School of Finance

University of St.Gallen

THE REAL COSTS OF INDUSTRY CONTAGION

EMILIA GARCIA-APPENDINI

WORKING PAPERS ON FINANCE NO. 2014/10

SWISS INSTITUTE OF BANKING AND FINANCE (S/BF – HSG)

JUNE 2014

The real costs of industry contagion

Emilia Garcia-Appendini^{*}

This draft: June 2014

Abstract. In this paper I analyze whether the higher financing costs following the distress or bankruptcy of one firm affect the real investment decisions of non-distressed industry competitors. To achieve identification of the causal effect of contagion on investment, I use a difference-in-differences approach that compares within-firm changes in investment around the industry distress for non-distressed competitors with large proportions of their debt maturing immediately after the industry distress, relative to other non-distressed competitors in the same industry but that did not have debt maturing immediately after the industry distress. Results suggest that the former firms, which are more affected by the higher costs of financing due to contagion, reduce their capital expenditures to capital ratio by around 10% more than the less-sensitive firms. Further results show that contagion effects are milder in concentrated and low-leveraged industries, as well as in industries that do not rely too heavily on external financing.

Keywords: Corporate investment, contagion, bankruptcy, distress, market structure

Classification: G31, G32, G33

^{*} University of St Gallen, Rosenbergstrasse 52, 9000 St Gallen, Switzerland. E-mail: emilia.garcia@unisg.ch. For their helpful comments, I would like to thank the seminar participants at the University of Zurich, as well as Zeno Adams, Alin Andries, Marc Arnold, Martin Brown, Vicente Cuñat, and Angelo Ranaldo.

The real costs of industry contagion

1. Introduction

How does bankruptcy and financial distress affect the real activity of non-distressed industry rivals? Previous studies have found that bankrupt firms impose negative externalities on the cost of non-bankrupt competitors' external financing. For example, Lang and Stulz (1992) find that the announcement of a bankruptcy has an overall negative effect on the equity prices of competitors. Similarly, Jorion and Zhang (2007) find substantial increases in credit default swap spreads of industry competitors after bankruptcy announcements. Benmelech and Bergman (2011) document significantly higher spreads on collateralized debt when industry rivals are in bankruptcy. Finally, Hertz and Officer (2012) find that spreads on new and renegotiated corporate loans increase following the bankruptcy filings of industry rivals. These findings suggest that non-distressed firms in distressed industries could face difficulties in raising external financing due to contagion.

In spite of the relatively large literature on the higher costs of financing due to contagion, little is known about its consequences in the real economy. This paper fills the gap in the literature by analyzing firm-level investment of non-distressed industry rivals following the distress or bankruptcy of a competitor.

Whether a bankruptcy or distress in an industry should cause a reduction in investment of non-bankrupt competitors is unclear. On the one hand, a classic line of research shows that higher costs of external financing can affect the real economy by changing the investment decisions of firms (Fazzari, Hubbard and Petersen, 1988; Kaplan and Zingales, 1997). Recent contributions to this literature have convincingly argued that firms reduce their capital expenditures as a consequence of supply shocks to external financing (Lemmon and Roberts, 2010; Duchin, Ozbas, and Sensoy, 2010; Almeida, Campello, Laranjeira, and Weisbenner, 2011). In a similar fashion, by limiting the amount of external resources available to finance investment, the higher costs of financing to industry competitors following a rival firm's bankruptcy could curtail the firms' ability to invest in real assets.

However, a rival's bankruptcy could also bring competitive benefits to industry survivors. In fact, the bankruptcy of one firm in an industry could allow industry rivals to capture the demised firm's clients and suppliers. As explained by Lang and Stulz (1992), if firms are able to adjust the prices for their products, the higher demand from new clients could increase the rents of the surviving competitors. Through higher cash flows derived from these higher rents, firms could reduce their needs for external finance to fund investment, eliminating or mitigating the decrease in investment implied by the higher financing costs. More in general, a rival's bankruptcy could change the market concentration of the industry and hence the bargaining power of

competitors as well as their clients and suppliers. Therefore, one objective of this paper is to analyze whether the changes in the market concentration following a bankruptcy in the industry can offset the negative consequences of the higher costs of finance.

The view on contagion that is consistent with previous studies is that on average, the negative effects dominate the potentially beneficial competitive effects. One reason for this could be that contagion reveals negative information to suppliers and customers about the components of cash flows that are common to all firms in the industry.¹ Thus, they could be unwilling to do business with the remaining affected firms, possibly due to a loss in reputation (Maksimovic and Titman, 1991). In fact, the results of Lang and Stulz (1992) and Jorion and Zhang (2007) mentioned above imply that investors update negatively their information on the risk of bankruptcy for the rivals of the demised firms. This suggests that on average, the potential benefits of increasing market share following the demise of industry competitors are limited.

However, the previous literature has also found heterogeneous effects on the increase in financing costs depending on the industry market structure or firm characteristics. Lang and Stulz (1992), for example, found that the negative effects of the announcement of bankruptcy hold only on competitive industries, and become positive in highly concentrated industries with low leverage ratios. In a similar spirit, Jorion and Zhang (2007) found that the negative contagion effects are milder with Chapter 7 liquidations than in Chapter 11 bankruptcies. This is because concessions granted to the failed firm in Chapter 11 reorganizations can lower the costs for the failed firm, affecting its industry competitors. In this paper, I also analyze whether there are heterogeneous effects of contagion on investment depending on the industry market structure, and on the changes in the industry market structure following the distress or bankruptcy of one or more firms.

Identification of a causal link from the financial distress or bankruptcy filings of some players in the industry to the investment decisions of these firms' solvent competitors is difficult because financial distress is potentially driven by common economic factors, such as negative shocks to cash flows across the industry. To overcome this identification problem, I focus on solvent competitors of the distressed firms and exploit the ex-ante heterogeneity of their long-term debt maturity structures, using a strategy similar to Almeida et al. (2011). Specifically, I use a difference-in-differences estimation to examine whether firms with large fractions of their long-term debt maturing right after a competitor's distress had to adjust their behavior (e.g., cut capital expenditures) in ways that were more pronounced than otherwise similar firms in the same industry that did not have to refinance their long-term debt at that time. By calculating the within-firm differences in investment

¹ A complementary view is that higher costs of financing are due to lower collateral prices, which are driven by a lower demand for assets in the industry and higher supply of assets in the industry (Benmelech and Bergman, 2011).

behavior before relative to after the distress event, it is possible to account for unobservable, idiosyncratic firm effects that are fixed throughout the distress period. I also control both parametrically and non-parametrically for observable firm characteristics such as size, profitability, investment opportunities, and leverage ratios, that could simultaneously determine investment and debt maturity structures (Barclay and Smith, 1995; Guedes and Opler, 1996; Choi, Hackbarth, and Zechner, 2013). Finally, I use firm-year fixed effects, which control for common negative shocks to the cash flows of all industry participants in a given year, and thus to isolate the part of investment that changes due to financing frictions.

Results show that firms that had to refinance their debt immediately after the distress episode cut their yearly investment to capital ratio by 5 to 6 percentage points more than other firms in the same industry that did not have to refinance substantial amounts of debt at that time. These results suggest that the latter firms were less affected by the higher costs of capital due to contagion. The estimated changes in investment are statistically and economically significant, representing a fall in investment of around 10% of their pre-distress levels, thus indicating that the real costs of financial contagion can be substantial. Further analyses reveal that the effects of contagion presented above are absent in normal periods with no industry-specific distress. Similarly, these effects do not seem to reflect differences in the quality of the firms that had to refinance large portions of their debt after the industry distress. Moreover, the results are stronger within industries that largely depend on external financing for investment. These findings reinforce the interpretation that the observed decline in investment is due to higher financing costs caused by contagion.

Compared to the decrease in investment due to a shock to the supply of credit, the decrease in investment caused by contagion that is documented in this paper is smaller. For example, Almeida et al. (2011) estimate the quarterly decrease in investment to capital ratios for treated firms following the 2007 credit crisis at 2.5 points, i.e. a yearly decrease of 10 points or around a third of the pre-crisis investment levels. The decrease in investment documented in this paper is milder, i.e. 5 to 6 points annually, or 10% relative to pre-distress levels. These more modest quantities suggest that there may be positive competitive effects that partly offset the negative consequences of contagion.

In the final part of the analysis, I explore whether the market structure or industry characteristics can mitigate or accentuate the negative effects of contagion. Results show that the negative effects of contagion are stronger in competitive industries, as well as when competition increases following the industry distress. These results are consistent with participants in competitive industries not fully internalizing the negative externalities of competition on prices and cash flows (Hoberg and Phillips, 2010). It is also consistent with the higher loan spreads faced by firms in competitive markets (Valta, 2012).

Contagion is also stronger in industries with high leverage, suggesting that investors factor in a greater probability of bankruptcy of peers following a high-leveraged industry distress and therefore increase the financing costs more for high-leveraged industries. The higher observed cost of contagion in leveraged industries is consistent with a lower flexibility of these firms to respond to the new market conditions (Bolton and Scharfstein, 1990).

