economically large. The presence of a cheating customer is associated with a 38% increase in the likelihood of misconduct over 1.27% the unconditional likelihood of misconduct. This result is robust to a host of firm and industry controls. The result is also robust to excluding lawsuits that were dismissed, and using other proxies of misconduct like restatements and SEC enforcement actions.

We next examine the channels through which fraudulent customers potentially impact the decision of a firm to engage in misconduct. If the firm begins misconduct to preserve its relationship with the fraudulent customer or the value of its relationship specific assets, then the likelihood of engaging in misconduct should be increasing in the intensity of the relationship with the fraudulent customer. We test the *Relationship Hypothesis* by using several measures to capture the strength of the relationship with the fraudulent customer. As firms report the value of sales to customers, we use share of sales to the fraudulent customer along with the duration and trend of the relationship. In line with prior work, we also use firm's R&D expenses and cross citations of patents with the fraudulent customer to capture the relationship specific investment at stake. Overall, there is little evidence to support the *Relationship Hypothesis*. The likelihood of adopting wrongful practices is not increasing in the strength of the economic relationship with the fraudulent customer.

Firms may begin misconduct in the presence of fraudulent customers not to preserve the relationship but because they get exposed to and learn about these practices. According to the *Exposure Hypothesis*, the likelihood of engaging in wrongful practices increases with the exposure to these practices. To test this hypothesis, we identify exposure in the supply chain that is unlikely to involve relationship specific investment. First, we identify customers that were important in the past but not currently. Though they do not meet the 10% of sales threshold currently they are likely to still be customers of the firm with regular interactions. Presence of fraudulent prior customers exposes a firm to wrongful practices without risk to relationship specific assets. Second, we identify shared suppliers, that is, firms that are suppliers to the same customer and shared customers, that is, firms that have the same supplier. A firm is unlikely to have any relationship specific assets with a shared supplier or a shared customer but is likely to be exposed to and learn from their practices. We test and find that the likelihood of misconduct increases in the presence of fraudulent prior customers and fraudulent shared suppliers and customers providing support for the *Exposure Hypothesis*.[5]

Lastly, we examine if the higher likelihood of misconduct in the presence of a fraudulent customer is due to increased likelihood of detection. Discovery that a customer is cheating is likely to increase oversight on the firm and consequently its likelihood of detection. To examine this *Detection Hypothesis*, we begin by examining if detection is faster if a customer is recently discovered as cheating. Using both OLS and COX proportional Hazard model and controlling for other factors that impact detection, we find that recent discovery of a fraudulent customer is likely to hasten the discovery of misconduct in a firm by about 92 days. As the unconditional days to discovery in our sample is 497 days, this is a 18.5% reduction in the time to detection.

As we observe only detected fraud, the above analysis suggests that conditional on being detected, the recent discovery of a fraudulent customer is associated with faster discovery. However, it is likely that many firms that engage in misconduct do not get caught. Dichev et al (2013) report that 60% of CFOs say that managers misreport because they feel they will go undetected. Recent discovery of a fraudulent customer

[5] The results are similar when we exclude dismissed lawsuits. However, the evidence in support of the *Exposure Hypothesis* is much weaker when we examine restatements.

may increase the likelihood that a firm gets detected or reduces the likelihood that the firm's misconduct is never revealed. To shed light on this we attempt to proxy for the likelihood of committing wrongdoing irrespective of whether it is detected. Several papers find that short sellers are able to predict misconduct (see Desai, Krishnamurthy, and Venkataraman (2006), Karpoff, and Lou (2010), and Efendi, Kinney, and Swanson (2005)). In line with Call, Kedia and Rajgopal (2016) we estimate the abnormal short interest and use it to proxy for the firm's likelihood of having cheated. We validate the measure and find that high abnormal short interest is associated with significantly higher detected misconduct. Using high abnormal short interest to capture firms more likely to be cheating, we find that recent discovery of a fraudulent customer is associated with a significantly higher likelihood of detection. In summary, discovery of misconduct in a customer significantly increases the likelihood of detection conditional on the firm having committed a violation.

As mentioned earlier, the incidence of suppliers is substantially smaller in our sample. Though we find that the presence of a fraudulent supplier is associated with a significantly higher likelihood of adopting wrongful practices, we do not find any evidence in support of the *Relationship, Exposure* or the *Detection Hypothesis*. This likely reflects data limitations in constructing the supplier dataset.

Our results make several contributions. The results highlight that firms are more likely to engage in misconduct when they encounter cheating in customers or suppliers. This suggests that wrongful practices are likely to cluster within supply chain networks. As discussed earlier over the period from 2000 to 2008, Cardinal Health and three of its suppliers InterMune Inc, Bradley Pharmaceuticals, and Medicis Pharmaceutical

Corporation Inc. were all subject to class action lawsuits for issuing false and misleading statements regarding their financial performance.[6] This result that misconduct spreads and is clustered in the supply chain is important for understanding the perpetuation and mitigation of misconduct. Regulatory reforms directed at improving governance and disclosure practices within a firm can increase their efficacy by factoring in the sensitivity of the firm to its customers and suppliers policies. Further, customer and suppliers of fraudulent firms have the potential to be among the first to be aware of the firm's wrongful practices. Regulations that increase the incentives of customers and suppliers to "whistle blow" can be effective in the mitigation of misconduct.

The results also highlight that economic links between customers and suppliers can serve as a conduit of learning and information about corporate practices. Existing literature highlights the importance of industry membership, geographic proximity, common directors and auditors as potential conduits of learning. The results in this paper highlight that having a principal customer or a supplier, seen in 53% of firm years in COMPUSTAT can be a significant channel for the diffusion of corporate practices. Regulations aimed to deter misconduct or influence corporate practices are likely to be more effective if they focus on firms and industries more central in the supply chain networks.

[6] Only Medicis Pharmaceutical was charged for issuing material inaccurate financial statements. Specifically, Cardinal Health was sued on July 2, 2004 for violations over the period Oct 24, 2000 to June 30 2004. InterMune Inc. was sued on September 13 2000 for violations over the period April 18 2000 to August 18 2000. Bradley Pharmaceuticals was sued on March 2 2005 for violations over October 8 2003 to Feb 25, 2005. Medicis Pharmaceutical Corp. was sued on Oct 3 2008 for violations over Oct 30, 2003 to Sept 24 2008.

Lastly, the results also suggest that individual firms may underestimate the likelihood of detection if they fail to see the links with other firms. A firm's likelihood of detection increases significantly if its customer firm gets caught with wrongdoing. Firms with several supply chain linkages should internalize this higher risk of detection in their decision to engage in wrongdoing.

2. Hypothesis and Literature Review

Key customers that account for 10% or more of the firm sales are important to the firm. Patatoukas (2012) documents that concentrated customers are associated with higher firm performance due to efficiency gains in selling costs and enhanced asset utilization.[7] Along with the importance of key customers for firm value, the firms dealing with key customers and suppliers are often required to invest in relationship specific assets. As these investments are specific to the particular customers or supplier, the value of the relationship specific investment is higher within the relationship than outside it. Since the value of the relationship specific investment undertaken by customers and supplier declines when the firm is in financial distress, prior literature finds that firms commit to lower debt levels and a lower likelihood of distress to encourage relationship specific investment by suppliers and customers (See Maksimovic and Titman (1991) and Kale and Shahrur (2007)). In a similar vein, Raman and Shahrur (2009) document that firms are more likely to manage accruals and consequently report higher earnings to encourage suppliers to invest in relationship specific assets. This incentive to manage earnings in the supply chain is different from our interest which is on the spread of misconduct, and how the decision to engage in misconduct is impacted by the presence of fraudulent customers and suppliers.

When a firm's customer or supplier firm is cheating, it jeopardizes the firm's relationship and the value of its relationship specific investments. Indeed, Kang, Tham and Zhu (2012) document negative stock price reactions for dependent firms when

[7] Concentrated customers may come with higher risks due to their increased bargaining power and undiversified risk (See Klein, Crawford and Alchian (1978) and Williamson (1979) among others)

customers announce restatements. If the customer is not very important and relationship is weak, or if the relationship investment at stake is not large, the firm may choose to terminate its relationship with the fraudulent customer or supplier. However, the stronger the relationship with the fraudulent customer or supplier and the greater the value of relationship specific investment that is at stake, the greater is the chance that the firm will facilitate and potentially collaborate in the wrongdoing. This leads to the *Relationship Hypothesis* which can be stated as

H1: The stronger the relationship with the fraudulent customer or supplier and greater the value of relationship specific investment at stake, the greater is the likelihood that a firm will engage in misconduct.

Links with customers and suppliers also provide channels of information flows (Filson and Morales 2006). Vachon and Klassen (2006) find evidence of environmental collaboration with primary suppliers. Corbett (2006) reports that ISO 9000 series of quality management systems standards is widely diffused through global supply chains. In a recent paper, Cen et al (2014) document that customer supplier relationships promote the diffusion of tax avoidance knowledge. Firms can acquire information about specific fraudulent practices, along with the costs and benefits of misconduct from their supply-chain partners that are engaged in these activities. The evidence that customers or supplier are engaged in misconduct may also provide moral justification and increase comfort with unethical behavior. Recent literature examines how corporate misconduct and earnings management diffuse through channels of geographic proximity and industry membership (Kedia, Koh and Rajgopal (2015)) and common board members (See

Chiu,Teoh, and Tian(2012)). In this paper, we hypothesize the potential role of customer supplier linkages in the diffusion of wrongdoing across firms.

It might be argued that misconduct is not transparent or easily observed and therefore difficult to be mimicked by customers or suppliers. However, Briscoe and Murphy (2012) study the inter organizational diffusion of controversial practices and document that as adoption decisions are embedded within a web of conflicting interests, transparency may bring negative attention that may inhibit others from following suit. Opacity, in contrast avoids this. Briscoe and Murphy (2012) examine curtailment of health benefits for retirees among firms and document that transparent adoptions, in contrast to opaque one, inhibit future adoption.[8] This suggests that the diffusion of negative practices like misconduct is facilitated rather than hindered by the fact that the practices are opaque rather than widely known and observed. This leads to our *Exposure Hypothesis* that states

H2: The greater the exposure to wrongful practices in the supply chain, the greater is the likelihood that firms will adopt these practices.

Lastly, we examine the possibility that the higher observed misconduct of firms in the presence of a fraudulent customer or supplier is due to a higher likelihood of detection. Discovery of misconduct by a firm may increase regulatory and capital market oversight on its customers and suppliers, as highlighted by the case of Bosch discussed earlier. Prior work has examined the possibility that firm's influence the likelihood of detection of their wrongdoing. Yu and Yu (2011) document that corporate lobbying

[8] Briscoe and Murphy (2012) use partial or complete benefit cut as examples of transparent cuts and spending caps that trigger disenrollment as examples of opaque adoptions.

leads to a delay in detection of fraud. Khanna, Kim and Lu (2015) document that CEO connectedness helps to conceal frauds. In this paper, we examine another channel that affects the likelihood of detection. Discovery of misconduct in a firm may focus the spotlight on its supply chain and substantially increase oversight and the likelihood of detection. This leads to the *Detection hypothesis* that

H3: Likelihood of detection of misconduct increases with the recent Discovery of misconduct by a customer or supplier.

3. Data and empirical methodology

We proxy misreporting by class action litigation obtained from the Securities Class Action Clearinghouse. We identify 2,595 lawsuits with non-missing CUSIPs and class period information from 1996 to 2014. We exclude financial firms (SIC codes between 6000 and 6999) and utilities (SIC codes between 4900 and 4999) for a final sample of 1502 litigation.[9] The final samples of lawsuits used in the different tables vary based on the nature of tests and the control variables required. For the first set of tests that examine the decision to engage in misconduct, we restrict the sample to litigation where the first year of violation spans the period from 1998 to 2013. As the litigation sample begins in 1996 and we need the first two years to identify fraudulent customer and supplier firms.[10] The sample consists of 956 lawsuits for these tests. Later tests on detection include all litigations filed between 1997 and 2013 for a sample of 1,059 lawsuits.

Table 1, Panel A shows the frequency distribution for years when firms begin misconduct over the sample time period. Firms are classified as beginning misconduct in the earliest fiscal year that overlaps with the class period in the litigation. Not surprisingly, there is greater number of wrongdoing prior to 2002 with the numbers dropping after that possibly due to the implementation of SOX and the lowest levels over the financial crisis period of 2008 to 2009. Firms that begin cheating in any given year

[9] 2,218 lawsuits can be matched to COMPUSTAT. We include only the first lawsuit leaving us with 1,812 lawsuits. Excluding Financial and Utilities leaving us with a sample of 1502 lawsuits.

[10] As it takes time for the misconduct to be discovered, many of the firms that began misconduct in 2014 are unlikely to have been discovered by the end of 2014. Consequently, we end our sample in 2013.

are small: on average about 1.3% of firms begin misconduct. This is in line with other papers that use the class action litigation dataset.[11]

The next step is to identify supply chain relationships. In accordance with the Statement of Financial Accounting Standards (SFAS) No. 14 and 131, public firms have to disclose the identity of any customer that contributes at least 10% to the firm's revenues.[12] Column 4 of Table 1 displays the number of firms that report having a customer. On average, about 45% of firms over this period report having at least one important public or private corporate customer. Unlike customers, firms are not required to report important suppliers. We can however infer suppliers from the above customer disclosures. The coverage of suppliers is therefore limited, and on average we have only 8% of firm years having suppliers in the sample. Together, about 53% of firms in COMPUSTAT are associated with a customer or supplier.

As discussed we would like to examine how a firm's decision to cheat is impacted if it has customers or suppliers that are engaged in misconduct. To capture the presence of customers that are engaged in misconduct, we create an indicator variable, *Cheating Customer* that takes the value of one if a current customer is cheating. A customer is

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[11] See Kedia, Luo and Rajgopal (2016) and Peng and Roell (2008) among others.

[12] Some firms choose to report important customers that contribute less than 10% as well. We are grateful to Jayant Kale and Husayn Shahrur for providing us customer data from 1998 to 2004. For the later period we build the customer dataset. As only firm name, and often abbreviated firm names of customers are reported we use a combination of automatic and manual methods to match customer names with COMPUSTAT names. We follow Fee and Thomas (2004) by first using an algorithm that compares the number and order of the letters in the abbreviation with those in COMPUSTAT. Secondly, we use industry classification to verify matches. If we still cannot get a match, we use S&P capital IQ to find if the customer is a subsidiary, and if so match the customer to Parent Company.

considered current if it is disclosed as a key customer in either of the prior two years.[13] A current customer is considered as cheating if the prior two years was part of its class period. As seen in Table 2, 5.9% of firms that begin cheating have current customers that are cheating. In contrast, only 3.7% of clean firms, as proxied by class action litigation, have a current cheating customer. The difference is significant and suggests that presence of cheating customers is associated with a higher likelihood of engaging in misconduct.

To capture the presence of suppliers that are engaged in misconduct, we create a similar indicator variable, *Cheating Supplier* that takes the value of one if a current supplier is cheating. As before, a supplier is considered current if it disclosed the firm as an important customer in the prior two years. A current supplier is considered as cheating if the prior two years was part of its class period. As noted earlier, we do not have all the suppliers of a firm and consequently, the incidence of cheating suppliers is lower than that for cheating customers. About 3.8% of firms that begin cheating have current suppliers that are cheating. Whereas, only 0.8% of firms that do not cheat have current suppliers that are cheating. The difference is significant and suggests that the presence of cheating suppliers is associated with a higher likelihood of adopting misconduct. These are univariate results and below we control for other firm characteristics that have been shown to effect the decision to engage in misconduct.

[13] We include customers from two years prior as current customers. Important customers in year t-2 but not in year t-1, are likely to be those that do not meet the 10% of sales criteria for year t-1 but nevertheless continue to be significant customers.

4. Base Results

We begin by studying the decision of a firm to begin misconduct. We estimate a discrete logistic model where the dependent variable is Begin Misconduct, an indicator variable that takes the value of one if the firm begins misreporting in the year and zero otherwise.[14] We estimate the following empirical model:

$$BeginMisconduct_{it} = \gamma_0 + \gamma_1 CheatingCustomer_{it} + \gamma_2 CheatingSupplier_{it} + ControlVariables_{it-1} + \varepsilon_i,$$

The main variable of interest is the presence of a cheating customer and cheating supplier. We expect the coefficients of both to be positive and significant as the presence of cheating customer and supplier increases the likelihood of the firm adopting wrong practices.

We control for several firm characteristics that have been shown to impact misconduct. We control for firm size by including total assets. To control for growth opportunities, we include Tobin's Q and sales growth. We follow Richardson, Tuna, and Wu (2003) by including leverage as a proxy for closeness to debt covenant violations or cost of financial distress. To control for firm performance, we include accounting profitability as captured by ROA as well as stock return in the fiscal year. As firms with larger cash holding are more attractive to litigation, we include the ratio of cash to lagged total assets. As firms are more likely to misrepresent if they want to raise capital, we include Financing that is the ratio of new financing raised to total assets. Industry Q is the average industry Q and controls for industry level growth opportunities. We also include the ratio of R&D expenses to lagged total assets for the firm to control for its

[14] The subsequent years after the first year of misconduct are not included. Subsequent wrongdoing by the same firm is also not included. The first year of the misconduct is the earliest fiscal year that overlaps with the class period disclosed in the class action litigation.

relationship specific investment. Lastly we include two-digit SIC and year fixed effects. As stated earlier, the estimation includes all firms, which begin misconduct in 1998 and later as the earlier years are used to construct the cheating customer and cheating supplier variables.

