Financial distress and corporate 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 spillover effects continue to hold in the absence of industry downturns. However, the negative effects are temporary, and are mitigated for firms with stronger balance sheets or in concentrated markets. These results are consistent with theories suggesting that firms with strong balance sheets prey on their weaker rivals to improve their market position.

Keywords: Bankruptcy, distress, default, corporate investment, contagion, market structure.

Classification: G31, G32, G33

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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 affect the competitors' ability to obtain sufficient funds for investment.[1] However, a competitor facing financial difficulties could facilitate predation by other firms in the industry, who could exploit their rivals' weaknesses to invest in a higher market share (Fudenberg and Tirole, 1986; Bolton and Scharfstein, 1990; Opler and Titman, 1994).[2] The objective of this paper is twofold. On the one hand, 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. On the other, the analysis seeks to identify the characteristics of the firms that benefit most from their rivals' financial weaknesses.

The analysis starts by estimating the effect of the higher financing costs associated with financial distress in an industry on the investment of competitors.[3] The main challenge of this analysis is to identify a

[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.
[3] As will become clear from the data section, for the purposes of this paper a firm is distressed when it misses some payment in a debt obligation or it files for bankruptcy.

causal link from the financial distress of some firms in an industry to the investment decisions of these companies' solvent competitors. In fact, 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. A battery of robustness tests show that the results cannot be explained by an endogenous sorting of firms' of certain observed or unobserved characteristics and their debt maturity structures. Moreover, an extended analysis shows that the negative effects of distress on competitors' investment continues to hold in the absence of contemporaneous industry downturns, further alleviating the concern that the results are driven by common shocks to industry participants. 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.

The second part of the analysis consists in examining 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.

This paper contributes to the literature in two important ways. First, it shows that firms in financial distress affect the real economy 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

[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.

in the industry or its degree of competitiveness, can accentuate or dampen these negative effects by changing competitors' incentives.

This paper related to several strands of the literature. First, it is 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, for the first time, 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. Second, the paper relates 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; Carvalho, 2015, among others). The contribution to this literature is twofold. On the one hand, the paper shows that even distresses that are not systematically driven 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). Within this literature, the paper is closest to Benmelech et al. (2014) who also study how bankrupt firms may impose negative externalities to non-bankrupt peers. The focus in their paper is on how transmission of distress can happen through a weakening of the economies of agglomeration in a local area. In contrast, this paper studies the effects of the propagation of distress within an industry.

2. Data and methodology

2.1 Data construction and sample distribution

The base dataset for this analysis consists of yearly balance sheet information for all firms appearing in Compustat's North America Fundamentals Annual files between 1988 and 2006.[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 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,

[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 after the annual report), which is only available in the Compustat yearly files. The 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).

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 at period $t + 1$ (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 after the distress. 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 $treat_{ijt}$. 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 of contagion.[7]

The above specification has several elements that allow us to identify the causal effect of contagion 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).

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[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+1 (see Section 3.1 and Table A.3 in the Appendix).

[7] 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 3.1 and Table A.6 in the Appendix.

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 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 one year after. 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 the next year 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 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 period $t+1$ (i.e., treated firms), and those with lower percentages of long-term debt maturing at $t+1$ (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).[8]

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.[9] The horizontal axis represents the number of years until the distress, which

[8] 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 the 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 contained in Table 5 and discussed below in the text.

[9] 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.

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. 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. However, the changes in investment levels are different for treated and control firms around the defaults. 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. The results in the figure suggest that treated and control firms had similar trends in their investment decisions before the time of industry distress, as required by the parallel trends assumption.

