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*Performance of Suppliers to Under-pressure Customers: Pricing of Financial  
Distress Along the Supply Chain*

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### **List of Abbreviations**

AEPS: Actual earnings per share

AIES: Artificially intelligent expert system models

BM: Book-to-market ratio

CAR: Cumulative abnormal return

CAPM: Capital asset pricing model

CDS: Credit default swap

EBITDA: Earnings before interest, taxes, depreciation and amortization

EEPS: Expected earnings per share

EDF: Expected default frequency

HML: High-minus-low factor

LBO: Leveraged Buy-out

MB: Market-to-book ratio

MDA: Multiple discriminant analysis

PERSALES: Percentage of Sales

R&D: Research and Development

SMB: Small-minus-big factor

SUE: Standardized unexpected earnings

## 1. Introduction

### 1.1. Background and Objective

Financial distress has evoked a lot of attention in the finance literature. Lately, an increasing number of studies have investigated the empirical relation between distress risk and the cross-section of stock returns. For example, Dichev (1998) uses Altman's (1968) Z-score to proxy for financial distress and finds evidence for a negative relation between distress risk and stock returns. Garlappi, Shu and Yan (2008), who use a default measure based on Moody's KMV model and Avramov (2006), who determines default risk using credit ratings, come to a similar conclusion. Griffin and Lemmon (2002) use Ohlson's (1980) O-Score to measure financial distress and find that distressed growth stocks have particularly low returns. Campbell *et al.* (2008) illustrate that distressed stocks underperform in all quintiles of size and value distributions.

A negative relation between distress risk and stock returns contradicts the foundations of classic financial theory in which investors are awarded higher returns for bearing larger risks. The empirically observed underperformance of distressed stocks has been dubbed 'the distress anomaly'. It asserts that market participants do not fully absorb the available information on a firm's financial situation when pricing distressed stocks. In fact, Campbell *et al.* (2008) state that the anomaly "*is a challenge to standard models of rational asset pricing in which the structure of the economy is stable and well understood by investors*".<sup>1</sup>

If the information on financial distress is not fully incorporated into the stock prices at the single firm level, a natural question to ask is whether investors price this type of information across the supply chain. So far, the finance literature has provided some evidence for investors' underreaction to information of economically linked firms. Cohen and Frazzini (2008) sort supplier stocks according to their major customers' previous month return. They find a high level of return predictability stemming from a rather slow diffusion of information. Menzly and Ozbas (2006) also provide evidence for investors' attention constraints using upstream and downstream definitions of industries. Based on these findings, I expect that information on distress is not necessarily processed adequately across inter-firm linkages.

From an economic perspective, firms in distress may take strategic or operational measures that will inevitably translate into adverse effects for their economically linked partners.

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<sup>1</sup> Campbell et al. (2008, p. 2934)

Possible actions include a surcharge to existing bills, a reduction of order entry or a delay in invoice payment. For example, in the wake of the difficulties encountered by the US automobile industry in the late 2010s, Ford Motor Company was able to prevent a Chapter 11 filing by launching a major restructuring program involving the closure of several plants and an overall cut in production. In general, firms in distress may also go one step further and attempt to squeeze existing suppliers by delaying payment or enforcing price cuts.<sup>2</sup> Clearly, such drastic measures will impact the performance of supplier firms on both the operating as well as return level.

So far, academic research has examined the contagious effects of bankruptcy events. For example, Lang and Stulz (1992) study how firm bankruptcies affect the equity value at the intra-industry level. The authors show that the announcement of a bankruptcy has value implications on the firm's immediate competitors.

While, the research on intra-industry contagious effects of bankruptcy events is relatively comprehensive, little attention has been directed to contagious nature of bankruptcies at the inter-industry level.<sup>3</sup> Only Hertz et al. (2008) and Kolay and Lemmon (2012) examine how bankruptcy effects can ripple through the supply chain. Using a sample of customer-supplier relationships, both studies show that bankruptcy events can have a significant impact on the firm value of economically linked firms.

While extant research has clearly verified that a bankruptcy event is associated with material externalities for (economically) linked firms, the literature remains largely silent about spill-over effects of financial distress that are not *directly* associated with a bankruptcy filing. Given that only a very limited number of distressed firms eventually go into insolvency, existing studies may thus underestimate the true contagious nature of financial distress.<sup>4</sup>

I try to fill this gap by analysing the performance of suppliers to distressed customers. Hence, the objective of this work is to extend the research on inter-industry financial distress contagion. Specifically, I aim at answering the following broad research question:

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<sup>2</sup> For example, prior to filing for Chapter 11 in 2009, Chrysler enforced parts suppliers to cut prices and increased payment time to 90 days

<sup>3</sup> See Section 2.1.1 for an overview of the literature regarding the contagious effects in an intra-industry setting

<sup>4</sup> For example, Hillegeist et al. (2004) show that in the time period from 1980 to 2000 less than 1% of the firms filed for bankruptcy.



RQ1: *What are the effects of a firm's financial distress on the stock and operating performances of economically linked partners?*

I measure customer default risk using the expected default frequency (EDF) measure of the Merton (1974) model and estimate subsequent supplier performances. My central prediction is that higher customer default risk has an effect on the performance of supplier firms.<sup>5</sup> Increased probability of customer default should be associated with lower stock and operating performances of their respective suppliers. Consistent with my hypothesis, I find that suppliers to financially distressed customers experience significantly lower returns. The decreased returns cannot be explained by standard rational asset pricing models. I call the unexplained underperformance of suppliers to distressed customers the “*under-pressure customer anomaly*”.

Furthermore, contagious effects of financial distress may also be observable in the suppliers' books. In an analysis, I find that suppliers to under-pressure customers show significantly decreased operating performances as measured by standard financial ratios such as return on assets, operating margin and return on sales.

Having established a negative relation between customer distress risk and supplier performances, I turn to an investigation of the determinants of financial distress contagion. Specifically, I provide answers to the following research question:

RQ2: *What are the determinants of inter-firm contagious effects of financial distress?*

Titman and Wessels (1988) suggest that suppliers of a unique product may be more affected when their major customers become financially distressed. Intuitively, suppliers selling highly specialized products may find it more difficult to find alternative customers and experience higher costs of rerouting their output. Therefore, I expect suppliers to firms producing specialized products to experience larger contagious effects.

Hertzel et al. (2008) argue that firms that operate in concentrated industries have fewer switching alternatives. This results in a higher dependency between the linked firms. Thus, I expect the supplier distress contagion to be more prevalent in concentrated industries.

In addition, financial distress contagion may be stronger among suppliers that are more dependent on their customers with respect to revenue realization. Consequently, I expect

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<sup>5</sup> Throughout this study, I use the terms distress risk and default risk interchangeably.

increased contagious effects for suppliers that generate a higher percentage of their sales with a distressed customer.

I find that product specificity, industry concentration and revenue dependency have a reinforcing impact on the extent of financial distress contagion. Firms with high scores on these criteria tend to underperform their peers, on average.

So far, I have established that suppliers to under-pressure customers underperform and that this underperformance cannot be explained by standard rational asset pricing models. An intuitive question to ask is whether this “pricing anomaly” stems from asset mispricings. Potentially, investors may not incorporate the information on customer financial distress into the stock prices of supplier firms. I address this issue in the third research question:

*RQ3: Does the under-pressure customer anomaly result from asset mispricing due to investors' inattention?*

Generally, the finance literature has verified that many anomalies in stock prices are more pronounced for stocks with relatively poor dissemination of information, an unsophisticated investor base and poor liquidity. I investigate the under-pressure customer anomaly for a number of subsamples based on variables that measure the availability of information, the ease of trading and the tendency of sophisticated investors to hold supplier stocks. I find that the under-pressure customer anomaly is stronger among stocks with small market capitalization, low institutional holdings, low analyst coverage and low turnover. These findings suggest that the under-pressure customer anomaly is driven by behavioural factors rather than fully rational models in which investors have homogenous beliefs and preferences. In this context, limits to arbitrage are a plausible explanation for the persistence of the anomaly.

If the contagious effects of customer distress are neglected when pricing corresponding supplier stocks, then investors will be surprised when the true earnings quality is made public. I test this by examining the earnings announcements returns of suppliers to distressed customers in a fashion similar to La Porta et al. (1997). In line with my hypothesis, I find negative earnings announcement returns for suppliers to distressed customers, even if I correct for risk factors using conventional asset pricing models. An analysis of standardized unexpected earnings underline my results. Actual earnings seem to remain behind expectations for supplier stocks of high customer distress.

My work contributes to the existing body of research in several ways. First, I provide further evidence on the contagious nature of financial distress among contractually linked partners. So far, extant research has focused on distress related to bankruptcies exclusively. I measure distress risk using a failure probability measure based on the expected default frequency of Merton's (1974) model. This approach allows me to examine potential distress spill-over effects for a much broader sample including all suppliers traded on major US stock exchanges between 1980 and 2010. Thus, my approach delivers a more comprehensive picture of how distress at one firm can affect economically linked partners.

Second, I examine the operating performance of suppliers to distressed customers. To the best of my knowledge, this is the first paper that examines the operating performance of suppliers that suffer from financial distress as measured by the expected default frequency (EDF).

Third, I provide further evidence on the determinants of financial distress contagion. Specifically, I am able to overcome the small sample problem encountered by Hertz et al. (2008), who attribute the lack of statistical significance of their tests to the decreased size of the bankruptcy filing sample as well as the noise in measuring abnormal returns.<sup>6</sup>

Lastly, I show that the market is not fully efficient in pricing information on customer default risk across the supply chain. The under-pressure customer anomaly is more pronounced among stocks with decreased information dissemination and liquidity. Furthermore, the observed negative announcement returns and negative unexpected earnings surprises of suppliers to distressed customers suggest that investors are not aware of the customer-supplier relationships and hence fail to price this type of information across the supply chain.

## 1.2. Organization of the Dissertation

The dissertation is structured into five sections. Section 2 lays the theoretical foundation and presents the motivational background of the study. Section 3 discusses methodological and data-related issues. Section 4 presents the results of the empirical investigation and provides answers to the research questions as outlined above. Section 5 concludes.

Section 2 provides an extensive overview of the related finance literature. The overall objective is threefold: First, it introduces the major aspects concerning distress risk, investor attention and financial contagion. Second, the review establishes a basis for the theoretical motivation

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<sup>6</sup> Hertz et al. (2008, p. 384).

of the empirical investigation. Third, it builds the methodological foundation for the research design of this study.

Section 2.1 reviews the literature related to distress risk. Starting with a broad overview of the existing methods to estimate a firm's distress risk, Section 2.1.1 specifically discusses the most relevant and widely used accounting-based and market-based bankruptcy prediction models. Section 2.1.2 provides insights into the empirical findings regarding the relation between distress risk and the cross-section of stock returns. The discussion in this section focuses on two major questions: First, the question of whether distress risk is associated with a positive or negative return premium is addressed. Second, the section discusses the available theories explaining the observed return pattern. The section is structured by studies that find evidence for a mispricing explanation and studies that find alternative explanations.

Section 2.2 reviews the literature on investor attention. In Section 2.2.1, an overview of different theoretical models is provided. These models show how investors' attention constraints affect asset pricing dynamics which can cause prices to deviate from their fundamental values. In Section 2.2.2, the findings of studies that empirically investigate the relationship between investor inattention and stock prices are presented. This section is structured into three groups of variables: Competing stimuli, information salience and other variables. While competing stimuli suggests that investors can be distracted from relevant information, the information salience describes the ease of processing the relevant information. The third group includes other variables that can be used as proxies for measuring the level of investor attention such as trading volume or internet searches.

Section 2.3 provides an overview of the literature related to financial contagion. The section introduces the existing channels of distress contagion and then summarizes the empirical findings of studies that examine contagious effects at an intra-industry as well as inter-industry setting. A number of studies find that spill-over effects of financial distress can cause contagious and competitive effects for industry rivals. However, the question of whether financial distress impacts industry rivals in a causal manner or whether the observed contagious effects are a result of an information release remains largely unanswered. Moreover, empirical investigations that focus on stakeholder financial contagion are discussed. A growing number of studies finds that contagious effects of firm bankruptcies may extend beyond industry competitors to stakeholder firms such as customers, suppliers and creditors.

Section 3 is the outset of the empirical investigation. The objective is twofold: First, it addresses the question of whether increased customer distress risk has an effect on the performances of their respective suppliers. Second, an attempt is made to show that investors neglect information on customer distress risk when pricing corresponding supplier stocks.

Section 3.1 presents the methodologies used to assess the extent to which a customer firm suffers from distress risk. While Section 3.1.1 details the empirical implementation of the methodology to estimate default probabilities using the EDF measure of the Merton (1974) model, Section 3.1.2 outlines how the O-Score of the Ohlson (1980) model is applied in this study.

Section 3.2 gives an overview of the sample and data sources used in this study. Section 3.2.1 describes all databases that have become standard in the empirical asset pricing literature. Special attention is drawn to the matching procedure of securities across the different databases. Section 3.2.2 details the customer-supplier dataset. Given the fact that customers in the database are not listed with a unique identifier, I explicitly describe how the data is brought into a useable format. Section 3.2.3 gives a detailed description of the data sources required to estimate the expected default frequency of the Merton (1974) model.

Section 4 presents the results of the investigation. In Section 4.1, the main results of the investigation are presented. Suppliers to high distress customers significantly underperform suppliers to low distress risk customers, even if returns are corrected for risk factors. This relationship holds for both, equally-weighted supplier portfolios as well as sales-weighted supplier portfolios. Furthermore, the return pattern is robust to return adjustments with respect to DGTW-adjusted returns and industry-adjusted returns. In addition, I investigate whether the effects of customer distress are also observable in the books of the respective suppliers using a set of widely accepted variables that measure the operating performance. Furthermore, I examine whether suppliers change their trade credit policy when their major customer becomes distressed.

Section 4.2 performs a series of robustness tests. I show that the underperformance of suppliers to distressed customers does not depend on the model used for estimating default probabilities. Furthermore, the underperformance of suppliers to distressed customers persists through different time periods as well as different stages of the economic cycle. Most importantly, the observed return pattern does not stem from widely documented lead-lag effects with respect to market capitalization, trading volume, institutional ownership, analyst coverage or industries.

Section 4.3 concentrates on the variation of the contagious effects of financial distress. A number of studies have suggested that contagious effects of financial distress may vary with product uniqueness, industry concentration and revenue dependency. This section examines these existing hypotheses and finds evidence for product specificity, industry concentration and revenue dependency to be cross-sectional determinants of the variation in financial distress contagion.

Section 4.4 presents the results of a subsample analysis using proxies for investor attention. A number of papers have provided evidence for anomalies to be more pronounced among stocks that encounter the most severe information problems or are difficult to trade. I use a battery of variables to proxy for differences in ease of trading, the availability of information, and the tendency of institutional investors to hold them. I find that the under-pressure customer anomaly is more pronounced among smaller stocks, stock with lower analyst coverage, lower turnover, lower share prices, and a lower institutional investor base.

Section 4.5 presents the outcome of an earnings announcement analysis. Given the results in the subsample analysis in section 4.4, I investigate whether investors adequately process the information on customer distress risk. If investors are not aware of the relationship between customer distress and supplier return performances, they will be negatively surprised when the actual earnings quality is released. Negative abnormal returns around the earnings announcement dates imply that investors neglect information on customer distress risk. Furthermore, a standardized unexpected earnings analysis shows that actual earnings remain behind expectations for suppliers to distressed customers.

Section 5 concludes and presents the major implications of the study. Also, further research directions are provided.

## 2. Literature Review

This study is broadly related to three different strands of financial literature. The first strand concerns the literature on distress risk. Specifically, it addresses the question on how distress risk can be measured and whether investors price this information into the stock prices of the distressed firms. The second strand of literature is related to investor attention. Given the difficulty of processing complex information such as default probabilities, it is important to

understand the implication on underlying pricing dynamics. The last strand concerns literature on the contagious effects of financial distress. Given the research focus of this study, it is important to understand the various mechanisms through which distress risk can be transmitted to third parties.

## 2.1. Literature on Distress Risk

This section provides a thorough overview of the extant literature related to distress risk. The focus is on two central aspects: (1) the different techniques to measure and predict default risk and financial distress and (2) the pricing of distress stocks in capital markets. While Section 2.2.1 describes the different approaches to measure financial distress, Section 2.2.2 presents the results of empirical studies that examine the relation between stock returns and distress risk.

### 2.1.1. Measurement of Distress Risk

The application of models to measure and predict financial distress has a long history in the realm of financial management. As early as the 1850s, financial institutions and other lenders deployed qualitative type variables such as management experience or industry segments to assess the repayment risk of corporate credit assets.<sup>7</sup> Around the turn of the 19<sup>th</sup> century, single financial ratios such as the current ratio were used to assess a borrower's creditworthiness.<sup>8</sup> It was, however, not until the second half of the 20<sup>th</sup> century when academic research on innovative techniques of corporate distress estimation virtually began to accelerate with the pioneering work of Beaver (1966). From then onwards, the evolution of distress risk models continued unabated. Today, numerous different models exist relying on various sources of information including financial, economic and accounting data.