The results are displayed in Table 3. The coefficient of Cheating Customer is positive and significant at the one percent level (Model 1). The effect is also economically significant. The marginal effect of a cheating customer is 0.49%. As the unconditional likelihood of misconduct is 1.27%, the presence of a cheating customer entails an increase of 38% in the likelihood of engaging in misconduct. The estimated effect of the control variables is as expected. Larger firms, with higher performance and more cash are more likely to engage in misconduct. Leverage, financing and industry growth opportunities are not significant in explaining the beginning of misconduct.

The coefficient for Cheating Supplier, in Model 2 is also positive and significant and does not impact the estimated coefficient for cheating customer. In model 3, we control for the characteristics of customer and supplier industry – specifically the R&D intensity in line with Raman and Shahrur (2008). Customer Industry R&D is the weighted average value of R&D to total assets of all firms in the customer industry, where the weights capture the sales to the customer industry from the input output tables from the Bureau of Economic Analysis. Similarly, Supplier Industry R&D is the weighted average of supplier industry R&D intensity, with the weights being share of inputs. Details on the construction of the variables are in Appendix A. Both the customer and supplier industry R&D are positive and significant suggesting that firms whose customers and suppliers need to make relationship specific investments are more likely to engage in misconduct. This is consistent with prior literature that documents greater earnings management in the presence of important supply chain linkages. In summary, the presence of a fraudulent customer and supplier is associated with a significantly higher likelihood of misconduct. In the next section, we examine the reasons why presence of cheating customers leads to a higher propensity to adopt wrongful practices.

5. Channels for the Effect of Fraudulent Customers

In this section, we examine why presence of a cheating customer and supplier is associated with higher misconduct. As noted earlier, whereas we have the important customers for a firm we do not have all the suppliers and more importantly may not have the large suppliers. Therefore, in this section we concentrate on the study of cheating customers and examine the effect of cheating suppliers later in the paper.

5.1. Relationship Hypothesis

The *Relationship Hypothesis* predicts that the effect of the fraudulent customer is larger when the relationship with the customer is stronger. A firm that is dependent on its customer is more likely to follow in the wrongdoing to preserve its performance and maintain the value of its relationship specific assets. We use several proxies to capture the strength of the relationship between a firm and its fraudulent customer.

Sales Dependency

Along with the name of the key customers, firms also disclose the sales to these customers. We estimate the fraction of the firm’s sales to each customer, referred to as sales dependency. The median sales dependency ratio for our sample of fraudulent customers is about 13.8%. If the sales to the fraudulent customer in the year prior are more than the median sales dependency, we classify the relationship with the cheating customer as strong and if it is less than the median sales dependency we classify it as having a weak relationship. As seen in Model 1 of Table 4, cheating customers that account for higher sales have a positive significant impact on the likelihood of misconduct. In contrast, the effect of cheating customers with lower sales dependency is insignificant. However, the difference between the two coefficients is not statistically significant.

Largest Customer

Next, we use the sales to the customer to identify the largest customer, i.e., the customer that accounts for the highest sales for the firm. The relationship with the cheating customer is classified as strong (weak) if the cheating customer is (not) the largest customer among all customers reported by the firm in the prior year. About 10% of the cheating customers in our sample are classified as the largest customer of the firm. As seen in Model 2, the effect of the largest cheating customer is stronger than that of other cheating customers. In sum, if the cheating customer is the most important customer they have a significantly larger impact on the firm's likelihood of misconduct.

Duration of the relationship

We also use duration of the relationship with the cheating customer to construct proxies for the strength of the relationship. We examine the prior five years and count the number of times the cheating customer was listed as a key customer. [15] About 47% of the cheating customers have three or more years in which they have been listed as key customers and are classified as having a strong relationship with the firm. Cheating customers that are listed as key customers in less than three years are classified as having a weaker relationship. As seen in model 3, cheating customers with a longer relationship have a significant effect on the firm's likelihood of cheating but it is not different from cheating customers with shorter relationships.

[15] Firms may have a stronger relationship with customers who have been key customers for a long period of time even though they do not classify as "key" in all years.

Trend in the relationship

The trajectory of the firm's relationship with the fraudulent customer can also reflect the strength of the relationship. If a fraudulent customer is increasing in importance, that is accounts for increasing fraction of the firm sales, then it is likely to be more valued than other key customers with a declining trend in sales dependency. We examine the past five years and calculate the average growth rate of sales to the fraudulent customer over this period. For customers with only one year as a key customer, about a third of the cheating customers, the sales growth is regarded as zero. We classify cheating customers as having a strong relationship if the average annual sales to them are growing at faster than 24%, which is the 75% percentile of the sample. As seen in Model 4, the effect of cheating customers that are becoming increasing important is positive and significant while that of others is not significant. The difference between the two is significant suggesting that fraudulent customers with increasing importance have a significantly greater impact on the likelihood of misconduct.

R&D Intensity

R&D intensity is often used as a proxy for relation specific investment in empirical literature on transactions cost economics (see Boerner and Macher (2001) for a review). Levy (1985) posits that research-intensive industries have specialized inputs and require relationship specific investment by suppliers (See also Allen and Philips (2000) and Kale and Shahrur (2008)).[16] We use the past five years of R&D to capture the existence of investment in relationship assets. Specifically, firms that report some R&D

[16] Allen and Philips (2000) suggest that research-intensive industries are more likely to create relationship-specific assets. Kale and Shahrur (2008) use the firm's R&D expense to proxy for the extent of relationship specific investment for the firm.

expense over the past five years, about 68.8% of firms with cheating customers, are classified as having relationship specific assets at stake. As seen in Model 5, the effect of firm with R&D expenses is positive and significantly higher than those without R&D.

However, not all R&D undertaken by the firm is specific to the cheating customer. To better capture the extent of R&D investment specific to the cheating customer, we use cross citation of cheating customer patents. The cross-citation of patents indicates the presence of communication between the scientists of both firms and is evidence of the integration between the firms (see Jaffe, Tratjtenberf and Fogarty (2000)). In line with Kale, Kedia and Williams (2015) we construct a measure of mutual citations from NBER updated patent database.[17] For any year, a firm is classified as cross citing its cheating customer patent if in the prior five years it cites a patent owned by the cheating customer and/or if the cheating customer cites a patent owned by the firm. In the sample, about a third of the firms that have R&D expenses cross cite patents of the cheating customer. As seen in Model 6, the extent of cross citation does not impact the effect of cheating customer suggesting that R&D specificity is unlikely to explain why presence of cheating customers is associated with greater propensity of adopting wrongful practices.

Overall, there is mixed evidence that cheating customers that are more important are associated with a higher likelihood of adopting wrongful practices. Further, the evidence supporting the *Relationship Hypothesis* is weaker in robustness tests, discussed

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[17] We obtain patent citation file, cited76_06, which includes all patent numbers of the citing patent and cited patent. We match each patent number to NBER's unique patent assignee identifier (PDPASS) from information in patent assignee file, patassg. We use files dynass and pdpcohdr to link the patent identifier to COMPUSTAT GVKEY.

later in the paper, that drop dismissed lawsuits or those that use restatements to proxy for misconduct.

5.2 Exposure Hypothesis

Supply chain linkages expose firms to customer and supplier practices allowing them to learn and adopt these practices. A higher likelihood of misconduct in the presence of cheating customers and suppliers could arise from the exposure to and leaning about wrongful practices. We test the *Exposure Hypothesis* by developing two measures that capture exposure of firms to wrongful practices in the supply chain with little relationship investment at stake.

Prior Customers

Firms that were key customers in the past but do not meet requirements to be classified as currently important, are likely to still be customers albeit accounting for less than 10% of sales. As firms are likely to be in contact with these prior important customers they can learn about wrongful practices from them. Note that as these prior customers are not currently key customers the relationship specific assets that are at stake are likely to be low if any. Specifically, we create a dummy referred to as Cheating Prior Customers that takes the value of one if a prior key customer (in years t-3 or year t-4) but not currently (year t-2 or year t-1) is engaged in wrongful practices currently. As can be seen in Table 5, Model 1 the coefficient of Cheating Prior Customer is positive and significant suggesting that firms are more likely to begin misconduct when they have greater exposure to wrongful practices. Similarly, we create the variable Cheating Prior Supplier to capture the information channel from past suppliers. As seen in Model 2, the coefficient is not significant.

Shared Customers and Shared Suppliers

Next, we identify shared suppliers, that is, firms that are suppliers to the same key customer. As Firm A and Firm B are both suppliers to the same firm, they may know about each other practices but unlikely to make any relationship specific investment with each other. If Firm A is more likely to adopt wrongful practices in the presence of a cheating Firm B, then it is likely to arise from exposure and learning about these practices. The dummy variable Cheating Shared Supplier takes the value of one if a shared supplier is currently cheating[18]. As seen in Model 3, the coefficient of Cheating Shared Supplier is positive and significant. Similarly, we create a dummy variable referred to as Cheating Shared Customer that takes the value of one if a shared customer is currently cheating. A shared customer is a firm that is also a key customer of the same supplier. Both the Cheating Shared Customer and Suppliers capture cheating in the supply chain network without a direct relation to the firm in question. The coefficient of Cheating Shared Customer is also positive and significant (See Model 4).

Finally, the results do not change when we control for both prior cheating customers and cheating shared customers and suppliers (See Model 5). The results suggest that greater exposure to wrongful practices in the supply chain is associated with a higher likelihood of beginning misconduct. We also examined whether exposure to cheating customers with certain characteristics impacts the likelihood of adopting these practices. Specifically, we examine if larger cheating customers by total assets and market capitalization, higher growth and more profitable cheating customers are more

[18] For the construction of this variable we require that the shared supplier be current, i.e., be a supplier to the same customer in year t-2 or year t-1. We also require that the common customer not be cheating as this is captured in our main Cheating Customer variable.

likely to influence the adoption of wrongful practices. The results reported in Appendix Table 1 suggest that larger cheating customers have a significantly higher impact on the adoption of wrongful practices. However, this result is not robust to different proxies for misconduct. Specifically, it does not hold when we use restatements to capture misconduct.

5.3 Detection

Lastly, we examine the *Detection Hypothesis* that suggests that once a firm is discovered regulators and external agents increase oversight on its customers and suppliers. This suggests that discovery of misconduct by a customer firm increases the likelihood of detection for the firm. Analysis of detection is difficult as we observe only detected fraud and do not know which firms committed fraud but were not discovered. To shed light on the role of discovery of misconduct in a customer we do two sets of analyses. First, we examine the time to discovery and test if recent discovery of cheating in a customer hastens detection for the firm. This analysis is done for detected fraud and examines speed of detection conditional on being detected. In the second set of analysis, we estimate a measure of committed fraud, irrespective of whether it is detected, to examine if the recent discovery of cheating by a customer increases the likelihood of being detected as opposed to going free.

Days to Detection

We begin by examining if the time to detection is faster when a customer gets discovered. The variable of interest is *Days to Discovery*, which is the number of days from the beginning of the fraud (class period) to the detection of a fraud (filing date). We only include the first fraud if the firm is sued more than once over sample period. We have a sample of 1,059 discovered frauds with available data for all variables for this analysis over the period 1997 to 2013.

To understand the effect of customer discovery we identify cases when a current customer was discovered. Specifically, the indicator variable Recent Detected Customer takes the value of one if a current customer was discovered in the prior year. The average time to discovery for firms with a recent discovered customer is 394.24 days that is significantly smaller than 501.93 days for firms without a recent customer discovered (See Table 6, Panel A). The results are similar if we examine medians and if we restrict the sample to firms that have a current customer (Panel B).

However, there are several factors that might influence the time to detection and most important among these is the intensity of oversight by regulators, capital markets and other external agents. For example, regulatory oversight is potentially higher after the passage of SOX with higher detection and faster times to discovery. Often oversight by capital markets can be concentrated in a specific industry. For example, after the discovery of problems at Enron other firms in the same industry were also suspected of fraudulent practices and faced greater scrutiny. To capture this variation in the oversight, we estimate the average time to discovery of all misconduct, in that industry and all other industries discovered that year (See Parsons, Sulaeman, and Titman (2015) for a similar measure). Specifically, *Average Duration for SIC* is the average time to discovery for all misconduct discovered in that year in the same two digits SIC and captures the prevailing oversight intensity for that industry. Similarly, the average time to discovery of other misconduct discovered in that year, and referred to as *Average Duration Other* captures prevailing oversight intensity for all other firms.

We also control for other factors that might influence the likelihood of detection in line with prior work by Yu and Yu (2010). In particular, we control for analyst coverage, as it is an important external monitor as documented by Chang, Dasgupta and Hilary (2006) and Yu (2008). High industry litigation may increase an individual firm's litigation risk and we control for industry litigation risk (See Khanna, Kim and Lu (2015)). As suggested by Johnson, Nelson and Pritchard (2007) we include firm performance and stock return volatility as they may be positively correlated with litigation risk. We also include stock liquidity, as it might be associated with greater investor harm and faster discovery. Lastly, we control for firm size (total assets), leverage and sales growth. All variables are average values over the entire class period and described in detail in the appendix A.

Table 7 displays results of estimating both an OLS model and a COX Proportional Hazard Model with industry fixed effects. As seen in Panel A, the coefficient of Recent Detected Customer for the OLS estimation is negative and significant and implies that having a recently detected customer decreases the time to discovery by 92 days. As the unconditional average for the sample is 497 days, this is 18.5% reduction in time to discovery. The results are qualitatively similar when we restrict the sample to those that have a current customer (Model 2). Panel B reports the results of the COX Hazard model where the dependent variable is the hazard rate of being detected. As seen in Column 3, the estimated coefficient of Recent Detected Customer is positive and significant suggesting that it is associated with a higher hazard rate of being detected with fraud. This result suggests that having a detected customer increases the hazard of being detected.

As expected, Mean Duration Other is highly significant and Mean Duration SIC is significant in all specifications except model 1. As expected, greater stock liquidity, higher analyst coverage and greater industry litigation are associated with lower days to discovery while a higher stock returns increases the time to discovery.

Undetected Misconduct

Several firms that cheat do not get detected and are not part of the misconduct sample. Dichev et al (2013) report that 60% of CFOs say that managers misreport because they feel they will go undetected. Ideally, if we could capture committed rather than detected fraud, we could study the likelihood of getting detected if a customer was recently caught with misconduct. We shed light on this by attempting to capture the likelihood of engaging in misconduct irrespective of whether the misconduct was ultimately detected. We then examine if in this sample of firms, with a higher likelihood of engaging in misconduct there is greater detection if a customer was recently detected.

Several prior studies find that short sellers are successful in identifying misconduct (See Desai, Krishnamurthy, and Venkataraman (2006), Karpoff, and Lou (2010), and Efendi, Kinney, and Swanson (2005)). In line with Call, Kedia and Rajgopal (2016) we use abnormal short selling interest to proxy for the likelihood of misconduct. As informed investors also take short positions in "clean" firms when they believe they are overvalued, we control for the expected short interest based on the firm fundamentals. In line with Dechow, Hutton, Meulbroek, and Sloan (2001) and Drake, Rees, and Swanson (2011) we model expected short interest as follows

$$\text{Short}_{it} = \beta_0 + \beta_1\text{Log(MVE)}_{it} + \beta_2\text{EP}_{it} + \beta_3\text{BM}_{it} + \beta_4\text{Turnover}_{it} + \beta_5\text{Ret}_{it} + \beta_6\text{(CAPEX/TA)}_{it} + \varepsilon_{it},$$

Where Short is the average number of shares shorted during the fiscal year scaled by total shares outstanding, MVE is the market value of equity, EP the earnings to price ratio, BM the book to market, turnover is stock turnover, Ret is the annual stock return and CAPEX/TA is the ratio of capital expenditures to total assets. The variables are defined in detail in the Appendix A and the results of this estimation are reported in Appendix Table 2. The predicted value from the above estimation captures the short interest due to firm fundamentals and the residuals capture Abnormal Short Interest.

Firms with high abnormal short interest are likely the ones where the informed investors identified potential misconduct. The indicator variable, *High Abnormal Short Interest* takes the value of one if the residual from the above estimation is in the top three deciles of residuals for that year. The firm years with *High Abnormal Short Interest* are more likely to be engaged in wrongdoing and as a check we test and find that 4.2% of these firm years are later discovered to be associated with wrongdoing which is significantly higher than 3.53% for low abnormal short interest group (See Appendix Table 3 for results). For robustness we also create a tighter criteria for misconduct, requiring abnormal short interest to be in the top two deciles for that year to be classified as *High Abnormal Short interest*. About 5.35% of firm years with the restrictive measure are detected relative to 3.34% for the low group and the difference is highly significant.

In this subsample of firms with *High Abnormal Short Interest* deemed more likely to have committed fraud we examine if the recent discovery of cheating in a customer causes the firm's wrongdoing to be detected. The dependent variable, *Detection* takes the value of one if the firm was detected of misconduct in the year, i.e., in the year when the litigation was filed. The main variable of interest, like before, is Recent Detected

Customer. We also include firm level controls used in earlier estimation along with year and industry fixed effects.

As seen in Column 1 of Panel A in Table 8, the coefficient of Recent Detected Customer is positive and significant implying that firms engaged in misconduct are more likely to be discovered when a customer is detected. The coefficient of Recent Detected Customer is not significant in Column 2 that is estimated in a sample of clean firms (as captured by our proxy). As firms in this sample are not misreporting, recent discovery of a cheating customer does not impact the likelihood that they will get detected. The results are similar in Panel B where we use the 20% cutoff to identify high abnormal short interest. In summary, there is significant support that discovery of cheating by a customer firm increases the likelihood of detection. Firms that are engaged in misconduct are more likely to be detected, and in fewer days when their key customers are discovered as fraudulent.

6. Robustness Tests

In this section we explore the robustness of our results to changes in the measure of misconduct. Though class action litigation has been used by many papers to capture misconduct, it suffers from the likelihood that the litigation is frivolous.[19] To ensure that our results are robust we use three different proxies of corporate misconduct. Specifically, we 1) identify litigation that is subsequently dismissed and exclude these cases, 2) use restatements as well as 3) SEC enforcement actions to identify misconduct. Both the Restatements and SEC enforcement actions are proxies of misconduct that are not subject to the criticism of frivolous litigation or lawyers targeting large cash rich firms.

