MANAGERIAL DISCRETION, CORPORATE FINANCIAL FLEXIBILITY, AND INVESTMENT DYNAMICS

BY

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ABSTRACT

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In this dissertation, I try to advance our understanding of how managerial discretion and corporate financial flexibility affect various corporate outcomes such as failure, excessive (sub-optimal) continuation, firm growth and investment, in three novel ways. First, I show that the empirical effect of finance is not merely a misspecified real influence but rather that the financial structure of firms matter for firm growth and investment where the real effects of finance arise out of the imperfect substitutability between internal funding and external private credit. Second, using managerial mergers and acquisitions (M&A) investment decisions as an identification mechanism, I find that managerial discretion combined with corporate financial flexibility may lead to distortions in corporate investment and financing policies, and those distortions cost the various stakeholders of the firm dearly. Furthermore, using another sample of distressed firms worth more dead than alive, I, along with a co-author, show that most of these firms continue operations long after the optimal exit time. The failure to liquidate costs the typical sample firm over three years 8.7% of its assets in lost earnings relative to the industry median. Finally, I find that capital market does not fully internalize the costs associated with managerial sub-optimal behaviors in the short run. Although the market disciplines managerial sub-optimal behaviors in the long run, the market disciplinary mechanisms may not be swift enough to forestall falling values for the various stakeholders of the firm.

Succinctly, the findings in this dissertation suggest that managerial discretion and corporate financial flexibility entail real consequences for various firm dynamics. The traditional line of argument, “Blame It on the Market,” may not be well grounded, and firms need to carefully examine their investments and financing policies in good times to cushion against systematic shocks in bad times.

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"If I have seen further, it is by standing on the shoulders of giants" - Sir Isaac Newton

To many this thesis may be a symbol of an end, but to me it marks a new beginning of a journey that started in a small suburb in Bangladesh more than a decade ago. On a sunny Friday afternoon my father told me that truth lies in understanding, respect lies in humility, and success lies in pursuit of knowledge. Since then, I have crossed the Atlantic and the Pacific to seek knowledge at distant shores, and the journey continues until today. My father is my giant.

Like others in this journey, I was often lost, puzzled and wondered about the real meaning of this search. Then, an aura of light guided me through the darkest hours and helped me venture the mazes of uncertainty into the harbour of hope where I can sail once again. That light is my mentor, Professor Varouj Aivazian. The depth of his wisdom, the simplicity of his expression, the humility of his demeanour, and above all his indomitable passion for knowing the unknown helped shape my worldview and motivated me to pursue my interests in research. More than a mentor, Varouj is a dear friend.

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1. PREAMBLE

Why do some firms succeed and others fail? Do firms fail because of unintended adverse effects of managerial rational decisions arising from forces beyond their control, or do they fail because of flawed decision-making? Put simply, are managers of failed businesses villains or scapegoats? Do failing firms continue to use resources within the firm even if it is socially desirable to release the resources to higher-value users in the industry or elsewhere? What role do the capital market participants play in curtailing or exacerbating business failures? What is the interplay of the forces that lead to the failure of previously successful firms? These are some of the much debated issues in finance that financial economists sharply disagree on. Understanding these questions will potentially help investors (shareholders and creditors) design better financial contracts and management compensation structures to minimize ex-ante failure hazards while maximizing the ex-post recoveries of investments in failed businesses. From a policy perspective, it will potentially promote innovations in asset redeployment mechanisms and allow for efficient allocation of resources from distressed firms to higher-value users.

In this dissertation, I explore these questions in four distinct but related chapters. The first chapter following this preamble deals with the question of why some firms succeed and others fail. While competing economic theories explain the rationale for corporate failure, our empirical understanding of the causes of corporate failure is limited primarily because when firms fail, it is difficult to untangle the failures that arise as a result of unanticipated adverse effects of managerial rational decisions from failures that result from flawed decision making. To empirically identify the effect of managerial actions on firm failure hazard, I take a very narrow and specialized approach by focusing on managerial mergers and acquisition (M&A) investment decisions.

Using managerial M&A investment decisions as my identification mechanism, I show that distortions in corporate investment and financing policies can indeed precipitate corporate failure. After removing the failure risk arising from various industry and aggregate economic disturbances as well as idiosyncratic firm characteristics, I find that an additional acquisition above the average increases the conditional failure risk of an acquiring firm by 2.17% at all times compared to a typical firm in the industry. When conditioning the failure outcomes on managerial excessive acquisitiveness, there are not enough variations left in the outcome variable to be explained by economic disturbances. Furthermore, I show that managerial excessive acquisitiveness leads to pitfalls in the firm's financing policies creating imbalances between earnings and obligations. Excessive acquirers' immediate debt obligations rise, but liquid assets to finance these debts dry out. This mismatch between debt maturity and asset liquidity translates into an increased amount of default risk for the excessively acquisitive firms. In hindsight, these findings suggest that the traditional line of argument, "Blame It on the Market," may not be well grounded, and firms need to carefully examine their investment and financing policies in good times to cushion against systematic shocks in bad times.

However, casting the blame on managers by simply looking at the relationship between managerial action and failure hazard is rather unfair because an ex-post bad investment decision may very well be an ex-ante good investment decision when one factors in the uncertainties surrounding the business environment with which managers have to interact continuously. To this end, in the second chapter following the preamble, I test competing economic theories of corporate failure. I show that the effect from managerial excessive acquisitiveness to firm failure hazard could be explained by managerial excessive (irrational) risk taking and systematic bias in decision making. I find that the capital market, on average, punishes managerial excessive acquisitiveness, but that the market does not fully internalize the costs associated with managerial sub-optimal behaviors at the time of bid announcements. In the longer term, the external corporate control market also disciplines excessive acquirers by turning them into future targets of takeover. Results show that the assets of excessive acquirers are more likely to be reallocated to other firms via the external corporate control market than through other mechanisms such as bankruptcy/liquidation. These results suggest that managerial sub-optimal decision making precipitates corporate failure and that the market eventually disciplines these behaviors if not immediately, but surely in the long run.

Immediately following, I investigate whether failing businesses continue their loss-making operations for too long to the detriment of their creditors? This paper is a joint work with Sergei Davydenko at the Rotman School of Management of the University of Toronto. Using a sample of distressed firms worth more dead than alive, we find that most of them continue operations long after the optimal exit time. The failure to liquidate costs the typical sample firm over three years 8.7% of its assets in lost earnings relative to the industry median. Excessive continuations are financed by reductions in working capital, and are facilitated by low-current debt payments, high proportions of public bonds, and the absence of covenants prohibiting asset sales. Unlike bank covenants, bond covenants increase the probability of exit, but for many inefficient firms they may not be restrictive enough.

In the final chapter before the conclusion, I explore one of the fundamental questions in finance: do financial structures matter for firm dynamics? Although various observed and unobserved aspects of firms have been suggested as potential drivers of firm heterogeneity, economists disagree sharply on the role of finance as a source of heterogeneity in the cross section of firm growth. I find that after controlling for other sources of heterogeneity in the cross section of firm growth, superior financial performance enables the sample firms to finance higher growth, but the causality is primarily driven by small firms in the sample. The causality changes in an interesting way with a firm's access to external sources of financing. I uncover a pattern of substitutability between a firm's financial performance and its access to external sources of financing. Financial performance and firm growth causality is stable only for the small firms without any access to the public equity capital market whereas the causality vanishes all together for the small firms with access to the public equity market. Small firms finance growth with internal financing sources only to the extent that they are constrained by their abilities to raise additional funds from the public equity market. Results also indicate that the real effects of finance arise out of the imperfect substitutability between internal funding and external private credit.

Broadly speaking, this dissertation addresses the question of how managerial discretion and corporate financial flexibility affect various corporate outcomes such as failure, excessive (sub-optimal) continuation, firm growth and investment. It advances our understanding of the issues raised in the first paragraph of this preamble by arguing and empirically illustrating that managerial discretion and corporate financial flexibility entail real consequences for various firm dynamics. Distortions in corporate investment and financing policies cost the various stakeholders of the firm dearly. However, managers cannot get away with simply blaming it on the market tsunami; the capital market eventually disciplines managerial sub-optimal behaviors if not immediately, but surely in the long run.

2. BAD LUCK OR BAD POLICY: WHAT EXPLAINS THE HAZARD OF CORPORATE FAILURE?

2.1 Introduction

Why do firms fail? Do firms fail because of unintended adverse effects of managerial rational decisions arising from forces beyond their control, or do they fail because of flawed decision-making? Put simply, are managers of failed businesses villains or scapegoats? In this chapter, I investigate these questions, by separating the failure risk that arises as a result of exogenous economic disturbances beyond the realm of managerial control from the failure risk that results from sub-optimal decision making.

Using managerial mergers and acquisitions (M&A) investment decisions as an identification mechanism, I find a non-monotonic effect of managerial acquisitiveness on firm failure hazard: acquiring firms, on average, have lower failure risk profiles compared to non-acquiring firms, but more activism in the M&A market increases acquiring firms' failure risk.[1] I show that this non-monotonic effect can be explained by managerial excessive acquisitiveness relative to an industry benchmark in pursuing aggressive corporate growth strategies. Furthermore, I find that an excessive M&A investment policy has a bearing on the acquiring firm's financial structure, and the resulting distortion in corporate financing policy can precipitate corporate default even before the firm fails and exits the industry.

I use M&A to relate corporate investment and financing policies to the subsequent failure hazard primarily for three reasons. First, in recent years M&A deals have been ballooning both in terms of value and volume although empirical evidence in corporate finance shows that three-quarters of mergers and acquisitions never pay off; the acquiring firm's shareholders lose more than the acquired firm's shareholders gain.[2] Even though the M&A decisions have uncertain value

[1] Failure risk in this paper always refers to conditional failure risk, conditional on other firm characteristics and exogenous economic disturbances.

[2] See Lovallo and Kahneman (2003). Roll (1986) also argues that M&A can essentially be value neutral for the firm

implications for acquiring firms, conventional wisdom suggests that these decisions impose real consequences on corporate investment and financing policies and thus ultimately affect the survival of firms.[3] Second, figure 2.1 shows that M&A activities tend to cluster in good times whereas bankruptcies, one measure of failure, tend to cluster in bad times, and also that these series are negatively correlated. The pro-cyclicality of M&A activities and the counter-cyclicality of failure outcomes lend themselves to the postulation that distorted investment and financing policies in good times may explain the wave of failure in bad times. Finally, a quasi-natural experiment using two otherwise similar firms (WordCom versus Verizon Communication) shows that different approaches (aggressive versus conservative) towards using a risky investment mechanism (M&A) to pursue corporate growth strategies result in drastically different failure outcomes.[4]

Central to my empirical investigation is the identification of the causality from managerial acquisitiveness to firm failure hazard. When a number of firms create value through M&A while an equal or greater number of firms destroy value using the same investment technology, on average, we may not see any identifiable effect of managerial acquisitiveness on firm failure hazard. On the other hand, comparing a treatment sample of acquirers with a control sample of non-acquirers confounds the identification through selectivity and because of the arguably random effect of the treatment (in this case M&A) on firm value. In order to identify the effect of managerial M&A decision on firm failure hazard, I use a two-prong strategy.

First, after removing the variations in the failure outcome arising from various industry and aggregate economic disturbances and idiosyncratic firm characteristics, I find that, on average, M&A activities reduce the failure risk of acquiring firms compared to non-acquiring firms. When a non-acquiring firm moves from the non-acquiring sample to the acquiring sample, its conditional failure risk reduces by 55.56% (conditional on other exogenous variables evaluated at the mean). This positive effect of M&A cannot be attributed to any unobserved firm-specific initial conditions. However, when an acquiring firm uses M&A aggressively (relative to the average acquiring firm in

since we do not really know whether managerial hubris or economic fundamentals drive managerial acquisitiveness. Moreover, Bertrand and Schoar (2003) show that a significant extent of the heterogeneity in investment, financial, and organizational practices of firms can be explained by the presence of manager fixed effects. In hindsight, these results also suggest that managers exert a significant amount of control over the M&A decisions of the firm.

[3] Moeller, Schlingemann and Stulz (2005) show that acquiring-firm shareholders lost 12 cents around acquisition announcements per dollar spent on acquisitions for a total loss of $240 billion from 1998 through 2001, whereas they lost $7 billion in all of the 1980s, or 1.6 cents per dollar spent. The 1998 to 2001 aggregate dollar loss of acquiring-firm shareholders is so large because of a small number of acquisitions with negative synergy gains by firms with extremely high valuations. Without these acquisitions, the wealth of acquiring-firm shareholders would have increased. Firms that make these acquisitions with large dollar losses perform poorly afterwards.

[4] Please see the appendix for a discussion on the quasi-natural experiment.

the industry), the failure risk increases not only relative to the non-acquiring firms but also relative to the acquiring firm that uses this investment technology conservatively: an additional acquisition above the average number increases the failure risk by 2.17% at all times compared to the average firm in the industry.

Second, to bias my empirical investigation against the causality from managerial M&A decisions to firm failure hazard and to explain the non-monotonic effect of M&A decisions, I focus only on the acquiring sample and construct a measure of excessive acquisitiveness relative to the median acquiring firm in the industry. This construction is motivated by the industry equilibrium models where positioning with the typical firm within the industry serves as a natural hedge for a firm in formulating its real and financial policies, given the uncertainty associated with a particular investment decision. Using a non-linear instrumental variable analysis in a discrete-time hazard model, I show that excessive use of M&A investment technology does aggravate the acquiring firm's failure risk. After removing the failure risk arising from various industry and aggregate economic disturbances and idiosyncratic firm characteristics, a one standard-deviation increase around the mean of the excessive acquisitiveness measure can augment the conditional failure risk by 61%. When I condition the failure outcomes on managerial excessive acquisitiveness, there are not enough variations left in the outcome variable to be explained by exogenous economic disturbances, suggesting that managerial discretion is more important than a market tsunami to explain this extreme corporate outcome.

At the more disaggregate level, I find that a specific M&A deal structure matters in affecting the failure risk of acquiring firms. Most notably, a horizontal M&A (similar industry deals) reduces the conditional failure risk while a conglomerate M&A (unrelated industry deals) increases the conditional failure risk. In terms of deal financing, I find that pure stock-financed deals always increase the conditional failure risk while pure cash-financed deals have just the opposite effects on acquiring firms' failure hazard. These results are similar to the findings in the extant M&A literature.

M&A investment policy also affects the financial structure of acquiring firms. I find that excessively acquisitive firms shrink in market value, sink in operating performance, and distort the balance between their debts and assets structure by taking on more short-term debts but with less liquid assets in hand compared to conservative acquirers. This mismatch between debt maturity and asset liquidity manifests itself through an increased amount of default risk for the excessively acquisitive firms in my sample. A one standard-deviation increase around the mean of the excessive acquisitiveness measure can increase the conditional default risk by almost 34% after controlling for the other determinants of financial distress that are widely used in the bankruptcy prediction literature. These findings are economically significant and statistically robust to various alternative specifications and do not seem to be driven by endogeneity and reverse causality.

This research contributes to the existing literature by linking managerial M&A investment decisions, and the resulting distortions in financing policies with firm failure; it tries to shed light on the age-old debate in finance of whether managerial decisions or some kind of market tsunami beyond the control of managers are responsible for corporate failure waves in times of economic uncertainties. It also provides additional understanding of the competing theories of corporate failure in the economics and finance literature.

The remainder of the paper is organized as follows. Section II discusses the related literature. Section III illustrates the data and the construction of various variables. Sections IV and V estimate the effects of managerial (excessive) acquisitiveness on firm failure hazard with various robustness tests. Section VI explores the distortions in corporate financing policies resulting from excessive M&A investment policies. Section VII concludes the paper.

2.2 M&A and Corporate Failure: The Debate

Financial economists disagree sharply on the reason for firm failure. However, the related literature linking M&A and corporate failure is primarily focused on understanding the short-term and long-term effects of M&A on firms' equity prices and operating performance without directly relating M&A to firm failure hazard. In a review article, Roll (1986) concludes that the null hypothesis of zero abnormal performance of acquirers should not be rejected. While there have been many subsequent articles, the results appear to be mixed enough that Roll's conclusion appears to hold [Agrawal and Jaffe (1999)]. Lovallo and Kahneman (2003) argue that three-quarters of mergers and acquisitions never pay off; the acquiring firm's shareholders lose more than the acquired firm's shareholders gain. However, Moeller, Schlingemann and Stulz (2005) show that losses occur because of a small number of acquisitions with negative synergy gains done by firms with extremely high valuations. Without these acquisitions, the wealth of the acquiring-firm shareholders would have increased. Firms that make these acquisitions with large dollar losses perform poorly afterwards.

Studies on the long-term effect of M&A on shareholders' wealth gained momentum after Franks, Harris and Titman (1991). These authors and subsequent papers find some evidence of statistically significant negative abnormal returns. However, some studies have found evidence of significant underperformance only for subsets of bidders. Rau and Vermaelen (1998) find that low book-to-market "glamour" firms underperform following acquisitions, and Loughran and Vijh (1997) find that firms that use stock as the method of payment experience long-run underperformance. Mitchell and Stafford (2000) review the long-run return literature and question the common methodology of calculating buy-and-hold returns and forming event-time portfolios. They show that positive cross-correlations for event firms, especially in dealing with events that cluster in time and industry, such as M&A, invalidate the bootstrapping approach used for statistical inference in this methodology. Instead, they implement a calendar portfolio approach advocated by Fama (1998). This approach does not suffer from the above problems. Using the methodology proposed by Mitchell and Stafford (2000), Harford (2005) finds that evidence of long-run underperformance of M&A is mixed, consistent with the findings of Moeller, Schlingemann, and Stulz (2005) that large acquirers destroy billions in value while small acquirers actually create value in mergers.

Mitchell and Lehn (1990) document empirical evidence that firms that subsequently become takeover targets make acquisitions that significantly reduce their equity value, and that firms that subsequently do not become takeover targets make acquisitions that raise their equity value. More recently, Zhao and Lehn (2006) document a strong inverse relationship between acquiring firms' returns and the likelihood that their CEOs are subsequently fired, buttressing the disciplinary role of the internal corporate control to rein in CEOs with bad acquiring records.

In short, while it is fair to conclude from the existing literature that the long-term and short-term effects of M&A on firm performance are at best random, the literature has not addressed so far the issue of whether too much use of the investment technology can in fact precipitate failure. By focusing on managerial aggressive use of M&A investment technology, which has uncertain value implications for their firms, I wish to address this broader question of whether it is bad corporate policies that explain the most variations in the corporate failure outcomes or just bad luck.

2.3 Conceptual Framework and Data

2.3.1 Conceptual Framework

To empirically investigate the causality from managerial M&A actions to firm failure hazard, I construct a data set of acquiring and non-acquiring firms for the period of 1980-2006. In the data, I observe the bidding history of an acquiring firm and also the number of those bids that were actually made into acquisitions. From the information about the M&A actions of acquiring firms, I use the following conceptual framework to put meaning and structure into my empirical investigation in the subsequent sections. I assume that at time t_0, nature exogenously determines whether a firm is going to be an acquiring firm or a non-acquiring firm and that at any given time t after t_0, the value of a non-acquiring firm is given by some exogenous process.[5] The value of an acquiring firm, however, depends on the nature of the acquisitions the firm makes. I assume that at any given time t after t_0, both the acquiring firm and the non-acquiring firm are at the risk of failure, and the hazard function of failure is given by $\lambda(t, V_t)$, where V_t is the value of the firm at time t. I assume that $\lambda_v(.) < 0$ meaning that when firm value increases, the failure risk of the firm decreases conditional on no failure up to that time. Figure 2.2 shows how the nature of the M&A bid at time t affects the firm value at time $t+1$.

When I observe an M&A bid by an acquiring firm in the data, it signals the quality of the existing assets structure or behavioral bias of managers and agency problems within the acquiring firm. An M&A bid could be driven by a fundamental need of the firm (rational bid), or it could be due to the behavioral bias of managers or because of suboptimal agency driven factors (irrational bid). From the observed data, however, it is difficult to untangle what actually drives the managerial M&A bids. I assume that there is an exogenous transformation function that transforms a bid into an acquisition with positive probability. When a rational bid becomes an acquisition, I assume that the firm moves closer to its optimal assets structure and thus $E\big(V_{t+1}\big) > V_t$. When a rational bid fails to become an acquisition, the firm fails to move closer to the optimal assets structure and thus $E\big(V_{t+1}\big) < V_t$. When an irrational bid becomes an acquisition, I assume that corporate investments and financial policies become distorted with the positive adjustment costs of an unnecessary acquisition, and thus $E\big(V_{t+1}\big) < V_t$. Finally, when an irrational bid fails to

[5] This assumption is obviously too simplistic. I make this assumption here for the simple exposition of the conceptual framework. Later on in the paper, I take the sample selection issue more seriously while estimating the hazard regression.

become an acquisition, I assume that $E(V_{t+1}) = V_t$ if there are no costs associated with the bid or $E(V_{t+1}) < V_t$ if there are some costs associated with the bid.

At time t_0 and t, the only unobservable in my data set is whether the acquisition bid is driven by some fundamental necessities of the firm or by other factors unrelated to the asset structure of the firm. However, extending this simple exposition in a dynamic setting means that if I can show that M&A bids (acquisitions) over the life-cycle of the acquiring firm decreases the failure risk of the firm, then it must have been the case that those M&A bids were in general driven by changes in economic fundamentals that necessitated changes in the assets structure of the firm. On the contrary, if the M&A bids (acquisitions) over the life-cycle of the acquiring firm increases the failure risk of the acquiring firm, it could be either because of irrational bids or because of failed rational bids. Given this overly simple framework, my empirical strategy proceeds in two steps; first, I show that managerial M&A actions increase firm failure hazard. However, this result alone does not fully untangle the failure augmenting effects of failed rational bids from the effects of irrational bids. Thus, in the second step I show that when a firm deviates from the industry benchmark (median firm in the industry) and becomes excessively acquisitive relative to the benchmark, the failure risk-profile monotonically increases the more aggressive the firm becomes relative to the benchmark in using the M&A investment technology with an uncertain value implication.

2.3.2 Sample Construction

I use the Thomson Financial SDC Platinum Merger and Acquisition data set to identify the corporate M&A decisions. SDC details all public and private M&A transactions involving at least 5% of the ownership of a company where the transaction was valued at $1 million or more, but after 1992, deals of any value (including undisclosed values) are covered. I focus on the U.S. industrial firms and collect all SDC documented M&A deals involving U.S. acquirers and targets from 1979 until 2006 totaling 208,105 deals. I then match the SDC deals with the merged quarterly COMPUSTAT-CRSP industrial file using the 6-digit cusip, ticker symbol and company name. I apply a filter and keep only the deals for which I have CRSP daily stock price data on the transaction date, one day after the transaction date and at least two months of daily stock price data prior to the transaction date. This filter ensures that I have a sufficient history of daily stock prices data prior to and after the transaction date to calculate the cumulative abnormal return to the equity holders as a result of the transaction. The final deal data set contains 63,613 transactions involving 10,779 distinct acquiring firms and 3,582 deals involving 2,124 distinct target firms. Firms that are in the merged quarterly COMPUSTAT-CRSP but do not make any M&A bid in my deal data set I classify as non-acquirers.

I use Fama and French (1997) industry classifications to categorize the deals into one of the 49 industries based on the reported 4-digit SIC in SDC. To identify the final status of firms in my data set, particularly in cases when firms drop out of COMPUSTAT, I use the yearly COMPUSTAT data footnotes AFTNT33, AFTNT34 and AFTNT35 that code, respectively, the month, the year, and the reason for deletion from the COMPUSTAT data file. I also verify these footnotes with the CRSP de-listing codes to accurately identify the reason for as well as the precise time of exit. I also collect all defaults and subsequent bankruptcies and reorganization events from the Moody's Default Risk Services (DRS) database, SDC Corporate restructuring database, and LoPuki's Bankruptcy Research Database (BRD) for the period of 1980 to 2006. I then manually combine the default and bankruptcy data with the merged COMPUSTAT-CRSP data set by taking into account historical name changes, cusip and ticker symbol changes. My final data set consists of 14,191 non-acquiring firms and 10,779 acquiring firms and out of those 10,779 acquiring firms, 6,144 (57%) firms eventually drop out of COMPUSTAT-CRSP while the rest 4,635 (43%) firms remain active until the end of the sample period. Of the firms that eventually exit the industry, 445 (7.24%) are either bankrupt or liquidated, 4,338 (70.61%) are acquired, and the rest, 1,361 (22.15%), drop out for other reasons such as leverage buy out, management buy out, or dropping off the exchange.

2.3.3 Descriptive Statistics

Table 2.1 presents two panels of statistics describing the sample-firm characteristics. Panel-A compares the acquiring and the non-acquiring firms, and panel-B compares the acquiring firms with the target firms. Panel-A shows that acquiring firms are larger in size, better in operating performance and have longer maturity debt than the non-acquiring firms. Surprisingly, acquiring firms have a lower market-to-book ratio (a proxy for Tobin's q) than the non-acquiring firms; also, acquiring firms do not seem to fare better in terms of leverage and liquidity than the non-acquiring firms. In short, looking at the summary statistics in panel-A, one cannot conclude that one set of firms is systematically better or worse than the other set of firms and thus, being an acquiring or a non-acquiring firm in my sample may not be driven by sample selection issues.

In panel-B, however, acquiring firms are larger in size, better in operating performance, and have higher growth opportunities, a greater liquid assets structure and fewer debt obligations in the shorter term compared to the target firms. Acquiring firms also survive longer in the data set, and make more bids. In doing so, the average acquirer pays around 13% control premium to an average target reflected by the difference in the cumulative abnormal return at the time of the bid announcement. Taken together, the summary statistics presented here show that acquiring firms are systematically better than the target firms, but that they fare better than the non-acquiring firms along some dimensions while faring worse in other dimensions. Thus, focusing on them (the acquiring sample) makes good economic sense to bias my empirical investigation against finding a spurious relationship between managerial actions and firm failure since this set of firms is financially and economically sounder than others to begin with.

2.3.4 Variable Construction

Firm Failure

The primary dependant variable of interest in my investigation is firm failure. Failure is inherently linked with value destruction and, accordingly, I define failure when I believe that firms exit after destroying either debt holders' value or equity holders' value. Whenever a firm exits through liquidation, both the equity holders' and the debt holders' value get curtailed while in the case of exit through bankruptcy, typically, equity holders' wealth evaporates. In both cases, i.e., exit through bankruptcy and liquidation, the firm fails to preserve value for at least one of its stakeholders, and thus also fails according to my criterion. Whenever a firm exits through means other than bankruptcy/liquidation, I calculate the 'Buy-and-Hold' return from the monthly CRSP return (including dividend) from the first trading month until the firm is de-listed from CRSP in the following way:

$$BHR_{iT} = \prod_{t=1}^{T} (1 + r_{it}) - 1 \tag{2.1}$$

where BHR_{iT} is the 'Buy-and-Hold' return at the time of exit, $t = 1$ is the first trading month, $t = T$ is the last trading month in which the firm is delisted from CRSP, and r_{it} is the monthly CRSP return (including dividend) for firm i in my sample. If $BHR_{iT} < 0$, it means that if an investor put \$1 in the stock of that company in the beginning, at the exit he/she gets back less than \$1; that is, the equity's value has been destroyed. In other words, the firm fails according to my criterion. If the firm is still active while $BHR_{it} < 0$, I do not classify it as a failed firm simply because I do not want to ignore the potential of the firm in creating value in light of the future resolution of economic uncertainties. With this definition of firm failure, I classify 4,360 (30.72%) of the non-acquiring firms and 2,789 (25.87%) of the acquiring firms as failed firms. Of those failed acquiring firms, 445 (15.96%) exit the sample through bankruptcy/liquidation, 1,268 (45.46%) exit the sample through acquisition, and the remaining 1,076 (38.58%) exit the sample through other means such as leverage buy out, management buy out, or dropping off the exchange.[6]

Managerial Acquisitiveness

The primary explanatory variable in my empirical investigation is the extent to which managers use M&A investment technology to pursue their corporate growth strategies. An ideal measure of managerial acquisitiveness would be to see how much (in monetary terms) managers are effectively betting through M&A. This involves knowing how often they are bidding (extensive margin of the ideal measure of acquisitiveness) and what is the value of each bid (intensive margin of the ideal measure of acquisitiveness) in a given period. Since quite often deal values remain undisclosed, I focus on the number of bids (acquisitions). Although it may not be the ideal measure of acquisitiveness, it is very simple and easily reproducible. To construct the measure for firm i in period t, I count the total number of M&A bids (acquisitions) the firm has made (completed) until time t and use that number as a measure of managerial acquisitiveness for period t. I also normalize the total number of M&A bids (acquisitions) until period t with firm size (total assets) in period t and also with the total number of periods the firm has been active in my sample until period t. It captures how active the firm is in the corporate control market as well as managerial inclination and activism to pursue their corporate growth strategies through M&A adjusted for firm size and age for a given period.[7]

[6] I also use alternative measures of failure; for example, when a firm underperforms the industry median by 40% for three consecutive years before exiting the industry, I consider the firm a failed firm. Alternative measures of failure do not alter the core argument of the paper.

[7] Please see the data appendix for a discussion on constructing other explanatory variables.

2.4 Managerial Acquisitiveness and Corporate Failure

2.4.1 Estimation Methodology

I use a discrete-time hazard model to estimate the failure risk of the sample firms. I treat each firm-manager as a decision unit and assume that each decision unit is always at the risk of failure and that the risk process is governed by a simple form of proportional hazard function [Cox (1972)]:

$$\lambda(\tau, X) = \lambda_0(\tau) exp^{X\beta} \tag{2.2}$$

where λ_0 is the baseline hazard of failure over time τ under the condition $exp^{X\beta} = 1$, i.e., no heterogeneity among firm-managers. Heterogeneity among firm-managers reflected, for example, by differences in information set (X), might change the actual hazard. Here, the multiplicative effect of the covariates (X) has a clear and intuitive meaning. If $exp^{X\beta} > 1$, the risk of failure would increase over the whole sample period, whereas the failure risk would decrease if $exp^{X\beta} < 1$. Without any restriction on λ_0, however, this model postulates no direct relationship between X and τ. Cox (1972) proposed an extension of this proportional hazard model to discrete time by working with the conditional odds of failure at each time τ given no failure up to that point (conditional on the covariates X). Specifically, Cox (1972) proposed the model:

$$\frac{\lambda(\tau/X)}{1 - \lambda(\tau/X)} = \frac{\lambda_0(\tau)}{1 - \lambda_0(\tau)} exp^{X\beta} \tag{2.3}$$

Taking logs, I obtain a model on the logit of the hazard or conditional probability of failure at τ given no failure up to that time, $Logit\Big(\lambda(\tau/X)\Big) = \alpha + X\beta$, where $\alpha = Logit\Big(\lambda_0(\tau)\Big)$ is the logit of the baseline hazard and $X\beta$ is the effect of the covariates on the logit of the actual hazard. Note that the model essentially treats time as a discrete factor by introducing one parameter, α, for each possible failure time τ. Interpretation of the parameters β associated with the other covariates follows along the same lines as in a logistic regression. Shumway (2001) argues that hazard models are more suited to analyze the failure intensity of corporate events and shows that a multi-period logit model is equivalent to the discrete-time hazard model with the inclusion of log of firm age among the covariates as a proxy for the baseline hazard.

In this discrete-time hazard setting, covariates X affect the hazard rate of failure and the direction of the covariate specific effects are given by the associated β parameters. Moreover, I argue that the design considerations of my experiment also weaken the plausibility of reverse causation. My primary dependent variable, i.e., firm failure, is an absorbing state in the sense that once failure occurs, firms never recover, and I do not observe any of the explanatory variables for the failed firms anymore. That is, a causal effect from the outcome variable to any of the explanatory variables does not make sense since all the explanatory variables are measured temporally before the outcome variable. This, of course, assumes that managers cannot predict failure some period ahead. If managers can predict failure ahead of the actual failure time, then the reverse causality is still a concern. To alleviate this concern, I estimate the discrete-time hazard regression with up to three lags of all explanatory variables. Since the results do not vary with higher lags, I report the results where all explanatory variables are lagged by one period.

2.4.2 Estimation Results

Table 2.2 reports the regression results from the discrete-time hazard model. The dependent variable is a dichotomous variable that equals 1 for the last fiscal quarter in which a firm fails and 0 otherwise. All explanatory variables are lagged by one period. I also include industry-fixed effects, year-fixed effects, various deal structure dummy variables, correct for clustering of observations by firm, and use robust standard errors to test the significance of the estimated coefficients in each regression model. I present all coefficients in the form of a logarithm-of-odds ratio in the table.

Results show that the most important firm characteristics that cushion against failure are firm size, age (baseline hazard), asset liquidity and longer maturity debts. Non-acquiring firms are more susceptible to failure than the acquiring firms. In terms of economic significance, I find that if a sample firm moves from the non-acquiring sample to the acquiring sample, the conditional failure risk of that firm reduces by 55.56% (conditional on other exogenous variables evaluated at the mean).[8] Interestingly, conditional on being in the acquiring sample and various firm characteristics, a greater number of M&A activities actually aggravates acquiring firms' failure risk compared to that of the non-acquiring firms. This failure-augmenting effect of aggressive acquisitiveness remains robust to various alternative definitions of managerial acquisitiveness. In term of economic significance, I find that an additional acquisition over and above the average acquiring firm increases

[8] I fix all the exogenous variables in the hazard regression at their mean and calculate the average failure probability first by setting the acquiring sample dummy variable to 1, and then by setting the acquiring sample dummy variable to 0. The average failure probability increases from 0.36% to 0.56%, a 55.56% increase, when the acquiring sample dummy variable changes from 0 to 1 and all other exogenous variables remain fixed at their mean.

the conditional failure risk by 2.17% compared to that of the non-acquiring firms, and the acquiring firms that use this technology conservatively relative to the average acquiring firm (conditional on other exogenous variables evaluated at the mean).[9]

Among the set of economic disturbance measures, results show that industry and aggregate demand shocks increase the failure risk of the sample firms. Shleifer and Vishny (2003) posit that in a booming aggregate equity market, M&A activities are high, while in an uncertain aggregate equity market, M&A activities are low. Thus, not surprisingly, I find that a momentum in the aggregate equity market increases the impending failure risk while instabilities in the aggregate equity market reduce the failure risk of the firms in my sample. Together, the set of exogenous economic disturbances constitute 20% of the explained variations in the failure outcomes. Later on, I show that this explanatory power vanishes all together when I condition the failure hazard on managerial excessive acquisitiveness relative to an industry benchmark.

I also include various deal-structure dummy variables in the hazard regression but do not report the coefficients because of space limitations. Most notably, I find that a 100% stock-financed deal increases failure risk while a 100% cash-financed deal reduces failure risk. Deals in similar industries always reduce failure risk, and mergers of two equal firms always increase the failure risk of the acquiring firms in my sample.[10] These findings are economically significant as reported in Table 2.3.

Two caveats are in order. First, being an acquiring or non-acquiring firm may not be random as I assumed in the conceptual framework and argued from the summary statistics in panel-A of Table 2.1. Second, there may very well be some unobservable not captured by my set of explanatory variables that affect both the failure risk and the managerial acquisitiveness measures and thus plague the causality with an endogeneity problem.

[9] The average acquiring firm makes 6 acquisitions in my sample. An additional acquisition over and above the average acquiring firm refers to the 7th acquisitions. Once again, I fix all the exogenous variables in the hazard regression at their mean and calculate the average failure probability first by setting the cumulative number of bids to 6, and then by setting the cumulative number of bids to 7. The average failure probability increases by 2.17% when the cumulative number of bids changes from 6 to 7 and all other exogenous variables remain fixed at their mean.

[10] These results are similar to the findings in the extant literature on M&A. Please refer to the related literature section for more details on relevant papers in the M&A literature.

2.5 Managerial Excessive Acquisitiveness and Corporate Failure

To bias my empirical investigation against the causality from managerial M&A actions to firm failure hazard and to somewhat isolate the effect of irrational bids (acquisitions) from rational bids (acquisitions), I now focus only on the acquiring sample since this set of firms has a lower failure risk than the non-acquiring firms to begin with. I construct a measure of managerial excessive acquisitiveness which quantifies the extent to which acquiring firms' managers aggressively use an M&A investment technology relative to an industry benchmark of acquiring firms.[11] To construct the industry benchmark I focus on the importance of industry equilibrium forces to a firm's real and financial structure. Maksimovic and Zechner (1991) show that in industry equilibrium, a firm's financial structure is irrelevant because a technology's risk and profitability depend not only on ex-ante characteristics but also on how many firms adopt that technology. Thus, adoption of a technology with uncertain payoff is very risky for the first mover, but when more firms adopt the technology, risk dissipates and in industry equilibrium, positioning with the average firm in the industry serves as a natural hedge for the firm. Mackay and Philips (2006) empirically find that positioning with the median firm in the industry indeed serves as a natural hedge for firms simultaneously making investments, financing and business-risk decisions.

Motivated by this argument, I use the M&A bids of the median acquiring firm in the industry as a benchmark assuming that the median acquiring firm behaves as a typical firm in industry equilibrium. The distance from natural hedge $\left(DIST.\ NH_{ijt}\right)$ of firm i in industry j at time t is given by:

$$DIST.\ NH_{ijt} = \frac{\left|X_{ijt} - Median(X_{-ijT})\right|}{Range\left\{\left|X_{ijt} - Median(X_{-ijT})\right|\right\}\forall\, i \in\ \psi(j,T)} \tag{2.4}$$

where X_{ijt} is the cumulative number of M&A bids (acquisitions) of firm i in industry j until calendar quarter t, and is normalized by the total number of calendar quarters for which I observe the firm in my sample. $\psi(j,T)$ is the set of all firms in industry j and calender year T. I normalize the cumulative number of bids (acquisitions) of a firm to attenuate the survivorship bias in the excessive acquisitiveness measure; that is, the longer the firm remains active in the industry, the more likely it is to undertake a greater number of acquisitions. This construction design also assigns a greater

[11] This of course implicitly assumes that the acquisitiveness of the industry benchmark firm is, on average, driven by some rational decision-making process. This may be a somewhat strict assumption but I find support for this in the industry equilibrium models where positioning with the average firm in the industry serves as a natural hedge for firms in formulating risky investment decisions such as M&A.

importance to the most recent bids while giving less weight to the earlier bids.[12] I calculate the corresponding industry median for firm i in industry j for each calendar year T. When calculating the median for a particular firm i, I include all firms in calender year T in firm i's industry, but exclude firm i itself so that the benchmark remains exogenous to the firm.[13] Moreover, I divide $\left|X_{ijt} - Median(X_{-ijT})\right|$ by its range across all firms and industries at time T to make the distance from natural hedge comparable for all firms in all industries in a given period. This distance from a natural hedge proxy (i) reflects how different an acquiring firm is from its typical industry counterpart in using the M&A investment tool to pursue a corporate growth strategy; and (ii) it is comparable across all firms and industries since it is a unit-free measure and is bounded between 0 and 1. From the $DIST.\ NH_{ijt}$ proxy, I define my measure of managerial excessive acquisitiveness in the following way:

$$EXCESSIVE\ \ ACQ_{ijt} = DIST.\ \ NH_{ijt} \times I_{(X_{ijt} - Median(X_{-ijT}) > 0)} \tag{2.5}$$

where I is an indicator function that returns 1 if X_{ijt} is above the industry median and returns 0 if X_{ijt} is below the industry median.[14]

Table 2.4 reports the differential firm characteristics at the time of the bid announcement for the excessively acquisitive bidders vis-a-vis their relatively conservative counterparts.[15] It shows that excessively acquisitive bidders are larger in size and better in operating performance but fare worse in growth opportunities compared to their relatively conservative counterparts at the time of the bid announcement. To finance excessive acquisitiveness, bidders take on more leverage while their liquid assets in hand shrink. Moreover, the average and median stock price performance surrounding the bid announcement is worse for the excessively acquisitive bidders relative to their conservative counterparts; excessive acquirers, on average, lose 1% in value surrounding the announcement

[12] I also add some random noise to the weighting variable, i.e., the number of periods for which I observe a firm in my data set, so that the weighting metric remains exogenous and not determined endogenously.

[13] I impose the restriction of at least 5 or more firms to calculate the median in a given year.

[14] For example, lets assume that there are only two firms in my data set and that both of them are in the same industry and survive exactly 4 quarters or 1 year. Firm 1 makes 4 bids in total, one in each period, and firm 2 makes 2 bids in total, 1 in each of the first two periods and no bid in the last two periods. Then, the degree of acquisitiveness of firm 1 and firm 2 from period 1 to period 4 would be (1/4, 2/4, 3/4, 4/4) and (1/4, 2/4, 2/4, 2/4), respectively. The corresponding industry median for firm 1 and firm 2 would be 0.5 and 0.625, respectively. The excessive acquisitiveness for firm 1 and firm 2 before adjustment would be (0, 0, 0.25, 0.5) and (0, 0, 0, 0), respectively. After adjusting with the range of excessive acquisitiveness across both firms in the industry, the excessive acquisitiveness measure becomes (0, 0, 0.5, 1) for firm 1 and (0, 0, 0, 0) for firm 2.

[15] An acquiring firm is defined as conservatively acquisitive if it is not excessively acquisitive. In other words, I define conservative acquisitiveness as: $CONSERV\ \ ACQ_{ijt} = DIST.\ \ NH_{ijt} \times I_{(X_{ijt} - Median(X_{-ijT}) < 0)}$

event due to their aggressive acquisitiveness after correcting for a broad market return on that day. Furthermore, Figure 2.3 shows that excessive acquisitiveness also means an aggressive growth strategy for these firms; between the 1^{st} and the 9^{th} bid the median excessively acquisitive firm grows to 900% of its initial size (book assets) compared to a 300% size growth of the median conservatively acquisitive firm for the same number of bids.

2.5.1 *Excessive Acquisitiveness and Corporate Failure: A Quasi Experiment*

To uncover the patterns of change in the risk profiles of aggressive acquirers I do a quasi experiment comparing the failure risk profile of the acquiring sample with the failure risk profile of the non-acquiring sample. I estimate the failure risk profile (hazard function) of the acquiring and the non-acquiring sample using various baseline hazard specifications conditional on firms' age since incorporation, a dummy variable indicating whether the firm is in the acquiring sample, and the aggressive acquisitiveness of firms.[16] Figure 2.4 shows the risk profiles of the acquiring and the non-acquiring sample for various hazard model specifications.

The failure-risk profile of the acquiring sample is always below the failure risk profile of the non-acquiring sample, meaning that acquisitiveness actually lowers failure risk. However, when the acquiring sample-firms become aggressive in their use of M&A, the figure shows that their failure-risk profile shifts up, and as they become increasingly aggressive in their use of M&A, it becomes increasingly likely that they are going to fail more often than their non-acquiring counterparts. This pattern of a shifting failure-risk profile is even stronger if I use a matching sample of non-acquiring firms instead of the universe of all non-acquiring firms.[17] This simplest possible estimation of a hazard function shows that acquisitiveness, on average, lowers the failure risk of the acquiring firms relative to the non-acquiring sample, but excessive acquisitiveness induces these firms to fail more often, not only relative to the conservatively acquisitive firms, but also relative to the non-acquiring firms. Thus, it is not the M&A investment technology per se that precipitates failure, but rather that it is too much, perhaps inefficient, use of this technology that may explain the heterogeneity in the failure outcome.

[16] For the non-acquiring sample, excessive acquisitiveness is always 0.

[17] I use the propensity score matching using age of the firm since incorporation as the common support for both the acquiring and the non-acquiring firms so that both the acquiring and the non-acquiring samples have a similar risk profile to begin with. I then vary the use of M&A by these firms and find an even stronger shift in the pattern of the risk profile of the acquiring sample.

2.5.2 Excessive Acquisitiveness and Corporate Failure: Regression Results

Table 2.5 reports the regression results from the discrete-time hazard model estimated using only the acquiring sample. The dependent variable is a dichotomous variable that equals 1 for the last fiscal quarter in which an acquiring firm fails and 0 otherwise. All explanatory variables are lagged by one period. I also include industry-fixed effects, year-fixed effects, various deal-structure dummy variables, correct for clustering of observations by firm, and use robust standard errors to test the significance of the estimated coefficients in each regression model. I present all coefficients in the form of a logarithm-of-odds ratio in the table.

It shows that the most important acquiring firm characteristics that cushion against failure are firm size, age (baseline hazard), and growth opportunity (Market Value/Book Value). After removing the failure risk arising from the idiosyncratic firm characteristics, industry- and year-fixed effects, deal specificities, and exogenous economic disturbances, I find that an excessive use of M&A relative to the industry median does indeed aggravate the acquiring firm's failure hazard. The results also show that the further away the firm is from its natural hedge, the more likely it is to fail. However, the failure-augmenting effect of $DIST.\ NH_{ijt}$ is primarily due to the excessive acquisitiveness rather than to the conservative acquisitiveness since the coefficient of *Excess Acq.* is always higher in magnitude than that of the $DIST.\ NH_{ijt}$. Furthermore, inclusion of the excessive acquisitiveness measure in the hazard regression improves the model fit, measured by McFadden's Pseudo-R^2, by up to 36%. I can correctly identify the failure events for my sample firms 72% of the time using model 3 in table 2.5 and 75% of the time using model 9, and in both cases the inclusion of the excessive acquisitiveness measure increases the likelihood of correct identification by 6%.[18] When conditioned on managerial excessive acquisitiveness relative to the industry benchmark, there are almost no variations left in the explained variation of the hazard model to be attributed to the set of exogenous economic disturbances. That is, conditional on managerial excessive acquisitiveness, incorporating economic disturbances in the hazard model does not add to the model's explanatory power.

However, the effect of excessive acquisitiveness on a firm's failure hazard may be corrupted by endogeneity, omitted covariates, or errors in the excessive acquisitiveness measure. These problems

[18] My primary dependent variable, i.e., firm failure, is centered around .01. I consider a failure event as correctly identified if the predicted probability from the hazard model during the fiscal quarter in which the firm fails is higher than the centered value of the dependent variable.

can be addressed using instrumental variable estimation in a linear setting, but in a non-linear setting, instruments cannot in general be used to produce a consistent estimator of the desired causal effects. To this end, I use a methodology developed by Hardin, Schmeidiche, and Carroll (2003) to consistently estimate the effect of the excessive acquisitiveness on firm failure using an instrumental variable estimation in my discrete-time hazard model setting. A valid instrument must be highly correlated with the firm-level excessive acquisitiveness while having no effect on the dependent variable, i.e., firm failure, so that the correlation between the instrument and the error term is not significantly different from zero. I instrument the degree of excessive acquisitiveness with a measure of industry merger momentum.

The M&A literature has long recognized that intense mergers and acquisitions activities come in waves and tend to cluster within industries and across time although there are considerable debates about what drives those M&A waves. But it is well understood that firms are more active in M&A transactions during industry merger waves than in any other periods, and the effects of greater activism during merger waves on firm failure are not obvious in the existing literature. Harford (2005) argues that mergers before the optimal stopping point within a wave are value creating whereas mergers after the optimal stopping point are value destroying compared to non-wave mergers and acquisitions without any reference to firm failure. Thus, it is fair to conclude that firm-level acquisitiveness is related to industry merger waves but industry merger waves, as far as we know, do not have any clear effect on firm-failure hazard.

Using an industry-merger wave dummy as an instrument for the firm-level excessive acquisitiveness, I find a statistically significant effect of the excessive use of M&A on firm-failure hazard. I also interact the merger wave dummy with industry-level computerization to make sure that the industry-merger wave is associated with some structural change within the industry and also find a statistically significant effect of the excessive use of M&A on firm failure.[19] For diagnostic purposes, I also do two stage least-square (2SLS) estimations, and my instruments satisfy the non-excludability criterion in the first stage with very high F-statistics. The instruments also statistically significantly affect firm failure hazard in the second stage of my 2SLS estimation. For robustness purposes, I do a false instrument experiment in which I instrument the period $t-1$

[19] I collect industry-level computerization data from the Bureau of Economic Analysis (BEA). Chun et al. (2007) show that traditional U.S. industries with higher firm-specific stock return and fundamentals performance heterogeneity use information technology (IT) more intensively and post faster productivity growth in the late 20th century. They argue that elevated firm-performance heterogeneity mechanically reflects a wave of creative destruction disrupting a wide swath of U.S. industries, with newly successful IT adopters unpredictably undermining established firms.

excessive acquisitiveness with the period $t+1$, $t+2$, $t+3$, and $t+4$ industry-merger wave, and in all cases the false instruments do not have any statistically significant effect on firm-failure hazard, buttressing the statistical as well as temporal validity of my instrument.

One could very well argue from what I have discussed so far that bad firms are more active in M&A, and that firms fail not because of their relatively excessive use of M&A but because of their essentially inferior quality to begin with. In other words, if one could find a variable that influences both the excessive acquisitiveness and the firm failure measures, it would suffice to cast serious doubt on the regression results that I have presented above. One possible candidate for such a variable is the Gompers, Ishii, and Metrick (2003) governance score of firms, generally known as the G index. The G index is derived from the incidence of 24 unique governance rules that proxy for the level of shareholder rights in a firm. They show that an investment strategy of buying firms in the lowest decile of the index (strongest rights) and selling firms in the highest decile of the index (weakest rights) would have earned abnormal returns of 8.5% per year during their sample period. They also find that firms with lower G index values (stronger shareholder rights) had higher firm values, higher profits, greater sales growth, lower capital expenditures, and that they made fewer corporate acquisitions.

I use the average value of the G index as a measure of firm quality in the sense that firms with higher average governance scores (G index), i.e., bad corporate-governance firms, will be more acquisitive than firms with lower governance scores, i.e., good corporate-governance firms, as shown by Gompers, Ishii, and Metrick (2003). I find that inclusion of the governance score as a measure of firm quality does not alter the result that I discussed before. The governance score enters the hazard regression with or without the excessive acquisitiveness measure, and in both cases, irrespective of specifications, the governance score does not have any statistically significant effect on firm failure risk while the excessive acquisitiveness measure retains its significance although the logarithm-of-odds ratio declines.

2.5.3 Economic Significance of the Effect

The statistical significance of the effect that I discuss in the previous section does not necessarily imply economic significance. To this end, I estimate the marginal effects of the relevant variables from the hazard regression. I estimate the marginal effects at the mean, 1/2 standard deviation below the mean, 1/2 standard deviation above the mean, and 1 standard deviation around the mean. Table 2.7 reports the marginal-effect estimates from the hazard regression. The results are consistent with what I have found in Table 2.5, where I report the logarithm-of-odds ratio of the coefficients. It shows that the marginal effects are rising, as we move from 1/2 standard deviation below the mean to 1/2 standard deviation above the mean of the excessive acquisitiveness measure, by 77% in one specification and by 82.70% in the other specification, where I also include economic disturbances in the hazard regression. At the mean, a 1% increase in the excessive acquisitiveness measure increases the conditional failure risk by .33% (conditional on other exogenous variables evaluated at the mean) calculated using $\frac{\partial Y}{\partial X} \cdot \frac{\bar{X}}{\bar{Y}}$, where $\frac{\partial Y}{\partial X}$ is the marginal effect at the mean, and $\bar{Y}$ and $\bar{X}$ are the means of the predicted conditional-failure probability and the excessive-acquisitiveness measure, respectively. This translates into a 61% increase in conditional failure risk with a one-standard-deviation increase around the mean[20] of the excessive-acquisitiveness measure (conditional on other exogenous variables evaluated at the mean).

2.5.4 Some Robustness Tests

I report various robustness tests in Table 2.6. In the first robustness test, I estimate a linear probability model (LPM) of failure with firm-fixed effects which I cannot do in the discrete-time hazard model due to non-convergence. Inclusion of firm-fixed effects removes any firm-specific effects on failure hazard, such as an inherently bad-firm effect that is constant across time, and I find that excessive use of M&A increases the failure risk. In the second robustness test, I focus on the acquiring firms for which I observe the complete bidding history in the SDC data set since the time the firm went public, that is, after the year 1980 (almost 20% of the sample firms went public before 1980 for which I do not observe the complete bidding history). I find evidence of a statistically significant effect from excessive use of M&A to firm failure for the complete bidding history sample as well. One potential explanation for failure could be that excessively acquisitive firms suffer from winners' curse in the sense that they end up winning their bids, but they also end up with bad targets more often. I use the cumulative number of completed contested bids normalized by the total number of bids by firms to construct a measure of winners' curse and find that it does indeed increase failure risk, but winners' curse does not have enough explanatory power to soak up the explanatory power of the excessive acquisitiveness measure. I also condition the hazard regression on the total number of bad ($CAR < 0$) and good ($CAR > 0$) acquisitions

[20] One standard deviation around the mean is calculated from 1/2 standard deviation below the mean to 1/2 standard deviation above the mean.

normalized by the total number of bids made by a firm, and the excessive acquisitiveness measure is still statistically significant in affecting the failure risk to increase. Finally, I estimate the discrete-time hazard model with two-dimensional clustering (cluster the observations by firms and also by size) and find a robust effect of excessive acquisitiveness on firm failure hazard.[21]

2.5.5 Can the Deal Characteristics Discriminate between the Failed and Non-Failed Sample?

The focal point of the bidders and the target firms' interactions revolve around the specificity of the transaction in hand. Thus, one possible explanation for why excessively acquisitive firms end up failing more often than others could be that excessively acquisitive firms make deals that are inherently inferior along some characteristics relative to their conservative counterparts.[22] Table 2.8 presents two classes of statistics for failed and non-failed firms in my sample. Panel-A presents the class of statistics involving deal size and execution for which I can test the statistical significance of the estimates whereas panel-B presents descriptive statistics generated from dummy variables involving various specificities of the deal for which no test of significance is available.

In panel-A, the average deal size is US$ 41.37 million and the median is about US$ 7.93 million for the failed sample while the average and median are US$ 225.99 million and US$ 24.42 million, respectively, for the non-failed sample, which reveals the positive skewness of the deal-size distribution. Bidders who do not fail in my sample take on significantly larger deals than the firms that eventually fail and exit the sample through various routes. However, once I normalize the deal value with the book and market value of assets as well as the market value of equity, the regularity is not quite straightforward; in fact, it reverses in all cases, meaning that relative to their size the failed sample ends up making larger deals than the non-failed sample. Panel-A also shows that the average execution delay after the announcement is 46.47 days, and that the median delay is 0 days for the failed sample whereas these are 66.23 days and 12 days, respectively, for the non-failed sample. The failed firms in our sample take significantly less time to complete the deal than their non-failed counterparts.

Panel-B of table 2.8 details some salient features of the transactions involving the bidding

[21] If the market capitalization of the firm is in the 25th percentile, I classify the firm as small cap; if the market capitalization is between the 25th and 75th percentile, I classify the firm as medium cap; and if the market capitalization of the firm is more than the 75th percentile, I classify the firm as large cap.

[22] In all my hazard regressions, I control for deal-structure dummy variables that should suffice to address this concern. Nonetheless, I discuss some salient features of deal characteristics that are attributable to varying degrees of managerial acquisitiveness.

firms in my sample. In the table, I do not observe any significant difference in the likelihood of completing a bid between the failed and non-failed sample firms. It shows that 70.79% of total bids were eventually completed by the failed sample while 70.50% of total bids were eventually completed by the non-failed sample. The failed sample, however, is 3.17% less likely to make M&A bids in a related industry than the non-failed sample. Furthermore, failed firms are more likely to finance a deal purely with stock whereas non-failed firms are more likely to finance a deal with pure cash. Moreover, the failed sample is less likely to do block purchases and bid for divested assets or divisions of target firms relative to their non-failed counterparts. The propensity to finance the deal through internal funds is lower for failed firms while the propensity to finance the deal through a stock swap is lower for non-failed firms.

Two caveats are in order. First, examining the testable statistics in panel-A does seem to reveal some regularities although not universal about the acquisitiveness and failure hazard of bidding firms in the sense that failed firms take on larger bids relative to their size and also complete bids at a faster rate compared to their non-failed counterparts. Second, there also seem to be some regularities in the deal specificities of the non-failed and failed sample that might shed light on the failure hazard of the sample firms, but these are not statistically testable statistics. Thus, one needs to delve beyond the deal characteristics into the evolution of firms' debt and assets structure to better understand the question of why the use of a particular investment technology precipitates a corporate debacle.

2.6 Excessive Acquisitiveness and Corporate Financing Policies

In order to describe the evolution of debt and assets structure, I divide the firms that make exactly 3 bids (which is also the median number of bids by firms in my sample) into (i) the failed and non-failed sample and, (ii) the excessively acquisitive and non-excessively acquisitive sample.[23] The left panel of Table 2.9 presents the evolution of differential assets and debt structures between the failed (F) and non-failed (NF) samples at the fiscal quarter right before the first acquisition bid and the fiscal quarter right after the last acquisition bid (in this case the third acquisition bid). The right panel of Table 2.9 presents the evolution of differential assets and debt structures between the excessively acquisitive (X) and the non-excessively acquisitive (NX) samples at the fiscal quarter right before the first acquisition bid and the fiscal quarter right after the last acquisition bid (in

[23] The results are even stronger if I use firms with more than 3 bids.

this case the third acquisition bid).

