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Financial distress and competitors' investment

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Abstract. This paper analyzes whether the financial distress of a firm affects the investment decisions of non-distressed competitors. On average, firms in distress impose indirect costs to non-distressed competitors by increasing costs of credit in the industry and hence restricting credit access and investment. These average negative effects continue to hold in the absence of industry downturns and are temporary. However, negative effects are mitigated for firms with stronger balance sheets or in concentrated markets, suggesting that firms with strong balance sheets prey on their weaker rivals to improve their market position.

Keywords: Bankruptcy, distress, default, corporate investment, information spillovers, market structure.

Classification: G31, G32, G33

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Financial distress and competitors' investment

1. Introduction

This paper analyzes whether firms in financial distress impose indirect costs to their direct competitors and to the real economy by affecting the investment decisions of other firms in the industry. The analysis builds on previous findings that show that when some firms in the industry have financial difficulties, the costs of external financing to rivals increase (Lang and Stulz, 1992; Jorion and Zhang, 2007; Benmelech and Bergman, 2011; Hertzel and Officer, 2012). In principle, the higher financing costs that follow a distress in the industry could reduce investment by affecting the competitors' ability to obtain sufficient funds.[1] However, a competitor facing financial difficulties could facilitate predation by other firms in the industry, who could exploit their rivals' weaknesses and increase investment to obtain a higher market share (Fudenberg and Tirole, 1986; Bolton and Scharfstein, 1990; Opler and Titman, 1994).[2] The main objective of this paper is to examine whether competitors of the distressed firms are able to exploit the opportunity to increase their market share, in spite of the potentially higher costs of obtaining finance, or whether the increase in financing costs more than offsets the potential benefits of increasing investment in market share. In addition, the paper seeks to identify the characteristics of the firms that benefit most from their rivals' financial weaknesses.

The main analysis in this paper explores whether the higher financing costs associated with the financial distress of a competitor affect the real investment decisions of other non-distressed firms in

[1] A classic line of research shows that higher costs of external financing can affect the real economy because firms cannot obtain sufficient funds for investment (Fazzari, Hubbard and Petersen, 1988; Kaplan and Zingales, 1997). Recent contributions to this literature have argued that firms reduce their capital expenditures as a consequence of supply shocks to external financing (Duchin, Ozbas, and Sensoy, 2010; Almeida, Campello, Laranjeira, and Weisbenner, 2011).

[2] These so-called theories of predation suggest that firms with substantial financial resources – such as the large and public firms, which, as will become clear in the data section, are the object of study in this analysis –predate on weaker firms to drive them out of the market, and consequently increase their market share. As discussed by Tirole (1988), a firm can predate on competitors, among other strategies, by investing in capital.

the industry.[3] The identification challenge of this analysis is that common economic factors, such as negative demand shocks, could simultaneously lead the weakest firms to miss their debt payment obligations or even file for bankruptcy, and the rest of the firms to reduce their capital investments to adjust to the new economic situation. To overcome this fundamental endogeneity problem, the main identification strategy exploits the cross-sectional heterogeneity of firms' long-term debt maturity structures within a given industry and year. Specifically, estimations examine whether firms with large fractions of their long-term debt maturing right after a rivals' bankruptcy filing or debt default (treated firms) had to cut their investment expenditures more than otherwise similar firms that did not have to refinance their long-term debt at that time (control firms). Specifications include industry*year fixed effects, which control for common shocks to the cash flows of all industry participants in a given year. Additionally, the dependent variable is measured in differences to account for unobservable, idiosyncratic firm effects that are fixed around the distress period. Further, the models account for observable firm characteristics that could simultaneously determine investment and debt maturity structures – i.e. size, profitability, investment opportunities, cash flows, and leverage ratios (Barclay and Smith, 1995; Guedes and Opler, 1996; Choi, Hackbarth, and Zechner, 2013) – both as controls in the regressions and through a matching approach.

Results from this analysis show that, on average, treated firms cut their yearly investment ratios by significantly larger amounts than controls. Economically, the coefficients imply that the difference in the change in investment to capital ratios is approximately 4 percentage points higher for control firms relative to treated firms. This represents a level of investment that is around 10% lower than pre-distress levels. Overall, these findings suggest that the potential benefits of increasing investment are more than offset, on average, by the high costs of finance triggered by the distress.

[3] In this paper, a firm is defined as distressed when it misses some payment in a debt obligation or it files for bankruptcy.

A battery of robustness tests show that the above results cannot be explained by an endogenous sorting of firms' of certain observed or unobserved characteristics and their debt maturity structures. Specifically, results (i) are robust to using the median peers' debt maturity structure in the industry, rather than the own firm's debt structure, as an exogenous source of variation; and (ii) are non-existent during placebo distress events. Further, the negative effects of distress on competitors' investment continues to hold even in the absence of contemporaneous industry downturns, alleviating the concern that the results are driven by common shocks to industry participants. Results also show that the distress of a competitor has a temporary effect on investment.

The second part of the paper examines whether firms with strong balance sheets experience the negative effects of an industry distress episode on investment to the same degree as firms with weaker balance sheets. According to theory, firms with substantial financial resources (i.e., "deep pocket" firms) can afford to sustain losses for a long period of time; therefore, these firms can potentially prey on their weaker rivals to gain market share (Fudenberg and Tirole, 1986; Bolton and Scharfstein, 1990; Opler and Titman, 1994; Frésard, 2010).[4] In line with these theories and prior findings, the results in this paper show that the negative effects of higher financing costs cease to be significant among subsamples of firms that are likely to have strong balance sheets (large firms, firms with a credit rating, firms with lower leverage, cash-rich firms). These findings suggest that firms with strong balance sheets can partially offset the negative effects of higher financing costs. Moreover, the negative effects on investment are stronger among the most competitive industries, where the expected benefits of predating on weaker rivals are smaller in expected terms. An extended analysis further shows some suggestive evidence that the effects of a bankruptcy in an industry are not propagated through lower collateral values, as in the case of industry downturns (Shleifer and Vishny, 1992; Benmelech and

[4] The main assumption in these predation models is that capital markets are imperfect, creating a wedge between the price of internal and external funds. By increasing uncertainty, defaults in the industry could exacerbate this friction. This could make credit scarce for weak firms, while stronger firms could afford to continue investing in spite of the higher costs.

Bergman, 2011; Carvalho, 2015). Rather, bankruptcies seem to be propagated through an information channel in the spirit of King and Wadhwani (1990), Kodres and Pritsker (2002), or Cespa and Foucault (2014).

This paper contributes to the literature in two important ways. First, it shows that firms in financial distress affect the real economy (i.e. real investment decisions) through their effect on competitors' cost of finance. Importantly, the findings show that these ripple effects are economically significant even in the absence of recessions or industry downturns. Second, the paper shows that industry characteristics, such as the strength of firms in the industry or its degree of competitiveness, can accentuate or dampen these negative effects by changing competitors' incentives.

This paper is most related to studies that examine the indirect costs of bankruptcy and distress of a firm (Altman, 1984; Opler and Titman, 1994; Andrade and Kaplan, 1998, or Bris, Welch, and Zhu, 2006, among others). The contribution to this literature is to show that bankruptcies (and more in general, financial distress) can affect agents beyond the stakeholders of the firm itself. Thus, indirect effects of distress appear substantially higher than previously documented. However, the paper also documents that these effects are only temporary.

The paper also relates closely to the literature that highlights the role that financial markets play in the growth of the economy (Fazzari et al., 1988; Kashyap et al., 1994; Kaplan and Zingales, 1997; Duchin et al., 2010; Almeida et al., 2011). The paper is closest to Carvalho (2015), who finds that firms' valuation losses are amplified during an industry downturn. The contribution of this paper is twofold. On the one hand, the paper shows that even distresses that are not systematically driven, and are not associated to industry downturns, can negatively affect the real economy. On the other, findings suggest that industry characteristics can moderate or amplify these effects.

The paper also adds to the literature that examines the role of product market competition in corporate finance (Chevalier, 1995; Frésard, 2010; Frésard and Valta, 2016). The contribution to this literature is to uncover some evidence of a new mechanism (financial distress of competitors) which could affect the strategic behavior of firms. Finally, the paper is also related to the small but growing literature on the effect of peer firms on corporate financial policy (Leary and Roberts, 2014; Foucault and Frésard, 2014; Benmelech et al., 2014). This paper contributes to this literature by analyzing the effects of propagation of distress among peers in the same industry.

2. Data and methodology

2.1 Data construction and sample distribution

The main 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.[5] The sample excludes non-US firms listed in the US (ADRs), firms in the financial or government sectors, and non-for-profit organizations. Similarly, the sample excludes firms with missing assets or capital expenditures, as well as firms with asset or sales growth exceeding 100%, and firms with less than 10 million USD in assets. These filters eliminate the smallest firms with volatile accounting data and 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).

Data on bankruptcies come from the UCLA-LoPucki Bankruptcy Research Database, which contains information on 520 Compustat firms that filed for bankruptcy during the 1988-2006 period. Data on

[5] The use of yearly data is necessary to classify firms into treated and control firms. As shall be explained below, this classification requires using variable *dd1* (the amount of long-term debt which matures the year of the annual report), which is only available in the Compustat yearly files. The main data sample stops in year 2006 to avoid confounding the results with the credit crunch that occurred in year 2007 and the recession that followed (see e.g. Duchin et al, 2010 and Almeida et al, 2011). However, results are qualitatively similar when extending the information of bankrupt firms until 2014 (see Section 5.1).

defaults come from Moody's Ultimate Recovery Dataset, which discloses information about 408 firms that defaulted on a debt obligation during the sample period (i.e. they either were insolvent, suffered a distressed exchange, or missed any interest payments on a debt obligation). In this database, a firm is defined as distressed in a year t if it files for bankruptcy or defaults on a debt obligation during that year. Some of the defaults correspond to firms filing for bankruptcy; therefore, the information about defaults effectively identifies 217 additional firms, for a total of 737 firms in distress. For each 3-digit SIC industry code, I define a distress year in the industry as a year in which there was at least one firm in distress in that industry. Due to clustering of bankruptcies and defaults through time within an industry, these events correspond to 565 unique industry-level distress periods. The sample under consideration corresponds to all other firms, i.e. those potentially affected by a peer's bankruptcy or default, but that did not file for bankruptcy or suffer a credit event themselves during the sample period. All firms with missing values for the dependent or the main independent variables are eliminated from the sample. To reduce the impact of outliers, all variables are winsorized at the high and low 1% percentiles. Table A.1 in the Appendix contains a definition of all the variables used in the analysis.

Table 1 contains the distribution of the sample according financial distress and year (Panel A), and financial distress and industry (Panel B). For the benefit of space, industries in Panel B are reported at the 2-digit instead of the 3-digit SIC code level, which is the one effectively used in the classification of the industries in the rest of the paper. Table 1 shows that the final sample consists of 14,492 firms in periods coinciding with a peer in distress, and 36,143 firms in periods with no contemporaneous peer bankruptcy. This implies that firms in the sample suffer a competitor's industry distress event on average once every three and a half years. The sectors most affected by bankruptcies or defaults are services, mining, and retail trade, with oil and gas extraction (SIC code 13), food stores (SIC code 54), and business services (SIC code 73) being among the industries with the largest proportion of firm-years affected by a competitor's distress.

2.2 Methodology

The theories taken to the data rely on the central assumption that capital market imperfections affect the investment of a distressed firm's competitors. On the one hand, the higher costs of external financing could negatively affect the ability of firms to obtain external funds for investment (Fazzari, Hubbard and Petersen, 1988; Kaplan and Zingales, 1997). On the other hand, firms with easier access to finance (such as the public firms in the sample) could seize the opportunity to increase investment and obtain a higher market share at the expense of weaker rivals, in spite of the higher costs (Fudenberg and Tirole, 1986; Bolton and Scharfstein, 1990). Thus, the first step in the analysis is to explore whether a distress in an industry affects the investment decisions of the average competitor through a financing channel.

The identification strategy consists in comparing the changes in investment of firms that are more likely to suffer the consequences of higher financing costs ("treated" firms) with the more resilient "control" firms in the same industry and period, and evaluating whether these differences are stronger around distress episodes than around normal times. To be more precise, the main regression model is the following:

$$\Delta I_{ijt} = \beta_0 + \beta_1 * treat_{ijt} + \beta_2 * distress_{jt} + \beta_3 * (treat * distress)_{ijt} + \delta_{jt} + u_{ijt}. \quad (1)$$

The dependent variable ΔI_{ijt} is the change in the investment to capital ratio of firm i in industry j between years $t-1$ and $t+1$. The main regressors are the binary variable $treat_{ijt}$, which takes the value 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 zero otherwise; $distress_{jt}$, a dummy variable taking the value one if there is a bankruptcy or a default in industry j at time t; and the interaction between these two variables, $(treat * distress)_{ijt}$. The coefficient of the interaction term β_3 is the focus of this analysis and indicates whether treated firms are more likely to change their investment policies around an industry distress episode than during normal times. Coefficient β_1 will capture any differences in investment changes between treated firms ($treat_{ijt} = 1$) and control firms ($treat_{ijt}$ =0). All specifications include industry * time fixed effects, represented by the term δ_{jt}, to control for common economic shocks (such as negative demand shocks) that affect all the firms in the industry in a given period. In practice, this means that it is impossible to estimate coefficient β_2 because the dummy variable $distress_{jt}$ is redundant with the inclusion of this fixed effects. Standard errors are clustered at the 3-digit SIC industry level.