In our sample of 956 litigations, 351 cases were dismissed. Not all these are frivolous and without merit. However, for robustness we exclude these cases and re-estimate our results in the sample of 605 cases. As can be seen in Table 9, Model 1 the coefficients of both Cheating Customer and Cheating Supplier are significant in this subsample of litigation.

Secondly, we obtain data on restatements from Audit Analytics over the period 2002 to 2013. This database has been used previously in the literature (e.g., Johnston, Li, and Luo 2014; Srinivasan, Wahid, and Yu 2015). As Audit Analytics includes all restatements it has a number of minor restatements as well. To capture potentially more substantive restatements, we restrict the restatements to those where the violation or restated period is greater than a year. About 1,031 firm-years, or 2.2% of the sample, is

[19] See for example Dyck, Morse and Zingales (2010), Peng and Roell (2008) and Call, Kedia and Rajgopal (2016) among others for use of class action litigation to capture misconduct.

associated with beginning wrongdoing. The results of the base model using restatements as a proxy of misconduct are displayed in model 2 of Table 9 and show that the coefficients of both Cheating Customer and Cheating Supplier are significant.

Lastly, we use SEC enforcement actions to capture misconduct. The SEC data are obtained from the University of Berkeley's Center for Financial Reporting and Measurement and include all AAER releases from 1971 to 2011 We include all firms where the beginning of the violation is between 1990 and 2009. As the SEC enforcement actions are quite infrequent, we include all years in violation rather than only the first year of the misconduct. This increases the number of firm years associated with wrongdoing 266 to 831, accounting for 0.89% of all firm years in the sample period. We also expand our customer measure, defining current customers as those listed as key customer is the past five years instead of the previous two years. They are classified as cheating if they have a violation period in the last two years. Cheating suppliers are similarly defined. As seen in Model 3, the coefficient of cheating customers and cheating suppliers are positive and significant. However, the coefficient of Cheating Customer is not significant when we include customer and supplier industry R&D (See Model 4). The weaker results for SEC actions relative to other proxies of misconduct is not surprising due to lower frequency of SEC actions.

We further examine whether our evidence with respect to relationship, learning and detection hypotheses holds with the alternate measure of misconduct.[20] As can be seen in Table 10, there is little support for the *Relationship Hypothesis.* Except for customers that are increasing in importance, captured by trend in sales growth, there is

[20] We do not do these tests with SEC actions due to the infrequency of the data and the weak base results.

little evidence that more important customers are associated with greater misconduct. This result is the same for both alternate proxies of misconduct.

In Table 11, we examine the robustness of the Exposure Hypothesis to alternate proxies of misconduct. We continue to find significant results when we exclude dismissed cases. However, the results are weaker when we use restatements. Specifically, in the restatement data there is no support that restatements by prior customers is significant though there continues to be evidence that restatements by shared customer are associated with higher likelihood of restating.

Lastly, we test for the *Detection Hypothesis* with the alternate measure of misconduct. The presence of a recent detected customer significantly reduces the days to detections as seen in Panel A of Table 12. Non-dismissed litigations are discovered 85 days faster or 16% reduction in the time to detection. Restatements are discovered 192 days faster implying a 14% reduction in the time to detection.[21] We also find that when we use abnormal short interest to proxy for firms more likely to be cheating, recent detected customer significantly increases the likelihood of detection as captured by both measures (See Panel B of Table 12). In summary, there continues to be significant support for detection hypothesis with both the alternate measures of misconduct.

[21] As the unconditional days to detection for cases that are not dismissed is 526 days, this represents a 16% reduction in the time to detection. The unconditional days to detection for restatements is 1,367 days representing a 14% reduction in the time to detection.

7. Presence of Cheating Suppliers

As reported in Section IV, the presence of current fraudulent suppliers is also associated with a higher likelihood of engaging in misconduct. As discussed earlier, data limitations prevent us from observing all the suppliers and only about 8% of firm years in the sample are associated with a supplier. In this section, we briefly summarize the results of tests that examine whether the three hypothesis explain why cheating suppliers impact the firm's decision to begin misconduct.

First, to examine the *Relationship Hypothesis* we construct measures to capture the strength of the relationship with the supplier. In line with the customer relationship these measures are 1) Dependency, that is, the ratio of the sales purchased from the supplier to the cost of goods sold, 2) Duration, that is, number of years in the past five years that the firm was identified as a supplier, 3) Trend, that is the average growth rate in the purchases from the cheating supplier over the past five years, 4) R&D expenses, that is the firm is classified as having made relationship specific investment if it reports having some R&D expenses in the past five years and 5) Cross Citations of patents with the supplier. As can be seen in Appendix Table 4, there is no evidence that more important suppliers as captured by the above measures are associated with a higher likelihood of adopting wrongful practices.

Next, we examining whether recently detected cheating suppliers reduce the time to detection for a firm that is engaged in misconduct. As seen in Appendix Table 5, there are only 23 cases of cheating (and detected) firms with a recently detected supplier and the average time to detection for these firms is 496 days. For the remaining firms the average days to detection is 498 days. There is no difference in the days to detection for the two groups. The results do not change if we restrict the sample to firms that have a current supplier (Panel B) and when we control for other factors that impact detection (Appendix Table 6). We also test and find that for the *High abnormal short interest* group (meant to capture firms that most likely engaged in misconduct) there is no evidence that recently detected supplier is associated with a significant likelihood of detection (See Appendix Table 7). Overall, there is no evidence that a firm’s likelihood of detection is impacted by the recent detection of a cheating supplier. Theses result should be interpreted with caution. As noted earlier, we do not have all the firm’s suppliers and there are only 23 cases in which the firm’s suppliers are detected leading to low power of the tests.

8. Conclusions

We examine and find that firms are more likely to engage in misconduct if they have a fraudulent customer or supplier. We examine three channels of how firm's likelihood of engaging in misconduct is impacted by the presence of fraudulent customers and suppliers. We examine and find no support for the *Relationship Hypothesis* that implies that the stronger the relationship with the fraudulent customer the greater is the likelihood of engaging in misconduct. We find that firms exposed to wrongful practices in the supply chain are more likely to adopt these practices providing support to the *Exposure Hypothesis*. We find evidence that recently detected customer is associated with both a higher propensity of detection among firms more likely to have cheated, and significantly fewer days to detection providing strong support to the *Detection Hypothesis*.

The results highlight the importance of supply chain linkages in both the perpetuation and mitigation of misconduct. Whereas recent studies have substantially increased the understanding of corporate misconduct this paper is among the first to document the diffusion of wrongful practices in supply chain networks. The results highlight that linkages among firms in the supply chain can be a conduit for the diffusion of corporate policies even the wrongful ones. The paper is also among the few to shed light on detection intensity. The results underscore that detection intensity can be clustered around economically linked firms that not only varies over time but also may be independent of a firm's governance structure.

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Tables

Table 1: Data Description of Time Patterns

The table displays the number of firms beginning wrongdoing over the sample period 1998 to 2013. Wrongdoing is captured by class action litigation. Column 2 reports the number of firms that begin misconduct in that year. Begin Misconduct is the first year of the class or violation period. Column 3 reports the number of all firms covered in COMPUSTAT with required data and included in our analysis. Column 4 reports the number of firms that disclose having a customer, public or private, for that year. Column 5 reports the number of firms that have a supplier in that year. Column 6 reports the number of firms that have either a supplier or a customer.

Year	**Begin Misconduct**	**All Firms**	**Firms with Customer**	**Firms with Suppliers**	**Firms with Customers or Suppliers**
1998	93	5,815	2,677	306	2,983
1999	92	5,659	1,926	347	2,273
2000	92	5,489	2,274	344	2,618
2001	93	5,473	2,290	353	2,643
2002	60	5,458	2,429	326	2,755
2003	87	5,180	2,252	354	2,606
2004	63	4,907	2,138	420	2,558
2005	43	4,637	2,065	397	2,462
2006	36	4,472	2,023	382	2,405
2007	53	4,217	1,965	364	2,329
2008	29	4,147	1,957	367	2,324
2009	29	4,077	2,062	413	2,475
2010	35	3,897	1,977	404	2,381
2011	42	3,717	1,882	413	2,295
2012	63	3,620	1,846	417	2,263
2013	46	3,548	1,820	391	2,211
Average	59	4,645	2,099	375	2,474

Table 2: Summary Statistics for the Misconduct and Control Sample

The table reports summary statistics for sample over 1998 to 2013. Begin Misconduct includes firm years when the firm beginning wrongdoing, and all other years are those with required data in COMPUSTAT and not engaged in misconduct. Begin misconduct sample includes 956 firm years and all other years include 70,323 firm years. Cheating Customer (supplier) is an indicator variable if current customers (suppliers) are cheating. All other variables are described in Appendix A. *,**,*** indicate significance at the 10%, 5% and 1% level respectively.

	Begin Misconduct		**All Other Years**		**Tests**	
	Mean	Median	Mean	Median	T-Test	Wilcoxon test
Cheating Customer	0.059	0	0.037	0	3.46***	3.46***
Cheating Supplier	0.038	0	0.008	0	10.47***	10.46***
<u>Industry Characteristics</u>						
Customer Industry R&D	0.01	0.004	0.008	0.003	5.76***	4.69***
Supplier Industry R&D	0.007	0.004	0.005	0.003	5.54***	5.28***
Industry Q	17.14	7.97	16.99	7.18	-0.15	-1.94*
<u>Firm Characteristics</u>						
R&D	0.099	0.016	0.070	0	4.89***	8.16***
Q	3.482	2.212	3.249	1.465	0.72	16.39***
Leverage	0.164	0.078	0.178	0.094	1.70**	0.51
Total Assets	3.522	0.396	1.972	0.152	7.86***	14.55***
ROA	-0.031	0.061	-0.238	0.021	4.56***	12.03***
Cash	0.401	0.200	0.247	0.103	9.60***	11.05***
Stock Return	0.351	0.180	0.098	-0.016	11.7***	11.16***
Sale Growth	0.527	0.203	0.286	0.079	6.09***	14.38***
Financing	0.188	0.074	0.200	0.042	0.81	7.76***

Table 3: Beginning Misconduct

This tables displays results from a logistic regression. The sample consists of all firms with required data in COMPUSTAT over 1998-2013. The dependent variable, Begin Misconduct takes the value of one if the firm begins wrongdoing in that year. Cheating Customer (Supplier) is a dummy that takes the value of one if a current customer (supplier) is cheating. Non-cheating customer (Supplier) is a dummy that takes the value of one if the firm has only clean customer (supplier). Total assets are in billions of dollar. All control variables are measured in the prior year. The coefficient of Industry Q has been multiplied by 1000. Standard errors are clustered at firm level. *,**,*** indicate significance at the 10%, 5% and 1% level respectively.

	Model 1	**Model 2**	**Model 3**
Cheating Customer	0.452***	0.441***	0.404***
	(3.19)	(3.10)	(2.84)
Cheating Supplier		0.993***	0.964***
		(4.65)	(4.51)
Customer Industry R&D			7.957**
			(2.16)
Supplier Industry R&D			15.64**
			(2.04)
R&D	0.848***	0.830***	0.751***
	(4.18)	(4.08)	(3.58)
Tobin's Q	0.00979***	0.00960***	0.00930***
	(3.94)	(3.83)	(3.68)
Leverage	0.177	0.186	0.194
	(1.25)	(1.31)	(1.39)
Total Assets	0.0425***	0.0350***	0.0353***
	(10.41)	(7.67)	(7.70)
ROA	0.738***	0.734***	0.741***
	(4.47)	(4.45)	(4.40)
Cash	0.233***	0.232***	0.223***
	(5.28)	(5.27)	(4.94)
Stock Return	0.429***	0.431***	0.429***
	(9.62)	(9.64)	(9.64)
Sale Growth	0.0981***	0.0983***	0.0991***
	(5.68)	(5.70)	(5.76)
Financing	0.0837	0.0883	0.0900
	(0.90)	(0.95)	(0.96)
Industry Q	-0.156	-0.466	-0.586
	(-0.02)	(-0.07)	(-0.09)
Year and Industry Dummy	Yes, Yes	Yes, Yes	Yes, Yes
Observations	75,363	75,363	74,820
R Square	0.0619	0.0639	0.0647

Table 4: Relationship with the Cheating Customer

This tables displays results from a logistics regression. The sample period is 1998 to 2006 for Models 1 and 2 and 1998-2013 for the rest. The dependent variable, Begin Misconduct takes the value of one if the firm begins wrongdoing in that year. Cheating Customer – Stronger (Weaker) Relationship in Model 1 consists of cheating customers that account for sales dependency greater than or equal to (less than) the median for the sample. Sales dependency is the sales to the customer over total sales. Cheating Customer – Stronger (Weaker) Relationship in Model 2 consists of the largest cheating customers. The largest cheating customer is one with the highest sales dependency. Cheating Customer – Stronger (Weaker) Relationship in Model 3 consists of cheating customers that are key customer in three or more (two or less) of the past five years. Cheating Customer – Stronger (Weaker) Relationship in Model 4 consists of cheating customers with (not) increasing importance over the past five. A customer is classified as increasing important if the average growth in customer sales is in (below) the top quartile. Control variables are included in the estimation but not reported. Control variables included but not displayed in the table are Customer and supplier industry R&D, R&D/Assets, Tobin's Q, leverage, Total assets, ROA, Cash, Stock return, sales growth, financing and Industry Q.Standard errors are clustered at firm level. *,**,*** indicate significance at the 10%, 5% and 1% level respectively.

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
	Sales/ Total Sales	Largest Customer	Duration	Trend	R&D	Cross Citation
Cheating Customer – Stronger Relationship (A)	0.562***	1.047**	0.380*	0.851***		
	(3.15)	(2.08)	(1.91)	(3.81)		
Cheating Customer – Weaker Relationship (B)	0.340	0.358**	0.427**	0.248		
	(1.41)	(2.41)	(2.18)	(1.31)		
Cheating Customer in the presence of R&D (A)					0.609***	
					(3.38)	
Cheating Customer when No R&D (B)					-0.336	-0.282
					(-0.68)	(-0.57)
Cheating Customer with Cross Citation (A1)						0.490*
						(1.74)
Cheating Customer, in presence of R&D, No Citation (A2)						0.627***
						(2.65)
Cheating Supplier	0.940***	0.963***	0.964***	0.934***	0.980***	0.993***
	(4.39)	(4.49)	(4.51)	(4.34)	(4.01)	(4.09)
Year and Industry Dummy	YES	YES	YES	YES	YES	YES
Observations	74,436	74,820	74,820	74,484	47,208	47,100

R Square	0.066	0.0649	0.0647	0.0663	0.076	0.076
P-value for the Difference Test (A=B)	0.22	0.09*	0.57	0.018**	.036**	0.65

Table 5: Exposure to Wrongful Practices

The table displays results from logistics regression. The sample is from 1998-2013. The dependent variable, Begin Misconduct is a dummy that takes the value of one when the firm begins wrongdoing in the year. Cheating Customer (Supplier) is a dummy that takes the value of one if a current customer (supplier) is cheating. Cheating Prior Customer (Supplier) is a dummy variable that takes the value of one if prior key customer (supplier) is currently cheating. Cheating Shared Supplier (Customer) is a dummy that takes the value of one if a shared supplier (customer) is currently cheating. A shared supplier (customer) is one that has the same key non-cheating customer (supplier) as the firm. Control variables are included in the estimation but not reported. Control variables included but not displayed in the table are cheating supplier, Customer and supplier industry R&D, R&D/Assets, Tobin's Q, leverage, Total assets, ROA, Cash, Stock return, sales growth, financing and Industry Q. Standard errors are clustered at firm level. *,**,*** indicate significance at the 10%, 5% and 1% level respectively.

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Cheating Prior Customer	0.486**	0.485**			0.549***
	(2.30)	(2.29)			(2.58)
Cheating Prior Supplier		0.257			0.360
		(0.87)			(1.19)
Cheating Shared Supplier			0.560***	0.548***	0.562***
			(4.60)	(4.51)	(4.62)
Cheating Shared Customer				0.740***	0.764***
				(4.25)	(4.39)
Cheating Customer	0.378***	0.376***	0.461***	0.490***	0.460***
	(2.62)	(2.61)	(3.22)	(3.43)	(3.16)
Cheating Supplier	0.954***	0.905***	0.990***	1.149***	1.074***
	(4.45)	(3.91)	(4.61)	(5.36)	(4.57)
Customer Industry R&D(t-1)	7.597**	7.584**	7.391**	7.055*	6.628*
	(2.07)	(2.07)	(2.02)	(1.93)	(1.82)
Supplier Industry R&D(t-1)	15.62**	15.39**	15.00*	13.81*	13.42*
	(2.04)	(2.00)	(1.95)	(1.79)	(1.73)
Year Dummy	YES	YES	YES	YES	YES
Industry Dummy	YES	YES	YES	YES	YES
Observations	74820	74820	74,820	74,820	74,820
R square	0.0652	0.0653	0.0666	0.0683	0.0690

Table 6: Summary Statistics: Days to Detection

The table reports the mean and median values of Days to detection. Panel A consists of the full sample of 1,059 detected corporate misconduct. The sample period is from 1997 to 2013. Panel B restricts the detected misconduct to firms that report having a current customer at the time of detection. Days to detection measure the number of days from the beginning of the violation (the start of the class period) to detection (filing date) of the litigation. Recent Detected Customer takes the value of if any of the current customers of the firm was detected (filing date) in the prior year. *,**,*** indicate significance at the 10%, 5% and 1% level respectively.