In each panel, column (1) reports the differences in the sample median before the firm becomes active in M&A denoted as $\left(Z_{1,F} - Z_{1,NF}\right)$, where $Z_{1,F}$ is the median assets and debt characteristics of the failed sample in the fiscal quarter right before the first bid, and $Z_{1,NF}$ is the median assets and debt characteristics of the non-failed sample in the fiscal quarter right before the first bid.[24] Column (2) reports the differences in the sample median after the firm becomes inactive in M&A denoted as $\left(Z_{3,F} - Z_{3,NF}\right)$, where $Z_{3,F}$ is the median assets and debt characteristics of the failed sample in the fiscal quarter right after the last bid, and $Z_{3,NF}$ is the median assets and debt characteristics of the non-failed sample in the fiscal quarter right after the last bid. Column (3) reports the difference-in-difference estimates between columns (2) and (1) denoted as $\left(\left(Z_{3,F} - Z_{3,NF}\right) - \left(Z_{1,F} - Z_{1,NF}\right)\right)$, which can also be expressed as $\left(\left(Z_{3,F} - Z_{1,F}\right) - \left(Z_{3,NF} - Z_{1,NF}\right)\right)$. It portrays the relative changes in assets and debt structure during the periods when the firms were active in M&A. And finally, column (5) reports the relative changes in percentage from column (1) to column (2) calculated as $\frac{\left(Z_{3,F}-Z_{3,NF}\right)-\left(Z_{1,F}-Z_{1,NF}\right)}{\left|Z_{1,F}-Z_{1,NF}\right|} \times 100$.

Column (3), in the left panel of Table 2.9, shows that between the periods of first and last bids (inclusive), all performance measures decline for the failed sample relative to the non-failed sample with the logarithm of market value falling by almost 33%, net profit margin (Net Income/Total Assets) falling by 175%, and growth opportunity (Market-to-Book) falling by 127%. At the same time, both the market and book leverage of the failed sample sky rocket with immediate debt obligations (Short-term debts/Total Liabilities) increasing by 158.33% while the immediate asset liquidity (Cash/Total Assets) falling by 125% compared to the non-failed sample. Furthermore, the cash-flow volatility of the failed sample increases by 48.57% compared to the non-failed sample between these periods. In short, the failed sample fares worse in operating performance, takes on a higher leverage with an increased amount of debt maturing in the immediate future but with decreased liquid assets at their disposal to pay off immediate debt obligations. This portrays a classic picture of debt maturity and an asset-liquidity mismatch for the failed sample compared to the non-failed sample.

Column (3), in the right panel of Table 2.9 shows a similar picture for the excessively acquisitive

[24] For the excessively acquisitive and non-excessively acquisitive sample in panel-B the corresponding differences are $\left(Z_{1,X} - Z_{1,NX}\right)$, where $Z_{1,X}$ is the median assets and debt characteristics of the excessively acquisitive sample in the fiscal quarter right before the first bid and $Z_{1,NX}$ is the median assets and debt characteristics of the non-excessively acquisitive sample in the fiscal quarter right before the first bid.

firms compared to their relatively non-excessive counterparts. It shows that between the periods of first and last bids (inclusive), the logarithm of market value falls by 29%, net profit margin (Net Income/Total Assets) falls by 150%, gross profit margin (EBITDA/Total Assets) falls by 86%, and growth opportunity (Market-to-Book) falls by 120% for the excessively acquisitive sample relative to the non-excessively acquisitive sample. At the same time, both the market and book leverage shoot-up by 177% and 288%, respectively, with the bulk of the increase due to higher short-term debt, which increases by 76%. To finance the higher leverage, the relative asset liquidity (Current Assets/Current Liabilities) actually shrinks by 259%. Quite evidently, this looks similar to the assets and debt structure of the failed sample relative to the non-failed sample.

The set of statistics presented here clearly illustrates the fact that the excessively acquisitive sample, similar to the failed sample, during the periods of M&A activities gathered certain asset characteristics that decimate the healthy balance between operating performance, debt maturity, asset liquidity, and cash-flow volatility. When operating performance declines, short-term debt shoots up while liquid assets in hand to finance these immediate debt obligations dry out; it becomes a deadly recipe for failure since the firm suffers from both economic and financial distress.

2.6.1 Excessive Acquisitiveness and Corporate Default

The formidable combination of declining operating performance and imbalance in corporate assets and debt structure, augured by the excessive use of M&A investment technology, may become the precursor of financial distress for firms in my sample. To test this proposition, I identify firms that defaulted on their debt obligations before exiting the sample. From the Default Risk Services (DRS) database by Moody's, the SDC Corporate restructuring database, and the LoPuki's Bankruptcy Research Database (BRD), I could clearly identify 603 default events involving 578 firms in my sample for the periods of 1980 to 2006. Of those defaulted firms, 420 (73%) firms eventually exit the sample while the rest 158 (27%) firms remain active. Of the exited firms, 46% exit through bankruptcy/liquidation, 16% exit through acquisition, and the rest 38% exit for other reasons such as leverage buy out, management buy out, or dropping off the exchange.

I use the discrete-time hazard model discussed earlier to estimate the default hazard under alternative specifications incorporating Altman's (1968), Zmijewski's (1984), and Shumway's (2001) independent variables in their respective bankruptcy prediction models. Altman's variables are described extensively in Altman (1968, 2000) and Mackie-Mason (1990). Using those variables, I construct Altman's $ZSCORE$ as:

$$ZSCORE = \frac{(3.3 \times EBIT + Sales + 1.4 \times Retained\ Earning + 1.2 \times Working\ Capital)}{Total\ Assets} \quad (2.6)$$

Zmijewski's variables include the ratio of net income to total assets, the ratio of total liabilities to total assets, and the ratio of current assets to current liabilities. Shumway (2001) criticizes Altman (1968) and Zmijewski (1984) and offers market-driven predictors of bankruptcy. Shumway's variables include a logarithm of market value, firm's past excess returns, and the idiosyncratic standard deviation of each firm's stock returns. To measure a firms' past excess return, I take the value-weighted CRSP NYSE/AMEX index return as a benchmark and subtract the index return from the monthly stock return to calculate the firm's excess return. The final, perhaps the most important, market-driven variable Shumway (2001) uses is the idiosyncratic standard deviation of a firm's stock returns, denoted as *sigma* (σ) in this paper. Sumway (2001) argues that *sigma* is strongly related to bankruptcy, both statistically and logically. If a firm has more variable cash flows (and hence more variable stock returns), then the firm ought to have a higher probability of bankruptcy. *Sigma* may also measure something like operating leverage. To calculate *sigma* for each firm i in quarter t, I regress each stock's daily returns on the value-weighted NYSE/AMEX index returns for the same quarter. We then calculate *sigma* as the standard deviation of the residuals of this regression. To avoid outliers, all independent variables are truncated at the 99th and 1st percentile values in the same manner as all other independent variables.

Table 2.10 reports the estimated coefficients from the discrete time hazard model of corporate default. The dependent variable is a dichotomous variable that equals 1 for the quarter in which the firm defaults or files for bankruptcy and 0 otherwise. All explanatory variables are lagged by one period, and in all regression models I include industry-fixed effects, year-fixed effects, various deal-structure dummy variables and correct for clustering of observations and distress-related events, i.e., default/bankruptcy, by firms. I also use robust standard errors to test the significance of the estimated parameters. I report the estimates in logarithm-of-odds ratios for all explanatory variables and also report the marginal effects for my key explanatory variable.

It shows that irrespective of bankruptcy prediction models, excessive use of M&A measure increases the default risk of firms in my sample. The estimates from the hazard regression also show that the Gompers, Ishii, and Metrick (2003) governance score, as proxy for firm quality, has little or no predictive power irrespective of bankruptcy prediction model specifications. Results also show that Altman's (2000) $ZSCORE$ decreases default risk; the current ratio (Current Assets/Current Liabilities) attenuates default hazard in Zmijewski's (1984) model while the idiosyncratic stock-price volatility from Shumway's (2001) model always increases the default risk in my sample. These finding are consistent with the extant literature on default and bankruptcy prediction. More importantly, I show that the inclusion of an excessive-acquisitiveness measure among the set of covariates that are widely used in the default and bankruptcy prediction models reduces the forecast errors of the existing models and hence improves the model predictive power.

To assess the economic significance, I estimate the marginal effects of the excessive acquisitiveness measure and find that at the mean, a 1% increase in excessive acquisitiveness increases the conditional default risk by .19% (conditional on other exogenous variables evaluated at the mean) calculated using $\frac{\partial Y}{\partial X}.\frac{\bar{X}}{\bar{Y}}$, where $\frac{\partial Y}{\partial X}$ is the marginal effect at the mean, and $\bar{Y}$ and $\bar{X}$ are the mean of the predicted conditional default probability and the excessive acquisitiveness measure, respectively. The estimated marginal effects are statistically significant for the excessive acquisitiveness measure across all bankruptcy prediction models. This elasticity of the conditional default probability with respect to the excessive-acquisitiveness measure translates into up to a 34% increase in the conditional default risk (conditional on other exogenous variables evaluated at the mean) with a 1 standard deviation increase around the mean of the excessive acquisitiveness measure.

2.7 Conclusion

To explain the recent spectacular debacle of the Wall Street investment bank giant Bear Stearns, CEO Alan Schwartz blamed the market tsunami that he and others in his firm did not see coming.[25] Empirical evidence in corporate finance also shows that managers are more likely to blame external factors than themselves for the failure of their firms [John, Lang, and Netter (1992)] while authors like Lovallo and Kahneman (2003) argue that the large number of failures in the modern corporate landscape cannot be explained simply by external economic disturbances; instead, the managers who suffer from behavioral biases in their decision makings are partly to blame.

In this paper, I try to relate managerial investment and financing policy distortions to their firms' failure hazard with a very specialized identification strategy. I focus on managerial mergers and acquisitions (M&A) investment decisions which have uncertain value implications for the

[25] Lost Opportunities Haunt Final Days of Bear Stearns, The Wall Street Journal, May 27, 2008.

acquiring firms; yet, M&A are one of the most widely-used investment tools by managers pursuing aggressive corporate-growth strategies. I show that M&A investment technology, on average, reduces acquiring firms' failure risk compared to non-acquiring firms. In a world where agency problems within the firms and market frictions are on average netted out, access to M&A investment technology helps acquiring firms to move towards their optimal assets structure and exploit growth opportunities, which in turn translates into higher survival probabilities. However, when firms in the acquiring sample use M&A excessively relative to the typical acquiring firm in their industry, the conditional failure risk of aggressive acquirers increases not only relative to the non-acquiring firms but also relative to the acquiring firms that use this technology relatively conservatively.

Furthermore, conditioning the failure outcomes on managerial excessive acquisitiveness also shows that there are not enough variations left in the explained variations by the empirical model that could be attributed to exogenous economic disturbances. This seemingly sub-optimal managerial behavior also translates into a distorted financing policy for the firm, which in turn increases the likelihood of corporate default. These results are robust to various alternative specifications and do not seem to be driven by endogeneity and reverse causality.

Empirical findings in this paper suggest that the traditional line of argument, "Blame It on the Market," may not be well grounded, and firms need to carefully examine their investment and financing policies in good times to cushion against systematic shocks in bad times. However, I do not claim to have fully resolved the debate about why firms fail, and who is to blame for failure. To understand the yet unresolved question of whether it is bad luck or bad policy that causes a firm to fail, I take a very narrow and specialized approach by focusing on a particular investment decision and the resulting financing policy distortion. This strategy helps us understand the value implication of M&A while shedding light on the debate of whether managers of failed businesses are villains or scapegoats. It is a step forward towards understanding the complex interplay of forces that bring down a firm from the zenith of miracle to the nadir of debacle.

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Appendices

.1 M&A and Corporate Failure: A Quasi-Natural Experiment

Two firms in my quasi-natural experiment are WorldCom and Verizon Communication. WorldCom began operation as Long Distance Discount Services, Inc. (LDDS) in Hattiesburg, Mississippi in 1983. Under CEO Bernard Ebbers the company went through an explosive growth phase in the 1990s primarily through M&A (more than 70 M&A). When the Telecom industry entered into a downturn in the latter parts of the 1990s, WorldCom could not sustain growth through M&A, and various fraud and accounting scandals cropped up. Finally after more than 70 M&A, on July 21, 2002, WorldCom filed for Chapter 11 bankruptcy protection in the largest such filing in United States history at the time (since overtaken by the collapse of Lehman Brothers in September 2008). When it emerged from bankruptcy, previous bondholders ended up being paid 35.7 cents on the dollar, in bonds and stock in the new MCI company and the previous stockholders' stock was valueless.

Verizon Communication, on the other hand, was founded in 1983 (exactly at the same time as WorldCom) as the Bell Atlantic Corporation by the AT&T Corporation as one of seven Baby Bells that were formed due to an anti-trust judgment against them. It then inherited one of the seven Bell Operating Companies from American Telephone & Telegraph Company (later known as AT&T Corp.) following its breakup. Verizon pursued a growth strategy through M&A but it was a lot more conservative than WorldCom. Today, it is the second largest Telecom company in the U.S. behind AT&T.

These two companies were in the same industry and faced similar systematic shocks and economic disturbances in their exogenous environments. WorldCom took an aggressive approach to growth using M&A while Verizon took a conservative approach, and the ultimate survival outcomes are drastically different for these two companies - one destroyed massive value while the other created massive value.

.2 Construction of Exogenous Economic Disturbance Measures and the Instrumental Variable

Industry demand and supply shocks. For each of the Fama-French (1997) industries I calculate the total industry net sales from the quarterly COMPUSTAT data using item 2 as a proxy for industry demand. I also calculate the total industry costs of goods sold from the quarterly COM-

PUSTAT data using item 30 as a proxy for industry supply. I then decompose these series into trend and irregular components using the Hodrick-Prescott (H-P) filter. The H-P filter calculates the trend component by minimizing the following loss function:

$$\sum_{t=1}^{T}\left(X_t - \widetilde{X}_t\right)^2 + \lambda \sum_{t=3}^{T}\left\{\left(X_t - \widetilde{X}_{t-1}\right) - \left(X_{t-1} - \widetilde{X}_{t-2}\right)\right\}^2 \tag{.7}$$

where X_t is the actual series and $\widetilde{X}_t$ is the trend component of the series. The first term punishes the (squared) deviations of the actual series from the trend; the second term punishes the (squared) acceleration (change of change) of the trend level. The method thus involves a trade-off between tracking the original series and the smoothness of the trend level: $\lambda = \infty$ generates a linear trend, while $\lambda = 0$ generates a trend that matches the original series. Ravn and Uhlig (2002) have shown that the smoothing parameter should vary by the fourth power of the frequency observation ratios, so that for annual data a smoothing parameter of 6.25 and for monthly data a smoothing parameter of 129,600 are recommended, while for quarterly data a smoothing parameter 1600 is commonly used. After decomposing the actual series into trend and irregular components, I calculate the series' instability by estimating the acceleration (change of change) of the irregular component. Thus, the instabilities or shocks in the industry demand and the industry supply series are given by:

$$\left\{\left(X_t - \widetilde{X}_t\right) - \left(X_{t-1} - \widetilde{X}_{t-1}\right)\right\} - \left\{\left(X_{t-1} - \widetilde{X}_{t-1}\right) - \left(X_{t-2} - \widetilde{X}_{t-2}\right)\right\} \tag{.8}$$

Industry technology shocks. I collect information about all patents for the period of 1963-2002 from the NBER patent database and convert the assigned technology class of each of these patents into the international patent class using the methodology developed by Silverman (2002). From the international patent class I convert them back into 1987 Standard Industry Classifications (SIC) and assign the patents by grant year to each of our 49 Fama and French (1997) industries. I then apply the H-P filter on the total number of patents granted each year in each of the Fama-French industries to calculate our industry level technology shocks variable.

Industry regulatory shocks. I use major deregulatory initiatives during the sample period as proxies for industry regulatory shocks. Deregulatory events and dates for my sample industries are collected from Harford (2005) for the period of 1980-1996 and from the Wikipedia for the rest of the sample period.

Aggregate demand and supply shocks. I use the quarterly real GDP data from the Federal Reserve Bank of St. Louis as a proxy for aggregate demand and the real price of crude petroleum in the U.S. from the U.S. Energy Information Administration as a proxy for aggregate supply. Utilizing the H-P filter, I then calculate the aggregate demand and supply shocks series.

Capital-market instability and stock market momentum. To construct measures of capital-market instability, I apply the H-P filter on the Dow Jones Industrial Average and the bank prime lending rate. To capture the momentum in the aggregate equity market, I apply the H-P filter on the S&P 500 index and use the smoothed trend portion of the series as my proxy for momentum in the aggregate equity market.

Industry merger momentum. A plethora of evidence in corporate finance shows that mergers and takeovers come in waves. Identification of restructuring waves, however, has been difficult although it has been widely recognized in the literature that there were three distinct waves respectively in the 1980s, 1990s and 2000s [Harford (2005) and Andrade, Mitchell and Stafford (2001)]. Following Mitchell and Mulherin (1996), Harford (2005) defines a wave as the highest clustering of M&A bids in any of the adjacent 24 months in each of the distinct merger wave decades that conforms to a simulated empirical distribution. The 24-months length of a wave is rather arbitrary. I develop a distinct method of wave identification where the wave length is data driven rather than arbitrary. For each of the Fama-French industries, I decompose the monthly M&A bids series into trend, seasonal and idiosyncratic components using X-12-ARIMA, a seasonal adjustment software produced and maintained by the U.S. Census Bureau. It is used for all official seasonal adjustments at the U.S. Census Bureau. I use X-12-ARIMA instead of the H-P filter because there is evidence that the H-P filter is less accurate in higher frequency data. After extracting the idiosyncratic and seasonal components from the monthly M&A bids series, I calculate the potential merger momentum as the period with successive $\left(\widetilde{X}_{jdt} - \widetilde{X}_{jdt-1}\right) > 0$, where $\widetilde{X}_{jdt}$ is the X-12-ARIMA smoothed component of the monthly bids series in industry j and wave decade d and calender month t. Out of those potential waves in industry j and wave decade d, I classify the adjacent $\left(\widetilde{X}_{jdt} - \widetilde{X}_{jdt-1}\right) > 0$ period as a wave if it has the maximum clustering of bids among all potential waves in the industry j and wave decade d, and the maximum bids clustering must also be unique. For robustness, I also do all my estimations using Harford (2005) and the Mitchell and Mulherin (1996) definition of wave.

Fig. 2.1: **Aggregate M&A Activities and Business Bankruptcies in the U.S.**

This graph shows quarterly aggregate M&A activities and business bankruptcies in the U.S. from 1991 to 2006. To generate this figure I normalize the total number of M&A bids and business bankruptcies in each quarter by the total number of business establishments with more than 100 employees so that both series become comparable with each other. The first panel of the figure shows unadjusted series while the second panel shows the H-P filtered series. In both panels, aggregate M&A activities and business bankruptcies are negatively correlated and the correlation is statistically significant at the 10% level.

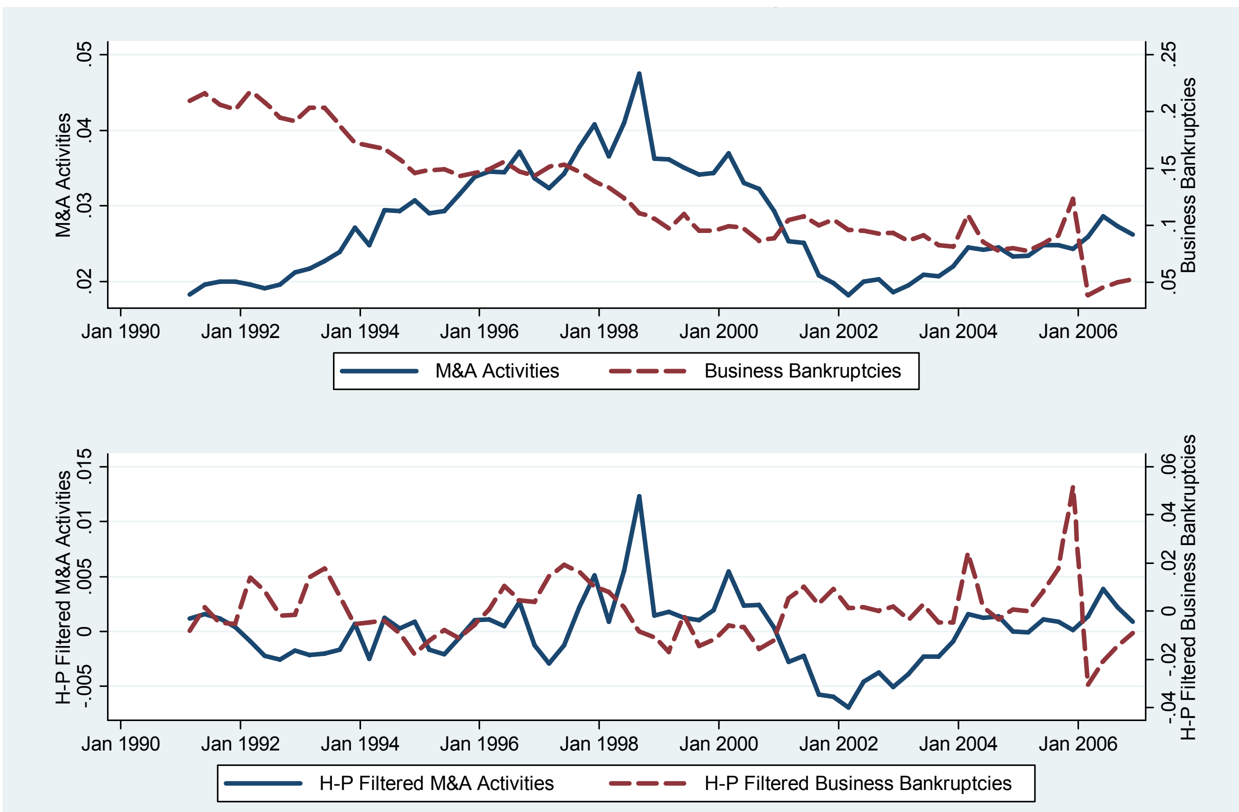


Fig. 2.2: **Managerial M&A Actions and Firm Value**

This figure depicts the framework of analysis linking managerial M&A activities with the firm value. It shows that at time t_0 nature exogenously determines whether a firm is going to be an acquiring firm or a non-acquiring firm, and at any given time t after t_0 the value of a non-acquiring firm is given by some exogenous process. The value of an acquiring firm depends on the nature of the acquisitions the firm makes. When a rational bid becomes an acquisition, the firm moves closer to its optimal assets structure, and on average firm value (V) increases, i.e., $E(V_{t+1}) > V_t$. When a rational bid fails to become an acquisition, the firm fails to move closer to the optimal assets structure and thus $E(V_{t+1}) < V_t$. When an irrational bid becomes an acquisition, corporate investment and financial policies become distorted with positive adjustment costs of unnecessary acquisition and thus $E(V_{t+1}) < V_t$. Finally, when an irrational bid fails to become an acquisition, $E(V_{t+1}) = V_t$ if there are no costs associated with the bid or $E(V_{t+1}) < V_t$ if there are some costs associated with the bid.

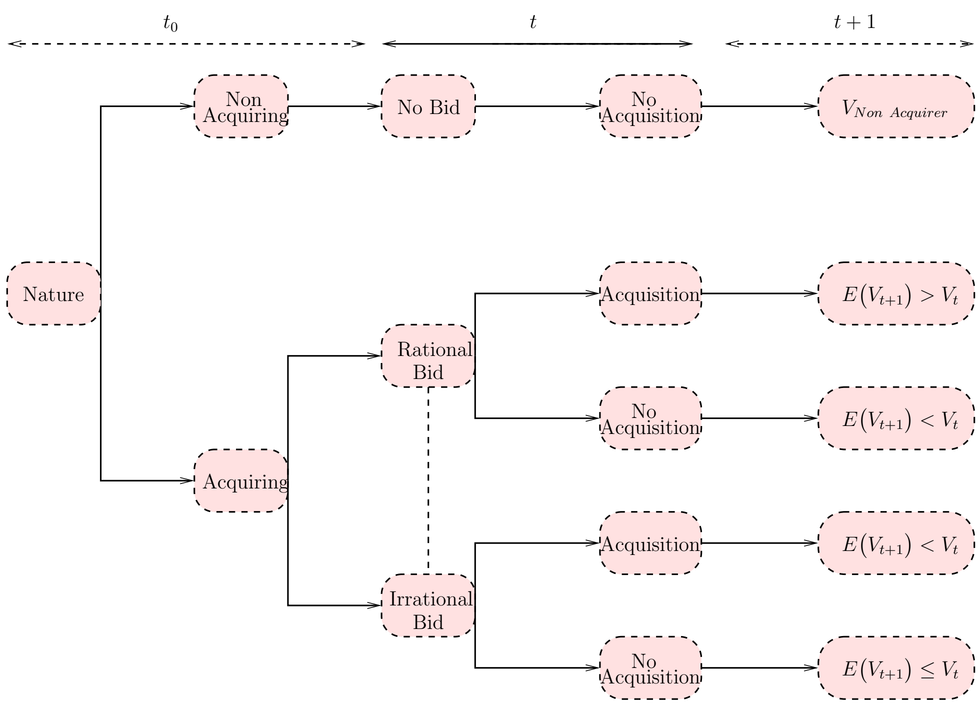


Fig. 2.3: **Excessive Acquisitiveness and Firm Size (Total Assets) Growth**

This figure compares the cumulative size (total assets) growth of the median excessively acquisitive firm with that of the median conservatively acquisitive firm. For the set of firms that make n number of M&A bids, I calculate the size of the median excessively acquisitive firm and the size of the median conservatively acquisitive firm. Cumulative size growth from the first M&A until the n^{th} M&A is defined to be: $\frac{Total\ Assets_n}{Total\ Assets_1}$. The figure shows that, from the first M&A until the 9^{th} M&A, a typical conservatively acquisitive firm grows 300% of its initial size while a typical excessively acquisitive firm grows 900% of its initial size. In other words, excessively acquisitive firms, on average, grow three times faster than conservatively acquisitive firms.

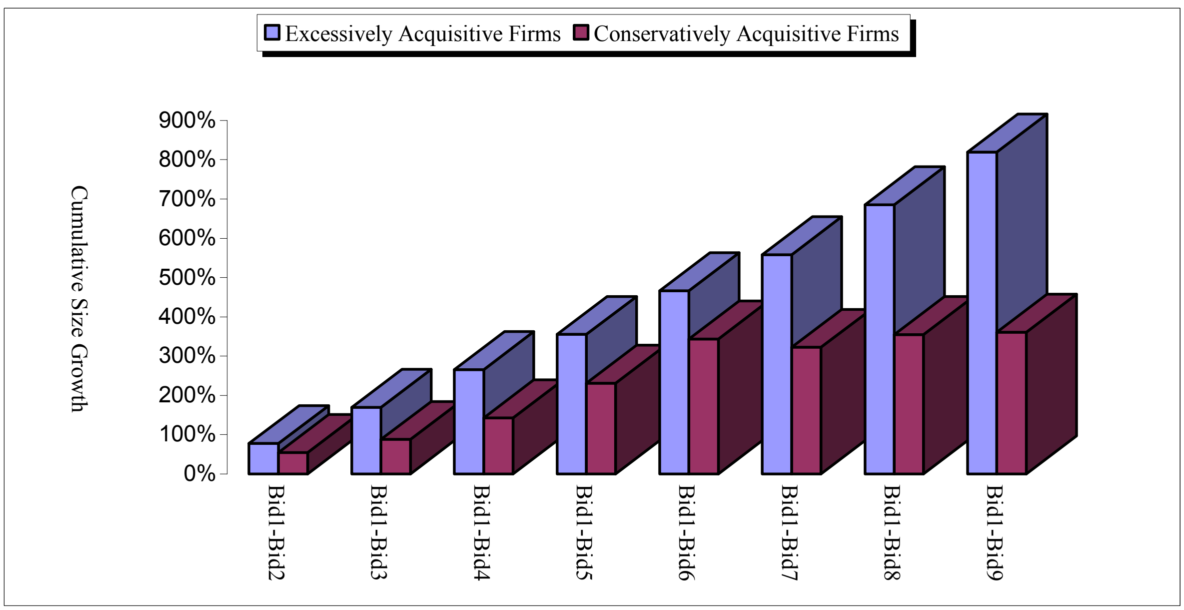
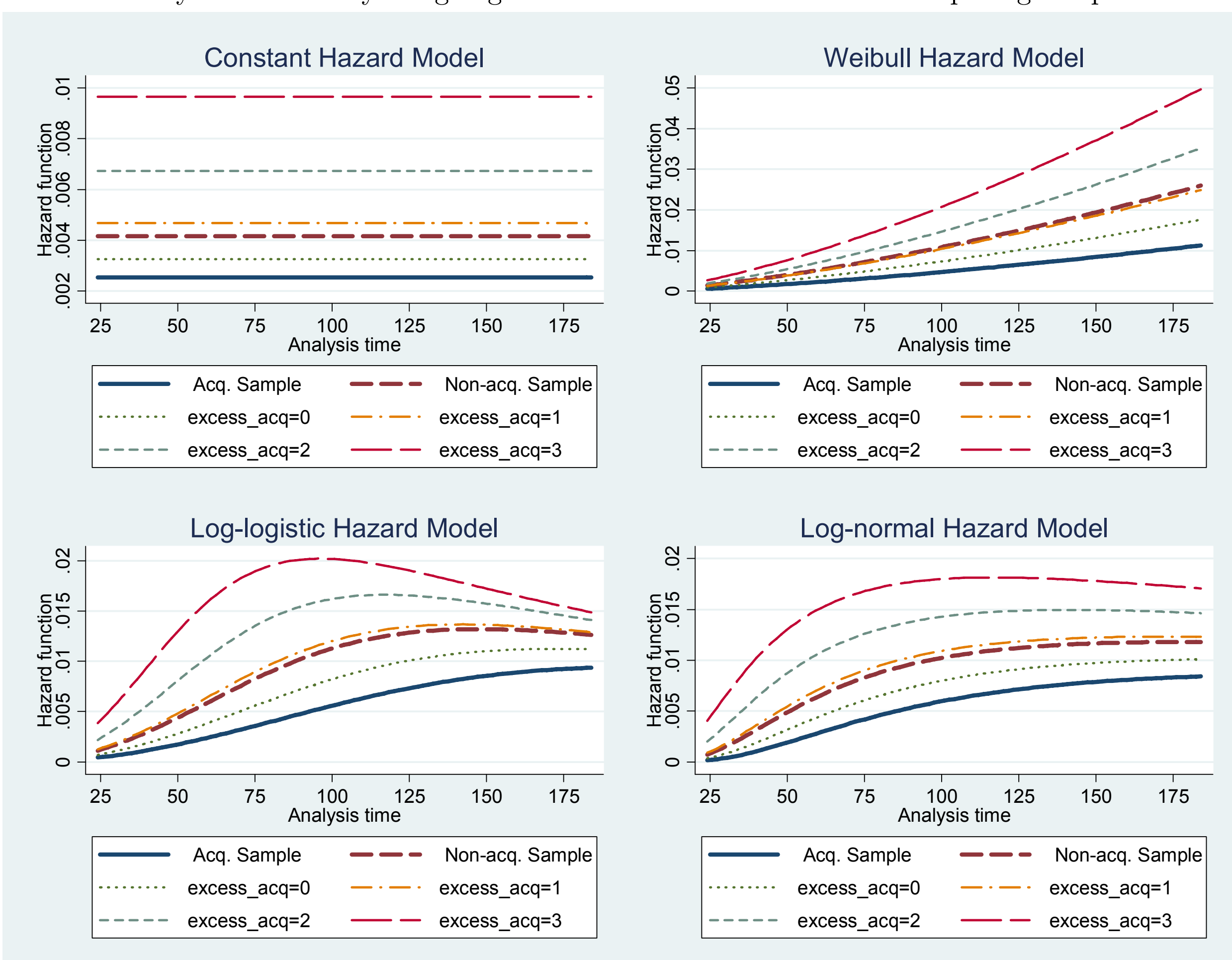


Fig. 2.4: **Excessive Acquisitiveness and Shift in the Failure-Risk Profiles**

This graph compares the failure risk profiles of the acquiring and the non-acquiring sample under various baseline hazard model specifications. To generate the graph, I construct a survival data set where each observation is one firm. Analysis time is the age of the firm since incorporation. I estimate the hazard (failure risk) function conditional on the baseline hazard, a dummy variable indicating whether the firm is an acquiring firm, and the excessive acquisitiveness measure of the firm (for non-acquiring sample excessive acquisitiveness is obviously 0). In this graph 'excess_acq' refers to the number of acquisitions a representative acquiring firm made over and above the industry median. It shows that acquiring firms, on average, have a lower failure-risk profile than the non-acquiring firms. However, the failure-risk profile of the acquiring sample changes as the firms in the acquiring sample become more and more aggressively acquisitive. From the graph, it is obvious that, on average, the more aggressive the acquiring sample becomes in their use of M&A, the more likely it is that they are going to fail more often than the non-acquiring sample.



Tab. 2.1: **The Sample Firm Characteristics**

This table reports the differential firm characteristics of the acquiring and the non-acquiring firms in panel-A. It also reports the firm as well as deal characteristics of the bidding and the target firms in panel-B at the time of the bid announcement. Among the size and performance measures, total assets is defined to be the total book value of firms assets at the end of the fiscal quarter in which firm announces the bid. Market value is defined to be the sum of market value of equity and the book value of debt. Net income is earnings after all interest and tax payment while EBITDA is earnings before interest, tax, depreciation and amortization. The market-to-book ratio is calculated by dividing the market value of a firm's assets with its book value. Among the leverage and liquidity measures, total liabilities measure all outstanding liabilities owed to outsiders other than to the shareholders of the firm. Book leverage is defined to be the ratio of a firm's total outstanding short-term and long-term debt to book value of total assets whereas market leverage is defined to be the ratio of total outstanding short-term and long-term debt to the market value of the firm's total assets. Cash is defined to be the value of cash and other cash equivalent marketable securities, current assets are cash plus account receivables, current liabilities are short-term debt plus accounts payable, short-term debts are debt obligations maturing within one year while long-term debts are debt obligations maturing in two years or more. PPE is defined as the net book value of the firm's Properties, Plants, and Equipment. And finally, cumulative abnormal return is calculated against a market model around a 3-day event window period consisting of the announcement date, one trading day prior to the announcement date and one trading day after the announcement date. In the table, "*" denotes significance at the 10% level; "**" denotes significance at the 5% level; "***" denotes significance at the 1% level.

Panel-A: Comparing the Acquiring and the Non-acquiring Sample

	Acquiring Sample				Non-acquisring Sample				Difference			
	Mean (1)	Median (2)	N	Num. Firms	Mean (3)	Median (4)	N	Num. Firms	(1-3)	Absolute t-stat	(2-4)	Absolute t-stat
Size and Performance Measures:												
Log (Tot. Assets)	5.27	5.19	519395	10635	3.79	3.6	336160	12868	1.48***	34.14	1.58***	220.41
Log (Mkt. Value of Assets)	5.76	5.66	482903	10623	4.14	3.88	234873	10596	1.63***	41.92	1.78***	251.55
Net Income/Tot. Assets	-0.01	0.01	516861	10635	-0.5	0	330533	12815	0.49***	4.52	0.01***	130.03
EBITDA/Tot. Assets	0.01	0.03	437606	10272	-0.36	0.02	279834	12033	0.37***	3.78	0.01***	113.80
Market-to-Book Ratio	2.11	1.28	482798	10623	19.43	1.31	233867	10594	-17.32***	4.00	-0.03***	14.03
Leverage and Liquidity Measures:												
Tot. Liab./Tot. Assets	0.74	0.56	518565	10616	3.28	0.61	335654	12846	-2.54***	4.49	-0.05***	67.30
Book Leverage	0.74	0.56	518979	10635	3.39	0.61	335572	12866	-2.65***	4.12	-0.05***	67.63
Market Leverage	0.44	0.41	482903	10623	0.42	0.39	234873	10596	0.01***	3.55	0.02***	13.21
Cash/Tot. Assets	0.16	0.07	429807	8891	0.17	0.06	291285	11565	-0.02***	6.13	0.01***	22.56
Cash/Curr. Liab.	1.57	0.28	429980	8891	3.06	0.2	292597	11568	-1.49***	8.76	0.08***	48.87
St. Debt/Tot. Liab.	0.11	0.05	481029	10588	0.15	0.06	316417	12737	-0.04***	22.54	-0.02***	55.00
Lt. Debts/Tot. Liab.	0.3	0.26	513200	10614	0.29	0.22	333412	12837	0.01***	2.92	0.04***	29.53
Fix. Assets/Tot. Assets	0.27	0.2	504699	10507	0.32	0.22	329718	12787	-0.04***	10.38	-0.02***	24.55

Panel-B: Comparing the Bidding Firms and the Target Firms Sample

	Bidding Firms				Target Firms				Difference			
	Mean (1)	Median (2)	N	Num. Firms	Mean (3)	Median (4)	N	Num. Firms	(1-3)	Absolute t-stat	(2-4)	Absolute t-stat
Size and Performance Measures:												
Log (Tot. Assets)	6.29	6.22	61289	10374	5.83	5.74	2962	1782	0.45***	5.08	0.48***	9.22
Log (Mkt. Value of Assets)	6.76	6.69	60510	10248	6.23	6.04	2899	1747	0.53***	5.60	0.65***	15.26
Net Income/Tot. Assets	0.00	0.01	61131	10359	-0.01	0.00	2928	1780	0.02***	5.04	0.01***	33.23
EBITDA/Tot. Assets	0.03	0.03	51641	9403	0.01	0.02	2485	1540	0.01***	5.54	0.01***	15.31
Market-to-Book	1.97	1.40	60510	10248	1.83	1.22	2899	1747	0.14***	2.18	0.18***	14.51
Leverage and Liquidity Measures:												
Tot. Liab./Tot. Assets	0.56	0.56	61221	10352	0.59	0.59	2953	1774	-0.03***	3.05	-0.03***	3.63
Book Leverage	0.56	0.56	61255	10368	0.59	0.59	2951	1771	-0.03***	3.02	-0.03***	3.49
Market Leverage	0.41	0.38	60510	10248	0.47	0.46	2899	1747	-0.05***	4.98	-0.08***	8.63
Cash/Tot. Assets	0.13	0.06	60960	10329	0.14	0.06	2933	1762	-0.01***	2.17	-0.00***	2.02
Cash/Curr. Liab.	1.10	0.30	47860	8445	1.29	0.29	2388	1309	-0.19**	1.71	0.00	0.12
Curr. Assets/Curr. Liab.	2.67	1.93	47661	8367	2.79	2.01	2382	1303	-0.13	1.12	-0.09***	2.55
St. Debts/Tot. Liab.	0.09	0.04	56076	9998	0.10	0.05	2792	1669	-0.01	1.46	-0.01***	6.28
Lt. Debts/Tot. Liab.	0.33	0.29	60683	10321	0.30	0.27	2926	1754	0.03***	2.55	0.02***	2.67
PPE/Tot. Assets	0.24	0.18	58500	10137	0.27	0.23	2884	1725	-0.03***	2.88	-0.06***	7.85
Deal Characteristics:												
Tot. Deal Announcements	6.00	3.00	10779	10779	1.67	1.00	2124	2124	4.33***	7.04	2.00***	10.12
Num. of qtr. survived	47.63	39.00	10779	10779	36.16	30.00	3582	2124	11.47***	7.06	9.00***	21.28
Cumulative Abnormal Return	0.01	0.00	63613	10779	0.14	0.10	2124	2124	-0.13***	22.30	-0.09***	38.45

Tab. 2.2: **Managerial Acquisitiveness and Corporate Failure**

This table reports the estimates from a discrete-time hazard model linking managerial M&A actions and corporate failure. The dependent variable is 1 for the last fiscal quarter in which a firm fails. Otherwise it is 0. Definitions of various firm characteristics are the same as in the previous table. Firm age is defined as the total number of quarters since incorporation. Construction of the industry and aggregate economic disturbance variables are explained in detail in the data appendix of the paper. 'Cumulative Bids' is defined to be the total number of M&A bids the acquiring firm made until period t, and 'Cumulative Acquisitiveness' is defined to be the total number of acquisitions the acquiring firm made until period t. All explanatory variables are lagged by one period. Robust z statistics are given in brackets and "*" denotes significance at the 10% level; "**" denotes significance at the 5% level; "***" denotes significance at the 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log (Total Assets)	-0.1662***	-0.1646***	-0.1738***	-0.1710***	-0.1574***	-0.1574***	-0.1884***	-0.1865***	-0.1963***	-0.1932***	-0.1787***	-0.1787***
	[8.12]	[8.07]	[8.42]	[8.30]	[7.92]	[7.92]	[8.71]	[8.67]	[9.02]	[8.89]	[8.53]	[8.54]
Log (Age)	-1.7312***	-1.7229***	-1.6787***	-1.6787***	-1.7088***	-1.7085***	-1.8345***	-1.8267***	-1.7778***	-1.7801***	-1.8135***	-1.8134***
	[48.90]	[48.84]	[48.27]	[48.08]	[48.64]	[48.63]	[48.81]	[48.72]	[47.80]	[47.70]	[48.48]	[48.48]
Net Income/Tot. Assets	-0.0002	-0.0002	-0.0001	-0.0001	-0.0003	-0.0003	0.0020	0.0020	0.0021	0.0021	0.0020	0.0020
	[0.11]	[0.12]	[0.05]	[0.07]	[0.16]	[0.16]	[1.37]	[1.36]	[1.43]	[1.41]	[1.30]	[1.30]
Tot. Liab./Tot. Assets	0.0109	0.0108	0.0110	0.0110	0.0106	0.0105	0.0084	0.0083	0.0084	0.0084	0.0081	0.0081
	[0.82]	[0.82]	[0.83]	[0.82]	[0.81]	[0.81]	[0.67]	[0.66]	[0.67]	[0.67]	[0.66]	[0.66]
Cash/Tot. Assets	-1.1787***	-1.1841***	-1.1303***	-1.1433***	-1.2096***	-1.2090***	-1.4314***	-1.4380***	-1.3770***	-1.3933***	-1.4663***	-1.4658***
	[13.26]	[13.34]	[12.64]	[12.79]	[13.76]	[13.75]	[14.16]	[14.25]	[13.56]	[13.73]	[14.65]	[14.64]
Lt. Debts/Tot. Assets	-0.5611***	-0.5605***	-0.5859***	-0.5835***	-0.5421***	-0.5420***	-0.5424***	-0.5412***	-0.5664***	-0.5637***	-0.5187***	-0.5185***
	[7.96]	[7.96]	[8.30]	[8.27]	[7.72]	[7.72]	[7.00]	[6.98]	[7.30]	[7.27]	[6.72]	[6.72]
PPE/Tot. Assets	0.1006	0.0992	0.1405*	0.1359*	0.0823	0.0816	0.0627	0.0610	0.1072	0.1011	0.0439	0.0432
	[1.24]	[1.23]	[1.73]	[1.67]	[1.02]	[1.02]	[0.71]	[0.69]	[1.21]	[1.14]	[0.50]	[0.49]
Market-to-Book	-0.0108	-0.0108	-0.0110	-0.0109	-0.0105	-0.0105	-0.0081	-0.0080	-0.0082	-0.0081	-0.0078	-0.0077
	[0.81]	[0.81]	[0.82]	[0.82]	[0.80]	[0.80]	[0.64]	[0.64]	[0.65]	[0.64]	[0.63]	[0.63]
Acquiring-Firm Dummy	-0.2722***	-0.2611***	-0.3608***	-0.3257***	-0.2343***	-0.2333***	-0.3705***	-0.3578***	-0.4662***	-0.4262***	-0.3284***	-0.3276***
	[8.62]	[8.33]	[11.16]	[10.17]	[7.59]	[7.56]	[10.55]	[10.29]	[13.09]	[12.07]	[9.62]	[9.60]
Cumulative Bids	0.0219***						0.0260***					
	[5.82]						[5.43]					
Cumulative Acquisitions		0.0227***						0.0266***				
		[5.17]						[4.93]				
Cumulative Bids/Sample Age			2.5930***						2.8430***			
			[12.49]						[12.74]			
Cumulative Acq./Sample Age				2.6230***						2.8413***		
				[10.53]						[10.58]		
Cumulative Bids/Firm Size					0.0036***						0.0032***	
					[3.22]						[3.27]	
Cumulative Acq./Firm Size						0.0039**						0.0037**
						[2.33]						[2.53]
Deregulation Dummy							-0.2059	-0.2060	-0.2153	-0.2156	-0.2000	-0.2003
							[1.36]	[1.36]	[1.42]	[1.42]	[1.32]	[1.32]
Ind. Demand Shock							0.0018***	0.0018***	0.0018***	0.0018***	0.0018***	0.0018***
							[10.00]	[9.99]	[9.98]	[9.97]	[9.94]	[9.95]
Ind. Supply Shock							-0.0003	-0.0003	-0.0003	-0.0003	-0.0002	-0.0002
							[0.77]	[0.76]	[0.77]	[0.77]	[0.70]	[0.71]
Ind. Tech. Shock							-0.0344	-0.0346	-0.0347	-0.0347	-0.0350	-0.0356
							[1.48]	[1.48]	[1.48]	[1.48]	[1.50]	[1.53]
Agg. Demand Shock							2.0647***	2.0653***	2.0664***	2.0673***	2.0718***	2.0720***
							[6.59]	[6.59]	[6.59]	[6.59]	[6.61]	[6.60]
Agg. Supply Shock							-2.9111	-2.9133	-2.8770	-2.8776	-2.9367	-2.9001
							[1.47]	[1.47]	[1.45]	[1.45]	[1.48]	[1.46]
Agg. Equity Mkt. Shock							-0.1853***	-0.1853***	-0.1843***	-0.1841***	-0.1856***	-0.1851***
							[5.47]	[5.47]	[5.43]	[5.42]	[5.48]	[5.46]
Agg. Debt Mkt. Shock							0.0056	0.0055	0.0057	0.0056	0.0055	0.0058
							[0.28]	[0.28]	[0.29]	[0.28]	[0.28]	[0.29]
Agg. Equity Mkt. Momentum							2.8631***	2.8705***	2.8448***	2.8562***	2.9114***	2.9090***
							[8.34]	[8.36]	[8.29]	[8.32]	[8.48]	[8.47]
Constant	3.5678***	3.5177***	3.3921***	3.3635***	3.4097***	3.4085***	-9.1490***	-9.2319***	-9.2616***	-9.3330***	-9.5273***	-9.5168***
	[9.58]	[9.46]	[9.21]	[9.12]	[9.20]	[9.20]	[5.56]	[5.61]	[5.63]	[5.68]	[5.79]	[5.78]
Deal-Structure Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	571769	571769	571769	571769	571769	571753	465434	465434	465434	465434	465434	465421
Num. of Firms	17821	17821	17821	17821	17821	17821	16201	16201	16201	16201	16201	16201
Pseudo-R^2	0.10	0.10	0.11	0.11	0.10	0.10	0.12	0.12	0.13	0.12	0.12	0.12
Wald-χ^2	6698.65	6677.97	6770.78	6718.81	6646.91	6636.23	7006.54	6989.17	7083.12	7024.89	6965.91	6956.62

Tab. 2.3: **Managerial Acquisitiveness and Corporate Failure: Economic Significance**

This table reports the marginal effects of the explanatory variables evaluated at the mean, and changes in probabilities of failures when the explanatory variables change from their minimum value to their maximum value and from 1/2 standard deviation below the mean to 1/2 standard deviation above the mean. All estimates are derived from a discrete-time hazard model linking managerial M&A actions and corporate failure. Definitions of various firm characteristics are the same as in the previous table. Firm age is defined to be the total number of quarters since incorporation. Construction of the industry and aggregate economic disturbance variables are explained in detail in the data appendix of the paper. 'Cumulative Bids' is defined to be the total number of M&A bids the acquiring firm made until period t, and 'Cumulative Acquisition' is defined to be the total number of acquisitions the acquiring firm made until period t. All explanatory variables are lagged by one period. In the table, "*" denotes significance at the 10% level; "**" denotes significance at the 5% level; "***" denotes significance at the 1% level.

	Changes in Probabilities for Failure When Explanatory Variables Change and Marginal Effects at the Mean											
	(1)			(2)			(3)			(4)		
	Min. to Max.	1 Std Around the Mean	Marginal Eff. at the Mean	Min. to Max.	1 Std Around the Mean	Marginal Eff. at the Mean	Min. to Max.	1 Std Around the Mean	Marginal Eff. at the Mean	Min. to Max.	1 Std Around the Mean	Marginal Eff. at the Mean
Log (Total Assets)	-0.0303	-0.0019	-0.0008***	-0.0298	-0.0018	-0.0008***	-0.0358	-0.0019	-0.0008***	-0.0352	-0.0019	-0.0008***
Log (Age)	-0.0536	-0.0033	-0.0076***	-0.0531	-0.0032	-0.0076***	-0.0619	-0.0031	-0.0075***	-0.0614	-0.0031	-0.0075***
Net Income/Tot. Assets	-0.0052	0.0000	0.0000	-0.0057	0.0000	0.0000	0.0260	0.0001	0.0000	0.0258	0.0001	0.0000
Tot. Liab./Tot. Assets	0.9956	0.0016	0.0001	0.9956	0.0016	0.0001	0.9959	0.0008	0.0000	0.9959	0.0008	0.0000
Cash/Tot. Assets	-0.0209	-0.0012	-0.0053***	-0.0210	-0.0012	-0.0053***	-0.0105	-0.0013	-0.0060***	-0.0106	-0.0013	-0.0060***
Lt. Debts/Tot. Assets	-0.0054	-0.0007	-0.0026***	-0.0054	-0.0007	-0.0026***	-0.0049	-0.0006	-0.0023***	-0.0049	-0.0006	-0.0023***
PPE/Tot. Assets	0.0031	0.0001	0.0006	0.0031	0.0001	0.0006	0.0020	0.0001	0.0004	0.0019	0.0001	0.0004
Market-to-Book	-0.0048	-0.0281	-0.0001	-0.0048	-0.0278	-0.0001	-0.0043	-0.0171	0.0000	-0.0043	-0.0169	0.0000
Acquiring Firm Dummy	-0.0016	-0.0007	-0.0015***	-0.0016	-0.0007	-0.0015***	-0.0020	-0.0008	-0.0018***	-0.0019	-0.0008	-0.0018***
Cumulative Bids	0.0481	0.0004	0.0001***				0.0665	0.0005	0.0001***			
Cumulative Acquisitions				0.0417	0.0004	0.0001***				0.0572	0.0004	0.0001***
Deregulation Dummy							-0.0008	-0.0001	-0.0009	-0.0008	-0.0001	-0.0009
Ind. Demand Shock							0.0102	0.0007	.0001***	0.0102	0.0007	0.0001***
Ind. Supply Shock							-0.0007	0.0000	0.0000	-0.0007	0.0000	0.0000
Ind. Tech. Shock							-0.0015	-0.0001	-0.0001	-0.0015	-0.0001	-0.0001
Agg. Demand Shock							0.0025	0.0005	0.0087***	0.0025	0.0005	0.0087***
Agg. Supply Shock							-0.0006	-0.0001	-0.0122	-0.0006	-0.0001	-0.0123
Agg. Equity Mkt. Shock							-0.0023	-0.0003	-0.0008***	-0.0023	-0.0003	-0.0008***
Agg. Debt Mkt. Shock							0.0004	0.0000	0.0000	0.0004	0.0000	0.0000
Agg. Equity Mkt. Momentum							0.0498	0.0102	0.0111***	0.0503	0.0102	0.0112***
Deal-Structure Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Tab. 2.4: **Excessive and Conservative Acquisitive Sample Characteristics**

This table reports the differential firm characteristics of the excessively and the conservatively acquisitive sample firms at the time of bid announcement. From the $DIST.\ NH_{ijt}$ proxy in the paper, I define the measure of managerial excessive acquisitiveness as $EXCESSIVE\ \ ACQ_{ijt} = DIST.\ \ NH_{ijt} \times I_{(X_{ijt}-Median(X_{-ijT})>0)}$, where X_{ijt} is the is cumulative number of M&A bids (acquisitions) of firm i in industry j until calendar quarter t normalized by the total number of calendar quarters for which I observe the firm in the data set, I is an indicator function that returns 1 if X_{ijt} is above the industry median and returns 0 if X_{ijt} is below the industry median. Correspondingly, I define conservative acquisitiveness as $CONSERV\ \ ACQ_{ijt} = DIST.\ \ NH_{ijt} \times I_{(X_{ijt}-Median(X_{-ijT})<0)}$. Definitions of other variables are the same as in the previous tables. In the table, "*" denotes significance at the 10% level; "**" denotes significance at the 5% level; "***" denotes significance at the 1% level.