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 seem to be 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 in general, 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. Therefore, the only remaining concern is that this correlation occurs during distress episodes. To explore whether this phenomenon holds in the sample, 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.4 in the appendix I estimate a diff-in-diff linear probability model with industry*year fixed effects where the dependent variable is *Early Refinancing*, i.e., a dummy taking the value one when the amount of long-term debt that is due in year *t+1* is reduced between years *t-1* and *t*. 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. Finally, 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 in Table 3 show negative average spillover 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 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 Alternative stories and endogeneity concerns

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). However, this alternative story is especially plausible by observing that 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. 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. Economically, the interaction term is only slightly smaller than the coefficients estimated in Table 3. For example, the coefficient in column 2 implies that treated firms invest around 7% less than control firms when there is an industry bankruptcy that does not coincide with a recession.

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. Overall, the findings in Table 4 lend support to the identification strategy of this paper.

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.[10]

As a second robustness test, 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.4. If unobserved differences between treated and control firms are driving the results, the coefficient of the interaction term in these placebo

[10] Untabulated results show that the effect of bankruptcies on competitors' investment is qualitatively similar to the results of Table 3.

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.4 also shows that an industry distress has a temporary effect on peers' investment.

To further support the idea that the results show a causal effect from the distress of a competitor to the investment of firms, 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 following year.[11] 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.6 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 the treated firms in observable characteristics that matter for investment. In particular, the descriptive analysis contained in Table 2

[11] Specifically, I follow Carvalho (2015) and define a "high maturity firm" as a firm whose debt maturing the year after 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.

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.[12] 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.7 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 this subsample, reported in Table A.8 corroborate the results of Table 3, confirming once again the credibility of the identification strategy.

4. Heterogeneity analysis

Having established the soundness of the identification strategy of Equation (1), let us now turn to the important question of whether the 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

[12] 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.

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 debts 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.

One interpretation of the results in Table 5 is that they are consistent with theories of predation. Under this interpretation, financially strong firms use their financial slack to continue investing during the industry distress episodes as much as before the episodes, to maintain or even increase their market share, at the expense of weaker firms. An alternative interpretation is that financing costs increase more for weaker firms because of a "financial accelerator" mechanism leading to stronger negative effects of the higher interest rates on their balance sheets (Bernanke and Gertler, 1995; Bernanke, Gertler and Gilchrist, 1996; Ashcraft and Campello, 2007). These two different explanations for the findings are indistinguishable from the results in Table 5. To disentangle between these two stories, in Table 6 I analyze predictions that are unique to the theories of predation.

Theories of predation 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. 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 (columns 1 and 2 of Table 6). Similarly, 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 3 and 4). The results of Table 6 show stronger effects over the subsamples of concentrated markets. These results are consistent with the theories of predation, but are not predicted by the alternative "financial accelerator" theories pointed out before. 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).

5. 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 contagion 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 spillover effects are temporary, and that they exist even in the absence of recessions or industry downturns that coincide with the defaults in the industry.

The findings in this paper show that this contagion 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, contagion effects are stronger in 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 intepretation, the negative effects of financing costs on invested are also muted in markets that are relatively concentrated.

These results imply that 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 can be avoided when firms have 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

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
1988	8	5	11	11	2,198	183
1989	6	4	10	9	2,135	227
1990	20	19	34	31	1,650	718
1991	30	25	48	39	1,446	926
1992	24	14	32	25	1,849	574
1993	18	17	29	26	1,940	594
1994	10	14	20	19	1,996	675
1995	14	10	19	16	2,310	533
1996	13	12	21	19	2,431	537
1997	14	11	17	15	2,770	264
1998	21	8	24	19	2,455	542
1999	33	27	47	35	1,705	1,146
2000	54	23	64	49	1,525	1253
2001	76	71	113	73	1,129	1,816
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