	Mean	**Median**	**Number**
Panel A: Full Sample			
Recent Detected Customer	394.24	332.00	46
No Detected Customer	501.93	411.00	1,013
Difference	107.67**	79.0**	
P-value for Difference	0.0136	0.0365	
Panel B: Firms with Current Customers			
Recent Detected Customer	388.20	320.50	46
No Detected Customer	491.40	419.50	224
Difference	103.2**	99.00**	
P-value for Difference	0.023	0.0463	

Table 7: Days to Detection with Detected Cheating Customer

Panel A reports an OLS regression for the Days to detection that is the number of days from the beginning of the violation to the detection. The sample consists of detected corporate misconduct (columns 1 and 3) over the period 1997 to 2013. Columns 2 and 4 also require at least one disclosed customer in the year prior to the filing date. Recent Detected Customer takes the value of one if any current customer was detected in the prior year. Panel B reports the results of a COX Hazard estimation. Standard errors are clustered by two-digit SIC industry. *,**,*** indicate significance at the 10%, 5% and 1% level respectively.

	Panel A: OLS		**Panel B: COX**	
Recent Detected Customer	-92.20**	-93.68*	0.364**	0.310*
	(-2.37)	(-1.70)	(2.38)	(1.66)
Mean Duration SIC	0.0765	0.234**	-0.000305*	-0.000882**
	(1.42)	(2.28)	(-1.54)	(-2.23)
Mean Duration Other	0.524***	0.416**	-0.00191***	-0.00222***
	(5.56)	(1.70)	(-6.38)	(-3.14)
Total Asset	-0.134	-3.701	-0.000356	0.0173*
	(-0.17)	(-1.18)	(-0.13)	(1.89)
Annual Stock Return	62.62***	5.445	-0.230***	-0.0504
	(3.43)	(0.13)	(-3.73)	(-0.41)
ROA	44.38*	36.13	-0.201*	-0.322
	(1.85)	(0.76)	(-2.00)	(-1.51)
Leverage	58.41	218.7**	-0.199	-1.046***
	(1.21)	(2.20)	(-1.32)	(-2.55)
Sale Growth	9.525	5.780	-0.0483	-0.0629
	(0.88)	(0.32)	(-1.06)	(-0.60)
Stock SD	960.4	-237.5	-1.269	1.764
	(1.47)	(-0.22)	(-0.57)	(0.47)
Turnover	-19.55***	-25.02***	0.0679***	0.121***
	(-6.32)	(-3.96)	(4.47)	(3.73)
Analyst Coverage	-29.79***	-11.72	0.108***	0.0615
	(-4.46)	(-0.63)	(4.95)	(0.75)
Industry Litigation	-6891.8***	-11946.6***	30.84***	51.75***
	(-6.48)	(-2.51)	(8.08)	(4.13)
Industry Fixed Effect	YES	YES	YES	YES
Observations	1,059	268	1,059	268
R Square	0.201	0.332		

Table 8: The likelihood of Detection with Detected Cheating Customers

The table displays Logit estimates. Panel A and B use the top 30% and the top 20% criteria to classify firm years as High Abnormal Short Interest. The sample period is from 1997 to 2013. The first (second) columns in each Panel reports results in the subsample of firm years that had high (low) abnormal short interest. The dependent variable is Detection takes the value of one if the firm was detected of misconduct in the year. Recent Detected Customer that takes the value of one if any of the current customers was detected of misconduct in the prior year. Total assets are in billions of dollars and the reported coefficient is multiplied by 1000. All control variables are measured in the prior year. The standard errors are clustered at firm level. *,**,*** indicate significance at the 10%, 5% and 1% level respectively.

	Panel A: Measure 1 (30% Cutoff)		**Panel B: Measure 2 (20% Cutoff)**	
	High Short Interest	Low Short Interest	High Short Interest	Low Short Interest
Recent Detected Customer	0.774**	0.125	0.654*	0.359
	(2.52)	(0.34)	(1.72)	(1.19)
R&D	0.218	0.0322	0.630	-0.266
	(0.41)	(0.07)	(1.13)	(-0.61)
Tobin's Q	0.0625***	0.0511***	0.0443**	0.0583***
	(3.40)	(4.35)	(2.43)	(5.07)
Leverage	0.104	0.162	-0.172	0.246
	(0.33)	(0.63)	(-0.45)	(1.02)
Total Assets	0.476***	0.411***	0.308*	0.449***
	(4.02)	(8.31)	(1.91)	(9.48)
ROA	0.330*	0.610***	0.357	0.466***
	(1.88)	(3.14)	(1.51)	(2.66)
Cash	0.363***	0.291***	0.222	0.313***
	(2.65)	(3.19)	(1.38)	(3.66)
Stock Return	-0.0243	-0.0802	0.0127	-0.0797
	(-0.24)	(-1.19)	(0.12)	(-1.23)
Sale Growth	0.160***	0.0267	0.122**	0.0958***
	(3.89)	(0.63)	(2.49)	(2.59)
Financing	-0.0723	-0.165	-0.0362	-0.173*
	(-0.61)	(-1.50)	(-0.27)	(-1.71)
Industry Q	0.00192*	-0.00163*	0.000108	0.000154
	(1.83)	(-1.77)	(0.07)	(0.21)
Year Dummy	YES	YES	YES	YES
Industry Dummy	YES	YES	YES	YES
Observations	14,317	27,394	8,349	33,717
R Square	0.0742	0.0543	0.0759	0.0559

Table 9: Robustness Tests: Different Proxies for Misconduct

This tables displays results from a logistic regressions. The sample consists of all firms with required data in COMPUSTAT over 1998-2013. The dependent variable, Begin Misconduct takes the value of one if the firm begins wrongdoing in that year. Cheating Customer (Supplier) is a dummy that takes the value of one if a current customer (supplier) is cheating. Non-cheating customer (Supplier) is a dummy that takes the value of one if the firm has only clean customer (supplier). Model 1 uses class action litigation, excluding all dismissed cases, from 1998 to 2013 to capture misconduct. We exclude all firm years associated with dismissed lawsuits. Model 2 uses restatements with restated period greater than a year, from 2002 to 2013, to capture misconduct. Model 3 and 4 use SEC enforcements over the period 1990 to 2009 to capture restatements. Control variables are included in the estimation but not reported. Control variables included but not displayed in the table are R&D/Assets, Tobin's Q, leverage, Total assets, ROA, Cash, Stock return, sales growth, financing and Industry Q. Standard errors are clustered at firm level. *,**,*** indicate significance at the 10%, 5% and 1% level respectively.

	Litigation Excluding Dismissed Cases	Restatements	SEC Enforcement	SEC Enforcement
Cheating Customer	0.507***	0.333**	0.514*	0.479
	(2.62)	(2.28)	(1.66)	(1.52)
Cheating Supplier	0.690**	0.450***	1.250***	1.252***
	(2.29)	(2.20)	(2.67)	(2.68)
Customer Industry R&D	10.930	1.512		9.860
	(2.45)	(0.39)		(1.09)
Supplier Industry R&D	12.37	-2.055		-6.245
	(1.28)	(-0.27)		(-0.37)
Year Dummy	YES	YES	YES	YES
Industry Dummy	YES	YES	YES	YES
Observations	71,871	46,353	93,049	92,819
R square	0.055	0.0428	0.0847	0.0563

Table 10: Robustness for the Relationship Hypothesis

The dependent variable, Begin Misconduct takes the value of one if the firm begins wrongdoing in that year. Panel A (B) captures misconduct as class action litigation that was not dismissed (restatements) over the period 1998 to 2013 (2002 to 2013). Control variables included but not displayed in the table are Customer and Supplier industry R&D, R&D/Assets, Tobin's Q, leverage, Total assets, ROA, Cash, Stock return, sales growth, financing and Industry Q. Standard errors are clustered at firm level. *,**,*** indicate significance at the 10%, 5% and 1% level respectively.

Strong (Weak) relationship cheating customers are customers which have the sale dependency and other proxies of relationship above median (below or equal to median).

Panel A: Litigation excluding Dismissed Cases					
	Sale Dependency	Largest Customer	Duration	Trend	R&D
Cheating Customer – Strong (A)	0.555**	1.254*	0.569**	0.930***	
	(2.12)	(1.67)	(2.12)	(2.96)	
Cheating Customer – Weak (B)	0.645**	0.469**	0.447*	0.406	
	(2.22)	(2.35)	(1.67)	(1.63)	
Cheating Customer, R&D (A)					0.713***
					(2.84)
Cheating Customer, No R&D (B)					-0.233
					(-0.33)
Cheating Supplier	0.713**	0.694**	0.691**	0.710**	0.671*
	(2.37)	(2.30)	(2.29)	(2.09)	(1.88)
Year, Industry Dummy	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes
Observations	71,604	71,871	71,871	71,633	44,620
R square	0.0611	0.0594	0.0593	0.0613	0.0669
P-value for Difference Test (A=B)	0.59	0.15	0.37	.090*	0.90*
Panel B: Restatements					
Cheating Customer – Strong (A)	0.427***	0.148	0.467**	0.782***	
	(2.12)	(1.5)	(2.38)	(3.06)	
Cheating Customer – Weak (B)	0.203	0.337**	0.203	0.124	
	(0.82)	(2.11)	(0.97)	(0.64)	
Cheating Customer, R&D (A)					-0.0362
					(-0.15)
Cheating Customer, No R&D (B)					0.507*
					(1.94)
Cheating Supplier	0.462***	0.464**	0.447**	0.459**	0.442*
	(2.36)	(2.37)	(2.29)	(2.35)	(1.77)

Year, Industry Dummy	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes
Observations	46,040	46,353	46,102	46,102	22172
R square	0.0432	0.0429	0.0435	0.0435	0.0413
P-value for Difference Test (A=B)	0.24	0.57	0.17	.019**	0.94*

Table 11: Robustness for the Exposure Hypothesis

The dependent variable, Begin Misconduct takes the value of one if the firm begins wrongdoing in that year. Panel A (B) captures misconduct as class action litigation that was not dismissed (restatements) over the period 1998 to 2013 (2002 to 2013). Control variables included but not displayed in the table are Customer and Supplier industry R&D, R&D/Assets, Tobin's Q, leverage, Total assets, ROA, Cash, Stock return, sales growth, financing and Industry Q. Standard errors are clustered at firm level. *,**,*** indicate significance at the 10%, 5% and 1% level respectively.

	Panel A: Litigation without Dismissed Cases		**Panel B: Restatements**	
	Model 1	Model 2	Model 3	Model 4
Cheating Prior Customer	0.779***	0.849***	0.116	0.140
	(2.78)	(3.02)	(0.37)	(0.45)
Cheating Prior Supplier	0.473	0.561	-0.767	-0.727
	(1.19)	(1.37)	(-1.07)	(-1.01)
Cheating Shared Supplier		0.610***		0.120
		(4.30)		(1.04)
Cheating Shared Customer		0.566***		0.520**
		(2.67)		(2.15)
Cheating Customer	0.458**	0.546***	0.337**	0.363**
	(2.28)	(2.70)	(2.31)	(2.47)
Cheating Supplier	0.578*	0.733**	0.437**	0.486**
	(1.75)	(2.15)	(2.22)	(2.49)
Year, Industry Dummy	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes
Observations	71,871	71,871	46,353	46353
R square	0.0605	0.0638	0.0429	0.0435

Table 12: Robustness for Detection Hypothesis

Panel A: Days to Detection

The table reports partial results from OLS and Cox Hazard Model for the number of days from the beginning of the violation to the detection. It replicates Table 7 in a different sample and includes all detected frauds. In Column 1 and Column 2, the sample consists of all litigation filed between 1997 and 2013 that is not dismissed. In Column 3 and Column 4, the sample includes all restatements with duration greater than 1 year. The data is from Audit Analytics and from 2001 to 2013.Recent Detected Customer takes the value of one if any current customer was detected in the prior year. Control Variables included but not reported are Mean Duration SIC, Mean Duration Other, Total Assets, Annual Stock Return, ROA, Leverage, Sales Growth, Stock SD, Turnover, Analyst Coverage and Industry Litigation. Standard errors are clustered by industry (two-digit SIC). *,**,*** indicate significance at the 10%, 5% and 1% level respectively.

	Litigation Sample		**Restatement Sample**	
	OLS	COX	OLS	COX
Recent Detected Customer	-85.16*	0.337**	-192.0**	0.253*
	(-1.85)	(2.43)	(-2.50)	(1.70)
Industry Fixed Effect	YES	YES	YES	YES
Observations	638	638	1,124	1,124
R Square	0.218	0	0.156	0

Panel B: Likelihood of Detection

The table displays partial results from a Logit estimates. The table replicates Table 9 in a sample that excludes dismissed litigation and sample with restatements whose duration is greater than 1 year. We use the top 30% criteria to classify firm years as High Abnormal Short Interest. The first (second) columns for each measure reports results in the subsample of firm years that had high (low) abnormal short interest. The dependent variable is Detection takes the value of one if the firm was detected of misconduct in the year. The variable is Recent Detected Customer that takes the value of one if any of the current customers were detected of misconduct in the prior year. Control variables included in the estimation but not reported in the table are R&D, Tobin's Q, Leverage, Total Assets, ROA, Cash, Stock Return, Sales growth, Financing and Industry Q. The standard errors are clustered at firm level. *,**,*** indicate significance at the 10%, 5% and 1% level respectively.

	Litigation Sample		**Restatement Sample**	
	High Short Interest	Low Short Interest	High Short Interest	Low Short Interest
Recent Detected Customer	0.738*	-0.361	0.591*	0.427
	(1.77)	(-0.62)	(2.14)	(0.64)
Year Dummy	YES	YES	YES	YES
Industry Dummy	YES	YES	YES	YES

Observations	12,896	25,694	11,321	22,623
R Square	0.08	0.0505	0.0726	0.0581

Appendix A: Variable Definition

Begin Misconduct: An indicator variable that takes the value of one for the earliest fiscal year that overlaps with the class period.

Cheating Customer: An indicator variable that takes the value of one for firm i in year t, if any of its current customers were engaged in wrongdoing in year t-1 or year t-2. A customer is classified as a current customer if it was reported as one in either year t-1 or year t-2.

Cheating Supplier: An indicator variable that takes the value of one for firm i in year t, if any of its current suppliers were engaged in wrongdoing in year t-1 or year t-2. A supplier is classified as a current supplier if it reported the customer in either year t-1 or year t-2.

Customer Industry R&D: The sum of R&D expenses of all industry firms divided by the sum of their total assets. The customer industry is obtained from Input-Output tables provided by the Bureau of Economic Analysis. For the years 1997 to 1999 we used the 1997 IO table, for the years 2000-2013 we use the 2000 IO table. R&D data is from COMPUSTATA with missing values replaced with zero. If there are more than one customer industry, we take the weighted average R&D for all customer industries where the weights are the share of the output.

Supplier Industry R&D: The sum of R&D expenses of all industry firms divided by the sum of their total assets. The supplier industry is obtained from Input-Output tables provided by the Bureau of Economic Analysis. For the years 1997 to 1999 we used the 1997 IO table, for the years 2000-2013 we use the 2000 IO table. R&D data is from COMPUSTATA with missing values replaced with zero. If there are more than one supplier industry, we take the weighted average R&D for all supplier industries where the weights are the share of the input.

R&D: R&D expense/ Lagged Total Assets. Missing value of R&D is replaced with zeros.

Tobin's Q: The market value of common equity plus the book value of total debt (item lt) divided by total assets.

Industry Q: The average Q for all firms in the same two-digit SIC in that year.

Leverage: The ratio of long-term debt to lagged total assets.

Total Assets: Book value of assets in billions

ROA: Net Income/ Lagged total assets

Cash: Cash holding/ Lagged Total assets. Cash holdings is item che(cash and cash equivalent).

Stock Return: Annual Stock return over fiscal year

Sales Growth: Annual growth rate of total sales over the prior fiscal year, i.e., sales growth from year t-2 to year t-1.

Financing: The ratio of new financing raised to total assets. New financing is the sum of sales of common and preferred stock (item sstk) and long-term debt issuance (item dltis).

Calendar Stock Return: 12 month buy and hold stock return in given year from CRSP

Stock Volatility: The standard deviation of a firm's daily stock returns in a given calendar year

Turnover: The number of shares traded in a year divided by the number of shares outstanding

Days to Detection: The number of days between the start of the class period and filing date.

Mean Duration SIC: The average number of days between the class start date and filing date for all misconduct in the two digit SIC discovered that year. This is constructed from data from the Securities Class Action Clearinghouse.

Mean Duration Other: The average number of days between the class start date and filing date for all misconduct other two digit SIC discovered that year This is constructed from data from the Securities Class Action Clearinghouse.

Recent Detected Supplier: An Indicator variable that takes the value of one for firms subject to litigation if it has current supplier that was sued (filing date) in the fiscal year prior to its filing date.

Recent Detected Customer: Takes the value of one for firm subject to litigation if any of the firm current customers has a lawsuit that is filed in the fiscal year prior to its filing date.

Industry Litigation: Industry litigation intensity is defined as the number of lawsuits against public listed firms in the two-digit SIC divided by total number of firms in COMPUSTAT in the two-digit SIC in the year.

Analyst Coverage: The log of one plus the number of analysts that follow the firm in the year. Analyst coverage data is from IBES. Firms that were not covered in IBES were assumed to have zero analyst coverage.

Short Interest: The average number of shares shorted during fiscal year t divided by the total shares outstanding.

EP: The earnings to price ratio

CAPEX/TA: Ratio of CAPEX in year to total assets in year t.

Cheating Prior Customer: An indicator variable that takes the value of one for firm i in year t, if any of its prior customers were engaged in wrongdoing in year t-1 or year t-2. A customer is classified as a prior customer if it was reported as one in either year t-3 or year t-4, while it was not reported in year t-2 and year t-1.