To the best of my knowledge, this is the first paper that quantifies the effects of industry-wide financial contagion on the real economy, by showing how the investment decisions of firms are affected by distress of industry rivals. This finding therefore extends our knowledge on contagion by showing that the higher costs of financing following the distress of one firm can lead to significant reduction in investment by competitors, and that the market structure matters for the transmission of these shocks. This paper is related to the vast literature that highlights the role that financial markets play in the growth of the economy, and in particular to the papers that study the impact of credit constraints on investment. Examples in this literature include Fazzari et al. (1988), Whited (1992), Kashap, Lamont, and Stein (1994), Kaplan and Zingales (1997), and Faulkender and Petersen (2012). None of the papers in this literature consider the effect of industry contagion on firm investment.

The results of this paper have important policy implications, both for policymakers and firm managers. To the former, this paper shows that interventions to mitigate the negative consequences of contagion are more effective in highly-leveraged industries, as well as in industries with higher degrees of competition, but may be redundant in concentrated industries or industries that do not depend much on external financing. For the latter, it highlights the importance of having a much more granular debt maturity to avoid or mitigate further costs due to financing frictions in periods of distress (see Choi et al., 2013).

This paper proceeds as follows. In Section 2, I describe the data and provide the first univariate analyses. In Section 3 I present the main results of the paper. Robustness and falsification tests are presented in Section 4. In Section 5, I extend the analysis to explore the effects of contagion within given market structures or dependence on debt. Finally, I present the conclusions in Section 6.

2. Data and methodology

2.1 Data construction and sample distribution

The base dataset for this analysis consists of yearly balance sheet information for all firms appearing in Compustat's North America Fundamentals Annual files between 1988 and 2006.² I eliminate non-US firms listed in the US (ADRs), firms in the financial or government sectors, as well as non-for-profit organizations. I also disregard firms with missing assets or capital expenditures, asset or sales growth exceeding 100%, or less than 10 million USD in assets. These filters eliminate the smallest firms with volatile accounting data, as well as firms that participated in mergers or other significant restructuring, and whose investment patterns may be skewed as a result; the filters have become standard in the related literature (see e.g. Almeida et al., 2011 or Duchin et al., 2010).

I use Moody's Ultimate Recovery Dataset and the Center for Research in Security Prices files to identify firms in the database that suffered a distress event during this period. A distress event is defined as bankruptcy, insolvency, distressed exchange or missed interest payments on a debt obligation. With this procedure it is possible to identify 337 distress events (firm-years). For each 3-digit SIC industry code, I identify a distress year in the industry as a year in which there was at least one distressed firm in that industry. Due to clustering of defaults through time within an industry, the 337 firm distresses episodes correspond to 275 unique industry distress periods. Next, I eliminate all firms in industries with no distress events in the sample, as well as the firms that suffered at least one distress event between 1986 and 2006. These filters place the main focus of the analysis on firms that were potentially affected by contagion, but were never themselves distressed. Table 1 contains the distribution of the sample according to year, distress status, and industry. For the benefit of space, I report industries in Table 1 at the 2-digit instead of the 3-digit SIC code level, which is the one effectively used in the classification of the industries.

From Table 1, we can observe that many of the distresses are found in the early 1990's and the early 2000's, corresponding to recessions. Column 3 contains all of the non-distressed firms; however, to analyze the effects of contagion we are interested only on these non-distressed firms during periods of industry distress (i.e., the firms in column 4). The tabulations show that our target population corresponds to around 20% of all the non-distressed firms, suggesting that non-distressed firms are suffering an industry distress on average once every five years. To make it into the final sample, the non-distressed firms in a distressed industry should have non-

² I use yearly instead of quarterly data because, as explained below, the classification of firms into treated and control firms requires using variable *ddl* (the amount of long term debt which matures the year after the annual report), which is only available in the Compustat yearly files. I stop in year 2006 to avoid confounding our results with the credit crunch that occurred in year 2007 (see e.g. Duchin et al, 2010 and Almeida et al, 2011), and the recession that followed.

missing investment to capital data for one year before and one year after the industry distress, as well as non-missing pre-distress data for size, cash flows, long-term leverage, profitability, and market-to-book ratios (Q) (for variable definitions, refer to the appendix). The final sample consists of 8,676 non-distressed firms in distressed industries. To reduce the impact of outliers, I winsorize all variables at the high and low 0.5% percentiles.

2.2 Methodology

The identification strategy in this paper relies on estimating the difference in the difference of investment levels before and after the industry distress, for non-distressed firms that are more likely to suffer the consequences of higher financing costs (treated firms), relative to those that are less sensitive to changes in the costs of financing (non-treated firms). In other words, the main regression model for the next section is the following:

$$\Delta I_{ijt} = \beta_0 + \beta_1 * treated_{ijt} + \delta_{jt} + u_{ijt}. \quad (1)$$

Here, ΔI_{ijt} is the change in the investment ratio of firm i in industry j , from the year previous to industry j 's distress (which occurs at time t) to the year after this distress; $treated_{ijt}$ is a dummy variable taking a one if firm i in industry j is sensitive to changes in the costs of financing at time t (as defined in the following paragraph); and δ_{jt} represent industry * time fixed effects.

As anticipated in the introduction, in this paper I borrow the methodology from Almeida et al. (2011). Therefore, I classify the non-distressed firms as “treated” if they have more than 20% of long-term debt maturing right after the industry distress (i.e., the ratio of variable ddl to $ddl + dlit$ is greater than 0.2). These firms are more likely to be sensitive to changes in the costs of financing due to distress than non-distressed firms with less than 20% of their debt maturing after the industry distress. In other words, these firms are more likely to suffer the negative consequences of contagion. The amount of debt maturing right after the industry distress should be plausibly exogenous to the timing of the distress in another firm in the industry, as it is the result of a decision made several years before the event and is difficult to renegotiate on short notice. This exogenous variation in debt contracting allows us to identify firms that are more susceptible to the higher costs of financing, and thus to estimate the effects of contagion.

The above specification has three elements to identify the causal effect of contagion on investment. First, by calculating the within-firm changes in investment, we can control for idiosyncratic firm effects that are fixed around the distress event. Second, the industry * time fixed effects allow us to estimate the effect of the

treatment of firms within the same industry distress episode. This restriction makes it possible to control for common economic shocks that affect all the firms in the same industry, such as common shocks to the cash flows of the industry. Moreover, the industry fixed effects also ensure that the firms being compared have a similar dependence on long-term debt, as industry leverage has been shown to be the most important determinant of capital structure (Frank and Goyal, 2009; Lemmon, Roberts, and Zender, 2008). Finally, the treated dummy allows us to distinguish firms that are more likely to suffer the negative effects of increases in the price of external financing, relative to firms that are less affected.

The identification strategy pursued in this paper requires that there is enough variation in the long-term debt maturity across firms. If firms were able to perfectly diversify their maturity structures, we would not be able to identify firms that are more likely to suffer the consequences of the higher costs of debt due to contagion. Almeida et al. (2011) find evidence for a large variation in debt maturity structures during the recent crisis years. More recently, Choi et al. (2013) confirm these findings for the wider period comprising years 1991 to 2009, which covers most of our sample period.

Besides variation in debt maturities, for this paper's identification strategy we should additionally require that the distribution of the long-term maturity structures is similar in distress and non-distress years. Identification would be compromised due to potential reverse causality concerns if the concentration of firms with long-term debt expiring during distress years were larger than in non-distress years. Indeed, if this were the case one could argue that the debt maturity structures are endogenous to the industry distress. Previous literature has not shed light on this issue. Choi et al. (2013) find that firms that issue bonds during recessions tend to make maturity structures more dispersed; however, whether firms enter into the recession with a more concentrated maturity structure is unclear.

In support of the above two requirements of the identification strategy, I (i) explore the variation of debt maturity structures in the sample, and (ii) analyze how the distribution compares in distress and non-distress years. For the first analysis, Figure 1 provides a visual illustration of the within-industry distribution of debt maturities throughout the years. For the sake of brevity, I only graph the distributions of debt maturities for all 3-digit SIC industry groups of the three most numerous 2-digit SIC code industries (chemicals and allied products manufacturers, electronic and other electrical equipment manufacturers, and business services); however, the distribution is similar also within other unreported industries. Within each industry, columns in red correspond to industry distress years, while those in blue correspond to non-distress years. The figure suggests that there is a substantial amount of variation in the debt structures within each industry and within each year. For every industry and year combination, numerous firms have more than 50% of their long-term

debt maturing one year after. The figure does not show obvious differences in the distribution of the maturity structures of distress vs. non-distress years.

To test whether the second identification requirement holds, in Table 2 I perform tests for the difference of the average percentage of long-term debt maturing the next year in non-distressed relative to distressed years, for each 2-digit SIC-code industry. The results do not show evidence that distress years are associated to higher proportions of maturing debt. In fact, the difference is statistically indistinguishable from zero in most industries; the average difference across industries is positive and very close to zero; the number of industries in which firms have to refinance larger portions of their debt in distress years is close to half (55%); and the number of industries for which the differences are statistically significant are similar when the difference is positive and when it is negative (5 and 7 cases, respectively). These results suggest that the distribution of the long-term maturity of debt is indeed exogenous to the incidence of distress in the industry, as required for identification.