A categorization of the different prediction models of financial distress and bankruptcy can be tackled from different angles. One intuitive possibility involves a classification according to a chronological order. In this context, research on distress models can be broadly subsumed into two distinct time periods: before and after the 1990s. The research on models that evolved before the 1990s predominantly entails single-period classification models.<sup>9</sup> These models are

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<sup>7</sup> Altman and Hotchkiss (2006), p. 233

<sup>8</sup> Beaver (1966), p. 71

<sup>9</sup> Scott (1981), Zavgren (1983), Altman (1984), and Jones (1987) provide an excellent review of the literature on static bankruptcy prediction models.

static in nature in that they use one set of explanatory variables for each firm and that the distinction between distressed and non-distressed firms is made at a single point in time.<sup>10</sup>

After the 1990s, the development of techniques to assess and predict corporate failures was dominated by dynamic models.<sup>11</sup> In contrast to static models, these models are able to estimate bankruptcy possibilities continuously at each given point in time. Figure 1 depicts an example of an evolutionary listing of methodologies that are used to assess the distress risk of a particular firm.<sup>12</sup>

Qualitative assessment	<ul style="list-style-type: none"> <li>• Subjective assessment of business environment (economy, industry management etc.)</li> </ul>
Univariate analysis	<ul style="list-style-type: none"> <li>• Financial ratio analysis (accounting- and market-based measures)</li> </ul>
Multivariate analysis	<ul style="list-style-type: none"> <li>• Discriminant analysis, Logit models, probit models (both, linear and quadratic), nonlinear models e.g. recursive participating analysis (RPA)</li> </ul>
Discriminant models	<ul style="list-style-type: none"> <li>• Consumer models, Z-Score-based models (manufacturing, industry, financials, private firm models etc.)</li> </ul>
Artificial intelligence systems	<ul style="list-style-type: none"> <li>• Expert systems, neural networks</li> </ul>
Option claims models	<ul style="list-style-type: none"> <li>• Risk of ruin, KMV, credit monitor model</li> </ul>
Market value models	<ul style="list-style-type: none"> <li>• Moody's Risk Calc, BondScore (CreditSights), Z-Score (Market value model)</li> </ul>

Figure 1: Listing of Credit Risk Assessment Methodologies

In the 2010's, no entirely new methodology for measuring and predicting bankruptcy probabilities and financial distress has been introduced<sup>13</sup>. Lately, research has concentrated on the refinement and extension of existing models as well as on the assessment of their underlying forecasting accuracy. Cybinski (2003) notes that model extensions generally coincide with the development of new statistical methods or the availability of new databases.

<sup>10</sup> Shumway (2001), p. 101

<sup>11</sup> Mossmann et al. (1998) and Altman and Hotchkiss (2005) provide an extensive review of the literature on dynamic models in comparison to discriminant models.

<sup>12</sup> Adapted from Altman and Hotchkiss (2006, p. 234)

<sup>13</sup> Cybinski (2003, p. 11)



An alternative way to group bankruptcy prediction models involves a classification by means of the statistical or mathematical underpinnings applied by the model. For example, Aziz and Dar (2006) group bankruptcy prediction models into three distinct model categories: Statistical models, artificially intelligent expert system models (AIES hereafter) and theoretical models.

Statistical models can be univariate or multivariate in nature and mainly focus on the symptoms of corporate failure retrieved from company account information. Examples include univariate financial ratio analysis, multivariate discriminant analysis, probit and logit models and linear probability models.<sup>14</sup>

AIES models are based on artificial intelligence applying the concept of “supervised machine learning” to measure the extent to which a firm suffers from financial distress. Similar to statistical models, AIES models focus on the symptoms of bankruptcies and rely on information retrieved from company accounts. Generally, these models are multivariate in nature. Examples include neural networks, genetic algorithms and recursive partitioned decision trees.<sup>15</sup>

Theoretical models concentrate on the factors that trigger corporate bankruptcy. These models rely on various sources of data depending on the information required of making the “theoretical argument” for firm failure. Prominent examples include credit risk theories such as JP Morgan’s CreditMetrics or Moody’s KMV model, cash management theory, balance sheet decomposition measures and gambler’s ruin theory.<sup>16</sup>

A detailed explanation and review of the implications of all available models clearly exceeds the scope of this work. Therefore, the next section concentrates on the models that have predominantly been applied in the context of empirical financial research. The classification is based on the sources of data used in the models: First, models that rely on accounting data (accounting-based models) will be discussed. Second, prominent models utilizing market data (market-based models) are presented.

#### 2.1.1.1. Accounting-based Models

Accounting-based models utilize the information contained in a firm’s financial statements to estimate the extent to which a firm is financially distressed. Classically, these models are based

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<sup>14</sup> Aziz and Dar (2006, p. 20)

<sup>15</sup> Aziz and Dar (2006, p. 21)

<sup>16</sup> Aziz and Dar (2006, p. 22)

on a weighted combination of a set of financial ratios that measure the profitability, liquidity and solvency of a firm. Accounting-based models are typically dichotomous in nature in that they distinguish only between two groups: distressed and non-distressed firms. Here, the classification follows from a comparison of the firm's financial ratios with a predefined benchmark or cut-off measure. Given the fact that accounting data is by definition backward looking, models relying on accounting data to estimate distress risk are always computed ex-post. The usefulness of these models has widely been debated, the results remain mixed. Whereas proponents stress the simplicity and intuition of the models as well as the availability of the information required for their computation, opponents emphasize the lack of accuracy in predicting corporate failures. Despite this ongoing discussion, accounting-based models remain to be one of the most prominent techniques for distress risk assessments.

#### 2.1.1.1.1. Beaver's Analysis of Financial Ratios

In his pioneering work on the prediction of firm failure, Beaver (1966) uses a univariate statistical analysis to test for the usefulness of various financial ratios with respect to their ability to estimate and predict corporate failure. Using a sample of 79 failed industrial firms operating in 38 different industries in the time period from 1954 to 1964, Beaver (1966) uses an univariate analysis in conjunction with a paired-sample design, in which the difference of a variety of financial ratios between a sample of failed firms and a sample of non-distressed matched peer firms is analysed. Beaver (1966) accounts for both industry as well as firm size effects in the matching procedure.

The selection of the financial ratios to investigate with respect to their ability to predict firm failure follows three basic criteria:<sup>17</sup>

- a) Popularity: frequent appearance in the finance literature
- b) Performance of ratios in previous studies
- c) Ratio is defined in accordance with the "cash-flow theory" (liquid asset-flow model) concept<sup>18</sup>

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<sup>17</sup> The presence of any of these criteria would satisfy the requirement for being included in the analysis

<sup>18</sup> Beaver (1966, p. 79)

Whereas the motivation to include financial ratios in accordance with criterion (a) and (b) simply rests on the facilitation of an adequate comparison with historically widely used and generally accepted financial ratios, the last criterion (c) has to be explained.

According to the concept of cash-flow theory, the firm is viewed as a “*reservoir of liquid assets, which is supplied by inflows and drained by outflows*”.<sup>19</sup> As long as the reservoir is large enough to mitigate the variations of in- and outflows of cash, the firm remains solvent. Distress risk is then defined as the probability that the firm’s cash-flow cushion is depleted, at which point the firm is no longer able to service maturing debt obligations. In the context of establishing a relation between the liquid asset-flow model and financial ratios, four factors play a vital role: First, the size of the cash reservoir. Intuitively, the larger the cash buffer the smaller is the probability to default. Second, a larger the net liquid-asset flow from operations the lower the probability of failure.<sup>20</sup> Third, higher leverage in a firm’s capital structure increases the risk to default. Last, the larger the operating expenditures of a firm the more likely it will not be able to meet its debt obligations.

Based on these propositions, Beaver (1966) compares the mean financial ratios of the sample of failed firms to the sample of pair-matched non-failed firms. He finds that throughout the five years prior to default, firms in the failed firm sample show lower cash-flows and a lower reservoir of liquid assets, on average. Moreover, all financial ratios appear to deteriorate as the firm approaches bankruptcy. Furthermore, the author analyses the prediction ability of various financial ratios in a dichotomous classification tests. The following six ratios appear to be the most powerful accounting measures for predicting corporate failure: (1) cash-flow-to-total debt, (2) net income-to-total assets, (3) total debt-to-total assets, (4) working capital-to-total assets, (5) current ratio, and (6) no-credit interval.<sup>21</sup>

In a contingency analysis, Beaver (1966) investigates the accuracy of the predictive power of the financial ratios.<sup>22</sup> For the cash-flow-to-total debt ratio – the ratio with the highest predictive power – the probability of a Type I and Type II error in the first year prior to default is equal to 22% and 5%, respectively. This result indicates that the financial ratios are not able to classify failed and sound firms with equal success. Put differently, the ratio classifies more

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<sup>19</sup> Beaver (1966, p. 80)

<sup>20</sup> In this context, Beaver (1966) defines net liquid-asset flow from operations as the difference between inflows and outflows of operating cash-flows

<sup>21</sup> The ratios are listed in descending order of their estimated prediction ability

<sup>22</sup> Generally, contingencies are expressed in terms of Type I and Type II errors. While a Type I error entails a misclassification of a defaulted firm, a Type II error comprises a false classification of a sound firm.

firms as non-distressed firms than failed firms. From an investor's perspective, a sole dependence on financial ratios in predicting whether a firm will default or not appears to be insufficient, particularly given the larger probability of Type I errors.

Overall, the accounting-based predictors as suggested by Beaver (1966) – foremost the cash-flow-to-total debt ratio – appear to perform moderately well in the short term.<sup>23</sup> However, a univariate statistical analysis is flawed with a number of limitations. First, the focus on a single financial ratio appears to be far too narrow given the complexity of financial failure and multidimensionality of corporate entities. It remains highly questionable whether single accounting-based measures are able to fully capture all relevant dimensions of a corporate entity. Second, the different single ratios cannot be used indiscriminately to predict firm failure. While some ratios suggest firm failure, other ratios may point into an entirely different direction. Third, Beaver's (1966) univariate analysis implicitly assumes a linear relationship between the variables in the numerator and the variables in the denominator of the underlying financial ratio. However, Keasey and Watson (1991) and Whittington (1980) argue that a linear relationship may not be existent in practice implicating the need for a constant term. This, in turn, would lead to a non-proportionate outcome.<sup>24</sup> On these grounds, Altman (1993) concludes that univariate analyses of financial ratios may be susceptible to misleading interpretations.

In summary, financial distress and bankruptcy prediction models based on univariate analyses of financial ratios lack profoundness and require further specifications. In an attempt to “*overcome the potentially conflicting indications that may result from using single variables*”, multivariate techniques have paved their way into the research literature on distress risk.<sup>25</sup> Specifically, Altman (1968) has addressed the following three issues: First, the determination of the most important financial ratios for identifying distress risk. Second, the estimation of the weights associated with the different ratios. Last, the ways in which the weights should be computed. The next section will discuss Altman's (1968) Z-score model in detail.

#### 2.1.1.1.2. Altman's Z-Score

Given the severe drawbacks of Beaver's (1966) univariate analysis of financial ratios, financial research has put forward enhanced techniques to estimate and predict the likelihood of business failure. Specifically, Altman (1968) attempted to overcome the model's inherent shortcomings

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<sup>23</sup> Cybinski (2003, p. 12) and Sheppard (1994, p. 10)

<sup>24</sup> Keasey and Watson (1991, p. 90) and Whittington (1980, pp. 220-224)

<sup>25</sup> Cook and Nelson (1998, p. 3)

concerning the contractive implications of single accounting measures by introducing a multivariate statistical analysis. In this context, Altman (1968) utilizes multiple discriminant analysis (MDA) using the connotations of several different financial ratios to predict bankruptcies. In general, MDA facilitates the classification of variables into one of several a priori groupings. Here, the groupings are based on individual characteristics of the observation. MDA then evaluates the data by determining a linear combination of the variables that “best” discriminate between the defined groups.<sup>26</sup>

In his study, Altman (1968) applies the MDA approach to a sample of 33 manufacturing firms that went bankrupt in the time period between 1946 and 1965. Similar to the study of Beaver (1966), the author compares the sample of bankrupt firms to an industry and size matched sample of sound firms to determine the usefulness of financial ratios in the process of predicting corporate bankruptcy.

The investigation starts with an initial set of 22 different financial ratios measuring a company’s profitability, solvency, leverage, liquidity and activity. The financial ratios used in the study are selected on the basis of their popularity in the previous literature as well as on the potential relevancy to the study.<sup>27</sup> From these 22 ratios, Altman (1968) determines five accounting measures that seem to be the most powerful predictors of distress risk. The procedure of narrowing the original set down to five ratios includes a number of tests concerning the inter-correlations of ratios, their predictive accuracy, analyst judgment and the determination of their relative contributions.

It is important to note that the financial ratios are not evaluated with respect to their bankruptcy prediction ability independently, but rather in conjunction. That is, Altman (1968) tests the bankruptcy prediction accuracy of various combinations of financial ratios, and not their individual validity. This is one of the most significant differences compared to Beaver’s (1966) investigation.

Altman’s (1968) final discriminant function, commonly known as the Z-Score, is shown in the following equation:<sup>28</sup>

$$Z = 0.012 \times X_1 + 0.014 \times X_2 + 0.033 \times X_3 + 0.006 \times X_4 + 0.999 \times X_5 \quad (1)$$

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<sup>26</sup> Altman (1968, p. 592)

<sup>27</sup> Altman (1968, p. 594)

<sup>28</sup> Altman (1968, p. 594)

where,  $X_1$  = working capital divided by total assets

$X_2$  = retained earnings divided by total assets

$X_3$  = earnings before interest and taxes divided by total assets

$X_4$  = market value of equity divided by book value of total liabilities

$X_5$  = sales divided by total assets

$Z$  = overall index

Compared to Beaver's (1966) univariate analysis, the Z-Score model shows an improved performance in terms of prediction accuracy. In particular, the probability of a Type I and Type II error is equal to only 6% and 3%, respectively. The overall accuracy of the Z-Score is 96% in the first year prior to default.<sup>29</sup> However, the model's prediction accuracy considerably drops as we move more years away from the bankruptcy event. For example, two years prior to the actual bankruptcy, the prediction accuracy of the Z-Score is merely equal to 72%.<sup>30</sup>

One appeal of the Z-Score model is that its overall index uses certain cut-off points that can be used as indicators for allocating firms to the distressed and non-distressed samples. In this context, an index score of greater than 2.99 implies a bankrupt firm, while an index score of smaller than 1.81 suggests a sound firm.<sup>31</sup> The range between 1.81 and 2.99 is defined as a "zone of ignorance", in which the model is not able to distinguish between healthy and bankrupt firms.<sup>32</sup> The majority of misclassification occurs for firms that have an overall Z-Score that falls in this "grey area". Altman (1968) proposes a guideline for classifying those firms. In an empirical analysis of all misclassifications, the author identifies a "best critical value" that minimizes the number of misclassification. This value is equal to a Z-Score of 2.675.<sup>33</sup> Consequently, this value becomes the main indicator of separating distressed from non-distressed firms for bankruptcy prediction purposes.

The Z-Score model has attracted a lot of attention in the finance literature. After its introduction, numerous studies have made an attempt to extend and refine the Z-Score model.<sup>34</sup>

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<sup>29</sup> Altman (1968, p. 599)

<sup>30</sup> Altman (1968, p. 600)

<sup>31</sup> Altman (1968, p. 606)

<sup>32</sup> Altman (1968, p. 606)

<sup>33</sup> Altman (1968), p. 606

<sup>34</sup> See e.g. Deakin (1972), Edmister (1972), Taffler (1982), Taffler (1983), Goudie (1987), Grice and Ingram (2001), Agarwal and Taffler (2008), Boritz, Kennedy, and Sun (2007),

Other studies have put the validity of Altman's (1968) Z-Score model into question. For example, Begley et al. (1996) show that the model's performance deteriorates when applied to more recent time periods. Using a dataset of bankrupt firms in the time period from 1980 to 1992, the authors provide evidence for an increased probability of Type I and Type II errors. Begley et al. (1996) argue that the inferior performance mainly stems from a transformation of investors' acceptance of corporate debt levels and changes in the legal environment.<sup>35</sup> Given the fact that one important variable in Altman's (1968) Z-Score model is related to a firm's leverage, the former reason becomes exceedingly relevant. While a firm with increased debt levels may be associated with bankruptcy in earlier time periods, a more recent view comes to an entirely different conclusion.

In a further study, Grice and Ingram (2001) confirm the decreased performance of Altman's (1968) Z-Score model. The authors argue that the model's coefficients should be re-estimated for bankruptcy prediction purposes on the basis of different time periods as well as different industries. In a similar line of reasoning, Mensa (1984) argues that the distribution of accounting ratios varies over time, and hence suggests a periodic redevelopment of the discriminate function.

In summary, Altman's (1968) Z-Score model seems to be a natural improvement over the univariate analysis of accounting ratios in the prediction of corporate bankruptcy. The model applies MDA to discriminate distressed firms from non-distressed firms using a weighted combination of different financial ratios. This technique successfully addresses the issues of contradictory implications as encountered in Beaver's (1966) analysis. Furthermore, the Z-Score model outperforms Beaver's (1966) univariate analysis in terms of bankruptcy prediction accuracy. Both the probability of Type I and Type II errors are significantly lower. However, the Z-Score model is not flawless. Particularly, its sensitivity to industry and sample size appears to be one of the major shortcomings. The Z-Score model cannot simply be applied to different industries and has to be re-estimated periodically to remain an adequate tool for estimating and predicting business failure. In spite of these drawbacks, it has still remained one of the most widely used models in the finance literature.