	Excessively Acquisitive Firms				Conservatively Acquisitive Firms				Difference			
	Mean (1)	Median (2)	N	Num. Firms	Mean (3)	Median (4)	N	Num. Firms	(1-3)	Absolute t-stat	(2-4)	Absolute t-stat
Size and Performance Measures:												
Log (Tot. Assets)	6.41	6.36	51630	8319	5.65	5.52	9630	5014	0.75***	14.27	0.84***	31.10
Log (Mkt. Value of Assets)	6.88	6.83	51019	8227	6.12	6.02	9464	4925	0.76***	14.08	0.81***	26.59
Net Income/Tot. Assets	0.00	0.01	51490	8303	0.00	0.01	9612	5008	0.00***	3.64	0.00***	8.26
EBITDA/Tot. Assets	0.03	0.03	43139	7462	0.02	0.03	8477	4514	0.01***	6.81	0.00***	10.66
Market-to-Book	1.94	1.40	51019	8227	2.12	1.39	9464	4925	-0.17***	4.00	0.02*	1.67
Leverage and Liquidity Measures:												
Tot. Liab./Tot. Assets	0.56	0.56	51564	8297	0.54	0.53	9628	5013	0.03***	5.14	0.03***	9.27
Book Leverage	0.56	0.56	51597	8313	0.54	0.53	9629	5013	0.03***	5.17	0.03***	9.20
Market Leverage	0.42	0.38	51019	8227	0.40	0.35	9464	4925	0.02***	3.21	0.03***	6.06
Cash/Tot. Assets	0.12	0.05	51344	8275	0.16	0.07	9587	4997	-0.03***	10.49	-0.01***	10.65
Cash/Curr. Liab.	1.01	0.28	40175	6789	1.61	0.40	7656	3998	-0.61***	5.14	-0.11***	12.83
Curr. Assets/Curr. Liab.	2.55	1.91	39977	6717	3.26	2.09	7655	3991	-0.71***	4.37	-0.18***	9.36
St. Debts/Tot. Liab.	0.09	0.04	47049	7998	0.08	0.03	8998	4767	0.01***	3.69	0.01***	8.85
Lt. Debts/Tot. Liab.	0.33	0.30	51108	8273	0.28	0.21	9546	4983	0.05***	8.37	0.08***	14.95
PPE/Tot. Assets	0.24	0.17	49161	8116	0.23	0.15	9310	4858	0.01**	2.38	0.02***	7.35
Deal Characteristics:												
Cumulative Abnormal Return	0.01	0.00	53494	8651	0.02	0.01	10087	5227	-0.01***	6.80	-0.01***	9.25

Tab. 2.5: **Excessive Use of M&A Investment Technology and Corporate Failure**

This table reports the estimates from the discrete-time hazard model to determine the effect of managerial excessive acquisitiveness on acquiring firms' failure hazard. The dependent variable is 1 for the last fiscal quarter in which a firm fails. Otherwise it is 0. Definitions of all the explanatory variables are the same as in the previous tables. The first instrumental variable (IV1) is a dummy variable that identifies the industry merger wave. I discuss the construction of that instrument in the data appendix of the paper. The second instrument (IV2) is industry-level computerization interacted with the industry merger wave dummy variable. I collect the industry-level computerization from the U.S. Bureau of Economic Analysis. Robust z statistics are given in brackets and "*" denotes significance at the 10% level; "**" denotes significance at the 5% level; "***" denotes significance at the 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log (Total Assets)	-0.4754**	-0.5505***	-0.5722***	-1.5211***	-0.8188***	-0.4914***	-0.4825*	-0.5858**	-0.5939**	-1.1915***	-1.2200***	-0.4769***
	[2.33]	[2.64]	[2.89]	[4.95]	[4.30]	[7.13]	[1.91]	[2.38]	[2.35]	[5.01]	[4.28]	[6.35]
Log (Age)	-0.6620***	-0.5329***	-0.4860***	-0.4325***	-0.5122***	-0.7564***	-0.6358***	-0.4744***	-0.4374***	-0.3736***	-0.2745	-0.7079***
	[7.89]	[7.47]	[6.98]	[3.22]	[6.57]	[5.58]	[6.05]	[4.86]	[4.60]	[2.82]	[1.37]	[4.56]
Net Income/Tot. Assets	-0.3038	-0.1776**	-0.1375***	0.8125*	0.0348	-0.8591***	-0.4654	-0.2828	-0.1353*	0.1997	0.3270	-0.6636**
	[1.36]	[2.34]	[2.77]	[1.88]	[0.13]	[3.34]	[1.27]	[0.61]	[1.90]	[1.00]	[0.90]	[2.40]
Tot. Liab./Tot. Assets	0.8813	1.0149*	0.8871	1.4641**	1.8958***	3.0104***	0.6639	0.8270*	0.7599	1.0252***	1.4301***	3.3770***
	[1.41]	[1.70]	[1.61]	[2.10]	[4.52]	[11.65]	[0.83]	[1.92]	[1.18]	[8.69]	[4.75]	[10.04]
Cash/Tot. Assets	-0.7037	-0.2779	-0.1833	3.9786***	2.0625**	0.7907*	-1.3053	-0.6672	-0.6590	1.8586*	2.5818**	0.1490
	[0.78]	[0.30]	[0.21]	[3.17]	[2.38]	[1.66]	[1.13]	[0.58]	[0.57]	[1.95]	[2.09]	[0.26]
Lt. Debts/Tot. Assets	-0.3762	-0.6463	-0.5789	-0.1519	-0.0439	-1.7790***	-0.3558	-0.2990	-0.6188	-0.0523	-0.0391	-1.9146***
	[0.07]	[0.12]	[0.11]	[0.91]	[0.86]	[4.57]	[0.06]	[0.05]	[0.10]	[0.85]	[0.73]	[4.35]
PPE/Tot. Assets	0.1013	0.4201	0.4672	1.6873***	0.8860*	1.4064***	0.1237	0.3398	0.5294	2.0635***	2.7578**	1.5792***
	[0.06]	[0.23]	[0.26]	[2.86]	[1.81]	[2.68]	[0.06]	[0.17]	[0.26]	[2.97]	[2.45]	[2.72]
Market-to-Book	-0.5803***	-0.7105***	-0.5746***	-0.7504***	-0.5934***	-1.8362***	-0.5393***	-0.6299***	-0.5479***	-0.7435***	-0.6038***	-1.9155***
	[3.53]	[3.36]	[3.33]	[5.34]	[11.33]	[7.75]	[2.93]	[3.19]	[2.60]	[9.68]	[10.25]	[6.33]
Distance to N. Hedge		3.0573***						3.2250***				
		[6.02]						[5.36]				
Excessive Acquisitiveness			3.2038***			2.0882***			3.4053***			2.4438***
			[6.66]			[8.11]			[5.61]			[8.90]
Excessive Acquisitiveness (IV1)				48.5988***						28.1320***		
				[3.48]						[2.81]		
Excessive Acquisitiveness (IV2)					17.9145**						34.3793**	
					[2.17]						[2.52]	
Governance Score						-0.0282						-0.0203
						[0.92]						[0.56]
Deregulation Dummy							-0.2173	-0.1893	-0.1794	0.1748	0.4205	0.9269
							[1.00]	[0.90]	[0.82]	[0.63]	[1.21]	[1.14]
Ind. Demand Shock							0.0005**	0.0006**	0.0005**	0.0008***	0.0007**	0.0003
							[2.35]	[2.57]	[2.54]	[3.38]	[2.49]	[0.38]
Ind. Supply Shock							-0.0005	-0.0006	-0.0006	-0.0007	-0.0005	-0.0001
							[1.24]	[1.34]	[1.35]	[1.53]	[0.98]	[0.07]
Ind. Tech. Shock							0.0331	0.0351	0.0341	0.0472*	0.0485	0.0671
							[1.09]	[1.16]	[1.14]	[1.86]	[1.60]	[0.81]
Agg. Demand Shock							1.1390***	1.2248***	1.1736***	0.7879*	0.4241	1.3058
							[2.73]	[2.89]	[2.88]	[1.80]	[0.79]	[0.91]
Agg. Supply Shock							0.9736	1.1694	1.0823	-1.1664	-0.5709	-28.1788*
							[0.32]	[0.39]	[0.35]	[0.45]	[0.18]	[1.87]
Agg. Equity Mkt. Shock							-0.1516***	-0.1375***	-0.1357***	-0.0688	-0.0824	-0.2882*
							[3.02]	[2.68]	[2.66]	[1.21]	[1.09]	[1.71]
Agg. Debt Mkt. Shock							-0.0562	-0.0587	-0.0481	-0.0459*	-0.0674**	0.0463
							[1.46]	[1.42]	[1.25]	[1.68]	[2.20]	[0.23]
Agg. Equity Mkt. Momentum							1.6728**	1.5650**	1.6568**	1.0019***	1.0250***	1.1156
							[2.34]	[2.40]	[2.38]	[14.88]	[12.05]	[0.47]
Constant	-2.1845**	-5.3420***	-3.4628***	-1.1072	-1.3753**	-13.5522***	-9.9036***	-11.3501***	-10.9760***	-7.3640***	-8.8991***	-17.8389
	[2.51]	[6.22]	[4.40]	[1.18]	[2.28]	[10.46]	[3.18]	[3.99]	[3.48]	[12.67]	[8.85]	[1.07]
Deal-Structure Dummy	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes	No	No	Yes
Industry Dummy	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes	No	No	Yes
Year Dummy	Yes	Yes	Yes	No	No	Yes	Yes	Yes	Yes	No	No	Yes
N	410133	406306	406306	409105	293581	104764	316502	313169	313169	315740	223235	78421
Num. of Firms	10438	10438	10438			2658	8677	8677	8677			2337
Pseudo-R^2	0.15	0.18	0.19			0.21	0.14	0.18	0.19			0.24
Wald-χ^2	10298.23	8403.91	6111.25				9586.71	6422.39	5617.19			

Tab. 2.6: **Excessive Use of M&A Investment Technology and Corporate Failure: Robustness Tests**

This table reports various robustness tests of the causal effects of excessive acquisitiveness on firm failure hazard. The dependent variable is 1 for the last fiscal quarter in which a firm fails. Otherwise it is 0. Definitions of firm characteristics and other exogenous variables are the same as in the previous tables. 'Winner' is defined to be the total number of contested, completed acquisitions normalized by the total number of bids. 'CAR' refers to the cumulative abnormal return to the acquiring firm shareholders at the time of the M&A bid announcement. Robust z statistics are given in brackets and "*" denotes significance at the 10% level; "**" denotes significance at the 5% level; "***" denotes significance at the 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Linear Probability Model with firm FE		Focusing on the 1980s sample only		Winners' Curse Explanation		CAR<0 Acquisitions		CAR>0 Acquisitions		Two-Dimensional Clustering (by firm and size)	
Log (Total Assets)	-0.0099***	-0.0109***	-0.5111***	-0.5113***	-0.5732***	-0.5950**	-0.5760***	-0.5960**	-0.5601***	-0.5814**	-0.5511***	-0.5694**
	[24.91]	[23.53]	[29.52]	[26.73]	[2.88]	[2.34]	[2.99]	[2.46]	[2.78]	[2.30]	[2.63]	[2.05]
Log (Age)	0.0344***	0.0468***	-0.4813***	-0.4158***	-0.4867***	-0.4384***	-0.4849***	-0.4408***	-0.5010***	-0.4514***	-0.5891***	-0.5311***
	[31.46]	[27.78]	[11.45]	[8.90]	[6.96]	[4.60]	[7.07]	[4.97]	[7.49]	[5.07]	[6.13]	[4.40]
Net Income/Tot. Assets	0.0012	0.0014	-0.0893	-0.0967***	-0.1373***	-0.1352*	-0.1133**	-0.1050	-0.1320**	-0.1238	-0.1290	-0.1912
	[0.94]	[1.04]	[1.60]	[3.07]	[2.70]	[1.87]	[2.06]	[1.38]	[2.36]	[1.45]	[0.28]	[0.39]
Tot. Liab./Tot. Assets	0.0041	0.0035	1.5808***	1.6305***	0.8868	0.7592	0.8231	0.6908**	0.8164	0.6843	0.7996	0.8286*
	[1.44]	[1.43]	[13.10]	[13.84]	[1.61]	[1.18]	[1.54]	[2.47]	[1.54]	[1.39]	[1.46]	[1.76]
Cash/Tot. Assets	-0.0146***	-0.0148***	0.2015	-0.1786	-0.1820	-0.6582	-0.1261	-0.5609	-0.1067	-0.5495	-0.1554	-0.6206
	[7.16]	[6.98]	[1.31]	[1.00]	[0.21]	[0.57]	[0.15]	[0.48]	[0.12]	[0.49]	[0.17]	[0.48]
Lt. Debts/Tot. Assets	-0.0002	-0.0001	-0.9444***	-1.1273***	-0.5815	-0.6190	-0.6024	-0.6104	-0.5991	-0.6003	-0.5219	-0.7096
	[0.88]	[0.79]	[8.20]	[8.99]	[0.11]	[0.10]	[0.12]	[0.10]	[0.11]	[0.10]	[0.09]	[0.10]
PPE/Tot. Assets	0.0041*	0.0066**	0.6190***	0.7049***	0.4636	0.5244	0.4645	0.5265	0.5411	0.5970	0.4193	0.4926
	[1.79]	[2.52]	[4.61]	[4.78]	[0.26]	[0.25]	[0.26]	[0.25]	[0.30]	[0.29]	[0.21]	[0.20]
Market-to-Book	-0.0008***	-0.0007**	-0.5669***	-0.5126***	-0.5749***	-0.5479***	-0.5406***	-0.5070***	-0.5357***	-0.4981***	-0.6279***	-0.6329***
	[2.66]	[2.53]	[8.51]	[7.01]	[3.33]	[2.60]	[3.16]	[2.82]	[3.18]	[2.71]	[3.65]	[2.65]
Excessive Acquisitiveness	0.0312***	0.0349***	3.1663***	3.3653***	3.2057***	3.4076***	2.9279***	3.1202***	2.8470***	3.0161***	3.1747***	3.3892***
	[18.27]	[17.28]	[36.12]	[35.73]	[6.64]	[5.60]	[6.08]	[5.10]	[6.36]	[5.42]	[5.25]	[4.19]
Winners' Curse					2.3470***	2.2955***						
					[5.53]	[4.25]						
Bad Acquisitions							1.4903***	1.5142***				
							[18.40]	[17.48]				
Good Acquisitions									1.2991***	1.3342***		
									[17.44]	[15.34]		
Deregulation Dummy		-0.0018*		0.0655		-0.1765		-0.1679		-0.1651		-0.2677
		[1.91]		[0.32]		[0.80]		[0.76]		[0.76]		[1.05]
Ind. Demand Shock		0.0000***		0.0005**		0.0005***		0.0006***		0.0006***		0.0007***
		[3.08]		[2.13]		[2.62]		[2.60]		[2.63]		[2.99]
Ind. Supply Shock		-0.0000		-0.0005		-0.0006		-0.0006		-0.0006		-0.0008*
		[1.60]		[1.11]		[1.42]		[1.45]		[1.35]		[1.66]
Ind. Tech. Shock		0.0003		0.0226		0.0346		0.0365		0.0366		0.0384
		[1.52]		[0.67]		[1.15]		[1.24]		[1.17]		[1.13]
Agg. Demand Shock		0.0089***		1.3907***		1.1772***		1.1902***		1.1978***		1.4562***
		[2.80]		[3.04]		[2.89]		[2.93]		[2.93]		[3.34]
Agg. Supply Shock		0.0145		-0.8796		1.1187		0.9221		1.0872		1.1664
		[0.79]		[0.24]		[0.36]		[0.30]		[0.36]		[0.35]
Agg. Equity Mkt. Shock		-0.0011**		-0.1286**		-0.1363***		-0.1337***		-0.1359***		-0.1576***
		[2.06]		[2.33]		[2.68]		[2.70]		[2.71]		[3.03]
Agg. Debt Mkt. Shock		-0.0001*		-0.0517		-0.0469		-0.0436		-0.0469		-0.0761
		[1.66]		[1.04]		[1.22]		[1.22]		[1.26]		[1.62]
Agg. Equity Mkt. Momentum		-0.0011		2.0098***		1.6694**		1.5491**		1.4668**		1.9064**
		[0.32]		[2.98]		[2.38]		[2.32]		[2.23]		[2.41]
Constant	-0.0818	-0.1181***	-3.3737***	-14.4373***	-3.4487***	-11.0176***	-3.2819***	-10.3531***	-3.2914***	-10.0327***	-3.2555***	-13.5048***
	[0.00]	[7.08]	[5.53]	[4.16]	[4.39]	[3.47]	[4.51]	[3.60]	[4.79]	[3.39]	[3.77]	[4.13]
Deal-Structure Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Dummy	Yes	Yes	No	No	No	No	No	No	No	No	No	No
Observations	412220	318760	262847	193356	406306	313170	406306	313170	406306	313170	397869	310295
Num. of Firms	10439	8678	8134	6645	10438	8677	10438	8677	10438	8677		
Pseudo-R^2/Adjusted-R^2	0.07	0.07	0.18	0.19	0.19	0.19	0.20	0.20	0.20	0.20		

Tab. 2.7: **Excessive Use of M&A Investment Technology and Corporate Failure: Marginal Effects**

This table reports the marginal effects of managerial acquisitiveness and other exogenous variables on a firm's failure hazard at the mean, 1/2 standard deviation below the mean, 1/2 standard deviation above the mean and 1 standard deviation around the mean. The definitions of the variables are the same as in the previous table. In the table, "*" denotes significance at the 10% level; "**" denotes significance at the 5% level; "***" denotes significance at the 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	At the Mean	1/2 Std. Below the Mean	1/2 Std. Above the Mean	1 Std. Around the Mean	At the Mean	1/2 Std. Below the Mean	1/2 Std. Above the Mean	1 Std. Around the Mean
Log (Total Assets)	-0.0012***	-0.0009***	-0.0016***	-0.0007***	-0.0013***	-0.0009***	-0.0017***	-0.0008***
Log (Age)	-0.0009***	-0.0007***	-0.0013***	-0.0006***	-0.0009***	-0.0006***	-0.0012***	-0.0006***
Net Income/Tot. Assets	-0.0003***	-0.0002***	-0.0004***	-0.0002***	-0.0003***	-0.0002***	-0.0004***	-0.0002***
Tot. Liab./Tot. Assets	0.0019	0.0014	0.0025	0.0011	0.0017	0.0012	0.0022	0.0010
Cash/Tot. Assets	-0.0004	-0.0003	-0.0005	-0.0002	-0.0014	-0.0010	-0.0019	-0.0009
Lt. Debts/Tot. Assets	-0.0013	-0.0010	-0.0017	-0.0007	-0.0015	-0.0011	-0.0020	-0.0009
PPE/Tot. Assets	0.0010	0.0008	0.0014	0.0006	0.0012	0.0009	0.0017	0.0008
Market-to-Book	-0.0012***	-0.0009***	-0.0016***	-0.0007***	-0.0012***	-0.0009	-0.0016	-0.0007
Excessive Acquisitiveness	0.0064***	0.0048***	0.0085***	0.0037***	0.0070***	0.0052***	0.0095***	0.0043***
Deregulation Dummy					-0.0004	-0.0003	-0.0006	-0.0003
Ind. Demand Shock					0.0000***	0.0000***	0.0000***	0.0000***
Ind. Supply Shock					0.0000	0.0000	0.0000	0.0000
Ind. Tech. Shock					0.0001	0.0001	0.0001	0.0000
Agg. Demand Shock					0.0025***	0.0018***	0.0034***	0.0016***
Agg. Supply Shock					0.0027	0.002	0.0036	0.0016
Agg. Equity Mkt. Shock					-0.0003***	-0.0002***	-0.0004***	-0.0002***
Agg. Debt Mkt. Shock					-0.0001	-0.0001	-0.0001	0.0000
Agg. Equity Mkt. Momentum					0.0023	0.0017	0.0031	0.0014
Deal-Structure Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Tab. 2.8:

Can the Deal-Characteristics Discriminate between the Failed and Non-Failed Sample?

This table reports the deal characteristics of the 'Failed' (F) and 'Non-Failed' (NF) sample. Panel-A reports the differences in the deal characteristics of average as well as median 'Non-Failed' firms from the those of the 'Failed' firms (F-NF). Panel-B, on the other hand, reports the difference in the deal characteristics generated from various dummy variables. Deal value is the reported deal value in million U.S. dollars from the SDC. Total assets is defined to be the book value of all assets while market value is calculated by adding the market value of equity with the book value of debt at the end of each fiscal quarter. In the table, "*" denotes significance at the 10% level; "**" denotes significance at the 5% level; "***" denotes significance at 1% level using t statistics.

	Failed Sample Deals (F)		Non-Failed Sample Deals (NF)		Difference (F-NF)	
	(1)	(2)	(3)	(4)	(1-3)	(2-4)
	Panel-A: Deal Summary Statistics					
	Mean	Median	Mean	Median	F-NF$_{Mean}$	F-NF$_{Median}$
Deal Value ($ Million)	41.37***	7.93***	225.99***	24.42***	-184.62***	-16.49***
	[11.79]	[29.18]	[17.72]	[90.47]	[13.96]	[22.33]
Deal Value/Tot. Assets	0.42***	0.09***	0.15***	0.04***	0.27***	0.05***
	[8.52]	[43.35]	[26.87]	[81.45]	[5.47]	[33.04]
Deal Value/ Mkt. Value	0.25***	0.06***	0.08***	0.03***	0.17***	0.03***
	[5.16]	[48.55]	[40.49]	[101.58]	[3.56]	[37.91]
Deal Value/Equity Value	0.71**	0.10***	4.09	0.06***	-3.38	0.04***
	[2.86]	[47.02]	[1.04]	[132.03]	[0.86]	[35.96]
Days to Completion	46.47***	0.00	66.23***	12.00***	-19.76***	-12.00***
	[26.67]	[.02]	[52.81]	[22.13]	[9.20]	[11.36]
	Panel-B: Deal Characteristics Dummy					
	N	%	N	%	N (1-3)	% (2-4)
Completed Deals	6,455	70.79	38,417	70.50	-31962	0.29
Target is in Similar Industry	5,614	61.56	35276	64.73	-29662	-3.17
Acquisition is Merger-Wave	1,942	21.30	11791	21.64	-9849	-0.34
100% Cash-Finance Deal	644	7.06	5502	10.10	-4858	-3.04
100% Stock-Finance Deal	842	9.23	4270	7.84	-3428	1.39
Financing through Borrowing	174	1.91	1218	2.24	-1044	-0.33
Financing through Internal Funds	173	1.90	1626	2.98	-1453	-1.08
Financing through Line of Credit	211	2.31	1299	2.38	-1088	-0.07
Stock Swap	941	10.32	5211	9.56	-4270	0.76
Block Purchase	604	6.62	5075	9.31	-4471	-2.69
Divestiture of Target	1,822	19.98	12343	22.65	-10521	-2.67
Division Sell-off of Target	476	5.22	4521	8.30	-4045	-3.08
Financial Acquirer	118	1.29	1145	2.10	-1027	-0.81

Tab. 2.9: **Evolution of Firms' Assets and Debt Structure**

This table reports the evolution of firms' debt and assets structure from one quarter before the first M&A bid to one quarter after the last M&A bid for the median firms in our sample. All firms for which differential firm characteristics are reported here make exactly 3 acquisition bids because the median number of bids firms make in my sample is 3. The first panel on the left of the table reports the difference in firm characteristics of non-failed median firms from the failed median firms (F-NF). The second panel on the right of the table reports the difference in the firm characteristics of the median excessively acquisitive sample from the non-excessively acquisitive sample (X-NX). Definitions of all variables are the same as in the previous tables. Cash flow volatility is calculated as $log(abs(EBITDA_{it} - EBITDA_{it-1}))$ for each firm i and time period t. In the table, "*" denotes significance at the 10% level; "**" denotes significance at the 5% level; "***" denotes significance at the 1% level using t statistics.

	Diff. between the Failed and Non-Failed Sample (F-NF)					Diff between the Excess Acq. and Non-Excess Acq. Sample (X-NX)				
	(1) Qtr. Before First Bid	(2) Qtr. After Last Bid	(3) Diff-in-Diff	(4) Absolute t-stat	(5) % Change from First to Last Bid	(1) Qtr. Before First Bid	(2) Qtr. After Last Bid	(3) Diff-in-Diff	(4) Absolute t-stat	(5) % Change from First to Last Bid
Performance Measures:										
Log (Market Value)	-1.112***	-1.474***	-0.362*	1.75	-32.55%	-0.464***	-0.597***	-0.133	0.70	-29%
Net Income/Tot. Assets	-0.004***	-0.011***	-0.007***	3.61	-175.00%	0.002	-0.001*	-0.003*	1.88	-150%
EBITDA/Tot. Assets	-0.003	-0.013***	-0.010**	2.67	-333.33%	0.007***	0.001	-0.006*	1.61	-86%
Market-to-Book	0.328***	-0.089**	-0.417***	4.80	-127.13%	0.117	-0.023	-0.140*	1.64	-120%
Leverage Measures:										
Tot. Liab./Tot. Assets	-0.097***	0.017	0.114**	2.65	117.53%	-0.034	0.059**	0.093**	2.57	274%
Book Leverage	-0.093***	0.015	0.108**	2.58	116.13%	-0.032	0.060**	0.092**	2.60	288%
Market Leverage	-0.100***	0.058**	0.158***	4.14	158.00%	-0.066**	0.051*	0.117**	2.92	177%
St. Debts/Tot. Liab.	0.024***	0.062***	0.038***	3.39	158.33%	0.017***	0.030***	0.013*	1.63	76%
Lt. Debts/Tot. Liab.	-0.039	-0.013	0.026	0.50	66.67%	0.053	0.077**	0.024	0.51	45%
Liquidity and Risk Measures:										
Cash/Tot. Assets	0.032**	-0.008	-0.040**	2.20	-125.00%	-0.004	-0.024***	-0.020	1.19	-500%
Cash/Curr. Liab.	0.044	-0.188***	-0.232*	1.78	-527.27%	-0.104	-0.215***	-0.111	0.97	-107%
Curr. Assets/Curr. Liab.	0.010	-0.434***	-0.444**	2.60	-4440.00%	0.152	-0.241**	-0.393**	2.44	-259%
PPE/Tot. Assets	-0.022	0.008	0.030	1.20	136.36%	0.017	0.048***	0.031	1.35	182%
Cash Flow Volatility	0.558***	0.829***	0.271	1.34	48.57%	0.324***	0.447***	0.123	0.75	38%

Tab. 2.10: **Excessive Use of M&A Investment Technology and Corporate Default**

This table reports the estimates from the discrete-time hazard regression to determine the effects of managerial excessive acquisitiveness and various determinants of financial distress on a firm's default hazard. The dependant variable is a dummy variable which equals 1 for the fiscal quarter in which an acquiring firm defaults on its debt obligations. "Total Assets" is defined to be the book value of a firm's assets while market value is the book value of debt plus the market value of equity. "Net Income" is income from operation after all taxes and interest payment. " Total Liabilities" are obligations due to outsiders other than to the shareholders of the firms. "Current Assets" are cash plus accounts receivable. "Current Liabilities" are short-term debts plus accounts payable. *ZSCORE* is calculated from Altman (2000). *Sigma* and excess return are calculated following Shumway (2001). The G-score is from Gompers, Ishii and Metrick (2003) and the excessive acquisitiveness measure is explained in detail in the data section of the paper. Robust z statistics are given in brackets and "*" denotes significance at the 10% level; "**" denotes significance at the 5% level; "***" denotes significance at the 1% level.

	Altman (1968)		Zmijewski (1984)		Shumway (2001)	
	(1)	(2)	(3)	(4)	(5)	(6)
Log (Age)	0.195	0.350	0.116	0.245	0.189*	0.400**
	[1.63]	[1.47]	[1.06]	[0.96]	[1.89]	[2.02]
Excessive Acquisitiveness	1.591***	1.278***	1.472***	1.468***	1.948***	1.435***
	[6.83]	[3.39]	[6.43]	[3.88]	[10.39]	[4.28]
Governance Score		-0.069*		-0.077*		-0.045
		[1.75]		[1.80]		[1.40]
ZSCORE	-0.006***	-0.030***				
	[3.76]	[4.49]				
Net Income/Total Assets			-0.019	-1.812***		
			[0.65]	[4.09]		
Total Liabilities/Total Assets			0.019*	2.209***		
			[1.94]	[7.54]		
Current Assets/Current Liabilities			-0.355**	0.038		
			[2.48]	[1.09]		
Log (Market Value)					-0.026	-0.017
					[0.78]	[0.24]
Excess Return					-1.689	-2.145
					[1.51]	[1.29]
Sigma					9.587***	21.635***
					[6.87]	[8.59]
Constant	-21.821***	-20.457	-21.045***	-25.231	-25.751***	-29.754***
	[18.10]	[.]	[10.15]	[.]	[21.04]	[21.45]
Marginal Effect of Excess. Acq.	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
Deal-Structure Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummy	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes
N	250836	97002	324589	124339	407533	156464
Num. of Firms	7604	2076	8232	2226	10502	2787
Pseudo-R^2	0.07	0.10	0.08	0.20	0.11	0.17

3. WHY DO EXCESSIVE ACQUIRERS FAIL EXCESSIVELY?

3.1 Introduction

How do the competing economic theories fare in explaining the relationship between excessive M&A activities and corporate failure that I uncovered in the previous chapter? More importantly, if managers are making sub-optimal M&A decisions, how does the capital market discipline hyperactive acquirers and reallocate resources to higher value users? Understanding these questions are important for two reasons: first, corporate failure not only affect a firm's shareholders but also other stakeholders such as creditors, employees, customers, and suppliers; second, since extreme corporate outcomes such as financial distress, default, bankruptcy, and corporate failure affect more than one stakeholders of the firm, they have potential consequences for various industry and macroeconomic dynamics.

Despite the sheer importance of understanding the causes of corporate failure for investors, managers, and policy-makers alike, theoretical debates in the literature have been at best bifurcated. Standard rational economic theory posits that managers take rational risks in uncertain situations. Corporate failures are the results of the unintended adverse effects of managerial rational decisions arising from external economic disturbances beyond managerial control. Entrepreneurs and managers know and accept the odds because the reward of success is sufficiently enticing.

By contrast, behavioral theory argues that managers, just like any other economic agents, suffer from cognitive biases and make systematic errors in judgment by sometimes overestimating the odds of success due to excessive optimism and at other times by overestimating the odds of failure due to excessive conservatism. It is hard to arbitrage these irrationalities away because important corporate decisions are rather infrequent and involve noisy feedback. However, if these behavioral traits are random then, on average, behavioral biases may not have any identifiable effect on firm failure. Thus, the behavioral theory makes another critical assumption that these traits are persistent and eventually render the firm inefficient, pushing it to the brink of failure.

To empirically investigate the competing economic theories of failure, I focus on managerial mergers and acquisitions (M&A) investment decisions for the reasons explained in the previous chapter. I formulate three empirically testable hypotheses. Hypothesis 1, in the spirit of rational economic theory, argues that the frequency of poor outcomes is an unavoidable result of managers taking rational risks in uncertain situations. Given the hard-to-predict stochastic external environment, firm failure is a phenomenon that could be explained by managerial rational risk-taking behavior. To empirically test the hypothesis, I argue that managerial wealth is exposed to the idiosyncratic risk of a firm's operating cash flows since shareholders can diversify the idiosyncratic risk away, but managers cannot easily hedge against this component of risk. Thus, managers should rationally pursue an investment policy that serves as a hedge against the idiosyncratic cash-flow volatility of the firm. I follow Shumway (2001) and use the unsystematic component of a firm's total risk associated with the stock return to proxy for idiosyncratic cash-flow volatility. Using a mediating instrument methodology within a discrete-time hazard model framework, I find strong evidence of mediation of causality from managerial excessive acquisitiveness (relative to an industry benchmark) to firm failure hazard through aggravated (irrational) risk-taking. In other words, instead of rationally hedging against the idiosyncratic risk through the M&A investment policy, excessively acquisitive managers amplify cash-flow volatility and thus also fail more often than their conservative counterparts.

Hypothesis 2, in the spirit of behavioral theory, argues that when forecasting the outcomes of risky projects, executives all too easily fall victim to what psychologists call the planning fallacy. In its grip, managers make decisions based on excessive optimism or pervasive conservatism rather than on a rational balance of gains, losses and probabilities that ultimately affect the survival of their firms. To empirically test the hypothesis, I construct a metric that captures the distance between a firm's realized M&A investment policy and a frontier of an efficient M&A investment policy. In other words, the distance metric captures unobservable that systematically affects a firm's M&A investment policy, but is unrelated to economic fundamentals and also to random errors in M&A decision making. Using the distance metric as a mediating instrument, I find that the further the firm is away from the efficient frontier, the more likely it is to fail compared to the firm that follows the empirically estimated efficient frontier of the M&A investment policy.

Finally, hypothesis 3, in the spirit of bounded rationality theory, argues that managers have limited capacity to process information, and that excessively acquisitive managers suffer from this limitation more severely than their conservative counterparts because excessive acquisitiveness, demanding greater attention allocation, may divert managerial attention away from the relevant economic functions of the firm, in turn worsening operating performance and eventually leading to failure. I use the cumulative number of class-action, anti-trust, and other lawsuits filed against acquirers as a direct consequence of their M&A investment decisions (normalized by the firm's M&A activities up to that time) as a measure of managerial attention distortion and find weak evidence of mediation from managerial excessive acquisitiveness to corporate failure hazard. These findings suggest that the mediation of causality from excessive acquisitiveness to firm failure seems to be stronger through the behavioral channel than through the rational risk channel.

Next, I investigate whether the capital market disciplines aggressive acquirers and internalizes the cost associated with managerial excessive acquisitiveness. I find that the capital market reaction to M&A announcements and to various mediating instruments is sometimes inconsistent with the ultimate effects of these measures on the failure hazard of firms. In my sample, the market, on average, punishes aggressive acquirers by reacting negatively to their stock prices at the time of bid announcements. But the market reaction is not uniform at all quantiles of the conditional distribution of acquirers' cumulative abnormal returns from bid announcements: at some quantiles, the market reacts positively while at others, it reacts negatively revealing a sense of myopia in the capital market reaction. Despite this seeming myopia, I show that the external corporate control market eventually reins in the excessive acquirers by turning them into future targets of takeover: assets of excessive acquirers are more likely to be reallocated via the external corporate control (M&A) market than through other mechanisms, such as bankruptcy/liquidation.

This research contributes to the existing literature in two ways. First, by identifying the various channels of causality from excessive acquisitiveness to firm failure hazard, it provides additional understanding of the competing theories of corporate failure in the economics and finance literature. Second, it shows that the capital market eventually disciplines any sub-optimal managerial behavior and reallocates the assets of excessive acquirers to other firms. The question remains whether reallocating the assets of excessive acquirers via the external corporate control market is the first best use of these assets.

Immediately following, I discuss the related literature on corporate failure. Section III illustrates the data and the construction of various variables. Section IV outlines the estimation methodologies, develops the empirically testable hypotheses, and discusses the results. Section V discusses the role of the capital market in disciplining excessive acquirers. Finally, section VI concludes the paper.

3.2 Why Do Firms Fail? The Debate

The debate on why firms fail remains vibrant ever since Alfred Marshall (1890) argued that collapse may be the consequence of the firm's own success. Schumpeter (1942), on the other hand, argues that the stability of any economic equilibrium is constantly disturbed by the forces of creative destruction. As new innovations arrive, the competitive positions of existing technologies deteriorate and eventually succumb to the creative forces of destruction of new innovations. During the punctuated flux of creative destruction, resources move from lower to higher value users and remain with the state-of-the-art users until the process repeats itself. Self-interested firms do not internalize the destruction of rents generated by their innovations and hence introduce a business-stealing effect that forces others to leave the industry [Aghion and Howitt (1992)]. These models generate business failure as a consequence of endogenous growth dynamics while abstracting away from the firm and managerial idiosyncrasies.

Theoretical models incorporating managerial 'active-learning' [Nelson and Winter (1978), and Ericson and Pakes (1998)] allow firms to invest in uncertain but potentially profitable ventures and to grow if successful, shrink or exit if unsuccessful. By contrast, managerial 'passive-learning' model formulations [Jovanovic (1982), Hopenhayn (1992) and Cabral (1993)] depict firms as entering uncertain of their growth opportunities and then receiving noisy signals of their capabilities which in turn induce them to expand, contract or exit. In application to corporate finance, Denis and Denis (1995) analyze a sample of levered recapitalized firms and argue that poor operating performance is largely due to industry-wide problems such as surprisingly low proceeds from asset sales and negative stock price reactions to the economic and regulatory events associated with the demise of the highly levered transaction market. Lang and Stulz (1992) find evidence that industry rather than firm-specific factors matter for firm bankruptcy. Khanna and Poulsen (1995) show that managers of financially distressed firms make decisions similar to those of their financially healthy counterparts prior to their fall from grace. They argue that firms plunge into financial distress due to factors outside the domain of managerial control.

In contrast to standard economic theory, behavioral models depict economic agents as irrational or at best bounded rational. Behavioral models [Conlisk (1996)] argue that economic agents make systematic errors by using decision heuristics or rules of thumb. In application to corporate finance, these behavioral models [Lovallo and Kahneman (2003)] portray executives as suffering from excessive optimism, and in its grip they all too often fall victim to what psychologists call the planning fallacy. They overestimate benefits and underestimate costs, spin scenarios of success while overlooking the potential for miscalculation and mistake. Excessively optimistic executives do not easily evolve into rational decision makers since important corporate decisions are rather infrequent and involve noisy feedback [Heaton (2002)]. One viable way through which the managerial irrationality can be arbitraged away is corporate takeover although it involves high transaction costs and is difficult to implement. The resounding implication of behavioral models is that corporate debacles are not best explained by rational choices with adverse effects, but rather as a consequence of flawed decision making.

Empirically, Malmendier and Tate (2005) deem CEOs who persistently fail to reduce their personal exposure to company-specific risk as overconfident. They show that CEO overconfidence can account for corporate investment distortions by overestimating the return to investment projects and by perceiving external funds as unduly costly. In another paper, Malmendier and Tate (2003) argue that overconfident CEOs overestimate their abilities to generate returns, both in their current firms and in potential takeover targets. Thus, on the margin, they undertake mergers that destroy value. Aside from the behavioral trait of optimism, Hirshlifer and Thakor (1992) show that managers, concerned about reputation building, may be excessively conservative relative to the shareholders' optimum investment-policy. These managers favor relatively safe projects, thereby aligning managers' interests with those of the bondholders even though managers are hired and fired by the shareholders. They also argue that conservatism induced by managerial reputation-building may ex-ante make shareholders better off by enhancing the debt capacity of the firm.

The related literature linking M&A and corporate failure is primarily focused on understanding the short-term and long-term effects of M&A on firms' equity prices and operating performance without directly relating M&A to firm failure hazard. In a review article, Roll (1986) concludes that the null hypothesis of zero abnormal performance of acquirers should not be rejected. While there have been many subsequent articles on the subject, the results appear to be mixed enough that Roll's conclusion appears to hold [Agrawal and Jaffe (1999)]. Lovallo and Kahneman (2003) argue that three-quarters of mergers and acquisitions never pay off; the acquiring firm's shareholders lose more than the acquired firm's shareholders gain. However, Moeller, Schlingemann and Stulz (2005) show that losses occur because of a small number of acquisitions with negative synergy gains done by firms with extremely high valuations. Without these acquisitions, the wealth of the acquiring-firm shareholders would have increased. Firms that make these acquisitions with large dollar losses perform poorly afterwards.

In short, the extant literature shows that economists disagree sharply on whether some kind of market tsunami or managerial discretion in formulating corporate investment and financing policies matter for firm failure. Furthermore, while it is fair to conclude from the existing literature that the long- and short-term effects of M&A on a firm's performance are at best random, the literature has not so far addressed the issue of whether too much use of the investment technology can in fact precipitate failure. By focusing on managerial aggressive use of M&A investment technology, which has uncertain value implications for their firms, I wish to address this broader question of whether managers of failed businesses are villains or scapegoats.

3.3 Data and Variables

I use the same data set as in the previous chapter. Table 1.1 in the previous chapter describes various aspects of the sample firms. The primary dependent variable of interest in my investigation in this chapter is firm failure.[1] The definition of firm failure here is the same as it is in the previous chapter. I also construct a measure of managerial excessive acquisitiveness as my primary explanatory variable which quantifies the extent to which acquiring firms' managers aggressively use M&A investment technology relative to an industry benchmark of acquiring firms. I explain the rationale as well as the process of constructing this metric in the previous chapter. Table 1.4 in the previous chapter describes the various summary statistics of the excessively and conservatively acquisitive firms.

3.3.1 Why Some Firms are More Acquisitive than Others?

I find evidence that M&A activities of the acquiring firms are in general driven by broad fundamental factors related to firm size, operating performance, future growth opportunities (Tobin's q) and various exogenous economic disturbances conforming to the postulation of Jensen (1993) who relates the restructuring activities of the 1980s to changes in technologies, input prices, and regulations.[2]

[1] I also use alternative measures of failure. For example, when a firm underperforms the industry median by 40% for three consecutive years before exiting the industry, I consider the firm a failed firm. Alternative measures of failure do not alter the core argument of the paper.

[2] I do not report the regression results here due to space limitations, but these are available on request. Gort (1969) was one of the earliest to argue that economic disturbances alter the structure of expectations among the

However, some firms seem to be more acquisitive relative to their natural hedge counterpart within the industry. In order to understand why some firms are more acquisitive than others, I estimate the idiosyncratic productivity shocks of the sample firms in each year. I assume that all firms have access to the following production technology:

$$Y_{ijt} = A_{ijt} \times K_{ijt}^{\alpha} L_{ijt}^{1-\alpha} \tag{3.1}$$

where Y_{ijt} is the sales revenues, K_{ijt} is the capital stocks, L_{ijt} is the number of employees, and A_{ijt} is the idiosyncratic total factor productivity of firm i in industry j and at time t. By taking natural logarithm, we get:

$$y_{ijt} = a_{ijt} + \alpha.k_{ijt} + (1-\alpha).l_{ijt} \tag{3.2}$$

I then use the methodology developed by Olley and Pakes (1996) to estimate the productivity shocks of firms from the above trans-log production function. I also construct two dichotomous variables to characterize the nature of the M&A bids firms make. The first dichotomous variable equals 1 if the firm receives a negative productivity shock in period t but still announces an acquisition bid which I denote as an optimism-driven M&A bid. The second dichotomous variable equals 1 if the firm has a market-to-book ratio greater than 1 in period t and announces an acquisition bid which I denote as a growth-driven M&A bid.

Table 3.1 reports the correlation structure of these variables with my managerial excessive and conservative acquisitiveness measures. It shows that excessive acquisitiveness is significantly positively correlated with the positive productivity shocks firms receive in the year in which they announce M&A bids. Furthermore, both optimism-driven bids and growth-driven bids are significantly positively correlated with the excessive acquisitiveness measure and also significantly negatively correlated with the conservative counterparts. Excessively acquisitive firms also spend significantly more in capital and have higher acquisition expenses than their conservative counterparts. Moreover, firms with higher anti-takeover provisions, proxied by the Gompers, Ishii, and

market participants and generate discrepancies in valuations of income-producing assets. A non-owner with a higher valuation of a firm's assets than that of the owner places a bid for the firm's assets in pursuit of economies of scale, monopoly power or yet, other sources of gain. More recently, Jovanovic and Rousseau (2002) along the vein of Coase (1937) argue that technological change alters the available profitable capital reallocation opportunities at the disposal of firms and leads to restructuring. Empirical evidence by Mitchell and Murhelin (1996), Andrade, Mitchell and Stafford (2001), and Harford (2005) show that economic disturbances lead to a clustering of takeover activities within industries and across time. Shleifer and Vishny (2003), on the other hand, posit that bull markets lead groups of bidders with overvalued stock to use the stock to buy real assets of undervalued targets through mergers. Rhodes-Kropd et al. (2004), Ang and Cheng (2003), Dong et al. (2003) and Verter (2002) find evidence that the dispersion of market valuations is correlated with aggregate merger activities.

Metrick (2003) G index, tend to be more acquisitive than their conservative counterparts.

From the correlation structure of these variables, one may deduce that internal suboptimal corporate assets structure, future growth opportunities, corporate governance, and managerial behavioral biases drive excessive acquisitiveness in my sample. However, the primary focus of the current paper is not to delve into what drives (rational versus behavioral driver) managerial excessive acquisitiveness. Instead, I focus on the next step of the process that is conditional on managerial excessive acquisitiveness, whether it is managerial rational risk-taking or managerial flawed decision-making that better explain the causation from managerial excessive acquisitiveness to corporate failure.

3.4 Channels of Causality from Excessive Acquisitiveness to Firm Failure

In the previous chapter I show that managerial excessive acquisitiveness does indeed precipitate corporate failure. However, casting the blame on managers by simply looking at the relationship between managerial action and failure hazard is rather unfair because an ex-post bad investment decision may very well be an ex-ante good investment decision when one factors in the uncertainties surrounding the business environment with which managers have to interact continuously. Without proper theoretical guidance, however, one would be at sea to understand the question of whether managers of failed businesses are villains or scapegoats. Using the two predominant theoretical paradigms that try to explain the failure phenomena in the modern corporate landscape, I develop three hypotheses and use a mediating instrument methodology following Baron and Kenny (1986) and Judd and Kenny (1981) within a discrete-time hazard model framework to test those hypotheses.

3.4.1 Estimation Methodology

To estimate the effect of managerial excessive acquisitiveness on firm failure hazard, I use a discrete-time hazard model with a *logit* link. The methodology section of the previous chapter explains this estimation strategy in detail. To identify the channel via which managerial excessive acquisitiveness affects corporate failure hazard, I use a mediating instrument methodology within the discrete-time hazard framework. To understand the mediating instrument methodology, consider a variable X that is assumed to affect another variable Y. The variable X is called the initial variable, and the variable that it causes, or Y, is called the outcome variable. The effect of X on Y may be mediated by a process or mediating variable M, and the variable X may still affect Y. Complete mediation is the case in which variable X no longer affects Y after M has been controlled for, whereas partial mediation is the case in which the path from X to Y is reduced in absolute size but is still different from zero when the mediator is controlled for. Note that a mediational model is a causal model, meaning that the mediator is presumed to cause the outcome and not vice versa. If the presumed model is not correct, the results from the mediational analysis are of little value.

When the mediational model is correctly specified, Baron and Kenny (1986) and Judd and Kenny (1981) outline four steps in establishing mediation: (i) the initial variable must be correlated with the outcome in a regression model where Y is the criterion variable and X is a predictor establishing the fact that there is an effect that may be mediated; (ii) the initial variable X must be correlated with the mediator M in a regression model where M is the criterion variable and X is a predictor; (iii) the mediator M must affect the outcome variable Y in a regression model where Y is the criterion variable, and X and M are predictors; (iv) to establish that M completely mediates the $X \rightarrow Y$ relationship, the effect of X on Y controlling for M should be zero. The effects in both (iii) and (iv) are estimated in the same equation. It is not sufficient just to correlate the mediator M with the outcome Y; the mediator and the outcome may be correlated because they are both caused by the initial variable X. Thus, the initial variable X must be controlled in establishing the effect of the mediator M on the outcome variable Y.

To implement the mediation process I estimate the following regression models:

$$E\big(Y_{it} = 1 \mid X, Z\big) = F\big(\alpha + \beta X_{it-1} + \delta Z_{t-1}\big) + \varepsilon_{it} \tag{3.3}$$

$$E\big(Y_{it} = 1 \mid X, M, Z\big) = F\big(\alpha + \beta' X_{it-1} + \theta M_{it-1} + \delta' Z_{it-1}\big) + \varepsilon_{it} \tag{3.4}$$

where Y_{it} is the firm-failure dichotomous variable, X_{it-1} is the measure of managerial excessive acquisitiveness, M_{it-1} is a mediating instrument, and Z_{it-1} is the set of other control variables. If $F(.)$ is a linear function, then with an appropriate distributional assumption on ε_{it} the regression models collapse into linear probability models (LPM), whereas with $F(.)$ as a logistic function with an appropriate distributional assumption on ε_{it}, we get back our discrete-time hazard model. Although a mediation methodology is mostly applied to linear setting, it can easily be extended to a non-linear setting, particularly in the case of $F(.)$ as a logistic function.

I estimate both cases, i.e., LPM and discrete-time hazard, but report the results only for discrete-time hazard specification. In these models, β is called the 'total effect' of X on Y and β' is called the 'indirect effect' of X on Y after M has been controlled for. From these regression models, I calculate the percent reduction in the logarithm-of-odds ratio as a result of mediation using $\frac{(\beta-\beta')}{\beta} \times 100$ and bootstrap the percent reduction parameter to come up with confidence intervals. The design considerations of my mediating instrument methodology weaken the plausibility of reverse mediation. That is, mediation from the outcome variable to any of the explanatory variables does not make sense since in all regressions the explanatory variables are measured temporally before the outcome variable.

3.4.2 Channel of Causality and Hypotheses

Risk Channel

Consistent with the standard rational economic theory, I treat each M&A bid (acquisition) like a lottery with some positive probability of success, and also with some positive probability of failure. The uncertain value implications of M&A investment decisions have a bearing on the underlying business risk of acquiring firms. In a rational world, shareholders can fully diversify to immune themselves against the idiosyncratic component of the business risk of a firm, but managers remain exposed to the idiosyncratic risk since they cannot fully diversify. Thus, it makes sense for managers to make diversifying acquisitions to lessen being exposed to the idiosyncratic risk component of their firms. Instead, if managers pursue an excessively risky strategy disregarding the diversification, synergy, and economies-of-scale implications, excessive acquisitiveness can amplify cash-flow volatilities which in turn can increase the failure risk of firms.

To empirically measure the idiosyncratic business risk of a firm, I use Shumway's (2001) *sigma* measure which gives the standard deviation of a firm's idiosyncratic stock returns. Shumway (2001) argues that firms with more volatile cash flows should have higher *sigma*, and that higher *sigma* also implies higher operating leverage for firms. I follow Shumway (2001) and regress each stock's daily returns on the value-weighted NYSE/AMEX index returns for the same quarter and calculate *sigma* as the standard deviation of the residuals of this regression.[3]

[3] One of the advantage of using *sigma* as a proxy for idiosyncratic business risk of the firm as opposed to actual cash-flow volatility is that *sigma* is market driven variable whereas $EBITDA$ based cash-flow volatility measures are accounting based. Furthermore, it is difficult to separate the unsystematic component of $EBITDA$ based measures from the systematic component. I also use $log\Big(\mid EBITDA_{i}t - EBITDA_{it-1} \mid \Big)$ as a measure of business risk and the results are similar to what I report in the table using the *sigma* measure.

Table 3.2 reports the estimates from the mediating instrument methodology using a rational risk channel as a mediating instrument. Column 1 reports the 'total effect' of excessive acquisitiveness on failure hazard while columns 2-4 report the mediation of the causality between excessive acquisitiveness and firm failure hazard through the *sigma* measure. It shows that *sigma* is statistically significantly correlated with excessive acquisitiveness and also with firm failure outcome. Moreover, controlling for *sigma* along with the excessive-acquisitiveness measure reduces the absolute size of the 'total effect' by 3% while remaining statistically significant. This translates into a 9% decline in the odds ratio (I report the logarithm-of-odds ratio in the table) of the 'total effect' of excessive acquisitiveness on firm failure. The results here show evidence of partial mediation through *sigma* because the 'indirect effect' is still statistically different from 0. Thus, instead of stabilizing, the excessive use of M&A amplifies cash-flow volatilities which in turn increases the conditional failure risk of firms (conditional on exogenous economic disturbances and other firm characteristics).

"Planning Fallacy" Channel

Consistent with the behavioral argument, I assume that each acquisition bid involves some cognitive bias, and that excessively acquisitive firms are more prone to cognitive bias compared to their conservative counterparts. Through this channel, excessively acquisitive managers accumulate greater cognitive biases, and over time these decision biases, in hindsight, get imputed into the operational efficiency of the firm creating structural imbalances in the corporate assets and debt structure, precipitating failure of their firms.

To empirically measure managerial cognitive bias, I assume that the bidding decision of the benchmark firm $\left(Y_B\right)$ is governed by the following equation:[4]

$$E\left(Y_B = 1|X\right) = F(X\beta) + \varepsilon \tag{3.5}$$

where X is the set of economic fundamentals and ε is a stochastic error independent of X that captures noise and other unobservables, such as luck, and $\varepsilon \rightarrow_{iid} N\left(0, \sigma_\varepsilon^2\right)$. The acquiring decisions of the excessively optimistic firm-manager $\left(Y_{up}\right)$ and the excessively conservative firm-manager

[4] I assume that the benchmark firm is also the rational firm in the sense that the propensity of M&A bid of the firm can be explained by the observable characteristics.

$\left(Y_{down}\right)$ are given by, respectively:

$$E\left(Y_{up}=1|X\right)=F(X\beta)+\varepsilon+bias\ up_i \tag{3.6}$$

$$E\left(Y_{down}=1|X\right)=F(X\beta)+\varepsilon-bias\ down_i \tag{3.7}$$

I assume that both $bias\ up_i$ and $bias\ down_i$ are independent of X and ε, and are distributed as $bias\ up_i \rightarrow N^+\left(\mu_{up},\sigma^2_{up}\right)$ and $bias\ down_i \rightarrow N^+\left(\mu_{down},\sigma^2_{down}\right)$ with truncation at 0. From this specification, it is obvious that both $bias\ up_i$ and $bias\ down_i$ act as non-negative shifters in these models where $bias\ up_i$ captures unobservables that systematically push up the likelihood of M&A bids and $bias\ down_i$ captures unobservables that systematically pull down the likelihood of M&A bids compared to the benchmark firm. Moreover, both $bias\ up_i$ and $bias\ down_i$ are unrelated with any observables that may affect the M&A decision of the benchmark firm.

I fit a linear probability model (LPM) of Y_{up} and Y_{down} on a set of firm characteristics, industry-fixed effects, year-fixed effects, and a set of industry and aggregate economic disturbance variables to extract the $bias\ up_i$ and $bias\ down_i$ from the observed firm-managerial M&A bids. The ε term in the LPM is assumed to have two components; one component is assumed to have a strictly non-negative distribution, and the other component is assumed to have a symmetric distribution. In the econometrics literature, the symmetric distribution is referred to as the idiosyncratic error and the non-negative component is the measure of a particular type of managerial cognitive bias. From the $bias\ up_i$ and $bias\ down_i$, I construct the "Planning Fallacy" measure as: $Planning\ Fallacy_i = bias\ up_i + bias\ down_i$.

Columns 5-7 of table 3.2 report the mediation of the effect from excessive acquisitiveness to firm failure through the managerial cognitive bias measure. It shows that managerial decision bias relative to the benchmark firm is statistically significantly correlated with excessive acquisitiveness and firm failure outcome. Moreover, controlling for managerial cognitive bias along with excessive acquisitiveness measure reduces the absolute size of the 'total effect' by 9% while remaining statistically significant. This translates into a 26% decline in the odds ratio (I report the logarithm of odds ratio in the table) of the 'total effect' of excessive acquisitiveness on conditional failure risk of firms.

Attention Allocation Channel

The bounded rationality theory posits that agents experience limitations in formulating and solving complex problems and in processing (receiving, storing, retrieving, transmitting) information. Consistent with this observation, I assume that managers have limited attention spans or capacities to process information, and that excessively acquisitive managers suffer from this limitation more severely than their conservative counterparts. Because excessive acquisitiveness demands greater attention allocation from the limited attention span of managers, it may divert managerial focus from the relevant economic functions of the firms. Thus, in hindsight, managerial attention distortions may worsen operating performance and eventually mediate the causality from excessive use of M&A to firm failure.

In order to construct a proxy for the managerial attention allocation, I use the cumulative number of lawsuits filed against the acquirers as a direct consequence of their M&A bids. I also normalize the cumulative number of lawsuits filed against an acquirer by the total number of deals conducted by the firm.[5] From my data set I could clearly identify 491 lawsuits filed against the acquirers as a result of their M&A bids, and these lawsuits are unrelated to any other operational aspects of the acquiring firms.

Columns 8-10 of table 3.2 show that a greater number of litigations (and hence greater attention distortion) is statistically significantly correlated with excessive acquisitiveness and firm failure outcome; that is excessively acquisitive firms suffer from greater attention distortion which in turn brings failure at a faster rate. However, controlling for the cumulative number of lawsuits along with the excessive acquisitiveness measure reduces the absolute size of the 'total effect' by a meager 1% in terms of the odds ratio. It implies that almost all of the variations in attention allocation measure is explained by the excessive acquisitiveness measure. Thus, after controlling for the excessive-acquisitiveness measure, there is very little variation left in our attention allocation

[5] Litigation is an everyday fact of life for American corporations. According to the Fulbright & Jaworski's Litigation Trends Survey, 94% of U.S. counsels canvassed said that their companies had some form of legal dispute pending in a U.S. venue. For 89%, at least one new suit was filed against their company during the past year. One third of all companies and nearly 40% of $1 billion-plus firms project the amount of litigation to increase next year. The survey also indicates that U.S. companies spend 71% of their overall estimated legal budgets on disputes. Large U.S. companies, typically the public firms that we study in this paper, commit an average of $19.8 million to litigation, approximately 58% of total average legal spending of $34.2 million. More than two-thirds of large companies surveyed reported at least one new suit involving $20 million or more in claims; 17% faced a minimum of six suits in the $20 million-plus range. Given this gloomy state of corporate litigation involving U.S. firms, we argue that litigations arising as a result of M&A bids may drain corporate resources and distract managers' attention from firm's economic functions. Thus, a limited attention span may rightly mediate the causality from the excessive use of M&A to the eventual failure of firms.

measure to explain failure risk.

3.4.3 Which Channel Explains More?

Columns 11-12 of table 3.2 include all channels and show that *sigma* measure, managerial planning fallacy measure, and attention allocation measure are statistically significantly correlated with firm failure outcome. When these measures enter the discrete-time hazard regression in column 12 together with the excessive acquisitiveness measure, they reduce the absolute size of the 'total effect' by 12% which translates into a 32.51% reduction in the odds ratio of 'total effect'. Overall, the results from table 3.2 show clear evidence of mediation from excessive use of M&A investment technology to firm failure through managerial excessive (irrational) risk-taking, proxied by the *sigma* measure, and through the behavioral channel, proxied by the managerial planning fallacy measure.

I bootstrap the change in 'total effect' due to mediation via the managerial planning fallacy and the *sigma* measures. Figure 3.1 depicts the distribution of $\frac{(\beta-\beta')}{\beta} \times 100$ after 1000 replications. It shows that mediation takes place (absolute size of 'total effect' shrinks) with probability 1 through the planning fallacy channel while mediation through the sigma measure occurs with probability 0.9 illustrating the fact that the mediation process seems to be stronger through the behavioral channel than through the excessive (irrational) risk-taking channel.

3.5 Disciplinary Role of the Capital Market

3.5.1 Market Reaction to Managerial Excessive Acquisitiveness

In an efficient capital market, any adverse effects of suboptimal managerial decisions should be fully incorporated into the security prices without any substantial delay. Moreover, the disciplinary role of the external corporate control market may come into effect to arbitrage the managerial behavoiral biases away by turning the bad bidders into good targets, thus undoing the previous unprofitable acquisitions or preventing these firms from making future unprofitable acquisitions [Jensen (1986)]. Mitchell and Lehn (1990) document empirical evidence that firms that subsequently become takeover targets make acquisitions that significantly reduce their equity value, and that firms that subsequently do not become takeover targets make acquisitions that raise their equity value. More recently, Zhao and Lehn (2006) document a strong inverse relationship between acquiring firms' returns and the likelihood that their CEOs are subsequently fired, buttressing the disciplinary role of the internal corporate control to rein in bad acquiring CEOs.

To investigate the market reaction to managerial M&A actions I calculate the acquirers' cumulative abnormal return $\left(CAR_{(-1,+1)}\right)$ around a three-day event window which includes one trading day prior to the bid announcement, the day of announcement, and one trading day after the bid announcement. To calculate the $CAR_{(-1,+1)}$, I estimate a market model using stock returns from 60 trading days (estimation window) prior to the event window and use the parameters from the market model to calculate normal returns during the event window. I then subtract the estimated normal returns from the observed returns during the event window to calculate abnormal returns and cumulate the abnormal returns over three days to come up with my $CAR_{(-1,+1)}$ measure. I regress $CAR_{(-1,+1)}$ on the excessive acquisitiveness measure, various mediating instruments, Gompers, Ishii and Metrick (2003) governance score, and various deal-structure dummy variables.

Table 3.3 reports the estimates from the Ordinary Least Square (OLS) regression. It shows that the market reacts through $CAR_{(-1,+1)}$ negatively to deals if the firm has been excessively acquisitive in the past. The Gompers, Ishii and Metrick (2003) governance score has a negative and statistically significant effect on $CAR_{(-1,+1)}$. Quite interestingly, the idiosyncratic standard deviation of stock return (*Sigma*) has a positive effect on $CAR_{(-1,+1)}$. The results are similar in columns 8-14 where I also control for deal value normalized by the market value of the firm. To understand the confounding effect of the underlying business risk measure on $CAR_{(-1,+1)}$, I estimate the regression at various conditional quantiles of the $CAR_{(-1,+1)}$ distribution.[6]

A quantile regression is a statistical technique intended to estimate, and conduct inference about, conditional quantile functions.[7] While the OLS enables us to estimate models for conditional mean functions, quantile regression methods offer a mechanism for estimating models for the conditional median function, and the full range of other conditional quantile functions. By estimating an entire family of conditional quantile functions, a quantile regression is capable of providing a more complete statistical analysis of the stochastic relationships between $CAR_{(-1,+1)}$ and other explanatory variables of interest. Figure 3.2 depicts the effects of excessive acquisitiveness and other mediating instruments on $CAR_{(-1,+1)}$ at various quantiles of the condition distribution of $CAR_{(-1,+1)}$ along with the 95% confidence intervals.

[6] I also report the effects of some selected deal structure dummy variables on $CAR_{(-1,+1)}$ in table 3.3 but do not discuss these results here for the sake of brevity.

[7] See Koenker, R. and Hallock, K. (2001) for more about quantile regressions.