If debt maturity were randomly assigned across firms, then Equation (1) would be sufficient to compare the investment levels of firms that had significant debt maturing around the industry distress episode with those that refinanced at other times. However, previous studies have shown that firms with different maturity structures differ with respect to several variables that are likely to have an impact of investment, such as investment opportunities - as measured by Tobin's Q -, cash flows, size, leverage, and firm profitability (Barclay and Smith, 1995; Guedes and Opler, 1996; and Choi et al, 2013). Therefore, in additional specifications I will augment Equation (1) by adding the effect of omitted variables that are likely to affect investment, and are potentially correlated with the debt maturity structure of the firms.

2.3 Descriptive statistics

Table 3 contains some basic descriptive statistics for the main variables used in this paper. Panel A contains summary statistics for the complete sample of non-distressed firms affected by a distress event. Statistics for the investment ratios are calculated both before and after the distress event, while the statistics for size and other balance sheet ratios correspond to the pre-distress levels. The table shows how the average and median values of investment fall for all non-distressed firms in distressed industries following the distress events of the industry peers. This is consistent with the increased costs of finance for industry peers of distressed firms documented in previous studies; however, it is also consistent with a potentially lower demand for the industry products that causes lower investment levels in the industry, and leads some of the industry firms into distress.

In Panel B, I separate the sample into the treated and non-treated firms. Consistently with expectations, the table shows that debt maturity structures are not random: treated firms are smaller, less leveraged, less profitable, and have higher investment opportunities than non-treated firms. These differences show the importance of controlling for these sources of observable heterogeneity in the regression analyses of the following section.

As highlighted by Heckman et al. (1998) and explained in Almeida et al. (2011), controlling for the observable characteristics in parametric regressions does not necessarily address the fact that the groups being compared may have very different characteristics, especially when there is little distributional overlap for the control variables in the treated and non-treated groups. Therefore, in the main results I will also use the non-parametric matching estimator of Abadie and Imbens (2006) in addition to presenting standard regressions in which I control for the above-mentioned omitted variables. In this estimation method each treated firm is matched with a non-treated firm that is very similar in terms of the observable control variables (i.e. the non-treated firm with the smallest Mahalanobis distance to the treated firm). I match the firms in terms of their distance in pre-distress Q values, size, long-term leverage ratio, profitability, and cash flow, i.e. variables that have been identified as important determinants of investment, as well as of the maturity structure of debt. In addition, I require exact matching in the 3-digit industry SIC code and year to make sure that control firms are affected by the same industry distress episode as each treated firm. I perform the matching with replacement, which allows the non-treated firms to serve as matches for more than one treated firm. This restriction increases the accuracy of the matches, at the cost of lower power.

In Panel C, I report the differences in the pre-distress level of the covariates between treated and the matched control sample. I choose a single match for each treated firm, therefore the matched sample consists of an identical number of treated firms and controls. We can observe that the differences between treated firms and matched control firms are much smaller than in the original sample. In fact, there are no statistical differences in the median values of cash flow and profitability. However, possibly due to the relatively large sample sizes, the mean and median values are statistically significant at a 5% level or lower for the rest of the variables. Nevertheless, the economic magnitude of the differences is significantly reduced in the matched sample compared to the values in the complete sample, and is comparable to the differences reported in Almeida et al. (2011). For example, the average difference in Q in the matched sample is 0.17 (median is 0.074), or around a third to one fourth of the size of the difference that prevailed in the non-matched sample (mean difference was 0.48 and median difference 0.23). For size and long-term leverage, the average and median differences in the matched sample fall to around 10% of their levels in the non-matched sample, and are also small in economic terms. These small differences between the treated and the control firms will enhance the

identification strategy, by enabling us to compare the changes in the investment levels of firms that are very similar in several dimensions that matter for investment, but differ in the timing of the maturity of their long-term debt.

2.4 Parallel trends assumption

I conclude this preliminary exploratory analysis by examining whether the key identifying assumption for the difference-in-differences analysis holds in the sample. Intuitively, this restriction requires similar trends in the outcome variable during the pre-distress era for both treatment and control groups, i.e., “parallel trends” in the outcomes (Angrist and Krueger, 1999). In the current context, this assumption translates into similar growth rates in investment for treated and non-treated firms prior to the distress event. In other words, in the absence of distress, the observed difference-in-differences estimator should be zero. While this assumption cannot be tested formally, in Figure 2 we present a visual of the evolution of the average investment to capital ratio of treated and non-treated firms as they approach the industry distress episode. The horizontal axis represents the number of years until the industry distress, which is normalized at $t=0$. To avoid confounding effects of multiple distresses in subsequent periods, we only include in the graph those firms that suffered a distress event at $t=0$, but not in the other periods. The dashed line corresponds to treated firms, while the continuous line corresponds to all other non-distressed firms in distressed industries. The graph shows that investment prior to the distress event was around 20% lower for non-treated firms, but roughly constant throughout the pre-distress period. The fact that investment levels are higher for treated and non-treated firms highlights the importance of controlling for variables that determine investment levels in our regression analysis. However, the changes in investment levels were different for treated and non-treated firms around the distress date. In fact, during the distress period investment fell for all firms, but the decrease in investment was steeper for the treated firms than for the non-treated firms. As a consequence of these differences, after the distress event the difference in investment between treated firms and non-treated firms was halved to around 10%. The results in the figure suggest that treated and control firms had similar trends in their investment decisions before the time of industry distress, as requested by the parallel trends assumption.

3. Estimation results

Table 4 contains the main results of this paper. Panel A contains the results of OLS regressions performed over the original (non-matched) sample. The dependent variable is the within-firm difference in capital expenditures to lagged capital ratio the year after the distress event, relative to its value before the distress. In column 1 the

only independent variable is a dummy for the treatment. In the rest of the columns, regressions include covariates that could affect the firm investment levels.

Results show that the investment to capital ratio falls on average by 5.3 to 6.2 percentage points more for the firms with larger portions of their long-term debt maturing the year after the industry distress, relative to non-treated firms. This is the central result of this paper, and it suggests that there is a significant effect of contagion on investment. Economically, this effect means that treated firms reduce their investment levels by 8.7 to 10.3% more than they would have if their debt had not expired just after the distress. In Appendix B, it can be seen that results are similar for the investments to assets ratio. In this case, the difference in change in investment for treated firms relative to non-treated firms is around minus 1.4%, or approximately 13.7% of their pre-distress investment levels.

In Panel B of Table 3, firms in the treatment group are compared with their closer counterfactuals, i.e., the controls obtained by the non-parametric matching procedure explained above. To perform the matching, I use the control variables in column 2 of Panel A, as estimations are more conservative using these variables. However, results (not reported) are qualitatively similar when including also the additional control variables included in column 3 of Panel A. These results show that at 60.4%, the pre-distress investment to capital levels of treated firms was 9.4% higher than that of control firms. After the distress, however, treated firms were investing 34.6% of capital, which was only 3% higher than control firms. The difference-in-difference estimator in the matched sample is 6.4% and statistically significant. Panel B also reports the differential change in investment that is produced by the Abadie-Imbens matching estimator of the average effect of the treatment on the treated (ATT). The ATT difference is equal to minus 5.2 percentage points. The ATT matching estimator has a comparable magnitude as the estimator obtained in Panel A, in fact, it is well within a 95% confidence interval of the OLS estimator obtained in column 2, which controls for the same variables as I used to do the matching.

4. Discussion of the results

The estimates in Table 4 show that following the distress of a peer, firms that were more constrained due to their debt maturity structures reduced their corporate investment rates more drastically than other similar firms that were affected by the same shock. My interpretation of these findings is that there is a significant effect of pure financial contagion on investment. However, there could be other explanations driving the

observed relationships between investment and the treatment dummy. In this section I discuss other confounding stories, and analyze whether they are plausible.

The first alternative explanation for the results of Table 4 is that the observed decrease in investment is due to a lower demand for investment, rather than a lower supply for financing due to contagion. Such a demand-side explanation would be plausible if the shocks underlying the industry distress episode are generated by lower demand for the industry's products that decreases the economic activity in the industry.

For several reasons, I believe that a demand-side explanation is unlikely to drive the observed results. On the one hand, the sample used for this study contains a wide number of industry distress episodes, and is observed over a long time series span. Therefore, the sample contains distresses caused by a wide range of different reasons (i.e. low liquidity and cash flow problems, lawsuits, accounting scandals, etc.), and not only by a lower demand for the industry's products.