Sample firms are classified as "treated" if their amount of long-term debt maturing in period t (i.e., the ratio of variable *dd1* to *dd1 + dltt)* is greater than the corresponding 60th percentile of the distribution of this variable in the 3-digit code industry (see Almeida et al., 2011).[6] These firms are likely to have to refinance their debt; therefore, they are more likely to suffer the higher costs of financing due to a competitor's distress than firms with a lower proportion of their debt maturing during the distress.[7] The amount of debt maturing should be plausibly exogenous to the timing of the distress of another firm in the industry, as it is the result of a decision made several years before the event; any unobserved differences between treated and control firms will be captured by the inclusion of variable $treat_{ijt}$.

[6] In robustness checks, I consider different thresholds to define the treated firms, and use the continuous counterpart to these dummies, i.e. the portion of long-term debt expiring in period t (see Table A.3 in the Appendix).

[7] In Appendix A.4 I augment the data in this paper with information about the cost of syndicated loans (i.e. the all-in-spread) to provide direct evidence for the following identifying assumptions: (i) treated firms increase their long-term debt issuance when a large portion of their long-term debt matures; (ii) the cost of financing increases for firms following a distress in their industry, and (iii) treated firms have higher increases in financing costs following an industry distress.

The remaining 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 that we are interested on.[8]

The above specification has several elements that allow us to identify the causal effect of industry distress on investment. First, the dependent variable measures within-firm changes in investment, and hence controls for idiosyncratic firm effects that are constant around the distress event. Second, the industry * time fixed effects allow for the estimation of the differential effect of treatment vs. control firms within the same period, and, in particular, during the same distress episode. This restriction makes it possible to control for economic shocks that affect all of the firms in the same industry, such as common shocks to the cash flows of the industry. Moreover, this ensures that the firms being compared are in the same industry and hence 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 controls for any underlying differences between firms that tend to refinance their debt obligations several years ahead of their maturity, and firms that usually refinance their debt at their expiration.

This identification strategy requires that there is enough variation in the long-term debt maturity across firms. 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 the sample period. Figure A.1 in the Appendix provides a visual illustration of the within-industry distribution of debt maturities throughout the years in the sample under study. For the sake of brevity, the figure only displays the distributions of debt

[8] One concern about the classification into treatment and control firms is that it could capture unobserved differences between firms that renegotiate their debt contract maturity well before maturity and those that do not or cannot do it (see Roberts and Sufi, 2009). The inclusion of variable $treat_{ijt}$ in the main specification controls for these differences. An extended analysis considers a different specification with a more exogenous classification of firms into treated and control groups (namely, the proportion of firms in a given industry that have to refinance at the time of the bankruptcy). For a more complete discussion, see Section 3.2 and Table A.7 in the Appendix.

maturities for all the 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 distresses, while those in blue correspond to normal 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 significant portions of their long-term debt maturing during the year. The figure does not show obvious differences in the distribution of the maturity structures of distress vs. normal years.

Besides variation in debt maturities, the identification strategy additionally requires that the distribution of the long-term maturity structures is similar in distress and normal years. Identification would be compromised due to potential reverse causality concerns if the concentration of firms with long-term debt expiring during bankruptcy years were larger. To test for this identification requirement more formally, Table A.2 in the Appendix reports tests for the difference of the average percentage of long-term debt maturing in normal relative to distress years, for each 2-digit SIC-code industry. The results are not consistent with distress years being 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 very close to zero; and the number of industries for which the differences are statistically significant is eight both when the difference is positive and when it is negative. These results suggest that the distribution of the long-term maturity of debt is similar in all years, and hence it seems to be exogenous to the incidence of bankruptcies or defaults in the industry, as required for identification.

Previous studies have argued 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). The next section shows that some of these differences also hold in this sample. Therefore, in additional specifications I augment Equation (1) by conditioning on the first lag of each of these variables to mitigate concerns of omitted variables bias. For added robustness, I also match each treated firm with its closest counterfactual among the control firms, using these variables to perform the matching.

2.3 Descriptive statistics

Table 2 contains basic descriptive statistics for the main variables used in this paper. Statistics for the investment ratio are calculated both at periods $t-1$ and $t+1$, while the statistics for the independent variables correspond to period $t-1$. Panel A contains summary statistics for all the observations (firm-years) in the sample. In Panel B, statistics are calculated separately for firms with long-term debt largely maturing in the period (i.e., treated firms), and those with lower percentages of long-term debt maturing in the year (control firms). From this table, we observe that treated firms are smaller, less leveraged, and less profitable. They also have higher investment opportunities, and invest more than the non-treated firms do. These differences are, in fact, both economically and statistically significant; for example, the difference in average Q across both groups accounts for almost 9% of the standard deviation of this variable, and the differences in all other variables account for higher percentages of their standard deviations. These differences highlight the importance of controlling for these sources of observable heterogeneity in the regression analyses of the following section. Importantly, all of the normalized differences of the control variables are close to or lower than 0.25, as required for stability of these estimations (Imbens and Wooldridge, 2009).[9]

2.4 Parallel trends

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 period 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 control firms prior to the distress. In other words, in the absence of a distress, the observed difference-in-differences estimator should be zero. It is impossible to test this assumption formally; however, as an approximation Figure 1 shows a graph of the evolution of the average investment to capital ratio of treated and control firms as they approach an industry distress episode.[10] The horizontal axis represents the number of years until the distress, which is normalized at t=0. The continuous line corresponds to treated firms (surrounded by a 95% confidence interval), while the dashed line corresponds to the control firms. Importantly, the graph shows that investment prior to distress was around six percentage points lower for control firms, and this difference is roughly constant throughout the pre-distress period, as required by the parallel trends assumption. The changes in investment levels start to differ between treated and control firms

[9] The normalized difference is defined as $\Delta_x = \frac{\bar{X}_t - \bar{X}_c}{\sqrt{S_t^2 - S_c^2}}$, where $\bar{X}_t, \bar{X}_c$ are the sample means and S_t^2, S_c^2 are the sample variances of variable X on the treatment and control groups, respectively. Imbens and Wooldridge (2009) recommend focusing on the normalized difference, rather than on the t-statistic for the difference in averages, because larger samples automatically increase the t-statistics. As a rule of thumb, controlling for variables whose normalized differences across subsamples yield values of 0.25 or lower lead to linear regression estimators that are stable over different specifications (Imbens and Wooldridge, 2009). To address the fact that normalized differences for size and long-term leverage are larger than 0.25, in a robustness analysis I match each treated firm with the most similar non-treated firm, and estimate the same regression in the resulting sample. Results are discussed below.

[10] For an easier visual interpretation of the results, the sample in the figure is restricted to firms suffering an industry bankruptcy at t=0, and shows the *levels* of investment before and after the bankruptcy in the spirit of a standard diff-in-diff estimation. Notice that this is solely for illustration purposes and is not directly comparable to equation (1). In fact, the sample in the estimations (i) also includes firms in industries that are not hit by any default shock, and (ii) uses differences in investment as the dependent variable.

around the defaults, as expected. In fact, investment falls for all firms during the distress episode, but the decrease in investment is steeper for the treated firms than for the controls. Because of these differences, after the bankruptcy the difference in investment between treated firms and control firms falls to around two percentage points. Overall, Figure 1 shows suggestive evidence that the parallel trends assumption holds.

3. Baseline results

Table 3 contains the results of estimating equation (1) on the sample. The dependent variable is the within-firm difference in the investment ratio from period $t-1$ to $t+1$. In column 1 the only independent variable is a dummy for the treatment, the interaction between treatment and distress, and the industry*year fixed effects (recall that the distress dummy is subsumed with the industry-year fixed effects). Results show that during industry distress episodes, the investment to capital ratio falls on average by 4 percentage points more for the firms with larger portions of their long-term debt maturing the year after the bankruptcy, relative to the control firms. This is a central result of this paper, and it suggests that there is a significant negative effect of a competitor's defaults on firms' investment policies. Economically, this effect means that during an industry distress, treated firms reduce their investment levels on average by 11% more than they would have if their debt had not expired just after the distress. Results suggest that on average, the potential benefits of increasing investment to improve the market share following the distress of a firm in the industry are more than offset by the impossibility to invest due to higher costs of finance.

Column 2 shows an augmented specification which controls for variables that are likely to affect the firms' investment policies, and that, as shown in Table 2, are potentially correlated with the treatment variable: Q, cash flows, size, long-term leverage, and profitability (measured at $t-1$). The main result found in column 1 is only marginally changed. The coefficient for the interaction term implies that during industry distresses, treated firms reduce their investment levels by 9.6% relative to the pre-distress levels. Moreover, Table A.3 in the Appendix shows that these results are not driven by the choice of the threshold defining the treatment dummy.

One concern of the results in Columns 1 and 2 is the possibility of correlation between firm quality and debt maturity. Roberts and Sufi (2009) have argued that most of the debt contracts are renegotiated prior to maturity, which could imply that only the bad quality firms have to refinance at maturity (see also Mian and Santos, 2012). The empirical specification takes care of a potential unobserved correlation between firm quality and debt maturity, by considering not only periods of distress, but also normal periods, and estimating a coefficient for the uninteracted term $Treated$, which would capture such a correlation.[11] However, to further account for the possibility that differences in firm quality are driving the results, in columns 3 and 4 of Table 3 I include the z-score and three dummies for credit ratings (no rating, speculative grade, and investment grade), which are observable measures of firm quality. The results are qualitatively unchanged respect to the main estimations in columns 1 and 2.

Overall, results so far show negative average effects of an industry distress episode on firm investment. These results suggest that on average, the higher financing costs coinciding with defaults in the industry eclipse any potential positive benefits from predation, even in this sample of large, public firms. The natural question that follows is whether there are heterogeneous effects within the sample, that is, whether the financially stronger firms in the sample are able to mitigate the negative effects of a

[11] To deal with the additional concern that the correlation between firm quality and debt maturity occurs during distress episodes, I examine whether treated firms are less likely to refinance or repay their long-term debt early when there are defaults in the industry compared to normal times. For this purpose, in Table A.5 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* is reduced between years *t-1* and *t*. The coefficient for *Treated* in this table shows that treated firms are 13 to 14 percentage points less likely to do an early refinancing or to pre-pay their long-term debt during normal times, consistently with previous evidence. Crucially, however, these differences in the likelihood of early refinancing are statistically equal to zero during distress periods. The interaction term $Distress * Treated$ is, in fact, positive but statistically insignificant, suggesting that treated firms are equally likely to refinance early during recessions and normal times.

distress by investing on market share. Section 4 deals with this central question. Before we turn to this issue, however, it is important to establish that the results in Table 3 are truly driven by the higher costs of financing associated to defaults in an industry, and not by an endogenous relationship between the dependent and independent variables or other confounding stories. The rest of this section deals with these concerns.

3.1 Industry distress and industry downturns

I first address the question of whether, rather than showing the consequences of a default in the industry on investment, results in Table 3 are capturing the effects of negative demand shocks to firms in the industry (i.e., a downturn). A downturn would reduce the cash flows of firms in the industry – which could increase the incidence of defaults and bankruptcies – and simultaneously decrease investment due to a reduced demand for the industry's products. In principle, the identification strategy takes care of this concern with the industry * time fixed effects, which forces the comparison of investment changes within firms in the same industry and year (and hence, subject to similar demand shocks). Still, one might be worried that this alternative story drives the result because bankruptcies and defaults usually cluster around periods of generalized distress in an industry (Almeida and Philippon, 2007).

To address this issue, I follow the related literature and identify industry downturns as industry-year combinations in which the median annual stock returns of the firms are low; in particular, when they are respectively less than -30%, -20%, -10%, and 0% (Acharya et al., 2007). Panel C of Table 4 shows a cross-tabulation of the number of industry-years according to whether there is a distress or not, and whether there is an industry downturn or not, for three of the above definitions of a downturn. Consistently with previous evidence, several distress events coincide with downturns, and the incidence of defaults is high in the presence of a downturn. Still, several distress events occur outside of downturns, even when we consider mild downturns (industry returns lower than 0%). This fact allows us to estimate Equation (1) over the subsample of periods that do not coincide with downturns (Panel A of Table 4). Naturally, estimations in Table 4 have less observations (hence, lower power) as we move to the right hand side of the table, when we use milder definitions of a downturn and hence exclude more and more observations. Nevertheless, the results consistently show a negative and significant coefficient for the interaction term $Distress * Treated$ in all columns. These results suggest that defaults that do not coincide with downturns can also trigger significant reductions in investment by the affected competitors. This is a central contribution of the paper.

Arguably, defaults or bankruptcies could precede or follow industry downturns. To the extent that this is the case in many of the distress events in the sample, the estimations in Panel A of Table 4 could be still capturing the effects of downturns or recessions. To further control for this, in Panel B I repeat the estimations of Panel A on the subsamples of industry-year combinations that neither coincide, precede, nor follow a downturn. With this yet more restrictive definition, the sample size is reduced further relative to the sample size in Panel A. In spite of this loss of power, the coefficients for the interaction term are still all negative and significant. Moreover, the table shows no evidence that the negative effect of defaults in an industry on competitors' investment policies is worse when these events are associated to an industry downturn. In fact, the interaction terms in Tables 3 and 4 have a similar economic significance.[12] Overall, the findings in Table 4 lend support to the identification strategy of this paper.