Cheating Prior Supplier: An indicator variable that takes the value of one for firm i in year t, if any of its prior suppliers were engaged in wrongdoing in year t-1 or year t-2. A supplier is classified as a prior customer if it was reported as one in either year t-3 or year t-4, while it was not reported in year t-2 and year t-1.

Cheating Shared Supplier: An indicator variable equal to 1 if any of the firm's shared suppliers is cheating in year t-1 or year t-2.A shared supplier is one that has the same key non-cheating customer as the firm has.

Cheating Shared Customer: An indicator variable equal to 1 if any of the firm's shared customer is cheating in year t-1 or year t-2. A shared customer is one that has the same key non-cheating supplier as the firm has.

Appendix B: Supplementary Tables

Appendix Table 1: Learning Based on Cheating Customer Characteristics

The table displays results from logistics regression. The sample is from 1998-2013. The dependent variable, Begin Dummy, takes the value of one when the firm begins wrongdoing in that year. Cheating Customer – More (Less) Influential in Model 1 consists of cheating customers that are above (below and equal) the median total assets of cheating customers. Cheating Customer – More (Less) Influential in Model 2 consists of cheating customers that are above (below and equal) the median market value of cheating customers. Cheating Customer – More (Less) Influential in Model 3 consists of cheating customers that are above (below and equal) the median profit margin of cheating customers. Cheating Customer – More (Less) Influential in Model 4 consists of cheating customers that are above (below and equal) the median sales growth of cheating customers. Prior Customer cheating takes the value of one if a firm that was listed as an important firm in year t-3 and t-4 is cheating. Control variables are included in the estimation but not reported. Control variables included but not displayed in the table are cheating supplier, Customer and supplier industry R&D, R&D/Assets, Tobin's Q, leverage, Total assets, ROA, Cash, Stock return, sales growth, financing and Industry Q. Standard errors are clustered at firm level. *,**,*** indicate significance at the 10%, 5% and 1% level respectively.

	Model 1	**Model 2**	**Model 3**	**Model 4**
	Total Assets	Market Capitalization	Profit Margin	Sales Growth
Cheating Customer – More Influential (A)	0.608***	0.612***	0.248	0.360*
	(3.13)	(3.29)	(1.14)	(1.83)
Cheating Customer – Less Influential (B)	0.149	0.142	0.506***	0.415**
	(0.70)	(0.64)	(2.64)	(1.99)
Cheating Supplier	0.969***	0.973***	0.969***	0.972***
	(4.54)	(4.55)	(4.54)	(4.56)
Year Dummy	YES	YES	YES	YES
Industry Dummy	YES	YES	YES	YES
Observations	74,694	74,670	74,693	74,687
R square	0.0651	0.0652	0.0649	0.0649
P-value for the Difference Test (A=B)	.055*	.049**	0.18	0.43

Appendix Table 2: Estimating Short Interest

The sample includes all firms with available data over the period 1997 to 2013. The dependent variable is short interest, which is the average short interest over the year divided by the number of shares outstanding. Log (MVE) is the log of the market value of equity, EP is the earnings to price ratio, BM is the book to market ratio, Turnover is the stock turnover for the year. Errors are clustered at the firm level. *,**,*** indicate significance at the 10%, 5% and 1% level respectively.

	Short Interest
Intercept	-0.0236***
	(-17.94)
Log (MVE)	0.00356***
	(16.17)
EP	-0.000586
	(-1.03)
BM	-0.00121**
	(-2.38)
Turnover	0.0831***
	(48.25)
Stock Return	-0.00350***
	(-8.76)
CAPEX/TA	-0.0158***
	(-2.59)
Observations	61,938
R	0.2373

Appendix Table 3: Validation of the Abnormal Short Interest

The table displays mean and median values of the abnormal short interest. The sample period is from 1997 to 2013. This is the residual from a model that estimates average short interest for the firm. Class Period Dummy takes that value of one if the firm year was detected as being in the violation period, i.e., is part of the class period and zero otherwise. Filing Dummy takes the value of one for the year in which the violations was discovered, i.e., the year of filing. Panel A uses top 30% cutoff to classify years as High Abnormal Short interest while Panel B uses top 20% cutoff. *,**,*** indicate significance at the 10%, 5% and 1% level respectively.

	Panel A: Abnormal Short Interest Dummy (30%)		
	Class Period	Filing Dummy	N
High Abnormal Short Interest Dummy=1	4.20%	2.64%	14,317
High Abnormal Short Interest Dummy=0	3.53%	1.57%	27,394
P-value for Difference	0.027**	0.005***`	

	Panel B: Abnormal Short Interest Dummy (20%)		
	Class Period	Filing Dummy	N
High Abnormal Short Interest Dummy=1	5.35%	2.64%	8,349
High Abnormal Short Interest Dummy=0	3.34%	1.57%	33,717
P-value for Difference	0.0***	0.0***	

Appendix Table 4: Relationship with the Cheating Suppliers

This tables displays results from a logistics regression. The sample period is from 1998 to 2013 or Model 1 to 3 and from 1998 to 2006 for Models 4 and 5. The dependent variable, Begin Misconduct takes the value of one if the firm begins wrongdoing in that year. Cheating Supplier - Stronger (Weaker) Relationship in Model 1 consists of cheating suppliers with dependency greater than or equal to (less than) the median for the sample. Dependency is the purchases from the suppliers divided by COGS. For Model 2 (3) stronger relationship is based on the duration (growth) of the relationship. Control variables included but not displayed in the table are Customer and supplier industry R&D, R&D/Assets, Tobin's Q, leverage, Total assets, ROA, Cash, Stock return, sales growth, financing and Industry Q. Standard errors are clustered at firm level. *,**,*** indicate significance at the 10%, 5% and 1% level respectively.

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
	Dependency	Duration	Trend	R&D	Cross Citation
Cheating Supplier – Strong Relationship (A)	0.638**	0.828***	0.453		
	(2.17)	(2.89)	(1.01)		
Cheating Supplier – Weak Relationship (B)	1.429***	1.085***	1.106***		
	(4.64)	(4.30)	(4.82)		
Cheating Supplier in Presence of R&D (A)				1.060***	
				(3.48)	
Cheating Supplier in presence of no R&D (B)				0.846**	0.840**
				(2.22)	(2.20)
Cheating Supplier, with R&D and citation (A1)					0.818*
					(1.84)
Cheating Supplier, with R&D and No citation (A2)					1.239***
					(3.72)
Cheating Customer	0.414***	0.405***	0.413***	0.458***	0.460***
	(2.92)	(2.85)	(2.91)	(2.74)	(2.76)
Year Dummy	YES	YES	YES	YES	YES
Industry Dummy	YES	YES	YES	YES	YES
Observations	74,746	74,820	74,765	47,208	47,100
R Square	0.0642	0.0648	0.0645	0.0750	0.0753
P-value for Difference Test (A=B)	.98*	0.78	.92*	0.32	0.80

Appendix Table 5: Summary Statistics: Days to Detection with Recent Detected Supplier

The table reports the mean and median values of Days to detection. Panel A consists of the full sample of 1,059 detected corporate misconduct. Panel B restricts the detected misconduct to firms that report having a current suppler at the time of detection. Days to detection measure the number of days from the beginning of the violation (the start of the class period) to detection (filing date) of the litigation. Recent Detected Supplier takes the value of if any of the current suppliers of the firm was detected (filing date) in the prior year. *,**,*** indicate significance at the 10%, 5% and 1% level respectively.

	Mean	**Median**	**Number**
Panel A: Full Sample			
Recent Detected Supplier	479.22	368.00	23
No Detected Supplier	497.65	408.5	1,036
Difference	18.44	40.50	
P-value for Difference	0.39	0.31	
Panel B: Firms with Current Suppliers			
Recent Detected Supplier	496.36	398.00	23
No Detected Supplier	463.16	372.00	174
Difference	-33.3	-26	
P-value for Difference	0.33	0.08*	

Appendix Table 6: Days to Detection with Detected Cheating Suppliers

Panel A reports an OLS regression for the Days to detection that is the number of days from the beginning of the violation to the detection. The sample consists of detected corporate misconduct (columns 2 and 4) and those with at least one disclosed supplier in prior year before filing date over the period 1997 to 2013. Recent Detected Supplier takes the value of one if any current customer was detected in the prior year. Total Assets are measured in billions of dollars and the reported coefficient is multiplied by 1000. All control variables are averaged over the class period. Panel B reports the results of COX Hazard estimation. Standard errors are clustered at two-digit SIC industry level. *,**,*** indicate significance at the 10%, 5% and 1% level respectively.

	Panel A: OLS		**Panel B: COX**	
Recent Detected Supplier	-4.729	-14.07	-0.0149	0.0844
	(0.16)	(-0.14)	(-0.04)	(0.15)
Mean Duration SIC	0.0822	0.263**	-0.000322*	-0.00123**
	(1.54)	(2.54)	(-1.75)	(-2.50)
Mean Duration Other	0.513***	0.535**	-0.00187***	-0.00194**
	(5.72)	(2.55)	(-6.49)	(-2.17)
Total Asset	-0.0736	-0.341	0.000509	0.209
	(-0.10)	(-0.25)	(0.21)	(0.44)
Annual Stock Return	64.44***	147.3***	-0.239***	-0.501**
	(3.88)	(3.99)	(-3.86)	(-2.19)
ROA	44.13*	45.36	-0.193*	-0.501
	(1.75)	(0.42)	(-1.76)	(-1.24)
Leverage	58.13	-285.8***	-0.187	1.221**
	(1.20)	(-1.85)	(-1.23)	(2.47)
Sale Growth	10.03	36.74	-0.0479	-0.290
	(0.92)	(0.42)	(-1.12)	(-1.15)
Stock SD	918.0	2874.5	-0.922	-9.138
	(1.35)	(1.64)	(-0.39)	(-1.53)
Turnover	-19.74***	-9.979	0.0675***	0.0292
	(-6.36)	(-0.97)	(4.52)	(0.91)
Analyst Coverage	-30.18***	1.529	0.108***	-0.0304
	(-4.48)	(0.05)	(4.63)	(-0.33)
Industry Litigation	-6893.4***	-6579.9**	30.89***	31.84**
	(-6.31)	(-2.19)	(7.80)	(2.47)
Industry Fixed Effect	YES	YES	YES	YES
Observations	1,059	196	1,059	196
R Square	0.1975	0.3037		

Appendix Table 7: The likelihood of Detection with Detected Cheating Suppliers

The table displays Logit estimates. Panel A and B use the top 30% and the top 20% criteria to classify firm years as High Abnormal Short Interest. The first (second) columns in each Panel reports results in the subsample of firm years that had high (low) abnormal short interest. The dependent variable is Detection takes the value of one if the firm was detected of misconduct in the year. Recent Detected Supplier that takes the value of one if any of the current customers was detected of misconduct in the prior year. Total assets is in billions of dollars and the reported coefficient is multiplied by 1000. All control variables are measured in the prior year. Standard errors are clustered at firm level. *,**,*** indicate significance at the 10%, 5% and 1% level respectively.

	Panel A: Measure 1 (30% cutoff)		**Panel B: Measure 2 (20% Cutoff)**	
	High Short Interest	Low Short Interest	High Short Interest	Low Short Interest
Recent Detected Supplier	0.382	0.441	0.550	0.376
	(0.47)	(1.30)	(0.65)	(1.11)
R&D	0.264	0.0179	0.666	-0.273
	(0.50)	(0.04)	(1.19)	(-0.62)
Tobin's Q	0.0617***	0.0509***	0.0438**	0.0580***
	(3.35)	(4.33)	(2.39)	(5.05)
Leverage	0.129	0.168	-0.143	0.250
	(0.41)	(0.66)	(-0.38)	(1.04)
Total Assets	0.467***	0.386***	0.287*	0.428***
	(3.94)	(7.09)	(1.81)	(8.25)
ROA	0.332*	0.607***	0.362	0.466***
	(1.89)	(3.13)	(1.53)	(2.66)
Cash	0.358***	0.289***	0.219	0.310***
	(2.63)	(3.15)	(1.37)	(3.62)
Stock Return	-0.0265	-0.0795	0.00865	-0.0796
	(-0.26)	(-1.18)	(0.08)	(-1.22)
Sale Growth	0.159***	0.0267	0.122**	0.0961***
	(3.86)	(0.63)	(2.49)	(2.60)
Financing	-0.0817	-0.166	-0.0440	-0.175*
	(-0.68)	(-1.51)	(-0.33)	(-1.72)
Industry Q	0.00194*	-0.00162*	0.000141	0.000156
	(1.84)	(-1.78)	(0.09)	(0.22)
Year Dummy	YES	YES	YES	YES
Industry Dummy	YES	YES	YES	YES
Observations	14,317	27,394	8,349	33,717
R square	0.0725	0.0547	0.0750	0.0559

Chapter 2: Effect of Municipal Bond Defaults

"But the municipal bond market is complex and defaults happen much more frequently than most casual observers are aware."

By Jason Appleson, Eric Parsons and Andrew Haughwout[22]

1. Introduction

Over the last few years financial troubles at some states have generated concerns about potential defaults on their municipal bond offerings. Detroit's bankruptcy in July, 2013 with a total debt of $18 billion and the more recent struggle of Puerto Rico to make payments on its $72 billion debt have done little to mitigate these concerns. However, despite these well-publicized events some are not concerned. In the $3.8 trillion market, defaults still constitute a very small fraction. Further, general obligation municipal bonds are backed by the full faith and credit of the municipal issuers who are able to raise taxes to service their debt. Essential service revenue bonds are backed by revenue from services like utilities, water and sewer and issuers are able to adjust rates to cover debt payments. Consequently, even with defaults recovery rates for municipal bonds are high, especially relative to what is seen in corporate defaults.

However, unlike corporate issuers, municipal issuers cannot liquidate assets and disappear. Many municipalities access the capital market frequently for both operating and capital expenditure. Alienating investors by defaulting may restrict their ability to

[22] "The untold story of Municipal Bond Defaults" – August 15,2012 in Liberty Street Economics and available at http://libertystreeteconomics.newyorkfed.org/2012/08/the-untold-story-of-municipal-bond-defaults.html#.VzIWUOR0etE

raise financing in a cost effective way in the future. This concern to preserve its access to capital markets prompted Atlantic City NJ to make a $1.8 million debt payment in 2016 to avert defaults. The city has halted new purchases and hiring of additional staff. Mr. Guardian, the Mayor said "If we did not make the bond payment, it would be detrimental to everyone."[23] In this paper, we examine the economic impact of defaults in the municipal bond markets. Even if defaults of municipal bonds are rare and may be associated with high recovery rates, they are likely to signal deteriorating fiscal condition in the state and can be costly to other municipal issuers in the state.

In this paper, we analyze bond defaults in the municipal markets to answer three questions. First, we document the extent and nature of municipal bond defaults, and examine their effect on the price of the defaulted bond. Second, we study the effect of defaults on the price of the other non-defaulted bonds from the same state. Lastly, we examine whether municipal defaults have an effect on the cost of borrowing by issuers from the same state.

We collect bond issue information and bond default data from Mergent's Municipal Bond Securities Database (MBSD). We find that over the 2000 to 2014 period, there are 3,197 bonds that default. The number of municipal defaults increases in 2008 after the financial crises and stay at elevated levels till the end of the sample period. California, Florida and Illinois are among the top three states by the number of defaults and New Hampshire and Rhode Island having the lowest default.

[23] "Atlantic City Makes $1.8 million Bond Payment, Averting Default," by Timothy W. Martin, WSJ May 2, 2016 and available at http://www.wsj.com/articles/atlantic-city-makes-1-8-million-bond-payment-averting-default-1462203304.

In contrast to bond defaults, the bankruptcy of the municipal issuer is rare. Like Chapter 11 for corporate bankruptcy, Chapter 9 provides financially distressed municipalities with protection from creditors by creating a repayment plan. To date, only 12 states authorize cities to file for bankruptcy without condition and 15 permit filing with certain requirements.[24] The remaining 23 states either explicitly prohibit or have no statute regarding bankruptcy (Tima, Sharon and Bartley (2014)). In the past 60 years, only 63 cities, town or counties have sought chapter 9 protection (Spiotto (2013)).[25] The largest and most famous municipal bankruptcies since 2000 and over the period that we study are 1) Jefferson County, Alabama, 2) Stockton and San Bernardino, California, and 3) Detroit, Michigan. Though the bankruptcies generate a lot of publicity they are rare and potentially mask the impact of the more frequent defaults by municipal bonds. Further, all large bankruptcies involve actual defaults by their bonds and are included in our sample, including the defaults involved in the abovementioned bankruptcies that we discuss in the next section.

The MBSD data gives the reason for defaults, and violation of covenants (36%) and missed interest payments (30%) are the two most common reasons. About 30% of the defaulted bonds have credit enhancement and most of these defaults are for technical rather than monetary reasons. About 12% of the defaults are associated with general

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[24] States that allow local government to file chapter 9 without condition are Alabama Arkansas,Arizona, Idaho, Minnesota, Missouri,Montana, Nebraska, Oklahoma, South Carolina, Texas and Washington. States that permit filing with certain conditions are California, Colorado, Connecticut, Florida, Illinois, Kentucky, Louisiana,Michigan, North Carolina, New Jersey, New York,Ohio, Oregon, Pennsylvania and Rhode Island.

[25] Many bankruptcies are not related to municipal bonds. For instance, Mammoth Lake, California and Westfall Township, Pennsylvania, could not pay for multimillion-dollar legal judgments against them. Also, some municipalities that file for bankruptcy do not have public traded bond outstanding.

obligation bonds. About 13.5% of the defaulted bonds are able to resolve their issues and are subsequently reinstated.