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<sup>35</sup> Begley et al. (1996, p. 267)

#### 2.1.1.1.3. Ohlson's O-Score

In his seminal paper, Ohlson (1980) puts the MDA approach as a suitable tool for predicting and estimating business failure into question. Specifically, the author's critique rests on three major shortcomings:<sup>36</sup>

First, the model's implicit assumptions concerning the distributional properties of the underlying predictors may not be realistic. For example, MDA assumes that predictor variables are both randomly drawn and normally distributed.<sup>37</sup> In reality, this assumption may however not be satisfied. Consequently, it remains questionable whether the assumed equality of variance-covariance matrices between failed and non-failed firm exists.

Second, the overall index possesses a rather limited intuitive appeal. The score cannot be interpreted as a conditional probability of default, but only as a discriminating device.<sup>38</sup>

Third, the matching of the failed to non-failed firms appears to be somewhat arbitrary as it only based on industry and firm size. Ohlson (1980) argues that particularly the latter should not be used to match firms, but rather as a variable in the bankruptcy prediction process.

In order to mitigate the abovementioned problems associated with MDA, Ohlson (1980) introduces the conditional logit analysis as an alternative methodological approach for estimating and predicting bankruptcies and financial distress. This econometric technique avoids the restrictive assumptions concerning normality of the underlying predictors. Furthermore, the use of logit analysis facilitates the computation of actual default probabilities. This is one of the major advantages over the MDA approach.

A further improvement over Altman's (1968) study is related to the sample selection. Here, two issues are of utmost importance. First, Altman's (1968) study relied on Moody's Manual to collect the data of bankrupt firms. Data retrieved from Moody's Manual, however, lack time specification as it is not indicated at which point in time the required data was made available to the general public. Furthermore, the data in Moody's Manual is often condensed impeding the reconstruction of actual balance sheets and income statements.<sup>39</sup> These data problems become severely imperative for firms in distress as those firms tend to receive special

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<sup>36</sup> Ohlson (1980), p.112-113

<sup>37</sup> Altman et al. (1981)

<sup>38</sup> Ohlson (1980, p.112)

<sup>39</sup> Ohlson (1980, p.113)



treatments.<sup>40</sup> Ohlson (1980) uses a more accurate and comprehensive database in his study. The data is collected from the original bankruptcy filings and annual reports. In total, the sample spans from 1970 to 1976 and includes 105 bankruptcies of industrial firms. For the purpose of comparison, a data for a sample of 2,058 non-bankrupt firms is retrieved from the COMPUSTAT database.

Ohlson (1980) then defines a battery of financial ratios as predictors of business failure. These ratios are selected simply on the basis of their popularity in the previous literature on financial distress prediction. In fact Ohlson (1980) states that “*no attempt was made to develop new or exotic ratios*”.<sup>41</sup> Four basic factors are identified which have proved to be statistically relevant in assessing the probability of default. These include (a) the size of the firm, (b) measures of financial structure, (c) measures of performance, and (d) measures of current liquidity.

Based on these factors, the overall O-score model is developed. It consists of a total of nine different ratios including both quantitative as well as qualitative (dummy) ratios. The model is depicted mathematically as shown below: <sup>42</sup>

$$\begin{aligned}
 O - Score = & -1.32 - 0.407(SIZE) + 6.03(TLTA) - 1.43(WCTA) \\
 & + 0.076(CLCA) - 1.72(OENEG) - 2.37(NITA) - 1.83(FUTL) \quad (2) \\
 & + 0.285(INTWO) - 0.521(CHIN)
 \end{aligned}$$

where,

- SIZE = Log (total assets divided by GNP price-level index)
- TLTA = Total liabilities divided by total assets
- WCTA = Working capital divided by total assets
- CLCA = Current liabilities divided by current assets
- OENEG = One if total liabilities exceeds total assets, zero otherwise
- NITA = Net income divided by total assets
- FUTL = Funds provided by operations divided by total liabilities
- INTWO = One if net income was negative for the last two years, zero otherwise

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<sup>40</sup> This includes particularly issues related to taxes (loss-carry forward) and operating performances

<sup>41</sup> Ohlson (1980, p.118)

<sup>42</sup> The model depicted above is the Model 1, which shows the highest accuracy compared to different alternatives. In total, Ohlson (1980) establishes three different models: Model 1 is calibrated to predict default within one year, while Model 2 within two years, given that no default occurred in the first year. Model 3 is calibrated to predict default within one or two years.

- CHIN =  $(NI_t - NI_{t-1})$  divided by  $(|NI_t| + |NI_{t-1}|)$ , where NI is net income

The interpretation of the overall O-Score is intuitive. A higher the O-Score translates into a higher probability to default. Ohlson (1980) shows that 0.038 is the cut-off point that minimizes the sum of Type I errors and Type II errors.<sup>43</sup> The model misclassifies 17.4% and 12.4% of non-bankrupt and bankrupt firms, respectively. Notably, the misclassification rate is considerably higher compared Altman's (1968) study. Ohlson (1980) offers some explanation. The author argues that some of the misclassifications occur due to "lead times" in reporting financial results and shows that both the probability of Type I and Type II errors is reduced once subsequent annual reports are used to compute the relevant ratios. Moreover, Ohlson (1980) points out that it is difficult to compare the results due to differences in sample sizes and time periods. In a later study, Begley et al. (1996) compare the prediction accuracy of the Altman and Ohlson model using original coefficients and more recent data and find that Ohlson's (1980) model delivers more precise bankruptcy predictions.

To summarize, the O-Score model successfully tackles the methodological problems inherent in the MDA approach. It presents an elegant way to circumvent the unlikely premises of normally distributed prediction variables. Moreover, the model's overall index, or O-Score, has an intuitive appeal as it can be interpreted as a probability of default. Compared to Altman (1968) and other multivariate-based adaptations, this feature presents one of the major advantages. The implications of the various prediction models tested are enhanced by the use of a more comprehensive sample, which takes number of selection biases into account. Even though the accuracy of the model appears inferior to Altman (1968), it should be noted that a direct comparison clearly recommends Ohlson's (1980) O-Score over alternative, multivariate-based models. The ease of implementation as well as its prediction accuracy has made it one of the most widely used models in the prediction of financial distress and bankruptcies.<sup>44</sup>

Ohlson (1980) notes that the use of different accounting measures in his conditional logit analysis would not necessarily lead to a significant increase in the prediction accuracy of firm failures. However, he suggests that market-based information such as asset prices and most importantly asset volatility could lead to further improvement.<sup>45</sup> Approximately a decade after

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<sup>43</sup> Again, a Type I error is defined as a misclassification of a bankrupt firm, while a Type II error is defined as a misclassification of a non-bankrupt firm.

<sup>44</sup> See e.g. Burgstahler et al. (1989), Francis (1990), Stone (1991), Han, Jennings, and Noel (1992), Berger, Ofek, and Swary (1996), Subramanyam and Wild (1996), Dichev (1998), and Griffin and Lemmon (2002) for applications of the Ohlson O-Score in the realm of financial management

<sup>45</sup> Ohlson (1980), p. 113.

the establishment of the O-Score model, research concerning market-based models emerged. Some of the most prominent versions are discussed in the next section in detail.

#### 2.1.1.1.4. Section Summary

This section provides a detailed discussion of the most prominent accounting-based models. Beaver (1966) uses a univariate analysis of a set of accounting ratios and finds that the ratio of cash-flow-to-total debt best predicts bankruptcies. The probabilities of Type I and Type II errors are moderately low: 22% and 5%, respectively. Given the complexity of firm structures, the use of a single ratio to predict firm failure appears to narrow. Also, different ratios may deliver contradicting results.

Based on these major drawbacks, Altman (1968) introduces a multivariate analysis of accounting ratios to provide a more comprehensive picture of the firm's financial situation. In this approach, the ability of financial ratios to predict bankruptcies is tested in conjunction, rather than in a "stand-alone" solution. An overall index is estimated, consisting of five different financial ratios. This index has become known as the Z-Score. Altman's (1968) Z-Score model shows an improved performance: Type I and Type II error is equal to only 6% and 3%, respectively. However, the Z-Score has been criticized on the grounds of its unintuitive interpretation and its sensitivity to industry and sample size. Furthermore, the MDA makes the strong assumptions concerning the distributional characteristics of the underlying financial ratios.

Ohlson (1980) suggests conditional logit analysis to estimate and predict bankruptcies and financial distress. This technique circumvents the restrictive assumption inherent in Altman's (1968) Z-Score model. Furthermore, the use of logit analysis facilitates the computation of actual default probabilities. Similar to Altman (1968), an overall index is computed consisting of a set of seven different qualitative and quantitative ratios. This index is known as the O-Score and has a notable intuitive appeal: The higher a firm's O-Score, the higher the probability to default. Even the probabilities of a Type I and Type II error are somewhat higher relative to Altman (1968), a direct comparison concludes that "Ohlson's (1980) model displays the overall strongest performance."<sup>46</sup>

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<sup>46</sup> Begley et al. (1996), p. 267

### 2.1.1.2. Market-based Models

Even though bankruptcy prediction models based on accounting data are still widely used in empirical research, there has been an ongoing debate about their usefulness. Critics argue that accounting data does not contain all relevant information and related models are thus susceptible to false implications. For example, Begley et al. (1996) examine the most prominent accounting-based bankruptcy models and provide evidence for their relatively high misclassification rates.<sup>47</sup>

Hillegeist et al. (2004), Gharghori et al. (2006) and Agrawal and Taffler (2008) examine the benefits and shortcomings of accounting-based and market-based financial distress models. These studies unanimously agree upon the supremacy of market-based models concerning their theoretical groundings. The reasons for that are manifold:<sup>48</sup>

First, accounting data is, by definition, backward looking. Whereas market prices reflect an asset's potential future developments, accounting information only allows the view into the rear view mirror. Also, while accounting data is updated infrequently, market information is available in any chosen frequency including quarterly, monthly daily and even on an intra-day level.

Second, financial statement data is generated in accordance with underlying reporting standards. This may cause serious distortions. For example, conservative accounting principles can lead to understated book values of assets. This, in turn, overstates leverage ratios clouding the implications derived from accounting-based prediction models. For firms with high fixed and intangible assets, this problem becomes particularly severe.

Third, financial ratios vary noticeably with time and across industries. Therefore, the model's coefficients need to be redeveloped specifically for every industry and updated to the time period of the investigation.

Fourth, while market-based models are theoretically grounded and economically justified, accounting-based models are rather built in an “*ad hoc*” process. Given a specific set of bankrupt and non-bankrupt firms, coefficients and cut-off points are fitted in a way that minimizes the sum of Type I and Type II errors. Conceptual aspects play only a minor role.

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<sup>47</sup> The models included in the study are Altman's (1968) Z-Score and Ohlson's (1980) O-Score.

<sup>48</sup> Hillegeist et al. (2004, p.7); Gharghori et al. (2006 p. 208-209); and Agrawal and Taffler (2008, p. 1543)

Fifth, accounting-based models do not take the volatility of assets into account. The volatility, however, is a crucial parameter in assessing the likelihood that a firm will not be able to meet its debt obligations.

Given these severe drawbacks of models relying on accounting data, financial research has shifted the attention towards models that are based on information provided by the market. Here, two schools of thought have evolved: structural models and reduced-form models. The fundamental difference between these two types of models stems from the model's underlying assumptions concerning the timing of default.<sup>49</sup>

Structural models, which originated with the pioneering work of Black and Scholes (1973) and Merton (1974), assume a complete information set, that is, a detailed market knowledge including the information held by a firm's management.<sup>50</sup> According to these models, default occurs when some exogenously modelled asset value hits a certain boundary.<sup>51</sup> Hence, the time of default is entirely predictable.

Reduced-form models originated with the work of Jarrow and Turnbull (1995). These models make less strong assumptions about the information set. Here, only the observable market information is relevant. In these models, default is determined by an exogenous hazard rate (intensity) process.<sup>52</sup> Consequently, the time of default cannot be precisely estimated.

Empirical finance has tried to shed light on the question which frameworks better forecasts corporate bankruptcy. The results remain mixed. Whereas Jones et al. (1984) find evidence for structural models to under predict credit spreads, others such as Eom et al. (2004) suggest that this is not the case. Similarly, reduced-form models have generated diverging results.<sup>53</sup> However, one of the main arguments for these contradicting results stems from the use of different datasets and timeframes. In an attempt to resolve this problem of comparability, Gündüz and Uhrig-Homburg (2005) directly compare both bankruptcy prediction frameworks using identical data sets and come to the conclusion that both approaches yield similarly adequate performances.

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<sup>49</sup> Elizalde (2006, p. 1)

<sup>50</sup> Jarrow and Protter (2004, pp. 1-2)

<sup>51</sup> Uhrig-Homburg (2002, p. 24)

<sup>52</sup> Uhrig-Homburg (2002, p. 25)

<sup>53</sup> Gündüz and Uhrig-Homburg (2005, p. 6)

Despite this ongoing debate, market-based bankruptcy prediction models have become increasingly popular. Their theoretical justification, flexibility and performance with respect to forecasting firm failures have made them widely accepted among both practitioners as well as in academia. The introduction of commercial versions of market-based financial distress models such as Moody's KMV Model or JP Morgan CreditMetrics clearly underlines this ongoing trend.

Market-based models are, however, not without limitations. One major shortcoming includes the strong assumption about market efficiency. Only if market prices truly reflect all available information, distress risk can adequately be estimated. However, financial research has repeatedly provided evidence for numerous anomalies that cast doubt on this assumption.<sup>54</sup> A further disadvantage is that market-based distress risk prediction models can exclusively be applied to public firms. The information required to estimate distress risk is simply not available for private firms, since market prices are not observable.

In sum, market-based models of financial distress have become an indispensable tool for estimating default risks. The next sections discuss the most prominent and widely used structural and reduced-form model: the Merton (1974) model, the KMV model and Shumway's (2001) hazard model.<sup>55</sup>

#### 2.1.1.2.1. Structural Models: The Merton Model

The pioneering work of Black and Scholes (1973) and Merton (1974) can be considered the natal hour of many different strands of financial research including the theoretical work on structural financial distress prediction models.<sup>56</sup> As Merton (1974) notes in his original article:

*“While a number of theories and empirical studies has been published on the term structure of interest rates [default-risk-free], there has been no systematic development of a theory for pricing bonds when there is a significant probability of default”.*<sup>57</sup>

One fundamental insight provided by this seminal work includes an intuitive and internally consistent way of how a firm's debt can be valued in the presence of default risk. Applying Black and Scholes' (1974) option pricing model, Merton (1974) shows that a firm can be

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<sup>54</sup> See e.g. Ritter (1991), Jegadeesh and Titman (1993) Loughran and Ritter (1995), Sloan (1996), Daniel and Titman (2006), Campbell et al. (2008) for evidence of pricing anomalies in financial markets

<sup>55</sup> Shumway's (2001) Hazard Rate Model is a variant of a reduced-form model

<sup>56</sup> Crosbie and Bohn (2002, p. 14)

<sup>57</sup> Merton (1974, p. 449).

modelled in a contingent claim setting. Here, two assumptions are of critical importance:<sup>58</sup> First, a firm's assets consists of only equity ( $V_E$ ) and a zero-coupon bond that has a face value  $F$  and a maturity date  $T$ . Second, the value of the assets ( $V_A$ ) follows a geometric Brownian motion in the following form:

$$dV_A = \mu V_A dt + \sigma_A V_A dW \quad (3)$$

where,  $V_A$  denotes the market value of the firm's assets with an instantaneous drift  $\mu$ , volatility  $\sigma_A$  and a standard Wiener process  $W$ .

In this setting, the payoff structure of a firm's shareholders is equivalent to the payoff structure of a plain-vanilla European call option on the firm's assets. Thus, the shareholders can be regarded as residual claimants on the firm's assets, after all debt obligations have been fulfilled. The strike price of the option is equal to the face value of the outstanding debt. Consequently, shareholders possess the right, but not the obligation, to pay off all debt holders and absorb the remaining assets.<sup>59</sup> Here, the expiration date of the European call option is equal to the maturity date of the liabilities. Only if the market value of the firm's assets exceeds the book value of the firm's debt on the expiration date, will the shareholder exercise their option. In this case, all debt obligations are repaid and the firm continues to exist.<sup>60</sup> If, however, the market value of the firm's assets is smaller than the face value of debt on expiration date, the shareholders will discard their option, leaving all residual assets to the debt holders. In this case, the firm defaults.<sup>61</sup>

It is important to note that the firm can only default at maturity  $T$ . Otherwise, the Black and Scholes (1973) option pricing model cannot be applied to derive the value of the firm's equity. The equity value of the firm can then be expressed as a function of the total firm value as shown in the subsequent equation:<sup>62</sup>

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<sup>58</sup> Sundaram (2010, S. 803).

<sup>59</sup> Crosbie and Bohn (2002, p. 11).

<sup>60</sup> The payoff function to the shareholders can be shown in the following way:  $V_E = \max[V_A - F, 0]$ , where,  $V_E$  denotes the market value of the firm's equity,  $V_A$  denotes the market value of the firm's assets and  $F$  denotes the face value of the firm's liabilities. Hence, the shareholder are long the firm's assets, borrow the debt and also hold a put option enabling them to sell the firm's asset for an amount equal to  $F$ .