[12] The fact that the estimates in Tables 3 and 4 have similar magnitudes may appear surprising. However, this result can be explained with the existence of industry * year fixed effects, which force the comparison to be within the same industry and year and, hence, subsume the effect of any contemporaneous industry downturn in Table 3. In Section 5.4, I estimate the *differential* effect of investment when the distress of a firm coincides with several bankruptcies or distresses in the industry, relatively to when it does not coincide with a bankruptcy or distress wave. As shall be seen, the effect is stronger in the former case.

The results in Table 4 by themselves are a central contribution of this paper, as they show that a negative effect of the financial distress of a competitor on peers' investment occurs *even in the absence of an industry downturn*. This important result shows that the indirect costs of defaults and bankruptcies can be substantially larger than has been previously documented. Namely, bankruptcies and defaults can also have negative consequences on peers, and not only on the direct stakeholders of the creditors and other stakeholders of the firm itself.

3.2 Additional tests of robustness of the results

As an additional robustness test for the results of Table 3, I replicate exactly the same methodology as in Equation (1), but examining within-firm changes of investment around placebo distress periods. For each industry, I artificially set the placebo distress date at one, two, three, four, and five years before and after the actual industry distress dates. The results are contained in the appendix, in Table A.6. If unobserved differences between treated and control firms are driving the results, the coefficient of the interaction term in these placebo regressions should always be negative and significant. Results show that the difference between changes on investment to capital of treated and control firms cannot be distinguishable from zero in all specifications with placebo defaults. Therefore, it is not likely that the negative effect on investment holds in the absence of bankruptcies or defaults in the industry. Importantly, Table A.6 also shows that an industry distress has a temporary effect on peers' investment.

Next, to further alleviate concerns that the results are due to an endogenous relationship between debt maturity and firm quality, I modify the identification strategy of Equation (1) using a more exogenous, industry-level measure of the vulnerability to higher costs of finance. Specifically, I define an industry in a given year as treated if a vast fraction of the industry's firms has debt largely maturing in the period.[13] This method trades off the precision of classifying firms into treated and controls, with a more plausibly exogenous assignment of firms into the treatment group. Importantly, the treatment variable is constant for a given industry and year; hence, industry * year fixed effects cannot be included in this model and are substituted by additive industry and year fixed effects. Identification in this case is obtained by comparing firms across different industries or years and exploiting the cross-sectional variation of firms in industries with different levels of debt maturing after the industry bankruptcy. Results of these estimations are contained in Table A.7 in the appendix and show a negative and statistically significant coefficient of the interaction of the treated dummy with the bankruptcy dummy. As the previous robustness test, these results reinforce the identification strategy of this paper.

Finally, I address the concern that the control firms could be different from treated firms in observable characteristics that matter for investment. In particular, the descriptive analysis contained in Table 2 shows that treated and control firms are particularly different in terms of size and leverage: the normalized differences between these variables is larger than 0.25. To address this concern, for each treated firm I find the control firm in the same industry (same 3-digit SIC code) and year whose Mahalanobis distance (in terms of size and long-term leverage) is minimized.[14] Next, I re-run the estimations of Table 3 using the resulting subsample of matched firms. I perform the matching with replacement, which increases the precision of the match at the cost of lower precision of the estimates. Summary statistics for the resulting matched sample in Table A.8 in the Appendix show that that the sample of treated and control firms obtained through the matching procedure are similar, with normalized differences that are much lower than the 0.25 rule of thumb. The estimated coefficients on

[13] Specifically, I follow Carvalho (2015) and define a "high maturity firm" as a firm whose debt maturing the year is at or above the 60th percentile of its distribution across industries for that particular year. Then, I define an industry as "treated" if the ratio of high maturity firms to total number of firms in that industry and year is at or above the 50th percentile of the across industry distribution of the ratio for that year.

[14] To simplify the matching procedure and maximize the matched sample size I only match on the variables where the normalized differences between treated and control firms are greater than 0.25. The resulting histograms of the propensity scores on the matched sample (available on request) are very similar, confirming a good overlap between treated and controls.

this subsample, reported in Table A.9 corroborate the results of Table 3, confirming once again the credibility of the identification strategy.

4. Discussion of the main results

4.1 Predation theories

Having established the soundness of the identification strategy of Equation (1), let us now turn to the important question of whether, as suggested by theory, firms that are in better financial shape can mitigate the negative effects of a distress by investing on market share. Fudenberg and Tirole (1986) and Bolton and Scharfstein (1990) propose models in which firms with substantial financial resources (i.e., “deep pocket” firms) can afford to sustain losses for a long period of time; therefore, these firms can potentially prey on their weaker rivals to gain market share. The main assumption in these predation models is that capital markets are imperfect, creating a wedge between the price of internal and external funds. By increasing uncertainty, defaults in the industry could exacerbate this friction. This could make credit scarcer for the relatively weaker firms, while the stronger firms could afford to continue investing in spite of the higher costs. In fact, in this environment stronger firms should have higher incentives to increase their investments (or reduce them to a lower extent) precisely to weaken their competitors and benefit from relatively higher market shares.

To analyze this issue, in Table 5 I estimate Equation (1) on several mutually exclusive subsamples of firms classified according to their financial strength. I measure financial strength with the size (in terms of log of assets) and age (in terms of years since their IPO) of the firms. This captures the idea that larger and older firms are better established and as such, they face lower information frictions and can access external financing more easily than firms in their early development stage (Hadlock and Pierce, 2010). I also measure financial strength with standard variables used in related literature such as: a dummy capturing the existence of a rating on a debt issuance (e.g. Duchin et al., 2010), the ratio of cash to assets (Frésard, 2010), the ratio of total debt to assets (Chevalier, 1995), and the amount of intangible assets to total assets (as an inverse measure of debt capacity). For each of these variables, I divide the sample into groups of firms with higher and lower than median values.

The results, exhibited in Table 5, show that the interaction coefficient ceases to be statistically significant in the subsamples of stronger firms (large or old firms, firms with a debt rating, firms with a low leverage ratio or a high cash ratio, and firms with lower amounts of intangible assets on their balance sheet). With the sole exception of young firms – for which the sample is small, due to missing observations – the effect is always statistically significant within the subsamples of weak firms. The results show that financially strong firms that have to refinance their debt during industry distress episodes do not invest less than similarly strong firms that do not need to refinance their debts. In spite of the higher financing costs, these firms do not reduce their investments more than similarly strong control firms. This contrasts starkly with investment of treated firms within groups of weak firms. These results suggest that the treated strong firms continue to invest similar amounts as control firms, in spite of the higher financing costs. Overall, these results are consistent with the theories of predation.

Theories of predation also suggest that the benefits of exploiting financially weaker competitors to gain market share will be higher if the predator is able to obtain monopolistic rents after the predation. Under this hypothesis, the decrease in investment should be softer in concentrated markets, where firms have higher incentives to continue investing because they can plausibly obtain higher monopolistic power by predating their competitors. Following this idea, in Table 6 I estimate Equation (1) over mutually exclusive subsamples of firms in concentrated or competitive markets, and according to the change in competition following the distress period. In columns 1 and 2, 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. In columns 3 and 4, I define a market as competitive if the Boone index is larger than the median, and zero otherwise.[15] Finally, I classify the markets according to whether the change in the Herfindahl index after the bankruptcy relative to previous to the event is positive (suggesting an increase in market concentration) or negative (decrease in concentration) (columns 5 and 6). The results of Table 6 show stronger effects over the subsamples of competitive markets. These results are fully consistent with the theories of predation. These results are also consistent with previous evidence that shows that equity prices of bankrupt firms' competitors *increase* following bankruptcy announcements if the market is highly concentrated (Lang and Stulz, 1992).

4.2 Channels: Information vs collateral

As mentioned before, this paper has built on previous findings that show that the costs of external financing to rivals increase when some firms in the industry have financial difficulties. Additionally, the analysis in Table A.4 shows that this is also the case for the firms in this sample. However, one remaining question in this paper is why do the costs of financing rise for competitors following the demise of a peer. One possible channel is that financing costs increase due to the higher supply and lower demand for collateral in the industry (Shleifer and Vishny, 1992; Benmelech and Bergman, 2011). That is, during downturns peers' debt capacity falls due to the reduced collateral prices caused by fire sales and the consequent excess supply, paired with a reduced demand, for assets in the industry. Another theory, based on asymmetric information, suggests that investors learn information from other assets (King and Wadhwani, 1990; Kodres and Pritsker, 2002; Cespa and Foucault, 2014). These theories assume that information about some assets is difficult to obtain; therefore, investors use others as proxies. A bankruptcy is an easily observed event, which investors could plausibly use to

[15] The Boone index is defined as the absolute value of the coefficient for the log marginal cost (cost of goods sold divided by sales) in a regression of gross profits (defined as sales minus cost of goods sold divided by assets) on the log marginal cost. Results are similar if we use the Lerner index (defined as 1 minus the ratio of operating income before depreciation divided by sales) as an alternative measure of market competition.

infer the prices of debt and equity of firms in the same industry. This would affect peers' availability of finance, and hence, their investment schedules.

A priori it seems unlikely that, in the absence of an industry downturn, the collateral channel should cause the propagation of a bankruptcy shock. This is because in this case the excess supply of industry assets is limited, and there should not necessarily be a reduced demand for the failed firm's assets. In fact, results in Table 4 suggest that the effect documented in this paper does not necessarily have a systematic nature, as it survives in the absence of downturns. More likely, a bankruptcy shock which is unrelated to the underlying state of the industry should be propagated to the real economy through an information channel. Consistently with an information channel, the results in columns 1 to 6 and 11-12 of Table 5 show stronger effects among firms which are typically considered as opaque (small, young, not rated, with large amounts of intangibles). These results suggest that investors react more to a widely observed event such as a bankruptcy when there is not much information available.

To further analyze whether the collateral channel also plays a role, in Table 7 I estimate Equation (1) within mutually exclusive subsamples of firms classified according to their industry's asset specificity. Since fire sales in industries with specific assets affect asset prices of their competitors' assets only, then more negative coefficients for the interaction term in the subsample of firms within industries with industry-specific assets should be evidence in favor of the collateral channel. I follow related studies (e.g. Acharya et al., 2007) and identify high asset-specificity firms as those in industries with a ratio of machinery and equipment to total assets higher than the median. Results do not suggest that there are stronger effects in industries where assets are highly specific, and thus are not consistent with the collateral channel. In fact, we find stronger results in the industries where the assets are not highly specific.[16] These results contrast with Carvalho (2015), who finds that industry downturns are

[16] This latter result is consistent with predation together with a higher competition among firms with low asset specificity.

propagated through the collateral channel. Instead, evidence is suggestive that firm bankruptcies and distresses that are not necessarily linked to industry downturns are propagated through an information channel.

5. Extensions

To conclude the paper, I perform some extensions to analyze the nature of the effects documented in the paper. In particular, I explore whether the effects continue to hold if we extend the sample with more recent data, including a long period of crisis and recession. It is also interesting to document whether the results hold if we consider other shocks to the firms' peers (i.e. negative industry returns or only bankruptcies). Finally, I also investigate whether the effect is different according to characteristics of the distress episodes and of the distressed firms themselves, and whether effects are stronger if the distressed firms are located close to their peers. In the following sections I perform these extensions to the analysis.

5.1 Extended sample period

The results shown so far focus on the period 1988 to 2006. There are two main reasons for this choice. First, information about defaults is available only until 2007, so estimations considering posterior years would ignore any defaults, potentially leading to a measurement error. Second, for the sake of a cleaner identification it is important not to confound the effects of information spillovers or predation with the decreased investment suffered during the financial crisis and the recession that followed, in which many firms were affected by defaults and bankruptcies, and investment decreased at the same time due to lack of financing (Duchin et al., 2010; Almeida et al., 2011).

In spite of the above caveats, it is still interesting to explore whether the results continue to hold in more recent periods. For this reason, I replicate the analyses performed before on an extended sample that goes until 2014. For the benefit of space, I only report the results corresponding to the baseline estimations (in Table 8). As can be seen, the results are qualitatively very similar for the baseline case. And in fact, replicating the other tables presented before yield very similar results as the ones reported for the shorter sample period (results not reported).

5.2 Pure bankruptcy shocks

Another interesting question is whether our results also hold, more generally, when the shock to the peers consists exclusively of information about firms filing for bankruptcy (i.e., excluding defaults). In Table 9, I estimate Equation (1) ignoring firm defaults on debt obligation. That is, as the distress variable I use a dummy variable taking the value one if there was at least one bankrupt firm in the industry and year, and zero otherwise. The results are very similar to the ones reported in Table 3. In fact, the economic magnitude of the estimates in Table 9 is slightly stronger than in Table 3. One possible interpretation for this increase in magnitude is that information plays a crucial role. Thus, when we measure the information available for investors with a signal that is plausibly more easily accessible (bankruptcies), the results are strengthened. These results reinforce the previous interpretation that firm bankruptcies are propagated through an information channel.