To examine the effect of the default, we estimate the abnormal change in price of the municipal bond around default. We obtain municipal bond trading data from Municipal Securities Rulemaking Board (MSRB) over the sample period from 1999 to 2014. Municipal bonds trade very infrequently, and to maximize our sample we estimate price changes over the [-6, +6] month period around default. We have the trading data to estimate the price changes for only 825 defaulted bonds. After subtracting price changes over the same period in a maturity matched Treasury bond, we find that the average price change for defaulted bonds is -2.98%. Not surprisingly, bonds with credit enhancement have a less negative price change. The nature of the default, that is, whether it is monetary or technical does not appear to affect the magnitude of the price decline in defaulted bonds. Somewhat, surprisingly general obligation bonds experience a smaller price decline on default. This could be because the default may signal intervention by the state authorities and bode an improvement for the investors of these GO bonds.

Next, we examine the effect of the default on outstanding municipal bonds. Using trading data from MSRB, we estimate the adjusted price changes of non-defaulted bonds from the same state over the [-6, +6] month period around the default. In a sample of over 1.2 million non-defaulted bonds, we find that the mean price change around the default event is -1%. This price decline is larger if the defaulted bond experienced a larger price decline and if the state has higher default rate. We also find some evidence that the non-defaulted bonds from the same county as the default bonds experience a larger decline in prices around the default event.

Lastly, we examine the cost of new municipal borrowing in the aftermath of bond defaults from the same state. We obtain data on new bond issues over the period 2000 to 2013 from Mergent's Municipal Bond Database and after ensuring data requirements, have a sample of 149,880 new municipal bonds issues. We find that the offering yields of the new municipal bond issues are significantly higher when the state has experienced high municipal bond defaults in the past. This result is robust to measuring past defaults over the past one year, three or five years and is also robust to controls for the bond characteristics, state characteristics, state and time fixed effects. Specifically, we find that a one standard deviation increase in the number of defaults in the past three years increases the offering yield of the new municipal bonds from the same state by 5 basis points. We also find that the greater is the fraction of general obligation bonds in default the higher is the cost of new municipal borrowing from the same state.

Though there is some understanding of how corporate financial distress impacts other firms, there is little understanding of how municipal bond defaults impact other players in the municipal bond market. Our paper is among the first to document the incidence of defaults in the municipal bond markets and its impact on other non-defaulted bonds in the state. The results suggest that municipal bond defaults impose a non-trivial cost on other municipal issues from the same state. The rest of paper is organized as follows. Section 2 discusses related literature, Section 3 describes the data, Section 4 presents Univariate results, Section 5 reports the multivariate results, Section 6 discusses new bond issues and Section 7 concludes.

2. Related Literature

First, we discuss the major bankruptcies over the sample period and their relation to bond defaults. Second, we discuss the literature on corporate bankruptcy and its spillover effect to other firms.

2.1 Prominent Municipal Bankruptcies

In this section, we discuss the largest and most publicized municipal bankruptcies over our sample period.

2.1.1 Jefferson County Alabama

Jefferson County raised municipal debt to finance large sewer infrastructure projects that led the county to extreme debt. To lower interest payments a series of controversial interest rate swaps were initiated in 2002 and 2003, increasing the county's indebtedness to the point that it had to file for 4-billion bankruptcy on November 9, 2011. Prior to its bankruptcy, on March 31, 2008, the county had its first default through an unscheduled draw on reserve fund. Following this default, on July 29, 2009 the county has another technical default. A day later, on July 30 2009 the county missed interest payment, its first monetary default. There are two other defaults, a technical default on Feb 4, 2010 and a monetary default on Oct 1, 2010 before it filed for bankruptcy.

2.1.2 Detroit, Michigan

The city of Detroit, Michigan is the largest municipal bankruptcy filing in U.S history, estimated at $18.5 billion. Pension liabilities, accounting for 19% of debt were largely responsible for the weak financial conditions that lead to the filing. After Detroit's filing, a Judge ruled that the bankruptcy filing violated the law and ordered Governor Rick Snyder to withdraw the filing. The Bankruptcy Court added its own, federal stay of the state court proceedings and a trial on city's eligibility for Chapter 9 bankruptcy was held on October 23, 2013 that ruled Detroit eligible for Chapter 9. On June 3, 2014 the Michigan passed a package worth billions to help Detroit avoid further bankruptcy proceeding. The first default on municipal debt occurred on Oct 1, 2013 when Detroit missed the interest payment of its bonds, and the second one only three months later when the city again missed put payments. On April 1, 2014, 4 months after the court confirmed its eligibility of bankruptcy, there was a technical default, which is the last Detroit default recorded in over our sample period.

2.1.3 Stockton county and San Bernardino California

Stockton and San Bernardino sold millions of dollars of pension obligation bonds to help pay for their employee retirement benefits, but the interest costs exceeded the anticipated rate of return, which resulted in their bankruptcies. Stockton and San Bernardino filed for bankruptcy on June 28, 2012 and Aug 1, 2012 respectively. Prior to its bankruptcy filing, on Feb 1, 2011 San Bernardino missed the interest payment of its revenue bond. The first default by Stockton County was after the bankruptcy filing in April 1,2013.

2.2 Corporate Bankruptcies

Potential contagion of bankruptcy has been studied at corporate level. Prior research examines and finds negative effects of bankruptcy on other economic linked firms like suppliers (Hertzel, Li, Officer, and Rodgers(2008)) and strategic alliance partners (Bonne and Ivanov(2012)). Hertzel and officer (2012) find that bankruptcy impacts not just the equity returns, but also the debt issues of other firms. Dungey, Mardi, et al (2006) document the spillover effect in international bond markets during Russian and the LTCM crisis.

In a recent paper, Gospodinov, Nikolay, Brian, and Paula (2014) find that spillover from Detroit's bankruptcy for other municipalities as captured by the abnormal yield changes is relatively limited. However, the fact that Detroit's financial woes were long in the making and its bankruptcy not a surprise to the market may partially explain the results.

3. Data and empirical methodology

We collect bond issue information and bond default data from Mergent's Municipal Bond Securities Database (MBSD) from 2000 to 2014. The default section of MBSD includes information such as default date, default event information, default status, data sources and information about reinstatements. The default data is collected from Internet, news, underwriter, all related agents, and official filings. MBSD has data on municipal bond defaults from 1985 to 2014. However, the default data for the earlier period is meager and so we concentrate on default events over the 2000-2014 period. We exclude taxable municipal bonds as well as variable coupon bonds to obtain a final sample of 3,197 bonds in defaults that span 915 bond issues by 667 unique issuers over the sample period.

Table 1 shows the distribution of defaults over the sample period 2000 to 2014. There's a significant increase in defaults in 2008 due to the financial crisis, with the number of bonds in default jumping from 75 to 231. The number of defaults stays elevated till the end of the sample in 2014. Table 2 shows distribution of defaults for each state. The four states with most defaults, California, Florida, Illinois, and Texas have 687, 389, 208 and 190 bonds in default, respectively, over the sample period. The states with the least defaults are New Hampshire and Rhode Island with only 1-2 defaults.

As shown in Panel A of Table 3, the reasons for default vary with the most frequent reason for default being a violation of covenants, which is seen in about 36.17% of the sample. About 30% of the defaults are due to missed interest payments (MIP) followed by unscheduled draws from reserve funds (24.25%). The remaining reasons for default account for less than 5% of the sample each. In aggregate, about 41.1% of the defaults are classified as being monetary defaults and the remaining defaults are classified as Technical defaults. Some of the defaulted bonds are able to address the violations that led to the default, for example return to being in compliance with covenants, and are reinstated back from default. In our sample, we find that about 13.4% of the defaulted bonds are able to satisfy all criteria and are reinstated. The average duration in default for these reinstated bonds in our sample is 585 days.

About 12% of the defaulted bonds are General Obligation (GO). This is substantially lower than the share of GO bonds in all municipal bonds outstanding, which is approximately 54% over the sample period. As general obligation (GO) bonds are backed by the full faith and credit of the municipal issuers, who can increase taxes to avert defaults, it is not surprising that they are less likely to experience defaults. About 30% of the defaulted sample carried some kind of credit enhancement. This is lower than the share of bonds with credit enhancement in the full sample, which is about 51.6% over the sample period. These credit enhancements usually consist of bond insurance, whereby the private insurance firms guarantee payment of principal and interest on the bond issue if the issuer defaults. The credit enhancement can also be provided by larger state agencies. As credit enhancement increases the likelihood of interest and principal payment it is not surprising to find that the majority of the bonds with credit enhancement are in technical, as opposed to monetary, defaults. These technical defaults might involve a violation of a covenant and as it is not a missed interest or principal payment, it is not guaranteed by the insurer. The financial crisis tested the solvency of many municipal bond insurers as many of them had branched into insuring mortgage-backed securities. The financial troubles of bond insurers has resulted in a decline in the number of bond insurers as well as their credit rating. This has reduced the likelihood of issuers getting bond insurance. Whereas 60.75% of the municipal bonds carried insurance in 2007, only 13.5% did in 2014.

3.1 MSRB trading data

As we want to examine the price changes bond experience when they default, we obtain municipal bond trading data from Municipal Securities Rulemaking Board (MSRB) over the sample period from 1999 to 2014. We use bond CUSIP data to match MSRB with bond-specific default information from MBSD. Since the start of 1998, the MSRB has required dealers to report all municipal bond transactions, including inter-dealer trades and trades from customers. To obtain fundamental prices for traded municipal bonds from MSRB transaction data we follow Green, Li and Schurhoff (2010). Specifically, as we focus on price changes in the secondary market we drop transactions in the when-issued market.[26] Municipal bonds trade infrequently and intraday price variations can be large due to differences in terms of trade across type of investors. To address this problem, we construct daily "fundamental" prices by taking the midpoint of the highest price on purchases by dealers from customers and lowest price on sales by deals to customers on each day. If there are not both purchases from customers and sales to customer on a given day, then the daily fundamental price is the mean price on inter-dealer trades. If there is no inter-dealer trade, we take the purchase price or sale price as "fundamental price" for that day. We also exclude taxable and variable coupon bonds.

[26] We drop bonds with par value traded less than 5000 and maturity greater than 100. We also drop bonds with fewer than 10 trades over the sample period.

This results in 1,508,920 unique bond and 21,726,119 daily fundamental prices over the 1999 to 2014 period.

To examine the effect of the default on the bond, we calculate the abnormal price change around the default event. To maximize the number of observations with trading data both before and after the default event, we use the [-6, +6] month window around the bond default. To get the full bond price for each trading date, we add the accrued interest to each fundamental price. The accrued interests are calculated based on coupon payment and coupon frequency. The change in bond prices is the difference in the full price of bond on the last trading day in the six months prior to the default to the full price on the first trading day within six months after default. The abnormal price change is the difference between this bond price change and expected price change. We calculate expected price change based on zero-coupon Treasury yield curve estimated by Gurkaynak, Sack and Wright (2007). We convert yield into price and obtain the change in treasury price. We match each bond to Treasury with the same maturity. The abnormal price change is the price change of the bond minus price change of matched treasury and is referred to as Adjusted Price Change. As municipal bonds trade infrequently we are able to obtain data to calculate the [-6, +6] month price change for only 825 defaulted bonds.[27]

[27] If we shorten the window to a [-3, +3] month window the price change can be calculated for only 512 defaulted bonds.

4. Price Changes in Defaulted Bonds

4.1 Univariate Evidence

The average [-6,+6] month price change around default for defaulted bonds is -2.98% as seen in Table 4. The median is a much smaller (-0.2%). The results suggest that these defaults are significant negative events in the municipal bond market and that there is substantial skewness in the data with some defaulted bonds incurring large losses and others a price increase. It is quite possible that the above documented change in the bond price around default underestimates the impact of the default as many of the bond defaults might be expected. For example, in the Detroit case on Feb 2013, eight months before the date of their bond default, a state-appointed panel declared the city dysfunctional and set the stage for a possible financial takeover by Michigan's government, which was widely reported in the press. Consequently, Detroit's bond default was likely not a surprise.

The average adjusted price change for defaulted bonds is -5.45% if it is a MIP default and not surprisingly this is significantly lower than the -2.12% for other types of defaults. Bonds with credit enhancement have only a -0.53% price decline on default which is significantly lower than the -4.72% for defaulted bonds with no credit enhancement. As GO bonds are backed by the full faith and credit of the municipal issuer, and further as 86% of the GO bonds in our sample have credit enhancement, they experience a positive price reaction on defaults. The positive reaction may reflect the fact that defaults increase the likelihood of intervention by state authorities and a possible solution to the issuer's problems. Lastly, the reinstatement of defaulted bond suggests that issuer's problems were not severe and consistent with this, we find that the price change is less negative for reinstated bonds about, -1.11% as opposed to -3.26% for bonds that were not reinstated.

Gao, Lee and Murphy (2016) examine the state bankruptcy policies and document that some states, referred to as *Proactive* states which actively help distressed municipalities.[28] As issuers in default are likely to get state help, an announcement of the default is associated with only a -0.7% price decline that is significantly smaller than -3.6% for issuers from other states.

4.2 Multivariate Evidence

In this section, we estimate an OLS model where we control for the determinants of price changes around default. The dependent variable is Adjusted Price Change, that is, the difference between price change of default bonds and the price change of matched treasury over the same [-6,+6] month period around default. We control for the principal and maturity of the defaulted bonds, along with state and year fixed effects. These fixed effects control for the overall health of the state economy and any time effects in the data like the financial crisis.

We first examine whether the nature of defaults and bond characteristics impact the price declines around default announcement. We include a dummy variable, referred to as MIP Default that takes the value of one if the default was classified as a miss interest payment default. We also include an indicator variable if the bond had credit enhancement and was a general obligation bond (GO Dummy). We expect less negative

[28]In line with Gao, Lee, and Murphy (2016) classification there are 8 Proactive states. These are Maine(ME), Michigan (MI), North Carolina (NC), New Jersey(NJ), Nevada(NV), New York(NY), Ohio(OH), and Pennsylvania(PA).

price reactions for both these types of bonds on default. We also include an indicator variable for whether the bond was subsequently reinstated. As discussed earlier, for reinstated bonds the default was likely less severe. As seen in Column 1 of Table 5, the coefficient of MIP dummy is negative, consistent with the univariate results but is not significant. As expected the coefficient of Enhancement and GO Dummy are both positive and significant. Defaults impact general obligation bonds, and those with credit less severely. Lastly, the coefficient of Reinstated dummy is not significant. Somewhat surprisingly, the default of large issues is associated with a smaller price decline. In column 2, we include an indicator variable if the issuer was from a Proactive State and find that consistent with Gao, Lee and Murphy (2016) the price decline for these issuers is less negative on default.

5. Effect of Defaults on Other Bonds

The bond defaults convey information about the possible fiscal problems in the state and consequently have implications for the prospects of other municipal bonds from the state. In this section we examine the effect of any of bond defaults on other non-defaulted bonds from the same state to help shed light on the economic ramification of municipal defaults.

To understand the effect on other non-defaulted bonds from the same state we calculate the abnormal price change experienced by these bonds around the default event. In particular, we estimate the [-6, +6] month adjusted price change for all non-defaulted bonds in line with the estimation of price changes for defaulted bonds.

Bond issues include several bonds and there may be more than one bond that may default on a particular day. If there are more than one bond from the state that defaults on a particular day, they will together effect the prices of other non-defaulted bonds from the state. We exclude state days with GO defaulted bonds, since the portion of GO bonds in default with available price change information is very small and the market expectation may be already adjusted before default event thanks to larger media coverage. We find that in our data, there are 730 individual bonds defaults that result in 255 unique state days of default. We therefore estimate the average abnormal price change of all non-defaulted bonds from six months prior to six months after these state default days and are able to obtain 1,151,996 price changes for 341,673 unique non-defaulted bonds. We find that the average [-6, +6] month adjusted price change for other non-defaulted bonds from the same state is a significant -1.1%

The variable of interest is the characteristics of the default that are most value relevant for other non-defaulted bonds from the same state. As there are more than one defaults on a given day, we aggregate all default characteristics at state day level. For instance, if there're six California bonds that default in the same day we aggregate the characteristics of these six bonds to capture the nature of state day default event. First, we capture the nature of the default by the adjusted price change of the defaulted bonds. If the defaulted bond experienced a large price change it is likely to be more severe and relevant for the other bonds as well. We estimate the Default Price Change as the minimum abnormal price change for all the defaults on the event day (Price change of Defaulted Bonds). As this captures the most negative price change across all defaulted bonds it captures the severity of the default event.

To understand the factors that are most associated with negative news for other non-defaulted bonds we estimate a model for the adjusted price change of these bonds around the default event. We control for the characteristics of the non-defaulted bonds such as the log of the principal, maturity, GO Dummy, Enhancement Dummy along with state and time fixed effects. Lastly, we include the Price Change of Defaulted Bonds.

As seen in Model 1 of Table 6, the coefficient of Price Change of Defaulted Bond is positive and significant. This suggests that if the change in the price of the defaulted bonds is more negative, the change in the price of the non-defaulted bonds will also be more negative. This is consistent with the expectation that more severe defaults have stronger ramifications for other non-defaulted bonds. The coefficient of the control variables are as expected. Though principal of the bond does not have an impact the coefficient of maturity is positive and significant. Bonds with longer maturity have a less negative price change as do GO bonds when other bonds in the state default.

Next, we examine what characteristics of the defaulted bonds are likely to be most relevant for other bonds from the same state. The larger the default amount in the state, the more negative is the fiscal health of the state. We create a variable Default Fraction that is the proportion of the principal of the defaulted bonds to total principal of bonds outstanding in the same state. The defaulted bonds may be very small issues and hence may not represent a serious fiscal problem for the state. Second, monetary defaults may potentially indicate the presence of greater fiscal issues in the state than technical defaults. To capture this, we include MIP Fraction which is the fraction of all dollar amount of defaulted bonds that are classified as MIP defaults. As seen in Model 2 of Table 6, the coefficient of Default Fraction is negative and significant while the coefficient of MIP Fraction is insignificant. The bigger default fraction, the bigger is price response of non-defaulted bonds. In line with the results in Table 5, there is little information in whether the default was due to missed interest payment or other reasons.