Furthermore, the results in Table 4 would be confounded by demand effects only to the extent that the treated firms are more strongly affected by the demand shock than the non-treated firms. This could be the case if, for example, the treated firms have lower average quality than the control firms. However, previous literature does not seem to provide support to such a positive correlation between quality and debt maturity. Theoretically, Flannery (1986) argues that with asymmetric information, good firms have to pay higher prices for debt, and long-term debt is more expensive in relative terms. Therefore, in his model good firms use short-term debt and bad firms use long-term debt. Diamond (1991) argues that the benefits of short-term debt are traded off by the risk of having to refinance in periods of low liquidity; as a consequence, his model implies a non-monotonic relationship between firm quality and debt maturity. Empirical support for these information asymmetry theories can be seen, for example, in Barclay and Smith (1995), Stohs and Mauer (1996), and Guedes and Opler (1996). More recently, however, Mian and Santos (2012) have found that the strongest firms are able to refinance their loans and extend their maturities when credit conditions are good. This would suggest a positive correlation between firm quality and debt maturity during the distress periods.³

To mitigate the concern that demand effects could be driving the observed results, I perform several robustness tests. First, I estimate Equation (1) including observable measures of firm quality (the z-score and

³ In the appendix I examine whether treated firms are less likely to refinance or repay their long-term debt early during distress periods. Specifically, I estimate a diff-in-diff linear probability model (with industry-year fixed effects) where the dependent variable is *Early Refinancing*, i.e., a dummy taking the value one when the amount of long-term debt that is due in year $t+1$ is reduced between years $t-1$ and t . Results suggest that treated firms are, in general, 13 to 15 percent less likely to refinance or pay their long-term debt early than non-treated firms. However, these differences in the likelihood of early refinancing do not change during distress periods.

three dummies for credit ratings). The results, contained in column 3 of Table 4, are qualitatively unchanged respect to the main estimations in column 2. Similarly, I also enhance the ATT estimations by adding the z-score and the three rating dummies as additional dimensions for the matching procedure, with no qualitative changes (unreported).

To further reinforce my interpretation of the results as driven by financial contagion, I estimate Equation (1) on a subsample of firms that, due to revealed preferences, have a positive demand for external funds. Specifically, I follow an approach similar to Becker and Ivashina (2014) and identify the firms that have a positive demand for external funds as those firms that raised new debt during the distress period (i.e., the change in total debt to lagged assets ratio is positive). These firms are likely to have a positive demand for investment, and are thus less prone to the above criticism. The results, contained in column 1 of Table 5, show that treated firms with positive debt issuance invested less than non-treated firms with positive debt issuance following an industry distress, confirming the previous results.⁴

A related concern is that the variation in maturity structures between treated and non-treated firms reflects anticipated effects of the distress. In fact, the baseline estimations presented in Table 4 classify firms into treated and untreated by using the amount of long-term debt scheduled to mature one year after the distress, and this amount is measured during the year of industry distress. This choice guarantees that we capture the extent to which firms are constrained by debt maturity during the shock, and it also increases the precision of the estimates. However, it may raise the concern that higher quality managers were more likely to anticipate the industry distress of a peer one or two years prior to the event, and increased the maturity of the debt in anticipation of the distress. If this were the case, it is possible that unobservable managerial quality could explain both the longer maturity profile and lower reductions in investment following the distress of the peers. Such refinancing activity by the high-quality CEOs that anticipate a distress would leave only the lower quality managers with long-term debt maturing just after the industry distress event. In this way, it could be the case the latter firms cut investment for non-maturity-related reasons after the demise of an industry peer.

To analyze whether results are driven by the unobserved ability of managers that can correctly forecast and prepare for industry problems in advance, it is possible to use the debt maturity variables measured prior to the distress event. For example, we can examine firms' maturity profiles the year before the distress event, and identify the treated firms as those that had a large fraction of their long-term debt scheduled to mature two years thereafter (i.e., the year after the distress). Similarly, we can analyze the maturity structure of debt two

⁴ In the following section, I estimate Equation (1) over a subsample of firms that are exogenously more likely to depend on external financing. As shall be seen, the main results are reinforced in this estimation, further strengthening the claim that lower investment levels are driven by the scarce supply of capital that follows an industry distress.

years before distress, and examine the debt that was scheduled to mature three years later to define the treated dummy. Of course, the further back in time we go, the less precise is the measurement of the amount of debt that actually expired following the industry distress episode; therefore, the magnitudes of the coefficients should decrease and become less statistically significant. The results, contained in Table 5 (columns 2 and 3), show that when we classify firms into treated and non-treated according to the pre-determined debt maturity structures of one or two years previous to the distress event, the effect of treated on investment is still negative. This result is consistent with a causal effect of contagion on real decisions of the firms even if some managers could see the industry distress coming and adjusted their long-term debt maturities.⁵ As expected, however, the magnitude of the coefficients is smaller (and statistical significance weaker) as we measure the debt maturity structures further back in time, reflecting the fact that the information about debt maturity measured at a certain point becomes stale with time.

Yet another confounding story would be that the results in Table 4 are capturing the refinancing risk of treated firms, rather than the effect of contagion on investment. This would be the case if treated firms suffer from higher refinancing risk even in normal times. In this spirit, He and Xiong (2012) find that short-term debt exacerbates rollover risk.

The graph showing that the parallel trends assumption holds does not support the claim that the estimates in Table 4 are capturing refinancing risk. However, to further strengthen my interpretation of the results, I perform two additional conditional analyses. First of all, I perform a falsification test in which I replicate exactly the same methodology applied in Table 4, but examining within-firm changes of investment around placebo distress periods. For each industry, I artificially set the placebo distress date at two years before the actual industry distress dates. Thus, in this falsification test I examine the changes in investment for firms three years prior to the actual distress dates, relative to one year prior to the distress date. The results are contained in column 4 of Table 5. Results show a small positive difference between changes on investment to capital of treated and control firms, which cannot be distinguishable from zero. Therefore, it does not seem to be the case that the negative effect on investment is observed also in normal periods.

As a second robustness check for the claim that the results are driven by refinancing risk, I re-run the estimation in Equation (1) using all the observations of the non-distressed firms, i.e. adding also the periods in which there is no distress in the industry. I include as independent variable the interaction of variable *Distress* (i.e. a dummy containing a one when the industry is suffering a distress event, and zero when there is no

⁵ This analysis also helps mitigating the concern that our classification of treated firms is capturing unobserved variation in firm quality, i.e. if worse quality firms are not able to refinance early and thus are caught in a distress period with a large need of refinancing (Mian and Santos, 2012).

distress in the industry) with the treated dummy.⁶ In this regression model, variable *Treated* captures whether treated firms, i.e. those that have large portions of their debt maturing on year $t+1$, change their investment levels from period $t-1$ to period $t+1$ more than non-treated firms during normal times. The interaction term captures whether treated firms change their investment levels more than non-treated firms during distress periods, and hence this variable becomes the focus of the analysis in this specification. The results of this estimation, which are contained in column 5 of Table 5, show a negative effect of the treated dummy during normal periods, suggesting that there could be a negative effect of refinancing risk on investment; yet, the effect is economically small and not statistically significant. However, the interaction term is negative and statistically significant. This result confirms the main interpretation of the results in Table 4, i.e. as causal effects of contagion on investment.

As a final robustness check of the main results, I also estimate Equation (1) using the change in the capital expenditures to assets ratio as a dependent variable. The results, contained in column 6 of Table 5, also show a negative effect of the treatment on investment. With this dependent variable, the difference in change in investment for treated firms relative to non-treated firms is minus 1.4%. This is very similar and slightly larger to the estimated effect of the investment to capital ratio, as it represents a larger decrease on investment for treated firms of approximately 14% of their pre-distress investment levels.

5. Market characteristics, distress characteristics, and financial contagion

The results in the previous section show that an industry distress has negative consequences on the real investment decisions of non-distressed peers. In this section, I investigate whether these contagion effects are less severe depending on the market or industry structure or on the characteristics of the distressed firm.

Related studies have found heterogeneous effects on the costs of bankruptcy depending on the market or industry characteristics. For example, Lang and Stulz (1992) found that equity prices of the bankrupt firms' competitors decrease on average following the announcement of the bankruptcy of a peer. However, the effect is the opposite (i.e. equity prices *increase*) following bankruptcy announcements if the market is highly concentrated, and if the industry has low leverage. Similarly, Jorion and Zhang (2007) find that the negative effects of contagion on CDS spreads of non-bankrupt competitors are milder in Chapter 11 bankruptcy filings than in Chapter 7 filings. This is because the latter forces liquidation of the distressed firm, and there is no possibility of debt forgiveness or other concessions that could harm its competitors. These results have been also confirmed by Hertz and Officer (2012), using the cost of debt (syndicated loans). From these

⁶ The variable *Distress* cannot be estimated without interaction because it is constant for all firms in the same year and industry, and the regression contains industry-time fixed effects.

previous findings, there are reasons to believe that the market structure could also influence the extent to which the firms' investment decisions are affected by financial contagion.

To explore this issue, I estimate Equation (1) within several subsamples of firms classified according to market structure or firm characteristics, and compare the coefficients of the treated firms across the different subsamples. Table 6 contains the results of this subsample analysis. For simplicity, I report the results of this section using the OLS regression approach. However, untabulated results using the matched sample yield results that are qualitatively similar.