5.3 Local effects

Next, I analyze whether investment of firms located near the distressed firms is more affected by the shocks to competitors. Dougal et al. (2015) document that the local infrastructure, the political and institutional environment, and the endogenous interactions in the local economy (or "urban vibrancy"), should lead investment of a firm to be sensitive to the investment of other firms that are headquartered nearby, independently of the industry. Consistently with this intuition, it is plausible to assume that firms should be more affected by the distress of a local competitor, than by the distress of competitors that are located further away. Moreover, the "urban vibrancy" is likely to reinforce the effects documented in this paper, given that firms in the same industry are likely to collocate in the same areas (Ellison et al., 2010).

To explore this issue, I download from Compustat information about the county where each firm is headquartered and identify the counties where distressed firms are located in each year (independently of the industry). Then, I generate a dummy variable "*Same county"* which equals the value one if the firm is located in a county where there is at least one distressed firm in the year, and zero otherwise. I estimate the main regression equation separately over the subsample of firms which are located in a county where there is at least one distressed firm, and over the subsample of firms which are located elsewhere. Results of these estimations are contained in Table 10. Consistently with intuition, the results show that the documented effects are almost twice as large if there is a local distress. Indeed, the coefficient for the sample of firms situated near a distressed firm is almost -0.06, while the coefficient for the other firms is -0.031. These results show that the local effects play an additional role in the investment of peers. Interestingly, though, the effect continues to hold even if the distressed competitors are located in a different county. Thus, results from this analysis also show that the effect documented in this paper exists also if the peers are located further away from their distressed competitors.

5.4 Distressed firm characteristics and firm investment

I next explore whether the characteristics of the distressed firms, or of the distressed sectors, can have a differential impact on investment of distressed firms' competitors. To the extent that the information channel is playing a key role, financing costs should become more expensive if there are many distresses or bankruptcies in an industry during a given period, as the problems in the industry in this case are more easily detected by investors. By the same token, the demise of a larger firm could lead to stronger effects on peers, as such an event is more likely to be accounted for by investors.

Following this idea, in Table 11 I analyze the differential effect of a distress in an industry according to characteristics of the distresses. In particular, for the estimations in this table I enhance Equation (1) with the triple interaction term *treat * distress * distress characteristic*, where *distress characteristic* refers to whether there are several bankruptcies or distresses in the same year (columns 1 and 2), the average size (columns 3 and 4) and age (column 8) of the distressed firms, the percentage of distressed firms in the industry that are unrated (column 5), and their average cash and leverage ratios (columns 6 and 7). As the distress characteristics can only be measured for the firm-years in which there is actually a distress in the industry, I assigned the value zero for these variables when the observations correspond to firm-years without an industry distress episode. Notice that the industry * year fixed effect subsumes all the variation in the distress characteristic; hence, it is impossible to estimate the coefficient for the un-interacted distress characteristic nor its interaction with the treated dummy, the shock dummy, and with the double interaction shock*treated. However, in these regressions the triple interaction term *treat * distress * distress characteristic* will inform us about whether there is a differential effect on investment for the treated and shocked firms when the distressed firms have a certain characteristic or not, which is what we are interested on for this exercise.

Results from this analysis show that effects are stronger when there is a bankruptcy or distress wave in the industry, or when the distresses correspond to large firms. The average age of the distressed firms also seems to have an effect, although it is only marginally not statistically significant (p-value is 0.14). However, there is no differential effects of other characteristics of the firms, such as whether they are unrated, their cash positions, or leverage.

As mentioned before, results from this analysis are consistent with the information channel being the driving force of the observed effects. In fact, it is easier for investors to detect problems in the industry when there is more than one bankruptcy or distress, so the information channel would predict a significantly negative effect in columns 1 and 2. Similarly, it would be easier for investors to detect industry problems when a large (or old, and hence better known) firm files for bankruptcy, than when a small (or young) one does.

5.5 Direct effect of negative industry stock returns

As a final extension for the paper, I analyze, similarly to Carvalho (2015), whether a different shock of a more systemic nature also leads to reduction in the investment of competitors. For this analysis, I estimate a similar regression model as in Equation (1), but replacing the distress dummy with a binary variable taking the value one if the stock returns of firms in the industry and year are negative, and zero otherwise. Results of this analysis are contained in Table 12. Results show that an industry wide shock also results in statistically different investment patterns for firms with more maturing debt. Indeed, such firms, which are more likely to be affected by the higher financing cost due to the negative returns in the industry, invest significantly lower amounts. These results are fully consistent with the findings of Carvalho (2015).

6. Conclusions

This paper finds evidence that defaults in an industry can have non-negligible negative effects on the real investment decisions of non-distressed peers. Due to this effect, firms which are more constrained (i.e., those firms whose long-term debt largely matures after the demise of a competitor) cut their yearly investment rates by around four percentage points (or 10 percent) more than otherwise similar firms in the same industry that do not need to refinance their debt. The paper shows that these negative effects are temporary, that they exist even in the absence of recessions or industry downturns that coincide with the defaults in the industry, and that their channel of propagation is different from the channel of propagation of industry downturns.

The findings in this paper show that this effect is stronger in the most competitive industries, where firms have little margin to adjust prices to compensate for the lower financing, and where information is more dispersed. Moreover, effects are stronger for smaller and unrated firms, cash-poor firms, highly indebted firms, and firms with reduced debt capacity, and are muted by large and rated firms, cash-rich firms, low leverage firms, and firms with large debt capacity. These findings are consistent with the latter firms failing to reduce their investment levels in spite of the higher financing costs, possibly to maintain their market share, or even to gain a higher future market share. Consistently with this interpretation, the negative effects of financing costs on invested are also muted in markets that are relatively concentrated.

These results imply that, through lower investment, financial distress can impose indirect costs to the real economy, and that the real costs of distress go way beyond first-order effects to the direct firm stakeholders. The results also show that these indirect costs are dampened for firms with strong balance sheets and in markets that are relatively concentrated.

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Table 1. Sample distribution

Panel A shows the distribution of sample firms across the years. Columns 1a-1c show respectively the number of bankrupt firms, firms that defaulted in their debt obligations, and distressed firms (i.e. firms that filed for bankruptcy or defaulted on a debt obligation) in each year. 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 distribution across years of the total number of sample firms in industries with a competitor suffering from a distress, and column 4 shows the total number of sample firms in industries where no firms were in distress. Finally, Panel B shows the distribution, across each 2-digit SIC-code industry, of firms in distress during the period 1988-2006 (column 5); sample firms during years with no distress event (column 6), and sample firms during years with at least one competitor in distress (column 7).

Panel A. Distribution by year for distress episodes | **Panel B. Distribution by industry**

Year	(1a) Bankrupt firms	(1b) Defaulted firms	(1c) Distressed firms	(2) Distressed industries	(3) Sample firms in industries with no distress	(4) Sample firms in industries with distress	2-digit SIC code	(5) Distressed firms	(6) Sample firms out of distress periods	(7) Sample firms in distressed periods
1988	8	5	11	11	2,198	183	1	2	146	18
1989	6	4	10	9	2,135	227	10	3	745	71
1990	20	19	34	31	1,650	718	12	1	91	3
1991	30	25	48	39	1,446	926	13	24	1,278	1,599
1992	24	14	32	25	1,849	574	14	2	157	22
1993	18	17	29	26	1,940	594	15	8	181	46
1994	10	14	20	19	1,996	675	16	4	221	32
1995	14	10	19	16	2,310	533	17	2	100	8
1996	13	12	21	19	2,431	537	20	16	1,497	161
1997	14	11	17	15	2,770	264	21	1	31	1
1998	21	8	24	19	2,455	542	22	22	271	86
1999	33	27	47	35	1,705	1,146	23	18	490	124
2000	54	23	64	49	1,525	1253	24	5	495	27
2001	76	71	113	73	1,129	1,816	25	3	222	23

2002	71	68	103	63	1,090	1,718
2003	49	38	65	46	1,600	1110
2004	27	23	39	39	1,607	980
2005	21	12	26	19	2,226	299
2006	11	7	15	12	2,081	397
Total	520	408	737	565	36,143	14,492
						50,635

26	13	728	147
27	9	649	76
28	23	3,655	835
29	1	408	24
30	16	515	192
32	12	292	48
33	28	614	335
34	20	715	165
35	33	2,043	928
36	33	3,124	1,432
37	18	967	402
38	12	2,790	465
39	11	563	99
41	3	45	8
42	10	333	238
44	6	241	95
45	23	224	163
47	1	118	5
48	88	1,063	888
49	31	2,960	836
50	29	1,398	312
51	15	733	121
52	8	128	36
53	28	211	207
54	23	127	348
56	9	517	71
57	13	249	70
58	14	556	583
59	26	807	285
70	8	182	102
72	2	162	22
73	36	2,233	2,453
75	4	155	16
76	1	21	1
78	10	225	63
79	9	467	200
Total	737	36,143	14,492

Table 2. Summary statistics

The sample consists of all firms that did not suffer a distress event (bankruptcy or default) during the period 1988-2006. Summary statistics are calculated for the main variables used in the analysis: The first lag of investment to capital (investment to capital, t-1), the first lead of investment to capital (investment to capital, t+1) the difference between these two quantities (change in investment), and the following lagged firm characteristics: Q, cash flow, size (log of inflation-adjusted assets), long-term leverage, and profitabaility. Table A.1 in the appendix contains the definitions of all variables. In Panel A statistics are calculated for all observations. In Panel B the sample is divided into firms having an amount of long-term debt maturing that is higher than the 60th percentile in the 3-digit SIC industry average ("Treated firms") and firms having an amount of long-term debt maturing which is lower than the industry 60th percentile ("Control firms"). The test of differences in the average values across groups is conducted with a parametric t-test. The normalized difference is defined as the ratio of the difference of the average values divided by the square root of the sum of the squared standard deviations.

Panel A. Distribution of sample firms, all periods.

		All periods N =	
	mean	median	s.d.
Investment to capital, t-1	0.370	0.209	0.522
Investment to capital, t+1	0.271	0.188	0.275
Change in investment, t-1 to t+1	-0.099	-0.011	0.532
Q, t-1	1.773	1.321	1.345
Cash flow, t-1	-0.085	0.233	2.704
Size, t-1	4.881	4.637	1.922
Long term leverage, t-1	0.241	0.214	0.197
Profitability, t-1	0.085	0.115	0.161

Panel B. Distribution of sample firms into treated and control groups.

		Treated firms N =			Control firms N =		Normalized difference
	mean	median	s.d.	mean	median	s.d.	
Investment to capital, t-1	0.400	0.212	0.568	0.353	0.208	0.493	0.062
Investment to capital, t+1	0.292	0.189	0.312	0.259	0.187	0.251	0.084
Change in investment, t-1 to t+1	-0.107	-0.011	0.585	-0.095	-0.011	0.498	-0.016
Q, t-1	1.847	1.305	1.496	1.730	1.327	1.247	0.060
Cash flow, t-1	-0.292	0.204	3.131	0.035	0.247	2.413	-0.083
Size, t-1	4.398	3.978	1.921	5.160	5.076	1.866	-0.285
Long term leverage, t-1	0.184	0.130	0.187	0.275	0.251	0.195	-0.336
Profitability, t-1	0.062	0.104	0.182	0.098	0.121	0.145	-0.153

Table 3. Baseline regressions: Estimations with industry * time fixed effects

The sampleconsists of all non-bankrupt, non-distressed firms in years 1988-2006.The dependent variable is change in annual investment rate from t-1 to t+1. Investment is defined as the ratio of capital expenditures to property, plant, and equipment. Treated is a dummy taking the value one for firms for which the percentage of long-term debt maturing in t is greater than the 3-digit SIC-level industry 60th percentile. Distress is a dummy taking a one if there was at least one firm filing for bankruptcy or with defaulted debt in the same industry and year. All regressions are estimated with OLS and include industry*year fixed effects. All control variables are defined in the appendix. Standard errors are clustered at the 3-digit SIC industry code level. ***, **, and * mean the coefficients are statistically significant at the 1, 5, and 10% level, respectively.

	(1)	(2)	(3)	(4)
Treated	-0.00115	0.0101*	0.00571	0.0168*
	(0.00695)	(0.00608)	(0.00618)	(0.00991)
Distress * Treated	-0.0399**	-0.0357**	-0.0332**	-0.0372***
	(0.0197)	(0.0163)	(0.0152)	(0.0135)
Q		-0.0429***	-0.0518***	-0.0405***
		(0.00973)	(0.00986)	(0.00792)
Cash flow		0.0341***	0.0358***	0.0345***
		(0.00508)	(0.00487)	(0.00474)
Size		0.00795**	0.00116	0.00273
		(0.00361)	(0.00470)	(0.00430)
Profitability		-0.0842	0.275***	0.223***
		(0.101)	(0.0762)	(0.0843)
Long-term leverage		-0.0676***	-0.141***	-0.173***
		(0.0234)	(0.0221)	(0.0213)
Rating = Speculative			0.0278***	0.0272***
			(0.00927)	(0.00945)
Rating = Investment grade			0.0678***	0.0436***
			(0.0206)	(0.0141)
Zscore			-0.0426***	-0.0400***
			(0.00507)	(0.00522)
Duration				0.00178
				(0.00185)
Cash				-0.248***
				(0.0613)
Observations	50,635	50,635	49,124	39,567
R-squared	0.111	0.147	0.158	0.167
Industry*Year F.E.	Yes	Yes	Yes	Yes

Table 4. Distress or industry downturns?