<sup>61</sup> Similarly, using the put-call parity framework, the option value to the debtholders at time of maturity  $T$  can be expressed mathematically in the subsequent equation:  $F_T = F - \max[F - V_A, 0]$ . This implies that the debtholders claim is equal to a portfolio consisting of a long position of a default free bond paying  $X$  at maturity  $T$  and a short position of a put option on the firm's assets with a strike price of  $X$  and maturity  $T$ .

<sup>62</sup> Vassalou and Xing (2004, p. 835).

$$V_E = V_A N(d_1) - F e^{-rT} N(d_2) \quad (4)$$

where,

$$d_1 = \frac{\ln\left(\frac{V_A}{F}\right) + \left(r + \frac{1}{2\sigma_A^2}\right)T}{\sigma_A \sqrt{T}} \quad (5)$$

$$d_2 = d_1 - \sigma_A \sqrt{T} = \frac{\ln\left(\frac{V_A}{F}\right) + \left(r - \frac{1}{2\sigma_A^2}\right)T}{\sigma_A \sqrt{T}} \quad (6)$$

$V_E$  is the market value of the equity,  $V_A$  is the market value of the total assets,  $F$  is the face value of debt with time to maturity  $T$ ,  $r$  is the risk-free rate,  $\sigma_A$  is the asset's volatility,  $F e^{-rT}$  is the present value of the debt, and  $N(\cdot)$  is the cumulative density function.

The Merton (1974) model then estimates the risk neutral probability that the value of the firm's assets exceeds the face value of its debt at time to maturity  $T$ . The risk neutral probability is calculated as follows:

$$\text{Probability } \{V_A < F\} = N(-d_2) \quad (7)$$

From the equations above, it can be observed that the risk neutral probability depends on the same factors as the value of an option. Specifically, there is a positive relation between the estimated default risk and the firm's leverage (either through a higher face value of debt or a lower asset value), the asset's volatility and the time to maturity. Conversely, a negative relation exists between default risk and the risk-free rate as well as the asset value.

The Merton model has an intuitive appeal as it directly applies the Black and Scholes' (1973) option pricing framework to estimate the probability of a firm's default at each given point in time. However, in addition to the abovementioned critical assumptions concerning the capital structure of the firm and the stochastic behaviour of the firm's asset value, a battery of further assumptions have to satisfy in order for the model to function. These include perfect capital markets (no taxes, no transaction costs, no informational advantages, only price takers), continuous trading, perfect liquidity, absolute dilution protection, constant volatility, bankruptcy protection, no borrowing-lending spread and a risk-free rate that is a nonstochastic,



known function of time.<sup>63</sup> Moreover, issues concerning the problematic use of normality in the return distribution and the static nature of the capital structure remain unresolved. These assumptions clearly draw a rather distorted picture of reality putting the estimated default probability as a true indicator of bankruptcy risk into question.

After the introduction of the Merton (1974) model, financial research has made a number of attempts to encounter the shortcomings related to these restrictive assumptions. Over the years, a variety of model extensions have been developed that relax one or more of the abovementioned assumptions.<sup>64</sup> For example, Black and Cox (1976) extended the original Merton (1974) model by allowing firms to default prior to the debt's maturity date. In their model, default is triggered if the asset value drops below a predefined boundary for the first time. Also, Black and Cox (1976) model safety covenants and consider senior and subordinated debt in the capital structure.<sup>65</sup>

Longstaff and Schwartz (1995) extend the Black and Cox (1976) model by allowing interest rates to follow a stochastic process. This addition influences the firm value process as the firm value now varies with different levels of interest rates. Leland (1994) and Leland and Toft (1996) further expanded this approach by integrating certain tax benefits of debt into the model. Specifically, the authors allowed for different debt structures with respect to amount and maturity. Also, the default boundary is endogenized in a way that shareholders can optimally choose the default time.

Anderson and Sundaresan (1996) and Mella-Barral and Perraudin (1997) relax the assumptions regarding the costs of liquidation. The authors argue that a liquidation process further induces costs to the debt holders in case of default. This, in turn, may incentivize equity holders to negotiate a slack in debt payments as the cost of liquidation is entirely born by the firm's debt holders. Zhou (1997) models the firm value process as a jump-diffusion, relaxing the assumption of normality in return distributions. Default can occur any time before debt maturity, but firm value is shaped in a way that allows for "jump-downs". This in turn, indicates that the value of the firm at default can be less than a pre-specified boundary as modeled by Black and Cox (1976) and Longstaff and Schwartz (1995). Collin-Dufresne et al. (2001)

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<sup>63</sup> Bohn (2000, p. 56).

<sup>64</sup> Only the most important extensions are described. It should be noted that the description is meant to be indicative, rather than comprehensive. For an extensive review of structural default risk models see e.g. Eom et al. (2004) or Uhrig-Homburg (2002)

<sup>65</sup> Sundaresam (2013)

integrate the tendency of firms to target a certain leverage structure into their model. Also, interest rate may follow a stochastic process, rather than being deterministic.

Given the diversity of structural models, it is only natural to raise the question of which model shows the most accurate performance. Unfortunately, empirical examinations of the various models lead to mixed results. For example, Eom et al. (2004) tests five of the abovementioned models on a common dataset in the time period from 1986 to 1997 and finds that none accurately predicts default spreads.<sup>66</sup> While the Merton (1974) model tends to under predict spreads, extended versions seem to suffer from over-prediction errors. Huang and Huang (2003) provide evidence for extended models to perform similarly inaccurate: All models predict substantially lower spreads. Hence, further investigations concerning structural models of financial distress remain inevitable.

To summarize, the Merton (1974) model is a simple, robust and intuitive technique for estimating and predicting failure probabilities of corporate entities. It applies the concepts of Black and Scholes' (1973) option pricing model and is based on sound economic reasoning. However, the model's robustness comes at the price of strong restrictive assumptions. Numerous model extensions have tried to tackle this shortcoming. However, empirical results remain mixed. Generally, structural distress risk models still seem to be one of the most widely accepted models in academia. Particularly, the well-known KMV Model, an offspring of the original Merton model appears to offer substantial advantages in the implementation process. Due to the fact that it has "*become a de facto standard for default risk measurement in the world of credit risk*", the next section will discuss the KMV model separately.<sup>67</sup>

#### 2.1.1.2.2. The KMV-Model

Generally, the KMV model is a variant of the original Merton (1974) model.<sup>68</sup> Both models draw from the insights that a firm can be viewed in an option-based framework. There are however, fundamental dissimilarities. The most important difference regards the overall objective: While the Merton (1974) model's major objective is to value a firm's risky debt based on the assets and volatilities, the KMV model specifically aims at assessing the

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<sup>66</sup> These models include Merton (1974), Geske (1977), Longstaff-Schwartz (1995), Leland and Toft (1996), and Collins-Dufresne et al. (2001)

<sup>67</sup> Kealhofer (2003, p. 30).

<sup>68</sup> KMV stands for Kealhofer, McQuown and Vasicek.

underlying credit risks by focusing on the relationship between a firm's asset and equity characteristics.<sup>69</sup>

In addition, there are also several other aspects in which the two models differ:<sup>70</sup> First, the KMV model treats the firm's equity as a perpetual call option on the assets. This feature mirrors the firm's ability to borrow and repay debt continuously. Second, a more realistic picture of a company's capital structure is assumed. Specifically, the model allows various types of equity including common stock, convertible stock, preferred stock, and warrants. Similarly, liabilities cannot not only consist of a single zero coupon bonds, but also any other classes of debt obligations such as short- and long-term debt, convertible debt and non-debt fixed liabilities. Here, it is assumed that all assets make fixed cash payments, that is, dividends in the case of equity and coupons for debt instruments. Third, the firm can default at any time, given that the asset value has dropped below a predefined threshold level.<sup>71</sup> A summary of the main differences between the Merton (1974) model and the approach adopted by KMV can be observed in Table 1 below.

**Table 1: Differences Between Merton's (1974) Model and the KMV Model**

Merton's (1974) Model	KMV Model
<ul style="list-style-type: none"> <li>• Two classes of liabilities: Short-term liabilities and common stock</li> </ul>	<ul style="list-style-type: none"> <li>• Five classes of liabilities: Short-term and long-term debt, common stock, preferred stock, and convertible stock</li> </ul>
<ul style="list-style-type: none"> <li>• No cash pay outs</li> </ul>	<ul style="list-style-type: none"> <li>• Cash pay outs: Coupons and dividends (common and preferred stock)</li> </ul>
<ul style="list-style-type: none"> <li>• Default occurs only at horizon</li> </ul>	<ul style="list-style-type: none"> <li>• Default an occur at or before horizon</li> </ul>
<ul style="list-style-type: none"> <li>• Default barrier is total debt</li> </ul>	<ul style="list-style-type: none"> <li>• Default barrier is empirically determined</li> </ul>
<ul style="list-style-type: none"> <li>• Equity is a call option on assets, expiring at the maturity of the debt</li> </ul>	<ul style="list-style-type: none"> <li>• Equity is a perpetual call option on assets</li> </ul>
<ul style="list-style-type: none"> <li>• Gaussian relationship between probability of default and distance to default</li> </ul>	<ul style="list-style-type: none"> <li>• Distance to default to expected default frequency mapping empirically determined from calibration of historical data</li> </ul>

Essentially, the KMV model uses the firm's value and volatility to compute its implied probability to default. In this context, the model relies on the two fundamental insights as

<sup>69</sup> Kealhofer (2003, p. 32).

<sup>70</sup> Kealhofer (2003, p. 32).

<sup>71</sup> This feature is similar to the work of Black and Cox (1976).

provided by the Merton (1974) model. First, the value of the equity is equal to the difference of the value of the assets and the value of the debt.<sup>72</sup> Second, the volatility of the equity is related to the volatility of the assets. Given the assumption in the Merton (1974) model, it follows directly from Ito's Lemma that

$$\sigma_E = \frac{V_A}{V_E} \times \frac{\partial V_E}{\partial V_A} \times \sigma_A = \frac{V_A}{V_E} \times N(d_1) \times \sigma_A \quad (8)$$

where,  $\frac{\partial V_E}{\partial V_A}$  is the partial derivative of the equity value with respect to the asset value.<sup>73</sup> The equation verifies that the volatility of the firm's asset depends on the volatility of the firm's equity. Whereas the value of the firm's equity as well as the corresponding volatility is readily computable, both the firm value and volatility must be estimated.<sup>74</sup> Once the numerical solution is found, a distance to default (DD) can be estimated using the subsequent equation:

$$DD = \frac{\ln\left(\frac{V_A}{F}\right) + \left(\mu - \frac{1}{2\sigma_A^2}\right)T}{\sigma_A\sqrt{T}} \quad (9)$$

where  $\mu$  is devoted to an estimate of the expected annual return of the firm's assets. The implication of the distance-to-default measure is intuitive: It shows "*the number of standard deviation moves required to bring the company to the default point within a specified time horizon*".<sup>75</sup> Put differently, the distance-to-default expresses the distance of the firm's assets to its default point, normalized by its standard deviation.

The distance-to-default measure, however, is an ordinal, absolute number that tells nothing about the actual probability to default.<sup>76</sup> In the Merton (1974) model, a normal distribution of returns is assumed translating into risk neutral probabilities of firm failures. The KMV model, however, takes a different approach. Instead of using a Gaussian function it applies the distribution of a large propriety database of actual defaults to compute the expected default frequency (EDF).<sup>77</sup> Specifically, it compares the firm's computed distance-to-default measure to the distance-to-default values in the database and examines whether firms with similar

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<sup>72</sup> Equation 4 in the section above shows this relationship mathematically.

<sup>73</sup> See e.g. Hull et al. (2004) for a detailed description

<sup>74</sup> KMV uses a complicated iterative procedure to solve for  $V_A$  and  $\sigma_A$ . This procedure takes certain dynamics in the capital structure into account. Please see Section 3 for a detailed explanation. As Crosbie and Bohn (2001, p.16) note "In practice the market leverage moves around far too much [...] to provide reasonable results"

<sup>75</sup> Kealhofer (2003, p. 32).

<sup>76</sup> Kealhofer (2003, p. 32).

<sup>77</sup> KMV collected information on defaulted firms for over 30 years.

distance-to-default measures defaulted within a given year or not.<sup>78,79</sup> One major advantage of using this database of actual defaults is that it takes potential excess kurtosis in the default distributions into account. Clearly, this draw a more realistic picture of reality since the use of a normal distribution may lead to an underestimation of default probabilities.<sup>80</sup>

It remains rather difficult to rigorously test the KMV model on the performance in estimating and predicting the likelihood of business failure. This mainly stems from the unavailability of the propriety database used to estimate a firm's EDF. Barath and Shumway (2004) make an attempt to compare the performance of a slightly adapted KMV model to a simpler, so-called "naïve" alternative.<sup>81</sup> This "naïve" approach is constructed in a way that approximates the functional form of the KMV model and captures the same informational contents. However, it circumvents the difficulties associated with the complicated iterative process and simultaneously solving for  $V_A$  and  $\sigma_A$ . Therefore, several approximations are assumed. First, the market value of a firm's debt equals its face value (Naïve  $D = F$ ). Second, the volatility of a firm's debt can be approximated by the following equation:

$$naive \sigma_D = 0.05 + 0.25 \times \sigma_E \quad (10)$$

where  $\sigma_D$  and  $\sigma_E$  are the volatilities of debt and equity respectively. The intuition of this approximation stems from the fact that firms under financial pressure have very risky debt, and that this debt is then positively correlated with its equity. The numerical value in the equation 0.05 and 0.25 are intended to represent the term structure volatility and default risk volatility, respectively.

The total volatility can then be computed as shown in the equation below:

$$\begin{aligned} Naive \sigma_V &= \frac{V_E}{V_E + Naive D} \times \sigma_E + \frac{Naive D}{V_E + Naive D} \\ &\times Naive \sigma_D \\ &= \frac{V_E}{V_E + F} \times \sigma_E + \frac{F}{V_E + F} \times (0.05 + 0.25 \times \sigma_E) \end{aligned} \quad (11)$$

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<sup>78</sup> Sundaram (2010, p. 817).

<sup>79</sup> The time horizon in the KMV model can be altered up to five years of default prediction

<sup>80</sup> See e.g. Jones et al. (1984), Ogden (1987), Lyden and Saraniti (2000)

<sup>81</sup> The main difference between the original KMV model and the version used by Bharath and Shumway (2008) is that the former uses its propriety database for EDF calculation, whereas the latter uses a lognormal distribution. The authors note that "that it is entirely possible that the proprietary features of KMV's model make its performance superior to what I document here" (Bharath & Shumway, 2004, p. 8).

Then, the firm's expected return on its assets is set equal to the return on its equity over the previous year.

$$Naive \mu = r_{it-1} \quad (12)$$

This feature captures some of the information gathered in the iterative process in the original KMV model. Finally, the naïve distance-to-default can be computed in the following way:

$$Naive DD = \frac{\ln \left[ \frac{(V_E + F)}{F} \right] + (r_{it-1} - 0.5 \times Naive \sigma_V^2)T}{Naive \sigma_V \sqrt{T}} \quad (13)$$

Barath and Shumway (2008) show that the naïve approach outperforms the KMV model in terms of default prediction accuracy in an out-of-sample test. Furthermore, this alternative is easy to compute, retains a similar structure and utilizes equivalent information as the KMV model.<sup>82</sup>

To summarize, The KMV model provides a more realistic default measure compared to the “vanilla” Merton (1974) model. Even though the two models possess common roots, there are significant differences. The KMV model allows for different security types with interim pay outs and circumvents the problem of nonnormality in default distributions. Furthermore, default may occur any time before maturity. An exact empirical investigation remains difficult as the default database is strictly exclusive for KMV clients. An approximation, however, shows that there are superior models with respect to prediction accuracy. In the next section, reduced-form models will be discussed, which have exhibited improved performances<sup>83</sup>.

#### 2.1.1.2.3. Reduced-form Models: Shumway's (2001) Hazard Model

Reduced-form credit risk models – which are also known as hazard rate or intensity-based models – were originally introduced by Jarrow and Turnbull (1992), Jarrow and Turnbull (1995) and Duffie and Singleton (2000).<sup>84</sup> This tool for estimating and predicting default risk differs substantially from structural models. Particularly, these models are structured in a way that allows them to overcome one of the major shortcomings of structural credit risk models: The computation of a firm's asset value and volatility. While the implementation process of structural models concerning the valuation of a firm's asset value proved problematic, reduced-form models approach default risk predictions from an entirely different direction. Information

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<sup>82</sup> Bharath and Shumway (2008, p. 1348).

<sup>83</sup> Bharath and Shumway (2008, p. 1367).

<sup>84</sup> Gündüz and Uhrig-Homburg (2005, p. 5).

on a firm's capital structure is no longer required as default does not depend on firm values dropping below a certain threshold level. Instead, it is estimated according to some exogenously specified intensity process.<sup>85</sup>

A further significant difference between structural and reduced-form models concerns the estimation of the default time. Whereas structural models make an attempt to stipulate the exact point in time of default, reduced-form models assume that default comes as a surprise. That is, the default time is a totally inaccessible stopping time.<sup>86</sup> This implication is intuitive given the fact default prediction is based on a shift of an exogenously modelled variable.