I first examine the effect of contagion on investment according to the ex-ante market competition. I define a market as concentrated if the Herfindahl index of sales concentration in the market is larger than the median; otherwise I classify the market as competitive. The first two columns in Table 6 show that the negative effects of contagion are not statistically distinguishable from zero at a 10% level in concentrated markets, but are strong in competitive markets, consistently with the higher costs of financing in competitive markets due to contagion found by Lang and Stultz (1992) and Hertz and Officer (2012). As explained by Lang and Stulz (1992), in perfectly competitive markets firms cannot earn rents from an increase in demand stemming from capturing the customers of the distressed firms. However, when markets are more concentrated, the higher demand increases the rents of the remaining firms because these firms can raise the prices of their products. These results are also consistent with the results of Hoberg and Phillips (2010), who show that investors and industry participants in competitive industries do not fully internalize the negative externality of competition on prices and cash flows.

Extending the above reasoning, contagion should be stronger if the market becomes more competitive after the distress, as the remaining firms will have more difficulties adjusting the prices in the more competitive environment. To explore this, I classify the markets according to whether the change in the Herfindahl index after distress relative to previous to the distress is positive (suggesting an increase in market concentration) or negative (decrease in concentration). The results, contained in columns 3 and 4, confirm this intuition. This finding is consistent with Jorion and Zhang's (2007) discovery that the negative effects on CDS spreads are milder with Chapter 7 liquidations, as competition is likely to drop following firm liquidations. The results are also consistent with Valta (2012), who finds that the cost of debt is higher in more competitive markets.

Next, I analyze the effects of industry leverage on contagion. Lang and Stulz (1992) find milder effects of contagion on equity prices when the industry is not very leveraged. This result can be explained if investors factor in a greater probability of bankruptcy of peers following a high-leveraged industry distress. In columns 5 and 6, I classify industries according to whether they have a larger than median leverage or not and estimate

Equation (1) on each subsample. The estimates suggest that contagion effects are offset when the industry has low leverage, consistently with expectations and with previous research.

Another industry characteristic that could affect the extent of contagion is the external finance dependence. To the extent that the observed patterns in the data are due to the financial constraints triggered by contagion, we should observe stronger effects within firms in industries that rely more on external financing, rather than on internal cash flows, to finance their investments. For this analysis, I classify the firms according to whether their industries are dependent on external financing, as measured by the index defined by Rajan and Zingales (1998), and estimate Equation (1) on each subsample.⁷ The results, contained in columns 7 and 8, show that the coefficient for treated is significantly negative for firms that are highly dependent on external finance, but it is not distinguishable from zero in industries that can satisfy their financing needs through internally-generated capital. This result is expected, since the latter are less sensitive to changes in the pricing of external debt. Moreover, this result reinforces the identification strategy in this paper, by showing how the effects are stronger among firms which rely more on external financing for exogenous reasons.

Finally, in columns 9 and 10 I explore the effects of contagion according to the characteristics of the industry distresses. Hertz and Officer (2012) find higher spreads on loans for firms in the middle of a bankruptcy wave. I explore whether this effect is reflected also in the investment decisions of firms. In column 9, I estimate Equation (1) on the subsample of 3-digit SIC industries that involve more than one bankruptcy during the same year (i.e., a bankruptcy wave), and in column 10 over the subsample of industries that involve a single distressed firm. Results show that the contagion effects on real investment are larger during industry distress waves than for single bankruptcies, consistently with the results of Hertz and Officer (2012).

6. Conclusions

In this paper I find evidence that the bankruptcy of an industry competitor has negative effects on the real investment decisions of non-distressed peers, which go beyond the expected drop in investment due to common economic factors with the distressed competitor. Due to this contagion effect, firms whose long-term

⁷ The external financing dependence (EFD) index is defined as the proportion of capital expenditures in excess of cash flows within firms of the same industry. A positive EFD means that the cash flow generated by the firms in the industry is not sufficient to cover the capital expenditures and, therefore, firms have to issue debt or equity to finance investments. A negative EFD value indicates that firms have free cash and, therefore, less need for external financing. I use Compustat firms between the years 1980 and 1996 and use firms that have been on Compustat for at least 10 years to calculate the EFD index. The reason for this choice is to capture firms' demand for credit and not the amount of credit supplied to them. I sum across all years each firm's total capital expenditures minus cash flows from operations and then divide it by total capital expenditures. Next, I aggregate the firm-level ratios of external financial dependence using the median value for all firms in each two-digit standard industrial classification category.

debt was largely maturing after the demise of a competitor cut their yearly investment rates by 5 to 6 percentage points more than otherwise similar firms in the same industry whose debt was due after the industry distress. The findings in this paper show that this contagion effect is milder in concentrated industries, as well as in industries with low leverage and low external financing needs; it is stronger in the middle of bankruptcy waves.

Identification of the real effects of contagion is based on three crucial points. First, by calculating the differences in investment for each firm, I control for fixed unobserved idiosyncratic factors that could affect investment. Second, by comparing firms in the same distressed industry and year, I control for all economic factors that are common to firms within the same industry, such as lower demand for the industry products or overall cash flow problems. Finally, by comparing firms that are similar in all dimensions but their debt maturity structure, I am able to identify the part of investment that falls due to financing frictions arising from contagion.

These results have important policy implications. For firm managers, these results highlight the importance of spreading out the debt maturity structures across different time horizons to mitigate the risk of having to refinance a substantial portion of the debt when the industry is in distress. The results could also guide policymakers when deciding whether to intervene following an industry distress. In fact, the results show that interventions aimed at more competitive markets, or for more highly leveraged industries, could be more effective to boost investment than interventions in competitive markets or in industries that do not require too much external financing.

References

- Abadie A. and G. Imbens (2006), "Large Sample Properties of Matching Estimators for Average Treatment Effects," *Econometrica* 74, p. 235–267.
- Almeida, H., M. Campello, B. Laranjeira, and S. Weisbenner (2011), "Corporate Debt Maturity and the Real Effects of the 2007 Credit Crisis", *Critical Finance Review* 1, pp. 3-58.
- Angrist, J. D., and A. B. Krueger (1999), "Empirical Strategies in Labor Economics," *Handbook of Labor Economics*, Vol. 3A, O. Ashenfelter and D. Card, eds. Amsterdam, The Netherlands: Elsevier Science.
- Barclay, M. and C. Smith Jr. (1995), "The Maturity Structure of Corporate Debt." *Journal of Finance* 50, p. 609–631.
- Becker, B. and Ivashina, V. (2014). "Cyclicality of Credit Supply: Firm Level Evidence," *Journal of Monetary Economics*, 62, pp. 76-93.
- Benmelech, E. and N. K. Bergman (2011), "Bankruptcy and the Collateral Channel", *Journal of Finance* 66 (2), p. 337-378
- Bolton, P. and D. S. Scharfstein (1990), "A Theory of Predation Based on Agency Problems in Financial Contracting," *American Economic Review*, 80 (1), pp. 93-106
- Choi, J., D. Hackbarth, and J. Zechner (2013), "Granularity of Corporate Debt", CFS Working Paper, No. 2013/26
- Diamond, D. W. (1991), "Debt Maturity Structure and Liquidity Risk," *Quarterly Journal of Economics*, pp- 709-737
- Duchin, R., O. Ozbas, and B. Sensoy (2010), "Costly External Finance, Corporate Investment, and the Subprime Mortgage Credit Crisis." *Journal of Financial Economics* 97, pp. 418–435.
- Faulkender, M. and M. A. Petersen (2012), "Investment and Capital Constraints: Repatriations Under the American Jobs Creation Act," *Review of Financial Studies* 25 (11), pp. 3351-3388.
- Fazzari, S., R. Hubbard, and B. Petersen (1988), "Finance Constraints and Corporate Investment," *Brookings Papers on Economic Activity* 1, 141–195.
- Flannery, M. J. (1986), "Asymmetric Information and Risky Debt Maturity Choice" *Journal of Finance* 41 (1), pp. 19-37.
- Frank, M. Z. and V. K. Goyal (2009), "Capital Structure Decisions: Which Factors are Reliably Important?," *Financial Management* 38 (1), pp. 1-37
- Guedes, J. and T. Opler (1996), "The Determinants of the Maturity of Corporate Debt Issues." *Journal of Finance* 51, pp. 1809–1833.
- He, Z., and W. Xiong, (2012) "Rollover Risk and Credit Risk," *The Journal of Finance* 67 (2), pp. 391-430.