Panel A reports coefficients of Equation (1) estimated on a subsample of firms that excludes all industry-year combinations coinciding with an industry downturn. In Panel B, coefficents are estimated on a sample that excludes all industry-year combinations that coincide, are preceded, or are followed by a downturn. Downturns are defined as industry-year combinations in which the median annualized returns of the firms is -30% (columns 1 and 5), -20% (colunms 2 and 6), -10% (columns 3 and 7), and 0% (columns 4 and 8). All regressions are estimated with OLS and include industry*year fixed effects, as well as the base controls in column 2 of Table 3. Standard errors are clustered at the 3-digit industry level. Panel C contains the cross distribution of the sample industry-years according to whether there was a downturn and a distress episode in the industry and year, where a downturn is defined as an industry-year in which the median value of the annualized firm returns is respectively lower than -30% (C.1), -10% (C.2), and 0% (C.3).

Panel A. Subsample of periods with no contemporary industry downturns

	(1)	(2)	(3)	(4)
	Returns	Returns	Returns	Returns
VARIABLES	< -30%	< -20%	< -10%	< 0%
Treated	0.0101	0.0105	0.00842	0.00928
	(0.00640)	(0.00688)	(0.00621)	(0.00693)
Distress * Treated	-0.0355**	-0.0258**	-0.0289*	-0.0325*
	(0.0146)	(0.0124)	(0.0147)	(0.0178)
Controls	Yes	Yes	Yes	Yes
Observations	46,340	42,107	34,468	24,875
R-squared	0.132	0.106	0.097	0.096
Industry*Year F.E.	Yes	Yes	Yes	Yes

Panel B. Subsample of periods with no lagged, contemporary, or leading industry downturns

	(5)	(6)	(7)	(8)
	Returns	Returns	Returns	Returns
VARIABLES	< -30%	< -20%	< -10%	< 0%
Treated	0.0102	0.0133	0.0133	-0.00151
	(0.00737)	(0.00867)	(0.00826)	(0.0119)
Distress * Treated	-0.0346***	-0.0315***	-0.0303*	-0.0370*
	(0.0101)	(0.0115)	(0.0155)	(0.0194)
Controls	Yes	Yes	Yes	Yes
Observations	39,549	29,938	15,958	5,507
R-squared	0.104	0.097	0.090	0.104
Industry*Year F.E.	Yes	Yes	Yes	Yes

Panel C: Distribution of firms into downturn and no downturn periods

C.1 Strong industry downturn

Strong industry downturn Industry returns < -30%	No downturn	Downturn
No industry distress	2,529	219
Industry distress	494	71

C.2: Mild industry downturn

Mild industry downturn Industry returns < -10%	No downturn	Downturn

No industry distress	1,921	827
Industry distress	361	204
C.3: Weak industry downturn		
Very mild industry downturn		
Industry returns <0%	No downturn	Downturn
No industry distress	1,463	1,285
Industry distress	266	299

Table 5. Investment during distress episodes, financially weak vs. financially strong firms.
The sample consists of all non-bankrupt, non-distressed firms in years 1988-2006. The dependent variable is change in annual investment rate from t-1 to t+1. Investment is defined as the ratio of capital expenditures to property, plant, and equipment. Treated is a dummy taking the value one for firms for which the percentage of long-term debt maturing is greater than the 3-digit SIC-level industry 60th percentile. Distress is a dummy taking a one if there was at least one firm filing for bankruptcy or with defaulted debt in the same industry and year. Firms are divided into mutually exclusive subsamples according to whether they are financially weak or strong. The criteria for classifying firms as weak or strong are: Size (columns 1 and 2), age (columns 3 and 4), possession of debt rating (columns 5 and 6), cash to assets ratio (columns 9 and 10), ratio of intangible assets to total assets (columns 11 and 12). All regressions are estimated with OLS and include industry*year fixed effects. All regressions contain the following control variables: Firm size, cash flows, profitability, Q, and long-term leverage (defined in the appendix). Standard errors are clustered at the 3-digit SIC industry code level. ***, **, and * mean the coefficients are statistically significant at the 1, 5, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Size		Age		Rated		Debt / Assets		Cash / Assets		Intangible assets / Assets	
VARIABLES	Small	Large	Young	Old	No	Yes	High	Low	High	Low	High	Low
Treated	0.0373**	0.00317	0.106	0.0104	0.0112	0.00621	0.0124*	0.00637	0.00759	0.0109	0.0162	0.00731
	(0.0171)	(0.00639)	(0.0672)	(0.0127)	(0.00759)	(0.00772)	(0.00717)	(0.0114)	(0.0112)	(0.00934)	(0.0101)	(0.00814)
Distress * Treated	-0.0853***	-0.0182	-0.105	-0.00807	-0.0386*	-0.0289	-0.0361***	-0.0289	-0.0237	-0.0424**	-0.0412**	-0.0349
	(0.0294)	(0.0138)	(0.0763)	(0.0240)	(0.0196)	(0.0222)	(0.0120)	(0.0336)	(0.0218)	(0.0184)	(0.0157)	(0.0223)
Q	-0.0480***	-0.0622***	-0.0556***	-0.0228***	-0.0460***	-0.0430**	-0.0420***	-0.0444***	-0.0397***	-0.0464***	-0.0442***	-0.0438***
	(0.00914)	(0.0130)	(0.0151)	(0.00763)	(0.00932)	(0.0192)	(0.00712)	(0.0125)	(0.00984)	(0.0110)	(0.00665)	(0.0133)
Cash flow	0.0407***	0.0259**	0.0580***	0.0243***	0.0365***	0.00637	0.0142	0.0412***	0.0414***	0.0226***	0.0132	0.0405***
	(0.00363)	(0.0105)	(0.0108)	(0.00486)	(0.00476)	(0.0185)	(0.0104)	(0.00387)	(0.00620)	(0.00648)	(0.00878)	(0.00411)
Size	-0.0607**	0.0154***	0.0292	-0.0132**	-0.00414	0.00682**	0.0126***	0.000668	-0.00161	0.0139***	0.0116***	0.00552
	(0.0244)	(0.00223)	(0.0282)	(0.00651)	(0.00639)	(0.00325)	(0.00180)	(0.00709)	(0.00598)	(0.00269)	(0.00249)	(0.00524)
Long-term leverage	-0.0612	-0.0610**	-0.0507	-0.0650***	-0.0702**	-0.123***	-0.0770***	-0.0561	-0.0678**	-0.0623**	-0.0319	-0.0938**
	(0.0383)	(0.0238)	(0.129)	(0.0217)	(0.0282)	(0.0376)	(0.0204)	(0.0403)	(0.0280)	(0.0255)	(0.0202)	(0.0363)
Profitability	-0.266	0.448***	-0.369	-0.141	-0.133	0.511***	0.269***	-0.241	-0.156	0.0254	0.248**	-0.193

	***							***				**
	(0.0888)	(0.0999)	(0.262)	(0.0969)	(0.100)	(0.144)	(0.0733)	(0.0805)	(0.147)	(0.0909)	(0.121)	(0.0948)
Observations	17,327	33,308	4,804	14,665	38,409	12,226	29,213	21,422	22,522	28,111	18,200	32,435
R-squared	0.196	0.214	0.397	0.172	0.158	0.286	0.136	0.150	0.222	0.159	0.128	0.156
Industry* Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 6. Investment during distress episodes, different industry structures

The sample consists of all non-bankrupt, non-distressed firms in years 1988-2006. The dependent variable is change in annual investment rate from t-1 to t+1. Investment is defined as the ratio of capital expenditures to property, plant, and equipment. Treated is a dummy taking the value one for firms for which the percentage of long-term debt maturing in t is greater than the 3-digit SIC-level industry 60th percentile. Distress is a dummy taking a one if there was at least one firm filing for bankruptcy or with defaulted debt in the same industry and year. Firms are divided into mutually exclusive subsamples according to their industry characteristics. The criteria for classifying industries are: Concentration (columns 1 and 2), Competition (columns 3 and 4), and change in competition (columns 5 and 6). All regressions are estimated with OLS and include industry*year fixed effects. All regressions contain the following control variables: Firm size, cash flows, profitability, Q, and long-term leverage (defined in the appendix). Standard errors are clustered at the 3-digit SIC industry code level. ***, **, and * mean the coefficients are statistically significant at the 1, 5, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Herfindahl market concentration		Market competition (Boone)		Change in concentration	
VARIABLES	Concentrated	Competitive	High	Low	High	Low
Treated	0.00797	0.0162*	0.0115	0.0108	-0.00184	0.0200**
	(0.00867)	(0.00844)	(0.00833)	(0.00977)	(0.00794)	(0.00897)
Distress * Treated	-0.0249*	-0.0468**	-0.0619***	-0.0152	0.00803	-0.0708***
	(0.0134)	(0.0231)	(0.0179)	(0.0212)	(0.0173)	(0.0160)
Q	-0.0453***	-0.0426***	-0.0514***	-0.0375**	-0.0430***	-0.0431***
	(0.00526)	(0.0141)	(0.00477)	(0.0148)	(0.00934)	(0.0112)
Cash flow	0.0122*	0.0415***	0.0293***	0.0374***	0.0269***	0.0394***
	(0.00712)	(0.00444)	(0.00949)	(0.00409)	(0.00596)	(0.00702)
Size	0.0143***	0.00157	0.00872**	0.00725*	0.00989***	0.00646
	(0.00224)	(0.00602)	(0.00391)	(0.00375)	(0.00311)	(0.00516)
Long-term leverage	-0.0741***	-0.0693**	-0.0413**	-0.0937**	-0.0603***	-0.0733**
	(0.0259)	(0.0310)	(0.0204)	(0.0373)	(0.0207)	(0.0335)
Profitability	0.151*	-0.180*	0.0861	-0.204*	-0.0579	-0.102
	(0.0788)	(0.102)	(0.0866)	(0.114)	(0.124)	(0.0986)
Observations	24,910	25,725	27,303	23,319	22,881	27,754
R-squared	0.140	0.152	0.169	0.129	0.133	0.156
Industry*Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes

Table 7. Distress and the collateral channel

The sample consists of all non-bankrupt, non-distressed firms in years 1988-2006. The dependent variable is change in annual investment rate from t-1 to t+1. Investment is defined as the ratio of capital expenditures to property, plant, and equipment. Treated is a dummy taking the value one for firms for which the percentage of long-term debt maturing is greater than the 3-digit SIC-level industry 60th percentile. Distress is a dummy taking a one if there was at least one firm filing for bankruptcy or with defaulted debt in the same industry and year. Firms are divided into mutually exclusive subsamples according to whether the ratio of machinery and equipment to total assets is higher or lower than the median.All regressions are estimated with OLS and include industry*year fixed effects. Standard errors are clustered at the 3-digit SIC industry code level. ***, **, and * mean the coefficients are statistically significant at the 1, 5, and 10% level, respectively.

	Asset specificity	
VARIABLES	High	Low
Treated	-0.000364	0.0138
	(0.00733)	(0.00851)
Distress * Treated	-0.00472	-0.0705***
	(0.0170)	(0.0215)
Q	-0.0453***	-0.0426***
	(0.00810)	(0.0121)
Cash flow	0.0301***	0.0362***
	(0.00909)	(0.00553)
Size	0.0110***	0.00539
	(0.00248)	(0.00569)
Long-term leverage	-0.104***	-0.0420
	(0.0208)	(0.0360)
Profitability	0.173*	-0.170
	(0.0908)	(0.103)
Constant	-0.0511**	-0.0360
	(0.0237)	(0.0412)
Observations	20,798	29,837
R-squared	0.156	0.142
Industry*Year F.E.	Yes	Yes

Table 8. Baseline regressions on updated sample, 1988-2014

The sample contains all non-bankrupt, non-distressed firms in the period 1988-2014. The dependent variable is change in annual investment rate from t-1 to t+1. Investment is defined as the ratio of capital expenditures to property, plant, and equipment. Treated is a dummy taking the value one for firms having a large percentage of long-term debt maturing in the period. Distress is a dummy taking a one if there was at least one firm filing for bankruptcy or with defaulted debt in the same industry and year. All regressions are estimated with OLS and include industry*year fixed effects. All control variables are defined in the appendix. Standard errors are clustered at the 3-digit SIC industry code level. ***, **, and * mean the coefficients are statistically significant at the 1, 5, and 10% level, respectively.