Jarrow and Protter (2004) note that the assumptions underlying reduced-form models are more realistic compared to structural credit risk models. Instead of assuming a complete information set, these models only use the information as it is observable by the market. These less stringent assumptions, their functional flexibility as well as mathematical tractability has made them a widely accepted tool for credit risk estimation and in the credit trading arena<sup>87</sup>

A detailed discussion of all available reduced-form models of credit risk is clearly beyond the scope of this paper.<sup>88</sup> Therefore, this section will focus on Shumway's (2001) Simple Hazard Model because this model (or slight adaptations of it) has found its application in many empirical studies related to equity capital markets.<sup>89</sup> The model is based on the idea of survival analysis as outlined in Cox and Oakes (1984). That is, the model relates the underlying covariates to the time that passes before the bankruptcy event occurs. Consequently, the model captures the changes in default risk through time adjusting for time-varying intensities automatically.

Shumway's (2001) Simple Hazard Model assumes that default can occur only at discrete points in time ( $t = 1, 2, 3 \dots$ ). The failure time of firm  $i$ , is defined as the time when a firm leaves the sample ( $t_i$ ). The total sample consists of  $n$  firms. A dummy variable is denoted  $y_i$ , being equal to one if the firm  $i$  is bankrupt and zero otherwise. The probability mass function of firm failure is given by  $f(t, x; \theta)$ , where  $\theta$  is denoted the vector of parameters of  $f$  and  $x$  represents a

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<sup>85</sup> Jarrow and Protter (2004, p. 4).

<sup>86</sup> Jarrow and Protter (2004, p. 2).

<sup>87</sup> Arora et al. (2005, p. 3)

<sup>88</sup> See Onmus-Baykal (2010) for a detailed overview of the work on reduced-form credit risk models

<sup>89</sup> See e.g. Campbell et al. (2008), Chava and Purnanandam (2010), Hackbarth et al. (2013), Conrad et al. (2012)

vector of explanatory variables. The survival function  $S(t, x; \theta)$ , that is, the probability that the firm survives the time period  $t$  can be depicted in the following form:

$$S(t, x; \theta) = 1 - \sum_{j < t} f(t_j, x; \theta) \quad (14)$$

The hazard function  $\phi(t, x; \theta)$ , that is, the probability that the firm defaults at  $t$  given the survival until  $t$  can then be expressed in the following equation:

$$\phi(t, x; \theta) = \frac{f(t, x; \theta)}{S(t, x; \theta)} \quad (15)$$

Thus, the hazard function relates the probability density function to the survival function and can be seen as an instantaneous risk of default. The parameter estimates are computed by maximizing the likelihood function of the following form:

$$\varphi = \prod_{i=1}^n \phi(t, x; \theta)^{y_i} S(t, x; \theta) \quad (16)$$

While hazard model in general have nonlinear likelihood function which are difficult to estimate, Shumway (2001) shows that the likelihood function of the discrete-time hazard model equals the likelihood function of a multiperiod-logit model. This feature facilitates an easy implementation in empirical studies. One can simply use the output of a logit program and adjust the test statistics for issues related to interdependencies of observations.<sup>90</sup> Shumway (2001) suggests to include an age indicator into the hazard function to model the assumption of homogeneity between firms that were listed in the same period of time. Partitioning  $\theta$  into  $\theta_1$  and  $\theta_2$ , the hazard function is then given by the following equation:

$$\phi(t, x; \theta_1, \theta_2) = \frac{1}{1 + \text{Exp}(g(t)' \theta_1 + x' \theta_2)} \quad (17)$$

Where  $g(t)$  is denoted a function of the firm's age. The second part in the denominator  $x_2 \theta_2$  represents some variables describing the financial health of the company. Shumway (2001)

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<sup>90</sup> Shumway (2001, p. 13) states that in "the hazard model, each firm's entire life span is one observation. Thus, the correct value of  $n$  for test statistics is the number of firms in the data, not the number of firm-years. The  $\chi^2$  test statistics produced by logit programs are of the form  $\frac{1}{n} (\hat{\mu}_k - \mu_0)' \Sigma^{-1} (\hat{\mu}_k - \mu_0) \sim \chi^2(k)$ , where there are  $k$  estimated moments being tested against  $k$  null hypotheses,  $\mu_0$ . Dividing these test statistics by the average number of firm-years per firm makes the logit program's statistics correct for the hazard model".



uses three market-based and two accounting-based variables as explanatory variables. Specifically, these include past stock returns, market size, a stock's idiosyncratic volatility, net income-to-total assets ratio, and total liabilities-to-total assets ratio.<sup>91</sup>

Naturally, various other variables can be included in the hazard model specification. For example, Hillegeist et al. (2004) includes macroeconomic variables such as volatility of exchanges rates or changes in interest rates into the hazard function. This feature guarantees a sufficient degree of model flexibility.

Generally, Shumway (2001) argues that the Simple Hazard Model is preferable over other standard bankruptcy prediction models such as Altman's (1968) Z-Score model or Ohlson's (1980) O-Score model. Specifically, the Shumway (2001) states three reasons: First, hazard models take a firm's risk in every period into account. That is, these model control for the fact that many firms are financially under pressure many years before the actual bankruptcy filing. This is particularly important when forecasting periods are rather long. Second, hazard models incorporate time-varying covariates or explanatory variables that may change through time. Third, hazard models are based on richer information by simply employing larger set of time-series data. Intuitively, this will produce more accurate default predictions.

Empirically, Shumway's (2001) Simple Hazard Model exhibits an enhanced performance in predicting firm bankruptcies. Three-quarters of the bankrupt firms are ranked into the highest default risk decile, while only 3.5% are ranked below the median bankruptcy probability. Overall, the model's flexibility, ease of implementation and prediction accuracy has made them a widely used tool for assessing default risk in the empirical finance literature.

#### 2.1.1.2.4. Section Summary

Market-based models can be divided into structural and reduced-form models. Structural models, which originated with the seminal work of Black and Scholes (1973) and Merton (1974) assume a complete information set and thus suggest that the timing of the default is entirely predictable. These models are based on sound economic underpinnings in that default occurs to an endogenously variable falling behind a pre-specified threshold. In contrast, reduced-form model, which were introduced by Jarrow and Turnbull (1992), only rely on the information that is actually observable by the market. Here, default is modelled by an

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<sup>91</sup> Shumway (2001) also tries different hazard models using only market variables. A model that combines accounting-based and market-based variables outperforms in terms of bankruptcy classification.

exogenously variable that follows a certain intensity process. Consequently, default timing is inaccessible and comes as a surprise.

In section 2.2.1.2, three market-based models are discussed in detail: Merton's (1974) option pricing model, Moody's KMV model and Shumway's (2001) hazard rate model. The Merton (1974) model suggests that the firm can be viewed in an option-based framework. Here, equity holders can be regarded as residual claimants as they possess a European call option on the firm's assets. Only if all debt obligations have been fulfilled, shareholders can extract the remaining assets. The strike price of the option is then equal to the face value of the outstanding debt. Similarly, the time to maturity equals the time to maturity of the debt. Moody's KMV model is a variant of the Merton's (1974) model. The major differences concern assumptions about the firm's capital structure, default timing and the use of an empirically estimated dataset of actual default probabilities.<sup>92</sup>

Shumway's (2001) Hazard Model is based on survivor analysis and relates the covariates to the time that passes before the bankruptcy event. Thus, the model explicitly considers the financial condition of a firm prior to the bankrupt event when estimating the likelihood of default. Explanatory variables include both, market-based and accounting-based variables. The model can be estimated using a standard multi-period logit model as the likelihood functions of the model are identical. This facilitates an easy implementation and as well as simple and intuitive statistical inferences. Given the enhanced performance, the hazard model of bankruptcy prediction has found many applications in the empirical finance literature.

#### 2.1.2. Distress Risk and the Cross-section of Stock Returns

Modern financial theory as put forward by Markowitz (1952) suggests that investors should be provided with a return premium for bearing larger risks. This fundamental understanding later found application in the Capital Asset Pricing Model (CAPM henceforth).<sup>93</sup> In the CAPM model, the beta factor relates a stock's returns to its underlying risk. The higher the beta, the higher the expected return on the stock. Theoretically, the beta captures all the information relevant to compute the expected returns. Empirically, however, the beta has done a poor job in predicting equity returns. Instead, Fama and French (1992) show that a large part of the cross-sectional variation in stock returns can be explained by two simple variables: size and

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<sup>92</sup> Table 1 in Section 2.2.1.2.2 provides a summary

<sup>93</sup> See Sharpe (1964) and Lintner (1965)

the book value-to-market value ratio. Firms with higher loadings on the size and book-to-market (BM henceforth) factor are associated with higher returns. A natural question to ask is whether these two factors can be regarded as proxies for certain risks not captured in the beta factor. Fama and French (1993) argue that the size and BM factors are proxies for distress risks.<sup>94</sup> The underlying reasoning is as follows: The small market capitalization of firms increases the probability of default, particularly in times of economic recessions. Similarly, high BM stocks have been found to exhibit low earnings, higher leverage, increased earnings uncertainty and are more likely to cut dividends.<sup>95</sup> Clearly, this makes them more risky and investors naturally charge a return premium. This line of reasoning has been dubbed the distress factor hypothesis. On the other hand, behavioural factors may explain the existence of a size and value premium. For example, DeBondt and Thaler (1987) suggest that the high returns to high BM stocks are driven by investors' irrationality concerning the extrapolation of past performances.<sup>96</sup>

In order to provide answers to the distress factor hypothesis, research has focused on a direct examination of the relation between distress risk and equity returns. Surprisingly, a number of studies find evidence for a negative relation. This empirical result is even more puzzling. While a positive relation would clearly challenge the CAPM and its beta factor, a negative relation entirely contradicts the fundamentals of financial theory: Higher risk produce lower expected returns.

This section provides a thorough review of the literature on the cross section of equity returns and distress risks. Specifically, the following two questions are addressed: First, what is the relation between measures of bankruptcy risks and stock returns? Second, what can explain the observed relation? The section is structured into the two following positions: Views supporting a mispricing hypothesis and other explanations to the distress puzzle.

#### 2.1.2.1. Mispricing Hypothesis

Dichev (1998) is one of the first to specifically examine the relation between distress risk and the cross-section of equity returns. Particularly, the author approximates the extent to which a firm suffers from financial distress by a measure of bankruptcy probability and investigates

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<sup>94</sup> In related studies, Chan et al. (1983) show that the size effect can be explained by a default factor consisting of the difference between the returns on high-grade and low-grade bond. Fama and French (1993) and Chen, Roll, and Ross (1986) provide evidence for a similar default factor to be significant in explaining stock returns

<sup>95</sup> See e.g. Chen and Zhang (1998)

<sup>96</sup> See also Lakonishok et al. (1994) and Haugen (1995)

corresponding return performances. The probability of bankruptcy is computed using well-known credit risk models including Altman's (1968) Z-score and Ohlson's (1980) O-Score. The main findings clearly contradict modern financial theory:<sup>97</sup> First, stocks with high probabilities of default appear to earn significantly lower returns compared to stocks with low default probabilities. A zero cost, long-short trading strategy that buys financially sound stocks and sells short high default stocks yields monthly returns of 1.17%. This returns difference is statistically significant at the 1% level. Thus, financial distress as proxied by bankruptcy probabilities appears not to be associated with higher returns. Second, the book-to-market effect is not reliably related to the return premium of distressed stocks. Even though distressed stocks have generally higher BM ratios, the relation is not monotonic: the most distressed stocks deciles exhibit considerably lower BM ratios. This erases the possibility that the observed return premiums can explain the BM effect. Similarly, the size effect – while being virtually non-existent in more recent periods – appears not to be related to bankruptcy risks.<sup>98</sup> In fact, an analysis of earlier periods indicates that bankruptcy risk cannot explain the size effect.<sup>99</sup> Last, Dichev (1998) examines the performance of distressed and non-distressed stocks over longer return windows of up to four years. The analysis suggests that the observed phenomenon is likely to be related to market mispricing. Even though the returns to distressed stocks are increasing over a longer time window, they clearly remain behind those of non-distressed stocks. Thus, Dichev (1998) concludes that “market prices do not fully impound the implications of available bankruptcy information”.<sup>100</sup>

Similarly to the picture drawn by Dichev (1998), Griffin and Lemmon (2002) document that the distress effect – the negative relation between distress risk and stock returns – cannot entirely be subsumed under the BM effect. Specifically, the authors sort the stocks according to their distress risk as measured by Ohlson's (1980) O-score and examine corresponding return performances and stock characteristics. The analysis shows that the group of high default risk firms indeed includes high BM ratio stocks with weak earnings, high leverage and low sales growth – characteristics that are usually associated with distress risk.<sup>101</sup> The respective returns of this group are only slightly larger compared to other high BM firms. For these firms, the distress factor does not seem to add any significant information not captured by the BM ratio.

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<sup>97</sup> Dichev (1998, p. 1140 – 1144).

<sup>98</sup> Dichev (1998, p. 1132) notes that the disappearance of the size effect after the 1980s is “somewhat of a puzzle”.

<sup>99</sup> Dichev (1998, p. 1146).

<sup>100</sup> Dichev (1998, p. 1146).

<sup>101</sup> Griffin and Lemmon (2002, p. 2318).

However, most of the firms in the high distress segment consist of low BM firms that exhibit admittedly low earnings, but high R&D expenditures and sales growth.<sup>102</sup> The returns are significantly lower compared to firms with similar BM ratios. Griffin and Lemmon (2002) conclude that the inferior performance of distressed stocks as observed by Dichev (1998) mainly stems from this particular group of low BM stocks. Given the fact that the low BM, high distress risk stocks appear not to be considerably riskier, the authors argue that the documented return pattern is caused by mispricing.<sup>103</sup> That is, low BM stocks are underpriced, while high BM stocks are overpriced. Consistent with this hypothesis, the degree of informational asymmetries and limits to arbitrage tend to be stronger among low BM stocks. An analysis of abnormal earnings announcement returns provides further evidence for the mispricing story. The difference in earnings announcement returns between low and high BM stocks is largest in the highest O-score segment.<sup>104</sup> While low BM firms show negative earnings announcement returns – indicating that investors are disappointed with the firms’ fundamentals, high BM firms exhibit positive earnings announcement returns.

Campbell et al. (2008) develop an own empirical measure of distress risk to address the question of whether distressed stocks have historically underperformed or not. Their approach for estimating the degree to which a firm may be financially under pressure is based on the methodologies as put forward by Shumway (2001) and Chava and Jarrow (2004).<sup>105</sup> Specifically, they use a reduced-form credit risk model consisting of both market and accounting-based data. Using a “fitted” estimate of default probability, Campbell et al. (2008) examine the return performance, risk attributes and stock characteristics of distressed firms. They find that these stocks have high market betas, large standard deviations as well as high loadings on Fama and French’s (1993) BM and SMB factors, but produce low returns.<sup>106</sup> This relation is difficult to explain using fully rational asset pricing models. Campbell et al. (2008) demonstrate that the return differential between distressed and non-distressed stocks persists across all deciles of value and size distributions. Thus, the BM and SMB factor do not capture the risk information contained in distressed stocks. In further analyses, the Campbell et al.

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<sup>102</sup> Griffin and Lemmon (2002, p. 2318).

<sup>103</sup> Griffin and Lemmon (2002) show that low BM firms in the highest distress risk segment have larger Fama and French (1992) three-factor model loadings compared to firms with similar BM ratios. Also, an increase risk cannot be observed in the profitability of these firms

<sup>104</sup> Griffin and Lemmon (2002, p. 2319).

<sup>105</sup> Specifically, the authors develop a dynamic panel model using a logit specification. Please see Campbell et al. (2008) for a detailed description

<sup>106</sup> Campbell et al. (2008, p. 2933).

(2008) relate the stock returns to a measure of implied volatility and demonstrate that even though returns to distressed stocks are particularly low when market volatility is high, the observed return patterns cannot be explained by increases in market wide risks or risk aversion. Furthermore, the low returns are not clustered around earnings announcement dates. This observation rules out the possibility that overoptimistic investor expectations about the stock's future earnings growth cause an overvaluation and thus decreased future returns. Moreover, classic asset pricing irregularities such as momentum or volatile stocks appear to be unrelated to the "distress anomaly". Campbell et al. (2008) however, find some evidence for behavioural factors driving down the returns to risky distressed stocks. First, there is a possibility that some investors favour stocks with positively skewed returns. For example, Barbaris and Huang (2008) argue that the high prices and low returns of IPOs are related to their generally observed positively skewed return distribution. Similarly, distress stocks show a positively skewed returns, which may be preferred by a group of certain investors.<sup>107</sup> Second, distressed stocks may produce certain non-measurable "extra" returns to investors. For example, von Kalckreuth (2005) argues that majority owners of distressed firms are able to extract private benefits in the form of bargain assets or output when a firm defaults. This extra return induces investors to hold these stocks, rather than selling them. Campbell et al. (2008) argue that the persistence of the distress anomaly stems from the fact that these stocks are generally difficult to arbitrage. They show that distressed stocks have lower analyst coverage, intuitional investors, price per share, turnover and are smaller in size – characteristics that usually limit an investor's ability to perform arbitrage trading strategies.<sup>108</sup>

Avramov et al. (2009) approximate financial distress with S&P credit ratings and document a negative relation between default risk and equity returns. However, this negative relation is mainly driven by low-rated stocks experiencing financial distress around credit downgrades.<sup>109</sup> Specifically, the authors study the returns to low-rated and high-rated firms in two economic settings: periods of credit downgrades and stable periods. The analysis reveals that a negative relation between credit risk and equity returns only prevails in the former setting and is entirely attributable to low-rated stocks experiencing significant price slumps three months before and after the actual credit downgrade.<sup>110</sup> Furthermore, these stocks exhibit deteriorated fundamentals and are negatively price pressured by institutional investors liquidating their long

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<sup>107</sup> See also the work of Tversky and Kahneman (1992) on prospect theory

<sup>108</sup> See e.g. Hong et al. (2000) and Nagel (2005)

<sup>109</sup> Avramov et al. (2009, p. 469).