- Heckman, J., H. Ichimura, J. Smith, and P. Todd (1998), "Characterizing Selection Bias Using Experimental Data." *Econometrica* 66, pp. 1017–1098.
- Hertzel, M. G. and M. S. Officer (2012), "Industry Contagion in Loan Spreads", *Journal of Financial Economics* 103, pp. 495-596.
- Hoberg, G. and G. Phillips (2010), "Real and financial industry booms and busts." *The Journal of Finance*, 65(1), pp. 45-86.
- Jorion, P., and G. Zhang (2007), "Good and Bad Credit Contagion: Evidence from Credit Default Swaps," *Journal of Financial Economics* 84, pp. 860–881.
- Kaplan, S., and L. Zingales (1997), "Do investment-cash flow sensitivities provide useful measures of financing constraints?" *Quarterly Journal of Economics* 112, pp. 169–215.
- Kashap, A. K., O. A. Lamont and J. C. Stein (1994), "Credit Conditions and the Cyclical Behavior of Inventories," *The Quarterly Journal of Economics* 109 (3), pp. 565-592.
- Lang, L. H. P. and R. M. Stulz (1992), "Contagion and Competitive Intra-industry Effects of Bankruptcy Announcements," *Journal of Financial Economics* 32, pp. 45–60.
- Lemmon, M. and M. Roberts (2010), "The Response of Corporate Financing and Investment to Changes in the Supply of Credit," *Journal of Financial and Quantitative Analysis* 45, pp. 555-587.
- Lemmon, M., M. Roberts and Jaime F. Zender (2008), "Back to the Beginning: Persistence and the Cross-Section of Corporate Capital Structure," *The Journal of Finance* 63 (4), pp. 1575-1608.
- Maksimovic, V. and S. Titman (1991), "Financial policy and reputation for product quality", *Review of Financial Studies* 4 (1), pp. 175-200.
- Mian, A. and J. A. C. Santos (2012), "Liquidity Risk and Maturity Management Over The Credit Cycle", Working Paper.
- Rajan, R., and L. Zingales, (1998), "Financial Dependence and Growth," *American Economic Review* 88 pp. 559–586.
- Stohs, M. H. and D. C. Mauer (1996), "The Determinants of Corporate Debt Maturity Structure," *Journal of Business* 69 (3), pp. 279-312.
- Valta, P. (2012), "Competition and the cost of debt," *Journal of Financial Economics* 105, p. 661-682.
- Whited, T. (1992), "Debt, Liquidity Constraints, and Corporate Investment: Evidence from Panel Data", *The Journal of Finance* 47 (4), pp. 1425-1460.

Table 1. Sample distribution

This table illustrates how our sample is constructed and how the sample firms are distributed across the years (Panel A) and across industry sectors (Panel B). Columns (1) and (6) show the number of distressed firms in each year and industry, respectively. A distressed firm is a firm that is declared bankrupt or had at least one distress event during the year (had a distressed exchange or missed payment on interest or principal of at least one debt obligation). Column 2 shows the number of 3-digit SIC-code industries that had at least one distressed firm during the year. Column (3) shows the total number of non-distressed firms in each year, and column (4) shows the number of non-distressed firms that were affected by the distress of an industry competitor in each year. Finally, columns (5) and (7) show the total number of non-distressed firms affected by the distress of an industry competitor that have non-missing values for all the requisite variables to make it into our final sample.

Panel A. Distribution by year

	(1)	(2)	(3)	(4)	(5)
	Distressed firms	Distressed industries	Non-distressed firms	Non-distressed firms when industry suffers distress	Final sample
Year					
1988	10	9	2,935	490	362
1989	4	4	2,858	136	103
1990	19	17	2,874	467	296
1991	29	24	2,923	952	691
1992	33	22	3,127	797	517
1993	21	16	3,323	737	501
1994	10	10	3,608	655	436
1995	10	9	3,857	496	337
1996	10	10	3,982	670	421
1997	4	4	3,922	240	177
1998	4	4	4,035	101	75
1999	18	14	4,000	1,110	674
2000	21	20	3,706	714	456
2001	37	30	3,666	1,613	1,175
2002	59	40	3,476	1,701	1,187
2003	18	14	3,296	842	543
2004	15	14	3,223	431	318
2005	12	11	3,173	241	176
2006	3	3	3,100	338	231
Total	337	275	65,084	12,731	8,676

Panel B. Distribution by industry

	(6)	(7)
2-digit SIC code	Distressed firms	Final sample
10	10	111
13	21	1,115
14	2	17
15	7	45
16	2	15
17	2	3
20	7	75
21	1	1
22	9	47
23	7	71
24	5	32
25	2	16
26	4	46
27	4	16
28	9	455
30	8	94
32	5	18
33	18	277
34	7	85
35	13	482
36	22	1,157
37	10	242
38	4	186
41	2	4
42	4	96
44	2	31
45	10	117
47	1	5
48	31	507
49	10	300
50	8	100
51	5	34
52	6	12
53	13	117
54	9	256
56	7	58
57	2	22
58	6	332
59	13	134
70	2	32
73	12	1,703
75	2	6
76	1	2
78	4	3
79	8	199

Figure 1. Distribution of debt maturity by industry and year

This figure depicts the distribution of the percentage of debt maturing the following year, for each year from 1986 to 2006, for a sample of 3-digit SIC code industries in the following sectors: CHEMICALS & ALLIED PRODUCTS MANUFACTURERS (2-digit SIC code = 28), ELECTRONIC & OTHER ELECTRICAL EQUIPMENT MANUFACTURERS (2-digit SIC code= 36), and BUSINESS SERVICES (2-digit SIC code= 73). Each subgraph corresponds to the 3-digit SIC-code industry that is shown in the subgraph title. Columns in red correspond to industry distress years, those in blue correspond to non-distress years.

Table 2. Long term debt maturity structures in distress and non-distress years

This table contains the results of t-tests for the difference in the average percentage of long-term debt expiring the following year for distress years vs. non-distress years, within each 2-digit SIC industry group. T-tests are performed independently for each 2-digit SIC industry. ***, **, and * mean that the difference in the averages is significant at the 1, 5, and 10% levels, respectively.

2-digit SIC code	% Long-term debt expiring the following year		Difference Non-distress - Distress	T-stat	S.E.	
	Distress years	Non-distress years				
16	0.101	0.238	0.137	3.880	0.035	***
14	0.166	0.248	0.082	1.250	0.066	
17	0.209	0.286	0.077	1.352	0.057	
76	0.176	0.242	0.066	0.465	0.142	
27	0.131	0.182	0.051	1.659	0.030	
44	0.104	0.153	0.049	1.815	0.027	*
25	0.106	0.155	0.049	2.110	0.023	**
47	0.171	0.219	0.048	0.726	0.067	
41	0.165	0.213	0.048	0.953	0.050	
52	0.082	0.122	0.041	1.821	0.022	*
30	0.160	0.193	0.034	2.261	0.015	**
23	0.164	0.195	0.031	1.326	0.023	
75	0.197	0.218	0.020	0.433	0.047	
38	0.280	0.285	0.005	0.288	0.017	
13	0.157	0.161	0.004	0.639	0.007	
51	0.171	0.175	0.004	0.121	0.029	
37	0.178	0.180	0.002	0.186	0.013	
79	0.159	0.161	0.002	0.162	0.014	
45	0.165	0.167	0.001	0.085	0.016	
20	0.150	0.151	0.001	0.058	0.018	
57	0.174	0.173	-0.001	-0.031	0.045	
59	0.208	0.206	-0.002	-0.109	0.017	
78	0.256	0.252	-0.004	-0.059	0.070	
58	0.175	0.167	-0.008	-0.737	0.011	
49	0.107	0.098	-0.010	-1.418	0.007	
54	0.092	0.081	-0.011	-1.237	0.009	
26	0.135	0.122	-0.013	-0.567	0.023	
53	0.129	0.113	-0.015	-0.993	0.016	
28	0.272	0.250	-0.022	-1.998	0.011	**
42	0.219	0.196	-0.022	-0.927	0.024	
22	0.167	0.145	-0.022	-0.763	0.029	
33	0.153	0.130	-0.023	-1.682	0.014	*
56	0.175	0.147	-0.028	-1.031	0.027	
35	0.294	0.265	-0.028	-2.527	0.011	**
15	0.242	0.211	-0.031	-0.894	0.034	
48	0.172	0.140	-0.033	-3.418	0.010	***
10	0.296	0.262	-0.034	-1.537	0.022	
50	0.245	0.210	-0.035	-1.568	0.022	
34	0.217	0.179	-0.038	-1.584	0.024	
73	0.386	0.346	-0.040	-6.406	0.006	***
36	0.300	0.254	-0.046	-6.090	0.008	***
24	0.175	0.126	-0.048	-1.272	0.038	
32	0.250	0.174	-0.076	-1.297	0.059	
70	0.207	0.131	-0.076	-1.967	0.039	*
Average	0.187	0.189	0.002			
% negative			55%			

Table 3. Summary statistics

This table contains summary statistics for the main variables used in the analysis: The outcome variables (investment to capital and investment to assets), and the pre-distress firm characteristics: Q, cash flow, size, long-term leverage, and profitability. The appendix contains the definitions of all variables. Panel A contains statistics for all the non-distressed firms in distressed industries. In Panel B the sample is divided into firms with more than 20% of long term debt maturing after the industry distress ("Treated firms") and firms with less than 20% of long-term debt maturing after the industry distress ("Non-treated firms"). In Panel C, "Control firms" are a sample of the non-treated firms, selected as the closest match to each treated firm based on the 3-digit SIC-code industry, year, and pre-distress values of Q, cash flow, size, long-term leverage, and profitability. The test of differences in the average values for each of the variables is conducted with a parametric t-test, while the test for median differences is conducted using the non-parametric Chi-squared test.