	(1)	(2)	(3)	(4)
Treated	-0.00115	0.0101*	0.00571	0.0168*
	(0.00695)	(0.00608)	(0.00618)	(0.00991)
Distress * Treated	-0.0399**	-0.0357**	-0.0332**	-0.0372***
	(0.0197)	(0.0163)	(0.0152)	(0.0135)
Q		-0.0429***	-0.0518***	-0.0405***
		(0.00973)	(0.00986)	(0.00792)
Cash flow		0.0341***	0.0358***	0.0345***
		(0.00508)	(0.00487)	(0.00474)
Size		0.00795**	0.00116	0.00273
		(0.00361)	(0.00470)	(0.00430)
Profitability		-0.0842	0.275***	0.223***
		(0.101)	(0.0762)	(0.0843)
Long-term leverage		-0.0676***	-0.141***	-0.173***
		(0.0234)	(0.0221)	(0.0213)
Rating = Speculative			0.0278***	0.0272***
			(0.00927)	(0.00945)
Rating = Investment grade			0.0678***	0.0436***
			(0.0206)	(0.0141)
Zscore			-0.0426***	-0.0400***
			(0.00507)	(0.00522)
Duration				0.00178
				(0.00185)
Cash				-0.248***
				(0.0613)
Observations	50,635	50,635	49,124	39,567
R-squared	0.111	0.147	0.158	0.167
Industry*Year F.E.	Yes	Yes	Yes	Yes

Table 9. Information set includes only bankruptcies

The dependent variable is change in annual investment rate from t-1 to t+1. Investment is defined as the ratio of capital expenditures to property, plant, and equipment. Treated is a dummy taking the value one for firms for which the percentage of long-term debt maturing is greater than the 60th percentile in the 3-digit SIC-level industry. Distress is a dummy taking a one if there was at least one firm filing for bankruptcy in the same industry and year. All regressions are estimated with OLS and include industry*year fixed effects. All control variables are defined in the appendix. Standard errors are clustered at the 3-digit SIC industry code level. ***, **, and * mean the coefficients are statistically significant at the 1, 5, and 10% level, respectively. Sample period corresponds to 1988-2006 in Panel A, and to 1988-2014 in Panel B.

	(1)	(2)	(3)	(4)
Treated	-0.00389	0.00807	0.00369	0.0130
	(0.00607)	(0.00589)	(0.00593)	(0.00912)
Distress * Treated	-0.0455**	-0.0429**	-0.0392**	-0.0351**
	(0.0219)	(0.0178)	(0.0161)	(0.0144)
Q		-0.0429***	-0.0518***	-0.0405***
		(0.00973)	(0.00986)	(0.00791)
Cash flow		0.0341***	0.0358***	0.0345***
		(0.00507)	(0.00487)	(0.00473)
Size		0.00795**	0.00118	0.00275
		(0.00361)	(0.00470)	(0.00430)
Profitability		-0.0839	0.275***	0.223***
		(0.101)	(0.0764)	(0.0845)
Long-term leverage		-0.0674***	-0.140***	-0.173***
		(0.0235)	(0.0223)	(0.0214)
Rating = Speculative			0.0276***	0.0270***
			(0.00928)	(0.00947)
Rating = Investment grade			0.0676***	0.0435***
			(0.0205)	(0.0141)
Zscore			-0.0425***	-0.0400***
			(0.00505)	(0.00519)
Duration				0.00180
				(0.00186)
Cash				-0.248***
				(0.0615)
Observations	50,635	50,635	49,124	39,567
R-squared	0.111	0.147	0.158	0.167
Industry*Year F.E.	Yes	Yes	Yes	Yes

Table 10. Local effects

The sample consists of all non-bankrupt, non-distressed firms in years 1988-2006. The dependent variable is change in annual investment rate from t-1 to t+1. Investment is defined as the ratio of capital expenditures to property, plant, and equipment. Treated is a dummy taking the value one for firms for which the percentage of long-term debt maturing is greater than the 3-digit SIC-level industry 60th percentile. Distress is a dummy taking a one if there was at least one firm filing for bankruptcy or with defaulted debt in the same industry and year. Firms are divided into mutually exclusive subsamples according to whether (or not) firms are located in the same county where the distressed or bankrupt firms are located. All regressions are estimated with OLS and include industry*year fixed effects. Standard errors are clustered at the 3-digit SIC industry code level. ***, **, and * mean the coefficients are statistically significant at the 1, 5, and 10% level, respectively.

	Firm located in county where there is at least one distressed firm	
VARIABLES	Yes	No
Treated	0.0149	0.00896
	(0.0177)	(0.00629)
Distress * Treated	-0.0595**	-0.0309*
	(0.0270)	(0.0186)
Q	-0.0455***	-0.0427***
	(0.0106)	(0.0106)
Cash flow	0.0490***	0.0306***
	(0.00861)	(0.00502)
Size	0.00213	0.00940***
	(0.00848)	(0.00314)
Long-term leverage	-0.0455	-0.0740***
	(0.0629)	(0.0213)
Profitability	-0.238**	-0.0520
	(0.111)	(0.111)
Constant	0.00308	-0.0434
	(0.0521)	(0.0270)
Observations	9,451	41,184
R-squared	0.282	0.151
Industry*Year F.E.	Yes	Yes

Table 11. Differential effects of distress characteristics

The sample consists of all non-bankrupt, non-distressed firms in years 1988-2006. The dependent variable is change in annual investment rate from t-1 to t+1. Investment is defined as the ratio of capital expenditures to property, plant, and equipment. Treated is a dummy taking the value one for firms for which the percentage of long-term debt maturing is greater than the 3-digit SIC-level industry 60th percentile. Distress is a dummy taking a one if there was at least one firm filing for bankruptcy or with defaulted debt in the same industry and year. Distress characteristics refer to the following average characteristics of the distressed industry-years: There are at least 2 bankrupt firms (column 1), at least 2 distressed firms (column 2), average number of employees (column 3), size of distressed firms relative to non-distressed firms (column 4), fraction unrated (column 5), average cash ratio (column 6), average debt ratio (column 7), average age (column 8). All regressions are estimated with OLS and include industry*year fixed effects. All regressions contain the following control variables: Firm size, cash flows, profitability, Q, and long-term leverage (defined in the appendix).Standard errors are clustered at the 3-digit SIC industry code level. ***, **, and * mean the coefficients are statistically significant at the 1, 5, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Bankruptcy wave	Distress wave	Average size	Large	Fraction unrated	Average cash ratio	Average debt ratio	Average age
Treated	0.010*	0.011*	0.010*	0.011*	0.010*	0.011*	0.011*	0.011*
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Distress * Treated	-0.018	-0.018	-0.016	-0.021	-0.032**	-0.037***	-0.025	-0.027**
	(0.012)	(0.014)	(0.018)	(0.013)	(0.013)	(0.012)	(0.016)	(0.012)
Distress * Treated * Distress characteristic	-0.059**	-0.037*	-0.004	-0.044*	-0.021	-0.026	-0.019	-0.005
	(0.029)	(0.022)	(0.003)	(0.023)	(0.022)	(0.091)	(0.018)	(0.004)
Observations	50,635	50,635	50,635	50,635	50,635	50,635	50,635	50,635
R-squared	0.155	0.153	0.150	0.151	0.148	0.147	0.149	0.152
Industry*Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 12. Direct effect of negative industry returns

The sample contains all firms that did not file for bankruptcy or default on debt obligations during the period 1988-2006. The dependent variable is the change in investment to capital ratio between periods t-1 and t+1. Negative Returns is a dummy containing the value one if the average returns in the industry and year were lower than 0% . Treated is a dummy variable taking the value one if the firm has a large proportion of their debt maturing in period t. Regressions in the first column of all panels have no controls. Regressions in the second column include: Q, cash flow, size, profitability, leverage. Regressions in the third column of all panels contain, additionally, the rating and the z-score. Regressions in the last column also control for the duration and cash. All regressions contain industry * year fixed effects. Standard errors are in parentheses. ***, **, and * mean the coefficients are statistically significant at the 1, 5, and 10% level, respectively.

	(1)	(2)	(3)	(4)
Treated	0.00513	0.0156*	0.0111	0.0266***
	(0.00840)	(0.00817)	(0.00798)	(0.00936)
Negative Returns * Treated	-0.0308**	-0.0248**	-0.0240**	-0.0305***
	(0.0130)	(0.0117)	(0.0110)	(0.00991)
Q		-0.0429***	-0.0518***	-0.0405***
		(0.00973)	(0.00986)	(0.00790)
Cash flow		0.0341***	0.0358***	0.0345***
		(0.00509)	(0.00489)	(0.00476)
Size		0.00816**	0.00135	0.00285
		(0.00359)	(0.00470)	(0.00431)
Profitability		-0.0842	0.275***	0.222***
		(0.102)	(0.0767)	(0.0847)
Long-term leverage		-0.0653***	-0.139***	-0.172***
		(0.0240)	(0.0227)	(0.0214)
Rating = Speculative			0.0286***	0.0275***
			(0.00915)	(0.00945)
Rating = Investment grade			0.0677***	0.0432***
			(0.0205)	(0.0141)
Zscore			-0.0426***	-0.0399***
			(0.00510)	(0.00524)
Duration				0.00217
				(0.00182)
Cash				-0.249***
				(0.0621)
Observations	50,635	50,635	49,124	39,567
R-squared	0.110	0.147	0.158	0.167
Industry*Year F.E.	Yes	Yes	Yes	Yes

Figure 1. Parallel trends

This graph represents the evolution of the average investment to capital ratio of firms around the time in which there is an industry distress epoisode. The sample is restricted to all non-bankrupt firms suffering an industry distress at t=0. The horizontal axis represents the number of years to the industry distress episode. The continuous line corresponds to treated firms, i.e., those having a proportion of their long-term debt maturing after the distress that is larger than the industry 60th percentile; the dashed line corresponds to the remaining (control) firms. The pointed lines represent 95% confidence intervals around the point estimates. The shaded area corresponds to the distress period.

Figure A.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 MANUACTURERS (2-digit SIC code = 28) and ELECTRONIC & OTHER ELECTRICAL EQUIPMENT MANUFACTURERS (2-digit SIC code= 36). Each subgraph corresponds to the 3-digit SIC-code industry that is shown in the subgraph title. Each dot corresponds to one firm in a given industry and year. Columns in red correspond to industry bankruptcy years, those in blue correspond to normal years.

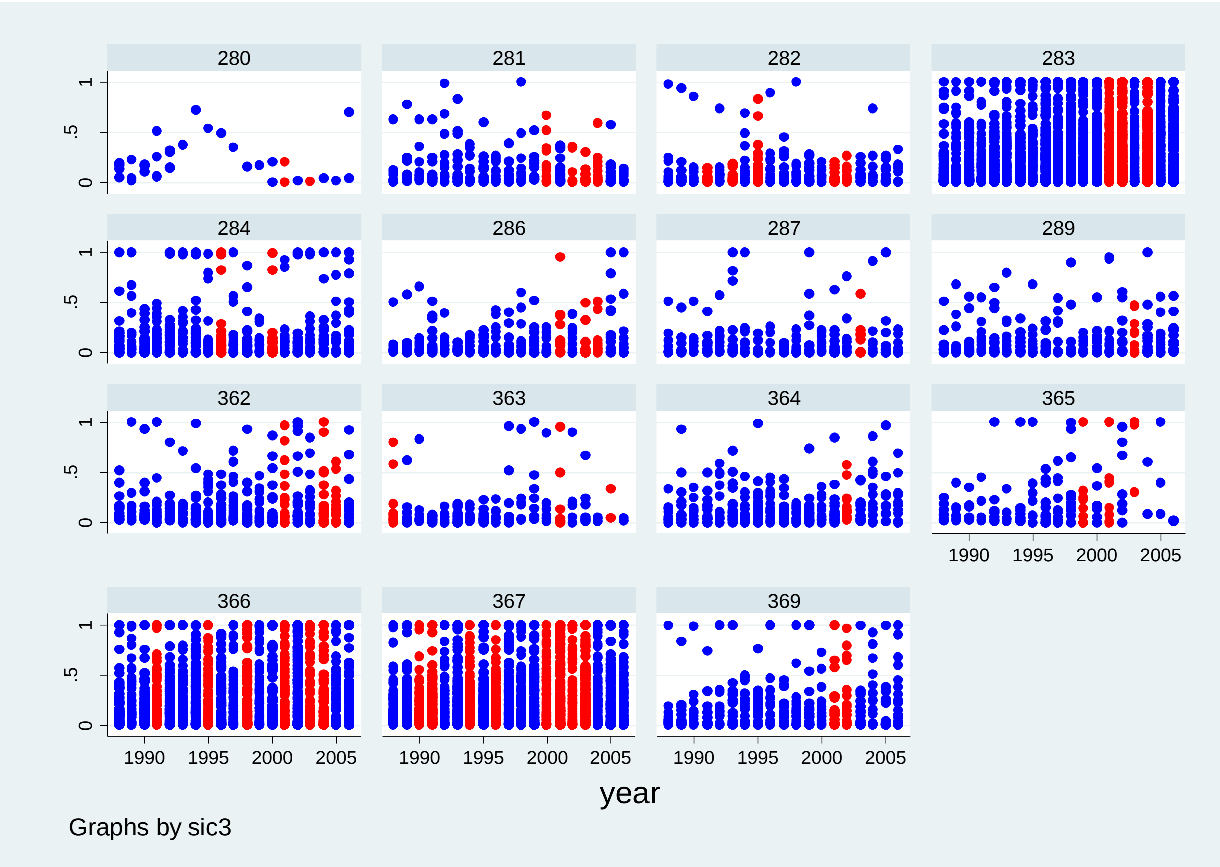


Table A.1. Definition of the main variables

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

Variable	**Formula or data source**	**Level of aggregation**	**Definition**
Outcome variable:			
Investment to capital	capx (t) / ppe (t-1)	Firm	Capital expenditures / lagged property, plant, and equipment
Treatment variables:			
Treated	dd1 / (dd1+dltt)	Firm	Dummy =1 if the ratio is greater than the 60th percentile of the distribution within the 3-digit industry code, =0 otherwise
Industry treated	dd1 / (dd1+dltt)	Industry and year	Dummy =1 if the fraction of firms with this ratio above than the 60th percentile for the 3-digit industry code distribution is more than 50% in the given year, =0 otherwise
Credit event variable:			
Distress	From UCLA LoPucki's Bankruptcy Research Data and Moody's Ultimate Recovery Dataset	Industry and year	Dummy=1 if at least one firm in the given year and industry filed for bankruptcy, was insolvent, or missed payment on a debt obligation, =0 otherwise
*Main control variables:**			
Q	(at+prcc_f*csho-ceq-txditc)/at	Firm	(Assets + market capitalization - common equity - deferred taxes and investment tax credit) / Assets
Cash flow	(ib (t)+dp (t))/ppent (t-1)	Firm	(Net income + depreciation and amortization) / lagged property, plant, and equipment
Profitability	oibdp / at	Firm	Operating income before depreciation / assets
Size	log(at)	Firm	Log of assets

Long-term leverage	(dd1+dltt) / at	Firm	Total long term debt / Assets
Year	fyear	Year	Year of the observation
Industry (3-digit SIC code)	floor(sic/10)	Industry	One dummy for each distinct value
Other control variables:			
Z-score	3.3*(oibdp-dp)/at + sale/at + 1.4*(re/at) + 1.2*(wcap/at)	Firm	Distance to default = 3.3* (Operating income / assets) + (sales / assets) + 1.4*(Retained earnings / assets) + 1.2 *(Working capital / assets)
Rating	splticrm	Firm	Dummy =2 if rating greater or equal to BBB- (investment grade), =1 if rating below BBB- (speculative grade), =0 if unrated

*NB: All control variables are lagged by one year in all model specifications

Table A.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 vs. normal 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.