It shows that the market reacts positively to excessive acquisitiveness until the 30th conditional quantile while the reaction becomes negative and increasingly stronger at the higher quantiles. The asymmetry of market reaction at various conditional quantiles of $CAR_{(-1,+1)}$ is also evident in measures of business risk and behavioral biases. It reveals a sense of myopia in the capital market response in the sense that even though the excessive use of M&A aggravates firms' failure hazard, and the *Sigma* and the *Planning Fallacy* mediate the effect from excessive acquisitiveness to firm failure, capital market reaction through $CAR_{(-1,+1)}$ does not fully reflect these failure-augmenting effects at all quantiles of the condition distribution of $CAR_{(-1,+1)}$.

3.5.2 *Reallocating Assets of Excessive Acquirers*

Despite the seeming market myopia in fully incorporating the failure-augmenting effects of excessive acquisitiveness and other mediating instruments, the external market for corporate control seems to be effective in turning the excessively acquisitive firms into future targets. In Table 3.4, I estimate a competing hazard model and also a multi-period multinomial logit model. In both empirical models, I assume that the assets of the sample firms are at a risk of being reallocated to other firms either through the market for takeovers or through other mechanisms such as bankruptcy, liquidation, leverage buy-outs, and management buy-outs. The only difference between the two models is that the risk of a firm's assets being reallocated either through takeover or through other mechanisms is independent in the competing hazard model, and the risk is relative to assets remaining within the existing firm in the multinomial logit model.

Columns 1-8 of Table 3.4 shows the estimates from the competing hazard model. It shows that excessive acquisitiveness increases the conditional risk of reallocating a firm's assets to other firms via either mechanisms, but the marginal effect is higher for reallocation via takeover than via other mechanisms. Conditional on other explanatory variables evaluated at their mean, sample firms' assets are almost 3 times more likely to be reallocated via takeovers compared to other mechanisms when excessive acquisitiveness increases. The results are also similar using the multinomial logit as the empirical specification.

Table 3.5 reports the marginal effects and other measures of economic significance from the multinomial logit specification. It shows, for example, when the excessive acquistiveness measure increases from a minimum (0) to a maximum (1), the conditional probability of assets being reallocated via takeover increases by 0.43 whereas the probability of allocation through other mechanisms increases by 0.34. In short, the statistical as well as economic significance estimates show that the market for takeover seems to be more effective relative to other mechanisms in reallocating the assets of excessive acquirers in the long run. These findings corroborate Jensen (1986) in the sense that the external corporate control market plays the role of preventing excessively acquisitive firms from making future failure-precipitating acquisitions by turning them into targets of takeover in its own way.

3.6 Conclusion

Economists disagree sharply on the reasons for firm-failure. Theoretical debates on causes of corporate failure have been at best bifurcated. While rational economic theory blames exogenous economic disturbances beyond managerial control for failure, behavioral theory argues that large numbers of failures in the modern corporate landscape cannot be explained simply by external disturbances. The managers of failed firms who suffer from behavioral biases in their decision makings are partly to blame. Despite serious attempts by the empirical corporate finance literature to understand the causes of firm failure, our understanding of this issue is limited; when firms fail it is very difficult to untangle the failures that arise as a result of the adverse effects of managerial rational decisions beyond their control from failures that result simply because of flawed decision-making.

Using managerial mergers and acquisitions (M&A) investment decisions as an identification mechanism, I show the effect of managerial excessive acquisitiveness on firm failure-risk (as shown in the previous chapter) could be explained through competing theories of corporate failure, but that the mediation of causality seems to be stronger through the behavioral channel than the (rational) risk channel. Furthermore, I find that the capital markets do not fully internalize the costs associated with managerial excessive acquisitiveness at the time of bid announcement. In the longer term, the external corporate control market also disciplines excessive acquirers by turning them into future targets of takeover. The reallocation of assets of excessive acquirers seems to be more prevalent via takeovers compared to other mechanisms such as bankruptcy, liquidation, LBO, and MBO. A question remains whether reallocating the assets of excessive acquirers via the external corporate control market is the first best use of these assets.

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Fig. 3.1: **Probability of Mediation by the Mediating Instruments**

This graph shows the bootstrap distribution of percentage changes $\left(\frac{\beta-\beta'}{\beta} \times 100\right)$ in the 'Total Effect' of excessive acquisitiveness on firm failure hazard as a result of mediation through the managerial cognitive bias and the sigma measures. The vertical axis denotes the probability with which mediation takes place, and the horizontal axis shows the % change in the 'Total Effect" of the excessive acquisitiveness measure. It clearly shows that 'Total Effect' decreases (% change is negative) with probability 1 using the managerial cognitive bias measure whereas 'Total Effect' declines (% change is negative) with probability .9 using the sigma measure. In other words, the mediation process seems to be stronger through the behavioral channel than through the risk channel.

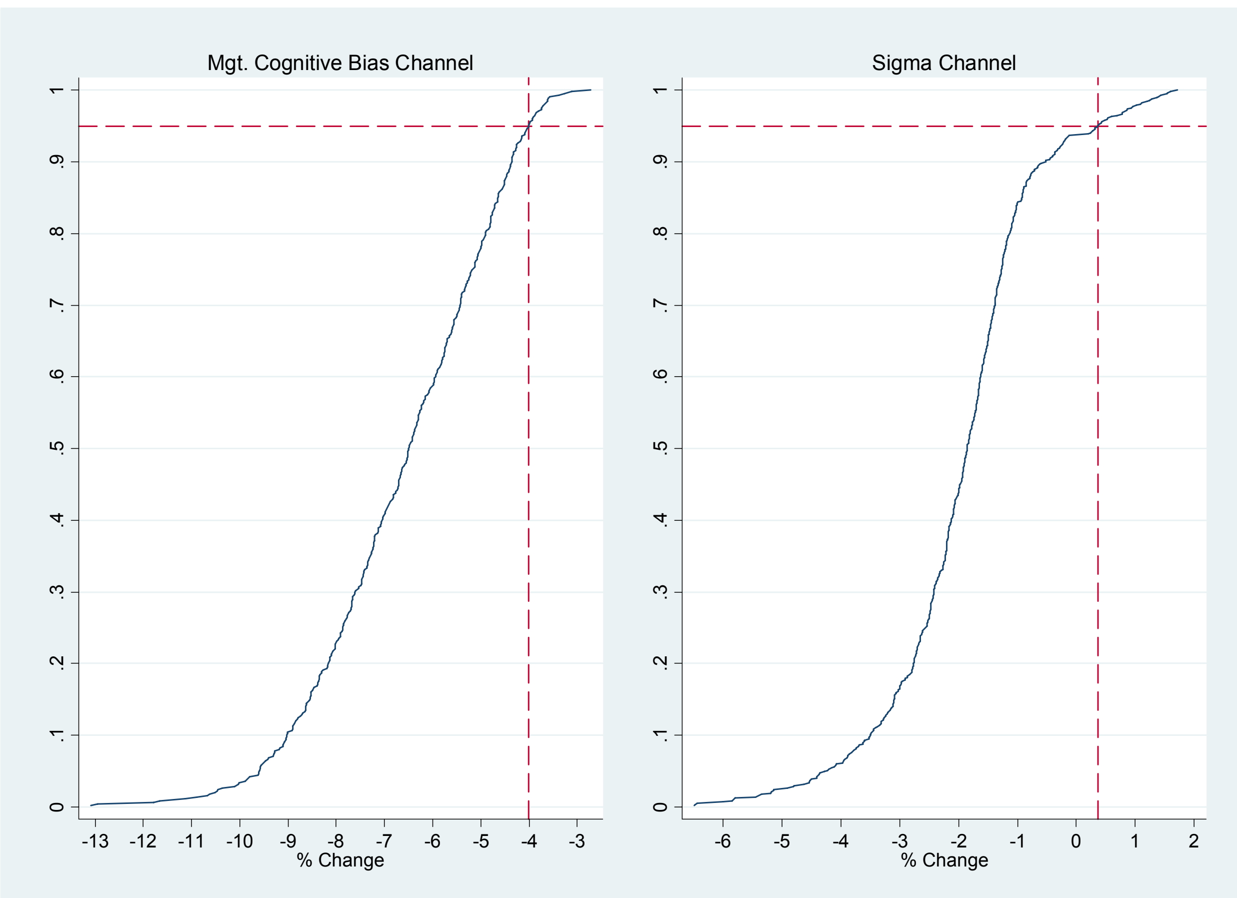
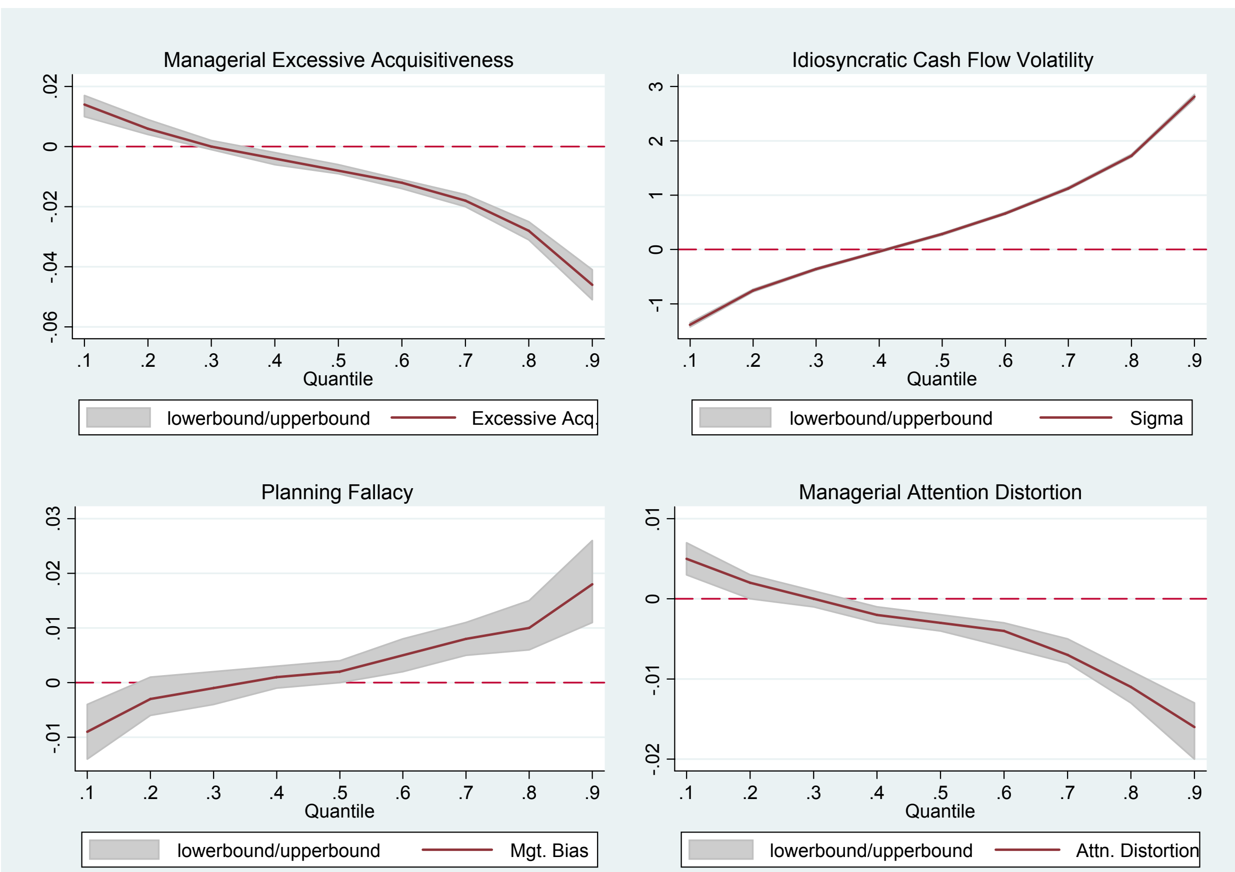


Fig. 3.2: **Conditional Quantile Functions of Cumulative Abnormal Return**

This figure depicts the conditional quantile functions of the Cumulative Abnormal Return (CAR) of the acquirers from the M&A announcement events. The vertical axis measures the effects of excessive acquisitiveness, idiosyncratic cash-flow volatility, managerial planning fallacy, and attention distortion at various conditional quantiles whereas the horizontal axis refers to those quantiles themselves. It shows that capital market does not always react negatively to the acquirer's excessive M&A behavior and other mediating instruments even though these factors eventually augment the conditional failure risk of the firm.



Tab. 3.1: **Why Some Firms Are More Acquisitive Than Others?**

This table shows the correlation structure of managerial excessive and conservative acquisitiveness with firm's productivity shocks, investment and acquisition expenditure, future growth opportunity, and governance proxies. The construction of the excessive and conservative acquisitiveness measures are the same as in the previous tables in Chapter 1. TFP stands for total factor productivity estimated using the methodology developed by Olly and Pakes (1996). 'Optimism-Driven Bid' is a dummy variable which equals 1 if the firm announces an acquisition bid even if it receives a negative productivity shock in that period while 'Growth-Driven Bid' is another dummy variable which equals 1 if the firm announces an acquisition bid when the market-to-book ratio is greater than 1. Firm-level capital expenditure and acquisition expenditure are from COMPUSTAT data item 90 and data item 94, respectively. Governance index (G) is from Gompers, Ishii and Metrick (2003). P-values are given in bracket.

	Managerial Acquisitiveness	
	Excessive Acquisitive Sample	Conservative Acquisitive Sample
Change in TFP	0.00670	-0.00550
	[0.00]	[0.00]
Optimism-Driven Bid	0.13160	-0.07300
	[0.00]	[0.00]
Growth-Driven Bid	0.28210	-0.14650
	[0.00]	[0.00]
Capital Expenditure	0.07090	-0.00580
	[0.00]	[0.00]
Acquisition Expenditure	0.10220	-0.01450
	[0.00]	[0.00]
Acquirer's G-Index	0.04680	-0.02690
	[0.00]	[0.00]

Tab. 3.2: **Mediation of the Causality through Various Mediating Instruments**

This table reports the estimates from a mediating instrument methodology to determine the channels through which managerial excessive acquisitiveness causes an increase in the acquiring firm's failure hazard. The definitions of firm characteristics and industry and aggregate economic disturbance measures are the same as in previous tables. *Sigma* is calculated following the Shumway (2001). I explain the construction of the "Planning Fallacy" measure in detail in the relevant section of the previous chapter. "Managerial Attention Allocation" for a given period is defined as the cumulative number of lawsuits filed against an acquirer as a direct consequence of its M&A decision normalized by the total number of bids up until that given period. Robust z statistics are given in brackets. In the table, "*" denotes significance at 10%; "**" denotes significance at 5%; "***" denotes significance at the 1% level.

	Direct Effect	Mediation Via Sigma			Mediation Via Planning Fallacy			Mediation Via Attention Distortion			All Channels	
Dependent Variable	FAILURE	SIGMA	FAILURE	FAILURE	MGT_BIAS	FAILURE	FAILURE	ATTN. ALLOCA	FAILURE	FAILURE	FAILURE	FAILURE
Estimation Methodology	(1) LOGIT	(2) TOBIT	(3) LOGIT	(4) LOGIT	(5) TOBIT	(6) LOGIT	(7) LOGIT	(8) OLS	(9) LOGIT	(10) LOGIT	(11) LOGIT	(12) LOGIT
Log (Total Assets)	-0.6098**	-0.0058***	-0.3884	-0.5122**	-0.0020***	-0.4864*	-0.6077**	0.0007***	-0.5188**	-0.6108**	-0.3940	-0.5130**
	[2.36]	[237.53]	[1.58]	[2.26]	[17.19]	[1.88]	[2.36]	[4.39]	[2.00]	[2.37]	[1.62]	[2.27]
Log (Age)	-0.4150***	-0.0034***	-0.6052***	-0.3893***	-0.0020***	-0.5244***	-0.3517***	0.0027***	-0.6465***	-0.4208***	-0.5348***	-0.3369***
	[3.83]	[42.73]	[5.32]	[3.46]	[5.41]	[3.94]	[3.12]	[4.57]	[5.24]	[3.98]	[4.35]	[2.91]
Net Income/Tot. Assets	-0.1365**	-0.0038***	-0.1538	-0.0657	-0.0009	-1.1539*	-0.1280*	0.0007	0.1181	-0.1358**	-0.1426	-0.0675
	[2.30]	[20.16]	[1.29]	[0.20]	[1.09]	[1.85]	[1.69]	[1.44]	[0.26]	[2.24]	[1.48]	[0.19]
Tot. Liab./Tot. Assets	0.7856	0.0021***	0.8088**	0.5942	0.0031***	0.6928	0.7410	0.0011	1.0388**	0.7815	0.7520**	0.5470
	[1.27]	[28.19]	[2.36]	[1.15]	[8.78]	[0.65]	[1.20]	[1.49]	[2.24]	[1.26]	[2.28]	[0.92]
Cash/Tot. Assets	-0.6743	-0.0042***	-1.0699	-0.6132	0.0105***	-1.2118	-0.6849	0.0006	-1.0712	-0.6766	-1.0570	-0.6231
	[0.57]	[16.09]	[0.87]	[0.57]	[8.53]	[1.09]	[0.58]	[0.32]	[0.92]	[0.58]	[0.86]	[0.60]
Lt. Debts/Tot. Assets	-0.7121	-0.0001*	-0.4797	-0.4149	0.0001	-0.4246	-0.7310	0.0000	-0.4869	-0.7132	-0.4962	-0.4253
	[0.11]	[1.73]	[0.08]	[0.07]	[0.57]	[0.07]	[0.11]	[0.71]	[0.08]	[0.11]	[0.08]	[0.07]
PPE/Tot. Assets	0.5790	0.0006**	0.1525	0.4264	0.0012	0.2269	0.6234	-0.0019	0.1999	0.5850	0.2271	0.4561
	[0.28]	[2.46]	[0.07]	[0.21]	[0.99]	[0.11]	[0.30]	[0.66]	[0.09]	[0.28]	[0.11]	[0.22]
Market-to-Book	-0.5551***	-0.0005***	-0.5978***	-0.4505***	-0.0012***	-0.5896***	-0.5356***	-0.0001*	-0.7154***	-0.5529***	-0.5523**	-0.4316***
	[2.62]	[34.14]	[2.66]	[2.60]	[18.09]	[3.08]	[2.62]	[1.89]	[3.02]	[2.61]	[2.57]	[2.61]
Excessive Acquisitiveness	3.3286***	0.0048***		3.2329***	0.0911***		3.0300***	0.0168***		3.3191***		2.9354***
	[5.16]	[20.07]		[5.22]	[81.92]		[4.47]	[7.60]		[5.13]		[4.52]
Sigma			8.9590***	8.6466***							8.5150***	8.4336***
			[6.01]	[4.52]							[5.28]	[4.08]
Planning Fallacy						4.7467***	3.4729***				4.6408***	3.2867***
						[12.97]	[9.52]				[12.96]	[10.18]
Mgt. Attn. Allocation									1.6759**	1.3479**	1.5587***	1.2460*
									[2.44]	[2.13]	[2.66]	[1.96]
Deregulation Dummy	-0.2085	-0.0013***	-0.1997	-0.1821	0.0048***	-0.2734	-0.2242	-0.0001	-0.2467	-0.2091	-0.2403	-0.2081
	[0.97]	[4.03]	[0.93]	[0.93]	[3.21]	[1.20]	[1.07]	[0.10]	[1.17]	[0.98]	[1.08]	[1.01]
Ind. Demand Shock	0.0005**	0.0000	0.0005**	0.0006**	-0.0000***	0.0005**	0.0006***	0.0000	0.0005**	0.0005**	0.0005**	0.0006**
	[2.56]	[1.17]	[2.26]	[2.51]	[14.31]	[2.40]	[2.73]	[0.74]	[2.57]	[2.55]	[2.44]	[2.55]
Ind. Supply Shock	-0.0006	-0.0000***	-0.0005	-0.0006	-0.0000***	-0.0005	-0.0006	-0.0000	-0.0005	-0.0006	-0.0005	-0.0005
	[1.38]	[3.93]	[1.25]	[1.33]	[2.92]	[1.20]	[1.26]	[0.90]	[1.31]	[1.38]	[1.10]	[1.14]
Ind. Tech. Shock	0.0352	0.0002***	0.0301	0.0347	-0.0004	0.0352	0.0376	-0.0000	0.0349	0.0357	0.0319	0.0365
	[1.16]	[4.41]	[0.87]	[1.06]	[1.50]	[1.12]	[1.22]	[1.08]	[1.10]	[1.17]	[0.92]	[1.11]
Agg. Demand Shock	1.1733***	0.0108***	0.9496**	0.9810**	0.0016	1.1288***	1.1294***	0.0011**	1.2150***	1.1802***	0.9470**	0.9797**
	[2.90]	[13.39]	[2.15]	[2.32]	[0.42]	[2.75]	[2.76]	[2.24]	[2.86]	[2.92]	[2.15]	[2.30]
Agg. Supply Shock	1.2174	0.0721***	-0.4744	-0.0401	0.0449*	0.6993	1.2217	-0.0002	0.9825	1.2309	-0.6726	-0.1487
	[0.40]	[12.43]	[0.15]	[0.01]	[1.65]	[0.23]	[0.40]	[0.03]	[0.32]	[0.40]	[0.22]	[0.05]
Agg. Equity Mkt. Shock	-0.1339***	0.0002	-0.1758***	-0.1550***	0.0005	-0.1584***	-0.1374***	-0.0000	-0.1585***	-0.1348***	-0.1756***	-0.1567***
	[2.61]	[1.38]	[3.25]	[2.91]	[0.99]	[3.09]	[2.70]	[0.19]	[3.16]	[2.63]	[3.22]	[2.94]
Agg. Debt Mkt. Shock	-0.0434	-0.0003***	-0.0246	-0.0177	0.0003*	-0.0593	-0.0451	0.0000	-0.0658	-0.0435	-0.0292	-0.0226
	[1.15]	[8.53]	[0.56]	[0.46]	[1.75]	[1.31]	[1.20]	[0.25]	[1.56]	[1.15]	[0.67]	[0.59]
Agg. Equity Mkt. Momentum	1.0292	-0.0124***	1.6027**	1.2625*	0.0899***	1.0984	0.7422	-0.0022*	1.3659*	1.0408	1.2687*	0.9141
	[1.24]	[10.43]	[2.08]	[1.72]	[16.15]	[1.21]	[0.94]	[1.95]	[1.88]	[1.26]	[1.68]	[1.24]
Constant	-7.9488**	0.1232***	-12.1997***	-10.2615***	0.3697***	-12.6808***	-9.6126***	-0.0011	-9.5868***	-7.9721**	-14.6042***	-11.4410***
	[2.21]	[21.86]	[4.02]	[3.38]	[14.02]	[3.08]	[2.64]	[0.12]	[3.34]	[2.21]	[4.62]	[3.55]
Industry Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	315595	318656	318825	315492	318760	318928	315595	318760	318928	315595	318825	315492
Num. of Firms	8678	8677	8677	8677	8678	8678	8678	8678	8678	8678	8677	8677
R^2/*Pseudo*-R^2	0.19		0.16	0.20		0.15	0.20	0.02	0.14	0.19	0.18	0.21
Wald-χ^2	5109.62		18782.93	5948.85		15864.67	5029.25		13751.80	5136.19	19122.14	5898.97

Tab. 3.3: **The Capital Market Reaction**

This table reports the estimates from OLS regression to determine the market reactions to managerial excessive acquisitiveness and various mediating instruments. The dependent variable is the cumulative abnormal return around a 3-day event window surrounding the announcement event of the M&A. Deal value is in U.S.$ million from the SDC database. Market value is defined as market value of equity plus book value of debt. Managerial excessive acquisitiveness, managerial panning fallacy, and managerial attention allocation measures are discussed in detail in the relevant section of the paper. *Sigma* is calculated following Shumway (2001). Governance index is from Gompers, Ishii and Metrick (2003). I include 32 dummy variables portraying various deal characteristics in these regressions but due to space limitation report the coefficients only for a few that are statistically significant. Robust z statistics are given in brackets. In the table, "*" denotes significance at 10%; "**" denotes significance at 5%; "***" denotes significance at the 1% level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Excessive Acquisitiveness	-0.019***					-0.012***	-0.006***	-0.020***					-0.010***	-0.007***
	[12.26]					[6.92]	[3.81]	[9.98]					[4.74]	[3.55]
Sigma		0.533***				0.507***	0.276***		0.749***				0.725***	0.252***
		[5.81]				[5.44]	[4.23]		[7.68]				[7.30]	[3.29]
Planning Fallacy			0.003			0.002	-0.002			0.005			0.003	0.000
			[0.80]			[0.65]	[0.56]			[1.43]			[0.87]	[0.04]
Mgt. Attention Allocation				-0.002		0.012	-0.027*				-0.009		0.002	-0.027
				[0.16]		[1.01]	[1.80]				[0.68]		[0.17]	[1.39]
Governance Score					-0.001***		-0.000***					-0.001***		-0.001***
					[4.51]		[3.19]					[4.62]		[3.61]
Deal Value/Mkt. Value								0.000	0.000	0.000	0.000	-0.009**	0.000	-0.010***
								[1.17]	[1.01]	[0.84]	[0.86]	[2.45]	[1.15]	[2.71]
Some Deal Structure Dummy Variables:														
Similar Industry Acquisition	0.004***	0.005***	0.004***	0.004***	0.004***	0.005***	0.004***	0.005***	0.008***	0.006***	0.006***	0.006***	0.007***	0.005***
	[3.69]	[5.40]	[4.30]	[4.34]	[5.52]	[4.91]	[5.07]	[3.46]	[5.26]	[3.76]	[3.85]	[4.80]	[4.98]	[4.50]
Stock Swap Deal	-0.010***	-0.011***	-0.010***	-0.010***	-0.011***	-0.011***	-0.012***	-0.019***	-0.018***	-0.020***	-0.020***	-0.014***	-0.018***	-0.014***
	[3.48]	[3.64]	[3.47]	[3.47]	[5.36]	[3.64]	[5.42]	[6.27]	[6.00]	[6.36]	[6.35]	[5.78]	[5.97]	[5.71]
Pure Cash-Financed Deal	-0.003***	-0.002**	-0.003***	-0.004***	-0.001	-0.002**	-0.000	-0.007***	-0.006***	-0.008***	-0.008***	-0.004***	-0.005***	-0.003***
	[3.21]	[2.31]	[3.30]	[3.31]	[0.50]	[2.28]	[0.46]	[5.79]	[4.91]	[6.39]	[6.39]	[3.13]	[4.64]	[2.84]
Hostile Deal	-0.013***	-0.012***	-0.013***	-0.013***	-0.009*	-0.011**	-0.008	-0.013***	-0.012***	-0.014***	-0.014***	-0.005	-0.012***	-0.004
	[2.75]	[2.59]	[2.89]	[2.89]	[1.65]	[2.53]	[1.47]	[3.06]	[2.84]	[3.27]	[3.27]	[0.91]	[2.74]	[0.65]
Financing through Borrowing	0.009***	0.009***	0.010***	0.010***	0.005*	0.009***	0.004	0.007***	0.007**	0.007***	0.007***	0.005	0.007**	0.005
	[3.62]	[3.66]	[3.81]	[3.80]	[1.73]	[3.56]	[1.56]	[2.62]	[2.55]	[2.75]	[2.74]	[1.59]	[2.50]	[1.53]
Financing through Internal Credit	0.009***	0.010***	0.009***	0.009***	0.007***	0.010***	0.006***	0.008***	0.009***	0.008***	0.008***	0.006**	0.009***	0.006**
	[3.48]	[3.94]	[3.67]	[3.66]	[2.68]	[3.81]	[2.64]	[2.82]	[3.29]	[2.89]	[2.88]	[2.25]	[3.25]	[2.23]
Financing through Lines of Credit	0.010***	0.011***	0.010***	0.010***	0.007**	0.010***	0.007**	0.009***	0.010***	0.010***	0.009***	0.007**	0.010***	0.007**
	[4.01]	[4.31]	[4.19]	[4.18]	[2.30]	[4.23]	[2.21]	[3.47]	[3.77]	[3.55]	[3.52]	[2.05]	[3.75]	[2.04]
Constant	0.014	0.001	0.011	0.013	0.005	0.000	0.001	0.037	0.017	0.031	0.035	0.019	0.016	0.014
	[0.70]	[0.03]	[0.51]	[0.63]	[0.21]	[0.02]	[0.03]	[1.20]	[0.54]	[0.97]	[1.13]	[0.68]	[0.49]	[0.50]
Deal-Structure Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	63556	63580	63581	63581	33771	63555	33761	38585	38600	38601	38601	20447	38584	20439
Num. of Firms	10771	10774	10774	10774	2925	10771	2925	9148	9153	9153	9153	2821	9148	2821
R^2	0.01	0.02	0.01	0.01	0.02	0.02	0.03	0.02	0.04	0.02	0.02	0.03	0.04	0.03
Adj-R^2	0.01	0.02	0.01	0.01	0.02	0.02	0.02	0.02	0.03	0.01	0.01	0.03	0.03	0.03

Tab. 3.4: **Managerial Excessive Acquisitiveness and Reallocation of Firms' Assets**

This table reports the estimates from the competing hazard model and the multinomial logit model. The dependent variable is 1 for the last fiscal quarter in which the firm exits. All explanatory variables are already defined in previous tables. For the competing hazard models, the column denoted *LOGIT* refers to the raw estimate of the hazard model, and the column denoted *MFX* refers to the marginal effect of the *LOGIT* competing hazard model. Marginal effects are estimated conditional on all other exogenous variables evaluated at their mean. Robust z statistics are given in brackets and "*" denotes significance at 10%; "**" denotes significance at 5%; "***" denotes significance at the 1% level.

	Competing Hazard Model								Multinomial Logit Model			
	Exit Via Bankruptcy, Liquidation, MBO, and LBO				Exit Via M&A and Takeovers				Exit Via Bankruptcy Liquidation, MBO, LBO		Exit Via M&A and Takeovers	
	LOGIT	MFX	LOGIT	MFX	LOGIT	MFX	LOGIT	MFX				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Log (Tot. Assets)	-0.6775*	-0.0010*	-0.5855*	-0.0008	-0.1255***	-0.0007***	-0.1198***	-0.0006***	-0.7562***	-0.6277***	-0.1336***	-0.1237***
	[1.81]	(-1.87)	[1.72]	(-1.61)	[10.49]	(-10.49)	[8.95]	(-8.92)	(-33.23)	(-22.89)	(-11.02)	(-8.96)
Log (Age)	-0.0747	-0.0001	-0.0830	-0.0001	-0.1074***	-0.0006***	0.0017	0.0000	-0.1061*	-0.0632	-0.1100***	0.0015
	[0.51]	(-0.49)	[0.56]	(-0.57)	[3.00]	(-3.02)	[0.05]	(0.05)	(-1.91)	(-1.12)	(-3.08)	(0.04)
Net Income/Tot. Assets	-1.0323	-0.0015	-0.0471	-0.0001	0.1143**	0.0006**	0.1789**	0.0009**	-0.1568***	-0.0960	0.1022**	0.1690**
	[1.35]	(-1.41)	[0.23]	(-0.23)	[2.25]	(2.24)	[2.33]	(2.33)	(-3.06)	(-1.60)	(1.97)	(2.17)
Tot. Liab./Tot. Assets	0.4853	0.0007	1.0878	0.0014	0.2433***	0.0013***	0.1414**	0.0007**	0.8248***	0.6356***	0.2526***	0.1501**
	[0.33]	(0.32)	[0.95]	(0.96)	[7.26]	(7.41)	[2.07]	(2.07)	(5.02)	(4.40)	(7.34)	(2.17)
Cash/Tot.Assets	-1.6943	-0.0025	-1.2568	-0.0016	0.2163*	0.0012*	0.1299	0.0007	-1.4077***	-1.3294***	0.2056*	0.1189
	[0.97]	(-0.99)	[0.74]	(-0.76)	[1.77]	(1.77)	[1.06]	(1.06)	(-5.06)	(-4.73)	(1.68)	(0.97)
Lt. Debts/Tot. Assets	-0.6552	-0.0010	-0.7939	-0.0010	-0.0038**	-0.0000**	-0.0041**	-0.0000**	-0.0074***	-0.0070***	-0.0040*	-0.0043**
	[0.07]	(-0.07)	[0.08]	(-0.08)	[2.09]	(-2.08)	[2.27]	(-2.26)	(-3.49)	(-3.35)	(-1.95)	(-2.14)
PPE/Tot. Assets	0.4460	0.0007	0.4249	0.0006	0.1937	0.0011	0.2096*	0.0011*	0.2824*	0.2292	0.1985*	0.2132*
	[0.16]	(0.16)	[0.15]	(0.15)	[1.62]	(1.62)	[1.74]	(1.74)	(1.79)	(1.46)	(1.66)	(1.77)
Market-to-Book	-0.3824**	-0.0006**	-0.3753*	-0.0005**	-0.1570***	-0.0009***	-0.1312***	-0.0007***	-0.6112***	-0.4646***	-0.1595***	-0.1320***
	[2.00]	(-2.17)	[1.83]	(-2.05)	[7.14]	(-7.38)	[6.08]	(-6.17)	(-4.79)	(-4.34)	(-7.22)	(-6.12)
Excessive Acq.	3.5247***	0.0052***	3.4070***	0.0045***	2.8566***	0.0158***	2.4012***	0.0121***	3.6467***	3.4909***	2.9149***	2.4553***
	[4.60]	(4.09)	[4.23]	(4.86)	[35.26]	(29.39)	[27.22]	(21.35)	(31.87)	(30.68)	(35.23)	(27.43)
Sigma			8.7111***	0.0114**			0.1689	0.0009		9.4165***		0.7776
			[2.60]	(2.35)			[0.24]	(0.24)		(10.43)		(0.97)
Planning Fallacy			0.7086	0.0009*			4.9182***	0.0249***		0.9087***		4.9257***
			[1.62]	(1.70)			[17.14]	(20.01)		(2.82)		(17.17)
Deregulation Dummy	-0.0276	-0.0000	0.0542	0.0001	-0.1447	-0.0007	-0.1646	-0.0008	-0.0195	0.0097	-0.1470	-0.1665
	[0.12]	(-0.12)	[0.20]	(0.20)	[0.81]	(-0.87)	[0.91]	(-0.98)	(-0.09)	(0.04)	(-0.83)	(-0.92)
Ind. Demand Shock	0.0004	0.0000	0.0004	0.0000	0.0007***	0.0000***	0.0008***	0.0000***	0.0005*	0.0005	0.0008***	0.0008***
	[1.39]	(1.41)	[1.51]	(1.50)	[4.12]	(4.11)	[4.38]	(4.35)	(1.67)	(1.53)	(4.16)	(4.40)
Ind. Supply Shock	-0.0005	-0.0000	-0.0005	-0.0000	-0.0007*	-0.0000*	-0.0006*	-0.0000*	-0.0005	-0.0005	-0.0007*	-0.0006*
	[0.91]	(-0.90)	[0.90]	(-0.91)	[1.84]	(-1.84)	[1.73]	(-1.72)	(-0.93)	(-0.82)	(-1.86)	(-1.74)
Ind. Tech. Shock	0.0762**	0.0001**	0.0791*	0.0001*	-0.0397	-0.0002	-0.0374	-0.0002	0.0811**	0.0822**	-0.0390	-0.0370
	[2.09]	(2.03)	[1.83]	(1.76)	[1.50]	(-1.50)	[1.41]	(-1.41)	(2.09)	(2.04)	(-1.47)	(-1.39)
Agg. Demand Shock	2.0387***	0.0030***	1.8760***	0.0025***	0.8360**	0.0046**	0.8064**	0.0041**	2.0672***	1.9149***	0.8661**	0.8323**
	[3.98]	(3.67)	[3.36]	(3.38)	[2.38]	(2.38)	[2.25]	(2.25)	(3.79)	(3.43)	(2.46)	(2.33)
Agg. Supply Shock	-2.4450	-0.0036	-4.0767	-0.0053	2.6345	0.0145	2.4366	0.0123	-2.9644	-4.5017	2.6011	2.3271
	[0.71]	(-0.72)	[1.08]	(-1.07)	[0.95]	(0.95)	[0.88]	(0.88)	(-0.81)	(-1.22)	(0.94)	(0.84)
Agg. Equity Shock	-0.1421**	-0.0002*	-0.1746**	-0.0002**	-0.0310	-0.0002	-0.0383	-0.0002	-0.1416**	-0.1717**	-0.0333	-0.0411
	[2.04]	(-1.89)	[2.20]	(-2.30)	[0.68]	(-0.68)	[0.83]	(-0.83)	(-2.13)	(-2.52)	(-0.73)	(-0.89)
Agg. Debt Shock	0.0206	0.0000	0.0483	0.0001	-0.0209	-0.0001	-0.0231	-0.0001	0.0287	0.0518	-0.0207	-0.0223
	[0.56]	(0.55)	[1.18]	(1.17)	[0.69]	(-0.69)	[0.77]	(-0.77)	(0.63)	(1.15)	(-0.68)	(-0.74)
Agg. Equity Momentum	1.8912*	0.0028	2.2491**	0.0029**	-1.7443***	-0.0096***	-2.1132***	-0.0107***	1.8834**	2.0921***	-1.7340***	-2.0940***
	[1.68]	(1.52)	[2.16]	(2.24)	[3.91]	(-4.00)	[4.59]	(-4.72)	(2.53)	(2.69)	(-3.89)	(-4.56)
Constant	-13.1561**		-16.9273***		-10.5904		-13.2476		-27.7295	-30.2492	-12.7205	-15.5223
	[2.52]		[3.78]		[.]		[.]		(.)	(.)	(.)	(.)
Deal-Structure Dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Ind.-Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	314896	314897	314793	314794	315595	315595	315492	315492	315595	315492	315595	315492
Num. of Firms	8658	8658	8657	8657	8678	8678	8677	8677	8678	8677	8678	8677
Pseudo-R^2	0.18	0.18	0.22	0.22	0.08	0.08	0.10	0.10	0.12	0.14	0.12	0.14

Tab. 3.5: **Managerial Excessive Acquisitiveness and Reallocation of Firms' Assets: Economic Significance**

This table reports various economic significance measures from the multinominal logit specification for variables of interest. The dependent variable is 1 for the last fiscal quarter in which the firm exits. All explanatory variables are already defined in previous tables. Marginal effects are estimated conditional on all other exogenous variables evaluated at their mean. The table also shows the changes in failure probability when an explanatory variable of interest changes from $Minimum$ to $Maximum$, from $(Mean - \frac{1}{2})$ to $(Mean + \frac{1}{2})$, and from $(Mean - \frac{sd}{2})$ to $(Mean + \frac{sd}{2})$, where sd refers to the standard deviation of the explanatory variable of interest. Robust z statistics are given in brackets and "*" denotes significance at 10%; "**" denotes significance at 5%; "***" denotes significance at the 1% level.

		(1)			(2)			(3)			(4)		
		All Firms	Acquired Firms	Other Exitors	All Firms	Acquired Firms	Other Exitors	All Firms	Acquired Firms	Other Exitors	All Firms	Acquired Firms	Other Exitors
Excessive Acquisitiveness	$Min \Rightarrow Max$	0.5122	0.4295	0.3388							0.4361	0.2305	0.4236
	$Mean \pm \frac{1}{2}$	0.0114	0.0139	0.0033							0.0093	0.0104	0.0036
	$Mean \pm \frac{sd}{2}$	0.0015	0.0019	0.0004							0.0013	0.0015	0.0004
	$Marginal Effect$	0.0081	0.0100	0.0020							0.0070	0.0082	0.0023
Sigma	$Min \Rightarrow Max$				0.6663	-0.0032	0.9995				0.6662	-0.0033	0.9993
	$Mean \pm \frac{1}{2}$				0.0716	0.0095	0.0979				0.0465	0.0023	0.0674
	$Mean \pm \frac{sd}{2}$				0.0003	0.0002	0.0002				0.0002	0.0001	0.0002
	$Marginal Effect$				0.0102	0.0084	0.0069				0.0058	0.0026	0.0061
Planning Fallacy	$Min \Rightarrow Max$							0.0155	0.0220	0.0012	0.0107	0.0155	0.0005
	$Mean \pm \frac{1}{2}$							0.0465	0.0680	0.0017	0.0256	0.0378	0.0006
	$Mean \pm \frac{sd}{2}$							0.0017	0.0023	0.0002	0.0014	0.0020	0.0001
	$Marginal Effect$							0.0138	0.0192	0.0015	0.0114	0.0165	0.0006

4. EXCESSIVE CONTINUATION AND THE COSTS OF FLEXIBILITY IN FINANCIAL DISTRESS

4.1 Introduction

Do failing businesses continue operations for too long? As demand falls and the firm's competitive advantage is eroded, there comes an optimal time for the ailing firm to close down and for its capital to be released for alternative uses. Abandoning the firm may be desirable even when the firm's assets are worth nothing in liquidation. Yet, managers may be reluctant to disinvest and liquidate the firm if doing so is likely to result in the loss of perks and possibly their jobs. In the presence of distressed debt, shareholders may also find excessive continuation desirable as even a remote chance of recovery is better for them than bankruptcy that is likely to wipe out existing equity completely. The failure of the unprofitable firm to reorganize in a timely manner hurts its creditors by reducing their expected recovery, and hence may increase the cost of debt ex ante. In this sense, excessive continuation is a stark example of the overinvestment (asset substitution) problem hypothesized by Jensen and Meckling (1976) to be a potentially important agency cost of debt.

Financial economists have yet to fully understand the empirical costs of asset substitution, and in particular the extent and consequences of the failure by unprofitable firms to liquidate in a timely manner. Jensen (1993) argues that historically firms' internal control systems have failed to bring about timely exits and downsizing. Grinblatt and Titman (1998) note that the exit decision is one of the most difficult decisions a firm must make, and that in the presence of debt excessive continuations are likely. Lambrecht and Myers (2007) model managerial incentives to exit, and find that when managers can appropriate cash flows and investor intervention is costly, the firm is shut down too late. Décamps and Faure-Grimaud (2002) use the contingent-claims approach to show that in the presence of debt, equityholders' exit decisions exhibit excessive continuation, which reduces firm value.

Since bankruptcy is a natural way to reorganize for highly-levered firms, a related question concerns the optimality of the timing of bankruptcy filings. Davydenko (2005) finds that many highly levered firms that appear very distressed are able to avoid default for several years, but he does not investigate whether such delays are suboptimal. While bankruptcy studies' findings convey a sense that most firms file "too late," there is no convincing evidence to that effect [Jackson (1986)]. To our knowledge, our paper is the first to use a sample of highly levered firms worth more dead than alive in order to investigate the extent and costs of excessive continuations.[1]

To identify firms whose assets should be optimally released to alternative uses, we use Tobin's q, defined as the ratio of the market value of the firm's assets to their replacement costs, which summarizes the market's view of the firm's ability to create value for investors. The market value of the firm's physical assets under the "status quo" of being operated within the firm is the value of the future cash flows that the firm is expected to generate by utilizing the assets in conjunction with the human capital of its managers and staff. This value is reflected in the value of all financial claims on those cash flows, such as equity and debt, which constitutes the numerator of Tobin's q. Crucial to our sample construction is the availability of market prices of debt, which for highly-levered distressed firms is often by far the largest claim on the assets, yet traded at deep discounts relative to book values. Thus, our study is based on a sample of speculative grade firms for which we observe market values of debt and equity, and can therefore accurately estimate the value of assets as utilized within the firm.

We compare the value of the firm under the status quo with the replacement cost of the firm's assets, which constitute the denominator of Tobin's q, and identify firms with q below one as those whose assets should be optimally sold to competitors. The replacement cost is defined as "the dollar outlay needed to purchase the current productive capacity of the firm at minimum cost and with the most modern technologies available" [Lindenberg and Ross (1981)]. Thus, replacement costs provide the lower limit on the price that outsiders should be expected to pay to acquire the firm's physical assets. When this price exceeds the market value of the firm under the status quo (implying Tobin's q below one) the firm's investors would be better off if the firm sold its assets to alternative users for their replacement costs. Moreover, to the extent that potential buyers can use

[1] The term "asset substitution" is often used to refer to the wealth transfer from creditors to equityholders induced by increases in the volatility of the firm's cash flows. While harmful to creditors, such risk shifting does not necessarily adversely affect the firm as a whole. More generally, asset substitution may involve adoption of value-destroying projects if they result in a similar wealth transfer. Operating the firm whose assets are more valuable in other uses is an example of such negative-value investments.

the assets to create value in excess of the costs of the productive capacity, they would be prepared to pay more than the assets' replacement cost. Thus, $q < 1$ is a relatively conservative criterion for identifying firms that should optimally cease operations and sell their assets to better users.[2] As Lewellen and Badrinath (1997) point out, "[U]nless assets are used by a firm so as to create at least as much market value as the cost of reproducing them, the assets would be better employed elsewhere."

Our sample consists of 371 high-yield firms whose q falls below one. These firms can transfer assets to alternative users by either being acquired, or by filing for Chapter 11 bankruptcy, which over the past decade has evolved into a mechanism for a quick sale of the firm's assets and the release of the capital for better use, where existing equity is typically fully wiped out.[3] We find that three years after their q falls below one, 5.4% of firms have been acquired, 20% have defaulted, another 21% are still in distress with q below one, and the remaining 54% have "recovered" in the sense that their q is raised above one. However, 25% of recovered firms become seriously distressed again within 18 months after recovery, indicating persistent problems. Thus, many distressed firms continue operations for many years. Moreover, even though threshold values q below one imply higher probabilities of exit, the proportion of continuations remains very high. Thus, of those firms whose q falls below 0.8, as many as 47% neither file for bankruptcy nor are acquired within three years.

We show that the failure of these firms to exit is costly by comparing their operating performance with that of other firms in the industry, which is a natural benchmark for the performance of the firm's assets in alternative use. We find that, once the firm enters the sample, with 80% probability it underperforms the industry median over the next three years. This underperformance is economically significant: The mean cumulative return on assets over three years for sample firms is -9.4%, compared with 7.4% for other firms in the industry, while the median difference is -8.7%. Accounting for the costs of bankruptcy and merger for the firms that do exit further increases this difference. By comparison, the direct costs of bankruptcy are generally found to be close to 5% of firm value [Warner (1977); Altman (1984); LoPucki and Doherty (2004)]. Our estimates quantify the costs of this type of asset substitution behavior, and suggest that even indiscriminate

[2] To be conservative, in our study we understate the case for reorganization even more by looking only at the replacement costs of the firm's *tangible* assets, such as fixed and current assets, and excluding other assets such as goodwill, whose value for distressed firms may be difficult to ascertain. By doing so, we bias ourselves against finding excessive continuations.

[3] See Baird and Rassmunsen (2003), Skeel (2003), and Bris, Welch, and Zhu (2006) on modern Chapter 11 practices.

liquidation of all our sample firms as soon as their q falls below one would still result in substantial savings net of costs.

Furthermore, we find that the money-losing operations of our firms are at least partially financed by asset sales. By the time firms exit the distressed sample, their tangible assets, measured at replacement cost, are reduced on average by 9.3%. This erosion of the creditors' asset base exceeds typical estimates of direct bankruptcy costs. As sales of fixed assets by distressed firms can potentially be challenged as fraudulent conveyance, these asset reductions come primarily from contractions in working capital. Such behavior reduces the expected recovery rate for creditors, and may increase the cost of debt ex ante. A detailed study of the determinants of exit reveals that excessive continuations are facilitated by high asset liquidity, low current debt service, and a high proportion of public bonds in the capital structure. We find no evidence that managerial shareholding affects the probability of exit.

We also study the role of covenants in mitigating excessive continuations. We construct a database of various bond and loan covenants, and relate them to the probability of exit through bankruptcy or acquisition. We find that the only loan covenant that significantly increases the probability of exit is that restricting asset sales. This is consistent with the hypothesis that banks are willing to waive technical defaults, but do not allow the firm to reduce the banks' asset base by selling assets. In contrast to loans, a number of bond covenants reduce the ability of the firm to continue past the optimal liquidation point. Of note, the presence of restrictions on leverage or net worth in bond indentures is positively associated with bankruptcy. This said, we find that these covenants may not be set tightly enough for our sample firms: While 77.3% of sample firms have such covenants, only 42.9% of those firms file for bankruptcy. With hindsight, for many of these firms the flexibility afforded by lax covenants appears to backfire for bondholders, as the bondholders have little power to enforce a reorganization and prevent the firm from destroying value in unprofitable operations.

The remainder of the paper is organized as follows. Section 4.2 discusses related literature and our empirical hypotheses. Section 4.3 describes our data. Section 4.4 documents the ability of distressed firms to avoid or delay liquidation, and shows that excessive continuations are costly. Section 4.5 uses regression analysis to determine the firm characteristics that allow firms to avoid exit. Section 4.6 discusses the role of covenants in curbing asset substitution. Section 4.7 concludes.

4.2 *Related Literature and Empirical Hypotheses*

4.2.1 *The Exit Decision*

The exit of unprofitable firms is an integral part of the Schumpeterian "creative destruction" of capitalism [Schumpeter (1942)]. Jensen (1993) reviews changes in the worldwide economy between 1973 and 1993, and argues that, as the corporate landscape changed, corporate internal control systems failed to deal effectively with the requirement to exit. Theoretically, the decision to exit has been modeled within the real-option framework. Lambrecht and Myers (2007) present a model of takeovers and disinvestment in which managers can appropriate cash flows and investors' intervention is costly. They show that managers of unlevered firms always liquidate too late even in the presence of golden parachutes although the latter partially restore efficiency.[4] They also find that the presence of debt mitigates the excessive continuation problem, essentially because it reduces the free cash flow that managers can expropriate [Jensen (1986)].[5]

A number of models of the exit decision of levered firms are found in contingent claims models of corporate debt. Using a continuous-time model, Décamps and Faure-Grimaud (2002) show that the option of keeping the firm alive is valued differently by equity- and debtholders, giving rise to excessive continuations. As a result, equityholders may prefer excessive continuation even when liquidation proceeds are large enough for equity to receive a positive distribution. Mella-Barral (1999) shows that excessive continuation is likely when the ongoing debt service is low. By contrast, when the debt coupon is too high, the firm is liquidated too early as equityholders become unwilling to keep their option alive by servicing the debt. Morellec (2001) studies how covenants and asset liquidity affect the liquidation and downsizing decision of levered firms.

On the empirical side, we know of no systematic study of the optimality of exit decisions for distressed firms.[6] DeAngelo, DeAngelo and Wruck (2002) provide a case study of L.A. Gear, a firm that, having been a top performer in the late 1980s, experienced a sharp decline, but was able to continue money-losing operations for many years due to its liquid asset structure, long debt maturity, low ongoing debt payments, and the lack of restrictive bond covenants. The L.A.

[4] Horn *et al.* (2006) argue that overconfidence, anchoring, and other psychological biases may exacerbate this problem and make divestments of failing projects difficult even when managers' jobs are not at risk.

[5] Vaysman (2006) studies compensation contracts that address managerial incentives related to investment and abandonment under asymmetric information.

[6] A sizeable literature studies empirical predictors of bankruptcy and mergers and acquisitions (see, for example, reviews by Siegfried and Evans (1994) and Caves (1998)). These studies, however, do not investigate whether the timing of reorganizations is optimal, or whether suboptimal continuations are typical for levered firms.

Gear case illustrates that managers of distressed firms may have significant discretion over the timing of reorganization, and that the role of the creditors may in some cases be reduced to that of powerless spectators witnessing the destruction of their value in unprofitable going-concern operations. Consistent with this observation, Davydenko (2005) finds that a large proportion of firms that are so distressed that they appear below their theory-predicted "default boundary" in practice are able to avoid default or delay it for many years. Unlike our paper, these studies do not explicitly address the question of whether delays in the exit decision appeared suboptimal at the time without the benefit of hindsight.

As discussed above, our maintained assumption is that the value of (conservatively estimated) Tobin's q below one implies that the firm's assets should be redeployed elsewhere. We focus on two major means of reorganizing that involve a transfer of asset ownership to alternative users: merger/acquisition and bankruptcy. We summarize the above discussion in the following hypothesis.

Hypothesis 1: *Despite their q falling below one, highly-levered firms have incentives to delay reorganization or try to avoid it for extended periods of time. On average, these firms underperform relative to their industry peers after their q falls below one.*

Which firms are more likely to be successful in delaying exit? Morellec (2001) and DeAngelo, DeAngelo and Wruck (2002) discuss characteristics of firms that are more likely to delay exit for long periods of time, such as asset liquidity, tangibility, and debt structure. We also hypothesize that Tobin's q should be a predictor of which firms are reorganized. Indeed, our sample consists entirely of firms with a q ratio below one, which indicates that the market places a lower value on the firm's assets under the status quo, lower than the costs of the firm's productive capacity. Generally, low values of Tobin's q indicate market scepticism regarding the prospect of the firm under the current management, and therefore the probability of reorganization should be higher for low-q firms. This is consistent with the q-theory of mergers by Jovanovic and Rousseau (2002) and with evidence in Servaes (1991), who studies a sample of mergers and acquisitions, and finds that, typically, low-q firms are acquired by high-q firms.

Managerial entrenchment and equity holding may be an important determinant of the timing of reorganization. High equity ownership by managers may result in excessive continuation, since it is consistent with equity value maximization. But even managers who do not act to maximize the value of equity may find it optimal to continue than to release the firm's resources to higher-value uses because of the potential loss of managerial perks. Various authors [Gilson (1989, 1990), Sutton and Callahan (1987), LoPucki and Whitford (1991)] find an adverse effect on the firm's pre-distress managers, which are much more likely to be replaced when the firm is reorganized. Shleifer and Vishny (1989) state that: "[B]y making manager-specific investments, managers can reduce the probability of being replaced, extract higher wages and larger perquisites from shareholders, and obtain more latitude in determining corporate strategy." Hotchkiss (1995) shows that continued involvement of pre-bankruptcy management in the restructuring process is strongly associated with poor post-bankruptcy performance. Thus, reorganization may expose managerial incompetence and ex ante may deter managers from letting the firm reorganize and to hang on as long as he/she can even when the firm is deeply in trouble. Thus, entrenched managers that have more to lose may have a stronger incentive to avoid liquidation.

Hypothesis 2: *Firms with high asset liquidity, low current-debt payments, long debt maturities, and a high degree of managerial entrenchment wait longer before reorganizing. Furthermore, the probability of exit is negatively correlated with q.*

4.2.2 The Role of Banks and Debt Covenants

We also study the role of banks and debt contract design in curbing the firm's ability to continue operations when liquidation is optimal. Why do creditors fail to force reorganization when continuation results in value destruction for creditors, and does the lack of protective covenants exacerbate the problem?

Public bondholders may be unable to force reorganization because of coordination problems and a lack of restrictive covenants that, when violated would allow them to trigger bankruptcy. Bulow and Shoven (1978) and Gertner and Scharfstein (1991) argue that public bondholders lack coordination and are subject to the hold-out problem. Moreover, unless the firm misses a bond payment or violates a bond covenant, creditors cannot force the firm into bankruptcy. Yet, public bonds come with relatively few covenants compared to bank debt (Bradley and Roberts (2004)). The case study of L.A. Gear [DeAngelo, DeAngelo and Wruck (2002)] provides an example of a firm that replaced its bank debt, whose covenants it constantly violated, with covenant-free public bonds, and was able to continue money-losing operations for six years before it eventually collapsed.

Sweeney (1994) and DeAngelo, DeAngelo, and Skinner (1994) find that a large majority of technical defaults (covenant violations) involve private debt rather than public bonds.

Jensen and Meckling (1976), Myers (1998) and Smith and Warner (1979) point out that debt covenants can curb a borrowing firm's opportunism and reduce agency costs of debt. Smith (1993) argues that banks' "dynamic flexible monitoring" involves setting covenants tightly enough to ensure an ongoing ability to quickly lower their risk exposure should a troubled borrower's financial position deteriorate. Indeed, bank covenants are violated for about one-quarter to one-third of all loans, and most of these violations do not indicate distress [Dichev and Skinner (2002), Chava and Roberts (2006)]. These covenant violations typically result in renegotiation of bank debt rather than bankruptcy [Beneish and Press (1995)]. Unlike public bondholders, who may have incentives but not the ability to liquidate the struggling firm to preserve value, banks may have the ability but no incentives to force bankruptcy, as they benefit from the ongoing relationship, but are less concerned about possible losses due to their superior monitoring abilities and senior status. Indeed, banks are most often paid in full in bankruptcy [Bris, Welch, and Zhu (2006)], and their recovery rates are significantly higher than those of public bondholders [Acharya, Bharath, and Srinivasan (2006)]. Welch (1997) argues that "[I]n the typical situation in large U.S. bankruptcies, the senior creditors are so deep-in-the-money that he/she would get fully satisfied even if liquidation drags on for years." Moreover, banks are likely to control their risk by reducing their exposure to the troubled firm, and by constraining the firm's managers. Stulz (1990) and Berger, Ofek and Yermack (1997) argue that managers will seek to avoid this constraint altogether by replacing bank debt with less restrictive public debt. Indeed, the case study by DeAngelo, DeAngelo and Wruck (2002) documents that, upon becoming distressed, L.A.Gear violated covenants on its bank debt, and as a result, it replaced the bank debt with covenant-free public bonds. We summarize this discussion in the following hypothesis.