Panel B. Distribution by industry

2-digit SIC code	(5) Distressed firms	(6) Sample firms out of distress periods	(7) Sample firms in distressed periods
1	2	146	18
10	3	745	71
12	1	91	3
13	24	1,278	1,599
14	2	157	22
15	8	181	46
16	4	221	32
17	2	100	8
20	16	1,497	161
21	1	31	1
22	22	271	86
23	18	490	124
24	5	495	27
25	3	222	23
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 in the following period 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 in the following period 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 = 50,635		
	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 = 18,574			Control firms N = 32,061			Difference in means			Normalized difference
	mean	median	s.d.	mean	median	s.d.	Difference	T-stat	p-value	
Investment to capital, t-1	0.400	0.212	0.568	0.353	0.208	0.493	0.046	-9.292	0.000	0.062
Investment to capital, t+1	0.292	0.189	0.312	0.259	0.187	0.251	0.034	-12.607	0.000	0.084
Change in investment, t-1 to t+1	-0.107	-0.011	0.585	-0.095	-0.011	0.498	-0.013	2.454	0.014	-0.016
Q, t-1	1.847	1.305	1.496	1.730	1.327	1.247	0.117	-9.024	0.000	0.060
Cash flow, t-1	-0.292	0.204	3.131	0.035	0.247	2.413	-0.328	12.299	0.000	-0.083
Size, t-1	4.398	3.978	1.921	5.160	5.076	1.866	-0.762	43.483	0.000	-0.285
Long term leverage, t-1	0.184	0.130	0.187	0.275	0.251	0.195	-0.091	51.828	0.000	-0.336
Profitability, t-1	0.062	0.104	0.182	0.098	0.121	0.145	-0.036	22.841	0.000	-0.153

Table 3. Baseline regressions: Estimations with industry * time fixed 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 in t+1 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

Panel 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 in t+1 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)
Constant	0.167**	-0.109***	-0.407***	0.0419	0.0131	-0.0438	-0.0836***	-0.00816	0.0200	-0.0781***	-0.0854***	-0.0102
	(0.0689)	(0.0250)	(0.128)	(0.0373)	(0.0334)	(0.0303)	(0.0156)	(0.0501)	(0.0392)	(0.0263)	(0.0179)	(0.0403)
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+1 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: Competition (columns 1 and 2), change in competition (columns 3 and 4). 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)
	Market concentration		Change in concentration	
VARIABLES	Concentrated	Competitive	High	Low
Treated	0.00797	0.0162*	-0.00184	0.0200**
	(0.00867)	(0.00844)	(0.00794)	(0.00897)
Distress * Treated	-0.0249*	-0.0468**	0.00803	-0.0708***
	(0.0134)	(0.0231)	(0.0173)	(0.0160)
Q	-0.0453***	-0.0426***	-0.0430***	-0.0431***
	(0.00526)	(0.0141)	(0.00934)	(0.0112)
Cash flow	0.0122*	0.0415***	0.0269***	0.0394***
	(0.00712)	(0.00444)	(0.00596)	(0.00702)
Size	0.0143***	0.00157	0.00989***	0.00646
	(0.00224)	(0.00602)	(0.00311)	(0.00516)
Long-term leverage	-0.0741***	-0.0693**	-0.0603***	-0.0733**
	(0.0259)	(0.0310)	(0.0207)	(0.0335)
Profitability	0.151*	-0.180*	-0.0579	-0.102
	(0.0788)	(0.102)	(0.124)	(0.0986)
Constant	-0.0721***	-0.00476	-0.0430*	-0.0305
	(0.0155)	(0.0489)	(0.0233)	(0.0384)
Observations	24,910	25,725	22,881	27,754
R-squared	0.140	0.152	0.133	0.156
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.