<sup>110</sup> Avramov et al. (2009, p. 498).

positions.<sup>111</sup> Notably, the credit risk effect is non-existent in periods of stable credit conditions or among high-rated firms. Hence, only the performance of a small fraction of stocks in a limited time period accounts for the contradicting empirical findings regarding the risk-return relationships of distressed stocks. Avramov et al. (2009) argue that default risk is idiosyncratic in nature as no evidence can be provided that downgrades and the inherent credit risk effect are dependent on the business cycle. Rather, downgrades occur in both, up and down markets as well as recessions and expansions. Moreover, Avramov et al. (2009) show that downgrades do not occur simultaneously for all firms with similar credit ratings. A natural question to ask is why low-rated, high credit risk firms consistently underperform otherwise comparable stocks. Similar to the conclusions drawn by Campbell et al. (2008), Avramov et al. (2009) argue that these stocks have characteristics that limit the ability to arbitrage them. In fact, the authors show that low-rated stocks are difficult to arbitrage, followed by a restricted number of analysts and are highly illiquid. Thus, investors are prevented from exploiting this obvious mispricing.

Conrad et al. (2012) use a bankruptcy prediction model similar to Campbell et al. (2008) as a proxy for distress risk and argue that a characteristic inherent in distress stocks drives the observed negative returns. The distress anomaly consequently results from investors' preferences for a certain type of stocks. Specifically, the authors suggest that the return pattern of distress stocks resemble a "lottery tickets with a small probability of extremely high returns"<sup>112</sup> In fact, the realized probability of generating more than 100% return per annum increases from 1.4% for low distress firms to 3.7% for high distress firms.<sup>113</sup> This small probability of extremely high returns makes them sufficiently attractive for investors to hold these stocks in their portfolios. This, in turn, causes stock prices to remain high and expected returns to be low, on average. Due to their lottery-like pay-off structure, these stocks have been dubbed "glory stocks". Conrad et al. (2012) argue that the overlap between glory stocks and distress stocks is large enough to explain the low expected returns of distress stocks.<sup>114</sup> The authors provide evidence for a strong correlation between the glory effect and the distress effect. Particularly, the distress effect is only observable for stocks that intersect with the portfolio of glory stocks.

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<sup>111</sup> Avramov et al. (2009, p. 498).

<sup>112</sup> Conrad, Kapadia and Xing (2012, p. 1).

<sup>113</sup> Conrad et al. (2012, p. 1).

<sup>114</sup> In a related study, Barberis and Huang (2008) develop a model using utility functions based on prospect theory. The authors verify that investors can have strong preferences for assets with lottery-like pay-offs, and that this preferences results in high prices but low expected returns

In a recent study, Gao et al. (2012) using expected default frequencies of Moody's KMV model as a proxy for distress risk, examine whether the distress puzzle is also existent in global capital markets. In general, an international investigation sheds further light on the relation between the cross-section of stock returns and default probabilities as well as the validity of potential explanations as offered in previous studies. For example, the enlarged data set provides the opportunity to explicitly address the "out-of-sample" critique as put forward by Chava and Purnanadam (2010).<sup>115</sup> Furthermore, the "shareholder advantage"- argument of Garlappi and Yan (2011) can be re-examined by comparing the relation between stock returns and distress risks across legal environments that differ on the basis of shareholder bargaining powers.<sup>116</sup> Moreover, due to the fact that psychological traits vary across countries, behavioural arguments concerning the distress puzzle can be reviewed.<sup>117</sup> Overall, Gao et al. (2012) verify that the distress puzzle extends beyond the US stock market. Financially distressed firms produce significantly lower returns compared to non-distressed firms. In fact, the authors show that a long-short strategy that sells short the top 10% and buys the lowest 10% of distressed firms generates a monthly premium of 50 basis points, on average.<sup>118</sup> The evidence for a shareholder advantage-based explanation of the distress puzzle is limited. No explicit relation between shareholder expropriation and the downward-sloping relation between equity returns and distress risk can be documented.<sup>119</sup> Instead, Gao et al. (2012) provide evidence that support an explanation based on behavioural factors. In countries with high levels of overconfidence-scores, the distress puzzle is particularly strong.<sup>120</sup> The authors conclude that "investors appear to place too much weight on their prior beliefs, and are thus sluggish to update when confronted with new information".<sup>121</sup> The fact that the negative relation between distress risk and stock returns is concentrated around small capitalization stocks points into a limits-of-arbitrage direction as put forward by Campbell et al. (2008).

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<sup>115</sup> See Section 2.2.2.2 for an explanation of the out-of-sample critique

<sup>116</sup> See Section 2.2.2.2 for a discussion of the "shareholder advantage" argument

<sup>117</sup> See e.g. Chui, Titman and Wei (2010) for an analysis of how country-specific psychological traits affects the momentum in global capital markets

<sup>118</sup> Gao et al. (2013, p. 3).

<sup>119</sup> Gao et al. (2012, p. 33-34).

<sup>120</sup> Overconfidence is measured by Hofstede's (2001) individualism index. The same was used in Chui, Titman and Wei (2010)

<sup>121</sup> Gao et al. (2012, p. 4)



### 2.1.2.2. Alternative Explanations for the Distress Puzzle

In contrast to the findings of Dichev (1998) and Griffin and Lemmon (2002), Vassalou and Xing (2004) find that Fama and French's (1993) high-minus-low (HML henceforth) and small-minus-big (SMB henceforth) factors are related to distress risk. The authors use Merton's (1974) option pricing model as a proxy for distress risk and argue that the SMB and HML factors can be viewed as default effects. Specifically, Vassalou and Xing (2004) show that the size effect is only existent among firms in the highest default risk group and that default risk decreases monotonically as size increases. Thus, the SMB factor captures much of the default risk information. Similarly, the HML effect only exists among firms in the two highest default risk groups.<sup>122</sup> Firms in the highest default risk segment consist of high BM firms that are small in size. Again, a monotonic relation between default risk and the BM factor can be observed. Vassalou and Xing (2004) further provide evidence for a positive relation between default risk and the cross-section of equity returns. This positive relation, however, only pertains to the extent that stocks are small in size and have high BM ratios. For all other stocks, no positive relation can be observed, even if default risk is relatively high. Thus, the authors disclaim the existence of a distress anomaly. A relation between default risk and Fama and French's (1993) SMB and BM factors does not provide answers, however, to the following two questions: First, is default risk is priced in equity returns, that is, can default risk be regarded as a systematic or idiosyncratic risk component? Second, do the Fama and French (1993) SMB and BM factors capture all relevant information about a stock's default risks? Vassalou and Xing (2004) investigate these issues by means of an empirical asset pricing specification that includes default risk as a separate explanatory variable. Vassalou and Xing (2004) demonstrate that default risk is systematic, but cannot be entirely explained by the Fama and French (1993) three-factor model. In fact, they conclude that "SMB and HML appear to contain other significant price information, unrelated to default risk".<sup>123</sup>

In a more recent study, Da and Gao (2010) question the findings of Vassalou and Xing (2004). The authors argue that the observed positive relation between default risk and equity returns is not due to the fact that default risk is systematic, but instead simply driven by the well-documented short-term return reversal effect.<sup>124</sup> Similar to Vassalou and Xing (2004), Da and Gao (2010) use Merton's (1974) option pricing model to estimate a firm's distress risk. The

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<sup>122</sup> Vassalou and Xing (2004, p. 832).

<sup>123</sup> Vassalou and Xing (2004, p. 866)

<sup>124</sup> The short-term return reversal effect was first documented by Jegadeesh (1990) and Lehmann (1990)

study reveals that the most distressed stocks produce high returns only in the first month after portfolio formation. In the second month, returns to distressed stocks already plunge by more than one quarter and further stabilize in later months.<sup>125</sup> Thus, the observed high returns of distressed stocks appear to be only of temporary nature and do not represent a systematic risk premium. In an analysis, Da and Gao (2010) demonstrate that the returns to distressed stocks can fully be explained by rational asset pricing models when one month is skipped between return measurement and portfolio formation. Furthermore, risk characteristics as measured by loadings on Fama and French's (1993) SMB and HML factors as well as the likelihood of default do not significantly change between the first and second month after portfolio formation.<sup>126</sup> Also, the positive returns of the group of distressed firms mainly stem from a small subset of stocks that have experienced sharp increases in default risk and large negative returns in the recent past.<sup>127</sup> Hence, the positive return in the first month after portfolio formation can be regarded as a return reversal effect of these "loser" stocks. Da and Gao (2010) argue that the observed returns reversals of distressed stocks in the first month after portfolio formation are caused by negative selling pressure around portfolio formation. This price pressure results mainly from liquidity shocks and clientele changes. The economic reasoning is as follows: An increase in a firm's probability to default will induce institutional investors to liquidate their positions.<sup>128</sup> This sudden supply shock changes the clientele as market makers will provide liquidity by picking up the slack. Typically, prices recover once the price pressure has decreased. In line with this argument, Da and Gao (2010) find that mutual funds significantly reduce their position in stocks as their probability to default jumps up. Also, observed changes in a variety of liquidity-based measures of distressed stocks confirm this explanation.

Garlappi et al. (2008) use the expected default frequency (EDF) measure of Moody's KMV model to examine the relationship between equity returns and default risk.<sup>129</sup> The authors find that default risk is generally not associated with higher equity returns. However, they propose an economic mechanism that attempts to reconcile the empirically contradicting findings between default risk and stock returns. The mechanism is based on the idea that equity holders possess a "shareholder advantage", that is, a certain bargaining advantage over debt holders in

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<sup>125</sup> Da and Gao (2010, p. 28)

<sup>126</sup> Da and Gao (2010, p. 28)

<sup>127</sup> Da and Gao (2010, p. 28)

<sup>128</sup> For a detailed explanation of the why institutional investors are confined in their investment set see e.g. Almazan et al. (2004)

<sup>129</sup> See Section 2.2.1.2.2 for a detailed description of Moody's EDF measure

case of default. Specifically, the shareholder advantage is defined as the “ability of shareholders to extract rents in renegotiation with other claim holders in the event of financial distress”.<sup>130</sup> Garlappi et al. (2008) argue that strategic interactions between debt and equity holders are specifically important in settings related to default as distressed firms often try to renegotiate debt contracts with the objective to maximize their respective rents. Using the basic elements of Fan and Sundaresan (2000) renegotiation setup, Garlappi et al. (2008) develop a model that captures this aspect and argue that the equity risk of firms in which shareholders have an increased advantage to retain value in case of default is considerably lower. This, in turn, translates into lower expected returns. On the other hand, firms in which the bargaining ability of shareholders is limited, default risk is larger resulting in higher expected returns. An empirical investigation of the model confirms the proposed relation between default risk, shareholder advantage and stock returns.<sup>131</sup> While firms with a substantial shareholder advantage exhibit a positive relation between returns and probability to default, the risk-return relation of firms with low shareholder advantage are downward-sloping and hump-shaped. Thus, Garlappi et al. (2008) provide evidence for a model that is clearly in line with a risk-based explanation of the observed “distress anomaly”.

In a related study, Garlappi and Yan (2011) extend the idea of strategic default and its implications on the relation between distress risk and equity returns. The authors develop an equity valuation model that “explicitly accounts for financial leverage and recognizes that shareholders, by strategically defaulting on their debt, may recover part of the residual firm value upon the resolution of financial distress”.<sup>132</sup> In this context, the resolution of financial distress does not entail a bankruptcy process per se, but also the possibility of debt restructuring or debt equity swaps. In the latter case, no formal bankruptcy process is triggered. This possibility of value recovery that goes beyond the violation of absolute priority in the bankruptcy process constitutes the major difference compared to the earlier work of Garlappi et al. (2008). The authors show that the likelihood of value recovery in case of default considerably changes the risk profile of distress stocks. Consequently, the most important determinant of a stock’s underlying risks is not necessarily an estimate of the “pure” probability of default, but rather the default likelihood in conjunction with potential of shareholder value recoveries. Using expected default frequencies of the Moody’s KMV model, Garlappi and Yan

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<sup>130</sup> See Garlappi et al. (2008, p. 2744)

<sup>131</sup> Garlappi et al. (2008, p. 2761 – 2771).

<sup>132</sup> Garlappi and Yan (2011, p. 790)

(2011) empirically verify their model by showing that “equity beta and expected returns are hump shaped in default probability”.<sup>133</sup> This theoretically predicted and empirically observed non-monotonic relationship has further implications for value spreads and momentum profits. Particularly, Garlappi and Yan (2011) demonstrate that the model is able to explain stronger BM effects and momentum profits of high default risk firms. This reconciles the observed “anomalous” relationship of stock returns and default risk as documented by Griffin and Lemmon (2002) and Avramov et al. (2006).

George and Hwang (2010) measure financial distress using Ohlson’s (1980) O-Score and Vassalou and Xing’s (2004) default index and find a negative relation between default risk and equity returns. The authors argue that this may not be puzzling, but instead is a result of certain market frictions: Generally, firms with high distress risk are those that have depleted their capacity to issue additional low-risk debt. According to Modigliani and Miller (1958), leverage amplifies the exposure of equity towards priced systematic risk. Put differently, equity risk is increasing in leverage.<sup>134</sup> In frictionless markets, high-leverage firms should then be associated with higher returns as their equity exposure towards priced risks is larger. In markets with frictions, however, low-leverage firms may not necessarily have a larger exposure to systematic risk, leading to decreased expected returns. Specifically, George and Hwang (2010) develop a simple rational model that takes a certain market friction – a firm’s potential distress costs – into account and show that expected returns are negatively related to leverage and default intensities. More importantly, the authors show that this negative relation is fully rational. The line of reasoning is based on two central aspects:<sup>135</sup> First, distress costs contribute to a firm’s exposure to priced risks: The higher the firm’s costs of financial distress, the higher its systematic risk. This follows from the fact that distress costs depress asset payoffs in low states, which are to some extent systematic. Second, distress costs are a central determinant of a firm’s capital structure choices. Firms with high distress costs choose capital structures with low leverage.<sup>136</sup> This decreased leverage results, in turn, in a low probability to default. George and Hwang (2010) find empirical evidence consistent with this hypothesis. The authors claim that an explicit consideration of distress costs in a rational model “explains the puzzle”.<sup>137</sup>

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<sup>133</sup> Garlappi and Yan (2011, p. 818)

<sup>134</sup> George and Hwang (2010, p. 58)

<sup>135</sup> George and Hwang (2010, p. 57)

<sup>136</sup> See e.g. Titman and Wessels (1988), Hovakimian et al. (2001), Faulkender and Petersen (2005) and Kayhan and Titman (2007)

<sup>137</sup> George and Hwang (2010, p. 76)

Accordingly, the negative relation between distress risk and stock returns is in line with rational investor behaviour under the assumption of an existence of distress costs.

Similar to George and Hwang (2010), Anginer and Yildizhan (2013) argues that the anomalous negative relation between default risk and equity returns as documented in earlier literature is due to an incorrect measurement equity exposure to systematic risk. Based on an observation of historical default rates, the authors suggest that default risk is conditional on the stages in the business cycle.<sup>138</sup> Therefore, at least to some extent, default risk appears to possess a systematic risk component. Anginer and Yildizhan (2013) suggest that a firm's equity exposure to systematic risk must be taken into account when examining the relation between distress risk and equity returns. This is not done in earlier studies which simply derive physical probabilities of default risk from historical data and relate this to equity returns. Recognizing that high default probabilities must not necessarily translate into high equity exposure to systematic default risk, Anginer and Yildizhan (2013) relate only the systematic component of default risk to equity returns. Based on findings in the fixed-income literature, credit risk premiums computed from corporate credit spreads are used as a proxy for a firm's exposure to the portion of non-diversifiable risk.<sup>139,140</sup> This measure of default risk has two notable advantages:<sup>141</sup> First, while "traditional" approaches may also include information about a firm's future developments unrelated to distress risk, credit risk premiums constitute a "pure" measure in a way that it is estimated using market data specifically on credit risk. Second, credit spreads are "a proxy for the market-implied risk-adjusted probability of default". Thus, it only contains the systematic component of default risk. Using this advanced measure of default risk, Anginer and Yildizhan (2013) document a positive relation between credit risk premiums and expected stock returns. Consequently, the distress puzzle dissolves into methodological errors related to the estimation of the systematic component in default risk.

Chava and Purnanandam (2010) using both, the hazard model of Campbell et al. (2008) and Merton's (1974) option pricing model as a proxy for distress risk find, in contrast to other studies, a positive relation between distress risk and the cross-section of equity returns. The

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<sup>138</sup> The default rates are made available by Moody's Investor Services.