Panel A. Complete sample

	All firms N = 8,676		
	mean	median	s.d.
Investment to capital, pre	0.457	0.237	0.766
Investment to capital, post	0.293	0.198	0.315
Investment to assets, pre	0.115	0.064	0.160
Investment to assets, post	0.091	0.051	0.120
Q	1.809	1.311	1.515
Cash flow	-0.540	0.191	5.154
Size	5.298	5.045	1.947
Long term leverage	0.248	0.208	0.227
Profitability	0.066	0.108	0.192

Panel B. Sample of treated and non-treated firms

	Treated firms N = 2,880			Non-treated firms N=5,796			Difference in means			Difference in medians		
	mean	median	s.d.	mean	median	s.d.	Difference	T-stat	p-value	Difference	Chi-squared	p-value
Investment to capital	0.604	0.314	0.921	0.384	0.214	0.665	0.220	-11.450	0.000	0.100	166.507	0.000
Investment to assets	0.099	0.053	0.150	0.124	0.070	0.164	-0.025	6.988	0.000	-0.017	94.323	0.000
Q	2.128	1.487	1.862	1.650	1.262	1.280	0.478	-12.395	0.000	0.225	92.560	0.000
Cash flow	-1.227	0.191	6.654	-0.198	0.191	4.174	-1.029	7.592	0.000	0.000	0.000	1.000
Size	4.387	4.175	1.558	5.751	5.615	1.962	-1.365	35.153	0.000	-1.441	846.253	0.000
Long term leverage	0.131	0.057	0.184	0.306	0.275	0.224	-0.175	38.661	0.000	-0.218	1350.606	0.000
Profitability	0.011	0.077	0.246	0.093	0.118	0.151	-0.082	16.397	0.000	-0.041	187.112	0.000

Panel C. Treated and control firms

	Treated firms N = 2,880			Control firms N=2,880			Difference in means			Difference in medians		
	mean	median	s.d.	mean	median	s.d.	Difference	T-stat	p-value	Difference	Chi-squared	p-value
Q	2.128	1.487	1.862	1.953	1.412	1.649	0.175	3.785	0.000	0.074	4.669	0.031
Cash flow	-1.227	0.191	6.654	-1.030	0.201	6.148	-0.197	-1.170	0.242	-0.010	0.711	0.399
Size	4.387	4.175	1.558	4.550	4.318	1.494	-0.163	-4.055	0.000	-0.143	6.400	0.011
Long term leverage	0.131	0.057	0.184	0.159	0.108	0.164	-0.028	-6.002	0.000	-0.050	156.025	0.000
Profitability	0.011	0.077	0.246	0.027	0.085	0.212	-0.016	-2.566	0.010	-0.008	2.669	0.102

Figure 2. Parallel trends

This graph represents the evolution of the average investment to capital ratio of non-distressed firms in distressed industries, as they approach the industry distress episode. The horizontal axis represents the number of years until the industry distress, which is normalized at $t=0$. To be included in this graph, firms suffered a distress event at $t=0$, but not in the other periods. The dashed line corresponds to treated firms, i.e., those having more than 20% of their long-term debt maturing after the distress episode; the continuous line corresponds to all other non-distressed firms in distressed industries.

Table 4. Baseline estimations

This table presents estimates of the change in annual investment rate for non-distressed firms in distressed industries from the year before the industry distress to the year after the distress. In Panel A, estimations are done using a parametric regression analysis, with standard errors clustered at the 3-digit SIC industry code level. The dependent variable is the change in investment to capital ratio. Treated firms as those for which the percentage of long-term debt maturing after the industry distress is greater than 20%. All control variables are defined in the appendix. All estimations include industry*year fixed effects. In Panel B, each treated firm is matched to its nearest neighbor according to pre-distress values of Q, cash flow, size, profitability, and long-term leverage, as well as industry (at the 3-digit SIC code level) and year. There are 2,880 treated and 2,880 control firms in Panel B. ***, **, and * mean the coefficients are statistically significant at the 1, 5, and 10% level, respectively.

Panel A. Parametric regression analysis

Dependent variable:	(1)	(2)	(3)
	Change in investment to capital ratio		
Treated	-0.0532*** [0.0185]	-0.0593*** [0.0179]	-0.0622*** [0.0208]
Q		-0.0389*** [0.00565]	-0.0481*** [0.00519]
Cash flow		0.0412*** [0.00304]	0.0423*** [0.00291]
Size		-0.00565 [0.0105]	-0.0242 [0.0157]
Profitability		-0.136* [0.0740]	0.283*** [0.0767]
Long-term leverage		-0.105*** [0.0376]	-0.157*** [0.0382]
Rating = Speculative			0.0491** [0.0216]
Rating = Investment grade			0.183*** [0.0698]
Z-score			-0.0474*** [0.00721]
Constant	-0.146*** [0.00616]	0.0136 [0.0648]	0.134* [0.0786]
Observations	8,676	8,676	8,420
R-squared	0.111	0.179	0.192
Industry*Year F.E.	Yes	Yes	Yes

Panel B. Non-parametric matched sample

Outcome variable:	Investment to capital ratio		
	(1)	(2)	(3)
	Before Distress	After Distress	After - Before
Treated	0.604*** [0.0172]	0.346*** [0.00694]	-0.258*** [0.0179]
Control	0.510*** [0.0150]	0.316*** [0.00608]	-0.194*** [0.0154]
Difference	0.0943*** [0.0178]	0.0299*** [0.00812]	-0.0644*** [0.0193]
Matching estimator (ATT)			-0.0518** [0.0260]

Table 5. Robustness and falsification tests

This table presents robustness and falsification tests for the results in Table 4. The dependent variable in column 1 is investment to capital rate from t-1 to t+1, in column 6 it is the change in annual investment to assets rate from non-distressed firms in distressed periods. In column 1 the sample is further restricted to the firms with positive sample also includes non-distressed periods. Estimations are done using an OLS regression analysis, with standard errors at industry code level. In columns 1, 5, and 6, treated firms are those for which the percentage of long-term debt at time t, is greater than 20%. In column 2, treated firms are those for which the percentage of long-term debt at time t-1, is greater than 20%. In column 3, treated firms are those for which the percentage of long-term debt at time t-2, is greater than 20%. In column 4, treated firms are those for which the percentage of long term debt maturity in industry "distress" is greater than 20%, where "distress" is set to two years before the true distress date. All coefficients are significant at the 1% level. ***, **, and * mean the coefficients are statistically significant at the 1%, 5%, and 10% level, respectively.

Panel A: Parametric regression analysis

	(1)	(2)	(3)	(4)
Dependent variable:	Change in capital expenditures to capital ratio			
	Sample of issuing firms	Predetermined debt, 2 years before	Predetermined debt, 3 years before	Placebo, Fictitious distress
Treated	-0.0849*** [0.0264]	-0.0498* [0.0297]	-0.0316* [0.0188]	0.0117 [0.0215]
Distress * Treated				
Q	-0.0437*** [0.00715]	-0.0269*** [0.00686]	-0.0280*** [0.00706]	-0.0509*** [0.0171]
Cash flow	0.0432*** [0.00409]	0.0424*** [0.00708]	0.0457*** [0.00567]	0.0396*** [0.00942]
Size	-0.00281 [0.00684]	-0.00538 [0.00965]	-0.00840 [0.00802]	0.00705* [0.00360]
Profitability	-0.205** [0.0980]	-0.0224 [0.0855]	-0.0594 [0.0899]	-0.255** [0.115]
Long-term leverage	-0.0536 [0.0560]	-0.0760 [0.0522]	-0.0737** [0.0353]	-0.0612 [0.0467]
Constant	-0.0353 [0.0529]	-0.00831 [0.0666]	0.0136 [0.0561]	0.0249 [0.0381]
Observations	4,100	6,834	6,616	5,945
R-squared	0.206	0.180	0.193	0.105
Industry*Year F.E.	Yes	Yes	Yes	Yes