Hypothesis 3: *The probability of exit for inefficient distressed firms is positively correlated with the presence of bond covenants, but less so with the presence of loan covenants.*

4.3 Data Description

Our study focuses on highly-levered firms whose market value is below the value of their assets in the best alternative use, implying that it is socially optimal to cease operations and sell the assets. The value of the firm's assets under the status quo, i.e., within the firm, should be close to the sum of the market values of the financial claims on the firm, including equity, debt, and other liabilities. In addition to the liquidating value of assets, the market value of the firm's financial claims reflects the firm's market power, human capital, and other intangible assets. In particular, if the firm engages in value-destructive activities, the market value of these 'intangible assets' may be negative, resulting in the market value of the firm below the value that can be realized by simply selling the 'hard' assets to outsiders. We proxy for the minimum value of assets in liquidation by the replacement costs of the firm's assets. The replacement cost is defined as the investment outlay required to replicate the firm's productive ability at minimum cost and using the latest technology available. Thus, we assume that the firm should optimally be liquidated when the Tobin's q falls below the threshold value of one. To the extent that replacement costs provide only the lower bound of the value of the firm's assets to outsiders, this assumption is conservative in identifying firms that are worth more dead than alive.

Motivated by this argument, we select our study sample from a data set of speculative-grade firms for which we observe the market values of debt and equity and can estimate the replacement cost of assets. In estimating Tobin's q, it is common practice to use some variant of the Brainard, Shoven, and Weiss (1980) procedure to approximate the market value of the firm's debt.[7] However, the potential accuracy of this approximation for highly-indebted firms in distress, which we focus on, is questionable. For this reason, we use as a starting point the set of firms included in the Merrill Lynch High Yield Master Index II (MLI), for which we have monthly observations of the market prices of public bonds between December 1996 and March 2004. We manually merge MLI data with Compustat, CRSP, the Fixed Income Securities Database (FISD), and the Loan Pricing Corporation's DealScan, taking account of mergers, name changes, and parent-subsidiary relationships. We use quarterly Compustat, available through December 2005, for financial information and for market equity prices of delisted firms. We use FISD as a source of information on corporate bonds, including coupons, maturity, covenants, and the history of outstanding amounts. Information on bank loans, including maturity, coupon structure, yield spread, and covenants, is taken from DealScan. We use ExecComp for managerial characteristics and compensation structure. Information on bankruptcy filings is extracted from the May 2006 issue of the Default Research Services (DRS) database provided by Moody's Investor Services. Information on mergers and acquisitions is from the SDC database. Finally, details of the firm's debt structure, used to study the evolution of bank debt as well as to improve the accuracy of the estimates of the market value of debt, is

[7] See, for example, Lewellen and Badrinath (1997).

manually collected from the firms' 10-K filings and from the long-term debt section of Mergent Manuals.

From the list of MLI constituents, we exclude all firms other than industrial U.S. firms. We estimate Tobin's q using the following procedure. First, the market value of the firm's assets is estimated as a sum of the market values of equity (taken from CRSP or, when missing, from Compustat) and debt. The market value of public debt is estimated using monthly prices from Merrill Lynch. Bonds that are not included in the MLI (these are bonds with a par value less than $100 million, as well as with remaining maturity below one year) are valued assuming that their yield equals the weighted-average yield for the firm's bonds that are included in the MLI for that month. To estimate the market value of bank debt, we first construct promised loan cash flows using information on coupons and maturity of the firm's most recent loan in the DealScan database.[8] We discount these cash flows assuming that the applicable discount rate equals the median contemporary yield for all new loans with the same rating in Dealscan. Finally, we assume that all debt other than bonds and loans, such as mortgages and capitalized lease obligations, has the same ratio of market-to-par value as bank loans. Hence, the procedure essentially classifies all of the firm's debt into two categories, bonds and institutional debt, with different market discounts relative to par. To improve accuracy, we manually collect data on the composition of long-term debt from firms' 10-K filings and hard copies of Mergent manuals for half of the firms with the highest difference between the market discounts for bonds and loans. For other firms, for which the precise split between bonds and other debt is not crucial, we infer that split by aggregating the history of outstanding bond amounts, reported in FISD for the firm and its wholly owned subsidiaries.[9] To sum up, the market values of equity, bonds, and other debt is our estimate of the market value of the firm, or the numerator of Tobin's q.

The denominator of Tobin's q is estimated as the sum of the replacement costs of fixed assets and inventories, calculated using the Lee-Tompkins (1999) modification of the Lewellen-Badrinath (1997) algorithm, plus the book value of current assets other than inventories. Hence, unlike other studies [e.g., Lindenberg and Ross (1981)], we do not include the book value of *all* assets other than fixed assets and inventories. By focusing on tangible assets and ignoring other components of total assets, such as goodwill and other intangibles, we may underestimate the sale value of assets and

[8] More precisely, we use DealScan information on the initial yield spread over LIBOR, and assume that this spread remains constant over the life of the bond.

[9] This procedure generally results in a reasonable approximation of the ratio of bonds to other debt. The median ratio of FISD-predicted amount of bonds to that reported in 10-K filings equals one.

overestimate Tobin's q. We do this in order to be conservative, as it may be difficult to ascertain for potential buyers the value of such assets in distress. As a result, we may bias ourselves against finding excessive continuations.

Our final study sample consists of 371 firms for which q falls below one for at least three months in a row between December 1996 and March 2004. We study the subsequent reorganizations of these firms by means of bankruptcy or merger. The information on bankruptcy filings is extracted from the Default Research Services data base. We also query the SDC data base to find all mergers and acquisitions targeting our firms where the resulting equity ownership by the acquiror exceeds 50%.

4.4 Excessive Continuations and Value Destruction

4.4.1 The Incidence and Types of Exit

Our sample consists of 371 high-yield rated firms. We define the firm as being "in distress," in the sense that its assets are worth less within the firm than outside when its q ratio falls below one for at least three months in a row. Firms exit the distressed sample by either filing for bankruptcy, being acquired (when the acquiror gains majority equity ownership), or by "recovering," whereby the firm's q rises above one for at least three months in a row. For our purposes, this recovery is a form of exit, in the sense that the firm no longer should be liquidated according to our sample selection criterium. Several comments are in order. First, we study the determinants of the decision to exit through bankruptcy or acquisition, but not through recovery, essentially treating recovery as an exogenous random event.[10] By contrast, managers can decide to exit through bankruptcy at any time. Second, while we treat continuations of firms that (randomly) have recovered ex post as no longer wasteful once their q rises above one, their failure to exit prior to that point is still classified as a result of a suboptimal continuation decision. Third, even though we consider recovered firms as no longer being under the threat of liquidation, and exclude them from our analysis of factors that predict exit (see Sections 4.5 and 4.6), we do continue to include them in calculations of various statistics over time (see Subsection 4.4.4.4.3). For example, in estimating the average return on assets for our sample firms three years after they enter the sample, we look at all firms that survive until that time, regardless of whether they have recovered or still are distressed. Finally, it should

[10] While recovery can be a consequence of managers' actions aimed at rectifying distress, we do not observe such actions, nor is it our purpose to explain which actions result in recovery.

be noted that, since our estimates of the replacement costs of assets are conservative, some of these "recovered" firms may still be worth more dead than alive. In practice, however, we find that few firms file for bankruptcy when their q is above one.

Figure 4.1 illustrates the dynamics of entry and exit of our firms after they enter the sample. For the first event of distress that we observe in our sample, 8% of firms are acquired, 26% file for bankruptcy, 14% remain distressed for as long as data are available, and 52% recover. However, of the 194 firms that recover, 73 firms, or 38%, become distressed again during the sample period. The distribution by exit type for the firms that become distressed for the second time is broadly similar, except that the proportion of "no-exit" firms is higher due to shorter data histories. Overall, of the 371 sample firms that entered the sample, 112 firms (30%) eventually file for bankruptcy, 35 firms (9%) are acquired, and 151 firms (41%) recover. The average firm in our sample remains distressed for 25 months before exiting either through bankruptcy, acquisition or recovery. In addition, as many as 73 firms, or 20% of the sample, still have q below one at the latest available observation date, having spent on average 59 months in distress.

Thus, bankruptcy (distress-duration of 22 months) is a much more common means of exit for these firms than acquisition (distress duration of 25 months). In fact, potential aquirors of assets may insist that the firm first file for bankruptcy, as otherwise the transaction may be made void as fraudulent conveyance. Interestingly, we do see acquisitions by outside parties after firms file for Chapter 11, as well as announcements of acquisitions by the firms' own creditors made prior to bankruptcy. Figure 4.2 shows the cumulative probability of bankruptcy and acquisition over time; it suggests that the bankruptcy hazard decreases over time. It is likely that the most distressed firms exit the sample quickly, and that the longer the firm remains in the distressed sample, the lower is the marginal probability of reorganization. However, as reported in Section 4.5, this dependence on time disappears once we control for firm characteristics. Overall, three years after their q falls below one, 5.4% of firms have been acquired, 20% have defaulted, another 21% are still in distress with q below one, and the remaining 54% have "recovered" in the sense that their q has risen above one. However, 25% of recovered firms become seriously distressed again within 18 months after recovery.

The fraction of non-exiting firms with q below one that we document is so high that it may suggest that, even conservatively estimated, the value of q below one may not be a good criterion in deciding when the firm should be liquidated. If, for example, exercising the option to exit involves costs (as bankruptcy and mergers are costly), then the firms' optimal policy should account for these costs, so that liquidation as soon as q falls below one is no longer optimal. However, the direct costs of bankruptcy are usually found to be a modest 5% of the firm value, while merger costs are smaller still [Warner (1977), Altman (1984), LoPucki and Doherty (2004)].[11] Moreover, we find that lowering the threshold value of q below one does not affect our conclusions dramatically. For instance, of those firms whose q falls below 0.8, as many as 47% neither file for bankruptcy nor are acquired within three years. Another potential criticism of our methodology is that the replacement costs of tangible assets may overestimate the value of assets in alternative use. While we believe that our selection criterion is in fact conservative rather than liberal, the high incidence of non-exiting firms that we find may leave room for doubt. To address such concerns, we show below that, even though many of our firms "recover," the operating performance of the vast majority of them falls well short of industry benchmarks. In fact, most of our firms are money losers, and, even accounting for bankruptcy costs, it is still beneficial to bankrupt all our sample firms indiscriminately as soon as their q falls below one.

4.4.2 Descriptive Statistics

Table 4.1 reports descriptive statistics for sample firms in the quarter when their q falls below one. Firms that recover and then become distressed again are included in this table twice. As all our sample firms have public bonds in their capital structure, it comes as no surprise that they are relatively large compared to their industry peers. The median book value of assets is \$1.4 Billion, which is almost six times the size of the sample firms' median 3-digit industry counterpart, which is \$318 Million. Firms that are subsequently acquired are small, and firms that later recover are large when we compare median book assets; the averages for recovering and bankrupt firms are similar. Comparing replacement costs with book values of assets, we see that the former amount to about 83% of the latter at the time when firms enter the distressed sample. It is interesting to note that this ratio is the somewhat higher for firms that are eventually acquired than for other firms in the sample. The market-to-book asset ratio is around 70%, and is substantially below the contemporaneous estimates of Tobin's q (not shown), whose mean is 85% and median, 90%.[12]

[11] While the indirect costs of financial distress are higher, our firms are already distressed, and are likely to experience the impact of distress on customers, employees and management despite the absence of bankruptcy. Moreover, the failure of the firm to exit in a timely manner is itself an important component of these indirect costs of distress, and, as we show below, the costs are economically significant.

[12] The fact that the average q is substantially rather than slightly below one is explained by the presence of firms that do not cross the threshold value of one from the above, but are instead already distressed the first time we

These differences suggest that our q ratios are indeed conservative.

The productive capacity of the median firm's assets is considerably lower than that of its median 3-digit industry counterpart. The median asset turnover (Operating income/Total assets) in the sample is 1.02%, compared to 3% for other firms in the industry. The earnings before interest and taxes of the median sample firm are just slightly above its current interest payments, so that the interest coverage ratio is 1.2. Market leverage ratios in excess of 60% suggest that our firms are highly indebted. Overall, these statistics show that the firms in our sample are financially distressed in addition to the fact that they are also inefficient in the sense that their Tobin's q is below one. Finally, Table 4.1 shows that about two thirds of the firms' debt consists of public bonds. These univariate comparisons suggest that there are systematic differences between firms that later recover, are acquired, or file for bankruptcy. In Section 4.5 we test whether such factors predict exit in multivariate regressions.

Table 4.2 documents changes in book and market values of total assets and their replacement costs, total and bank debt, and debt and equity returns for sample firms between entry and exit.[13] The table shows that, by the time the distressed firms exit the sample, they have liquidated on average 9.3% of their tangible assets at replacement costs. This reduction is the highest for firms that end up in bankruptcy, but are also substantial at 6.6% for those firms that eventually recover. This reduction in the "liquidation value" of assets is in the order of a magnitude of the direct costs of bankruptcy, and may be twice as high as the costs of a merger. A detailed look at the asset structure reveals that it is the reduction in current assets that reduces the overall asset base. This is consistent with the finding of DeAngelo, DeAngelo, and Skinner (1994) that, "[M]anagers are liquidating working capital to conserve cash in response to an unanticipated decline in the demand." The L.A. Gear case provides anecdotal evidence of a firm whose continuing existence was sustained for six years by liquidation of inventories [DeAngelo, DeAngelo, and Wruck (2002)]. Given that the sales of fixed assets by distressed companies may be challenged as fraudulent conveyance, working-capital reductions may be the only viable source of cash for many ailing firms.

The reduction in tangible assets is likely to reduce the expected recovery rate for creditors if the firm does eventually default. Table 4.2 shows that the tangible assets as a proportion of outstanding debt are reduced on average by 11.81%. Such behavior can potentially increase the

measure their q.

[13] Unlike Table 4.1, this table excludes firms for which the first measurement of q that we have is already below one, as well as firms that remain distressed at the end of the sample period.

cost of debt ex ante. While the total debt of sample firms remains roughly constant between entry and exit, the proportion of bank debt drops by 12.41%, primarily due to significant contractions for firms that manage to recover. In Section 4.6 we show that, unlike bond covenants, loan covenants generally do not increase the probability of bankruptcy. Taken together, these results suggest that upon covenant violation banks may be more interested in reducing their exposure to the ailing firms than in precipitating their bankruptcy.

The remaining statistics in Table 4.2 show the changes in market asset values and returns. While on average for all firms the market value of assets rises by 11% by the time surviving firms recover, bankrupt firms lose almost 48% of their market value. We also find a negative cumulative change in the market assets for acquired firms, perhaps because acquirors prefer to wait before buying distressed firms. These statistics, however, should be interpreted with caution as there are only 10 acquired firms in this table.[14] The table also suggests that unadjusted equity and bond returns are significantly negative in the sample. These results, however, are likely to be specific to the time period under observation, which coincided with the dot-com crash, low equity returns, and an increase in bankruptcy filings, in conjunction with the fact that our sample consists of junk bond issuers only. It is doubtful that returns will remain significantly negative once the normal return is subtracted.

But how important is this reduction in the market value of a distressed firm's assets? In other words, how economically significant are those lost values due to wasteful excessive continuation to warrant a spinal shiver for the investors? We need an appropriate benchmark to address this question.

4.4.3 The Costs of Excessive Continuations

Our conclusion that excessive continuations are widespread is based on the assumption that the firm should be liquidated once its q falls below one.[15] We now proceed to demonstrate that the failure of sample firms to transfer their assets to alternative users is indeed wasteful, by comparing their operating performance to that of their industry peers. Other firms in the same industry provide a natural benchmark for assessing the operating performance of our firms. Specifically, for

[14] Two conditions must be satisfied for the firm to be in this table: (1) we observe that its q is higher than 1 before entering the sample, and (2) we also observe the market value of assets at the time of the acquisition announcement.

[15] However, as noted above, the proportion of continuations remains very high when a lower threshold value of q is used.

each sample firm, the control sample consists of all firms in the same 3-digit SIC industry for which Tobin's q exceeds one.[16] Thus, we exclude firms in the same industry that, by our sample selection criterium, should themselves be liquidated.[17] This assumption is made for consistency, and, while slightly improving the operating performance of the average firm in the control sample, does not affect our comparisons dramatically. We then compare the performance of our firms with that of the median firm in the industry.

We track asset returns, profit margins, and the stock of tangible assets of our firms for three years since they enter the data set. For firms that exit the sample through bankruptcy or acquisition, we calculate cumulative changes up to the point of exit, and then fix them at that value. We ignore the direct costs of exit, and by so doing we underestimate the difference between sample and control firms. For recovering firms, we continue to track the operating performance after their q rises above one. Table 4.3 reports the results of these comparisons and shows that distressed firms consistently underperform the control firms, and that the differences in asset returns and profit margins are statistically significant. Moreover, on entering the sample, the average firms can expect to lose over the next three years 9.4% of its value in unprofitable operations, compared to the return on assets of industry peers of 7.4% over the same period. Assuming that our firms' assets could produce a similar return of assets if sold to the competitors, these estimates suggest that by not exiting on time the firms lose a staggering 16.8% of book assets. While more modest, the median difference is still substantial at 8.7% of assets. Accounting for the costs of bankruptcy and merger for those firms that do exit during the three-year period, these differences would be even higher. Only for 20% of the sample firms the cumulative return on assets exceeds that of the median firm in their industry. These findings suggest a significant cost of the failure to exit in terms of lost operating performance.

The novelty of our contribution is in providing a direct estimate of the costs of excessive continuation based on the measures of operating performance. By comparison, the existing estimates of the direct bankruptcy costs are typically in the 1.4% to 7.5% range [Warner (1977), Altman (1984), Ang, Chua, and Mc-Connell (1982), Lubben (2000) and LoPucki and Doherty (2004)]. While estimates by Bris, Welch and Zhu (2005) range from zero to a daunting 20% of assets, their firms are

[16] In calculating Tobin's q for the comparison sample, we assume that the market value of debt equals its book value, which is a reasonable approximation for non-distressed firms. Calculating q ratios with higher accuracy is unlikely to affect our conclusions in any material way.

[17] If there are fewer than three industry peers (excluding the distressed firm) with q greater than one, we use 2-digit industries rather than 3-digit industries.

much smaller than those in our sample, and therefore their estimates of bankruptcy costs should be expected to be higher. The indirect costs of financial distress, documented by Andrade and Kaplan (1998) for 31 highly leveraged transactions (HLTs) that subsequently became financially distressed, are likely to be between 10% and 20% of firm value. Thus, our estimates suggest that the costs of asset substitution, and in particular the failure of levered firms to exit in a timely manner, are high by all conventional standards. Even the simple rule of indiscriminately placing all our sample firms in bankruptcy as soon as their q falls below one would result in substantial savings net of bankruptcy costs.

The last set of statistics in Table 4.3 shows the evolution of the stock of tangible assets at replacement costs. As previously documented in Table 4.2, the average decline in this proxy for the liquidation value of assets between entry and exit is 9.3%, which is observed for both exiting and recovering firms. However, firms that recover subsequently reverse the decline in the asset stock. Nevertheless, Table 4.3 demonstrates that for more than a year average and median values of tangible assets continue to decline, while industry peers are in fact accumulating capital. Overall, over three years the median sample firm has lost almost 11% of its tangible assets at replacement cost, compared to more than a twofold increase by other firms in the industry. Thus, our sample firms have not only substandard operating performance but also appear to finance their losses by reducing their tangible assets, in particular, their working capital. Such behavior is socially wasteful, and is also likely to increase the cost of debt ex ante.

4.5 Which Firms Can Avoid Exit?

If continuation beyond the efficiency threshold is so costly for the creditors, what are the factors that facilitate continuation for inefficient firms? Hypothesis 2 states that excessive continuation is more likely if the bulk of the debt is long term, and that the firm has sufficient liquid assets to honor its current obligations. Moreover, when creditors are public bondholders, there is a lack of coordination among them, and the lack of enforcement mechanisms exacerbate the problem. Finally, more entrenched managers favor continuation beyond the efficiency threshold because even the remote chance of recovery creates enough incentives to substitute assets away from the creditors to the equity holders. We employ a survival-time analysis framework to test how asset liquidity, debt maturity, the composition of debt, and managerial entrenchment affect the hazard of bankruptcy and acquisition.

4.5.1 Empirical Proxies

Managers of levered firms can choose to file for bankruptcy as a means of exit at any time. In addition to bankruptcy, they may actively seek an exit through acquisition. However, acquisitions of financially distressed firms outside of bankruptcy may be difficult in the presence of multiple public bondholders. Moreover, the sale of the distressed firm may be challenged as a fraudulent conveyance. For these reasons, even in the presence of a viable acquiror, a bankruptcy filing may precede the sale. We study the determinants of exit through bankruptcy or acquisition, treating them as decisions that the firm's management can adopt. By contrast, even though the distressed firm can also exit our sample by "recovering" in the sense that its q rises above one, we treat this type of exit as a random event since managers do not influence the q ratio directly, and therefore recovery in this sense is not a result of a conscious decision.[18]

A number of empirical models have been developed for predicting bankruptcy.[19] By contrast, empirical studies of the determinants of mergers have thus far met with only limited success in explaining which firms are acquired.[20] Our purpose in this paper is not so much to improve the existing general models as to understand which factors related to the debt structure and managerial incentives facilitate continuation for our sample of inefficient firms. In view of this, since most exits are likely to be through bankruptcy, we use the augmented bankruptcy prediction model by Zmijewski (1984) to account for factors considered important in the existing literature. While this choice of the baseline model is arbitrary for our purposes, Shumway (2001) and Davydenko (2005) find that the Zmijewski model has significant predictive power, outperforming in particular the z-score model of Altman (1968).

The Zmijewski model includes three accounting-based predictors of bankruptcy, *net income over total assets*, *total liabilities over total assets* (a measure of book leverage), and the *current ratio*, defined as current assets over current liabilities, which measures the firm's balance sheet liquidity. To these three variables, we add the logarithm of the total assets as a measure of size, which the studies of both bankruptcies and mergers and acquisitions find to be an important predictor. Shleifer and Vishny (1992) argue that industry conditions may affect the sale price of the firm's

[18] Recovery, of course, may be facilitated by managers' actions. However, since we do not observe such actions, their effect in our tests would be absorbed by the error term.

[19] Important contributions include Altman (1968), Ohlson (1974), Zmijevski (1984), Shumway (2001), Hillegeist *et al.* (2004), to name but a few.

[20] See reviews by Siegfried and Evans (1994) and Caves (1998).

assets in distress. Empirically, Acharya, Bharath, and Srinivasan (2007) find that recovery rates in distressed industries are lower, providing empirical support for this argument. To control for this possibility, we include the dummy variable for *industry distress*, which equals one when the median industry return is below -30%, as well as the median *industry sales growth*. We also control for the competitive environment in the industry by including the industry *Herfindahl* sales index. Finally, in test specifications that do not explicitly allow for changes in the hazard rate over time, we add (the square root of) the number of months the firm has spent in distress.

We hypothesize that the probability of exit is higher for a firm with a low Tobin's q. In addition, we include variables that affect the degree of discretion that firms may have in deciding whether to exit, or, put differently, to be able to continue servicing their debt without defaulting. We hypothesize that higher proportions of bonds relative to institutional debt decreases the probability of exit due to the hold-out problem and the lack of monitoring by public bondholders. By contrast, the presence of short-term debt could potentially be a disciplining device, as firms will find it easier to continue when debt payments are in the distant future than when they are in the current period. As the impact of debt maturity is likely to be non-linear, we use the proportion of *long-term to total debt*, expecting it to be negatively correlated with the probability of exit. Another factor that can facilitate survival is the ability of the firm to sell assets in distress. Since most of our firms have covenants that restrict asset sales (see Section 4.6), and since asset sales may be challenged by creditors as fraudulent conveyance, we focus on the possibility of reducing current assets, and in particular, working capital, as a source of raising cash. DeAngelo, DeAngelo, and Wruck (2002) illustrate how a highly unprofitable firm could survive for many years due to the large inventories that it could simply fail to replace on an ongoing basis. Based on these considerations, our proxy for asset liquidity is *working capital divided by total assets*.[21] Finally, we also include the proportion of the common equity owned by the top five executives as an additional proxy, to test whether the alignment of the CEO's interests with those of equityholders affects the probability of exit for inefficient firms.

4.5.2 Econometric Specification

In our econometric specification, we assume that, while in the sample, each low-q firm is at the risk of bankruptcy and acquisition, unless other competing risks have already claimed its life. The failure-

[21] Altman (1968) argues that working capital is a proxy for balance sheet liquidity. However, we already include the current ratio in the set of our control variables.

risk process can be analyzed using a simple form of hazard function, $\lambda_j(\tau, X) = \lambda_{0,j}(\tau)\exp^{(X\beta_j)}$. Here $\lambda_{0,j}(\tau)$ is the baseline hazard of event $j \in \{1, 2, \ldots, k\}$, over time under the condition $\exp^{(X\beta_j)} = 1$ that is no heterogeneity among the decision units. Firm heterogeneity, reflected in covariates X, may therefore affect the actual hazard. Here the multiplicative effects of the covariates have a clear and intuitive meaning: If $\exp^{(X\beta_j)} > 1$, the risk of the event j for this firm would increase over the whole period; the opposite holds if $\exp^{(X\beta_j)} < 1$. The hazard function $\lambda_j(\tau, X) = \lambda_{0,j}(\tau)\exp^{(X\beta_j)}$ causes failure and gives insight into how the risk changes with the covariates.[22]

Which econometric specification is the most suitable for an estimation of the effects of covariates on hazard depends on the underlying data-generating process for the sample. If time is truly discrete, then the discrete hazard model with a logit link would be appropriate, which has a direct interpretation in terms of conditional odds, and is easily implemented using standard software for logistic regression. Indeed, Shumway (2001) shows that its likelihood function coincides with that of the standard logit specification, and that logit regressions can be used to estimate these models, provided that standard errors are adjusted for cross-correlation. However, if time is continuous, but we only observe it in grouped form, then the complementary log-log link is more suitable. In particular, tests based on the complementary log-log link should be more robust to the choice of categories than results based on the logit link. However, we cannot take into account partial exposure in a discrete time context, no matter which link is used. If time is continuous and we are willing to assume that the hazard is constant over each interval, then the piecewise exponential approach based on the Poisson likelihood is preferable. This approach is reasonably robust to the choice of categories and is unique in allowing the use of information from cases that have partial exposure. Finally, if time is truly continuous and we wish to estimate the effects of the covariates without making any assumptions about the baseline hazard, then Cox's (1972) partial likelihood is a very attractive approach. Moreover, hazard could be a "single destination" (treating bankruptcy and acquisition as equivalent) or competing destinations (where the two types of exit are distinct). In a competing-destination hazard model, multiple risk factors compete with each other to claim the life of the firm.

Since most of our independent variables are constructed using quarterly Compustat and, therefore, observed at quarterly intervals, we treat each fiscal quarter as a life-at-risk interval. In a

[22] See Kalbfleisch and Prentice (2002) for a detailed discussion of survival time analysis models.

"single-destination" hazard model, the censoring variable is 1 if the decision unit exits the sample either through bankruptcy or acquisition, and 0 otherwise. In a competing risk or "competing-destination" hazard, the censoring variable for bankruptcy is 1 if the decision unit exits through bankruptcy, and 0 otherwise, and the censoring variable for acquisition is 1 if the decision unit exits through acquisition, and 0 otherwise.

We use four different survival analysis specifications with clustering by firm to correct for multiple entries into our survival data set. Assuming that the time is discrete, we estimate a proportional hazard of bankruptcy and acquisition using logit and a complementary log-log link. We treat each quarter as independent Bernoulli observations [see Kalbfleisch and Prentice (2002)], and the dependent variable is the censoring variable itself. To control for baseline hazard in discrete-time proportional hazard, we use log of the survival quarters for each decision unit. Assuming that the time is continuous but that we observe exit only in discrete interval, we estimate the piecewise exponential proportional hazard model. We control for baseline hazard in the piecewise exponential proportional hazard model by introducing a time dummy for each of the quarters in our sample for which we observe exit along with no constant restriction. Finally, assuming that time is truly continuous, but we are interested in the effects of the covariates not in the baseline hazard, we estimate Cox's (1972) partial likelihood proportional hazard.

Having estimated all these different specifications, we find that the results that concern our proxies of interest are not sensitive to the particular methodology used. For this reason, we report the discrete time hazard model, which is the easiest to reproduce. As Shumway (2001) shows, its estimation is equivalent to an estimation of a simple logit model where all other exit events are treated as censored observations, provided that standard errors are adjusted for cross-correlation and heteroscedasticity. The results of tests using other methodologies are available from the authors upon request.

4.5.3 Regression Results

Table 4.4 reports the estimation results for the discrete-time proportional hazard model with the logit link. Our baseline model is reported for different types of exit in columns (1) to (3). Models (1) and (2) are for competing hazard risks of bankruptcy and acquisition, respectively, and models (3) to (8) are single-destination hazard, that is, for exit either through bankruptcy or acquisition. Hence, in model (1) the dependent variable is 1 if within the next quarter the firm files for bankruptcy, and 0 otherwise. In model (2), the dependent variable is 1 if within the next quarter the firm is acquired, and 0 otherwise. In models (3) to (8) the dependent variable is 1 if within the next quarter the firm files for bankruptcy *or* is acquired, and 0 otherwise.

The effect of the control variables reported in Table 4.4 is consistent with the expectations for bankruptcy predictions. However, they are usually insignificant for acquisitions, which is broadly consistent with a generally low explanatory power for acquisitions in extant papers. Larger firms are less likely to exit although the effect is rarely statistically significant. Consistent with Zmijevski (1984), less profitable, more highly levered, and less liquid (as measured by the current ratio) firms have a higher probability of bankruptcy. With few exceptions, industry variables are usually insignificant although there is a tendency for fewer bankruptcies in more levered industries.

Table 4.4 demonstrates that the probability of exit is negatively related to the firm's q ratio. This supports the hypothesis that lower-q firms are less efficient, and are therefore the first candidates for exit. This tendency has been documented empirically in studies of mergers and acquisitions [Servaes (1991)]. The effect of other variables is also generally consistent with Hypothesis 2. We see that public debt and long-term debt both decrease the probability of exit. Moreover, a high proportion of working capital, which can be converted to cash relatively easily, also facilitates continuation. All these variables have the predicted sign, and are strongly significant statistically. We do not find that managerial shareholding affects the decision to exit, perhaps because their reluctance to exit due to a fear for their jobs aligns with equityholders' desire for continuation due to the asset substitution incentives.

Overall, our tests reported in Table 4.4 show that disciplinary pressure of debt can be materially undercut by highly liquid asset structures, longer debt maturities, and high proportions of uncoordinated public bondholders among the firm's creditors. We now turn to the question whether by incorporating restrictive covenants creditors can to some extent mitigate the excessive continuation problem.

4.6 The Role of Debt Covenants

Starting from Jensen and Meckling (1976), Myers (1977), and Smith and Warner (1979), it has been argued that agency conflicts between the firm's shareholders and its creditors can be mitigated by the appropriate design of debt covenants. We test whether the incidence of excessive continuations is reduced by the presence of particular covenants in bond indentures and bank loan contracts.

We extract information on bond covenants from the Fixed Income Securities Database (FISD). FISD includes information on a number of different covenants, both negative (prohibiting certain actions) and affirmative (restricting admissible performance and prescribing actions in certain contingencies, for instance, upon a rating downgrade). Information on bank loan covenants is taken from DealScan. Compared to FISD, DealScan describes fewer 'general' covenants, and provides more details on financial covenants that restrict a firm's financial ratios.[23]

We focus on eight major covenant groups that may potentially be relevant in reducing excessive continuations of unprofitable firms. The first five restrict the firm's decisions regarding: (1) dividend payments, (2) investment policy, (3) asset sales, (4) new debt issuance, and (5) new equity issuance. We group financial covenants that require a certain level of financial performance in two categories: (6) leverage tests, including various types of minimum net worth covenants, and (7) cash flow tests, which restrict measures of earning, such as EBITDA divided by interest expense. Finally, category (8) includes the put provision activated upon the change in control (poison put). This covenant is available in FISD but not in DealScan.[24]

For each firm on each date, we check the presence of each of these covenant types in at least one of the outstanding debt contracts. Thus, we construct a set of indicator variables describing the presence of each covenant type, separately for bonds and loans. We then use these dummy variables as predictors in logit regressions of exit, to see whether the presence of particular covenant types in bonds and loans reduces excessive continuations.

Panels A and B of Table 4.5 describe the results of these tests for loan and bond covenants, respectively. The first column in each panel shows the incidence of each covenant type. For both bonds and loans, restrictions on asset sales and leverage are common in our sample. Covenants that restrict the firm's ability to incur additional debt appear for 88.5% of our firms when we look at bond contracts, but only for 34.8% of firms when we look at bank loans. Banks may be less concerned with this covenant either because there are other covenants that allow them to exert influence on the firm's financing policy, or simply because their debt is senior, and the issuance of new lower-priority debt does not hurt banks as much. Loan contracts, however, include an

[23] See Billett, King, and Mauer (2007) for a detailed description of FISD covenants, and Bradley and Roberts (2004) for DealScan covenants.

[24] FISD includes another covenant that restricts mergers. We cannot use that covenant in our tests because almost all our firms have it, including all acquired firms, and as a result it has no predictive power. In addition, FISD reports some other covenants not included in DealScan, such as cross-default provisions. These covenants are not significant predictors of exit in our sample, and we do not include them here to conserve space.

equity issuance sweep provision more often than bond indentures include restrictions on new equity financing. Finally, we find the incidence of financial covenants specifying a required minimum cash flow, such as a fixed-charge covenant, for only 4.7% of sample firms, according to FISD. Such covenants are far more common in bank loans: restrictions on various ratios of cash flow to debt are found for 68.8% of firms. Overall, the incidence of bond covenants for our sample of distressed junk firms is high compared to the 9% to 44% range reported in the earlier literature for broader samples [see, for instance, Nash, Netter and Poulsen (2003)], although not much higher than that found in other studies based on FISD data (Billett, King, and Mauer (2007)). We do not see that bond covenants are much less frequent than loan covenants. This is consistent with the tendency of riskier firms to have more bond covenants, documented in the extant studies cited above.

We test whether the presence of a particular covenant affects the decision to exit by estimating logit regressions of exit on the covenant dummy. These regressions are reported in columns (2) to (4) of Table 4.5. Because of the high degree of correlation between different covenants [Billett, King, and Mauer (2007)], and because explaining such correlations in observed contracts is not directly related to our study question, we estimate these regressions separately for each covenant, rather than for all of them together. Thus, in these tests, we take the covenant structure as given; other studies investigate how the presence of covenants is related to firm characteristics.[25] In each regression reported in each row for columns (2) to (4) of Table 4.5, the only independent variable in addition to the intercept is the covenant dummy while the dependent variables are bankruptcy, acquisition, and "bankruptcy or acquisition" dummies, respectively.[26]

Panel A of Table 4.5 shows that, in general, loan covenants do not significantly affect the likelihood of exit. This is consistent with the notion that banks renegotiate covenants upon violation, rather than trigger bankruptcy. Thus, private debt covenants are of little relevance for public bondholders, and cannot be relied on as means of controlling asset substitution. Interestingly, the data suggest that the presence of cash flow restrictions even makes a merger marginally less likely. The only important bank covenant that increases the probability of bankruptcy is that of restricting asset sales, which ensures the preservation of the asset base for creditors in default. Banks appear unwilling to relax restrictions on asset sales to save the firm from bankruptcy, even though they may waive all other covenants.

[25] See, for instance, Nash, Netter and Poulsen (2003), Bradley and Roberts (2004), and Billett, King, and Mauer (2007).

[26] The first two regressions in column (3) cannot be estimated due to the low variation of the covenant dummies, coupled with the low number of acquisitions in the sample.

Panel B shows that asset sale restrictions are also important in bond indentures. In addition, and in contrast to loans, a number of other bond covenants also affect the probability of exit through bankruptcy. Similar to asset sale restrictions, equity issuance restrictions limit the ability of the firm to resolve liquidity problems, and increase the probability of bankruptcy. This corroborates the findings of Franks and Sanzhar (2006) that many distressed firms raise new equity in distress, thereby overcoming the debt overhang problem. By contrast, restrictions on dividend payments reduce the probability of bankruptcy as cash is conserved within the firm, even though creditors of our firms may in fact prefer earlier bankruptcy. (Their preference for bankruptcy, of course, is unlikely to extend to those cases in which the firm runs out of cash because it pays large dividends to shareholders.) The presence of the poison put provision significantly increases the probability of bankruptcy.

Importantly, firms are more likely to file for bankruptcy when the bond indenture includes restrictions on leverage or net worth. These financial covenants appear to serve as a tripwire, which is triggered when the firm's performance deteriorates, and which allows the creditors to stop the destruction of value through unprofitable operations. These leverage-based covenants in FISD are much more common than cash-flow-based covenants, which are not significant in our tests. However, with hindsight, these covenants may not have been set tightly enough to allow creditors more control over firms that with hindsight turned out to be inefficient. Indeed, even though restrictions on leverage or net worth are observed for 77.3% of sample firms, only 42.9% of those firms do file for bankruptcy. (For comparison, only 18.6% of firms without a leverage-type bond covenant declare bankruptcy.) In contrast to bond covenants, the slack incorporated in banks' financial covenants is found in other studies to be very small, so that for a broad set of firms, most of which are not even distressed, covenant violations occur for about one-quarter to one-third of all loans [Dichev and Skinner (2002), Chava and Roberts (2006)].

Overall, Table 4.5 suggests that the presence of bond covenants may mitigate asset substitution. However, financial covenants in bond contracts may not always be set tightly enough for the creditors to be able to trigger reorganization when it is efficient. By contrast, bank covenants may be set tightly, but their presence per se rarely affects firm exit. An exception is restrictions on asset sales, which increases the probability of bankruptcy both for public and for private debt.

4.7 Conclusions

In this paper, we study a sample of highly-levered firms whose q ratios suggest that they are worth less under current management than the costs of their productive capacity. We find that, even though 80% of these firms underperform the industry median over time, few of them are acquired or file for bankruptcy in a timely manner. Given a liquid asset structure, low current debt service, and a low proportion of institutional debt, they are able to continue money-losing operations for many years. They finance their losses by liquidating working capital, reducing the pool of assets available to creditors. Restrictions on asset sales facilitate exit of these firms, but most other private debt covenants do not. While many public bond covenants help, with hindsight they may not be restrictive enough as the majority of sample firms do avoid exit.

Our study suggests that the costs of asset substitution may be quantitatively important. An interesting symmetric research question is: do many profitable firms exit too early due to debt overhang? Quantifying this and other aspects of the agency costs of debt is an important step towards a better understanding of firms' financing decisions.

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Fig. 4.1: **Exits of Sample Firms**

These picture shows the number of firms by the type of exit, as well as subsequent distress of recovered firms.

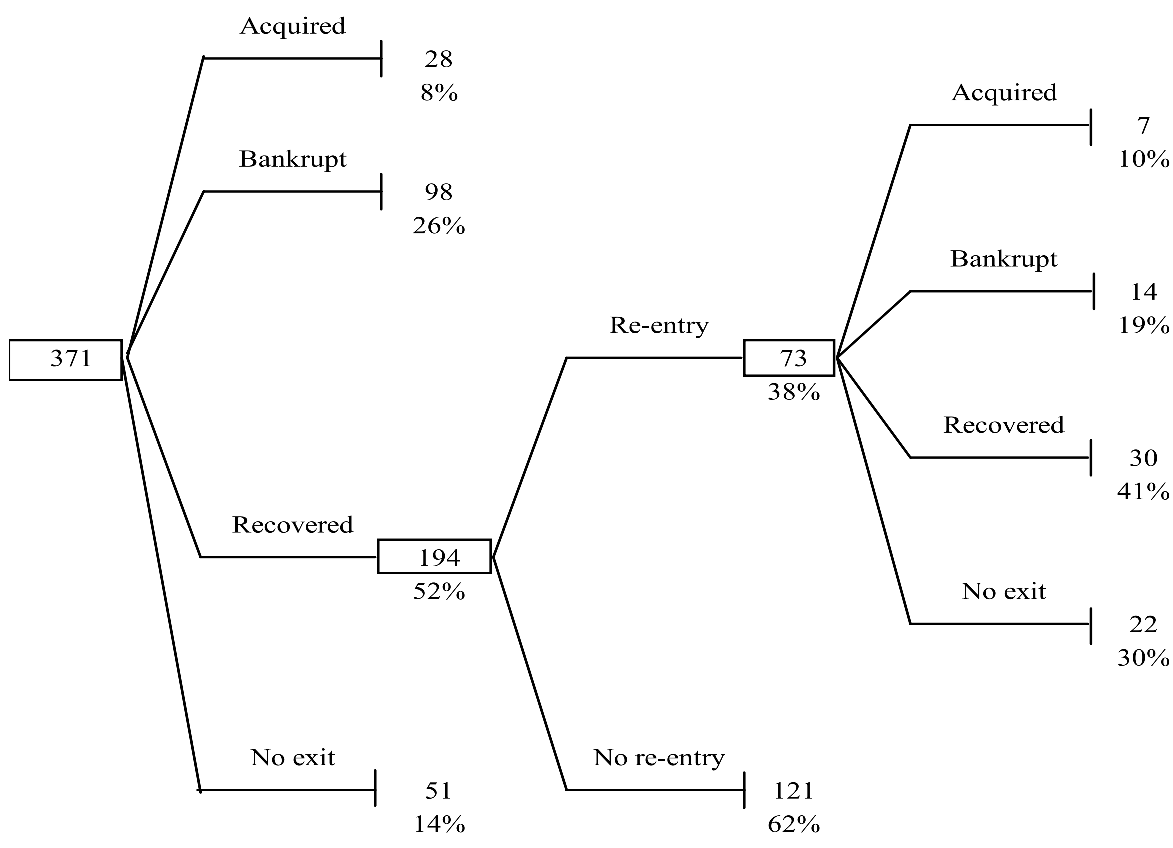
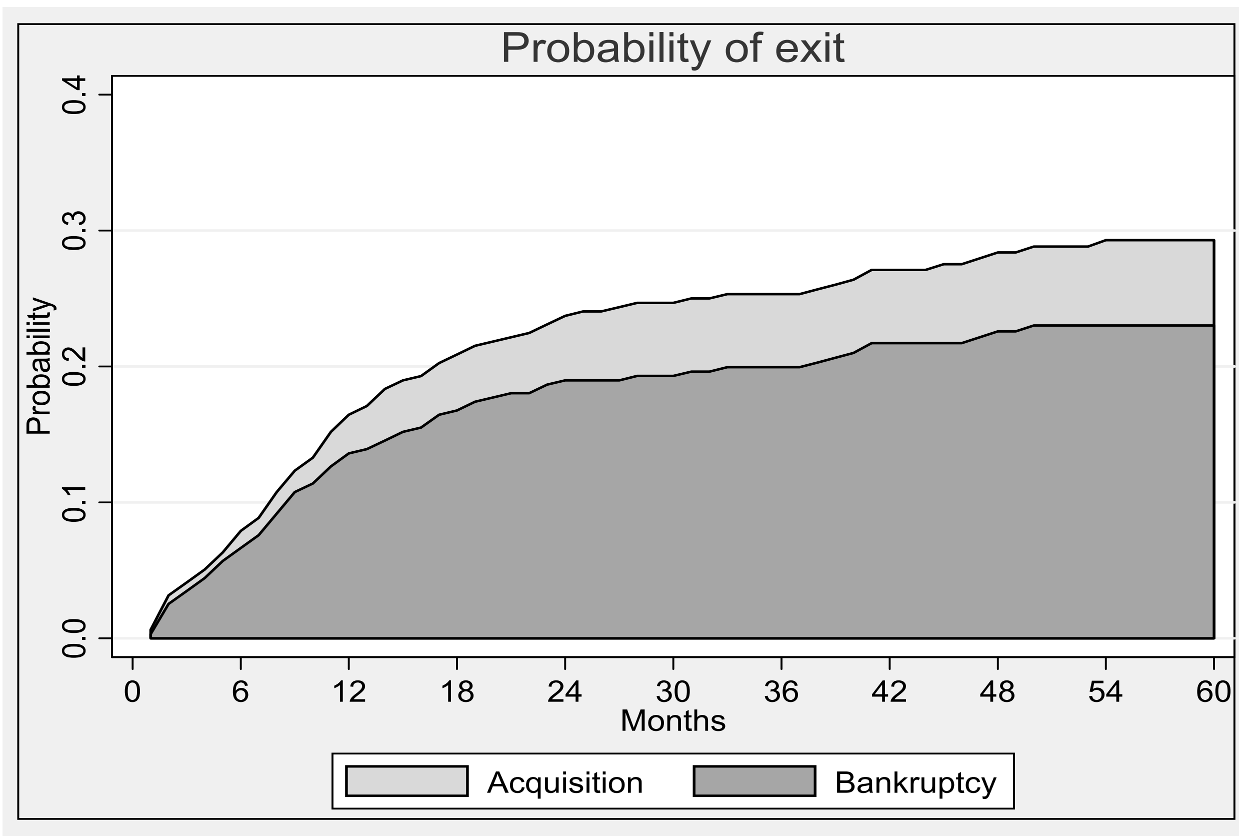


Fig. 4.2: **Bankruptcies and Acquisitions of High-Yield Low-q Firms**

These graphs show the percentage of firms that file for bankruptcy and that are acquired after their Tobin's q falls below one.



Tab. 4.1: **Descriptive Statistics**

The table reports descriptive statistics for high-yield firms whose Tobin's q falls below one. Column (1) is for all firms in the month when the q falls below one for the first time. Columns (2) to (4) are for firms that subsequently exit the sample through recovery (defined as q rising above one), acquisition, and bankruptcy, respectively, or were acquired during the sample period, in the month before they filed (were acquired, respectively).

		All firms	By outcome		
			Recovery	Acquisition	Bankruptcy
		(1)	(2)	(3)	(4)
Book assets	mean	3,506	3,194	2,409	3,274
($ Mil.)	median	1,446	1,381	738	1,027
	std. dev.	6,197	5,104	4,027	7,949
	N	444	224	35	109
Replacement cost	mean	2,759	2,430	1,959	2,540
($ Mil.)	median	1,196	1,149	715	802
	std. dev.	4,683	3,771	3,014	5,715
	N	444	224	35	108
Operating income/Assets	mean	0.025%	-0.042%	-0.373%	-8.53%
	median	1.20%	1.34%	0.29%	-2.24%
	std. dev.	6.07%	11.7%	2.46%	17.6%
	N	437	217	34	105
MTB Assets	mean	0.69	0.87	0.56	0.39
	median	0.70	0.87	0.56	0.40
	std. dev.	0.16	0.18	0.22	0.17
	N	444	224	23	70
Market leverage	mean	0.61	0.56	0.66	0.89
	median	0.62	0.55	0.76	0.95
	std. dev.	0.21	0.22	0.26	0.17
	N	444	224	23	70
Book leverage	mean	0.47	0.51	0.49	0.70
	median	0.43	0.46	0.43	0.66
	std. dev.	0.22	0.25	0.27	0.35
	N	444	224	34	108
Bonds/Total debt	mean	0.65	0.66	0.68	0.64
	median	0.64	0.67	0.71	0.63
	std. dev.	0.24	0.25	0.23	0.24
	N	444	224	25	74

Tab. 4.2:
Changes in Assets and Liabilities, and Market Returns between Entry and Exit

The table reports descriptive statistics for high-yield firms whose Tobin's q falls below one. Column (1) is for all firms in the month when the q falls below one for the first time. Columns (2) to (4) are for firms that subsequently exit the sample through recovery (defined as q rising above one), acquisition, and bankruptcy, respectively, or were acquired during the sample period, in the month before they filed (were acquired, respectively).

		All	By outcome		
		firms (1)	Recovery (2)	Acquisition (3)	Bankruptcy (4)
Replacement cost	mean	-9.30%	-6.56%	-4.55%	-16.17%
	median	-6.55%	-4.75%	-4.73%	-15.03%
	std. dev.	24.1%	26.1%	17.6%	19.5%
	N	190	120	13	57
	significance	***	***		***
Repl. cost/Total debt	mean	-11.81%	-11.26%	-0.84%	-15.59%
	median	-5.17%	-4.00%	-1.63%	-14.22%
	std. dev.	47.1%	48.8%	59.3%	39.9%
	N	188	120	13	55
	significance	***	**		***
Total debt	mean	0.28%	3.43%	-1.05%	-6.05%
	median	-0.32%	-0.59%	-0.48%	0.00%
	std. dev.	37.9%	43.4%	22.9%	26.0%
	N	190	120	13	57
	significance				*
Bank debt	mean	-12.41%	-18.81%	-2.25%	-6.05%
	median	0.00%	-2.92%	0.00%	0.00%
	std. dev.	37.0%	44.4%	12.6%	27.5%
	N	76	40	7	29
	significance	***	***		
Market value of assets	mean	-5.12%	10.97%	-32.39%	-47.63%
	median	0.65%	8.32%	-24.60%	-45.66%
	std. dev.	37.4%	28.0%	29.9%	25.2%
	N	169	120	10	39
	significance	*	***	***	***
Equity returns	mean	-17.89%	11.93%	-51.71%	-77.76%
	median	-7.84%	13.73%	-57.84%	-89.29%
	std. dev.	53.1%	37.1%	32.4%	25.3%
	N	185	120	12	53
	significance	***	***	***	***
Bond returns	mean	-3.14%	16.47%	-24.60%	-44.30%
	median	3.21%	10.37%	-7.86%	-52.66%
	std. dev.	38.1%	22.7%	29.0%	33.4%
	N	178	117	11	50
	significance		***	***	***

Tab. 4.3: **Firm Profitability and Asset Values over Time**

For each quarter after entering the sample, this table reports the return on assets, the profit margin, the cumulative return on assets since entering the sample, and the cumulative change in replacement costs. The number of quarters passed since the quarter end in which Tobin's q falls below one, referred to as quarter zero, is given by column headers. *Return on assets* is net income in each quarter divided by total assets. *Profit margin* is EBIT divided by sales. *Cumulative return on assets* is total net income since quarter zero divided by the initial value of total assets. *Cumulative change in replacement cost* is the percentage change in replacement cost of fixed and current assets since quarter zero. Firm mean and median are statistics for sample firms. Control samples for each firm consist of all firms in the same three-digit industry. Fraction underperforming is the proportion of sample firms in each quarter with the value of the variable below its control sample's median. All differences in medians between sample and control firms are significant at 1%.

	Quarter since entering the sample											
	1	2	3	4	5	6	7	8	9	10	11	12
Return on assets												
Firm mean	-2.14%	-3.01%	-1.90%	-0.89%	-1.75%	-1.46%	-0.30%	-0.43%	-1.07%	-0.70%	-0.14%	-0.07%
Control sample mean	-0.30%	-0.62%	-0.09%	-1.02%	-0.23%	-1.93%	0.43%	0.00%	-0.39%	0.24%	-6.02%	-6.00%
Firm median	0.03%	-0.15%	-0.02%	0.05%	-0.03%	0.07%	0.28%	0.36%	0.21%	0.29%	0.31%	0.35%
Control sample median	0.58%	0.50%	0.66%	0.63%	0.62%	0.63%	0.67%	0.77%	0.74%	0.77%	0.68%	0.84%
Fraction underperforming	69.1%	67.7%	70.9%	67.4%	71.6%	64.8%	63.7%	63.1%	64.3%	64.1%	60.6%	64.4%
N	362	347	330	316	303	290	281	271	263	256	246	233
Profit margin												
Firm mean	-102%	-165%	-223%	-312%	-337%	-379%	-443%	-499%	-522%	-568%	-764%	-1002%
Control sample mean	5.36%	2.35%	4.66%	7.53%	7.16%	12.97%	11.32%	12.27%	13.27%	16.08%	14.57%	16.95%
Firm median	3.58%	2.43%	2.95%	3.54%	3.61%	3.77%	4.69%	5.07%	3.95%	5.07%	4.83%	4.84%
Control sample median	5.59%	5.20%	5.76%	6.72%	7.58%	7.92%	7.83%	8.64%	8.95%	9.81%	10.34%	11.62%
Fraction underperforming	59.7%	62.0%	56.6%	57.2%	61.2%	56.2%	54.8%	55.0%	56.3%	60.6%	58.2%	57.7%
N	350	334	320	304	291	281	270	260	256	249	237	227
Cumulative return on assets												
Firm mean	-2.11%	-4.43%	-5.71%	-6.39%	-7.33%	-8.01%	-8.02%	-8.20%	-8.66%	-9.15%	-9.36%	-9.39%
Control sample mean	0.09%	0.14%	0.60%	1.38%	2.50%	1.85%	2.52%	3.79%	4.63%	5.53%	6.29%	7.43%
Firm median	0.02%	-0.34%	-0.97%	-1.23%	-1.69%	-2.35%	-2.29%	-2.64%	-3.25%	-4.44%	-4.62%	-4.28%
Control sample median	0.40%	0.74%	1.22%	1.61%	2.19%	2.81%	3.30%	3.40%	3.85%	4.08%	4.28%	4.43%
Fraction underperforming	70.0%	73.2%	75.7%	76.7%	79.2%	78.6%	78.4%	77.8%	79.4%	79.5%	80.1%	79.7%
N	367	365	367	365	365	365	365	365	364	365	361	359
Cumulative change in replacement cost												
Firm mean	-0.51%	-1.31%	-1.98%	-3.07%	-4.18%	-4.62%	-3.16%	-0.80%	-0.93%	-2.71%	-1.05%	2.20%
Control sample mean	19.98%	41.51%	96.82%	118.02%	149.70%	214.36%	243.21%	271.37%	306.25%	338.49%	502.73%	547.33%
Firm median	-0.38%	-1.02%	-2.19%	-4.65%	-5.40%	-6.84%	-6.74%	-8.10%	-11.06%	-12.43%	-12.05%	-10.74%
Control sample median	3.07%	10.71%	18.45%	23.33%	26.26%	38.84%	38.71%	52.03%	57.67%	75.44%	88.26%	108.85%
Fraction underperforming	59.9%	62.2%	63.9%	65.5%	65.4%	64.7%	65.5%	66.7%	67.9%	68.7%	68.7%	68.0%
N	354	352	352	357	353	351	351	354	352	348	348	344

Tab. 4.4: **Determinants of Exit**

This table reports the results of logit regressions of the exit decision. In regressions (1) and (2) the dependent variable equals one if within the next quarter the firm files for bankruptcy (for regression (1)) or is acquired (for regression (2)), and zero otherwise. In regressions (3) to (8) the dependent variable equals one if within the next quarter the firm either files for bankruptcy or is acquired, and zero otherwise. The sample consists of firm-quarter observations where Tobin's q is below one. *TA* is the book value of total assets. *Current ratio* is current assets divided by current liabilities. *Working capital* is the difference between current assets and current liabilities. *Long-term debt* is total debt less debt in current liabilities. *Managerial shareholding* is the percentage of common equity owned by the five highest-paid executives. Absolute values of robust Huber-White z-statistics are reported in parentheses. Coefficients marked ***, **, and * are significant at the 1%, 5%, and 10% significance levels, respectively.

	Bankr.	Acq.	Exit	Exit				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log-TA	-0.13	-0.22	-0.14	-0.01	-0.24**	-0.10	-0.32**	-0.27
	(1.06)	(1.58)	(1.46)	(0.13)	(2.40)	(0.97)	(1.99)	(1.44)
Net income / TA	-3.39**	1.85	-2.75**	-1.10	-2.46*	-1.37	1.70	2.65
	(1.99)	(0.60)	(2.09)	(0.62)	(1.75)	(0.77)	(0.57)	(0.78)
Total liabilities / TA	3.89***	1.52	3.39***	3.68***	3.87***	2.64***	4.16***	4.07***
	(4.73)	(1.30)	(5.11)	(4.93)	(5.30)	(3.54)	(4.50)	(2.90)
Current ratio	-1.35***	0.22	-0.65**	0.03	-0.54*	0.28	-0.43	0.29
	(3.48)	(1.13)	(2.19)	(0.11)	(1.85)	(1.38)	(0.74)	(0.49)
Ind. sales growth	-2.18	5.23	-1.02	-1.05	-0.75	-2.31	-4.06	-3.60
	(0.56)	(1.03)	(0.33)	(0.34)	(0.24)	(0.68)	(1.00)	(0.93)
Ind. Herfindahl	4.16	-17.43	0.77	-1.70	-0.89	0.43	10.81	3.04
	(1.19)	(1.25)	(0.22)	(0.33)	(0.24)	(0.10)	(1.64)	(0.41)
Ind. leverage	-2.37*	-1.44	-2.04*	-0.23	-2.03*	-2.18*	-1.15	-0.71
	(1.70)	(0.87)	(1.78)	(0.19)	(1.81)	(1.82)	(0.62)	(0.35)
Tobin's q	-4.99***	-3.39***	-4.40***	-4.26***	-5.33***	-4.58***	-4.63***	-5.41***
	(6.54)	(3.71)	(6.89)	(5.92)	(7.26)	(7.17)	(5.10)	(4.90)
Long term / Total debt				-3.00***				-2.33*
				(5.70)				(1.93)
Bonds / Total debt					-2.49***			-2.87***
					(3.97)			(2.85)
Working capital / TA						-3.76***		-0.77
						(5.30)		(0.40)
Managerial shareholding							-1.73	-2.90
							(0.95)	(1.01)
Log-time	-0.14	-0.17	-0.16	-0.18	-0.17	-0.15	-0.15	-0.02
	(0.98)	(0.89)	(1.41)	(1.53)	(1.54)	(1.28)	(0.91)	(0.14)
const.	-0.43	-1.43	-0.59	-0.68	1.84	-1.26	-0.02	2.54
	(0.25)	(0.71)	(0.41)	(0.51)	(1.23)	(0.91)	(0.01)	(1.19)
N	2711	2711	2711	2711	2711	2711	1590	1590

Tab. 4.5: **Debt Covenants as Exit Triggers**

This table reports the incidence of various debt covenants (column (1)), and their impact on the exit decision. Columns (2) to (4) report coefficients from logit regressions of exit on each individual covenant dummy and a constant. These regressions are estimated separately for each covenant. In regressions (2) and (3) the dependent variable equals one if within the next quarter the firm files for bankruptcy or is acquired, respectively, and zero otherwise. In regressions (3) the dependent variable equals one if within the next quarter the firm either files for bankruptcy or is acquired, and zero otherwise. The sample consists of firm-quarter observations where Tobin's q is below one. Panel A is for bank debt covenants included in the DealScan database. Panel B is for covenants included in the FISD database for outstanding bonds. Absolute values of robust Huber-White z-statistics are reported in parentheses. Coefficients marked ***, **, and * are significant at the 1%, 5%, and 10% significance levels, respectively.