We next explore the effect of the state's bankruptcy policies. As seen in column 3, the coefficient of Proactive Dummy is positive and significant suggesting that the price response of other bonds to the default is smaller in Proactive states, as documented by Gao, Lee and Murphy (2016). As Proactive states provide help to distressed municipalities, a bond default is not very negative news for investors that hold the defaulted bond or investors that hold other bonds of issuers in the state.

Lastly, the defaults from the same local area may convey more relevant information about the financial condition of issuers. For example, the woes of Atlantic

City in Southern New Jersey from declining Casino business is likely to impact issuers from the Atlantic county but may have less implications for issuers from Bergen County in Northern New Jersey as the mainstay of resident's incomes is substantially different across the two regions and the local government is different. To examine if the effect on other bonds is stronger if the issuers are from the same county as the defaulted bonds we obtain information on the issuer and their geographic location. We obtain county information from SDC platinum. We match MBSD with SDC platinum by using CUSIP. If there's no match, we match most available county information of issuer to bonds in SDC platinum to bonds in MBSD by using 6-digit CUSIP. Since locations of issuers are unlikely to change over our sample, this method can yield accurate county information for municipal bonds. County information is not available for all issuers and it reduces the sample of other non-defaulted bonds by 44%, for a final sample of 679,334. The dummy variable Local Dummy takes the value of one if the bond issuer is from the same county as the issuer of the defaulted bond. As seen in Model 4, the coefficient of Local Dummy is negative and significant. This suggests that bond bonds issued by other issuers in the same county have a significantly stronger price reaction to defaults.

6. Cost of Financing

In this section, we examine how defaults impact the cost of raising capital for municipalities in the state. We obtain data on new bond issues over the period 2000 to 2013 from Mergent's Municipal Bond Database (MBSD). The data in MBSD is at tranche level. One issue will include multiple tranches with different maturity dates, coupon rates and offering yields. Tranches of one issue share the same issuer, underwriter and offering date. To construct issue level data from tranches, we follow Gao and Qi (2014). First, we aggregate continuous variables such as offering yield and maturity by calculating a dollar value weighted average. For categorical variables such as credit rating, we identify the tranche with highest principal with non-missing information, and take its attributes for the issue.[29] We exclude Build American Bonds (BAB), taxable bonds, and variable coupon bonds. The final sample includes 149,880 new municipal bond issues and 83,366 issues.

In this sample of new issues of municipal bonds, we examine if prior defaults of bonds from the same state impact the cost of raising new capital. Specifically, we examine if the prior defaults increase the offering yield on new bond issues. To examine this effect we estimate a multivariate model where the dependent variable is the offering yield on new bonds issued and the main variable of interest is Past Default, which is the

[29] MBSD only provides most recent ratings rather than ratings at issuance. To get credit ratings at issuance, we first identify all rating in MBSD issued prior to or on offering date. If we do not have this rating, we supplement MBSD with data from SDC platinum. We use issuer's CUSIP, bond-offering date, bond offering amount and states of issuers to match MBSD with the SDC. We take the S&P rating at issuance from SDC. If S&P ratings is not available, we take Moody's ratings and if that is not available we take Fitch if available.

number of bonds from the same state that defaulted in the prior three year.30 We use all defaults, rather than the 825 defaults for which we have price changes, to construct this measure of Past Default. We also create a variable, referred to as Past Default Rate, that is, the ratio of the number of defaults in the year prior to the total number of bonds outstanding.

In estimating the effect of Past Defaults on municipal borrowing costs we control for several bond, state and economy level characteristics. We include the natural logarithm of the size of the issue, bond maturity and several indicator variables. First we include an Enhancement Dummy, which takes the value of one if the bond issue has any credit enhancement. Also included are GO dummy, Negotiated Deal Dummy and Call dummy if the bond is a general obligation bond, was sold through a negotiated bid and includes call provisions respectively. Lastly we control for the credit rating of the bond and also include the No Rating Dummy that takes the value of one if the credit rating is not available.

In line with prior literature in corporate bonds, we include two macroeconomic variables associated with yields on corporate bonds (See Collin-Dufresne et al. (2001), Longstaff and Schwartz (1995), Campbell and Taksler (2003), and Chen, Lesmond and Wei (2007)). First, we include the yield on the maturity-matched treasury, referred to as Matching Treasury. Secondly, we include the difference between 10-year and 2-year Treasury bills, referred to as Term Slope, which captures the slope of the yield curve.

[30] Note that this is the number of defaults in the 365 days prior to the offering date and include all bonds defaulted not just those for with available price changes.

We also control for time varying characteristics of the states. Specifically, we control for the state's indebtedness by including the ratio of state debt to state GDP and state's fiscal profile by including the ratio of state revenue to state expenditure. The higher the state's level of debt and the lower its revenue the higher will be the yield on the municipal bonds. We also include log of state population and the state's unemployment rate.[31] We include the variable, State tax that is the highest marginal personal state income tax rate. The details of the construction of all variables are provided in Appendix A[32].

As seen in Model 1 of Table 7, the coefficient of Past Default is positive and significant. The larger is the number of defaults in the past year the greater is the yield on new municipal debt from the same state. The coefficients of the other variables are as expected. General obligation bonds, with a larger principal and credit enhancement have lower offering yields (negative significant coefficients). In contrast, bonds with longer maturity, sold through negotiated bids and with call provisions have higher offering yields. The coefficient of credit rating is positive and significant as better rated bonds (with smaller numerical values) have lower yields and higher offering prices. For state level variables, states with higher revenue to expenditure have significantly lower yields and those with higher unemployment have higher yields. In model 2, we include Past Default Rate and find that it is also significant.

[31] Larger states have a broader revenue base and likely to be less risky. States with high unemployment rate are likely to have lower revenues and limited ability to increase taxation to support bond payments and hence associated with higher yields.

[32] The unemployment data is from U.S. Bureau of Labor Statistics (BLS). The state GDP data is obtained from BEA. The marginal tax rate is derived from National Bureau of Economic Research (NBER). All other state financials are from State Government Finances reported by the Census.

The effect of prior defaults appears to be economically meaningful. A one standard deviation increase in the number of defaults in past three years is associated with a 4.77 basis points increase in offering yield. As the unconditional offering yield is 3.37%, this represents an increase of 1.42% in the cost of municipal borrowing. Given that the average total offering amount per year is 267 billion, this results in an increase of 127.36 millions in annual interest costs.[33]

Next we examine if the nature of the default, and the information conveyed by it impact the cost of borrowing of new municipal issues. We first examine the effect of default severity on cost of new issues that like before is captured by the Price change of defaulted bonds in the past three years to construct the variable Past Default Price Change, which is the largest price decline of a defaulted bond in the past three years. As seen in column 3, the severity of the defaults does not impact the cost of borrowing after we control for the number of defaults. We also created the weighted average price decline of all defaulted bonds in the past three years, with the weights being their par values. The results are similar and have not been tabulated for brevity. In column 4, we include the dollar fraction of all defaults in the past three years that were due to MIP (MIP Fraction of Past Default) and the dollar fraction of all defaults that were GO bonds (GO Fraction of Past Default). In line with prior results that MIP defaults have no additional information, the coefficient of MIP fraction is not significant. However, we find that the coefficient of GO Fraction of Past Default is positive and significant. The greater the number of past defaults, and the greater is the fraction of these that are GO bonds the

[33] Standard deviation of the increase in the number of defaults in past three years is 50.95 defaults. This is associated with 4.77 basis points (0.000937*50.95) rise in offering yield.

greater is the cost of new municipal issues. This is consistent with the hypothesis that defaults of GO bonds convey more information about the overall fiscal health of the state.

As seen in table 1, defaults increase during the financial crisis. As all states are experiencing fiscal problems the effect of default on cost of new issues is likely relative to what the other states are experiencing. If the past defaults in the state are such that it is one of the top states by the number of defaults, this suggests that relative to other states the fiscal problems are higher and the cost of new issues will be higher. To examine this, we create an indicator variable Top 5 if the state is one of the top five states by the number of defaults in the past three years. As can be seen in Table 7B, the impact of past default on the cost of new borrowing is concentrated only if the state is among the states experiencing the most difficulty. For the remaining states, increase in the default rate does not significantly impact the cost of borrowing. The difference in the how past defaults impact the cost of new issues is significantly different for the Top 5 states and others. This effect is robust to use the fraction of default rather than the number of default (Panel B) or if we use top 10 states by default rather than top 5 (Column 2 of each Panel).

Municipal bond investors are exempt from federal income taxes. Municipal bond investors are also exempt from state and local taxes on bonds issued by their own state and in nine states there is no income tax on municipal bonds issued by any authority. [34] Consequently, municipal bonds are mostly held by investors from within states though there is some substitutability between municipal bonds from different states. Investors from the nine states that are exempt from taxes irrespective of the state of the issuing

[34] This is either because the state does not have state income tax or choose to exmept interest income on all municipal bonds (DC, Indiana and Utah). For further details see Pirinsky and Wang (2011)

municipality are likely to consider investing municipal bonds from all states. High defaults in some states may move the demand away from these states to other states that are doing better fiscally. To examine this, we include the past default rate in other states. Past Default Other States is the number of bond defaults in all other states in the past three years. As seen in column 3, greater default in other states increases the demand for instate bonds and reduces the cost of new issues from the state.

Lastly, we examine if the effect of default on cost of new issues varies by the nature of the bankruptcy policies of the state. We examine the effect of past default on cost of new issues in Proactive and other states. As seen in Table 7C, the effect of past defaults is not significant in Proactive states and is only seen in other states. As Proactive states provide relief to distressed municipalities, new issues implicitly carry the benefit of state protection and are not impacted by the past default rate. As similar result is seen when we use the fraction of past defaults as in Model 2.

If past defaults in Proactive States do not convey negative news for new issues from the state, they are unlikely to be perceived as negative news by investors from other states. It is only the default in Non Proactive states that will likely reduce the out of state demand for bonds from these states. To test this we create the variable Past Default – Proactive Outside. This is the number of bond defaults from other states that are proactive in the past three years. We also create, Past Default – Non Proactive Outside as the number of bond defaults in non-proactive states in the past three years. As seen in Model 3, only the coefficient of Past Default for Non Proactive Outside states is negative and significant. In summary, defaults in Proactive states convey less negative information for other non defaulted bonds, do not significantly impact the cost of new issues and do not reduce demand for bonds from out of state investors. However, for the majority of the states that are not proactive past default of municipal bonds significantly decrease the price of traded municipal bonds as well as the cost of new bond issues.

7. State Borrowing

Lastly, we investigate whether past defaults have an effect on the borrowing amount of municipalities. As seen in the prior section, the cost of new borrowing is higher but do defaults also impact the amount of debt state municipalities are able to raise? The increased cost of borrowing may cause many issuers to postpone the debt offering to reduce the amount of debt raised. If this is so, then past defaults will be associated with reduction in the new debt raised by municipalities in the state. However, if municipalities have no choice but to raise the amount they need to, then there may be no impact of past default on the debt raised.

As seen above, there is no impact of past default on costs of new issues for Proactive states due to the expectation of implicit help that distressed municipalities receive from the state. However, if the state is implicitly helping distressed issuers this may limit the amount of debt that can be raised. In other words, Proactive states may discourage state issuers from raising new debt in the face of past defaults. We also examine how past defaults impact Proactive state borrowing.

To study this, we calculate the total principal of new offering from the state every year. We estimate a model for the total debt raised by the state. The variable of interest is the intensity of default in the past, that is Past Default. We also examine if the nature of past default impact the amount of debt raised by issuers in the state.

We control for other variables that are likely to impact state borrowing. First, we include the amount of debt raised last year by state issuer (Prior State Borrowing) as it proxies for the borrowing need of the state. We also include the total amount raised in the municipal debt markets last year (Prior Muni Debt) to capture any concerns that impact the municipal debt markets. Several state economy indicators and financial ratios are included as well such as Debt/GDP, Revenue/Expenditure and Unemployment Rate. We control state fixed effect and year fixed effect to capture time invariant effects.

We find that the coefficient of Past Default is not significant though that of the fraction of defaults in the past is negative and significant (Table 8). As the fraction of bonds in default increases, the amount of state borrowing drops. The debt level of the state (Debt/GDP) and the unemployment rate both negatively impact the amount borrowed by the state. We also examine whether the nature of past defaults impacts the state borrowing. The Price Change of past default is positive and significant. The more negative was the price change of defaulted bonds in the past three years, the lower is the state borrowing (Model 3). As seen before the fraction of past defaults that are MIP does not impact state borrowing though higher fraction of defaults by general obligation bonds negatively impacts state borrowing (Model 4).

Lastly, we examine if the effect of default on state borrowing is different for proactive states. A higher fraction of past defaults decreases state borrowing in both Proactive and Non Proactive states, though the effect is significantly stronger for Proactive states (Model 5). Though defaults do not significantly impact other bonds or the cost of new issues, though significantly reduce total state borrowing in Proactive states. For Non Proactive states, defaults increase the cost of new issues and though they reduce state borrowing, the effect is smaller than that for Proactive states.

8. Conclusion

In this paper, we study defaults in the municipal bond market and find that these are significant negative events for the bond markets. Not only does the price of the defaulted bond decline, but there is also a significant decline in the price of other bonds from the state. Further, there is an increase in the cost of financing of new municipal bond issues from states that experience several defaults. The evidence suggests that even though municipal bond investors are likely to eventually collect their principal in full for most of these defaults, these defaults have significant impact on the other municipal issuers. The effect of default is lower for Proactive states that offer state help to distressed issuers. We are one of the first papers to examine defaults in the municipal bond markets.

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Tables

Table 1: Municipal Bond Defaults over Time

This table displays distribution of defaults over the sample period 2000 to 2014. The sample consists of 3.244 tax-exempt bonds that defaulted as obtained from Mergent's municipal bond database. Column 2 reports the number of bonds in default, Column 3 reports total principal of default bonds (in millions), Column 4 reports number of unique issues that defaulted and Column 5 reports number of unique issuers, counted by 6 digits CUSIP that defaulted.

Year	Number of Defaulted Bonds	Default Amount (in Millions)	Number of Defaulted Issues	Number of Defaulted Issuers
2000	87	181	19	17
2001	75	120	18	16
2002	78	183	24	22
2003	168	277	36	33
2004	119	405	26	19
2005	53	306	20	17
2006	98	529	22	19
2007	75	415	20	17
2008	231	2,710	38	28
2009	366	2,790	142	100
2010	226	2,190	79	60
2011	276	2,250	115	75
2012	677	2,960	148	101
2013	312	2,150	109	79
2014	356	2,060	99	64
Total	3,197		915	667

Table 2: Distribution of Defaults Across States

This table reports the distribution of municipal bond defaults across states over the 2000 to 2014. Column 2 reports the number of bonds in default and Column 3 reports total principal of default bonds (in millions). Column 4 reports number of defaulted issues and their unique issuers. The table only reports states with 10 or more defaults over the sample period.

State	# of Bonds	Default Amount	# of Issues	# of Issuers
CA	687	1,200	88	60
FL	389	3,480	225	160
IL	208	1,100	60	30
TX	190	1,860	77	50
AL	173	827	34	28
PA	160	1,850	19	15
MI	140	710	27	14
CO	98	73	20	18
KS	98	454	39	34
MN	94	147	19	16
MO	90	252	27	23
VA	82	1,230	24	17
AR	67	104	29	19
NY	63	1,060	20	12
GA	59	893	20	16
IN	49	303	18	13
TN	49	132	14	9
SC	46	197	7	6
IA	46	254	10	8
NV	40	396	7	6
MA	40	760	12	9
AZ	39	190	13	10
OH	37	271	14	13
LA	33	212	16	13
WI	29	48	9	9
NJ	28	116	7	6
MD	24	242	9	7
NE	23	36	4	3
WV	19	155	8	7
CT	17	333	5	2
WA	14	120	4	3
MS	12	55	4	4
Total	3,197		915	667

Table 3: Summary Statistics for Default Bonds

This table displays summary characteristics for municipal bonds in default over the 2000 to 2014 period.

Panel A: Default Characteristics

	# of Bonds	**Portion (%)**
Reason for Default		
Violation of Covenant (VOC)	1,157	36.17
Missed Interest Payment (MIP)	960	30.04
Unscheduled Draw on Reserve Funds (DRAW)	775	24.25
Bankrupt Lessor (BKLE)	143	4.47
Missed Tender or Put Payment (REPL)	100	3.13
Missed Principal or Redemption (MPP)	49	1.53
Monetary Failure of Guarantor (MFOG)	13	0.41
	3,197	
Type of Default		
Monetary Default	1,314	41.10
Technical Default	1,883	58.90
Reinstated Status		
Never Reinstated	2,765	86.49
Reinstated	432	13.51

Panel B: Type of Bonds

General Obligations bonds are backed by the full credit of the issuer. Revenue bonds are tied to the revenue from specified sources.

	# of Bonds	**Portion (%)**
General Obligation Bonds (GO)	386	12.07
Revenue Bonds	2,811	87.79
With Credit Enhancement	963	30.12

Table 4: Univariate Results for Defaulted Bonds

This table reports mean and median abnormal price change for defaulted bonds over 2000 to 2014. Sample includes all bonds with available trading information to calculate price change in [-6,+6] month window around the default. Abnormal price change is the difference between price change of defaulted bonds and price change in matched Treasury. MIP refers to bonds that default due to missed interest payments. Reinstated bonds are defaulted bonds that are no longer in default. Proactive States are states that provide help to distressed municipalities. Column 4 reports p values of the T test for the difference in the two groups except for row 1 (All).