Table 6. Subsample analysis

This table presents estimates of the change in annual investment rate for non-distressed firms in distressed industries from the year before the industry distress to the year after the distress. Each pair of columns contain estimations performed over the following mutually exclusive subsamples of firms: Post-distress change in market concentration (columns 1 and 2); pre-distress market concentration (columns 3 and 4); Size of bankrupt firms (columns 5 and 6); external finance dependence (columns 7 and 8); industry leverage (columns 9 and 10); and number of bankruptcies in wave (columns 11 and 12). The dependent variable is the change in investment to capital ratio. Treated firms as those for which the percentage of long-term debt maturing after the industry distress is greater than 20%. All control variables are defined in the appendix. All estimations include industry-year fixed effects. Standard errors are clustered at the industry level (3-digit SIC codes). ***, **, and * mean that the coefficients are significant at the 1, 5, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Market concentration		Change in concentration		Industry Leverage	
VARIABLES	Concentrated	Competitive	More concentrated	More competitive	High	Low
Treated	-0.0342 [0.0210]	-0.0824*** [0.0262]	-0.0325 [0.0235]	-0.0796*** [0.0254]	-0.0894*** [0.0292]	-0.0361 [0.0254]
Q	-0.0308*** [0.00904]	-0.0473*** [0.00660]	-0.0478*** [0.0126]	-0.0342*** [0.00742]	-0.00631 [0.0131]	-0.0486*** [0.00507]
Cash flow	0.00525 [0.0104]	0.0489*** [0.00371]	0.0184 [0.0122]	0.0542*** [0.00544]	0.0521*** [0.0151]	0.0402*** [0.00274]
Size	0.000950 [0.00548]	-0.0137 [0.0188]	0.00694 [0.0107]	-0.0169 [0.0141]	0.00606* [0.00361]	-0.0261 [0.0185]
Long-term leverage	-0.0523 [0.0629]	-0.158*** [0.0407]	-0.0867 [0.0579]	-0.139*** [0.0448]	-0.122*** [0.0448]	-0.0919 [0.0659]
Profitability	0.0811 [0.114]	-0.168** [0.0755]	0.00639 [0.109]	-0.227** [0.0965]	0.198* [0.112]	-0.252*** [0.0568]
Constant	-0.0278 [0.0444]	0.0654 [0.116]	-0.0379 [0.0509]	0.0608 [0.0885]	-0.0810** [0.0378]	0.0566 [0.0937]
Observations	4,244	4,432	3,717	4,959	5,134	3,542
R-squared	0.059	0.236	0.098	0.225	0.135	0.195
Industry*Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Difference		0.0483		0.0471		-0.0533
S.E.		0.0450		0.0447		0.0455

	(7)	(8)	(9)	(10)
	External finance dependence		Bankruptcy wave	
VARIABLES	High	Low	Yes	No
Treated	-0.0707*** [0.0255]	-0.0363 [0.0245]	-0.117** [0.0457]	-0.0484*** [0.0171]
Q	-0.0420*** [0.00826]	-0.0360*** [0.00869]	-0.0147 [0.0216]	-0.0410*** [0.00665]
Cash flow	0.0388*** [0.00878]	0.0427*** [0.00216]	0.0473 [0.0308]	0.0410*** [0.00404]
Size	0.00573 [0.00493]	-0.0315 [0.0190]	0.000813 [0.00540]	-0.00732 [0.0131]
Long-term leverage	-0.130** [0.0507]	-0.0427 [0.0423]	-0.174** [0.0661]	-0.0901** [0.0413]
Profitability	-0.115 [0.105]	-0.127 [0.0852]	-0.0248 [0.163]	-0.160** [0.0731]
Constant	0.00930 [0.0378]	0.0186 [0.126]	0.0142 [0.0773]	0.00985 [0.0842]
Observations	5,934	2,742	1,642	7,034
R-squared	0.110	0.217	0.120	0.187
Industry*Year F.E.	Yes	Yes	Yes	Yes
Difference		-0.0344		-0.0688
S.E.		0.0511		0.0540

Appendix A. Definition of the variables

This table contains the definitions of the most important variables used in the analysis.

Variable	Formula with Compustat codes	Definition
<i>Outcome variables:</i>		
Investment to capital	$\text{capx (t) / ppe (t-1)}$	Capital expenditures / lagged property, plant, and equipment
Investment to assets	$\text{capx (t) / at (t-1)}$	Capital expenditures / lagged assets
<i>Treatment variable:</i>		
Treated	dd1 / (dd1+dltt)	Dummy =1 if the ratio is greater than 0.2, =0 otherwise
<i>Main control variables:</i>		
Q	$(\text{at} + \text{prcc_f} * \text{csho} - \text{ceq} - \text{txditc}) / \text{at}$	(Assets + market capitalization - common equity - deferred taxes and investment tax credit) / Assets
Cash flow	$(\text{ib (t)} + \text{dp (t)}) / \text{ppent (t-1)}$	(Net income + depreciation and amortization) / lagged property, plant, and equipment
Profitability	oibdp / at	Operating income before depreciation / assets
Size	$\log(\text{at})$	Log of assets
Long-term leverage	$(\text{dd1} + \text{dltt}) / \text{at}$	Total long term debt / Assets
Year	fyear	Year of the observation
Industry (3-digit SIC code)	$\text{floor}(\text{sic}/10)$	One dummy for each distinct value
<i>Other control variables:</i>		
Z-score	$3.3 * (\text{oibdp} - \text{dp}) / \text{at} + \text{sale} / \text{at} + 1.4 * (\text{re} / \text{at}) + 1.2 * (\text{wcap} / \text{at})$	Distance to default = $3.3 * (\text{Operating income} / \text{assets}) + (\text{sales} / \text{assets}) + 1.4 * (\text{Retained earnings} / \text{assets}) + 1.2 * (\text{Working capital} / \text{assets})$
Rating	splticrm	Dummy =2 if rating greater or equal to BBB- (investment grade), =1 if rating below BBB- (speculative grade), =0 if unrated

Appendix B. Investment to assets ratio

This table presents estimates of the change in annual investment rate for non-distressed firms in distressed industries from the year before the industry distress to the year after the distress. In Panel A, estimations are done using a parametric regression analysis, with standard errors clustered at the 3-digit SIC industry code level. The dependent variable is the change in investment to assets ratio. Treated firms as those for which the percentage of long-term debt maturing after the industry distress is greater than 20%. All control variables are defined in the appendix. All estimations include industry-year fixed effects. In Panel B, each treated firm is matched to its nearest neighbor according to pre-distress values of Q, cash flow, size, profitability, and long-term leverage, as well as industry (at the 3-digit SIC code level) and year. There are 2,880 treated and 2,880 control firms in Panel B. ***, **, and * mean the coefficients are statistically significant at the 1, 5, and 10% level, respectively.

Panel A. Parametric regression analysis

	(1)	(2)	(3)
VARIABLES			
Treated	-0.00700 [0.00541]	-0.0136* [0.00701]	-0.0147* [0.00816]
Q		-0.00910*** [0.00129]	-0.0103*** [0.00175]
Cash flow		0.00236*** [0.000497]	0.00229*** [0.000612]
Size		-0.00104 [0.00109]	-0.00374** [0.00173]
Profitability		0.0146 [0.00929]	0.0766*** [0.0148]
Long-term leverage		-0.0613*** [0.0135]	-0.0681*** [0.0153]
Rating = Speculative			0.00785 [0.00670]
Rating = Investment grade			0.0265*** [0.00633]
Z-score			-0.00669*** [0.00199]
Constant	-0.0218*** [0.00180]	0.0179 [0.0114]	0.0348** [0.0169]
Observations	8,676	8,676	8,420
R-squared	0.075	0.097	0.104
Industry*Year F.E.	Yes	Yes	Yes

Panel B. Non-parametric matched sample

	Investment to assets ratio		
	(4) Before Distress	(5) After Distress	(6) After - Before
Treated	0.0989*** [0.00280]	0.0668*** [0.00179]	-0.0321*** [0.00271]
Control	0.0921*** [0.00253]	0.0695*** [0.00185]	-0.0225*** [0.00237]
Difference	0.00682** [0.00333]	-0.00276 [0.00205]	-0.00959*** [0.00336]
Matching estimator (ATT)			-0.0104** [0.0043]

Appendix C. Early refinancing

The sample consists of all non-distressed in distressed industries. The dependent variable is Early Refinancing, a dummy taking the value one when the amount of long-term debt that is due in year $t+1$ is reduced between years $t-1$ and t (i.e., $dd1 < \text{lagged } dd2$). Treated firms as those for which the percentage of long-term debt maturing after the industry distress is greater than 20%. Distress is a dummy variable taking the value one for periods in which there was an industry distress. All control variables are defined in Appendix A. All estimations include industry-year fixed effects. $***$, $**$, and $*$ mean the coefficients are statistically significant at the 1, 5, and 10% level, respectively.

VARIABLES	(1)	(2)	(3)
	Dep. var. = Early refinancing		
Treated	-0.147*** [0.00528]	-0.132*** [0.00585]	-0.128*** [0.00595]
Treated * Distress	0.00876 [0.0108]	0.00640 [0.0115]	0.00775 [0.0117]
Q		0.000612 [0.000559]	2.45e-05 [0.000628]
Cash flow		0.000875*** [9.16e-05]	0.000871*** [9.16e-05]
Size		0.00975*** [0.00153]	0.00980*** [0.00184]
Profitability		0.000521 [0.00500]	0.00884* [0.00521]
Long-term leverage		-0.0537*** [0.00922]	-0.0576*** [0.0101]
Rating = Speculative			0.0113 [0.0102]
Rating = Investment grade			0.0122 [0.0126]
z-score			-0.000605*** [0.000212]
Constant	0.435*** [0.00330]	0.403*** [0.00908]	0.403*** [0.00969]
Observations	67,340	58,088	56,505
R-squared	0.082	0.090	0.090
Industry * Year F.E.	Yes	Yes	Yes