	Freq. (1)	Bankr. (2)	Acq. (3)	Both (4)
Panel A: Bank loan covenants				
Dividend restr.	6.0%	0.01		-0.24
		(0.03)		(0.44)
Investment restr.	3.6%	0.37		0.12
		(0.65)		(0.21)
Asset sale restr.	47.9%	0.65***	-0.05	0.53***
		(3.37)	(0.15)	(3.00)
Debt issuance restr.	34.8%	0.32	-0.16	0.21
		(1.54)	(0.42)	(1.14)
Equity issuance restr.	30.7%	0.34	-0.26	0.28
		(1.58)	(0.60)	(1.39)
Leverage test	49.9%	0.02	-0.32	-0.04
		(0.10)	(0.91)	(0.26)
Cash flow test	68.8%	0.20	-0.55*	0.04
		(1.03)	(1.65)	(0.22)
Panel B: Bond covenants				
Dividend restr.	8.2%	-0.70	-0.49	-0.76*
		(1.50)	(0.67)	(1.78)
Investment restr.	5.5%	0.46	0.59	0.45
		(1.18)	(0.92)	(1.22)
Asset sale restr.	64.1%	0.77***	0.22	0.59***
		(3.54)	(0.64)	(3.08)
Debt issuance restr.	88.5%	0.37	0.36	0.32
		(1.27)	(0.74)	(1.23)
Equity issuance restr.	8.5%	0.82**	-0.05	0.71**
		(2.41)	(0.07)	(2.23)
Leverage test	77.3%	0.98***	0.16	0.73***
		(3.71)	(0.45)	(3.29)
Cash flow test	4.7%	-0.46	-0.45	-0.72
		(0.80)	(0.45)	(1.24)
Poison put	80.8%	0.98***	0.16	0.74***
		(3.62)	(0.44)	(3.24)

5. DO SOURCES OF FINANCING MATTER FOR FIRM GROWTH?

5.1 Introduction

A central question in economics and finance is why some firms grow faster than others. Although the extant literature allows firm heterogeneity to be driven by firm size, age and underlying productivity differences, economists disagree sharply on the role of finance as a source of heterogeneity in the cross section of firm growth. Empirical effects of financial structure on firm growth and investment have long been interpreted as proxies for misspecified "real" influences largely because with a perfect capital market a firm's investment decisions are independent of its financial condition. If all firms have equal access to capital markets, a firm's financial structure is irrelevant in financing firm growth and investment because external funds provide a perfect substitute for internal capital. In reality, however, firms have uneven access to capital markets, and internal and external funds are not perfect substitutes for reasons such as transaction costs, tax advantages, agency problems, costs of financial distress, and asymmetric information. In these circumstances, firm growth and investment may very well depend on its financial condition and its access to various sources of financing.

Although a considerable amount of research has tried to disentangle the linkage between financial structure and firm growth, our understanding of this issue to date is limited and mostly at the aggregate level. In macroeconomics, researchers study the linkage between firms' technology and productivity shocks with aggregate business-cycle fluctuations which, in turn, have a real effect on all agents in the economy. In the finance literature, numerous studies have successfully established the link between financial development and real economic growth, and the channel through which finance entails real economic effects is by relaxing the firm's constraint on access to external financing.[1] A firm with limited or no access to external capital may be seriously constrained in its abilities to pursue optimal financial and investment policies which, in turn, may hinder the firm's

[1] See, for example, Rajan and Zingales (1998), Levine (2004) and Demirguc-Kunt and Maksimovic (1998).

growth. Since small and younger firms are generally more financially constrained in terms of their access to external capital markets than their relatively larger and older counterparts, they are, with hindsight, less likely to be the engines of growth in the business sector.

Despite this conventional wisdom, a growing literature in industrial economics argues that small and younger firms grow at a disproportionately faster rate than their relatively large and older counterparts. This body of literature dissects firms' size, age, and growth dynamics and documents that at the firm level, growth and volatility of growth decrease with firms' size and age, generating heteroscedasticity in firms' size and growth distribution.[2] These seemingly dichotomous findings in two different strands of literature motivate the question that I study in this paper. I investigate the causal relationship between a firm's sources of financing and its growth. After controlling for various sources of heterogeneity in the cross section of firm growth, I study whether uneven access to various sources of financing can give rise to real effects of financial structure in the sense that financial structure can become an additional source of heterogeneity in the cross section of firm growth.

A large finance literature already studies the relationship between corporate investment and cash flow to test for the presence and the importance of financing constraints.[3] These studies classify firms according to an a priori measure of financing constraints[4] and show that financially constrained firms exhibit higher investment-cash-flow sensitivity than financially unconstrained firms. There are, however, several limitations with this approach. First, all of these studies use a sample of public firms, and hence there are no variations at all among these firms with respect to their access to external equity capital, an important source of financing for firm growth. Second, Kaplan and Zingales (1997) argue that there is no strong theoretical reason for investment-cash-flow sensitivities to increase monotonically with the degree of financing constraints. Using a sample of firms with very high investment-cash flow sensitivities, they show that in 85% of the firm-year, the firms could have increased their investment if they had so chosen. And finally, if firms can successfully anticipate future profitable investment opportunities some periods ahead and can invest in those

[2] See, for example, Dunne and Hughes (1994), Evans (1987), Hart (1962), Hall (1987), Hart and Oulton (1996), Mansfield (1962), Singh and Whittington (1968).

[3] See Fazari, Hubbard and Peterson (1988), Kaplan and Zingales (1997), Cleary (1999)

[4] This classification criterion was first proposed by Fazari, Hubbard and Peterson (1988). They argue that if the wedge between the internal and external costs of funds is small, retention practices should not convey any information about investment because firms can very easily use external funds to smooth investments when internal financing fluctuates. However, if the wedge between internal and external costs of funds is indeed very large, firms that retain and invest most of their funds may have a cost advantage in using internal financing over external financing, and their investment should be driven by fluctuations in cash flows.

projects in advance with their high retained earnings, then the reverse might be true in the sense that cash flows are sensitive to how well firms can anticipate their future investment opportunities.

I deviate from the existing approach in four ways. First, I study a sample of firms that include both private and public firms, and thus in my sample I have variations across firms in terms of their access to the public equity market. Second, instead of investment I focus on firm's employment growth because it is very difficult to separate the flow component of investment from the stock component. A firm's employment growth, however, is easily identifiable and also an economically meaningful measure of a firm's real effect on the business sector. Third, I focus on financial performance measures rather than cash-flows as it is in the extant literature because recent evidence in the corporate finance literature shows that a firm's cash-holding is endogenously determined and thus treating cash-flow as a right-hand-side variable in any regression analysis introduces endogeneity as well as simultaneity problems. Finally, I use a variant of the Granger causality method to exploit the variations in sources of financing across firms and also across time, and at the same time address the potential reverse causality problem in the existing literatures on investment-cash-flow sensitivity.

Put simply, I investigate whether conditional on firm size, age and unobserved unit heterogeneity, superior financial performance (internal source of financing) can enable otherwise financially constrained firms to finance their higher employment growth (job creation), and how this causality changes with a firm's access to external sources of financing. My empirical identification strategy proceeds in two steps. In the first step, I investigate whether superior financial performances can cause higher employment growth (job creation). If there is causality in the first step, then in the second step I investigate whether the causality from superior financial performance to employment growth remains stable across the samples of firms with and without access to the private credit market and to the public equity market. This identification strategy helps us to understand (i) whether a firm's superior financial performance trickles down into the real economy through employment generation and (ii) how this important real effect of financial performance varies with a firm's access to different types of external sources of financing.

I construct four financial performance measures, namely Profit Margin (PM), Return to Shareholders (ROS), Return on Invested Capital (ROC) and Return on Total Assets (ROA) and apply a variant of the Engle and Granger (1987) causality method on a sample of firms fairly representative of the U.K. business sector. I find that financial performance does have real consequences in the business sector. Conditional on firm size and age, 'Return to Shareholders' and 'Return on Invested Capital' cause the sample firms to finance more job creation in my sample. In order to understand the size dynamics, I decompose the sample firms into small, medium and large-size classes at the beginning of the sample period by strictly following the European Economic Commission size classifications.[5] I find that the causality from the firm's financial performance to firm-level job creation is primarily driven by the small firms in my sample.

Delving more deeply into the small firms' financial performance and job creation causality, I uncover a pattern of substitutability between a firm's financial performance and its access to external capital to finance greater employment growth. I find that the causality from financial performance to firm-level employment growth remains robust after controlling for a firm's debt capacity, proxied by the fraction of pledgable assets or collateral to total assets, and a firm's access to private bank credit, proxied by the fraction of short-term bank loans and over-drafts to total liabilities. These findings suggest that access to the private credit market may not be a substitutable alternative to financial performance to finance higher employment growth.

I then divide my sample firms into private firms with no access to the public equity market, and public firms with access to the public equity market. I find that the causality from financial performance to firm-level job creation is stable only for the sample of firms with no access to the public equity market, and the causality vanishes completely for the sample of firms with access to the public equity market. Quite interestingly, I find that the causality is even more pronounced for the small private firms without any access to the public equity market, and for the sample of small public firms with access to the public equity market, the previous causal relationship between financial performance and employment growth vanishes altogether. Even more interestingly, I find that for the sample of large public firms with access to the public equity market, financial performance causes employment growth, but unlike the small private firms, the superior financial performance actually reduces employment growth. These findings delineate a pattern of substitutability between a firm's financial performance and its access to the external public equity capital. The sample firms in my data set use their superior financial performance to finance greater employment growth only to the extent that they are constrained by their abilities to raise additional funds from the public equity market.

This paper contributes to the existing literature by identifying a previously unexplored robust

[5] Please see the data section for detailed size classification of my sample firms.

causal effect of financial performance on firm growth by showing that this real effect of financing arises out of the imperfect substitutability between internal sources of funds and external private credit. It also reconciles the seemingly contradictory wisdom in the industrial economics and the corporate finance literature by showing that firms with a tighter external financing constraint can generate employment at a disproportionately faster rate than their relatively unconstrained counterparts by substituting the sources of external financing with their superior financial performances.

The remainder of the paper proceeds as follows. Section II discusses the related literature with section III describing the data set and explaining the construction of relevant variables. Section IV illustrates the causality estimation methodology with a discussion of the results from the causality regressions presented in section V. Finally, section VI concludes the paper.

5.2 Related Literature

In a classic study, Rajan and Zingales (1998) show that financial development facilitates economic growth by reducing the cost of external financing, and that the industries that are more dependent on external financing grow disproportionately faster in a more financially developed market. Since then, numerous papers have argued that finance (more specifically financial development) does have real effects on economic growth.[6] Demirguc-Kunt and Maksimovic (1998) investigate how differences in legal and financial systems affect firms' use of external financing to fund growth. They show that in countries whose legal systems score high on an efficiency index, a greater proportion of firms use long-term external financing and that an active, though not necessarily large, stock market and a large banking sector are also associated with externally financed firm growth. In a separate note, Huang and Kracaw (1984) also show that aggregate stock market volatility Granger causes various macroeconomic instruments, such as aggregate national output and unemployment. These studies clearly delineate the link between finance and the real economy at the aggregate level, but our understanding of the real effects of finance at a more disaggregate level is still very limited. And, more specifically, the effects of a firm's financial performance and its access to external financing on its job-creation ability have never been addressed in the finance literature.

However, a separate strand of literature addresses the determinants of the employment growth of a firm without any reference to the firm's financial performance and its access to external financing. Hart and Paris (1956) in a classic empirical study of British companies find that growth is roughly

[6] See Levine (2004) for a review of the financial development and economic growth literature.

independent of a firm's size suggesting evidence of the celebrated Gibrat's Law which states that the current growth rate of a firm is independent of its current size and past growth. This has led to the development of various industrial economics theories that take the Gibrat's Law as a desirable implication. Many studies do find that Gibrat's law holds, but most of the studies use large firms in their sample construction. Many other studies find a negative relationship between a firm's size and growth, but the departure from the Gibrat's law decreases as the firm's size increases.[7]

Jovanovic (1982) argues in a theoretical model that in a general form, a firm's growth decreases with age when size is held constant. Nelson and Winter (1982) propose an evolutionary theory of the firm to capture the dynamics of Schumpeter's (1934) creative destruction process into the birth, growth and death dynamics of a firm in a competitive environment. They argue that 'organizational routines' are an economic analogue of the gene in biology. Routines, as 'organizational memory' of the firm, carry forward the learning through stochastic processes to the future management just like the human gene carries through generation the attributes of human personalities. Evolutionary theories of the firm put more emphasis on the process of learning and development within an organization, and see the economic agents as explorers and creators rather than strict profit maximizers. Hopenhayn (1992) allows firm heterogeneity to be driven by underlying productivity differences. Cooley and Quadrini (2001) extend Hopenhayn (1992) by incorporating the effects of financial frictions, so that productivity and internal equity provide the two underlying sources of firm heterogeneity.

Empirically, Evans (1987) and Dunne et al. (1989) show that both the average growth rate and its variance are related to a firm's age. Dunne et al. (1989) investigate the U.S. business sector and Dunne and Hughes (1990b) investigate the U.K. business sector; both find that young firms have higher odds of exit than the old firms, and thus they (young and inexperienced firms) are more likely to destroy jobs when they exit the industry. Succinctly, these studies illustrate the importance of firms' size and age in understanding the employment growth dynamics of firms in the business sector.

Taken together, the extant literature in corporate finance and industrial economics suggests that in order to understand the effects of a firm's financial performance and its access to external financing on its job-creation ability, we must condition any causal regressions on firm size, age and productivity differences. Thus, conditional on firm size, age and unobserved unit heterogeneity

[7] See Dunne and Hughes (1994), Hart and Oulton (1996), Hall (1987) and Mansfield (1962).

(initial productivity differences) my empirical strategy investigates whether the heterogeneity in the job-creation abilities of the sample firms in the business sector could be explained by the heterogeneity in their financial performances and by the differences in terms of their access to the various external financing sources.

5.3 *Conceptual Framework and Data*

5.3.1 *Conceptual Framework*

To relate a firm's performance with growth, let us assume that in any given period t, firm i receives a productivity shock a_{it} which is positively correlated across time as: $a_{it} = \rho.a_{it-1} + \varepsilon_{it}$, where $\rho \in (0,1)$ and $\varepsilon_{it} \rightarrow N(0, \sigma_\varepsilon)$. In the absence of any external financing sources, all new investments come from the profits the firm generates in each period. Any remaining profits after additional investments are distributed to the stakeholders of the firm so that no earnings are retained across time. I assume that new investment occurs in the form of hiring additional labor (L_{it}) in each period. Thus, the additional investment in L_{it} can be written as:

$$L_{it} = a_{it}.\Pi_{it} - D_{it} \tag{5.1}$$

where Π_{it} is the gross profit of firm i in period t, and D_{it} is the part of profit $\left(\Pi_{it}\right)$ that is distributed to the stakeholders of firm i in period t. From this simple economic framework, the employment growth of the firm can be written as:

$$\frac{L_{it}}{L_{it-1}} = \alpha + \beta.\frac{\Pi_{it}}{\Pi_{it-1}} + \upsilon_{it} \tag{5.2}$$

where $\alpha = -\frac{D_{it}}{L_{it-1}}$, $\beta = \rho.\left(1 + \frac{D_{it-1}}{L_{it-1}}\right)$ and $\upsilon_{it} = \frac{\Pi_{it}}{L_{it}}.\varepsilon_{it}$. This simple framework illustrates that when a firm's performance is correlated across time, performance in period t contains information about future performance and hence generates an incentive to invest in firm growth to realize future profits.

If the firm has access to external sources of financing, it is no longer constrained by internally generated funds and thus financing in new investment (L_{it}) can be written as:

$$L_{it} = I_{it} + E_{it} \tag{5.3}$$

where $I_{it} = a_{it}.\Pi_{it} - D_{it}$ is financing from an internal source, and E_{it} is the financing from external sources. When the firm has access to external sources of financing, it is going to finance new investments so that the marginal benefit from each type of financing is exactly equal to the marginal cost of that financing source. This means that when the cost of internal financing is exactly equal to the cost of external financing, I_{it} and E_{it} are perfect substitutes. If there are external financing constraints (external financing is more costly than internal financing), I_{it} and E_{it} become imperfect substitutes, and firm growth crucially depends on its performance.

This overly simple conceptual framework illustrates two points. First, financial performance (internal financing source) has a bearing on firm growth. Second, the stability of the relationship between financial performance and firm growth depends on the extent to which internal sources of financing are substitutable to external sources of financing. I put these insights to test using a unique firm-level data set that is fairly representative of the United Kingdom (UK) business sector.

5.3.2 Sample Construction

I collect my sample firms from the Financial Analysis Made Easy (FAME) database for the sample period of 1991-2001. FAME comprises the private and publicly incorporated businesses in the U.K. and Ireland and contains financial information for up to 1.8 million firms, of which 500,000 appear in detailed format. The database is compiled from records filed at Companies House in Cardiff, London, Edinburgh, and Dublin and is supplemented by information taken from the London and Edinburgh Gazette. I collect employment level, assets, liabilities and various financial performance data for my sample firms. I apply the following filters on the FAME firms: (i) a firm must be alive for the whole sample period (1991-2001) so that the causality analysis is not biased by sample attrition, and (ii) I must observe employment level and at least one of the financial performance measures for the whole sample period (1991-2001).[8] These filters return 5,214 firms.

The European Commission classifies a firm with 1-99 employees as a small firm, a firm with 100-499 employees as a medium firm and a firm with 500 or more employees as a large firm. Using this definition, I stratify my sample into small, medium and large firms sample for the

[8] Mansfield (1962) argues that slow or no-growing firms eventually exit the sample and introduce a survivorship bias in the sample. Thus, any test of Gibrat's Law becomes essentially a test of the law of proportional growth conditional on firm survival. My sample is not subject to the same criticism since I am not testing the Gibrat's Law. Furthermore, by focusing only on the surviving firms, I neutralize an important source of heterogeneity in the cross section of firm growth, i.e., firm survival hazard, which in turn helps identification of the financial structure effects on firm growth more robustly.

period of 1991-2001 using the year 1991 employment level as the initial employment size of the firm. Out of 5,214 firms in my sample, 2,741 (52.57%) are small firms given their initial year 1991 employment size; 1,777 (34.08%) are medium firms; and 696 (13.35%) are large firms. Hart and Oulton (1996) argue that it is essential to have an adequate number of firms at the lower end of the size distribution to examine the relative importance of small firms in job creation. My sample is dominated by the small firms followed by the medium and the large firms. Thus, my sample along with the argument of Hart and Oulton (1996) is fairly representative of the business sector to analyze financial performance and job creation causality more robustly. The selection of the sample period is based on two justifications. First, this is the longest period for which data are available on the FAME. Second, Storey (1994) argues that at least one decade of sample is needed to analyze the job creation/destruction dynamics of the business sector as it goes through turbulent growth trajectories.

5.3.3 Variable Construction

Employment Growth

The primary dependent variable of interest in my causality analysis is the firm-level employment growth. The distribution of employment size in level is highly (positively) skewed, which is typical in a data set containing both very small firms with a few employees and also very large firms with thousands of employees. I take the natural logarithm of the employment level to alleviate the positive skewness in the employment size distribution. Figure 5.1 shows the distribution of the logarithm of employment size of my sample firms with the superimposing normal distribution. It shows that the log transformation of the level series greatly minimizes the positive skewness. From the logarithm of the level employment series I construct my employment growth measure as:

$$GROWTH_{it} = log\big(Num.\ of\ Employee_{it}\big) - log\big(Num.\ of\ Employee_{it-1}\big) \tag{5.4}$$

where $\big(GROWTH_{it}\big)$ is the employment growth between period t and $t-1$. One may argue that the employment growth measure might underestimate the growth potential of highly capital-intensive firms while overestimating the growth potential of highly labor-intensive firms. Any such unit heterogeneity (differences in firm-level initial conditions) should be captured by firm fixed effects in the causality regression and thus should not confound the identification of the financial structure effects on firm growth.

Size, Age and Financial Performance Measures

To characterize firm-level financial performance, I closely follow the intense debate in the corporate finance and the industrial economics literature [Copeland and Weston (1992), Krouse (1990), Bain (1952), and Bosworth et al. (1997)] on appropriate measures of a firm's performance. The performance measures suggested by the literature are either partial or total. They could also be static or dynamic. The partial performance measures, such as labor productivity, deal with one aspect of the firm's efficiency whereas the total performance measures, such as total factor productivity, deal with the overall economic efficiency of the firm. Static measures indicate a firm's performance at a particular point in time while dynamic measures track performance over a period of time. Bosworth and Kells (1998) argue that given the limitations of various performance measures, economic profit tends to lessen the limitations of other measures, and that by tracking the economic profitability of the firm over time, one could explain the dynamic as well as the total performance of a firm.

Economic profit, however, is very hard to measure, and to get around with this difficulty I use four different financial performance measures of firms, namely, Profit Margin (PM), Return to Shareholders (ROS), Return on Invested Capital (ROC), and Return on Total Assets (ROA). I calculate the PM performance measure by dividing the net income from operations by the net sales revenues of the firm. I divide the net income by the total shareholders' or owner's equity (in the case of sole proprietorship and private limited firms) to construct the ROS performance measure. I calculate the total amount of invested capital and divide the net income by the total invested capital to construct the ROC performance measure. Finally, by dividing the net income by the total book value of a firm's assets, I construct the ROA performance measure.

Since firm size is predominantly identified by the extant industrial economics literature as one of the sources of heterogeneity in explaining a firm's growth, I also control for size in the causality regression. The empirical literature in industrial economics and corporate finance use varieties of size measures, including total assets, net assets, net sales, and market capitalization. If size measures are perfectly interchangeable, a comparison of various studies become easy. By contrast, if empirical results are size-measure specific, i.e., size measures are not interchangeable, then each study has to be analyzed in isolation and a comparison across various studies to enrich the literature is difficult. Earlier studies on firm-size interchangeability [Jackson and Dunlevy (1982), Smyth, Boyes and Peseau (1975), Shalit and Sanker (1977)] generally conclude that firms' size measures are not interchangeable. However, most of the earlier studies base their models on the assumption of linearity and homoscedasticity that are rarely met in practice, and hence the empirical results of these earlier studies fall short of robustness.

Dissanaike and Wang (2003) argue that given the methodological biases, the general conclusion of the previous studies, i.e., that size measures are not interchangeable, is too restrictive. They argue that the interchangeability of the size measures depends on the nature of the estimation technique used for the empirical study. If the underlying theory does not specify a size measure, empirical economists should be more cautious if they are estimating precise elasticity using log regression. Dissanaike and Wang find that alternative measures of size almost surely give different values of elasticity. If empirical economists are not concerned about the precise elasticity but the sign or magnitude of the relationship in a regression context, or if the various size measures are used in a grouping or ranking test, then size measures are weakly interchangeable. I control for size in my causal experiment only to isolate the causality from financial performance to firm-level job creation, not to measure elasticity. Thus, in my experiment, size measures are weakly interchangeable. I use the logarithm of a firm's total assets as well as the firm's net sales revenues interchangeably to control for size in my causal regressions. Since my results hold irrespective of the size measures used, I report the summary statistics and regression results only for the logarithm of total assets.

A growing literature in the industrial economics literature argues that firm age is an important determinant of its performance variability. Small firms, on average, are younger than large firms, and that lack of industry experience, relative to their large counterparts, explains the turbulent growth trajectories and the increased odds of failure of small firms in the industry. I thus control for a firm's age in the causality regression. To control for a firm's age I use the number of years a firm has been active in the business sector since its incorporation. Figure 5.2 depicts the age distribution of the sample firms. It clearly shows that, on average, a sample small firm is younger than a sample large firm in the sense that small firms' age distribution stochastically dominates the large firms age distribution.

Hopenhayn (1992) allows firm heterogeneity to be driven by underlying productivity differences. In my empirical framework, I assume that underlying productivity differences emanate from the unobserved firm quality which can be captured by the firm-fixed effects in the causality regression. Thus, for each firm I introduce a fixed-effect to control for differences in their respective productiveness (firm quality).

Access to the External Financing Measures

In order to measure a firm's access to the external private credit market, I construct two different measures. The first measure captures the debt capacity or collateral base of the firm. I use the tangible assets of the firm as proxy for pledgeable assets in terms of collateral and divide the pledgable assets by the book value of total assets to construct the collateral base or debt capacity of the firm. I also observe the amount of short-term bank loans and over-drafts in the debt structure of my sample firms. I divide the total short-term bank loans and over-drafts by the total liabilities of the firm to construct the second measure of access to the private credit market. These essentially measure the degree of a firm's access to the private credit market rather than dichotomous measures of excess to private credit. Finally, I also observe whether a firm is a private firm without any common shares traded in the public equity market or a public firm with common shares traded in the public equity market. Based on that information, I classify my sample firms without any publicly-traded common stocks as firms without access to the public equity capital market, and firms with publicly-traded common stocks as firms with full access to the public equity capital market.

Summary Statistics

Table 5.1 reports the summary statistics from the final sample of firms for three different years over the sample periods. It shows that the assets sizes (total assets) of both the median firm and the average firm are increasing along with their level of employment. However, all sample firms are growing in assets size, but only the small and the medium firms are creating jobs while growing in assets size. The large firms are growing in assets size but, on average, they are destroying jobs (their employment levels shrink). This, however, does not mean that there is no heterogeneity within the size classes. Figure 5.3 decomposes the overall kernel density of the logarithm of employment size into different size classes based on the initial employment level in the year 1991. It quite vividly illustrates that there are dynamic as well as stalled firms in each size class, and that they either pull their respective logarithm of employment size distributions together or push them far apart, generating heterogeneity in the employment growth distribution.

Thus, job creation/destruction is not necessarily driven by size as predominantly argued by numerous papers in the literature. The firm size and age may just be the proximate causes of employment growth, and beneath the proximate causes there might be other fundamental causes that generate the heterogeneity in employment growth even within a particular size class. I posit in this paper that a firm's financial performance and its access to external financing may drive the growth dynamics within a particular size class. Thus, sources of financing may very well be the possible candidates for fundamental drivers of firm heterogeneity in the business sector.

In terms of financial performance, Table 5.1 shows that the large and the medium firms fare better at the beginning of the sample period, but that the small firms seem to catch-up with their large and medium counterparts as they continue to thrive. It also shows that at the beginning of the sample period, small firms rely more on bank credit relative to their large and medium counterparts, but their dependence on bank credit declines as the year passes by. There seems to be a pattern of substitutability between the use of bank credit as a source of financing versus financial performance for my sample firms. Finally, not surprisingly, I find that large firms have higher collateral bases than small firms although I do not see any clear relationship between the collateral bases and firms' use of private bank credit from the summary statistics presented in the table.

To stress the point of heterogeneity in the job-creation abilities within a particular size class, I construct the transition matrix that illustrates the transition dynamics between groups in terms of employment size in level for the whole sample periods and also for three intermediate periods. Table 5.2 shows that for the three intermediate transition periods (1991-1995, 1995-1998, 1998-2001), the small firms' sector consistently climbs up the size class while the medium and the large firms show considerable fluctuations in their transition between size classes. For the whole sample period of 1991-2001, out of 2,741 small firms of the year 1991, 2,255 firms remain small, 458 firms climb up to become medium firms, and 28 firms become large firms by the year 2001. On the other hand, out of the 696 large firms of the year 1991, 520 firms remain large, 153 firms become medium firms and 23 firms become small firms by the year 2001. Medium firms also portray a similar pattern as the large firms.

Two caveats are in order. First, more small firms migrating to a higher size class may simply be because of their greater representation in my sample (53% of the sample firms are small). Second, more small firms transiting to a higher size class does not necessarily mean that their relative contribution to the aggregate employment level is sizeable enough for one to conclude that they are the engines of employment growth in the business sector. Thus, beyond size I investigate whether other fundamental factors, such as superior financial performance and access to external financing, can cause higher employment growth in the business sector. In other words, I investigate whether the heterogeneity in financial performance and access to external financing can lead to heterogeneity in the job-creation abilities of my sample firms.

5.4 Estimation Methodology

I employ a variant of the Granger (1969) causality test to isolate the direction of causality from financial performance to firm-level job creation. Engle and Granger (1987), however, show that the traditional Granger test of causality is not appropriate if time-series variables included in the analysis exhibit co-integration properties. To obtain the proper statistical inferences, the causal relationship must be tested on the basis of an error-correction model. Given the panel structure of my data, instead of time-series co-integration, a panel co-integration test is more appropriate to obtain proper statistical inference. Thus, I use the Im, Pesaran and Shin (2003) testing procedure and reject the null hypothesis of panel co-integration in my panel data. Having rejected the null hypothesis of panel co-integration, I proceed with the simple linear Engle-Granger causality test.

Formally, causality may be defined in the following way. Let $\left(\hat{Y}_{it}|Y_{it-1},..,Y_{it-p},X_{it-1},..,X_{it-p}\right)$ be the unbiased predictor of Y_{it} for firm i at time t based on information in the series $\big(Y_{it-1},..,Y_{it-p}$, $X_{it-1},..,X_{it-p}\big)$. The prediction error for firm i at time t is given by $\varepsilon_{it} = Y_{it} - \big(\hat{Y}_{it}|Y_{it-1},..,Y_{it-p}$, $X_{it-1},..,X_{it-p}\big)$ and a variance of this error series is denoted as $\sigma^2\Big(Y_{it} - \big(\hat{Y}_{it}|Y_{it-1},..,Y_{it-p},X_{it-1},..,$ $X_{it-p}\big)\Big)$. If a similar error series is generated solely based on Y_{it} then the variance of the predicted error would be $\sigma^2\Big(Y_{it} - \big(\hat{Y}_{it}|Y_{it-1},..,Y_{it-p}\big)\Big)$. Variable $\left(X_{it},..,X_{it-p}\right)$ is said to Granger-cause variable Y_{it} if $\sigma^2\Big(Y_{it} - \big(\hat{Y}_{it}|Y_{it-1},..,Y_{it-p}\big)\Big) > \sigma^2\Big(Y_{it} - \big(\hat{Y}_{it}|Y_{it-1},..,Y_{it-p},X_{it-1},..,X_{it-p}\big)\Big)$. Put simply, variable $\left(X_{it-1},..,X_{it-p}\right)$ is informative in predicting variable Y_{it} if inclusion of $\left(X_{it-1},..,X_{it-p}\right)$ reduces the forecast error. However, for $\left(X_{it-1},..,X_{it-p}\right)$ to cause Y_{it} it must not be the case that $\left(Y_{it-1},..,Y_{it-p}\right)$ is useful in predicting X_{it}, i.e., that the causality is from $\left(X_{it-1},..,X_{it-p}\right)$ to Y_{it} not the the reverse or $\sigma^2\Big(X_{it} - \big(\hat{X}_{it}|X_{it-1},..,X_{it-p}\big)\Big) \leqslant \sigma^2\Big(X_{it} - \big(\hat{X}_{it}|Y_{it-1},..,Y_{it-p},X_{it-1},..,X_{it-p}\big)\Big)$. My test of causality consists of estimating the following equation:

$$Y_{it} = \alpha + \sum_{p=1}^{k} \beta_p.Y_{it-p} + \sum_{p=1}^{k} \delta_p.X_{it-p} + \varepsilon_{it} \tag{5.5}$$

$$\varepsilon_{it} = \mu_i + \eta_t + \nu_{it}$$

where α is the constant, β_p are the estimable coefficients from p lags of Y_{it}, and δ_p are the estimable coefficients from p lags of X_{it} . Since the explanatory variables $\left(Y_{it-1}, .., Y_{it-p}\right)$ are correlated with the individual firm fixed-effects μ_i in the error term ε_{it}, I need to eliminate the individual firm-fixed effects and find instrumental variables that correlate with the explanatory variables $\left(Y_{it-1}, .., Y_{it-p}\right)$, but not with the error term. The first-difference transformation eliminates the individual firm-fixed effects μ_i from equation (2).

$$\Delta Y_{it} = \sum_{p=1}^{k} \beta_p . \Delta Y_{it-p} + \sum_{p=1}^{k} \delta_p . \Delta X_{it-p} + \Delta\varepsilon_{it} \tag{5.6}$$

$$\Delta\varepsilon_{it} = \Delta\eta_t + \Delta\nu_{it}$$

Although first-differencing eliminates individual firm-fixed effects, it introduces an additional correlation between ΔY_{it-p} and $\Delta\nu_{it}$ rendering OLS estimation inconsistent. Arellano and Bond (1991) have developed a differenced-GMM estimator that uses lagged levels of the dependent variable and the predetermined variables and differences of the strictly exogenous variables as instruments under the condition of no second-order autocorrelation in the ε_{it}. I use the Arellano and Bond (1991) differenced-GMM estimator for my causality analysis.

In this dynamic panel estimation, too many lags increase the degrees of freedom, and hence reduce the power of the test, but too few lags increase the likelihood of error in causality. Some studies use maximum likelihood ratios and Akaike's Information Criterion to choose the optimum number of lags. By closely following the literature [Huang and Kracaw (1984)] and also by relying on the the Akaike's Information Criterion (the Akaike's Information Criterion decreases in value steadily until the fourth lag), I include four lags in my causal regressions. I test for causality for the whole business sector irrespective of firm-size classifications and also for the small, medium, and large firms. I also use White's (1980) heteroscedasticity consistent standard errors in all estimations. My estimation strategy proceeds in two steps:

In the first stage, I estimate the restricted and unrestricted version of (6) with a constant using the Arellano and Bond (1991) differenced-GMM estimator where the restricted and unrestricted regression models, respectively, are:

$$\Delta GROWTH_{it} = \alpha + \sum_{p=1}^{k} \beta_p.\Delta GROWTH_{it-p} + \sum_{p=1}^{k} \delta_{1p}.\Delta Size_{it-p} + \sum_{p=1}^{k} \delta_{2p}.Age_{it-p} + \Delta\varepsilon_{it} \quad (5.7)$$

$$\begin{aligned} \Delta GROWTH_{it} &= \alpha + \sum_{p=1}^{k} \beta_p.\Delta GROWTH_{it-p} + \sum_{p=1}^{k} \delta_{1p}.\Delta Size_{it-p} + \sum_{p=1}^{k} \delta_{2p}.Age_{it-p} \\ &+ \sum_{p=1}^{k} \delta_{3p}.\Delta Financial\ Performance_{it-p} + \Delta\varepsilon_{it} \end{aligned} \quad (5.8)$$

The null hypotheses of 'over-all-significance' and 'valid-restriction' are $\big(H_0 : \beta_p = \delta_{1p} = \delta_{2p} = \delta_{3p} = 0,\ \forall\ p = 1,..,4\big)$ and $\big(H_0 : \delta_{3p} = 0,\ \forall\ p = 1,..,4\big)$, respectively. I estimate both the restricted and the unrestricted models using a large sample. In a large sample, the Wald, Lagrange, and Likelihood ratio tests are equivalent. Moreover, when both the restricted and unrestricted models are estimated, the Wald-test is easier to implement than the others. Thus, I use Wald-test statistics to test the rejection of the null hypotheses.

In the second stage, I re-estimate everything but in reverse order, i.e., interchanging X_{it} and Y_{it} to infer that only $\big(X_{it-1}..X_{it-p}\big)$ causes Y_{it} but not vise-versa. For evidence of causality from $\big(X_{it-1}..X_{it-p}\big)$ to Y_{it}, the null hypotheses must be 'rejected' in the first stage, but $\big(H_0 : \delta_{3p} = 0,\ \forall\ p = 1,..,4\big)$ 'must not be rejected' in the second stage.

5.5 Estimation Results

5.5.1 Financial Performance and Firm Growth Causality

In none of my causal regressions, can I reject the null hypothesis of "no second-order autocorrelation" in the ε_{it} validating the use of the Arellano and Bond (1991) differenced-GMM as my estimation procedure. Table 5.3 reports the estimates from my causality regressions for all firms in the sample. It shows that in the first stage, Return to Shareholders (ROS), Return on Invested Capital (ROC) and Return on Total Assets (ROA) significantly predict job creation at the first lag. However, for ROA I cannot reject the null hypothesis $\big(H_0 : \delta_{3p} = 0,\ \forall\ p = 1,..,4\big)$ in the first stage suggesting that the only possible candidates for causal instruments are ROS and ROC. In the second stage of the causality regression, my primary dependent variable $GROWTH_{it}$ does not significantly predict ROS and ROC and, most importantly, I cannot reject the null hypothesis $\left(H_0 : \delta_{3p} = 0,\ \forall\ p = 1, .., 4\right)$ in the second-stage regressions where ROS and ROC are dependent variables. The results here show that for the whole sample representing the U.K. business sector, I find causality from financial performance to firm-level employment growth after conditioning the causality regressions on firm size, age and unobserved unit heterogeneity. Among various financial performance measures, my analysis shows that Return to Shareholders (ROS) and Return on Invested Capital (ROC) Granger cause firm growth in my sample.

I stratify the sample firms into various size classes and estimate the causality regressions for each size class separately. Tables 5.4 to 5.6 report the results from the causality regressions for the small, medium, and large firms, respectively. In table 5.4, I report the results for small firms. It shows that all financial performance variables significantly predict job creation in the small firms sample at the first lag, but I reject both null hypotheses only for Return to Shareholders (ROS) and Return on Invested Capital (ROC). Furthermore, in the second-stage regression, my primary dependent variable $GROWTH_{it}$ does not significantly predict any of the financial performance indicators, and I also cannot reject the null hypothesis $\left(H_0 : \delta_{2p} = 0,\ \forall\ p = 1, .., 4\right)$ in the second stage. The results presented here clearly show that the causal relationship that I have uncovered in the whole sample remains stable for the small firms in my sample.

Table 5.5 reports the first- and second-stage causality regressions for the medium firms, and I do not find any evidence of causality from financial performance to firm-level employment growth at any lag of a firm's financial performance. Finally, Table 5.6 reports the estimates from the causality regressions for the large firms. It shows that the only financial performance measure that Granger causes employment growth in large firm is Return on Total Assets (ROA). However, Return on Total Assets is significant at the first lag (negative effect on job creation) and also significant at the fourth lag (positive effect on job creation). The confounding effects of ROA on employment growth suggest either of the two things. First, the causality here may be more the result of a statistical artefact than of any economic significance. Second, more interestingly, this result may capture the time-varying effects of financial performance on firm-level job-creation abilities; that is, the effect of financial performance changes with the growth of the firm: at the earlier lags, ROA causes the firm to finance greater employment growth; then, it becomes neutral and, finally, at the most recent lag, ROA actually has a negative effect on the job-creation abilities of the large firms in the sample.

5.5.2 *Access to External Financing and Firm Growth Causality*

The causality from financial performance to firm-level employment growth makes economic sense for firms without any access to alternative sources of financing because the only way financially-constrained firms can support higher employment growth is by generating a superior return on their investments. The same rationale does not apply to firms with access to alternative sources of financing. The direction of causality that I have uncovered in the previous discussion may not be robust once I control for the firm's access to alternative sources of financing. To test the robustness of the direction of the causality that I uncovered previously, I control for a firm's access to the private credit market as well as its access to the public equity market in the causal regressions.

Tables 5.7 to 5.9 report the estimates from the causality regressions where I control for a firm's collateral base which reflects the debt capacity of a firm. Table 5.7 shows that previous causality from financial performance to firm-level employment growth is stable even after controlling for the debt capacity of the firm. It shows that Return to Shareholders (ROS) and Return on Invested Capital (ROC) cause the sample firms to finance more job creation. The causality is even more pronounced for the small firms as shown by the regression results in Table 5.8. Yet again, I find confounding effects of Return on Total Assets (ROA) on employment growth for the large firms, and Table 5.9 shows the estimates from the causality regressions for these firms. The results here also indicate that a higher collateral base enhances the debt capacity of a firm, and that, in turn, has a negative effect on employment growth although not statistically significant in all cases.

In a separate set of regressions I also control for a firms's access to private bank credit, and Tables 5.10 to 5.12 show the estimates from this set of causality regressions. Table 5.10 shows that the direction of the causality from financial performance to firm-level employment growth remains stable after controlling for firms' access to private bank credit (short-term bank loan and over-draft/total liabilities), and once again causality is more pronounced for small firms. A firm's access to private bank credit seems to have a negative effect on its job-creation ability although not statistically significant in all cases and at the first lag.

Succinctly, the results here show that access to private credit may not be a substitutable source of financing to the firm's superior financial performance. More generally, expanding firms' access to private credit may not be a conducive instrument to foster employment growth in the business sector; the more viable way through which job creation capabilities of firms with greater access to private credit get expanded is by achieving superior financial performances.

In the final set of causality regressions, I divide the sample firms into public and private firms. Public firms (4% of the sample firms) have publicly-traded common stocks in the public equity market whereas the private firms (96% of the sample firms) do not have common stocks traded in the public equity market. Tables 5.13 to 5.18 show the estimates from the causal regressions with control for a firm's access to the public equity market. Table 5.13 presents the estimates from the causal regressions for all private firms whereas Table 5.14 presents the results for all public firms. The results from both tables show that the causality from financial performance to firm-level employment growth is robust for the sample of firms without any access to the public equity market (private firms) whereas the causality vanishes all together for firms with access to the public equity market (public firms). This finding reveals a pattern of substitutability between a firm's financial performance and its access to the public equity capital market. The sample firms finance higher employment growth with their superior financial performance only to the extent that they are constrained by their abilities to raise additional funds in the public equity capital market. It also shows that among the constructed financial performance measures, the only performance measure that withstands all tests of robustness is the return firms get from their invested capital (ROC).

Tables 5.15 and 5.16 show the results for the small private firms and for the small public firms, respectively. Once again, the financial performance and job creation causality is more pronounced for small private firms whereas the causality vanishes completely for small public firms. It reveals that heterogeneity in small firms' job-creation abilities is explained by the heterogeneity in their financial performance only if small firms are constrained by their access to the public equity capital market. Surprisingly, I find causality in the large firms' sample with access to the public equity market, and in this case financial performance actually destroying rather than creating jobs in the business sector. However, this result has to taken with a caveat that sample size is too small while degrees of freedom are quite high in these regressions to draw any meaningful conclusion.

In short, these findings point towards the importance of the public equity capital market in fostering employment growth in the business sector. Without equity market development (and hence less access to the public equity market), firms in the business sector rely more on their financial performance to finance job creation whereas with a developed equity market (and hence more access to the public equity market) firms can substitute their financial performance with public funds to finance higher employment growth. Through this channel, equity market development can become an important driver of aggregate economic growth at the macro level.

I also estimate a set of causality regressions where I control for a firm's access to the private credit market as well as its access to the public equity capital market and find that causality from superior financial performance to firm-level employment growth is robust only for small firms without any access to the public equity market. Because of space limitations, I do not report these results here, but the results are available on request. For a lucid exposition, the following table summarizes the results from all causality regressions with various controls:

Summary of the Causality Regression Results

	Causality from Financial Performance to Employment Growth				Direction of the Causality			
	All Firms	Small Firms	Medium Firms	Large Firms	All Firms	Small Firms	Medium Firms	Large Firms
Sample Classification with Respect to External Financing Access:								
No Control for Access to External Finance	Yes	Yes	No	Yes	+	+	.	±
Firms with Access to Private Credit	Yes	Yes	No	Yes	+	+	.	±
Firms with Access to Public Equity Market (Public Firms)	No	No	No	Yes	.	.	.	-
Firms with No Access to Public Equity Market (Private Firms)	Yes	Yes	No	Yes	+	+	.	±
Firms with Access to Private Credit and to Public Equity	No	No	No	Yes	.	.	.	-
Firms with Access to Private Credit but Not to Public Equity	Yes	Yes	No	Yes	+	+	.	±

5.6 *Conclusion*

It is well understood in the finance literature that an important source of the empirical effects of financial structure on firm growth and investment is the fact that internal and external capitals are imperfect substitutes. This wedge between the costs of internal and external capitals give rise to an external financing constraint that may potentially limit a firm's growth. The empirical evidence in the finance literature suggests that (i) a relaxation of external financing constraints can foster economic growth; and (ii) firms with higher investment-cash-flow sensitivities seem to be more financially constrained than others. These two approaches show that there are real effects of financial structure as a result of a binding external financing constraint but shy away from the theoretical foundation of that finding, that is, to what extent an internal source of financing is substitutable to the external sources of financing.

In this paper, I take on this issue seriously and investigate whether the heterogeneity in firm-level job-creation abilities can be explained by the heterogeneity in firms' financial performance (internal source of financing) and by the differences in their access to the external sources of capital in the business sector. Using a sample of firms that is fairly representative of the U.K. business sector, I first show that a firm's financial performance Granger causes job creation in the business sector after controlling for other sources of firm heterogeneity suggested by the literature. Firms with superior financial performances create jobs at a disproportionately faster rate than the firms with inferior financial performances. Decomposition of my sample firms into various size classes based on their initial employment size reveals that the causality from the firm's financial performance to the firm-level job creation is primarily driven by small firms in the business sector.

Delving deeper into the small firms' financial performance and job creation causality, I uncover a pattern of substitutability between a firm's financial performance (internal source of financing) and its access to external funds to finance greater employment growth. I find that the causality from financial performance to firm-level employment growth remains robust after controlling for a firm's access to the private credit market. These findings suggest that access to the private credit market may be an imperfect substitute to financial performance to finance greater employment growth. However, when I divide my sample firms into private firms with no access to the public equity market and public firms with access to the public equity market, I find that the causality from financial performance to firm-level employment growth is stable only for the sample of firms with no access to the public equity market, and the causality vanishes completely for the sample of firms with access to the public equity market. This pattern of the causality is even more pronounced for small firms without any access to the public equity market, and for the sample of small firms with access to the public equity market the previous causal relationship between financial performance and employment growth vanishes altogether.

These findings depict a pattern of substitutability between a firm's financial performance and its access to the external public equity capital market. Sample firms in my data set use their superior financial performance to finance higher employment growth only to the extent that they are constrained by their abilities to raise additional funds from the public equity market. It also suggests that the real effects of finance arise out of the imperfect substitutability between internal funding and external private credit. Taken together, these findings allude to the importance of equity-market development in understanding the real consequences of financial structure in the business sector. Firms in a highly developed equity market can substitute their internal sources of financing (financial performance) with external equity capital and finance greater job creation than firms in a less developed equity market.

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Fig. 5.1: **The Logarithm of Employment Size Distribution of Sample Firms**

This figure reports the logarithm of the employment size distribution of the various size classes of firms. Size Classifications are Based on the initial employment size of the firm in the year 1991. It shows that taking natural log greatly minimizes the positive skewness in the employment-size distribution of the sample firms.

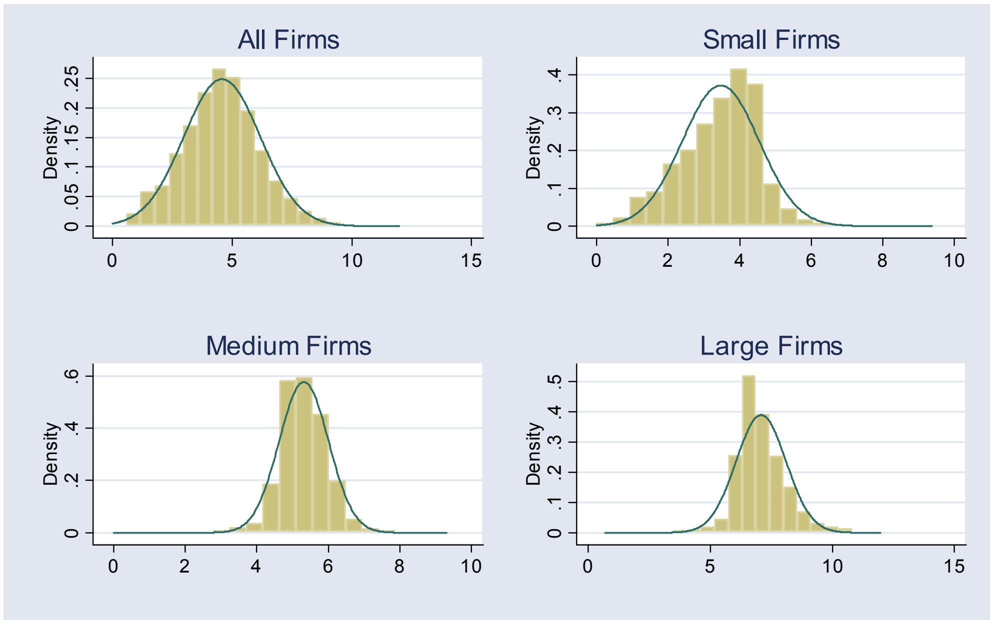


Fig. 5.2: **The Age Distribution of Small and Large Firms**

This figure depicts the age distribution of the small and larger firms in my sample. Size Classifications are based on the initial size of the firm in the year 1991. It shows that the sample of small firms are on average younger than the sample of large firms stressing the argument that age can be an important source of heterogeneity in the firm-growth distribution.

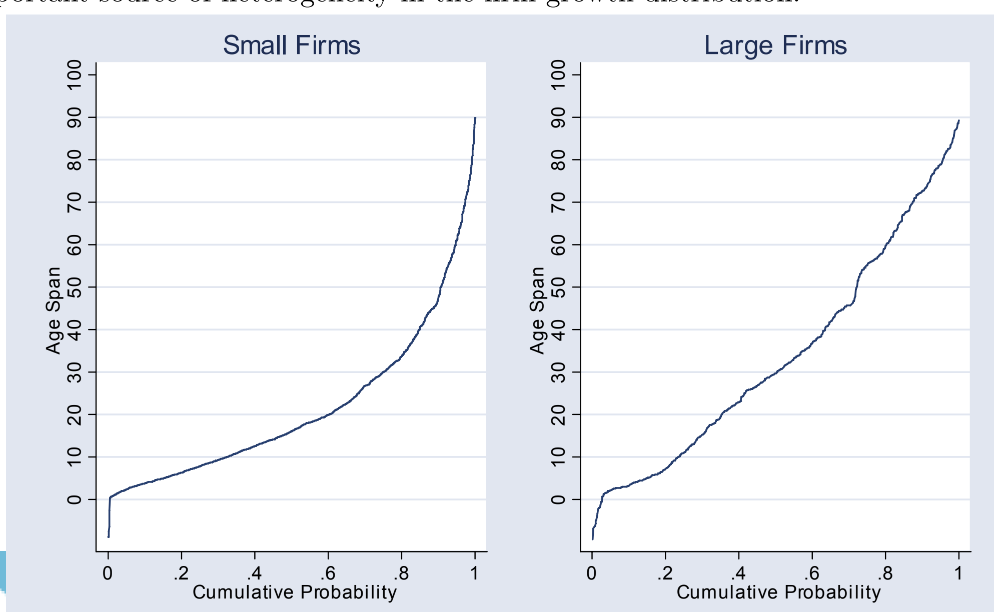
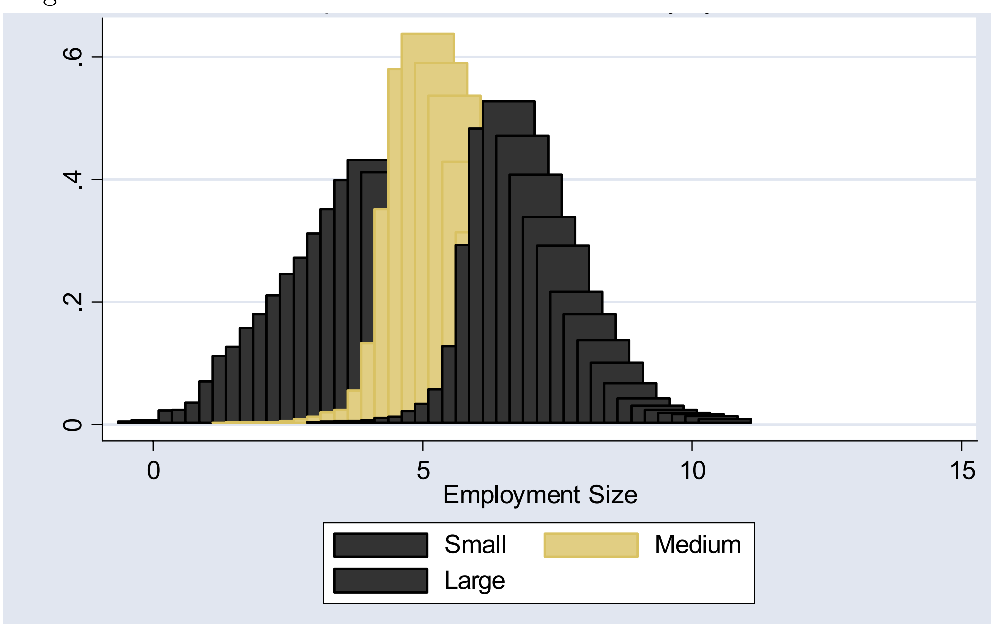


Fig. 5.3: **The Kernel Density of Various Size Classes of Firms**

This figure decomposes the kernel density of the logarithm of the employment-size distribution of the sample firms. The size classifications are based on the initial sizes of firms in the year 1991. It shows that there are considerable heterogeneity within each size class. That is, there are both stalled and dynamic firms in small, medium and large firm size classes that either pull their respective size distributions together or push them far apart, generating heteroscedasticity in the employment growth and size distribution.



Tab. 5.1: **Summary Statistics of the Sample Firms**

This table reports the summary statistics of the variables used in the causal regressions at various points in time of the sample periods. The sample firms are stratified into small, medium, and large classes using 1991 employment levels and following the European Commission size classification. The European Commission classifies a firm with 1-99 employees as a small firm, a firm with 100-499 employees as a medium firm and a firm with 500 or more employees as a large firm.

	1991			1995			2000		
	Mean	Median	N	Mean	Median	N	Mean	Median	N
All Firms:									
Num. of Employees	411.61	90	5214	419.19	96	5214	447.80	106	5214
Total Assets	6692.25	2619.00	5213	10109.02	3513.00	5214	15921.46	4612.00	5214
Profit Margin (%)	2.73	2.40	5214	5.35	3.68	5214	3.80	2.50	5214
Return to Shareholders (%)	21.75	14.12	4711	28.98	18.18	4854	15.31	12.10	4769
Return on Invested Capital (%)	15.33	9.81	4999	20.49	13.58	5086	11.41	9.04	4989
Return on Total Assets (%)	4.46	4.26	5213	7.35	6.24	5214	4.33	4.37	5214
Bank Credit/Tot. Liabilities	0.2878	0.2273	5213	0.2754	0.2166	5213	0.2909	0.2305	5212
Tangible Assets/Tot. Assets	0.3276	0.2802	5213	0.3098	0.2513	5214	0.3071	0.2409	5214
Small Firms:									
Num. of Employees	38.07	32	2741	51.67	37	2741	71.23	43	2741
Total Assets	2861.27	1017.50	2740	4259.75	1373.00	2741	7605.07	1811.00	2741
Profit Margin (%)	2.27	1.99	2741	5.27	3.33	2741	4.49	2.50	2741
Return to Shareholders (%)	21.20	13.80	2399	28.42	18.55	2507	19.80	12.32	2493
Return on Invested Capital (%)	14.85	9.52	2573	21.20	13.99	2649	15.38	9.78	2610
Return on Total Assets (%)	3.75	3.73	2740	7.35	6.00	2741	5.48	4.49	2741
Bank Credit/Tot. Liabilities	0.3058	0.2370	2740	0.2790	0.2113	2740	0.2828	0.2038	2739
Tangible Assets/Tot. Assets	0.3013	0.2151	2740	0.2849	0.1879	2741	0.2779	0.1747	2741
Medium Firms:									
Num. of Employees	220.85	192	1777	245.84	199	1777	308.78	213	1777
Total Assets	8661.44	4534.00	1777	12032.62	6190.00	1777	17632.11	8029.00	1777
Profit Margin (%)	3.18	2.69	1777	5.26	3.84	1777	3.26	2.39	1777
Return to Shareholders (%)	21.75	13.87	1670	28.08	17.61	1686	11.30	11.54	1654
Return on Invested Capital (%)	16.34	9.76	1747	20.05	13.19	1748	8.20	8.50	1718
Return on Total Assets (%)	5.30	4.75	1777	7.41	6.22	1777	3.83	4.25	1777
Bank Credit/Tot. Liabilities	0.2639	0.2131	1777	0.2654	0.2158	1777	0.2933	0.2439	1777
Tangible Assets/Tot. Assets	0.3555	0.3247	1777	0.3342	0.3003	1777	0.3388	0.3003	1777
Large Firms:									
Num. of Employees	2369.77	1040.5	696	2309.18	1040.5	696	2285.75	1040	696
Total Assets	16746.36	10196.00	696	28233.49	13939.50	696	44305.67	18270.00	696
Profit Margin (%)	3.38	3.32	696	5.89	4.66	696	2.46	2.82	696
Return to Shareholders (%)	23.82	15.70	642	33.37	18.37	661	7.97	13.64	622
Return on Invested Capital (%)	14.59	10.66	679	18.91	13.05	689	4.10	8.95	661
Return on Total Assets (%)	5.13	5.29	696	7.19	7.09	696	1.13	4.11	696
Bank Credit/Tot. Liabilities	0.2777	0.2307	696	0.2866	0.2406	696	0.3168	0.2711	696
Tangible Assets/Tot. Assets	0.3597	0.3476	696	0.3460	0.3308	696	0.3410	0.3129	696

Tab. 5.2: **Transition Matrix of Employment Size for the Sample Firms**

This table reports the transition dynamics of sample firms to various size classes at different points of the sample periods. The sample firms are stratified into small, medium, and large classes using 1991 employment levels and following the European Commission size classification. The European Commission classifies a firm with 1-99 employees as a small firm, a firm with 100-499 employees as a medium firm and a firm with 500 or more employees as a large firm. Each element of the size transition matrix is the number of firms that either remain with their initial size class or transit to a different size class. The diagonal elements of the transition matrix give the number of firms that remain with their initial size class while the off-diagonal elements capture the movement away from their initial size class.