<sup>139</sup> See for example Elton et al. (2001), Huang and Huang (2003), and Longstaff et al. (2005) for a detailed discussion of why credit spreads are related to the systematic part of default risk

<sup>140</sup> Anginer and Yildizhan (2013, p. 3): Credit spreads are estimated by the difference of a firm's bond yield and a treasury rate matched on the basis of maturity. Also, expected losses, taxes, and liquidity effects are taken into account to derive at the systematic fraction of default risk

<sup>141</sup> Anginer and Yildizhan (2013, p. 5).

authors argue the distress anomaly as observed in previous empirical studies is simply a result of methodological errors regarding the computation of expected returns. Specifically, former investigations use a stock's realized returns as a proxy for expected returns. However, Elton (1999) demonstrates that the use of realized returns may provide a distorted picture of the true relationship between equity returns and default risk, particularly when the sample size is small. In fact, Elton (1999) provides evidence for the return on a risk-free asset to exceed not only the realized returns on the equity market in a ten year time period (1973-1984), but also the realized returns on long-term bonds between 1927 and 1981, on average. Therefore, Chava and Purnanandam (2010) use the implied cost of capital as an improved proxy for expected equity returns.<sup>142</sup> Following Gebhardt et al. (2001), the implied cost of capital is defined as “the internal rate of return that equates current market price to the discounted value of future cash-flows based on the analysts forecasts”.<sup>143</sup> Empirical tests show that there is a positive relation between default risk and the implied cost of capital. Highly distressed stocks – the top 1% in the distress distribution – earn an expected annual premium over the median stock of around 1.45 %, after controlling for traditional risk using Fama and French's (1993) SMB and HML factors as well as Carhart's (1997) momentum factor.<sup>144</sup> This suggests that default risk is priced in equity returns. In addition to providing evidence for the existence of the “distress anomaly” to depend crucially on the computation methodology of expected returns, Chava and Purnanandam (2010) show that it is also contingent on the time period of the examination. While no distress anomaly can be documented in the pre-1980 period – even if realized returns are used to proxy for expected returns – an examination of the post-1980 period confirms the results of previous studies. Here, a negative relation between default risk and equity returns can be observed.<sup>145</sup> A more detailed analysis shows that realized returns remained behind expected returns for distressed stocks in the post-1980 period.<sup>146</sup> This suggests that investors were negatively surprised. Chava and Purnanandam (2010) provide evidence for the non-existence of the distress anomaly when a more accurate measure of expected returns is used. Investors expected a positive premium for bearing increased default risk, however, were negatively surprised in the post-1980 period.

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<sup>142</sup> Pastor et al. (2008) demonstrate the usefulness of implied cost of capital as a better proxy for expected returns.

<sup>143</sup> Chava and Purnanandam (2010, p. 2525).

<sup>144</sup> Chava and Purnanandam (2010 p. 2541).

<sup>145</sup> Chava and Purnanandam (2010, p. 2554).

<sup>146</sup> Chava and Purnanandam (2010, p. 2541).

Hackbarth et al. (2013) examine the relation between distress risk and equity returns around material changes in the legal environment of firms filing for bankruptcy. In 1978, the US government adopted The Bankruptcy Reform Act (BRA, henceforth), which shifted the degree of bargaining power from the creditors to debtors.<sup>147</sup> The authors argue that the change in the bankruptcy code offers an explanation which may reconcile the mixed evidence documented in earlier literature. Specifically, three predictions are tested:<sup>148</sup> First, a shift in bargaining power from creditors to debtors reduces the equity risk of distressed stocks. Consequently, high default risk firms may not necessarily produce higher expected returns. Hackbarth et al. (2013) find evidence in line with this hypothesis: While a monthly positive risk premium of 1.70% can be observed in the time period before the reform, a statistically insignificant risk premium of -0.07% per month is documented after the BRA has been enacted. Given a decreased equity risk, investors obviously adjusted their expectations of returns to distressed stocks downward. Furthermore, a decrease of risk characteristics of distressed stocks such as standard deviation and beta measures can be observed in the post-1978 period. Second, there should be cross-sectional variation of changes in risk premiums depending on the degree of an individual firm's "shareholder advantage" in both sub-periods: The implication of the BRA should more severe for firms that have a high shareholder advantage compared to firms with low "shareholder advantage". In fact, a more detailed analysis shows that the risk premium differences of distressed stocks with high "shareholder advantages" are negligible between the pre-reform and post-reform period.<sup>149</sup> In contrast, the risk premium of firm with low "shareholder advantage" changes significantly after the introduction of the BRA. Third, expected returns of stocks in the very high end of the distress risk distribution are low, suggesting an overall non-monotonic relation between distress risk and equity returns. This follows from the fact that equity holders of firms with a very high probability of default are "increasingly likely to exchange a risky (levered) equity position for a less risky (de- or unlevered)". Consequently, bad news about highly distressed firms will translate into even lower expected returns. The BRA and its associated shift in bargaining power should increase these momentum effects. Hackbarth et al. (2013) find evidence consistent with this line of argumentation. Before the

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<sup>147</sup> See Hackbarth et al. (2013) for a detailed discussion of The Bankruptcy Reform Act and its major changes in comparison to the former Chandler Act of 1938.

<sup>148</sup> Hackbarth et al. (2013, p. 2-4).

<sup>149</sup> Hackbarth et al. (2013) proxy shareholder advantage measures of asset tangibility, firm size and research and development costs.

BRA, a return continuation strategy produces statistically insignificant results. However, in the BRA period, this strategy generates a return of 1.67% per month.<sup>150</sup>

### 2.1.2.3. Section Summary

Numerous studies have investigated the empirical relation between distress risk and the cross-section of stock returns. The question of whether returns are negatively or positively related to distress risk, however, remains unsettled. While some papers find a positive relation between distress risk and stock returns, others provide evidence in support of the opposite. The negative relation between distress risk and stock returns has been dubbed “distress puzzle” as it contradicts the foundations of modern financial theory. In a rational risk-return trade-off, investors are awarded higher returns for bearing larger risks. A variety of explanations have been put forward to resolve the puzzle. These range from methodological errors in computing expected returns over sample and time period specificity to behavioural explanations. The empirical findings are summarized in Table 2 below. Clearly, further research remains inevitable.

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<sup>150</sup> Hackbarth et al. (2013, p. 4).



**Table 2: Summary of the Literature on Distress Risk**

This table summarizes the findings of the studies that empirically investigate the relation between default probabilities and the cross-section of stock returns. The table lists the studies in chronological order. \* indicates that the bankruptcy prediction model is a variant of Shumway's (2001) Hazard Model.

Author	Year	Model	Sample		Findings
			Time	Data	
Dichev	1998	Ohlson's O-Score	1981 - 1995	US	<ul style="list-style-type: none"> <li>Negative relation due to mispricing</li> <li>BM effect is not related to the return premium: Distressed stocks have low BM ratios</li> <li>Size effect disappeared in post-1980 period</li> </ul>
Griffin and Lemmon	2002	Ohlson's O-Score	1965 - 1996	US	<ul style="list-style-type: none"> <li>Negative relation is due to mispricing</li> <li>Low BM ratios for highly distressed firms</li> <li>High limits of arbitrage and informational asymmetries for low BM stocks</li> </ul>
Vassalou and Xing	2004	Merton Model	1971 - 1999	US	<ul style="list-style-type: none"> <li>Positive relation between distress and returns</li> <li>Size and BM capture some information on distress</li> <li>Default risk is priced</li> </ul>
Campbell et al.	2008	Hazard model*	1963 - 2003	US	<ul style="list-style-type: none"> <li>Negative relation due to mispricing</li> <li>Distress anomaly persists through all SMB and BM percentiles</li> <li>Limits of arbitrage</li> </ul>
Garlappi et al.	2008	Moody's KMV	1969 - 2003	US	<ul style="list-style-type: none"> <li>Negative relation is not irrational</li> <li>Equity risk differs with bargaining power of shareholders: Shareholder advantage</li> <li>Positive returns if shareholder advantage is low</li> </ul>
Avramov et al.	2009	S&P credit ratings	1985 - 2007	US	<ul style="list-style-type: none"> <li>Low returns for distressed stocks only around credit ratings and for low rated stocks</li> <li>Distress risk is idiosyncratic</li> <li>Limits of arbitrage</li> </ul>
Chava and Purnanandam	2010	Hazard* / Merton Model	1953 - 2006	US	<ul style="list-style-type: none"> <li>Methodological errors in estimating expected returns</li> <li>Implied cost of capital: positive relation</li> <li>"Out of sample" critique</li> </ul>
Da and Gao	2010	Merton Model	1971 - 1999	US	<ul style="list-style-type: none"> <li>Negative relation due to short term returns reversals induced by institutional liquidity shocks</li> <li>Distress risk not systematic</li> </ul>

Author	Year	Model	Sample	Findings	
George and Hwang	2010	Ohlson's O-Score / Merton Model	1965 - 2003	US	<ul style="list-style-type: none"> <li>• Market friction responsible for distress puzzle</li> <li>• Cost of financial distress negatively related to leverage and distress</li> <li>• Rational explanation for low returns</li> </ul>
Garlappi and Yan	2011	Moody's KMV	1969 - 2007	US	<ul style="list-style-type: none"> <li>• Negative relation is due to shareholder advantage</li> <li>• Possibility of restructuring or debt equity swaps alters risk profile of distressed stocks</li> </ul>
Anginer and Yildizhan	2012	Credit risk premiums	1974 - 1997	US	<ul style="list-style-type: none"> <li>• Negative relation due to incorrect measurement of equity exposure to systematic risk</li> <li>• Positive relation between credit risk premiums and stock returns</li> </ul>
Conrad et al.	2012	Hazard model*	1972 - 2010	US	<ul style="list-style-type: none"> <li>• Negative relation due to investors' preferences for glory stocks</li> <li>• Distress stocks very similar to glory stocks</li> </ul>
Hackbarth et al.	2012	Hazard model*	1972 - 1978	US	<ul style="list-style-type: none"> <li>• Changes in legal environment causes distress anomaly: shift of bargaining power from creditors to debtors</li> <li>• Shareholder advantage changes risk profiles</li> </ul>
Gao et al.	2013	Moody's KMV	1992 - 2010	Global	<ul style="list-style-type: none"> <li>• Negative relation between distress and returns in global financial markets due to mispricing</li> <li>• Strong distress puzzle in markets with high overconfidence-score</li> </ul>

This section has provided an understanding on the pricing of distress risk. While the vast majority of studies agrees that distress risk and stock returns are negatively related, there is an ongoing discussion about the underlying reason. The most comprehensive study of Gao et al. (2013), who investigate the relationship between distress risk and stock returns in a global setting, find evidence for a behavioural story. In fact, the authors argue that the anomaly is caused by investors who are “sluggish to update when confronted with new information”.<sup>151</sup> Potentially, this inattention towards distress risk may also be relevant across inter-form linkages. In the next section, I discuss the literature on investor attention and its implications for asset pricing dynamics.

## 2.2. Literature on Limited Attention

The efficient market hypothesis (EMH) asserts that asset prices fully reflect all available information.<sup>152</sup> This presupposes, however, that market participants are capable of processing

<sup>151</sup> Gao et al. (2013, p. 4).

<sup>152</sup> Bodie et al. (2008, p. 244).

all the information relevant to an asset. Hubermann and Regev (2001) provide an insightful anecdote that this may not always be the case: On May 3<sup>rd</sup> 1998, the New York Times published a front-page article about the biotechnology company EntreMed and its licensing rights regarding a major breakthrough in the field of cancer research. The reaction towards this news content was enormous: On the following trading day, EntreMed's stock price jumped up by approximately 330%, and continued to stay on a higher level compared to the pre-publication date for the remainder of the year. Interestingly, this front-page article did not reveal any new information: In fact, the journal Nature as well as other prominent press including the New York Times had already reported about this issue five months earlier. The conclusion is simple: Market participants fail to take all relevant information into account when pricing an asset.

The assessment of an individual's ability to obtain and adequately process available information pertains to the attention research in the psychological literature. This strand of literature has repeatedly provided evidence for an individual's inability to process many tasks simultaneously.<sup>153</sup> Kahneman and Tversky (1992) point out that attention is a scarce cognitive resource in that attention to one particular task requires an attention substitution from other tasks. Behavioral finance draws on these findings by relating an individual's limited cognitive capacity to the investment and corporate decision making process. Given an enormous amount of available information coupled with investors' cognitive constraints, optimal decision making appears to be severely impeded. This, in turn, affects the pricing of financial assets in a way that the efficient market assumption may be violated.<sup>154</sup>

This section reviews the theoretical and empirical work on limited attention in the asset pricing literature. Section 2.3.1 presents an overview of the most important theoretical models and also provides a detailed description of an adapted version of the model developed by Hirshleifer and Teoh (2003) and outlined in Lim and Teoh (2010). Section 2.3.2 concentrates on the empirical findings. The section is structured according to the variables used to measure investors' attention: competing stimuli, salience of information and ease of processing, and alternative proxies of attention.

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<sup>153</sup> A comprehensive review of the literature can be found in e.g. Nisbett and Ross (1980).

<sup>154</sup> Campbell (2000, p. 46) points out that behavioral finance assumes that "rational investors with standard preferences are limited in their desire or ability to offset the asset demands of the first group of investors" (irrational investors)

### 2.2.1. Theoretical Models

The concept of limited attention first found its way into the asset pricing literature by the work of Merton (1987). Merton (1987) develops a theoretical model in which investors only have information about an index security and a subset of stocks. Portfolio optimization occurs under incomplete information constraints: portfolio holdings are optimized based on the set of securities that the investors have information about.<sup>155</sup> Merton shows that, *ceteris paribus*, the required return varies with the degree of investor information about a specific security. The reasoning is as follows: if a majority of investors only uses the subset of stocks they know about for portfolio construction, the remaining, “unknown” stocks are held by relatively few investors. For these securities to clear in the market, the small group of investors must take large undiversified positions.<sup>156</sup> Intuitively, investors demand a return premium for holding this extra portion of idiosyncratic risk. This theoretical construct, the degree to which investors know about a certain security, has been dubbed the investor recognition hypothesis. Merton’s (1987) model makes three major predictions: (1) the value of a security is increasing in investor recognition, (2) the relation between expected returns and investors recognition is downward-sloping, (3) activities related to financing and investing are positively related to investor recognition. Thus, the investor base of a particular security becomes a key determinant of expected returns in Merton’s (1987) model. A number of papers find empirical support for the investor recognition hypothesis. These papers are detailed in the next section.

Hong and Stein (1999) develop a model with two boundedly rational investor types: so-called news-watchers and momentum traders. In this context, the term “boundedly rational investors” refers to agents that are “only able to process some subset of the available public information”.<sup>157</sup> The model makes three important assumptions: First, news-watchers base their returns forecasts on private observations of an asset’s fundamental data and neglect information on past performances. Second, the private information used is assumed to diffuse slowly across the group of news-watchers. Third, momentum traders solely process information on an asset’s past return history, but do not condition any other source of publically available information. Moreover, this group of agents can only use simple momentum strategies. Using this set of assumptions, Hong and Stein (1999) show that if information diffuses slowly, prices will underreact in the short run and overreact in the longer-run. More

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<sup>155</sup> Bodnaruk and Ostberg (2009, p. 208).

<sup>156</sup> Lehavy and Sloan (2008, p. 328)

<sup>157</sup> Hong and Stein (1999, p. 2144)

specifically, the model makes three predictions: (1) the effects of short-term return momentum as well as long-term returns reversals are stronger among stocks with slow information diffusion; (2) overreaction varies with the type of information: in the long-run, overreaction is stronger in cases where information is initially private compared to cases where new information is publically announced; (3) the investment horizon of momentum traders is related to the degree of return autocorrelation. Consequently, the model is able to reconcile the return patterns related to under- and overreaction.

Hirshleifer and Teoh (2003) and Hirshleifer et al. (2009) develop a model in which the absorption or processing of information differs with the degree of the information's underlying salience. The basic idea of the model is that investors take readily observable information into account when making investment decisions. However, implicit information, that is, information that has to be derived, is ignored or at least neglected. Given the fact that this model is closely related to the empirical work of this study, it will be discussed in more detail.<sup>158</sup>

The model assumes that there are two types of agents: attentive investors and inattentive investors. While attentive investors process all available information to form rational expectations, inattentive investors base their expectations only on a certain subset of the available information. Except for that, all agents are identical and have mean-variance preferences. The model setup is as follows: The portion of inattentive investors is denoted  $f$ . Consequently, the fraction of attentive investors is equal to  $(1-f)$ .<sup>159</sup> The economy in the model consists of one risky security and cash. While investors receive public information about the security's terminal at date 1, returns are realized at date 2. Hirshleifer and Teoh (2003) show that the equilibrium asset price is equal to the weighted average of the expectations of the two groups of investors:<sup>160</sup>

$$P_1 = kE^I[P_2] + (1 - k)E^A[P_2] \quad (18)$$

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<sup>158</sup> The model described is a simple variant of the original model as presented in Hirshleifer and Teoh (2003) and outlined in Lim and Teoh (2010).