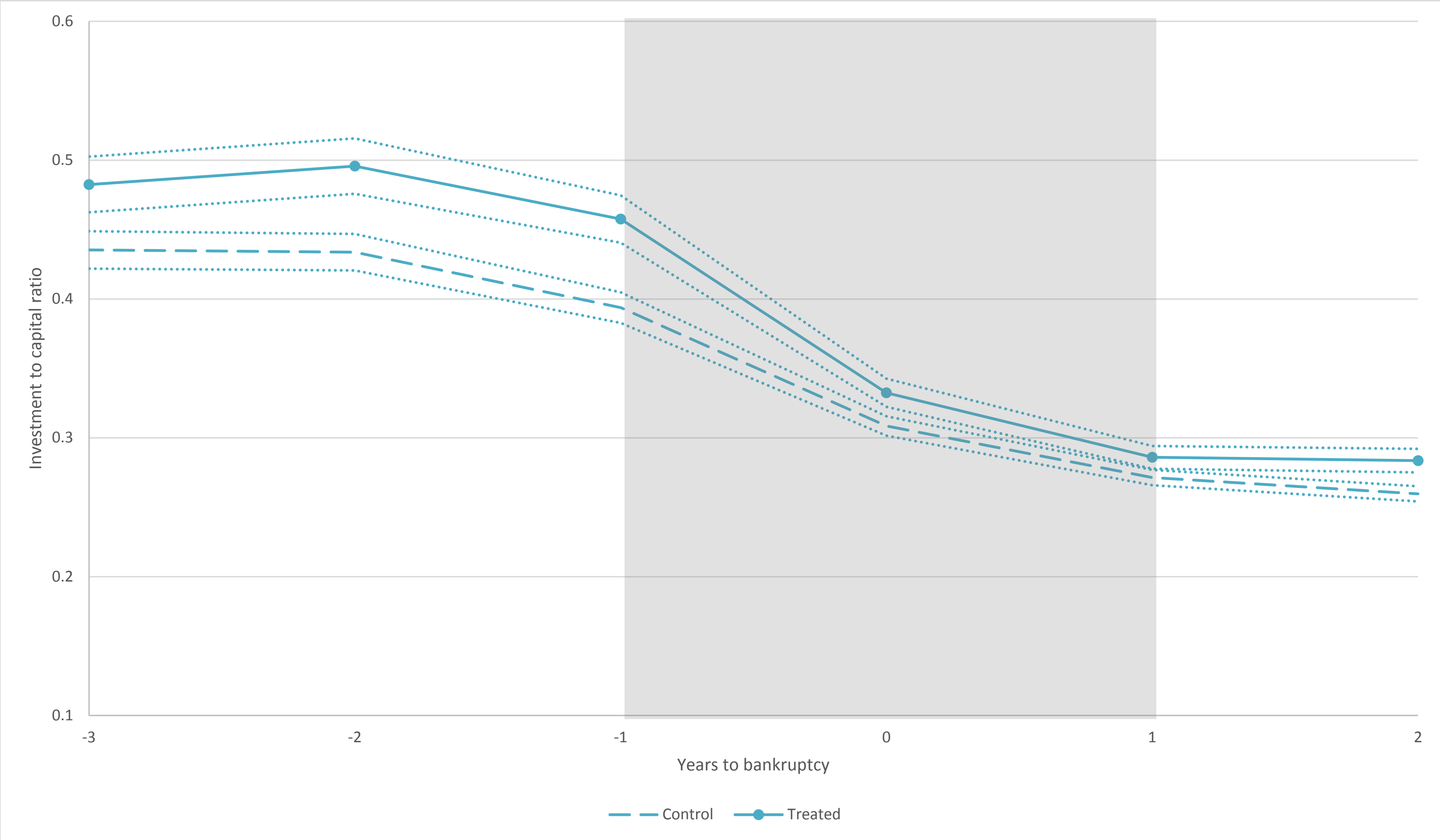

Figure A.1. Distribution of debt maturity by industry and year

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.