	% Long-term debt expiring the following year				Difference		
2-digit SIC code	Distress years	N	Normal years	N	Normal - Distress	T-stat	S.E.
17	0.385	8	0.264	100	-0.121	-0.869	0.140
12	0.215	3	0.133	91	-0.082	-0.885	0.093
1	0.207	18	0.135	146	-0.071	-1.026	0.069***
39	0.255	99	0.187	563	-0.068	-2.035	0.033
36	0.282	1432	0.228	3124	-0.054	-5.854	0.009*
73	0.362	2454	0.308	2233	-0.054	-5.740	0.009
70	0.167	102	0.115	182	-0.052	-1.753	0.030
24	0.161	27	0.112	495	-0.049	-1.130	0.043
10	0.286	71	0.241	745	-0.046	-1.154	0.039
50	0.215	312	0.171	1398	-0.044	-2.564	0.017***
26	0.139	147	0.101	728	-0.039	-2.437	0.016
21	0.114	1	0.080	31	-0.034	0.000	0.000*
75	0.186	16	0.153	155	-0.033	-0.512	0.065
35	0.254	928	0.221	2043	-0.032	-2.812	0.012
34	0.195	165	0.168	715	-0.026	-1.275	0.021
59	0.220	285	0.196	807	-0.024	-1.248	0.020***
51	0.176	121	0.154	733	-0.022	-0.997	0.022***
49	0.091	836	0.071	2960	-0.020	-3.747	0.005**
32	0.167	48	0.148	292	-0.020	-0.506	0.039
28	0.232	835	0.213	3655	-0.019	-1.768	0.011
58	0.151	583	0.134	556	-0.016	-1.435	0.011
56	0.156	71	0.142	517	-0.014	-0.523	0.027
54	0.089	348	0.076	127	-0.013	-1.105	0.012***
37	0.174	402	0.161	967	-0.013	-1.042	0.012
33	0.119	335	0.107	614	-0.013	-0.985	0.013
45	0.166	163	0.156	224	-0.010	-0.478	0.021
23	0.179	124	0.170	490	-0.009	-0.358	0.024
20	0.143	161	0.135	1497	-0.008	-0.474	0.016
29	0.099	24	0.094	408	-0.005	-0.142	0.035
53	0.123	207	0.119	211	-0.004	-0.255	0.015
30	0.170	192	0.167	515	-0.003	-0.191	0.018
72	0.134	22	0.134	162	0.000	-0.003	0.056***
38	0.243	465	0.243	2790	0.000	0.018	0.014
42	0.181	238	0.187	333	0.006	0.347	0.016**
52	0.102	36	0.110	128	0.007	0.242	0.031**

44	0.125	95	0.133	241	0.008	0.359	0.022
48	0.116	888	0.125	1063	0.009	0.915	0.010
27	0.127	76	0.141	649	0.014	0.617	0.022
25	0.108	23	0.126	222	0.018	0.557	0.033
13	0.108	1599	0.129	1278	0.021	2.542	0.008
16	0.188	32	0.212	221	0.024	0.617	0.039*
47	0.173	5	0.198	118	0.026	0.279	0.092***
79	0.125	200	0.153	467	0.028	1.452	0.019
22	0.105	86	0.141	271	0.037	1.973	0.019**
78	0.206	63	0.244	225	0.038	0.980	0.039***
15	0.152	46	0.192	181	0.039	1.195	0.033*
57	0.106	70	0.153	249	0.047	1.865	0.025
41	0.122	8	0.211	45	0.089	1.360	0.065
14	0.149	22	0.240	157	0.091	1.341	0.068

Table A.3. Different treatment thresholds

The dependent variable is the change in annual investment rate from t-1 to t+1. Investment is defined as the ratio of capital expenditures to property, plant, and equipment. In columns 1 to 3, Treated is a dummy taking the value one for firms for which the percentage of long-term debt maturing in t is greater than: the 3-digit SIC-level industry average (column 1), the 3-digit SIC-level industry 66th percentile (column 2), and the 3-digit SIC-level industry 75th percentile (column 3). In column 4, Treated is the amount of long-term debt maturing in t. Distress is a dummy taking a one if there was at least one firm in distress in the same industry and year. All regressions are estimated with OLS and include industry*year fixed effects. All control variables are defined in the appendix. ***, **, and * mean the coefficients are statistically significant at the 1, 5, and 10% level, respectively.

	(1)	(2)	(3)	(4)
Treated definition:	Dummy, =1 if % long-term debt maturing at t+1 greater than industry average	Dummy, =1 if % long-term debt maturing at t+1 greater than industry 66th percentile	Dummy, =1 if % long-term debt maturing at t+1 greater than industry 75th percentile	Continuous variable: Percentage of long-term debt maturing at t+1
Treated	0.00805	0.0114*	0.0193***	0.0203*
	(0.00605)	(0.00602)	(0.00702)	(0.0119)
Distress * Treated	-0.0399**	-0.0281**	-0.0411***	-0.0558**
	(0.0159)	(0.0139)	(0.0130)	(0.0236)
Q	-0.0428***	-0.0429***	-0.0430***	-0.0429***
	(0.00970)	(0.00974)	(0.00975)	(0.00973)
Cash flow	0.0341***	0.0341***	0.0340***	0.0341***
	(0.00508)	(0.00509)	(0.00509)	(0.00510)
Size	0.00775**	0.00814**	0.00828**	0.00806**
	(0.00361)	(0.00357)	(0.00350)	(0.00361)
Profitability	-0.0847	-0.0833	-0.0822	-0.0835
	(0.101)	(0.101)	(0.101)	(0.101)
Long-term leverage	-0.0698***	-0.0652***	-0.0639**	-0.0661***
	(0.0235)	(0.0240)	(0.0249)	(0.0233)
Constant	-0.0332	-0.0384	-0.0399	-0.0373
	(0.0285)	(0.0281)	(0.0269)	(0.0284)
Observations	50,635	50,635	50,635	50,635
R-squared	0.147	0.147	0.147	0.147
Industry*Year F.E.	Yes	Yes	Yes	Yes

Table A.4 Identifying assumptions

The dependent variable in Panel A and columns 1-4 of Column C is the net issuance of long-term debt in period t+1, defined as the change in long-term debt from t to t+1 divided by lagged assets. In Panel B, the dependent variable is the all-in-spread for syndicated loans, obtained from Deal Scan. In columns 5-8 of Panel C, the dependent variable is the change in the all-in-spread for syndicated loans.Treated is a dummy taking the value one for firms for which the percentage of long-term debt maturing in t is greater than the 3-digit SIC-level industry 60th percentile. Distress is a dummy variable taking a one if there is an industry distress in t. The sample consists of all non-distressed firms in years 1988-2006. All regressions are estimated with OLS. Regressions in Panels A and B include firm fixed effects. Regressions in Panel C include industry*year fixed effects. All control variables are defined in the appendix. ***, **, and * mean the coefficients are statistically significant at the 1, 5, and 10% level, respectively.

Panel A. Net long-term debt issuance in t+1

	(1)	(2)	(3)	(4)
Treated	0.0462***	0.0253***	0.0241***	0.0257***
	(0.00367)	(0.00308)	(0.00314)	(0.00392)
Q		0.00477***	0.00460***	0.00489***
		(0.00127)	(0.00125)	(0.00110)
Cash flow		-0.00103*	-0.000992*	-0.00187***
		(0.000529)	(0.000504)	(0.000661)
Size		-0.0328***	-0.0317***	-0.0313***
		(0.00425)	(0.00449)	(0.00449)
Profitability		0.0122	0.0197	0.0337**
		(0.0104)	(0.0145)	(0.0161)
Long-term leverage		-0.373***	-0.373***	-0.359***
		(0.0163)	(0.0176)	(0.0155)
Rating = Speculative			-0.0101*	-0.0136*
			(0.00576)	(0.00700)
Rating = Investment grade			0.00191	-0.000791
			(0.00565)	(0.00575)
Z-score			-0.00110	-0.00156
			(0.00141)	(0.00162)
Duration				0.00108*
				(0.000628)
Cash				-0.00506
				(0.0121)
Constant				
	48,997	48,997	47,500	37,823
	0.236	0.316	0.317	0.339
Observations	5,036	5,036	4,788	3,948
R-squared	0.802	0.824	0.837	0.850
Firm F.E.	Yes	Yes	Yes	Yes

Panel B. All-in-Spread

	(1)	(2)	(3)	(4)
Distress	17.48***	13.63***	14.48***	13.30***
	(4.018)	(4.343)	(4.156)	(4.214)
Q		-11.12***	-10.33***	-10.99***
		(3.114)	(2.988)	(3.474)
Cash flow		-1.366	-1.347	-0.794
		(1.328)	(1.614)	(2.500)
Size		-4.025	-3.868	-8.688
		(7.716)	(8.436)	(7.857)
Profitability		-223.4***	-94.30	-136.8
		(70.70)	(86.81)	(84.39)
Long-term leverage		120.8***	85.56***	101.6***
		(21.25)	(21.79)	(24.41)
Rating = Speculative			34.37***	47.56***
			(11.40)	(13.63)
Rating = Investment grade			-47.83***	-36.86**
			(14.17)	(15.57)
Z-score			-16.40***	-14.40**
			(5.990)	(6.479)
Duration				-2.571**
				(1.174)
Cash				-22.78
				(35.98)
Constant	141.9***	182.8***	212.8***	251.2***
	(1.431)	(54.02)	(52.18)	(56.06)
Observations	5,036	5,036	4,788	3,948
R-squared	0.802	0.824	0.837	0.850
Firm F.E.	Yes	Yes	Yes	Yes

Panel C. Debt issuance and costs for treated firms during a distress episode

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Net long-term debt issuance				Change in All-In-Spread			
Treated	0.017***	0.009***	0.008***	0.014***	-5.261	-4.906	-4.495	-5.184
	(0.002)	(0.002)	(0.002)	(0.003)	(7.457)	(7.369)	(8.968)	(10.499)
Distress * Treated	0.003	0.002	0.002	0.004	19.070**	19.293**	17.907*	19.351
	(0.005)	(0.005)	(0.005)	(0.005)	(8.423)	(8.651)	(9.909)	(12.754)
Q		0.006***	0.005***	0.006***		-6.013*	-5.458	-4.462
		(0.001)	(0.001)	(0.001)		(3.360)	(3.545)	(4.106)
Cash flow		-0.001	-0.001	-0.001***		1.536	1.556	2.577
		(0.000)	(0.000)	(0.001)		(2.382)	(2.562)	(3.127)
Size		0.001	-0.000	-0.001		0.324	3.411	4.413*
		(0.001)	(0.001)	(0.001)		(1.672)	(2.237)	(2.345)
Profitability		0.040***	0.062***	0.063***		-36.245	-52.062	-92.802
		(0.012)	(0.018)	(0.015)		(48.854)	(64.279)	(75.864)
Long-term leverage		-0.100***	-0.116***	-0.111***		-6.234	3.676	-4.916
		(0.009)	(0.010)	(0.010)		(20.183)	(22.376)	(25.639)
Rating = Speculative			0.018***	0.014***			-10.932	-4.040
			(0.004)	(0.004)			(11.165)	(12.147)
Rating = Investment grade			0.001	-0.003			-16.946**	-13.787
			(0.003)	(0.003)			(7.832)	(9.542)
Z-score			-0.003***	-0.002***			2.337	0.593
			(0.001)	(0.001)			(3.567)	(3.759)
Duration				0.002***				-0.834
				(0.001)				(1.297)
Cash				-0.024**				-43.821
				(0.010)				(38.34

								1)
Observations	50,608	50,608	49,097	39,552	1,958	1,958	1,831	1,554
R-squared	0.090	0.107	0.111	0.125	0.456	0.461	0.470	0.491
Industry*Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A.5. Treated firms and early refinancing in normal and distress periods
The sample consists of all non-distressed firms in the period 1988-2006. 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 is reduced between years t-1 and t (i.e., dd1< lagged dd2). Treated is a dummy taking the value one for firms for which the percentage of long-term debt maturing is greater than the 3-digit SIC-level industry 60th percentile. Bankruptcy is a dummy taking a one if there was at least one firm filing for bankruptcy in the same industry and year. 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.