From 1991 to 1995	Small	Medium	Large	Total-1991
Small	2492	243	6	2741
Medium	176	1500	101	1777
Large	3	70	623	696
Total-1995	2671	1813	730	5214

From 1995 to 1998	Small	Medium	Large	Total-1995
Small	2411	254	6	2671
Medium	102	1573	138	1813
Large	2	70	658	730
Total-1998	2515	1897	802	5214

From 1998 to 2001	Small	Medium	Large	Total-1998
Small	2325	185	5	2515
Medium	226	1556	115	1897
Large	15	121	666	802
Total-2001	2566	1862	786	5214

From 1991 to 2001	Small	Medium	Large	Total-1991
Small	2255	458	28	2741
Medium	288	1251	238	1777
Large	23	153	520	696
Total-2001	2566	1862	786	5214

Tab. 5.3: **Causality Regressions for All Firms**

This table reports the estimates from the causal regression for all firms in the sample. The sample firms are stratified into small, medium, and large classes using 1991 employment levels and following the European Commission size classification. The European Commission classifies a firm with 1-99 employees as a small firm, a firm with 100-499 employees as a medium firm and a firm with 500 or more employees as a large firm. Among the variables in the table, $GROWTH_{it}$ stands for the employment growth of firm i at time t, PM_{it} stands for $Profit\ Margin$, ROS_{it} stands for $Return\ to\ Shareholders$, ROC_{it} stands for $Return\ on\ Invested\ Capital$, and ROA_{it} stands for $Return\ on\ Total\ Assets$. Robust t statistics are given in brackets and beside the t-stat 'a' denotes significance at the 1% level, 'b' denotes significance at the 5% level, and 'c' denotes significance at the 10% level.

	First-Stage Regressions				Second-Stage Regressions			
	(1) $\Delta GROWTH_{it}$	(2) $\Delta GROWTH_{it}$	(3) $\Delta GROWTH_{it}$	(4) $\Delta GROWTH_{it}$	(1) ΔPM_{it}	(2) ΔROS_{it}	(3) ΔROC_{it}	(4) ΔROA_{it}
$\Delta GROWTH_{it-1}$	0.02164	0.01784	0.03853	0.02183	-0.60615	1.67418	1.72501	0.29777
	[0.97]	[0.74]	[1.51]	[0.97]	[1.24]	[0.77]	[1.29]	[0.50]
$\Delta GROWTH_{it-2}$	-0.05095	-0.07139	-0.05118	-0.05117	-0.36279	-2.06510	0.42240	0.02855
	[1.24]	[1.44]	[1.04]	[1.24]	[1.12]	[0.92]	[0.25]	[0.06]
$\Delta GROWTH_{it-3}$	-0.02650	-0.03963	-0.02663	-0.02727	-0.81093	0.36590	0.29568	-0.18447
	[1.38]	[1.83]c	[1.32]	[1.41]	[1.91]c	[0.15]	[0.18]	[0.34]
$\Delta GROWTH_{it-4}$	-0.00463	-0.01751	-0.01153	-0.00508	-0.01406	0.88752	1.74049	0.07910
	[0.39]	[1.20]	[0.92]	[0.43]	[0.05]	[0.37]	[1.33]	[0.16]
$\Delta Tot.\ Assets_{it-1}$	-0.00205	-0.00114	-0.00414	-0.00188	-0.06015	-0.76225	0.34187	0.16662
	[0.24]	[0.13]	[0.44]	[0.22]	[0.21]	[0.34]	[0.20]	[0.37]
$\Delta Tot.\ Assets_{it-2}$	-0.00486	-0.01764	-0.01775	-0.00466	0.01710	-3.23258	-1.89316	-0.46321
	[0.45]	[1.71]c	[1.76]c	[0.43]	[0.06]	[1.69]c	[1.21]	[1.11]
$\Delta Tot.\ Assets_{it-3}$	0.00330	0.00715	0.00937	0.00303	-0.21896	3.23221	0.22439	-0.81448
	[0.39]	[0.84]	[1.12]	[0.36]	[0.69]	[1.63]	[0.12]	[1.74]c
$\Delta Tot.\ Assets_{it-4}$	-0.00236	0.00558	0.00208	-0.00213	-0.07069	0.66301	0.56661	0.68954
	[0.27]	[0.66]	[0.24]	[0.24]	[0.26]	[0.34]	[0.36]	[1.58]
Age_{it-1}	-4.36816	-6.06839	-6.72810	-4.52904	243.96	631.76	1,960.76	375.39
	[0.95]	[1.20]	[1.44]	[0.99]	[1.71]c	[0.49]	[2.02]b	[1.27]
Age_{it-2}	4.31217	7.07857	7.91303	4.58752	-394.35	-1,107.14	-3,086.86	-580.76
	[0.62]	[0.92]	[1.12]	[0.66]	[1.83]c	[0.57]	[2.09]b	[1.32]
Age_{it-3}	-0.42462	-1.54858	-1.78896	-0.54859	162.99	509.99	1223.54	226.90
	[0.16]	[0.54]	[0.67]	[0.21]	[2.04]b	[0.71]	[2.20]b	[1.39]
Age_{it-4}	-0.05646	-0.01464	-0.01072	-0.05015	-6.37	-24.90	-38.31	-6.93
	[0.68]	[0.17]	[0.13]	[0.61]	[2.18]b	[1.03]	[1.85]c	[1.10]
ΔPM_{it-1}	0.00038				0.26363			
	[0.87]				[8.53]a			
ΔPM_{it-2}	0.00054				0.06169			
	[1.34]				[3.17]a			
ΔPM_{it-3}	-0.00007				0.02482			
	[0.25]				[1.67]c			
ΔPM_{it-4}	0.00006				-0.01541			
	[0.16]				[1.09]			
ΔROS_{it-1}		0.00010				0.28148		
		[2.53]b				[5.43]a		
ΔROS_{it-2}		0.00001				0.08138		
		[0.21]				[2.87]a		
ΔROS_{it-3}		-0.00001				0.01211		
		[0.18]				[0.50]		
ΔROS_{it-4}		0.00003				-0.00008		
		[0.83]				[0.01]		
ΔROC_{it-1}			0.00013				0.23899	
			[3.32]a				[4.74]a	
ΔROC_{it-2}			0.00008				0.08025	
			[1.60]				[2.42]b	
ΔROC_{it-3}			0.00003				0.06258	
			[0.52]				[2.23]b	
ΔROC_{it-4}			0.00003				0.01002	
			[0.70]				[0.48]	
ΔROA_{it-1}				0.00042				0.25668
				[1.87]c				[6.34]a
ΔROA_{it-2}				0.00016				0.07012
				[0.81]				[2.93]a
ΔROA_{it-3}				0.00011				0.01290
				[0.74]				[0.73]
ΔROA_{it-4}				0.00028				-0.02514
				[1.43]				[1.43]
Constant	0.00002	-0.00332	0.00045	0.00037	-0.80369	-6.49455	-5.88758	-1.81826
	[0.00]	[0.34]	[0.05]	[0.05]	[3.21]a	[2.68]a	[2.75]a	[3.81]a
N	25805	22351	23955	25802	25805	21895	23620	25784
Num. of Firms	5168	4759	4990	5168	5168	4694	4946	5168
F-Test	87.65	76.02	96.40	86.89	162.02	64.93	64.13	96.80
Prob.>F	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wald-Test	2.44	7.69	12.43	5.12	4.09	4.76	3.39	0.61
Prob.>Wald	0.66	0.10	0.01	0.28	0.39	0.31	0.49	0.96

Tab. 5.4: **Causality Regressions for Small Firms**

This table reports the estimates from the causal regressions for small firms in the sample. The sample firms are stratified into small, medium, and large classes using 1991 employment levels and following the European Commission size classification. The European Commission classifies a firm with 1-99 employees as a small firm, a firm with 100-499 employees as a medium firm and a firm with 500 or more employees as a large firm. Among the variables in the table, $GROWTH_{it}$ stands for the employment growth of firm i at time t, PM_{it} stands for $Profit\,Margin$, ROS_{it} stands for $Return\,to\,Shareholders$, ROC_{it} stands for $Return\,on\,Invested\,Capital$, and ROA_{it} stands for $Return\,on\,Total\,Assets$. Robust t statistics are given in brackets and beside the t-stat 'a' denotes significance at the 1% level, 'b' denotes significance at the 5% level, and 'c' denotes significance at the 10% level.

	First-Stage Regressions				Second-Stage Regressions			
	(1) $\Delta GROWTH_{it}$	(2) $\Delta GROWTH_{it}$	(3) $\Delta GROWTH_{it}$	(4) $\Delta GROWTH_{it}$	(1) ΔPM_{it}	(2) ΔROS_{it}	(3) ΔROC_{it}	(4) ΔROA_{it}
$\Delta GROWTH_{it-1}$	0.01839	0.02783	0.06943	0.02013	-0.82022	2.44139	1.61587	-0.31213
	[0.57]	[0.88]	[1.89]c	[0.62]	[1.02]	[0.79]	[0.80]	[0.54]
$\Delta GROWTH_{it-2}$	-0.01449	-0.02337	0.01234	-0.01488	-0.27563	-1.67192	-0.69384	0.13356
	[0.89]	[0.99]	[0.40]	[0.92]	[0.56]	[0.58]	[0.25]	[0.19]
$\Delta GROWTH_{it-3}$	-0.00249	-0.00944	0.01096	-0.00438	-0.95794	3.47261	-0.74710	0.23989
	[0.11]	[0.39]	[0.49]	[0.18]	[1.45]	[1.13]	[0.28]	[0.30]
$\Delta GROWTH_{it-4}$	0.00196	-0.01799	-0.00314	0.00101	0.04830	3.20162	2.16918	0.34111
	[0.14]	[0.90]	[0.20]	[0.07]	[0.11]	[1.21]	[1.11]	[0.55]
$\Delta Tot.\ Assets_{it-1}$	-0.00188	0.00056	-0.00150	-0.00147	-0.04077	-0.69291	1.00565	0.12829
	[0.18]	[0.06]	[0.13]	[0.14]	[0.10]	[0.24]	[0.46]	[0.20]
$\Delta Tot.\ Assets_{it-2}$	0.00152	-0.01508	-0.01693	0.00175	0.35393	-4.09049	-4.54301	-0.37758
	[0.10]	[1.04]	[1.18]	[0.11]	[0.82]	[1.59]	[2.11]b	[0.68]
$\Delta Tot.\ Assets_{it-3}$	0.00216	0.00823	0.01101	0.00217	-0.53789	5.76104	1.91486	-0.87369
	[0.19]	[0.69]	[0.94]	[0.19]	[1.29]	[2.13]b	[0.79]	[1.52]
$\Delta Tot.\ Assets_{it-4}$	-0.00766	0.00083	-0.00342	-0.00739	-0.26275	-1.90711	-1.35194	-0.00925
	[0.61]	[0.07]	[0.28]	[0.59]	[0.75]	[0.76]	[0.63]	[0.02]
Age_{it-1}	0.27925	-2.40372	-2.65227	-0.41087	209.84	1175.02	3931.95	334.46
	[0.04]	[0.30]	[0.33]	[0.06]	[0.86]	[0.57]	[2.18]b	[0.68]
Age_{it-2}	-2.58218	1.45998	1.82105	-1.51828	-349.91	-2039.47	-6124.05	-565.16
	[0.23]	[0.12]	[0.15]	[0.14]	[0.95]	[0.65]	[2.23]b	[0.76]
Age_{it-3}	2.01767	0.50516	0.38006	1.61039	146.75	900.74	2,395.31	242.17
	[0.48]	[0.11]	[0.08]	[0.38]	[1.06]	[0.76]	[2.30]b	[0.87]
Age_{it-4}	-0.12828	-0.08146	-0.07767	-0.11746	-4.01	-36.56	-84.42	-8.94
	[0.88]	[0.51]	[0.49]	[0.80]	[0.85]	[0.88]	[2.31]b	[0.95]
ΔPM_{it-1}	0.00126				0.25063			
	[1.82]c				[6.74]a			
ΔPM_{it-2}	0.00075				0.05243			
	[1.60]				[2.14]b			
ΔPM_{it-3}	0.00026				0.00277			
	[0.65]				[0.15]			
ΔPM_{it-4}	-0.00017				-0.02403			
	[0.34]				[1.33]			
ΔROS_{it-1}		0.00019				0.21024		
		[3.20]a				[3.12]a		
ΔROS_{it-2}		0.00004				0.04273		
		[0.67]				[1.08]		
ΔROS_{it-3}		0.00008				-0.01533		
		[1.39]				[0.46]		
ΔROS_{it-4}		0.00000				-0.02527		
		[0.06]				[1.49]		
ΔROC_{it-1}			0.00020				0.19543	
			[3.46]a				[3.28]a	
ΔROC_{it-2}			0.00009				0.06773	
			[1.38]				[1.77]c	
ΔROC_{it-3}			0.00007				0.05920	
			[0.96]				[1.49]	
ΔROC_{it-4}			-0.00003				-0.00167	
			[0.56]				[0.06]	
ΔROA_{it-1}				0.00075				0.23284
				[2.48]b				[4.79]a
ΔROA_{it-2}				0.00017				0.06243
				[0.69]				[2.15]b
ΔROA_{it-3}				0.00026				0.00288
				[1.41]				[0.13]
ΔROA_{it-4}				0.00017				-0.05798
				[0.67]				[2.69]a
Constant	0.01378	0.01714	0.01710	0.01413	-0.52360	-3.15820	-4.90256	-0.67268
	[1.55]	[1.61]	[1.74]c	[1.58]	[1.55]	[1.02]	[1.59]	[1.22]
N	13655	11620	12464	13652	13655	11411	12290	13641
Num. of Firms	2732	2477	2612	2732	2732	2447	2582	2732
F-Test	57.81	54.54	61.49	54.51	143.25	43.12	39.93	77.73
Prob.>F	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wald-Test	6.83	11.14	14.68	7.40	2.64	5.48	3.08	0.85
Prob.>Wald	0.15	0.03	0.01	0.12	0.62	0.24	0.54	0.93

Tab. 5.5: **Causality Regressions for Medium Firms**

This table reports the estimates from the causal regressions for the medium firms in the sample. The sample firms are stratified into small, medium, and large classes using 1991 employment levels and following the European Commission size classification. The European Commission classifies a firm with 1-99 employees as a small firm, a firm with 100-499 employees as a medium firm and a firm with 500 or more employees as a large firm. Among the variables in the table, $GROWTH_{it}$ stands for the employment growth of firm i at time t, PM_{it} stands for $Profit\ Margin$, ROS_{it} stands for $Return\ to\ Shareholders$, ROC_{it} stands for $Return\ on\ Invested\ Capital$, and ROA_{it} stands for $Return\ on\ Total\ Assets$. Robust t statistics are given in brackets and beside the t-stat 'a' denotes significance at the 1% level, 'b' denotes significance at the 5% level, and 'c' denotes significance at the 10% level.

	First-Stage Regressions				Second-Stage Regressions			
	(1) $\Delta GROWTH_{it}$	(2) $\Delta GROWTH_{it}$	(3) $\Delta GROWTH_{it}$	(4) $\Delta GROWTH_{it}$	(1) ΔPM_{it}	(2) ΔROS_{it}	(3) ΔROC_{it}	(4) ΔROA_{it}
$\Delta GROWTH_{it-1}$	0.01622	-0.00598	-0.00235	0.01597	-0.25273	1.95372	-0.96378	1.65106
	[0.59]	[0.19]	[0.08]	[0.58]	[0.41]	[0.53]	[0.46]	[0.95]
$\Delta GROWTH_{it-2}$	-0.03564	-0.06851	-0.06354	-0.03603	-0.25727	0.04835	0.85458	0.12893
	[0.76]	[1.24]	[1.23]	[0.77]	[0.51]	[0.01]	[0.32]	[0.14]
$\Delta GROWTH_{it-3}$	-0.03836	-0.05907	-0.05354	-0.03868	-0.39784	-1.08507	-0.25943	-0.96425
	[0.82]	[1.03]	[1.01]	[0.82]	[0.60]	[0.29]	[0.09]	[0.72]
$\Delta GROWTH_{it-4}$	-0.05420	-0.05717	-0.06128	-0.05420	-0.14643	-1.35348	0.10602	-0.75451
	[2.23]b	[1.96]c	[2.16]b	[2.23]b	[0.31]	[0.35]	[0.05]	[0.54]
$\Delta Tot.\ Assets_{it-1}$	0.00134	-0.00161	-0.00377	0.00123	-0.05032	-4.14507	-3.68069	0.24137
	[0.08]	[0.09]	[0.23]	[0.08]	[0.12]	[1.00]	[1.33]	[0.37]
$\Delta Tot.\ Assets_{it-2}$	0.00088	-0.00375	-0.00004	0.00092	-0.27134	-3.36417	0.11518	-0.37280
	[0.07]	[0.28]	[0.00]	[0.07]	[0.66]	[1.06]	[0.05]	[0.53]
$\Delta Tot.\ Assets_{it-3}$	-0.00602	-0.00428	-0.00243	-0.00587	-0.17595	0.59514	-2.36832	-0.88824
	[0.52]	[0.39]	[0.22]	[0.51]	[0.40]	[0.20]	[0.81]	[0.99]
$\Delta Tot.\ Assets_{it-4}$	-0.00042	0.00140	0.00145	-0.00011	0.24824	4.16594	2.37925	1.82672
	[0.04]	[0.13]	[0.14]	[0.01]	[0.64]	[1.20]	[1.03]	[2.52]b
Age_{it-1}	-12.37203	-10.09607	-14.29667	-12.73537	239.77	4620.13	39.19	302.45
	[1.16]	[0.90]	[1.28]	[1.19]	[0.77]	[2.04]b	[0.02]	[0.37]
Age_{it-2}	16.62103	13.36525	19.68904	17.26674	-444.26	-7776.20	-305.33	-486.72
	[1.00]	[0.77]	[1.14]	[1.04]	[0.92]	[2.18]b	[0.09]	[0.39]
Age_{it-3}	-5.09790	-3.93830	-6.37967	-5.41977	238.96	3,655.26	347.87	240.09
	[0.76]	[0.56]	[0.92]	[0.81]	[1.21]	[2.50]b	[0.25]	[0.49]
Age_{it-4}	0.17086	0.11156	0.25384	0.20340	-30.21	-371.62	-69.87	-31.69
	[0.40]	[0.25]	[0.59]	[0.48]	[2.38]b	[3.72]a	[0.79]	[1.05]
ΔPM_{it-1}	-0.00029				0.22938			
	[0.57]				[4.28]a			
ΔPM_{it-2}	-0.00057				0.03210			
	[0.99]				[0.86]			
ΔPM_{it-3}	-0.00042				0.04215			
	[1.02]				[1.46]			
ΔPM_{it-4}	-0.00022				-0.01712			
	[0.45]				[0.68]			
ΔROS_{it-1}		0.00002				0.33855		
		[0.49]				[3.31]a		
ΔROS_{it-2}		-0.00001				0.12645		
		[0.07]				[2.32]b		
ΔROS_{it-3}		-0.00007				0.03370		
		[0.67]				[0.91]		
ΔROS_{it-4}		0.00005				0.04034		
		[0.68]				[1.77]c		
ΔROC_{it-1}			0.00001				0.14547	
			[0.31]				[1.27]	
ΔROC_{it-2}			0.00005				0.02224	
			[0.65]				[0.28]	
ΔROC_{it-3}			-0.00003				0.01563	
			[0.59]				[0.36]	
ΔROC_{it-4}			0.00009				-0.00344	
			[1.06]				[0.08]	
ΔROA_{it-1}				0.00030				0.29444
				[0.67]				[4.09]a
ΔROA_{it-2}				-0.00012				0.06299
				[0.36]				[1.04]
ΔROA_{it-3}				-0.00033				0.00523
				[1.24]				[0.13]
ΔROA_{it-4}				-0.00003				0.02889
				[0.11]				[0.61]
Constant	-0.02842	-0.02988	-0.02776	-0.02746	-1.19325	-10.03489	-11.50770	-3.84163
	[2.04]b	[1.99]b	[1.94]c	[1.98]b	[2.60]a	[2.15]b	[3.56]a	[3.56]a
N	8740	7776	8261	8740	8740	7608	8151	8735
Num. of Firms	1750	1645	1705	1750	1750	1624	1698	1750
F-Test	44.58	32.85	40.77	42.55	69.46	66.08	38.29	71.27
Prob.>F	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00
Wald-Test	1.92	2.14	3.74	2.68	0.39	0.89	0.44	1.89
Prob.>Wald	0.75	0.71	0.44	0.61	0.98	0.93	0.98	0.76

Tab. 5.6: **Causality Regressions for Large Firms**

This table reports the estimates from the causal regressions for the large firms in the sample. The sample firms are stratified into small, medium, and large classes using 1991 employment levels and following the European Commission size classification. The European Commission classifies a firm with 1-99 employees as a small firm, a firm with 100-499 employees as a medium firm and a firm with 500 or more employees as a large firm. Among the variables in the table, $GROWTH_{it}$ stands for the employment growth of firm i at time t, PM_{it} stands for $Profit\ Margin$, ROS_{it} stands for $Return\ to\ Shareholders$, ROC_{it} stands for $Return\ on\ Invested\ Capital$, and ROA_{it} stands for $Return\ on\ Total\ Assets$. Robust t statistics are given in brackets and beside the t-stat 'a' denotes significance at the 1% level, 'b' denotes significance at the 5% level, and 'c' denotes significance at the 10% level.

	First-Stage Regressions				Second-Stage Regressions			
	(1) $\Delta GROWTH_{it}$	(2) $\Delta GROWTH_{it}$	(3) $\Delta GROWTH_{it}$	(4) $\Delta GROWTH_{it}$	(1) ΔPM_{it}	(2) ΔROS_{it}	(3) ΔROC_{it}	(4) ΔROA_{it}
$\Delta GROWTH_{it-1}$	-0.03007	-0.04540	-0.04750	-0.03048	-0.20829	-1.19261	5.74146	0.39663
	[0.57]	[0.80]	[0.90]	[0.57]	[0.23]	[0.22]	[1.75]c	[0.70]
$\Delta GROWTH_{it-2}$	-0.22220	-0.23992	-0.23645	-0.22148	-0.26867	-5.45919	2.66119	-0.06932
	[1.44]	[1.48]	[1.53]	[1.43]	[0.40]	[0.89]	[1.09]	[0.13]
$\Delta GROWTH_{it-3}$	-0.12808	-0.13637	-0.13760	-0.12745	-0.63010	-7.09059	2.80819	-0.09889
	[3.82]a	[3.79]a	[3.95]a	[3.79]a	[0.89]	[0.86]	[1.09]	[0.18]
$\Delta GROWTH_{it-4}$	0.00849	-0.00054	-0.00305	0.00796	-0.06333	-4.79722	1.00374	0.39652
	[0.29]	[0.02]	[0.10]	[0.27]	[0.10]	[0.59]	[0.51]	[0.68]
$\Delta Tot.\ Assets_{it-1}$	-0.01267	-0.01011	-0.00988	-0.01287	-0.09573	8.71646	7.40238	0.32380
	[0.53]	[0.39]	[0.42]	[0.54]	[0.10]	[1.28]	[1.09]	[0.22]
$\Delta Tot.\ Assets_{it-2}$	-0.06432	-0.08197	-0.07678	-0.06279	-0.96617	-0.12066	2.71514	-0.93323
	[1.83]c	[2.08]b	[2.16]b	[1.78]c	[0.90]	[0.03]	[0.54]	[0.71]
$\Delta Tot.\ Assets_{it-3}$	0.03675	0.04086	0.03396	0.03665	1.63571	-5.05727	-2.69439	0.24651
	[1.05]	[1.06]	[0.95]	[1.05]	[1.12]	[1.08]	[0.57]	[0.17]
$\Delta Tot.\ Assets_{it-4}$	0.01398	0.02589	0.02457	0.01211	0.08134	5.57310	5.93701	1.58180
	[0.61]	[1.06]	[1.06]	[0.53]	[0.07]	[1.12]	[1.33]	[0.96]
Age_{it-1}	-11.66695	-17.20528	-15.69845	-12.21945	860.65	1472.00	1,886.88	994.36
	[1.13]	[1.40]	[1.65]c	[1.21]	[2.63]a	[0.69]	[0.95]	[2.12]b
Age_{it-2}	14.46554	23.19248	20.58453	15.27691	-1,295.80	-2217.38	-3005.04	-1,471.01
	[0.93]	[1.25]	[1.44]	[1.00]	[2.67]a	[0.70]	[1.03]	[2.10]b
Age_{it-3}	-3.67228	-7.01878	-5.93762	-3.96277	481.14	814.61	1164.96	527.81
	[0.64]	[1.02]	[1.12]	[0.70]	[2.75]a	[0.71]	[1.11]	[2.06]b
Age_{it-4}	0.00102	0.10185	0.06789	0.01142	-14.13	-16.32	-27.61	-11.60
	[0.01]	[0.53]	[0.46]	[0.07]	[2.72]a	[0.49]	[0.87]	[1.36]
ΔPM_{it-1}	-0.00121				0.17053			
	[1.34]				[1.47]			
ΔPM_{it-2}	0.00189				0.06034			
	[1.02]				[0.93]			
ΔPM_{it-3}	-0.00094				0.02089			
	[1.05]				[0.46]			
ΔPM_{it-4}	0.00179				-0.00405			
	[1.35]				[0.09]			
ΔROS_{it-1}		-0.00007				0.20727		
		[0.60]				[1.92]c		
ΔROS_{it-2}		-0.00005				-0.02016		
		[0.45]				[0.38]		
ΔROS_{it-3}		-0.00030				0.01255		
		[1.68]c				[0.18]		
ΔROS_{it-4}		0.00003				-0.02171		
		[0.27]				[0.51]		
ΔROC_{it-1}			0.00010				0.25851	
			[0.77]				[2.31]b	
ΔROC_{it-2}			0.00002				0.05897	
			[0.19]				[0.76]	
ΔROC_{it-3}			-0.00027				0.03530	
			[1.53]				[0.57]	
ΔROC_{it-4}			0.00013				-0.03433	
			[0.64]				[0.72]	
ΔROA_{it-1}				-0.00102				0.16860
				[2.01]b				[1.79]c
ΔROA_{it-2}				0.00063				0.05192
				[0.68]				[0.87]
ΔROA_{it-3}				-0.00023				0.04091
				[0.49]				[0.98]
ΔROA_{it-4}				0.00144				0.04193
				[2.23]b				[1.02]
Constant	-0.00769	-0.02659	-0.01233	-0.00847	-0.97100	-6.71034	-0.68169	-1.69680
	[0.22]	[0.69]	[0.35]	[0.25]	[1.04]	[1.14]	[0.15]	[1.41]
N	3410	2955	3230	3410	3410	2876	3179	3408
Num. of Firms	686	637	673	686	686	623	666	686
F-Test	48.13	43.34	48.64	57.71	20.14	41.87	19.74	22.26
Prob.>F	0.00	0.00	0.00	0.00	0.21	0.00	0.23	0.13
Wald-Test	3.80	3.59	5.96	9.11	1.80	3.13	3.72	1.64
Prob.>Wald	0.43	0.46	0.20	0.06	0.77	0.54	0.44	0.80

Tab. 5.7: **Causality Regressions for All Firms: Controlling for Collateral Base**

This table reports the estimates from the causal regressions for all firms in the sample. The sample firms are stratified into small, medium, and large classes using 1991 employment levels and following the European Commission size classification. The European Commission classifies a firm with 1-99 employees as a small firm, a firm with 100-499 employees as a medium firm and a firm with 500 or more employees as a large firm. Among the variables in the table, $GROWTH_{it}$ stands for the employment growth of firm i at time t, PM_{it} stands for *Profit Margin*, ROS_{it} stands for *Return to Shareholders*, ROC_{it} stands for *Return on Invested Capital*, and ROA_{it} stands for *Return on Total Assets*. Robust t statistics are given in brackets and beside the t-stat 'a' denotes significance at the 1% level, 'b' denotes significance at the 5% level, and 'c' denotes significance at the 10% level.

	First-Stage Regressions				Second-Stage Regressions			
	(1) $\Delta GROWTH_{it}$	(2) $\Delta GROWTH_{it}$	(3) $\Delta GROWTH_{it}$	(4) $\Delta GROWTH_{it}$	(1) ΔPM_{it}	(2) ΔROS_{it}	(3) ΔROC_{it}	(4) ΔROA_{it}
$\Delta GROWTH_{it-1}$	0.02138	0.01774	0.03821	0.02158	-0.60703	1.68184	1.72808	0.29356
	[0.96]	[0.73]	[1.51]	[0.96]	[1.24]	[0.77]	[1.29]	[0.50]
$\Delta GROWTH_{it-2}$	-0.05111	-0.07131	-0.05125	-0.05130	-0.36198	-2.07811	0.41990	0.02595
	[1.24]	[1.44]	[1.05]	[1.25]	[1.12]	[0.93]	[0.25]	[0.06]
$\Delta GROWTH_{it-3}$	-0.02641	-0.03953	-0.02655	-0.02717	-0.81047	0.35526	0.28986	-0.18525
	[1.38]	[1.83]c	[1.31]	[1.41]	[1.91]c	[0.14]	[0.17]	[0.34]
$\Delta GROWTH_{it-4}$	-0.00471	-0.01754	-0.01159	-0.00515	-0.01539	0.89000	1.74372	0.07729
	[0.40]	[1.21]	[0.92]	[0.44]	[0.05]	[0.37]	[1.33]	[0.16]
$\Delta Tot.\ Assets_{it-1}$	-0.00313	-0.00149	-0.00494	-0.00297	-0.04927	-0.78731	0.31433	0.18506
	[0.36]	[0.17]	[0.53]	[0.34]	[0.17]	[0.35]	[0.18]	[0.41]
$\Delta Tot.\ Assets_{it-2}$	-0.00355	-0.01746	-0.01705	-0.00334	0.00198	-3.21540	-1.86816	-0.47870
	[0.32]	[1.69]c	[1.70]c	[0.30]	[0.01]	[1.68]c	[1.19]	[1.13]
$\Delta Tot.\ Assets_{it-3}$	0.00342	0.00785	0.01001	0.00316	-0.20955	3.36545	0.26958	-0.80412
	[0.41]	[0.93]	[1.20]	[0.38]	[0.66]	[1.69]c	[0.15]	[1.69]c
$\Delta Tot.\ Assets_{it-4}$	-0.00175	0.00552	0.00224	-0.00152	-0.06370	0.46825	0.47521	0.72388
	[0.21]	[0.65]	[0.26]	[0.18]	[0.24]	[0.24]	[0.30]	[1.65]c
Age_{it-1}	-0.07060	-6.17832	-0.06141	-0.07106	0.19	625.14	1958.06	0.17
	[0.98]	[1.42]	[1.47]	[2.43]b	[1.71]c	[0.49]	[0.24]	[1.28]
Age_{it-2}	4.51976	7.23794	8.12247	4.79116	-394.34	-1096.71	-3082.18	-1.34
	[0.39]	[0.95]	[1.15]	[0.41]	[1.83]c	[0.56]	[0.08]	[1.33]
Age_{it-3}	-0.49997	-1.60200	0.01624	-0.00242	0.19	505.98	1.60	-0.86
	[0.19]	[0.91]	[0.70]	[0.08]	[0.20]	[0.74]	[2.20]b	[1.40]
Age_{it-4}	-0.05409	-0.01349	-0.00867	-0.04783	-6.38	-24.78	-5.22	-6.94
	[1.25]	[0.15]	[1.21]	[1.23]	[0.70]	[1.04]	[0.84]	[0.51]
$\Delta Collateral_{it-1}$	-4.50531	-0.03963	-6.86795	-4.66341	243.88204	-3.19456	-1.62952	377.23158
	[2.41]b	[1.23]	[2.13]b	[1.02]	[0.20]	[0.48]	[2.02]b	[0.10]
$\Delta Collateral_{it-2}$	-0.01311	-0.03111	-0.02887	-0.01373	-0.62327	-0.29088	0.42708	-583.22318
	[0.65]	[1.03]	[0.97]	[0.69]	[0.66]	[0.05]	[2.09]b	[1.03]
$\Delta Collateral_{it-3}$	-0.00213	0.02391	-1.86283	-0.62255	163.05538	5.36871	1,221.54428	227.62588
	[0.07]	[0.56]	[0.62]	[0.24]	[2.04]b	[0.70]	[0.26]	[0.57]
$\Delta Collateral_{it-4}$	0.04311	0.03145	0.03866	0.04230	0.64653	-8.95708	-38.27493	0.75115
	[0.65]	[1.11]	[0.10]	[0.58]	[2.18]b	[1.03]	[1.86]c	[1.10]
ΔPM_{it-1}	0.00038				0.26366			
	[0.86]				[8.53]a			
ΔPM_{it-2}	0.00055				0.06174			
	[1.35]				[3.17]a			
ΔPM_{it-3}	-0.00006				0.02485			
	[0.20]				[1.68]c			
ΔPM_{it-4}	0.00007				-0.01533			
	[0.19]				[1.08]			
ΔROS_{it-1}		0.00010				0.28148		
		[2.54]b				[5.43]a		
ΔROS_{it-2}		0.00001				0.08141		
		[0.22]				[2.87]a		
ΔROS_{it-3}		-0.00001				0.01220		
		[0.16]				[0.50]		
ΔROS_{it-4}		0.00003				-0.00014		
		[0.86]				[0.01]		
ΔROC_{it-1}			0.00013				0.23907	
			[3.33]a				[4.74]a	
ΔROC_{it-2}			0.00007				0.08021	
			[1.60]				[2.42]b	
ΔROC_{it-3}			0.00003				0.06269	
			[0.52]				[2.23]b	
ΔROC_{it-4}			0.00003				0.01001	
			[0.71]				[0.48]	
ΔROA_{it-1}				0.00042				0.25655
				[1.87]c				[6.34]a
ΔROA_{it-2}				0.00017				0.07016
				[0.84]				[2.93]a
ΔROA_{it-3}				0.00011				0.01297
				[0.78]				[0.73]
ΔROA_{it-4}				0.00029				-0.02509
				[1.44]				[1.43]
Constant	-0.00044	-0.00363	-0.00010	-0.00010	-0.80471	-6.52699	-5.90446	-1.81802
	[0.05]	[0.37]	[0.01]	[0.01]	[3.21]a	[2.70]a	[2.77]a	[3.81]a
N	25805	22351	23955	25802	25805	21895	23620	25784
Num. of Firms	5168	4759	4990	5168	5168	4694	4946	5168
F-Test	106.08	87.61	108.45	105.65	164.27	66.34	65.11	99.51
Prob.>F	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wald-Test	2.42	7.73	12.48	5.18	4.10	4.81	3.41	0.60
Prob.>Wald	0.66	0.10	0.01	0.27	0.39	0.31	0.49	0.96

Tab. 5.8: **Causality Regressions for Small Firms: Controlling for Collateral Base**

This table reports the estimates from the causal regressions for the small firms in the sample. The sample firms are stratified into small, medium, and large classes using 1991 employment levels and following the European Commission size classification. The European Commission classifies a firm with 1-99 employees as a small firm, a firm with 100-499 employees as a medium firm and a firm with 500 or more employees as a large firm. Among the variables in the table, $GROWTH_{it}$ stands for the employment growth of firm i at time t, PM_{it} stands for $Profit\ Margin$, ROS_{it} stands for $Return\ to\ Shareholders$, ROC_{it} stands for $Return\ on\ Invested\ Capital$, and ROA_{it} stands for $Return\ on\ Total\ Assets$. Robust t statistics are given in brackets and beside the t-stat 'a' denotes significance at the 1% level, 'b' denotes significance at the 5% level, and 'c' denotes significance at the 10% level.

	First-Stage Regressions				Second-Stage Regressions			
	(1) $\Delta GROWTH_{it}$	(2) $\Delta GROWTH_{it}$	(3) $\Delta GROWTH_{it}$	(4) $\Delta GROWTH_{it}$	(1) ΔPM_{it}	(2) ΔROS_{it}	(3) ΔROC_{it}	(4) ΔROA_{it}
$\Delta GROWTH_{it-1}$	0.01703	0.02687	0.06788	0.01880	-0.81760	2.45994	1.61147	-0.31923
	[0.53]	[0.85]	[1.86]c	[0.58]	[1.02]	[0.80]	[0.80]	[0.56]
$\Delta GROWTH_{it-2}$	-0.01549	-0.02392	0.01147	-0.01584	-0.27143	-1.72603	-0.71184	0.13553
	[0.95]	[1.01]	[0.37]	[0.98]	[0.55]	[0.59]	[0.26]	[0.19]
$\Delta GROWTH_{it-3}$	-0.00319	-0.01000	0.01028	-0.00505	-0.95634	3.49551	-0.73759	0.23700
	[0.14]	[0.41]	[0.46]	[0.21]	[1.45]	[1.13]	[0.27]	[0.29]
$\Delta GROWTH_{it-4}$	0.00126	-0.01851	-0.00385	0.00032	0.04827	3.27811	2.22320	0.34644
	[0.09]	[0.93]	[0.25]	[0.02]	[0.11]	[1.24]	[1.14]	[0.56]
$\Delta Tot.\ Assets_{it-1}$	-0.00310	0.00069	-0.00228	-0.00267	-0.05009	-0.71444	1.05426	0.15767
	[0.28]	[0.07]	[0.19]	[0.24]	[0.13]	[0.24]	[0.50]	[0.24]
$\Delta Tot.\ Assets_{it-2}$	0.00224	-0.01624	-0.01719	0.00248	0.35304	-4.05888	-4.58483	-0.41903
	[0.14]	[1.12]	[1.20]	[0.15]	[0.80]	[1.58]	[2.14]b	[0.75]
$\Delta Tot.\ Assets_{it-3}$	0.00308	0.01026	0.01269	0.00310	-0.50936	6.01847	1.99944	-0.83242
	[0.26]	[0.87]	[1.09]	[0.27]	[1.21]	[2.22]b	[0.82]	[1.44]
$\Delta Tot.\ Assets_{it-4}$	-0.00713	0.00055	-0.00337	-0.00683	-0.26881	-2.13048	-1.46614	-0.01540
	[0.58]	[0.05]	[0.28]	[0.56]	[0.77]	[0.84]	[0.68]	[0.03]
Age_{it-1}	0.28193	-2.11595	-2.50841	-0.40896	210.35	1147.23	3927.29	335.58
	[0.04]	[0.26]	[0.32]	[0.06]	[0.86]	[0.55]	[2.18]b	[0.68]
Age_{it-2}	-2.59129	1.02097	1.60784	-1.52655	-350.77	-1996.91	-6116.47	-566.90
	[0.23]	[0.08]	[0.13]	[0.14]	[0.95]	[0.64]	[2.23]b	[0.76]
Age_{it-3}	2.02735	0.67546	0.46352	1.61988	147.17	884.10	2391.72	242.80
	[0.48]	[0.15]	[0.10]	[0.38]	[1.06]	[0.74]	[2.30]b	[0.87]
Age_{it-4}	-0.12966	-0.08848	-0.08172	-0.11882	-4.05	-35.96	-84.22	-8.96
	[0.89]	[0.55]	[0.52]	[0.81]	[0.85]	[0.86]	[2.30]b	[0.95]
$\Delta Collateral_{it-1}$	-0.08543	-0.03170	-0.07016	-0.08552	-1.08469	-6.00234	1.25765	0.42186
	[2.28]b	[0.94]	[1.88]c	[2.27]b	[0.86]	[0.70]	[0.13]	[0.21]
$\Delta Collateral_{it-2}$	-0.04964	-0.08294	-0.07503	-0.05136	-0.93732	-4.37174	-0.87375	-1.66941
	[1.13]	[2.20]b	[1.98]b	[1.17]	[0.75]	[0.53]	[0.11]	[0.97]
$\Delta Collateral_{it-3}$	0.00655	0.03510	0.02125	0.00435	0.51652	3.33934	0.24012	0.03680
	[0.17]	[1.06]	[0.64]	[0.11]	[0.41]	[0.36]	[0.03]	[0.02]
$\Delta Collateral_{it-4}$	0.04423	0.02449	0.03783	0.04288	-0.05956	-21.88957	-12.98003	-1.47214
	[0.89]	[0.66]	[0.83]	[0.87]	[0.05]	[1.81]c	[1.62]	[0.73]
ΔPM_{it-1}	0.00126				0.25041			
	[1.82]c				[6.73]a			
ΔPM_{it-2}	0.00077				0.05254			
	[1.64]				[2.14]b			
ΔPM_{it-3}	0.00028				0.00291			
	[0.70]				[0.16]			
ΔPM_{it-4}	-0.00015				-0.02394			
	[0.30]				[1.32]			
ΔROS_{it-1}		0.00019				0.20990		
		[3.20]a				[3.12]a		
ΔROS_{it-2}		0.00004				0.04257		
		[0.69]				[1.07]		
ΔROS_{it-3}		0.00008				-0.01542		
		[1.41]				[0.46]		
ΔROS_{it-4}		0.00000				-0.02554		
		[0.07]				[1.51]		
ΔROC_{it-1}			0.00020				0.19550	
			[3.43]a				[3.29]a	
ΔROC_{it-2}			0.00009				0.06738	
			[1.38]				[1.76]c	
ΔROC_{it-3}			0.00007				0.05919	
			[0.96]				[1.49]	
ΔROC_{it-4}			-0.00003				-0.00185	
			[0.55]				[0.07]	
ΔROA_{it-1}				0.00075				0.23269
				[2.49]b				[4.79]a
ΔROA_{it-2}				0.00018				0.06238
				[0.72]				[2.15]b
ΔROA_{it-3}				0.00026				0.00288
				[1.46]				[0.13]
ΔROA_{it-4}				0.00018				-0.05792
				[0.68]				[2.69]a
Constant	0.01310	0.01655	0.01606	0.01345	-0.53164	-3.14064	-4.85291	-0.66844
	[1.47]	[1.56]	[1.65]c	[1.51]	[1.57]	[1.02]	[1.58]	[1.21]
N	13655	11620	12464	13652	13655	11411	12290	13641
Num. of Firms	2732	2477	2612	2732	2732	2447	2582	2732
F-Test	71.61	62.54	70.76	66.69	147.54	46.10	42.67	79.63
Prob.>F	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wald-Test	6.93	11.15	14.48	7.53	2.66	5.67	3.17	0.88
Prob.>Wald	0.14	0.02	0.01	0.11	0.62	0.23	0.53	0.93

Tab. 5.9: **Causality Regressions for Large Firms: Controlling for Collateral Base**

This table reports the estimates from the causal regressions for the large firms in the sample. The sample firms are stratified into small, medium, and large classes using 1991 employment levels and following the European Commission size classification. The European Commission classifies a firm with 1-99 employees as a small firm, a firm with 100-499 employees as a medium firm and a firm with 500 or more employees as a large firm. Among the variables in the table, $GROWTH_{it}$ stands for the employment growth of firm i at time t, PM_{it} stands for $Profit\,Margin$, ROS_{it} stands for $Return\,to\,Shareholders$, ROC_{it} stands for $Return\,on\,Invested\,Capital$, and ROA_{it} stands for $Return\,on\,Total\,Assets$. Robust t statistics are given in brackets and beside the t-stat 'a' denotes significance at the 1% level, 'b' denotes significance at the 5% level, and 'c' denotes significance at the 10% level.

	First-Stage Regressions				Second-Stage Regressions			
	(1) $\Delta GROWTH_{it}$	(2) $\Delta GROWTH_{it}$	(3) $\Delta GROWTH_{it}$	(4) $\Delta GROWTH_{it}$	(1) ΔPM_{it}	(2) ΔROS_{it}	(3) ΔROC_{it}	(4) ΔROA_{it}
$\Delta GROWTH_{it-1}$	-0.03044	-0.04526	-0.04729	-0.03085	-0.21446	-1.27452	5.68995	0.39390
	[0.57]	[0.80]	[0.90]	[0.58]	[0.24]	[0.23]	[1.75]c	[0.70]
$\Delta GROWTH_{it-2}$	-0.22254	-0.24082	-0.23699	-0.22187	-0.28926	-5.31989	2.71512	-0.09266
	[1.44]	[1.49]	[1.53]	[1.44]	[0.43]	[0.87]	[1.11]	[0.17]
$\Delta GROWTH_{it-3}$	-0.12809	-0.13619	-0.13713	-0.12749	-0.64329	-7.07737	2.83688	-0.10942
	[3.83]a	[3.79]a	[3.94]a	[3.80]a	[0.90]	[0.86]	[1.11]	[0.20]
$\Delta GROWTH_{it-4}$	0.00838	-0.00079	-0.00309	0.00778	-0.07418	-4.54683	1.14443	0.38226
	[0.28]	[0.03]	[0.10]	[0.26]	[0.12]	[0.56]	[0.58]	[0.66]
$\Delta Tot.\ Assets_{it-1}$	-0.00980	-0.00499	-0.00481	-0.00977	-0.01397	8.37817	7.22155	0.44536
	[0.41]	[0.20]	[0.21]	[0.41]	[0.01]	[1.28]	[1.12]	[0.29]
$\Delta Tot.\ Assets_{it-2}$	-0.06461	-0.08399	-0.07865	-0.06328	-1.06908	0.50589	3.13459	-1.05538
	[1.81]c	[2.14]b	[2.23]b	[1.77]c	[0.99]	[0.10]	[0.61]	[0.79]
$\Delta Tot.\ Assets_{it-3}$	0.03823	0.04485	0.03843	0.03824	1.60283	-5.56867	-2.86788	0.23329
	[1.08]	[1.16]	[1.07]	[1.08]	[1.11]	[1.21]	[0.59]	[0.16]
$\Delta Tot.\ Assets_{it-4}$	0.01659	0.02773	0.02634	0.01465	0.09102	6.31014	6.77477	1.61158
	[0.74]	[1.16]	[1.15]	[0.66]	[0.08]	[1.27]	[1.51]	[0.97]
Age_{it-1}	-11.41073	-17.06085	-15.57355	-11.94243	874.22	1532.09	2,002.59	1,009.73
	[1.10]	[1.38]	[1.63]	[1.17]	[2.64]a	[0.72]	[0.99]	[2.15]b
Age_{it-2}	14.08592	22.93428	20.33780	14.86900	-1317.10	-2292.73	-3172.85	-1494.32
	[0.90]	[1.23]	[1.41]	[0.97]	[2.69]a	[0.72]	[1.06]	[2.13]b
Age_{it-3}	-3.53376	-6.90398	-5.81675	-3.81558	489.18	834.31	1223.74	536.34
	[0.61]	[1.00]	[1.09]	[0.67]	[2.78]a	[0.73]	[1.13]	[2.09]b
Age_{it-4}	-0.00271	0.09758	0.06335	0.00751	-14.36	-16.43	-28.98	-11.84
	[0.02]	[0.51]	[0.42]	[0.05]	[2.74]a	[0.49]	[0.90]	[1.38]
$\Delta Collateral_{it-1}$	-0.00371	0.04832	0.02609	0.00210	4.57124	-18.75276	-12.18320	4.83488
	[0.05]	[0.72]	[0.41]	[0.03]	[1.11]	[0.75]	[0.56]	[1.20]
$\Delta Collateral_{it-2}$	-0.11683	-0.20352	-0.19738	-0.12488	-0.31309	8.47696	-2.44724	-2.19568
	[1.01]	[2.09]b	[2.15]b	[1.11]	[0.12]	[0.61]	[0.15]	[0.74]
$\Delta Collateral_{it-3}$	-0.04143	0.00618	0.03900	-0.04123	-0.56551	-27.95751	-16.95476	-0.94985
	[0.39]	[0.07]	[0.45]	[0.38]	[0.18]	[1.35]	[1.00]	[0.28]
$\Delta Collateral_{it-4}$	0.08758	0.10253	0.09847	0.08180	0.30415	26.89445	29.28899	0.26313
	[1.03]	[1.13]	[1.14]	[0.96]	[0.12]	[1.48]	[1.63]	[0.09]
ΔPM_{it-1}	-0.00122				0.17275			
	[1.33]				[1.49]			
ΔPM_{it-2}	0.00187				0.06134			
	[1.01]				[0.94]			
ΔPM_{it-3}	-0.00097				0.02159			
	[1.07]				[0.48]			
ΔPM_{it-4}	0.00179				-0.00379			
	[1.36]				[0.09]			
ΔROS_{it-1}		-0.00006				0.21151		
		[0.54]				[1.94]c		
ΔROS_{it-2}		-0.00005				-0.01856		
		[0.45]				[0.34]		
ΔROS_{it-3}		-0.00031				0.01304		
		[1.70]c				[0.19]		
ΔROS_{it-4}		0.00004				-0.02057		
		[0.31]				[0.48]		
ΔROC_{it-1}			0.00011				0.25952	
			[0.84]				[2.30]b	
ΔROC_{it-2}			0.00003				0.05902	
			[0.23]				[0.75]	
ΔROC_{it-3}			-0.00028				0.03556	
			[1.55]				[0.57]	
ΔROC_{it-4}			0.00013				-0.03386	
			[0.66]				[0.71]	
ΔROA_{it-1}				-0.00102				0.16927
				[1.99]b				[1.80]c
ΔROA_{it-2}				0.00063				0.05205
				[0.68]				[0.87]
ΔROA_{it-3}				-0.00023				0.04096
				[0.50]				[0.98]
ΔROA_{it-4}				0.00145				0.04219
				[2.24]b				[1.02]
Constant	-0.00821	-0.02613	-0.01223	-0.00897	-0.90551	-6.68369	-0.76196	-1.65649
	[0.24]	[0.68]	[0.35]	[0.26]	[0.96]	[1.15]	[0.17]	[1.37]
N	3410	2955	3230	3410	3410	2876	3179	3408
Num. of Firms	686	637	673	686	686	623	666	686
F-Test	50.87	45.51	51.19	59.71	21.16	47.56	27.47	25.07
Prob.>F	0.00	0.00	0.00	0.00	0.39	0.00	0.12	0.20
Wald-Test	3.79	3.64	6.29	9.21	1.81	3.08	3.63	1.65
Prob.>Wald	0.44	0.46	0.18	0.06	0.77	0.55	0.46	0.80

Tab. 5.10: **Causality Regressions for All Firms: Access to Private Bank Credit**

This table reports the estimates from the causal regression for all firms in the sample. The sample firms are stratified into small, medium, and large classes using 1991 employment levels and following the European Commission size classification. The European Commission classifies a firm with 1-99 employees as a small firm, a firm with 100-499 employees as a medium firm and a firm with 500 or more employees as a large firm. Among the variables in the table, $GROWTH_{it}$ stands for the employment growth of firm i at time t, PM_{it} stands for $Profit\ Margin$, ROS_{it} stands for $Return\ to\ Shareholders$, ROC_{it} stands for $Return\ on\ Invested\ Capital$, and ROA_{it} stands for $Return\ on\ Total\ Assets$. Robust t statistics are given in brackets and beside the t-stat 'a' denotes significance at the 1% level, 'b' denotes significance at the 5% level, and 'c' denotes significance at the 10% level.

	First-Stage Regressions				Second-Stage Regressions			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	$\Delta GROWTH_{it}$	$\Delta GROWTH_{it}$	$\Delta GROWTH_{it}$	$\Delta GROWTH_{it}$	ΔPM_{it}	ΔROS_{it}	ΔROC_{it}	ΔROA_{it}
$\Delta GROWTH_{it-1}$	0.02169	0.01786	0.03858	0.02186	-0.60412	1.62493	1.69144	0.29806
	[0.97]	[0.74]	[1.52]	[0.97]	[1.23]	[0.75]	[1.26]	[0.50]
$\Delta GROWTH_{it-2}$	-0.05046	-0.07104	-0.05082	-0.05071	-0.35721	-2.16706	0.36044	0.03883
	[1.23]	[1.43]	[1.04]	[1.23]	[1.10]	[0.97]	[0.22]	[0.09]
$\Delta GROWTH_{it-3}$	-0.02594	-0.03916	-0.02616	-0.02673	-0.81188	0.21472	0.17644	-0.18890
	[1.35]	[1.81]c	[1.30]	[1.39]	[1.91]c	[0.09]	[0.11]	[0.34]
$\Delta GROWTH_{it-4}$	-0.00423	-0.01716	-0.01125	-0.00469	-0.01721	0.75877	1.65513	0.07570
	[0.36]	[1.18]	[0.90]	[0.40]	[0.06]	[0.32]	[1.27]	[0.15]
$\Delta Tot.\ Assets_{it-1}$	-0.00220	-0.00145	-0.00447	-0.00198	-0.04808	-0.96211	0.11658	0.22805
	[0.26]	[0.16]	[0.48]	[0.23]	[0.16]	[0.42]	[0.07]	[0.50]
$\Delta Tot.\ Assets_{it-2}$	-0.00585	-0.01805	-0.01825	-0.00566	0.00501	-3.41704	-2.09221	-0.49515
	[0.53]	[1.70]c	[1.77]c	[0.52]	[0.02]	[1.75]c	[1.32]	[1.18]
$\Delta Tot.\ Assets_{it-3}$	0.00280	0.00687	0.00895	0.00252	-0.20979	3.81616	0.87354	-0.77772
	[0.33]	[0.80]	[1.06]	[0.30]	[0.66]	[1.99]b	[0.50]	[1.65]c
$\Delta Tot.\ Assets_{it-4}$	-0.00153	0.00573	0.00270	-0.00131	-0.04967	0.66907	0.51545	0.68664
	[0.18]	[0.68]	[0.32]	[0.15]	[0.18]	[0.35]	[0.33]	[1.56]
Age_{it-1}	-4.76428	-6.31534	-7.01792	-4.92535	242.41	646.30	1974.74	375.41
	[1.04]	[1.25]	[1.50]	[1.08]	[1.70]c	[0.50]	[2.03]b	[1.27]
Age_{it-2}	4.95067	7.48327	8.38950	5.22664	-391.45	-1124.67	-3105.36	-579.91
	[0.71]	[0.97]	[1.18]	[0.75]	[1.82]c	[0.58]	[2.10]b	[1.32]
Age_{it-3}	-0.68757	-1.71837	-1.99049	-0.81201	161.53	513.84	1,228.71	225.97
	[0.26]	[0.60]	[0.75]	[0.31]	[2.02]b	[0.71]	[2.20]b	[1.39]
Age_{it-4}	-0.04574	-0.00789	-0.00213	-0.03938	-6.28	-24.76	-38.33	-6.80
	[0.55]	[0.09]	[0.03]	[0.48]	[2.15]b	[1.03]	[1.85]c	[1.08]
$\Delta Bank\ Credit_{it-1}$	0.01327	0.01100	0.01069	0.01279	-0.45423	-3.23634	-2.20297	-1.52832
	[0.85]	[0.66]	[0.65]	[0.82]	[0.87]	[0.85]	[0.78]	[1.52]
$\Delta Bank\ Credit_{it-2}$	0.01543	0.00377	0.00377	0.01598	-0.09994	-3.06012	-1.96033	-0.01840
	[1.08]	[0.26]	[0.28]	[1.13]	[0.20]	[0.84]	[0.64]	[0.02]
$\Delta Bank\ Credit_{it-3}$	-0.01339	-0.01042	-0.01065	-0.01280	-0.33809	-0.35694	-3.19844	-0.68577
	[0.98]	[0.75]	[0.79]	[0.94]	[0.73]	[0.11]	[1.21]	[0.91]
$\Delta Bank\ Credit_{it-4}$	-0.04301	-0.02972	-0.03790	-0.04261	-0.53720	-1.68800	-0.32490	-0.32563
	[3.03]a	[2.13]b	[2.65]a	[3.00]a	[1.16]	[0.53]	[0.12]	[0.44]
ΔPM_{it-1}	0.00038				0.26377			
	[0.87]				[8.54]a			
ΔPM_{it-2}	0.00055				0.06178			
	[1.35]				[3.17]a			
ΔPM_{it-3}	-0.00007				0.02461			
	[0.24]				[1.66]c			
ΔPM_{it-4}	0.00006				-0.01517			
	[0.14]				[1.07]			
ΔROS_{it-1}		0.00010				0.28066		
		[2.50]b				[5.40]a		
ΔROS_{it-2}		0.00001				0.08078		
		[0.21]				[2.84]a		
ΔROS_{it-3}		-0.00001				0.01101		
		[0.18]				[0.45]		
ΔROS_{it-4}		0.00003				0.00004		
		[0.79]				[0.00]		
ΔROC_{it-1}			0.00013				0.23846	
			[3.30]a				[4.72]a	
ΔROC_{it-2}			0.00008				0.08005	
			[1.59]				[2.42]b	
ΔROC_{it-3}			0.00003				0.06204	
			[0.54]				[2.21]b	
ΔROC_{it-4}			0.00003				0.01010	
			[0.67]				[0.48]	
ΔROA_{it-1}				0.00042				0.25623
				[1.87]c				[6.34]a
ΔROA_{it-2}				0.00016				0.06970
				[0.82]				[2.91]a
ΔROA_{it-3}				0.00011				0.01229
				[0.80]				[0.69]
ΔROA_{it-4}				0.00029				-0.02523
				[1.44]				[1.44]
Constant	0.00012	-0.00324	0.00057	0.00047	-0.79983	-6.48214	-5.84709	-1.81029
	[0.01]	[0.33]	[0.06]	[0.06]	[3.19]a	[2.68]a	[2.74]a	[3.79]a
N	25785	22332	23936	25782	25785	21877	23602	25764
Num. of Firms	5168	4759	4990	5168	5168	4694	4946	5168
F-Test	98.76	79.22	101.59	98.23	167.65	69.08	65.51	101.57
Prob.>F	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wald-Test	2.50	7.50	12.26	5.20	4.09	4.82	3.29	0.61
Prob.>Wald	0.65	0.11	0.02	0.27	0.39	0.31	0.51	0.96

Tab. 5.11: **Causality Regressions for Small Firms: Access to Private Bank Credit**

This table reports the estimate from the causal regression for the small firms in the sample. The sample firms are stratified into small, medium, and large classes using 1991 employment levels and following the European Commission size classification. The European Commission classifies a firm with 1-99 employees as a small firm, a firm with 100-499 employees as a medium firm and a firm with 500 or more employees as a large firm. Among the variables in the table, $GROWTH_{it}$ stands for the employment growth of firm i at time t, PM_{it} stands for $Profit\ Margin$, ROS_{it} stands for $Return\ to\ Shareholders$, ROC_{it} stands for $Return\ on\ Invested\ Capital$, and ROA_{it} stands for $Return\ on\ Total\ Assets$. Robust t statistics are given in brackets and beside the t-stat 'a' denotes significance at the 1% level, 'b' denotes significance at the 5% level, and 'c' denotes significance at the 10% level.