	Mean Price Change	**Median Price Change**	**P value of T Test**	**Num. of obs.**
All Defaulted Bonds	-0.0298	-0.0024	0***	825
MIP	-0.0545	-0.0190	0.004***	214
Other Type of Defaults	-0.0212	-0.0011		611
With No Credit Enhancement	-0.0472	-0.0129	0.00***	483
With Credit Enhancement	-0.0053	-0.0027		342
Revenue Bonds	-0.0413	-0.0122	0.000***	703
General Obligation Bond	0.0361	0.0295		122
Not Reinstated	-0.0326	-0.0047	0.099*	719
Reinstated	-0.0111	0.0187		106
Proactive States	-0.0078	0.0087	0.03**	191
Other States	-0.036	-0.0079		634

Table 5: Regression Model for Price Change for Defaulted Bonds

This table reports OLS regression where dependent variable is abnormal price change of default bonds. The price change is calculated around [-6,+6] month window around default adjusted for the change in price for matched treasury. MIP Dummy takes the value of one if the default is classified as a missed interest payment default. Enhancement (Reinstatement) Dummy is equal to 1 if the defaulted bond has credit enhancement (was reinstated). Maturity is the number of years from the date of trade to maturity. The coefficient reported is the estimated coefficient times 1000. Past Default is the number of default bonds in prior year in the same state and the reported coefficient is estimated coefficient times 10000. Log (Total Principal) is log value of total principal of bonds. Proactive Dummy is equal to one if the issuer is from a proactive state. Standard errors are clustered at state level. ***,**,* denote significance at the 0.1,0.05 and 0.1 levels. We include year fixed effect and state fixed effects.

	Model 1	**Model 2**
MIP Dummy	-0.0347	-0.0347
	(-1.51)	(-1.51)
Credit Enhancement	0.0673**	0.0673**
	(2.68)	(2.68)
Reinstatement Dummy	0.00324	0.0853***
	(0.21)	(3.90)
GO Dummy	0.0853***	0.00324
	(3.90)	(0.21)
log(total principal)	0.0111*	0.0111*
	(1.81)	(1.81)
Maturity	0.0629	0.0629
	(0.06)	(0.06)
Proactive Dummy		0.182***
		(3.78)
State, Year dummy	Yes, Yes	Yes, Yes
R square	0.2876	0.2876
Observations	825	825

Table 6: Regression Model for Price Change for Non-Defaulted Bonds

This table displays OLS regression for adjusted price change of non-defaulted bonds over the [-6,+6] month window around default. The default events associated with GO bonds are excluded. Price Change of Defaulted Bonds is the most negative or smallest price change across all bonds that default on the default event day. Default Fraction is the ratio of the defaulted principal to the total principal of bonds outstanding in the same state. Fraction MIP is the ratio of dollar value of MIP defaults to all defaults. Coefficient of GO dummy has been multiplied by 100. The coefficient of Fraction MIP, Credit Enhancement Dummy, Maturity and Log(Total Principal) has been multiplied by 1000. ***,**,* denote significance at the 0.1,0.05 and 0.1 levels, respectively. Standard errors are clustered at state level. We include state fixed effect and trade year fixed effect.

	Model 1	**Model 2**	**Model 3**	**Model 4**
Price change of Defaulted Bond	0.0809***		0.0809***	0.124***
	(6.41)		(6.41)	(6.03)
Default Fraction		-17.10*		
		(-1.87)		
Fraction MIP		-0.670		
		(-0.12)		
Proactive dummy			0.0629***	
			(4.14)	
Local Dummy				-0.00650**
				(-2.30)
log(Principal)	-0.698	-0.651	-0.698	-0.580
	(-1.01)	(-0.91)	(-1.01)	(-0.91)
Maturity	0.618***	0.618***	0.618***	1.09***
	(3.10)	(3.16)	(3.10)	(3.07)
GO Dummy	0.295***	0.296***	0.295***	0.386***
	(3.80)	(3.72)	(3.80)	(4.93)
Credit Enhancement	0.943	0.889	0.943	0.275
	(1.38)	(1.36)	(1.38)	(0.28)
State, Year dummies	YES	YES	YES	YES
R square	0.1661	0.1514	0.1661	0.2145
Observations	1,151,996	1,151,996	1,151,996	607,790

Table 7: Cost of Financing New Issues

The dependent variable is the offering yield of new municipal debt issued over the period 2000 to 2013. Past Default (Rate) is the number (fraction) of defaults in the past three year. Price Change of Past Default is the most negative price change of all defaulted bonds in the state in the past three years. Fraction MIP of Past Default is the fraction of all defaults in the past three years that are classified as MIP. Fraction GO past Default is the dollar fraction of default in the past three years that were by general obligation bonds. The remaining variables are defined in Appendix A. ***,**,* denote significance at the 0.1,0.05 and 0.1 levels, respectively. Standard errors are clustered at state level.

	Model 1	**Model 2**	**Model 3**	**Model 4**
Past Default	0.000937***		0.000906***	0.000935***
	(7.44)		(7.52)	(7.31)
Past Default Rate		34.17***		
		(2.68)		
Price Change Of Past Default			-0.0397	
			(-0.99)	
Fraction MIP of Past Default				-0.0185
				(-0.89)
Fraction GO Past Default				0.285***
				(3.07)
<u>Macro-Economic Variables</u>				
Treasury Yield	0.561***	0.562***	0.561***	0.561***
	(56.61)	(51.85)	(56.75)	(59.45)
Term slope	0.0446***	0.0431***	0.0444***	0.0450***
	(3.85)	(3.76)	(3.93)	(3.92)
<u>Bond Characteristics</u>				
Maturity	0.0547***	0.0546***	0.0547***	0.0547***
	(32.99)	(33.82)	(33.18)	(32.03)
Credit Enhancement Dummy	-0.165***	-0.166***	-0.165***	-0.163***
	(-9.53)	(-9.56)	(-9.51)	(-9.58)
Log(Principal)	-0.0544***	-0.0543***	-0.0543***	-0.0545***
	(-7.18)	(-7.19)	(-7.17)	(-7.05)
GO Dummy	-0.136***	-0.135***	-0.135***	-0.135***
	(-5.40)	(-5.37)	(-5.39)	(-5.37)
Call Dummy	0.0538***	0.0542***	0.0537***	0.0534***
	(3.55)	(3.57)	(3.55)	(3.53)
Negotiated Bid Dummy	0.160***	0.163***	0.160***	0.161***
	(11.16)	(11.24)	(11.14)	(11.28)
Average rating(1-21)	0.0597***	0.0597***	0.0597***	0.0598***
	(12.84)	(12.84)	(12.81)	(12.84)
No rating dummy	0.326***	0.326***	0.327***	0.328***
	(12.64)	(12.55)	(12.66)	(12.57)
<u>State Level Variables</u>				
State tax	-0.0159**	0.00267	-0.0141*	-0.0149

	(-2.06)	(0.23)	(-1.76)	(-1.67)
log(pop)	0.266	0.326	0.275	0.188
	(0.88)	(1.03)	(0.91)	(0.61)
Debt/GDP	0.000892	0.000790	0.000897	0.000863
	(1.58)	(1.42)	(1.57)	(1.54)
Revenue/expenditure	-0.124**	-0.120**	-0.121**	-0.0936
	(-2.26)	(-2.18)	(-2.19)	(-1.64)
Unemployment rate	0.0399***	0.0437***	0.0394***	0.0373***
	(3.24)	(3.22)	(3.26)	(3.49)
State, Year dummy	Yes, Yes	Yes, Yes	Yes, Yes	Yes, Yes
Observations	149,880	149,880	149,880	148,639
R square	0.8693	0.8690	0.8693	0.8697

Table 7B: Cost of Financing New Issues

The dependent variable is the offering yield of new municipal debt issued over the period 2000 to 2013. The table reports partial results. Panel A uses the number of defaults in the past three years while Panel B uses the fraction of bonds that defaults in the past three years to capture Past Default. Top 5 (Top 10) Dummy takes the value of one if the issuer is from a state that was one of the top 5 states by the defaults in the past three years. Past Default outside state is the number of defaults (Panel A) and the fraction of bonds that defaulted (Panel B) in all other states in the past three years. Variables that were included in the estimation but not displayed here are Treasury Yield, Term Slope, Bond Maturity, Credit Enhancement Dummy, Log(Principal), GO Dummy, Call Dummy, Negotiated Bid Dummy, Average Credit Rating, No Rating Dummy, State Tax, Lop(Population), Debt/ GDP, Revenue/ Expenditure and unemployment rate. These variables are defined in Appendix A. Also included are state and time fixed effects. ***,**,* denote significance at the 0.1,0.05 and 0.1 levels, respectively. Standard errors are clustered at state level.

	Panel A: Number of Default			**Panel B: Fraction of Default**		
Top 5 Dummy x Past Default	0.000915***			49.41***		
	(6.76)			(3.53)		
Non Top 5 Dummy x Past Default	-0.0000684			-12.96		
	(-0.14)			(-0.75)		
Top 10 Dummy x Past Default		0.000888***			36.30***	
		(7.00)			(2.86)	
Non Top 10 Dummy x Past Default		-0.00201**			-15.19	
		(-2.26)			(-0.71)	
Past Default			0.000712***			28.51**
			(5.55)			(2.37)
Past default - Outside State			-0.000265***			-229.5**
			(-4.90)			(-2.36)
Controls	YES	YES	YES	YES	YES	YES
State dummy	YES	YES	YES	YES	YES	YES
Year dummy	YES	YES	YES	YES	YES	YES
T-test (Top 5 == Non Top 5)	0.0365	0.0217		0.0011	0.0209	
Observations	149,880	149,880	149,880	149,880	149,880	149,880
R square	0.8693	0.8691	0.8694	0.8694	0.8691	0.8691

Table 7C: Cost of Financing New Issues

The dependent variable is the offering yield of new municipal debt issued over the period 2000 to 2013. The table reports partial results. Past Default is the number of defaults in the state in the past three years. Proactive (Non Proactive) Dummy takes the value of one if the issuer is from a state that is classified as Proactive (Non Proactive). Past Default Outside is the number of default outside the state in the past three years. Variables that were included in the estimation but not displayed here are Treasury Yield, Term Slope, Bond Maturity, Credit Enhancement Dummy, Log(Principal), GO Dummy, Call Dummy, Negotiated Bid Dummy, Average Credit Rating, No Rating Dummy, State Tax, Lop(Population), Debt/ GDP, Revenue/ Expenditure and unemployment rate. These variables are defined in Appendix A. Also included are state and time fixed effects. ***,**,* denote significance at the 0.1,0.05 and 0.1 levels, respectively. Standard errors are clustered at state level.

	Model 1	**Model 2**	**Model 3**	**Model 4**
Past Default x Proactive Dummy	-0.000412	-0.000355		
	(-0.48)	(-0.42)		
Past Default x Non Proactive Dummy	0.000962***	0.000717***		
	(7.63)	(4.98)		
Past Default Rate x Proactive			-32.44	-32.49
			(-1.33)	(-1.35)
Past Default Rate x Non Proactive			37.84***	25.88**
			(2.94)	(2.17)
Past Default Outside x Proactive		0.0000108		
		(0.03)		
Past Default Outside x Non Proactive		-0.000280***		
		(-4.08)		
Past Default Rate Outside x Proactive				80.93
				(0.55)
Past Default Rate Outside x Non Proactive				-331.5***
				(-3.67)
Controls	YES	YES	YES	YES
State dummy	YES	YES	YES	YES
Year dummy	YES	YES	YES	YES
Observations	149,880	149,880	149,880	149,880
R square	0.8693	0.8691	0.8695	0.8694

Table 8: Dollar Value of New Municipal Debt

The dependent variable is the logarithm of annual state new offering over the 2000 to 2013. Past Default (Rate) is the number (fraction) of defaults in the past three years. Price Change of Past Default is the most negative price change of all defaulted bonds in the state in the past three years. Fraction MIP of Past Default is the fraction of all defaults in the past three years that are classified as MIP. Fraction GO past Default is the dollar fraction of default in the past three years that were by general obligation bonds. Proactive Dummy takes the value of one if the issuer is from a Proactive state. Log (state borrowing) is the logarithm of annual state new offering in the prior year. Log (US borrowing) is the logarithm of annual U.S new offering. State Tax is the highest marginal personal state income tax rate. Log (Pop) is the logarithm of the state's total population. Debt/GDP is the ratio of state's total debt outstanding to state's total GDP. Revenue/Expenditure is the ratio of state's total revenue to state's total expenditure. Unemployment rate is the unemployment rate of the state.

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Past Default	-0.000178				
	(-0.39)				
Past Default Rate		-35.56**	-36.70**	-34.72**	
		(-2.47)	(-2.48)	(-2.37)	
Fraction MIP Past Default				-0.00860	
				(-0.26)	
Fraction GO Past Default				-0.0117*	
				(-1.68)	
Price Change of Past Default			0.134*		
			(1.93)		
Past Default Rate x Proactive					-115.0***
					(-5.32)
Past Default Rate x Non Proactive					-24.51*
					(-1.97)
Log(Prior State Borrowing)	0.0768	0.0674	0.0675	0.0687	0.0625
	(1.42)	(1.27)	(1.27)	(1.30)	(1.21)
Log(Total Prior Muni Debt Raised)	-5.139	-5.916	-5.591	-5.933	-7.602
	(-0.86)	(-1.05)	(-1.02)	(-1.06)	(-1.48)
State tax	-0.00857	-0.00812	-0.00803	-0.00830	-0.0102
	(-0.61)	(-0.60)	(-0.61)	(-0.62)	(-0.75)
Log(Population)	0.529	0.596	0.569	0.597	0.733*
	(1.07)	(1.28)	(1.26)	(1.29)	(1.72)
Debt/GDP	-0.000909	-0.00102*	-0.00106*	-0.00103*	-0.00109*
	(-1.44)	(-1.69)	(-1.74)	(-1.72)	(-1.79)
Revenue/expenditure	0.0162	0.0227	0.0131	0.0169	0.0332

	(0.17)	(0.25)	(0.14)	(0.19)	(0.37)
Unemployment rate	-0.0571***	-0.0548***	-0.0546***	-0.0547***	-0.0487***
	(-3.11)	(-3.30)	(-3.28)	(-3.26)	(-3.24)
State Fixed Effect	YES	YES	YES	YES	YES
Year Fixed Effect	YES	YES	YES	YES	YES
T-test (Proactive-other)					0.0003
Observations	700	700	700	700	700
R Square	0.9679	0.9682	0.9683	0.9683	0.9684

Appendix A: Variable Definitions

Variables name	Definition
Adjusted Price Change	Full price change of bonds minus price change of matched Treasury in the same time period. The full price is the traded price plus the accrued interest. The data is from MSRB.
MIP Dummy	An indicator variable that is equal to value of 1 if the bond is associated with missed interest payment defaults and otherwise 0.
GO Dummy	An indicator variable equal to value of 1 if the bond is general obligation bond, otherwise 0.
Maturity	The number of years from trade date to the maturity of the bond.
Past Default (Rate)	The number (fraction of principal in) of bond default bonds in the prior year from the same state.
Past Default Three Year (Rate)	The number (fraction of principal in) of bond default bonds in the prior three years from the same state.
Log (Total Principal)	Log value of total principal value of the bond.
Default Price Change	The most negative or smallest Price Change for defaulted bonds.
Default Fraction	Proportion of default amount to total principal of bond outstanding in same state.
GO Fraction	The ratio of total amount of default GO bonds to total default amount.
MIP Fraction	The ratio of total amount of bonds with MIP default to total default amount.
Enhancement	An indicator variable that takes value of 1 if the bond has either bond insurance or additional credit enhancement, otherwise 0.
Reinstatement	An indicator variable that takes value of 1 if the defaulted bond is reinstated, otherwise 0.
Local Dummy	An Indicator variable that takes value of 1 if the non-defaulted bond is the in the same county as the defaulted bond.
Offering Yield	The Bond yield to maturity at offering date. Weighted average of the offering yield of all the tranches in the issue.
Past Default Three Year	The Number of defaulted bonds within the same state in prior three years.

Past Default Three Year Rate	The number of defaulted bonds in prior three years divided by number of bonds outstanding in the same state.
Matching Treasure Yield	The yield of Treasury with same maturity.
Term Slope	The difference between 10-year and 2-year treasury rate at offering date. Estimated in line with Gurkaynak, Sack, and Wright (2007).
Log (Issue Offering Amount)	Logarithm of the Offering amount.
Call Dummy	An indicator variable equal to value of 1 if the bond is callable, otherwise 0.
Negotiated Dummy	An indicator variable that takes value of 1 if bonds are issued through a negotiated offer and 0 otherwise.
Credit Rating	A numerical scale of the bond's credit rating with smaller values representing better credit rating. We use S&P ratings, and Moody's when they are not available. If both of S&P ratings and Moody's ratings are missing, we use Fitch's ratings.
No Rating Dummy	An indicator variable that takes value of 1 if the bond does not have a credit rating from S&P, Moody's or Fitch.
State Tax	The highest marginal personal state income tax rate. The data is from NBER.
Log (Pop)	The logarithm of the state's total population. The data is from US Census and SGF (SGF is State Government Finances).
Debt/GDP	The ratio of state's total debt outstanding to state's total GDP. The data is from SGF (State Government Finances).
Revenue/Expenditure	The ratio of state's total revenue to state's total expenditure. The data is from SGF (State Government Finances).
Unemployment Rate	The state's unemployment rate. The data is from SGF.
Log (State Borrowing) - Prior Year	The logarithm of annual state new offering in the prior year.
Log (U.S. Borrowing) - Prior Year	The logarithm of annual U.S. new offering in the prior year.