	(1)	(2)
VARIABLES	Dependent variable = Early refinancing	
Treated	-0.140***	-0.127***
	(0.0110)	(0.0113)
Treated * Distress	0.0163	0.0158
	(0.0162)	(0.0158)
Q		-0.0145***
		(0.00341)
Cash flow		-0.000620
		(0.00194)
Size		0.0173***
		(0.00255)
Profitability		0.0173
		(0.0367)
Long-term leverage		-0.0493***
		(0.0185)
Constant	0.464***	0.410***
	(0.00421)	(0.0153)
Observations	42,285	42,285
R-squared	0.117	0.121
Industry * Year F.E.	No	Yes

Table A.6. Placebo distress dates

The dependent variable is change in annual investment rate from t-1 to t+1. Investment is defined as the ratio of capital expenditures to property, plant, and equipment. Treated is a dummy taking the value one for firms for which the percentage of long-term debt maturing in t is greater than the 3-digit SIC-level industry 60th percentile. Placebo distress is a dummy taking a one for a given industry respectively during the 5th, 4th, 3rd, 2nd, and 1st year before the actual industry distress period (columns 1 to 5), or during the 1st, 2nd, 3rd, 4th, and 5th period after the actual industry distress (columns 6 to 10). All regressions are estimated with OLS and include industry*year fixed effects. All control variables are defined in the appendix. Standard errors are clustered at the 3-digit SIC industry code level. ***, **, and * mean the coefficients are statistically significant at the 1, 5, and 10% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Placebo bankruptcy definition:	Distress -5	Distress -4	Distress -3	Distress -2	Distress -1	Distress +1	Distress +2	Distress +3	Distress +4	Distress +5
Treated	-0.000327	-0.00102	-0.00690	0.00113	0.00459	0.000920	-0.00110	0.00714	0.00141	0.00290
	(0.00653)	(0.00930)	(0.0101)	(0.00848)	(0.00659)	(0.00662)	(0.00716)	(0.00575)	(0.00774)	(0.00749)
Placebo distress * Treated	0.0101	-0.00475	0.00664	-0.00567	-0.0178	-0.00477	0.0113	-0.00765	0.0166	0.0127
	(0.0134)	(0.0217)	(0.0169)	(0.0151)	(0.0150)	(0.0107)	(0.0132)	(0.0177)	(0.0148)	(0.0131)
Q	-0.0290***	-0.0334***	-0.0393***	-0.0429***	-0.0429***	-0.0429***	-0.0413***	-0.0411***	-0.0397***	-0.0398***
	(0.00652)	(0.00811)	(0.00953)	(0.00973)	(0.00972)	(0.00973)	(0.0102)	(0.00978)	(0.0101)	(0.0108)
Cash flow	0.0205***	0.0247***	0.0337***	0.0341***	0.0341***	0.0341***	0.0333***	0.0337***	0.0337***	0.0343***
	(0.00336)	(0.00344)	(0.00454)	(0.00509)	(0.00509)	(0.00510)	(0.00571)	(0.00546)	(0.00603)	(0.00559)
Size	0.00150	0.00184	0.00463	0.00795**	0.00795**	0.00794**	0.00821**	0.00765**	0.00816***	0.00829**
	(0.00272)	(0.00340)	(0.00369)	(0.00364)	(0.00363)	(0.00364)	(0.00326)	(0.00329)	(0.00313)	(0.00328)
Profitability	-0.0218	-0.0441	-0.0828	-0.0843	-0.0845	-0.0843	-0.0931	-0.0828	-0.0924	-0.0989
	(0.0630)	(0.0749)	(0.0938)	(0.102)	(0.102)	(0.102)	(0.106)	(0.103)	(0.106)	(0.112)
Long-term leverage	-0.0961***	-0.0866***	-0.0749***	-0.0670***	-0.0674***	-0.0670***	-0.0696***	-0.0681***	-0.0693***	-0.0803***
	(0.0187)	(0.0227)	(0.0244)	(0.0236)	(0.0235)	(0.0237)	(0.0242)	(0.0245)	(0.0231)	(0.0215)
Constant	0.009	0.004	-	-	-	-	-	-	-	-

	33	92	0.0141	0.0359	0.0358	0.0358	0.0368	0.0333	0.0350	0.0303
	(0.0203)	(0.0250)	(0.0303)	(0.0292)	(0.0291)	(0.0292)	(0.0273)	(0.0262)	(0.0266)	(0.0278)
Observations	43,550	46,381	48,984	50,635	50,635	50,635	47,136	43,912	40,966	38,254
R-squared	0.116	0.123	0.145	0.146	0.146	0.146	0.144	0.148	0.149	0.152
Industry*Year F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table A.7. Across-industry estimations with exogenous industry-level treatment

The dependent variable is change in annual investment rate from t-1 to t+1. Investment is defined as the ratio of capital expenditures to property, plant, and equipment. Distress is a dummy taking a one if there was at least one firm in distress in the same industry and year. Industry treated is a dummy containing a one for those industries with above-median number of treated firms, where the distribution is calculated across years for the industry. All regressions are estimated with OLS. All control variables are defined in the appendix. Standard errors are clustered at the 3-digit SIC industry code level. ***, **, and * mean the coefficients are statistically significant at the 1, 5, and 10% level, respectively.

	(1)	(2)	(3)	(4)
Distress	-0.00208	-0.00781	-0.00532	-0.0175
	(0.00763)	(0.00755)	(0.00767)	(0.0118)
Industry treated	0.0155**	0.0183**	0.0163**	0.0135*
	(0.00725)	(0.00718)	(0.00723)	(0.00754)
Distress * Industry treated	-0.0403***	-0.0256**	-0.0251**	-0.0136*
	(0.0112)	(0.0110)	(0.0111)	(0.00789)
Q		-0.0468***	-0.0562***	-0.0439***
		(0.00328)	(0.00337)	(0.00382)
Cash flow		0.0352***	0.0373***	0.0356***
		(0.00290)	(0.00288)	(0.00354)
Size		0.00669***	-0.000144	0.00127
		(0.00140)	(0.00192)	(0.00215)
Profitability		-0.0789**	0.329***	0.271***
		(0.0322)	(0.0385)	(0.0433)
Long-term leverage		-0.0699***	-0.149***	-0.190***
		(0.0155)	(0.0169)	(0.0189)
ratings = 1			0.0285***	0.0246***
			(0.00826)	(0.00877)
ratings = 2			0.0723***	0.0456***
			(0.00636)	(0.00644)
Zscore			-0.0480***	-0.0450***
			(0.00277)	(0.00301)
Duration				0.00175
				(0.00133)
Cash				-0.255***
				(0.0286)
Constant	-0.197***	0.686***	-0.121***	-0.0565
	(0.0169)	(0.0860)	(0.0376)	(0.0469)
Observations	50,635	50,635	49,124	39,567
R-squared	0.037	0.079	0.093	0.094
Firm F.E.	Yes	Yes	No	No
Industry F.E.	Yes	Yes	Yes	Yes
Year F.E.	Yes	Yes	Yes	Yes
Industry*Year F.E.	No	No	No	No

Table A.8. Summary statistics of matched sample

This table presents summary statistics for a subsample taken from all of the of firms that did not suffer a distress event (bankruptcy or default) during the period 1988-2006. To construct the subsample, each "treated" firm is matched with the "control" firm in the same industry (same 3-digit SIC code) and year whose Mahalanobis distance (in terms of size, Q, cash flow, long-term leverage, and profitability) is minimized. Treated firms are those having an amount of long-term debt maturing that is higher than the industry average, and control firms are those having an amount of long-term debt maturing in the following period which is lower than the industry average. Summary statistics are calculated for the main variables used in the analysis: The one-year difference between the ratio of investment to capital (change in investment), and the following lagged firm characteristics: Q, cash flow, size (log of inflation-adjusted assets), long-term leverage, and profitabaility. Notice that the number of treated firms (16,329) is larger than the number of treated firms in the original sample (16,302). This is because the matching algorithm uses all controls with equal value of the minimizing Mahalanobis distance (in case there is more than one control observation that minimizes the distance). The test of differences in the average values across groups is conducted with a parametric t-test. The normalized difference is defined as the ratio of the difference of the average values divided by the square root of the sum of the squared standard deviations.

	Treated firms N = 16,610			Control firms N = 16,610			Difference in means			Normalized difference
	mean	median	s.d.	mean	median	s.d.	Difference	T-stat	p-value	
Investment to capital, t-1	0.409	0.215	0.580	0.392	0.214	0.555	0.018	-2.834	0.005	0.022
Investment to capital, t+1	0.296	0.191	0.315	0.284	0.194	0.281	0.013	-3.872	0.000	0.030
Change in investment, t-1 to t+1	-0.113	-0.011	0.597	-0.108	-0.008	0.562	-0.005	0.781	0.435	-0.006
Q, t-1	1.888	1.326	1.534	1.811	1.333	1.397	0.077	-4.798	0.000	0.037
Cash flow, t-1	-0.362	0.195	3.237	-0.068	0.244	2.816	-0.294	8.835	0.000	-0.069
Size, t-1	4.391	3.961	1.931	4.567	4.219	1.824	-0.176	8.529	0.000	-0.066
Long term leverage, t-1	0.181	0.127	0.186	0.191	0.155	0.168	-0.010	5.235	0.000	-0.041
Profitability, t-1	0.057	0.102	0.187	0.085	0.115	0.158	-0.028	14.906	0.000	-0.116

Table A.9. Baseline regressions on matched subsample

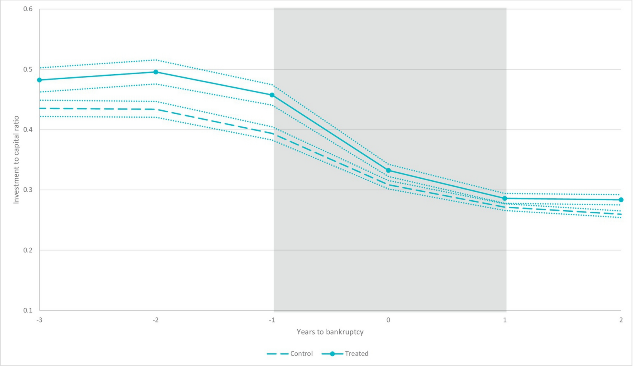
The dependent variable is change in annual investment rate from t-1 to t+1. Investment is defined as the ratio of capital expenditures to property, plant, and equipment. Treated is a dummy taking the value one for firms for which the percentage of long-term debt maturing is greater than the 3-digit SIC-level industry 60th percentile. Distress is a dummy taking a one if there was at least one firm in distress in the same industry and year. The estimations are done over the subsample of firms in which each treated firm is matched to its closest counterfactual among the control firms. The matched counterfactual is a control firm in the same industry and year whose Mahalanobis distance in terms of size and leverage is minimized. All regressions are estimated with OLS and include industry*year fixed effects. All control variables are defined in the appendix. ***, **, and * mean the coefficients are statistically significant at the 1, 5, and 10% level, respectively.

	(1)	(2)	(3)	(4)
Treated	0.00548	0.0121*	0.00583	0.0118
	(0.00735)	(0.00718)	(0.00727)	(0.00897)
Distress * Treated	-0.0331**	-0.0228*	-0.0183*	-0.0247*
	(0.0131)	(0.0127)	(0.0108)	(0.0141)
Q		-0.0459***	-0.0533***	-0.0382***
		(0.00238)	(0.00243)	(0.00283)
Cash flow		0.0440***	0.0452***	0.0432***
		(0.00134)	(0.00134)	(0.00156)
Size		0.00256	-0.00214	0.00176
		(0.00219)	(0.00271)	(0.00296)
Profitability		-0.200***	0.159***	0.153***
		(0.0256)	(0.0337)	(0.0387)
Long-term leverage		-0.135***	-0.201***	-0.259***
		(0.0209)	(0.0222)	(0.0258)
Rating = Speculative			0.0431**	0.0468**
			(0.0175)	(0.0190)
Rating = Investment grade			0.0628***	0.0378**
			(0.0144)	(0.0152)
Zscore			-0.0419***	-0.0415***
			(0.00256)	(0.00289)
Duration				-0.000895
				(0.00198)
Cash				-0.280***
				(0.0230)
Observations	33,220	33,220	32,464	25,946
R-squared	0.133	0.182	0.192	0.205
Industry*Year F.E.	Yes	Yes	Yes	Yes

Financial distress and competitors' investment

Highlights

- Firms in distress increase the cost of credit in the industry and hence reduce competitors' credit access and investment.
- Reduction in investment due to competitors' distress holds in the absence of systematic industry downturns, and is temporary.
- Reduction in investment due to competitors' distress is mitigated for firms with stronger balance sheets, and for firms in less competitive markets.



0.6
0.5
0.4
0.3
0.2
0.1
Investment to capital ratio
-3
-2
-1
0
1
2
Years to bankruptcy
Control
Treated

Figure 1