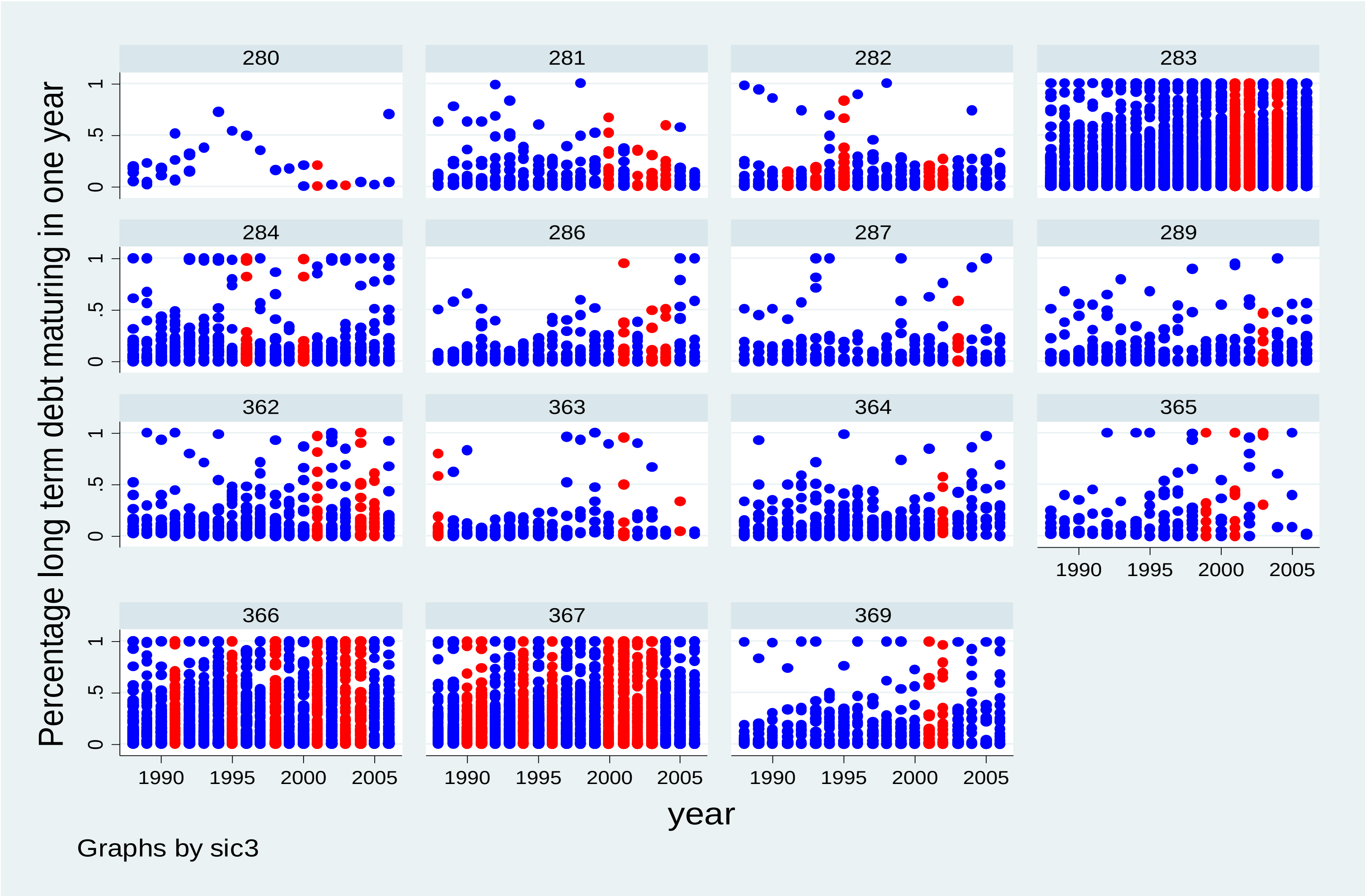

Table A.1. Definition of the main variables

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 variables:			
Bankruptcy	From UCLA LoPucki's Bankruptcy Research Data	Industry and year	Dummy =1 if at least one firm in the given industry and year filed for bankruptcy, =0 otherwise
Default	From Moody's Ultimate Recovery Dataset	Industry and year	Dummy =1 if at least one firm in the given industry and year 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.

2-digit SIC code	% Long-term debt expiring the following year: Distress years	N	Normal years	N	Difference 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+1 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+1. 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. 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+1 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 in t+1 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.5. 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+1 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	0.00933	0.00492	-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.6. 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.7. 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 in the following period 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
	mean	median	s.d.	mean	median	s.d.	Difference	T-stat	p-value	difference
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.8. 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 in t+1 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