	First-Stage Regressions				Second-Stage Regressions			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	$\Delta GROWTH_{it}$	$\Delta GROWTH_{it}$	$\Delta GROWTH_{it}$	$\Delta GROWTH_{it}$	ΔPM_{it}	ΔROS_{it}	ΔROC_{it}	ΔROA_{it}
$\Delta GROWTH_{it-1}$	0.01859	0.02799	0.06965	0.02028	-0.81937	2.33197	1.54254	-0.30563
	[0.58]	[0.89]	[1.90]c	[0.62]	[1.02]	[0.76]	[0.76]	[0.53]
$\Delta GROWTH_{it-2}$	-0.01351	-0.02246	0.01318	-0.01400	-0.27305	-1.90044	-0.83824	0.15281
	[0.83]	[0.95]	[0.43]	[0.87]	[0.56]	[0.66]	[0.30]	[0.21]
$\Delta GROWTH_{it-3}$	-0.00141	-0.00837	0.01192	-0.00336	-0.96011	3.22321	-0.99213	0.23249
	[0.06]	[0.34]	[0.53]	[0.14]	[1.45]	[1.05]	[0.37]	[0.29]
$\Delta GROWTH_{it-4}$	0.00237	-0.01758	-0.00291	0.00141	0.03863	2.95481	2.00815	0.33725
	[0.17]	[0.88]	[0.19]	[0.10]	[0.09]	[1.12]	[1.03]	[0.54]
$\Delta Tot.\ Assets_{it-1}$	-0.00258	-0.00007	-0.00218	-0.00212	-0.01673	-1.05055	0.59122	0.17955
	[0.25]	[0.01]	[0.19]	[0.20]	[0.04]	[0.36]	[0.27]	[0.28]
$\Delta Tot.\ Assets_{it-2}$	0.00068	-0.01531	-0.01714	0.00090	0.36351	-4.30975	-4.80671	-0.37935
	[0.04]	[1.03]	[1.17]	[0.06]	[0.84]	[1.66]c	[2.23]b	[0.69]
$\Delta Tot.\ Assets_{it-3}$	0.00056	0.00722	0.00972	0.00055	-0.54313	6.62012	3.00806	-0.80783
	[0.05]	[0.60]	[0.82]	[0.05]	[1.29]	[2.60]a	[1.32]	[1.40]
$\Delta Tot.\ Assets_{it-4}$	-0.00566	0.00180	-0.00183	-0.00545	-0.23613	-1.84743	-1.44915	-0.00311
	[0.45]	[0.15]	[0.15]	[0.44]	[0.67]	[0.74]	[0.68]	[0.01]
Age_{it-1}	-0.62976	-3.00001	-3.41767	-1.31807	205.17	1,166.23	3964.99	337.68
	[0.09]	[0.37]	[0.43]	[0.18]	[0.84]	[0.56]	[2.20]b	[0.68]
Age_{it-2}	-1.18200	2.37188	3.00201	-0.12140	-341.96	-2016.90	-6169.13	-568.47
	[0.11]	[0.19]	[0.25]	[0.01]	[0.92]	[0.64]	[2.25]b	[0.76]
Age_{it-3}	1.47413	0.15347	-0.08001	1.06850	143.28	886.99	2,409.40	242.58
	[0.35]	[0.03]	[0.02]	[0.25]	[1.03]	[0.74]	[2.31]b	[0.87]
Age_{it-4}	-0.10812	-0.06848	-0.06050	-0.09748	-3.86	-35.83	-84.82	-8.91
	[0.74]	[0.43]	[0.38]	[0.66]	[0.81]	[0.86]	[2.32]b	[0.94]
$\Delta Bank\ Credit_{it-1}$	0.03162	0.02723	0.02583	0.03168	-0.79241	-7.10409	-5.20472	-2.10377
	[1.55]	[1.28]	[1.20]	[1.55]	[1.25]	[1.54]	[1.32]	[1.55]
$\Delta Bank\ Credit_{it-2}$	0.01603	0.00913	0.00345	0.01693	-0.36976	-5.84640	-5.26061	-0.82710
	[0.84]	[0.48]	[0.19]	[0.90]	[0.59]	[1.24]	[1.25]	[0.70]
$\Delta Bank\ Credit_{it-3}$	-0.00789	-0.00609	-0.00706	-0.00698	-0.06386	0.30538	-4.40507	-1.35056
	[0.46]	[0.34]	[0.40]	[0.40]	[0.11]	[0.07]	[1.15]	[1.33]
$\Delta Bank\ Credit_{it-4}$	-0.05110	-0.03276	-0.04241	-0.04971	-0.77991	-5.45118	-0.59476	-0.89425
	[2.78]a	[1.81]c	[2.25]b	[2.70]a	[1.29]	[1.24]	[0.17]	[0.92]
ΔPM_{it-1}	0.00126				0.25146			
	[1.82]c				[6.76]a			
ΔPM_{it-2}	0.00075				0.05294			
	[1.59]				[2.15]b			
ΔPM_{it-3}	0.00026				0.00275			
	[0.65]				[0.15]			
ΔPM_{it-4}	-0.00019				-0.02351			
	[0.38]				[1.30]			
ΔROS_{it-1}		0.00019				0.20761		
		[3.17]a				[3.07]a		
ΔROS_{it-2}		0.00004				0.04110		
		[0.68]				[1.03]		
ΔROS_{it-3}		0.00008				-0.01757		
		[1.39]				[0.52]		
ΔROS_{it-4}		-0.00000				-0.02521		
		[0.02]				[1.48]		
ΔROC_{it-1}			0.00020				0.19401	
			[3.42]a				[3.25]a	
ΔROC_{it-2}			0.00009				0.06684	
			[1.37]				[1.75]c	
ΔROC_{it-3}			0.00007				0.05791	
			[0.97]				[1.46]	
ΔROC_{it-4}			-0.00003				-0.00165	
			[0.60]				[0.06]	
ΔROA_{it-1}				0.00075				0.23238
				[2.46]b				[4.79]a
ΔROA_{it-2}				0.00017				0.06222
				[0.69]				[2.14]b
ΔROA_{it-3}				0.00027				0.00198
				[1.48]				[0.09]
ΔROA_{it-4}				0.00018				-0.05825
				[0.67]				[2.72]a
Constant	0.01447	0.01781	0.01776	0.01483	-0.53151	-3.18068	-4.91194	-0.69443
	[1.62]	[1.67]c	[1.81]c	[1.66]c	[1.57]	[1.03]	[1.59]	[1.26]
N	13642	11608	12452	13639	13642	11400	12279	13628
Num. of Firms	2732	2477	2612	2732	2732	2447	2582	2732
F-Test	73.01	61.98	69.23	67.41	150.68	51.13	46.80	90.69
Prob.>F	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wald-Test	6.95	11.05	14.51	7.43	2.64	5.38	3.02	0.84
Prob.>Wald	0.14	0.03	0.01	0.11	0.62	0.25	0.55	0.93

Tab. 5.12: **Causality Regressions for Large Firms: Access to Bank Private Credit**

This table reports the estimates from the causal regressions for the large firms in the sample. The sample firms are stratified into small, medium, and large classes using 1991 employment levels and following the European Commission size classification. The European Commission classifies a firm with 1-99 employees as a small firm, a firm with 100-499 employees as a medium firm and a firm with 500 or more employees as a large firm. Among the variables in the table, $GROWTH_{it}$ stands for the employment growth of firm i at time t, PM_{it} stands for $Profit\,Margin$, ROS_{it} stands for $Return\,to\,Shareholders$, ROC_{it} stands for $Return\,on\,Invested\,Capital$, and ROA_{it} stands for $Return\,on\,Total\,Assets$. Robust t statistics are given in brackets and beside the t-stat 'a' denotes significance at the 1% level, 'b' denotes significance at the 5% level, and 'c' denotes significance at the 10% level.

	First-Stage Regressions				Second-Stage Regressions			
	(1) $\Delta GROWTH_{it}$	(2) $\Delta GROWTH_{it}$	(3) $\Delta GROWTH_{it}$	(4) $\Delta GROWTH_{it}$	(1) ΔPM_{it}	(2) ΔROS_{it}	(3) ΔROC_{it}	(4) ΔROA_{it}
$\Delta GROWTH_{it-1}$	-0.03002	-0.04574	-0.04772	-0.03047	-0.19241	-1.21063	5.76890	0.40057
	[0.56]	[0.81]	[0.90]	[0.57]	[0.22]	[0.22]	[1.76]c	[0.71]
$\Delta GROWTH_{it-2}$	-0.22199	-0.24006	-0.23650	-0.22130	-0.26460	-5.53659	2.68172	-0.07094
	[1.44]	[1.48]	[1.53]	[1.43]	[0.39]	[0.90]	[1.10]	[0.13]
$\Delta GROWTH_{it-3}$	-0.12770	-0.13642	-0.13752	-0.12713	-0.61868	-7.10442	2.83546	-0.09296
	[3.82]a	[3.81]a	[3.95]a	[3.79]a	[0.88]	[0.87]	[1.10]	[0.17]
$\Delta GROWTH_{it-4}$	0.00874	-0.00094	-0.00335	0.00815	-0.05082	-4.77827	1.04626	0.40095
	[0.30]	[0.03]	[0.11]	[0.28]	[0.08]	[0.59]	[0.53]	[0.69]
$\Delta Tot.\ Assets_{it-1}$	-0.00986	-0.00891	-0.00850	-0.01003	-0.17808	10.25963	8.12055	0.36678
	[0.37]	[0.30]	[0.32]	[0.38]	[0.16]	[1.36]	[1.11]	[0.22]
$\Delta Tot.\ Assets_{it-2}$	-0.07221	-0.08886	-0.08264	-0.07032	-1.14488	-0.38584	2.52093	-1.10301
	[1.94]c	[2.10]b	[2.18]b	[1.88]c	[1.01]	[0.07]	[0.46]	[0.77]
$\Delta Tot.\ Assets_{it-3}$	0.03900	0.04107	0.03444	0.03873	1.80859	-4.62731	-2.72732	0.32693
	[1.09]	[1.04]	[0.94]	[1.08]	[1.22]	[0.99]	[0.55]	[0.22]
$\Delta Tot.\ Assets_{it-4}$	0.01828	0.03031	0.02867	0.01613	0.01744	4.97759	5.95809	1.53878
	[0.79]	[1.24]	[1.23]	[0.70]	[0.01]	[0.98]	[1.34]	[0.93]
Age_{it-1}	-11.90055	-16.71198	-15.45542	-12.43129	853.92	1504.76	1849.99	995.64
	[1.16]	[1.35]	[1.62]	[1.23]	[2.55]b	[0.69]	[0.93]	[2.10]b
Age_{it-2}	14.95560	22.54666	20.31777	15.73438	-1286.98	-2273.61	-2953.27	-1471.83
	[0.97]	[1.20]	[1.41]	[1.04]	[2.60]a	[0.71]	[1.01]	[2.08]b
Age_{it-3}	-3.93367	-6.83889	-5.89856	-4.21160	478.71	838.34	1147.32	527.68
	[0.69]	[0.98]	[1.11]	[0.75]	[2.68]a	[0.72]	[1.09]	[2.05]b
Age_{it-4}	0.01722	0.10353	0.07333	0.02708	-14.17	-17.26	-27.16	-11.56
	[0.11]	[0.53]	[0.48]	[0.17]	[2.65]a	[0.50]	[0.86]	[1.35]
$\Delta Bank\ Credit_{it-1}$	-0.06043	-0.05310	-0.05153	-0.06149	1.30631	-6.04851	1.09376	-0.65994
	[1.08]	[0.83]	[0.86]	[1.11]	[0.69]	[0.48]	[0.12]	[0.25]
$\Delta Bank\ Credit_{it-2}$	0.04414	-0.00325	0.00455	0.04257	0.90011	-0.60538	4.85925	0.39768
	[0.89]	[0.07]	[0.10]	[0.85]	[0.55]	[0.07]	[0.53]	[0.20]
$\Delta Bank\ Credit_{it-3}$	-0.01436	0.02223	0.00552	-0.01024	-1.48247	-6.78915	-3.42965	-0.00483
	[0.28]	[0.42]	[0.11]	[0.20]	[0.83]	[0.77]	[0.47]	[0.00]
$\Delta Bank\ Credit_{it-4}$	-0.06238	-0.06001	-0.05505	-0.05783	1.64535	11.63943	-0.75133	1.45002
	[1.44]	[1.22]	[1.20]	[1.32]	[1.22]	[1.49]	[0.07]	[0.76]
ΔPM_{it-1}	-0.00123				0.17360			
	[1.36]				[1.49]			
ΔPM_{it-2}	0.00190				0.06135			
	[1.03]				[0.94]			
ΔPM_{it-3}	-0.00090				0.02124			
	[0.99]				[0.47]			
ΔPM_{it-4}	0.00180				-0.00392			
	[1.37]				[0.09]			
ΔROS_{it-1}		-0.00007				0.20801		
		[0.59]				[1.92]c		
ΔROS_{it-2}		-0.00006				-0.01955		
		[0.52]				[0.37]		
ΔROS_{it-3}		-0.00030				0.01217		
		[1.67]c				[0.18]		
ΔROS_{it-4}		0.00003				-0.02182		
		[0.24]				[0.51]		
ΔROC_{it-1}			0.00011				0.25893	
			[0.78]				[2.32]b	
ΔROC_{it-2}			0.00002				0.05977	
			[0.17]				[0.77]	
ΔROC_{it-3}			-0.00027				0.03570	
			[1.53]				[0.57]	
ΔROC_{it-4}			0.00012				-0.03450	
			[0.62]				[0.73]	
ΔROA_{it-1}				-0.00102				0.16853
				[1.99]b				[1.79]c
ΔROA_{it-2}				0.00061				0.05144
				[0.66]				[0.86]
ΔROA_{it-3}				-0.00020				0.04115
				[0.42]				[0.99]
ΔROA_{it-4}				0.00145				0.04216
				[2.24]b				[1.02]
Constant	-0.00796	-0.02606	-0.01193	-0.00878	-0.96945	-6.49919	-0.62906	-1.72258
	[0.24]	[0.68]	[0.34]	[0.26]	[1.02]	[1.09]	[0.13]	[1.43]
N	3408	2953	3228	3408	3408	2874	3177	3406
Num. of Firms	686	637	673	686	686	623	666	686
F-Test	61.00	59.99	59.37	69.50	24.03	43.12	20.72	24.31
Prob.>F	0.00	0.00	0.00	0.00	0.24	0.00	0.41	0.23
Wald-Test	3.82	3.41	5.90	9.04	1.80	3.20	3.74	1.66
Prob.>Wald	0.43	0.49	0.21	0.06	0.77	0.52	0.44	0.80

Tab. 5.13:

Causality Regressions for All Private Firms: With No Access to Public Equity Market

This table reports the estimates from the causal regressions for all private firms in the sample. The sample firms are stratified into small, medium, and large classes using 1991 employment levels and following the European Commission size classification. The European Commission classifies a firm with 1-99 employees as a small firm, a firm with 100-499 employees as a medium firm and a firm with 500 or more employees as a large firm. Among the variables in the table, $GROWTH_{it}$ stands for the employment growth of firm i at time t, PM_{it} stands for *Profit Margin*, ROS_{it} stands for *Return to Shareholders*, ROC_{it} stands for *Return on Invested Capital*, and ROA_{it} stands for *Return on Total Assets*. Robust t statistics are given in brackets and beside the t-stat 'a' denotes significance at the 1% level, 'b' denotes significance at the 5% level, and 'c' denotes significance at the 10% level.

	First-Stage Regressions				Second-Stage Regressions			
	(1) $\Delta GROWTH_{it}$	(2) $\Delta GROWTH_{it}$	(3) $\Delta GROWTH_{it}$	(4) $\Delta GROWTH_{it}$	(1) ΔPM_{it}	(2) ΔROS_{it}	(3) ΔROC_{it}	(4) ΔROA_{it}
$\Delta GROWTH_{it-1}$	0.02529	0.02370	0.04397	0.02558	-0.50324	1.42169	2.03381	0.32322
	[1.12]	[0.97]	[1.71]c	[1.13]	[1.01]	[0.66]	[1.48]	[0.53]
$\Delta GROWTH_{it-2}$	-0.05186	-0.07160	-0.05142	-0.05202	-0.36538	-2.19292	0.62952	0.00044
	[1.22]	[1.40]	[1.02]	[1.23]	[1.11]	[0.97]	[0.37]	[0.00]
$\Delta GROWTH_{it-3}$	-0.02690	-0.03891	-0.02617	-0.02763	-0.67257	0.56902	0.57785	-0.19388
	[1.35]	[1.75]c	[1.26]	[1.39]	[1.58]	[0.22]	[0.34]	[0.34]
$\Delta GROWTH_{it-4}$	0.00080	-0.01104	-0.00522	0.00034	0.06673	0.89533	1.94187	0.07289
	[0.07]	[0.77]	[0.42]	[0.03]	[0.21]	[0.36]	[1.43]	[0.14]
$\Delta Tot.\ Assets_{it-1}$	-0.00263	-0.00160	-0.00461	-0.00243	-0.05113	-1.04363	0.55650	0.17637
	[0.30]	[0.17]	[0.48]	[0.28]	[0.17]	[0.45]	[0.31]	[0.38]
$\Delta Tot.\ Assets_{it-2}$	-0.00424	-0.01750	-0.01721	-0.00400	-0.02352	-3.19028	-1.32739	-0.51853
	[0.38]	[1.65]c	[1.67]c	[0.36]	[0.08]	[1.69]c	[0.86]	[1.21]
$\Delta Tot.\ Assets_{it-3}$	0.00395	0.00839	0.01044	0.00366	-0.20944	3.33038	-0.31919	-0.88279
	[0.46]	[0.97]	[1.22]	[0.43]	[0.64]	[1.64]	[0.18]	[1.84]c
$\Delta Tot.\ Assets_{it-4}$	-0.00171	0.00690	0.00267	-0.00144	-0.09416	1.30229	1.34355	0.72320
	[0.19]	[0.80]	[0.31]	[0.16]	[0.34]	[0.66]	[0.84]	[1.64]
Age_{it-1}	-3.94973	-5.61327	-6.27019	-4.10786	210.94	376.14	1,785.63	337.73
	[0.84]	[1.09]	[1.31]	[0.88]	[1.47]	[0.29]	[1.83]c	[1.12]
Age_{it-2}	3.71065	6.44167	7.28387	3.98084	-342.51	-716.53	-2833.35	-522.75
	[0.52]	[0.82]	[1.00]	[0.56]	[1.59]	[0.37]	[1.91]c	[1.17]
Age_{it-3}	-0.21209	-1.33217	-1.57984	-0.33302	142.71	360.44	1130.30	204.41
	[0.08]	[0.45]	[0.58]	[0.13]	[1.78]c	[0.50]	[2.02]b	[1.24]
Age_{it-4}	-0.06200	-0.02003	-0.01577	-0.05619	-5.70	-19.82	-34.93	-6.15
	[0.73]	[0.22]	[0.18]	[0.66]	[1.94]c	[0.83]	[1.69]c	[0.97]
ΔPM_{it-1}	0.00045				0.26397			
	[1.01]				[8.39]a			
ΔPM_{it-2}	0.00048				0.06279			
	[1.16]				[3.18]a			
ΔPM_{it-3}	0.00004				0.02350			
	[0.14]				[1.59]			
ΔPM_{it-4}	0.00004				-0.01225			
	[0.11]				[0.86]			
ΔROS_{it-1}		0.00010				0.27797		
		[2.47]b				[5.28]a		
ΔROS_{it-2}		0.00001				0.07778		
		[0.24]				[2.69]a		
ΔROS_{it-3}		-0.00001				0.01430		
		[0.13]				[0.58]		
ΔROS_{it-4}		0.00004				-0.00045		
		[0.91]				[0.03]		
ΔROC_{it-1}			0.00015				0.24343	
			[3.48]a				[4.76]a	
ΔROC_{it-2}			0.00008				0.07965	
			[1.71]c				[2.35]b	
ΔROC_{it-3}			0.00003				0.06795	
			[0.67]				[2.35]b	
ΔROC_{it-4}			0.00002				0.00924	
			[0.54]				[0.43]	
ΔROA_{it-1}				0.00044				0.25123
				[1.93]c				[6.13]a
ΔROA_{it-2}				0.00015				0.06828
				[0.72]				[2.81]a
ΔROA_{it-3}				0.00013				0.01234
				[0.90]				[0.68]
ΔROA_{it-4}				0.00029				-0.02626
				[1.43]				[1.47]
Constant	-0.00149	-0.00508	-0.00179	-0.00117	-0.82332	-6.34748	-5.18182	-1.78684
	[0.18]	[0.51]	[0.20]	[0.14]	[3.20]a	[2.57]b	[2.38]b	[3.61]a
N	24845	21502	23046	24842	24845	21062	22717	24825
Num. of Firms	4976	4579	4805	4976	4976	4518	4761	4976
F-Test	85.79	73.52	95.48	85.96	148.89	61.20	62.51	90.86
Prob.>F	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wald-Test	2.12	7.44	13.79	5.42	3.15	4.50	3.86	0.64
Prob.>Wald	0.71	0.11	0.01	0.25	0.53	0.34	0.43	0.96

Tab. 5.14:

Causality Regressions for All Public Firms: With Access to Public Equity Market

This table reports the estimates from the causal regressions for all public firms in the sample. The sample firms are stratified into small, medium, and large classes using 1991 employment levels and following the European Commission size classification. The European Commission classifies a firm with 1-99 employees as a small firm, a firm with 100-499 employees as a medium firm and a firm with 500 or more employees as a large firm. Among the variables in the table, $GROWTH_{it}$ stands for the employment growth of firm i at time t, PM_{it} stands for $Profit\ Margin$, ROS_{it} stands for $Return\ to\ Shareholders$, ROC_{it} stands for $Return\ on\ Invested\ Capital$, and ROA_{it} stands for $Return\ on\ Total\ Assets$. Robust t statistics are given in brackets and beside the t-stat 'a' denotes significance at the 1% level, 'b' denotes significance at the 5% level, and 'c' denotes significance at the 10% level.

	First-Stage Regressions				Second-Stage Regressions			
	(1) $\Delta GROWTH_{it}$	(2) $\Delta GROWTH_{it}$	(3) $\Delta GROWTH_{it}$	(4) $\Delta GROWTH_{it}$	(1) ΔPM_{it}	(2) ΔROS_{it}	(3) ΔROC_{it}	(4) ΔROA_{it}
$\Delta GROWTH_{it-1}$	-0.13167	-0.20364	-0.17914	-0.13775	-2.59152	13.51305	2.54469	-0.44640
	[0.84]	[1.17]	[1.06]	[0.85]	[1.43]	[0.88]	[0.43]	[0.31]
$\Delta GROWTH_{it-2}$	-0.05660	-0.09311	-0.08565	-0.05409	1.30649	7.03826	1.13575	1.11985
	[0.86]	[1.06]	[1.14]	[0.84]	[0.94]	[0.56]	[0.15]	[0.88]
$\Delta GROWTH_{it-3}$	-0.05183	-0.08967	-0.08471	-0.05489	-3.68638	-4.04755	-4.64340	0.06857
	[0.98]	[1.34]	[1.43]	[0.99]	[1.96]c	[0.61]	[0.79]	[0.05]
$\Delta GROWTH_{it-4}$	-0.14841	-0.19755	-0.17400	-0.14877	-1.16902	0.65491	-2.53229	-0.08015
	[1.83]c	[1.91]c	[2.00]b	[1.83]c	[1.26]	[0.14]	[0.62]	[0.05]
$\Delta Tot.\ Assets_{it-1}$	0.02534	0.01381	0.02386	0.02625	-0.26947	6.44765	-1.23529	0.04406
	[0.67]	[0.37]	[0.65]	[0.70]	[0.32]	[1.03]	[0.22]	[0.04]
$\Delta Tot.\ Assets_{it-2}$	-0.02069	-0.00965	-0.02840	-0.02126	1.05550	-4.09410	-14.86805	0.99576
	[0.46]	[0.19]	[0.63]	[0.48]	[0.74]	[0.26]	[1.06]	[0.77]
$\Delta Tot.\ Assets_{it-3}$	-0.01212	-0.02153	-0.01294	-0.01114	-0.42312	1.28013	16.02680	0.92135
	[0.30]	[0.51]	[0.31]	[0.27]	[0.30]	[0.17]	[1.50]	[0.48]
$\Delta Tot.\ Assets_{it-4}$	-0.01960	-0.03083	-0.01880	-0.01736	0.62926	-18.43935	-14.02505	-0.84318
	[0.43]	[0.56]	[0.34]	[0.37]	[0.41]	[2.30]b	[2.09]b	[0.33]
Age_{it-1}	167.98044	202.10333	149.35489	176.85877	-2245.61	4275.04	35798.94	-7610.90
	[1.50]	[1.81]c	[1.35]	[1.58]	[0.50]	[0.17]	[1.23]	[2.10]b
Age_{it-2}	-336.05636	-402.73839	-302.67061	-353.77829	4905.72	-5799.16	-65407.10	15247.67
	[1.53]	[1.83]c	[1.40]	[1.60]	[0.56]	[0.12]	[1.17]	[2.12]b
Age_{it-3}	206.35700	246.16761	188.31299	217.26384	-3380.59	1465.34	35992.76	-9466.88
	[1.55]	[1.84]c	[1.44]	[1.62]	[0.65]	[0.05]	[1.08]	[2.14]b
Age_{it-4}	-36.97835	-43.88046	-34.17652	-38.96526	712.22	277.27	-5578.63	1756.91
	[1.55]	[1.84]c	[1.47]	[1.63]	[0.78]	[0.06]	[0.96]	[2.17]b
ΔPM_{it-1}	-0.00074				0.16257			
	[0.54]				[1.29]			
ΔPM_{it-2}	0.00138				-0.02541			
	[0.74]				[0.26]			
ΔPM_{it-3}	-0.00222				-0.00009			
	[1.46]				[0.00]			
ΔPM_{it-4}	-0.00012				-0.14590			
	[0.15]				[2.85]a			
ΔROS_{it-1}		0.00008				-0.00217		
		[0.57]				[0.02]		
ΔROS_{it-2}		0.00000				-0.04289		
		[0.01]				[0.71]		
ΔROS_{it-3}		-0.00004				-0.22436		
		[0.13]				[1.55]		
ΔROS_{it-4}		-0.00002				-0.02378		
		[0.11]				[0.57]		
ΔROC_{it-1}			-0.00008				-0.10402	
			[0.71]				[0.56]	
ΔROC_{it-2}			-0.00006				-0.06989	
			[0.34]				[0.80]	
ΔROC_{it-3}			-0.00009				-0.19261	
			[0.37]				[1.78]c	
ΔROC_{it-4}			0.00015				-0.07987	
			[0.53]				[1.09]	
ΔROA_{it-1}				-0.00027				0.40154
				[0.24]				[3.69]a
ΔROA_{it-2}				0.00081				0.08686
				[0.83]				[1.47]
ΔROA_{it-3}				-0.00073				0.00264
				[0.78]				[0.06]
ΔROA_{it-4}				-0.00050				0.01540
				[0.69]				[0.30]
Constant	-0.01334	-0.01312	-0.00042	-0.01225	0.09327	-14.92548	-31.42727	-0.91871
	[0.28]	[0.25]	[0.01]	[0.26]	[0.08]	[1.22]	[2.05]b	[0.62]
N	960	849	909	960	960	833	903	959
Num. of Firms	192	180	185	192	192	176	185	192
F-Test	18.95	27.26	19.95	20.69	58.67	12.66	18.33	38.46
Prob.>F	0.27	0.04	0.22	0.19	0.00	0.70	0.31	0.00
Wald-Test	2.94	0.41	0.95	2.31	4.75	2.31	1.23	2.45
Prob.>Wald	0.57	0.98	0.92	0.68	0.31	0.68	0.87	0.65

Tab. 5.15: **Causality Regressions for private Small Firms: With No Access to Public Equity Market**

This table reports the estimates from the causal regressions for the private small firms in the sample. The sample firms are stratified into small, medium, and large classes using 1991 employment levels and following the European Commission size classification. The European Commission classifies a firm with 1-99 employees as a small firm, a firm with 100-499 employees as a medium firm and a firm with 500 or more employees as a large firm. Among the variables in the table, $GROWTH_{it}$ stands for the employment growth of firm i at time t, PM_{it} stands for *Profit Margin*, ROS_{it} stands for *Return to Shareholders*, ROC_{it} stands for *Return on Invested Capital*, and ROA_{it} stands for *Return on Total Assets*. Robust t statistics are given in brackets and beside the t-stat 'a' denotes significance at the 1% level, 'b' denotes significance at the 5% level, and 'c' denotes significance at the 10% level.

	First-Stage Regressions				Second-Stage Regressions			
	(1) $\Delta GROWTH_{it}$	(2) $\Delta GROWTH_{it}$	(3) $\Delta GROWTH_{it}$	(4) $\Delta GROWTH_{it}$	(1) ΔPM_{it}	(2) ΔROS_{it}	(3) ΔROC_{it}	(4) ΔROA_{it}
$\Delta GROWTH_{it-1}$	0.02541	0.03894	0.08023	0.02747	-0.61964	1.94314	2.25841	-0.28443
	[0.80]	[1.29]	[2.22]b	[0.85]	[0.75]	[0.66]	[1.08]	[0.48]
$\Delta GROWTH_{it-2}$	-0.01358	-0.02154	0.01476	-0.01363	-0.26308	-2.05399	-0.46913	0.11779
	[0.82]	[0.89]	[0.46]	[0.83]	[0.53]	[0.72]	[0.16]	[0.16]
$\Delta GROWTH_{it-3}$	-0.00027	-0.00601	0.01466	-0.00193	-0.73939	3.56311	-0.61961	0.22572
	[0.01]	[0.24]	[0.64]	[0.08]	[1.12]	[1.12]	[0.22]	[0.27]
$\Delta GROWTH_{it-4}$	0.01052	-0.00789	0.00701	0.00945	0.19343	3.19556	2.38686	0.34462
	[0.77]	[0.41]	[0.48]	[0.70]	[0.43]	[1.18]	[1.17]	[0.54]
$\Delta Tot.\ Assets_{it-1}$	-0.00276	0.00048	-0.00217	-0.00232	-0.09473	-1.12264	1.05005	0.08590
	[0.25]	[0.05]	[0.18]	[0.21]	[0.23]	[0.37]	[0.47]	[0.13]
$\Delta Tot.\ Assets_{it-2}$	0.00485	-0.01242	-0.01431	0.00518	0.32368	-3.60128	-3.64852	-0.36786
	[0.30]	[0.83]	[0.96]	[0.32]	[0.74]	[1.44]	[1.72]c	[0.64]
$\Delta Tot.\ Assets_{it-3}$	0.00209	0.00854	0.01120	0.00209	-0.51035	5.90996	1.91373	-0.88169
	[0.18]	[0.71]	[0.94]	[0.18]	[1.19]	[2.13]b	[0.76]	[1.49]
$\Delta Tot.\ Assets_{it-4}$	-0.00779	0.00237	-0.00358	-0.00751	-0.25844	-0.94443	-0.64002	0.02454
	[0.62]	[0.20]	[0.29]	[0.59]	[0.73]	[0.37]	[0.29]	[0.04]
Age_{it-1}	1.74659	-0.15613	-0.90874	1.11020	137.40	559.37	3299.90	186.90
	[0.23]	[0.02]	[0.11]	[0.15]	[0.55]	[0.28]	[1.83]c	[0.37]
Age_{it-2}	-4.70742	-1.83122	-0.71586	-3.73256	-238.14	-1135.71	-5192.59	-343.38
	[0.41]	[0.15]	[0.06]	[0.32]	[0.63]	[0.37]	[1.89]c	[0.45]
Age_{it-3}	2.77135	1.69200	1.28806	2.40439	103.61	570.51	2052.14	159.10
	[0.64]	[0.35]	[0.27]	[0.55]	[0.73]	[0.49]	[1.96]b	[0.56]
Age_{it-4}	-0.14907	-0.11840	-0.10533	-0.14182	-2.47	-25.35	-72.47	-6.09
	[0.99]	[0.72]	[0.65]	[0.94]	[0.51]	[0.62]	[1.97]b	[0.63]
ΔPM_{it-1}	0.00138				0.24908			
	[1.93]c				[6.55]a			
ΔPM_{it-2}	0.00063				0.04920			
	[1.35]				[1.95]c			
ΔPM_{it-3}	0.00044				0.00494			
	[1.09]				[0.28]			
ΔPM_{it-4}	-0.00022				-0.02374			
	[0.44]				[1.29]			
ΔROS_{it-1}		0.00019				0.20946		
		[3.07]a				[3.05]a		
ΔROS_{it-2}		0.00005				0.03490		
		[0.72]				[0.88]		
ΔROS_{it-3}		0.00008				-0.01753		
		[1.32]				[0.51]		
ΔROS_{it-4}		0.00001				-0.02989		
		[0.11]				[1.73]c		
ΔROC_{it-1}			0.00022				0.20497	
			[3.55]a				[3.36]a	
ΔROC_{it-2}			0.00010				0.06529	
			[1.49]				[1.66]c	
ΔROC_{it-3}			0.00007				0.06282	
			[0.99]				[1.53]	
ΔROC_{it-4}			-0.00003				-0.00365	
			[0.52]				[0.13]	
ΔROA_{it-1}				0.00075				0.22532
				[2.44]b				[4.62]a
ΔROA_{it-2}				0.00015				0.05966
				[0.59]				[2.03]b
ΔROA_{it-3}				0.00027				0.00059
				[1.49]				[0.03]
ΔROA_{it-4}				0.00017				-0.05981
				[0.65]				[2.73]a
Constant	0.01067	0.01354	0.01377	0.01097	-0.50985	-2.07342	-3.68495	-0.53452
	[1.21]	[1.30]	[1.42]	[1.24]	[1.49]	[0.68]	[1.19]	[0.94]
N	13130	11165	11970	13127	13130	10964	11800	13117
Num. of Firms	2627	2380	2511	2627	2627	2352	2481	2627
F-Test	60.08	53.49	63.00	55.90	143.78	43.53	38.37	74.73
Prob.>F	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wald-Test	7.57	10.09	15.35	7.52	1.88	5.54	3.75	0.72
Prob.>Wald	0.11	0.04	0.00	0.11	0.76	0.24	0.44	0.95

Tab. 5.16:
Causality Regressions for Public Small Firms: With Access to Public Equity Market

This table reports the estimates from the causal regressions for the public small firms in the sample. The sample firms are stratified into small, medium, and large classes using 1991 employment levels and following the European Commission size classification. The European Commission classifies a firm with 1-99 employees as a small firm, a firm with 100-499 employees as a medium firm and a firm with 500 or more employees as a large firm. Among the variables in the table, $GROWTH_{it}$ stands for the employment growth of firm i at time t, PM_{it} stands for *Profit Margin*, ROS_{it} stands for *Return to Shareholders*, ROC_{it} stands for *Return on Invested Capital*, and ROA_{it} stands for *Return on Total Assets*. Robust t statistics are given in brackets and beside the t-stat 'a' denotes significance at the 1% level, 'b' denotes significance at the 5% level, and 'c' denotes significance at the 10% level.

	First-Stage Regressions				Second-Stage Regressions			
	(1) $\Delta GROWTH_{it}$	(2) $\Delta GROWTH_{it}$	(3) $\Delta GROWTH_{it}$	(4) $\Delta GROWTH_{it}$	(1) ΔPM_{it}	(2) ΔROS_{it}	(3) ΔROC_{it}	(4) ΔROA_{it}
$\Delta GROWTH_{it-1}$	-0.24461	-0.35249	-0.29266	-0.26707	-3.86548	12.86887	-4.54308	-0.62282
	[1.12]	[1.50]	[1.27]	[1.17]	[2.58]a	[0.70]	[0.52]	[0.42]
$\Delta GROWTH_{it-2}$	-0.13809	-0.17966	-0.15137	-0.14311	1.21919	5.64124	3.05336	1.53660
	[1.13]	[1.15]	[1.13]	[1.16]	[0.66]	[0.32]	[0.28]	[0.79]
$\Delta GROWTH_{it-3}$	-0.14054	-0.19015	-0.16648	-0.15870	-4.42408	-2.07415	7.64512	0.76465
	[1.91]c	[1.94]c	[1.90]c	[1.91]c	[2.47]b	[0.21]	[0.79]	[0.43]
$\Delta GROWTH_{it-4}$	-0.25212	-0.34159	-0.27195	-0.25586	-1.49005	-2.44569	4.91943	-0.76162
	[1.97]b	[2.30]b	[2.04]b	[1.98]b	[1.19]	[0.31]	[0.63]	[0.51]
$\Delta Tot.\ Assets_{it-1}$	0.06497	0.04665	0.06224	0.06586	1.87295	7.94648	1.69219	1.21533
	[1.08]	[0.73]	[0.99]	[1.11]	[1.55]	[0.76]	[0.19]	[0.93]
$\Delta Tot.\ Assets_{it-2}$	-0.08291	-0.05878	-0.07429	-0.07818	0.91565	-22.49637	-28.54027	-0.83041
	[1.38]	[0.89]	[1.21]	[1.32]	[0.45]	[0.98]	[1.46]	[0.53]
$\Delta Tot.\ Assets_{it-3}$	-0.00631	0.00432	-0.00233	-0.00095	-1.79056	13.97118	10.09311	-0.31292
	[0.12]	[0.07]	[0.04]	[0.02]	[0.84]	[1.33]	[1.07]	[0.16]
$\Delta Tot.\ Assets_{it-4}$	0.01609	-0.01754	0.01003	0.02081	0.02233	-34.87052	-22.00630	-1.09591
	[0.18]	[0.19]	[0.10]	[0.23]	[0.01]	[3.05]a	[1.94]c	[0.44]
Age_{it-1}	-36.07151	42.70555	-23.40448	-41.16099	-3237.28	17,984.23	47853.10	-10383.42
	[0.26]	[0.28]	[0.16]	[0.30]	[0.46]	[0.29]	[0.96]	[2.12]b
Age_{it-2}	54.33763	-102.09665	26.96938	62.95971	6910.79	-31126.13	-85840.27	21,257.84
	[0.20]	[0.34]	[0.10]	[0.24]	[0.51]	[0.27]	[0.90]	[2.18]b
Age_{it-3}	-22.62473	73.27061	-3.86235	-26.77799	-4645.17	15843.28	46116.82	-13530.98
	[0.14]	[0.41]	[0.02]	[0.17]	[0.58]	[0.24]	[0.83]	[2.24]b
Age_{it-4}	2.38116	-15.00364	-1.54896	2.87067	952.59	-2148.46	-6921.79	2584.16
	[0.09]	[0.48]	[0.05]	[0.10]	[0.68]	[0.19]	[0.73]	[2.32]b
ΔPM_{it-1}	-0.00001				0.14388			
	[0.01]				[1.03]			
ΔPM_{it-2}	0.00324				0.02927			
	[1.07]				[0.44]			
ΔPM_{it-3}	-0.00302				-0.09377			
	[1.32]				[0.53]			
ΔPM_{it-4}	0.00067				-0.10943			
	[0.45]				[1.42]			
ΔROS_{it-1}		0.00008				-0.27943		
		[0.61]				[2.56]b		
ΔROS_{it-2}		0.00013				-0.11330		
		[0.44]				[1.41]		
ΔROS_{it-3}		0.00034				-0.11694		
		[1.09]				[1.22]		
ΔROS_{it-4}		0.00006				-0.00467		
		[0.30]				[0.10]		
ΔROC_{it-1}			-0.00004				-0.32725	
			[0.25]				[2.23]b	
ΔROC_{it-2}			0.00005				-0.10641	
			[0.21]				[1.44]	
ΔROC_{it-3}			0.00015				-0.09723	
			[0.50]				[1.48]	
ΔROC_{it-4}			0.00005				-0.02520	
			[0.19]				[0.41]	
ΔROA_{it-1}				0.00060				0.29471
				[0.35]				[2.59]a
ΔROA_{it-2}				0.00136				0.02877
				[0.98]				[0.31]
ΔROA_{it-3}				0.00030				0.01546
				[0.19]				[0.31]
ΔROA_{it-4}				0.00030				-0.02670
				[0.30]				[0.42]
Constant	0.05462	0.03646	0.03378	0.05244	0.49394	-21.98778	-40.31024	-1.08288
	[0.69]	[0.35]	[0.37]	[0.64]	[0.30]	[0.79]	[1.77]c	[0.52]
N	525	455	494	525	525	447	490	524
Num. of Firms	105	97	101	105	105	95	101	105
F-Test	31.88	47.23	25.23	31.61	58.54	39.37	68.26	33.99
Prob.>F	0.01	0.00	0.07	0.01	0.00	0.00	0.00	0.01
Wald-Test	5.64	1.86	0.55	1.36	11.43	1.27	1.43	2.94
Prob.>Wald	0.23	0.76	0.97	0.85	0.02	0.87	0.84	0.57

Tab. 5.17: **Causality Regressions for Private Large Firms: With No Access to Public Equity Market**

This table reports the estimates from the causal regressions for the private firms in the sample. The sample firms are stratified into small, medium, and large classes using 1991 employment levels and following the European Commission size classification. The European Commission classifies a firm with 1-99 employees as a small firm, a firm with 100-499 employees as a medium firm and a firm with 500 or more employees as a large firm. Among the variables in the table, $GROWTH_{it}$ stands for the employment growth of firm i at time t, PM_{it} stands for $Profit\ Margin$, ROS_{it} stands for $Return\ to\ Shareholders$, ROC_{it} stands for $Return\ on\ Invested\ Capital$, and ROA_{it} stands for $Return\ on\ Total\ Assets$. Robust t statistics are given in brackets and beside the t-stat 'a' denotes significance at the 1% level, 'b' denotes significance at the 5% level, and 'c' denotes significance at the 10% level.

	First-Stage Regressions				Second-Stage Regressions			
	(1) $\Delta GROWTH_{it}$	(2) $\Delta GROWTH_{it}$	(3) $\Delta GROWTH_{it}$	(4) $\Delta GROWTH_{it}$	(1) ΔPM_{it}	(2) ΔROS_{it}	(3) ΔROC_{it}	(4) ΔROA_{it}
$\Delta GROWTH_{it-1}$	-0.03076	-0.04634	-0.04839	-0.03129	-0.13763	-0.86301	5.98618	0.51596
	[0.58]	[0.82]	[0.91]	[0.59]	[0.15]	[0.15]	[1.80]c	[0.91]
$\Delta GROWTH_{it-2}$	-0.22341	-0.24146	-0.23793	-0.22278	-0.20265	-5.19027	3.11668	0.05351
	[1.44]	[1.49]	[1.53]	[1.44]	[0.30]	[0.84]	[1.26]	[0.10]
$\Delta GROWTH_{it-3}$	-0.12910	-0.13750	-0.13877	-0.12855	-0.53209	-6.64723	3.31544	0.06380
	[3.83]a	[3.80]a	[3.96]a	[3.81]a	[0.75]	[0.80]	[1.29]	[0.12]
$\Delta GROWTH_{it-4}$	0.00776	-0.00146	-0.00402	0.00714	-0.00741	-4.75966	1.18698	0.46549
	[0.26]	[0.05]	[0.13]	[0.24]	[0.01]	[0.58]	[0.60]	[0.80]
$\Delta Tot.\ Assets_{it-1}$	-0.01144	-0.00980	-0.00791	-0.01161	0.02617	9.12898	7.84593	0.51010
	[0.47]	[0.38]	[0.33]	[0.48]	[0.03]	[1.32]	[1.14]	[0.33]
$\Delta Tot.\ Assets_{it-2}$	-0.06848	-0.08743	-0.08108	-0.06682	-1.07036	-0.63628	2.84925	-1.06516
	[1.89]c	[2.20]b	[2.22]b	[1.84]c	[0.97]	[0.13]	[0.55]	[0.78]
$\Delta Tot.\ Assets_{it-3}$	0.03804	0.04701	0.03569	0.03790	1.60558	-4.77626	-2.92822	-0.24044
	[1.06]	[1.21]	[0.97]	[1.06]	[1.07]	[1.01]	[0.61]	[0.17]
$\Delta Tot.\ Assets_{it-4}$	0.01349	0.02254	0.02216	0.01132	0.15366	5.77943	6.32761	2.21015
	[0.58]	[0.92]	[0.94]	[0.48]	[0.12]	[1.15]	[1.40]	[1.36]
Age_{it-1}	-12.21933	-18.41581	-16.39200	-12.76015	799.57	1269.41	1597.53	944.46
	[1.17]	[1.49]	[1.70]c	[1.24]	[2.44]b	[0.59]	[0.80]	[2.01]b
Age_{it-2}	15.42279	25.16317	21.77147	16.21875	-1205.60	-1922.85	-2583.96	-1398.49
	[0.98]	[1.35]	[1.50]	[1.05]	[2.49]b	[0.60]	[0.88]	[2.00]b
Age_{it-3}	-4.06564	-7.79054	-6.41951	-4.35203	448.76	708.74	1018.06	501.89
	[0.70]	[1.12]	[1.20]	[0.76]	[2.58]a	[0.61]	[0.96]	[1.96]b
Age_{it-4}	0.01253	0.12340	0.08176	0.02295	-13.24	-13.22	-23.95	-10.88
	[0.08]	[0.64]	[0.54]	[0.14]	[2.57]b	[0.39]	[0.76]	[1.28]
ΔPM_{it-1}	-0.00116				0.15527			
	[1.26]				[1.32]			
ΔPM_{it-2}	0.00192				0.05344			
	[1.03]				[0.80]			
ΔPM_{it-3}	-0.00091				0.01750			
	[1.00]				[0.38]			
ΔPM_{it-4}	0.00182				-0.00873			
	[1.36]				[0.20]			
ΔROS_{it-1}		-0.00006				0.20527		
		[0.51]				[1.89]c		
ΔROS_{it-2}		-0.00005				-0.02473		
		[0.47]				[0.47]		
ΔROS_{it-3}		-0.00030				0.01376		
		[1.65]c				[0.20]		
ΔROS_{it-4}		0.00004				-0.02151		
		[0.30]				[0.50]		
ΔROC_{it-1}			0.00012				0.24615	
			[0.86]				[2.25]b	
ΔROC_{it-2}			0.00002				0.05785	
			[0.17]				[0.75]	
ΔROC_{it-3}			-0.00027				0.03544	
			[1.49]				[0.57]	
ΔROC_{it-4}			0.00012				-0.03196	
			[0.62]				[0.67]	
ΔROA_{it-1}				-0.00097				0.16391
				[1.85]c				[1.76]c
ΔROA_{it-2}				0.00066				0.04811
				[0.70]				[0.81]
ΔROA_{it-3}				-0.00020				0.04460
				[0.42]				[1.03]
ΔROA_{it-4}				0.00146				0.04126
				[2.23]b				[1.00]
Constant	-0.01248	-0.03266	-0.01806	-0.01312	-1.00994	-6.43719	-1.12023	-1.65299
	[0.35]	[0.81]	[0.49]	[0.37]	[1.04]	[1.07]	[0.23]	[1.36]
N	3310	2861	3131	3310	3310	2783	3081	3308
Num. of Firms	666	618	653	666	666	604	646	666
F-Test	47.47	43.19	47.96	56.43	19.32	41.07	19.66	22.12
Prob.>F	0.00	0.00	0.00	0.00	0.25	0.00	0.24	0.14
Wald-Test	3.68	3.37	5.95	8.40	1.52	3.05	4.14	1.57
Prob.>Wald	0.45	0.50	0.20	0.08	0.82	0.55	0.39	0.81

Tab. 5.18:

Causality Regressions for Public Large Firms: With Access to Public Equity Market

This table reports the estimates from the causal regressions for the public large firms in the sample. The sample firms are stratified into small, medium, and large classes using 1991 employment levels and following the European Commission size classification. The European Commission classifies a firm with 1-99 employees as a small firm, a firm with 100-499 employees as a medium firm and a firm with 500 or more employees as a large firm. Among the variables in the table, $GROWTH_{it}$ stands for the employment growth of firm i at time t, PM_{it} stands for *Profit Margin*, ROS_{it} stands for *Return to Shareholders*, ROC_{it} stands for *Return on Invested Capital*, and ROA_{it} stands for *Return on Total Assets*. Robust t statistics are given in brackets and beside the t-stat 'a' denotes significance at the 1% level, 'b' denotes significance at the 5% level, and 'c' denotes significance at the 10% level.

	First-Stage Regressions				Second-Stage Regressions			
	(1) $\Delta GROWTH_{it}$	(2) $\Delta GROWTH_{it}$	(3) $\Delta GROWTH_{it}$	(4) $\Delta GROWTH_{it}$	(1) ΔPM_{it}	(2) ΔROS_{it}	(3) ΔROC_{it}	(4) ΔROA_{it}
$\Delta GROWTH_{it-1}$	0.27330	0.17804	0.30234	0.24719	-7.20064	-33.18625	-14.21399	-8.88936
	[1.65]c	[1.02]	[1.79]c	[1.50]	[1.54]	[1.32]	[0.72]	[1.34]
$\Delta GROWTH_{it-2}$	0.03600	-0.08445	-0.01627	0.00430	-4.33368	-21.96841	-42.45038	-6.38813
	[0.22]	[0.47]	[0.11]	[0.03]	[0.89]	[1.20]	[1.41]	[0.81]
$\Delta GROWTH_{it-3}$	0.08348	-0.03309	0.00684	0.02234	-13.88436	-77.74261	-56.80259	-21.05621
	[0.52]	[0.17]	[0.04]	[0.15]	[2.21]b	[3.23]a	[2.03]b	[1.94]c
$\Delta GROWTH_{it-4}$	0.04323	0.00947	-0.00740	0.01140	-2.17514	35.94814	32.32356	1.16533
	[0.19]	[0.06]	[0.03]	[0.05]	[0.31]	[0.88]	[0.72]	[0.08]
$\Delta Tot.\ Assets_{it-1}$	0.02925	0.21121	-0.01365	0.01959	-3.38037	-20.56950	-12.54658	0.35425
	[0.52]	[1.67]c	[0.19]	[0.34]	[0.92]	[0.78]	[0.87]	[0.09]
$\Delta Tot.\ Assets_{it-2}$	0.11544	0.32390	0.09444	0.12088	1.39709	18.90077	-8.69535	2.16497
	[0.99]	[1.77]c	[0.85]	[1.02]	[0.67]	[0.91]	[0.63]	[0.84]
$\Delta Tot.\ Assets_{it-3}$	0.03472	-0.32372	-0.00829	0.03061	1.76580	-13.41477	34.15321	12.09573
	[0.20]	[2.20]b	[0.05]	[0.18]	[0.43]	[0.70]	[0.79]	[1.40]
$\Delta Tot.\ Assets_{it-4}$	0.04909	0.19589	0.19377	0.09043	-1.46465	-24.71318	18.13550	-11.76682
	[0.42]	[1.04]	[1.20]	[0.77]	[0.40]	[0.85]	[0.81]	[1.97]b
Age_{it-1}	164.12	156.25	137.54	117.08	6051.90	5610.36	35540.13	2080.10
	[0.80]	[0.72]	[0.55]	[0.54]	[0.79]	[0.16]	[1.16]	[0.24]
Age_{it-2}	-304.41	-289.37	-254.19	-216.42	-9729.65	-6564.58	-59659.18	-1365.02
	[0.76]	[0.68]	[0.53]	[0.51]	[0.65]	[0.10]	[1.04]	[0.08]
Age_{it-3}	168.04	158.56	139.45	117.99	4205.85	456.72	28375.29	-1317.57
	[0.69]	[0.61]	[0.48]	[0.46]	[0.47]	[0.01]	[0.87]	[0.13]
Age_{it-4}	-25.73	-23.73	-21.17	-17.51	-342.72	858.75	-3279.16	762.27
	[0.58]	[0.51]	[0.41]	[0.38]	[0.22]	[0.13]	[0.59]	[0.40]
ΔPM_{it-1}	-0.00668				0.21438			
	[1.80]c				[1.25]			
ΔPM_{it-2}	-0.00134				-0.02711			
	[0.48]				[0.28]			
ΔPM_{it-3}	-0.00683				-0.07069			
	[2.48]b				[0.42]			
ΔPM_{it-4}	-0.00096				0.13808			
	[0.30]				[0.62]			
ΔROS_{it-1}		-0.00071				-0.21218		
		[1.27]				[1.05]		
ΔROS_{it-2}		0.00054				0.20235		
		[0.87]				[0.85]		
ΔROS_{it-3}		-0.00061				0.08422		
		[1.02]				[0.43]		
ΔROS_{it-4}		-0.00162				0.13860		
		[1.57]				[0.99]		
ΔROC_{it-1}			-0.00230				0.38858	
			[2.37]b				[2.81]a	
ΔROC_{it-2}			-0.00077				-0.93638	
			[0.72]				[2.27]b	
ΔROC_{it-3}			-0.00153				-0.50477	
			[2.07]b				[1.40]	
ΔROC_{it-4}			-0.00033				-0.07292	
			[0.41]				[0.24]	
ΔROA_{it-1}				-0.00394				0.14164
				[2.16]b				[1.59]
ΔROA_{it-2}				-0.00065				-0.02591
				[0.47]				[0.47]
ΔROA_{it-3}				-0.00303				-0.23157
				[2.68]a				[1.14]
ΔROA_{it-4}				-0.00137				0.11273
				[0.59]				[0.49]
Constant	0.06046	0.07094	0.06283	0.07484	-1.64672	-24.12854	-7.97017	-0.88119
	[0.72]	[0.76]	[0.71]	[0.86]	[0.65]	[1.48]	[0.52]	[0.23]
N	100	94	99	100	100	93	98	100
Num. of Firms	20	19	20	20	20	19	20	20
F-Test	147.61	340.75	316.86	306.13	55.56	201.47	658.08	203.90
Prob.>F	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Wald-Test	9.11	3.77	12.75	13.81	5.80	11.84	4.23	4.23
Prob.>Wald	0.06	0.44	0.01	0.01	0.21	0.02	0.38	0.38

6. CONCLUSION

As the business climate deteriorates or the guidance of the firm falls into the hands of people with less energy and less creative genius, a time may come when continuing the money-losing operations become infeasible and failure becomes imminent. Managers may buy time to save the sinking ship by liquidating assets to finance their money-losing operations, but as liquidity runs out, the inevitable reckoning with failure strikes hard and equity holders are faced with having to make the ultimate decision of being acquired or going bankrupt. This scenario is all too common in the modern corporate landscape. Yet, our understanding is limited about how managerial discretion and corporate financial flexibility affect various firm dynamics such as failure, excessive continuation, firm growth and investment.

In this dissertation, I try to advance our understanding of these issues in three novel ways. First, I show that the empirical effect of finance is not merely a misspecified real influence, but rather that the financial structure of firms matter for firm growth and investment. Second, managerial discretion combined with corporate financial flexibility may lead to distortions in corporate investment and financing policies, and those distortions cost the various stakeholders of the firm dearly. And finally, the capital market does indeed discipline managerial sub-optimal behaviors, but the market disciplinary mechanisms may not be swift enough to forestall falling values for the corporate stakeholders. However, as for any empirical study, these conclusions are not infallible, and I do not claim to have fully resolved those issues that the finance literature has been struggling with. Rather, this dissertation is a step forward toward understanding the complex interplay of forces that bring down a firm from the zenith of miracle to the nadir of debacle.