<sup>159</sup> Lim and Teoh (2010, p. 296) point out "that  $f$  can be modeled as a function of the salience of the information"

<sup>160</sup> Hirshleifer and Teoh (2003) assume that the security is in zero net supply and thus no risk premium is charged.

where  $E^I$  and  $E^A$  denote the expectation of inattentive and attentive investors, respectively. In the model,  $k$  is an increasing function of the fraction of inattentive investors  $f$ . That is,  $k$  is equal to

$$k = \frac{\frac{f}{\text{var}^I(P_2)}}{\frac{f}{\text{var}^I(P_2)} + \frac{1-f}{\text{var}^A(P_2)}} \quad (19)$$

Assuming that both groups of investors have equal expectations about the security's variance, the weight on inattentive investors' expectations in date 1 is equal to the fraction of inattentive investors.<sup>161</sup> Given information set  $\varphi$ , and replacing  $k$  with  $f$  in Equation 19, the expected price change can be depicted as follows:

$$E[P_2 - P_1|\varphi] = f(E^A[P_2|\varphi] - E^I[P_2|\varphi]) \quad (20)$$

The equation implies that the price change is predictable, given an information set and irrational expectations about future prices of the group of inattentive investors. For example, if attentive investors receive a signal at date 1 and update their expectation about the security's terminal value at date 2 from  $v$  to  $v+x$ , but inattentive investors ignoring the signal stick to their beliefs  $V$ , the expected price change becomes a function of  $x$  as shown in the following equation:

$$E[P_2 - P_1|\varphi] = f(v + x - v) = fx \quad (21)$$

It can be verified that the extent of predictability varies with the fraction of inattentive investors. This implication is similar to Merton (1987): The higher the number of inattentive investors in a security's investor base, the more predictable the underlying stock returns. Hirshleifer and Teoh (2003) use this model to explain widely documented empirical asset pricing puzzles such as the post earnings announcement drift and accrual anomaly.

While the abovementioned models put emphasis on how the characteristics of the information influence an investor's attention, others such as Peng (2005) and Peng and Xiong (2006) concentrate on the allocation process of an agent's limited attention.<sup>162</sup> In Peng's (2005) model, agents process information about fundamental factors and optimally allocate their constrained attention to form portfolios based on the inferences about these factors. Peng (2005) demonstrates that significantly more attention is allocated to fundamentally volatile assets.

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<sup>161</sup> Lim and Teoh (2010, p. 297)

<sup>162</sup> Lim and Teoh (2010, p. 303)

Thus, the speed of incorporating information with respect to fundamental shocks is considerably faster compared to stocks with low fundamental volatility. Peng and Xiong (2006), using a similar model of attention constraints, examine the relation between overconfidence and limited attention and how this impacts the pricing of assets (stock price dynamics). In the model, agents exhibit a certain learning behaviour in that they concentrate on information related to markets and sectors. Due to limited attention, firm specific information is neglected. The model helps in understanding empirically observed pricing patterns such as asset-comovement.

## 2.2.2. Empirical Findings

### 2.2.2.1. Investors' Attention and Competing Stimuli

Evidence from psychological studies suggests that the attention of individuals can be distracted in the presence of other stimuli. For example, Cherry (1953) shows that individuals face difficulties to recall the wording if exposed to two messages simultaneously. In a dichotic listening study, one message is played into the left ear while a different one is played into the right ear. The individuals decide at the beginning which of the two messages to attend to. In most cases, the subjects are not able to remember the content of the unattended message. The implication for capital markets is intuitive: Investors' capabilities are limited in absorbing all relevant information about a particular security, especially when other information signals compete for their attention. A number of studies have investigated this issue empirically.

Francis et al. (1992) are among the first to find indicative evidence for the effects of limited attention on security prices. The authors examine the stock market reaction to earnings announcements of NYSE firms during trading hours and non-trading hours in the time period from 1982 to 1986. They show that the reaction to earnings announcements during trading hours differs significantly from announcements during non-trading hours. In this context, investors' reaction is measured by means of announcement returns, trading volume and the time difference between announcement and the first transaction following the announcement. Overall, Pagach and Stephan (1992) find "no evidence that investors impound information conveyed in overnight disclosures in positions taken at the following open".<sup>163</sup> This result supports the limited attention hypothesis. While earnings announcements during trading hours tend to occur one at a time, the announcements of earnings during non-trading hours become

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<sup>163</sup> Francis et al. (1992, p. 181)

all available simultaneously when the market opens again.<sup>164</sup> The observed failure of investors to incorporate overnight released earning news into stock prices may thus be a result of distracted investors facing difficulties to process the large number of different signals at the same time.

Bagnoli, Clement and Watts (2005) confirm the findings of Francis et al. (1992) using a more comprehensive sample of approximately 49,000 quarterly earnings announcements of firms in the Reuters Forecast Pro database in the time period between 2000 and 2003. The authors demonstrate that the stock price reaction to earnings announcements made during non-trading hours is rather sluggish compared to earnings announcements made during the day. Thus, investors tend to underreact to earnings announcements when information is clustered and therefore more difficult to process.

DellaVigna and Pollet (2009) compare the stock returns and trading volume of firms that make their earnings announcements on Fridays to those that make their earnings announcements on other days of the week. The sample of the study is based on earnings announcements of all firms that have sufficient data available on CRSP, COMPUSTAT and I/B/E/S in the time period between January 1984 and June 2006. The authors hypothesize that “weekends distract investors and lower the quality of decision-making”.<sup>165</sup> Thus, investors’ attention is more likely to be limited on Fridays. This, in turn, should translate into a lower announcement response. In line with their hypothesis, DellaVigna and Pollet (2009) show that Friday announcements exhibit both a 15% lower immediate stock price as well as an 8% lower trading volume response. Furthermore, the post earnings announcement drift (PEAD) is stronger for Friday announcements suggesting that investors slowly realize their initial valuation mistakes and later correct stock prices accordingly.

Hirshleifer, Lim, and Teoh (2009) approach the effects of investors’ potential attention distractions from a different angle. Specifically, the authors compare the responses to earnings announcements made on “busy” days, that is, days with a high number of total earnings announcements to rather “quiet” days in which a relatively low number of total earnings announcements occur. The authors argue that the publication of a bulk of extraneous news such as earnings announcements draws investors’ attention away from single firms, leading to

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<sup>164</sup> Francis et al. (1992, p. 166) state that “about 30% of a random sample of Broad Tape earnings disclosures were made during nontrading hours”

<sup>165</sup> DellaVigna and Pollet (2009, p. 709)



sluggish responses to information. This setting enables them to test the investor distraction hypothesis directly. Using a sample of earnings announcements of firms with available data in the CRSP, COMPUSTAT and I/B/E/S database in the time period between 1995 and 2004, Hirshleifer, Lim, and Teoh (2009) show that both the announcement return and trading volume response to earnings surprises is weaker on days in which distraction is likely to be stronger. Also, the PEAD is stronger for firms releasing earning news on “busy” days. This clearly suggests that investors have limited capability of simultaneously processing information and are more likely to underreact to information if distraction by other competing stimuli is relatively high.

The studies mentioned above provide consistent evidence in line with the investor distraction hypothesis. Specifically, the observed lower immediate stock return reaction, the lower turnover and the stronger PEAD effects for a firm’s news announcements in times of high distraction potential clearly indicate an individual’s inability to process all available information if other stimuli compete for their attention.

#### 2.2.2.2. Investors’ Attention and Information Salience

The ability of perceiving and processing stimuli differs substantially among individuals. The psychological literature has identified two factors that are important to determine the extent to which stimuli are processed adequately:<sup>166</sup> First, the salience of the information. Stimuli are more salient if they “are more prominent or if they contrast more with other stimuli in the environment. More salient information is more likely to be processed adequately by individuals. Second, the accessibility of the information. Individuals tend to pay attention to information that is easily accessible. Given an individual’s tendency to ignore non-salient information or information that is hard to process, the implication for capital markets is intuitive: If investors do not take specific information into account when pricing assets, markets become inefficient which generates a certain degree of return predictability. The asset pricing literature has examined the effects of limited attention on security prices using proxies for information salience and accessibility. This section provides an overview of the most recent findings.

DellaVigna and Pollet (2007) investigate the effects of changes of an economy’s demographic structure on stock returns across various industries. Generally, fluctuations in cohort sizes

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<sup>166</sup> Lim and Teoh (2010, p. 299)

produce predictable demand shifts that substantially impact the profitability of age-sensitive goods such as toys or medical care products. Using US demographic and consumption data, DellaVigna and Pollet (2007) compute long-term demand growth rates and show that these forecasts predict future industry profitability and returns. Specifically, the authors find that “one additional percentage point of annualized demand growth due to demographics predicts a 5 to 10 percentage point increase in annual abnormal industry stock returns”.<sup>167</sup> DellaVigna and Pollet (2007) argue that the information on long-term demand growth rates is not salient enough for investors to pay attention, generating return predictability. In contrast, more salient information, that is, information on short-term demand growth rates, yields insignificant results with respect to return predictability. Obviously, investors are capable of processing this type of information adequately.

Cohen and Frazzini (2008) examine the effects of investors’ inattention on stock returns using economic linkages of firms as a proxy for information salience. Using a dataset of clearly defined customer-supplier relationships, the authors find that stock prices do not instantaneously incorporate the news of related firms. This generates return predictability. A rolling long-short strategy that sells the suppliers to customers with negative news and buys suppliers to customer with positive news generates abnormal, risk-adjusted returns of over 150 basis points per month.<sup>168</sup> This has been dubbed the customer momentum strategy. Investors obviously do not use the publically available relation across firms in the supply chain when pricing assets. Cohen and Frazzini (2008) also show that the return predictability is stronger when investors’ inattention is likely to be higher. For example, the customer momentum strategy is weaker when investors hold shares in both customer and supplier stocks. Also, the breadth of the shareholder base influences the profitability of the customer momentum strategy.

Similarly to Cohen and Frazzini (2008), Menzly and Ozbas (2006) find strong evidence of return predictability across the supply chain using upstream and downstream definitions of industries. The authors demonstrate that industry returns lag the returns of related industries: An investment strategy that buys the industries with large positive returns and sells industries with large negative returns yields an abnormal return of more than 6% annually.<sup>169</sup> This

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<sup>167</sup> DellaVigna and Pollet (2007, p. 1667)

<sup>168</sup> Cohen and Frazzini (2008, p. 1997)

<sup>169</sup> Menzly and Ozbas (2006, p. 1).

suggests that information about the interconnection of industries is not processed adequately by investors leading to a slow diffusion of information and return predictability.

Hong, Torous and Valkanov (2007) study the ability of industry returns in predicting the stock market and find that certain industries forecast the performance of the stock market by up to two months. This suggests that information diffuses slowly across assets generating a cross-sectional return predictability. The authors argue that this is caused by the limited ability of investors to adequately process all relevant information.

Engelberg (2008) analyses whether investors adequately process non-salient information using the responses to publications of earnings news as a setting. In contrast to the studies in the section above, however, Engelberg (2008) particularly acknowledges the heterogeneity of information: “While some news is easy to decipher and is incorporated quickly into market prices, other news requires more costly processing and – depending on the size of the information processing costs – will be incorporated into market prices only over time”<sup>170</sup> Consequently, the author groups the information on earnings news into two categories: Salient earnings news and non-salient earning news. In this respect, salient earnings news is defined as hard/quantitative information that can be readily processed. Examples include a firm’s earnings per share measure. In contrast, non-salient news consists of soft/qualitative elements that are more difficult to digest. This type of news is gathered in an unstructured fashion, e.g. the text of a conference call. Consistent with the limited attention hypothesis, Engelberg (2008) demonstrates that investors face severe difficulties in deciphering non-salient information: harder-to-process information has incremental return predictability and the observed predictability extends to longer time horizon compared to quantitative information. Thus, investors appear to be incapable of incorporating non-salient information immediately into stock prices. Instead, the observed return pattern suggests a rather gradual learning process.

Peress (2008) relates a firm’s earnings announcement returns to its media coverage in the press in order to investigate the investor attention hypothesis. The reasoning is as follows: If the documented under reaction to the publication of corporate events such as earnings news is due to investors’ inattention, there should be a difference between stocks that investors attend to and stocks which are likely to remain unattended. The degree of attention is proxied by a firm’s emergence in prominent newspapers such as the Wall Street Journal (WSJ). Peress (2008) shows that firms with more comprehensive media coverage exhibit stronger announcement

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<sup>170</sup> Engelberg (2008, p. 2)

reaction with respect to both returns and trading volume compared to firms with less extensive media coverage. Also, the PEAD is considerably weaker for more visible firms suggesting that investors' attention plays a role in determining the degree of return predictability following corporate events announcements.

Cohen and Lou (2012) investigate the limited attention hypothesis by comparing the responses to industry-wide information events of two different groups of stocks: one group of stocks is classified as easy-to-analyse (e.g. a standalone entity) while another group of stocks is more complex (e.g. a conglomerate). This specific setting enables a direct analysis of the extent to which investors are capable of pricing non-salient versus salient information. The authors hypothesize that the investors, due to limited processing capabilities, only gradually impound the information into complex firms. This should translate into return predictability. To investigate this issue and facilitate an adequate comparison, Cohen and Lou (2012) construct "pseudo-conglomerates", which consist of a portfolio of the conglomerate's single segments. For the portfolio construction process, only standalone firms from the respective industries are employed. The authors show that the returns to easy-to-process firms predict the returns of their more complex peers. Also, they demonstrate that the relation between a firm's complexity and returns predictability is upward-sloping. Hence, the firm's complexity is an important factor in determining whether information is impounded into stock prices immediately or rather gradually over time.

Belo, Gala and Li (2012) study the impact of changes in the political environment on stock returns and cash flows and provide evidence for a certain degree of return predictability. In Democratic presidencies, firms with an increased exposure to government spending exhibit increased return and operating performances. In Republican regimes, these firms tend to underperform. Belo et al. (2012) show that an investment strategy that exploits these differences provides a risk-adjusted return of 6.9% per annum. This suggests that investors underreact to the variation in government spending depending on the political party in charge.

While the last two sections present the empirical findings of investors' attention constraints related to competing stimuli, information salience and ease of processing, this subsequent section provides an overview of empirical studies that use other proxies for investor attention.

### 2.2.2.3. Investors' Attention and Other Proxies

Gervais, Kaniel, and Mingelgrin (2001) relate the informational content of a stock's trading activity to its returns. Postulating that large increases in trading volume attract the attention of investors, the authors investigate the ability of trading volume to predict future stock returns. According to Miller (1977) and Merton (1987), any event that grabs investors' attention towards a certain security should result in price increases. The reasoning is as follows: While the security's supply is limited to the set of current shareholders, the demand tends to appreciate as the set of potential buyers is enlarged.<sup>171</sup> Grullon, Kanatas and Weston (2004) empirically verify this relationship by demonstrating that firms with more visibility as measured by product marketing expenditures have a wider breadth of ownership and are more liquid. Thus, a positive relation between increased in trading volume and stock returns should be observable. In line with the visibility hypothesis, Gervais et al. (2001) find that stocks with considerably high trading volume over periods of a day or week experience large increases in returns in the subsequent month. Similarly, stocks with substantially low trading activity show decreased subsequent return performances. The authors argue that the high-volume return premium stems from "shocks in trader interest in a given stock" or, put differently, the stock's visibility.<sup>172</sup> Consequently, an increase of a stock's visibility as proxied by trading volume influences future returns. This suggests that investor attention varies among the universe of stocks causing a certain degree of return predictability.

Hou and Moskowitz (2005) study the impact of market frictions on the cross-sectional return predictability and find support for the investor recognition hypothesis as put forward by Merton (1987). Specifically, the authors develop a number of variables measuring the delay with which stock prices respond to information and demonstrate that these variables reliably predict the cross-section of stock returns. On average, delayed firms earn a superior returns compared to non-delayed firms.<sup>173</sup> Controlling for a variety of liquidity and size-related measures, Hou and Moskowitz (2005) provide evidence for the documented return premium to be driven by variables that proxy investors' recognition such as analyst coverage, institutional ownership, number of shareholders and employees, advertising expense and remoteness. Also, the delay effect is strongest among firms that are likely to be neglected: Delayed firms mainly consist of

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<sup>171</sup> This relation only holds under the assumption of certain market frictions such as short selling constraints

<sup>172</sup> Gervais, Kaniel, and Mingelgrin (2001, p. 877)

<sup>173</sup> Hou and Moskowitz (2005, p. 981).

small, value, volatile, illiquid and poorly performing stocks.<sup>174</sup> Consequently, investors' recognition of stocks or limited attention towards certain stocks appears to be responsible for a large extent of predictability in the cross section of stock returns.

Barber and Odean (2008) examine the buying and selling behaviour of different investors to test the investors' attention hypothesis. For that, investors are grouped into one of the following categories: (1) investors with an account at a large discount broker, (2) investors with an account at a large retail broker, (3) investors at a smaller discount broker that advertises its trade execution quality and (4) professional money managers.<sup>175</sup> Attention is proxied using three different variables: a stock's abnormal daily trading volume, the stock's previous one day return, and the appearance of the firm in prominent press. Based on Merton (1987), the authors assume that investors face difficulties in processing information on all stocks in the investment universe and hence focus on a few stocks only. In the process of deciding which stocks to purchase, investors are influenced by events that grab their attention. Barber and Odean (2008) postulate that the buying behaviour is driven by attention and that this attention-based buying is more pervasive among individual investors as institutional investors tend to "devote more time to searching for stocks to buy and sell than do most individuals".<sup>176</sup> In line with their prediction, Barber and Odean (2008) find that individual investors are net buyers in periods of high trade volume, following extreme one day returns and when stocks are in the press. The results indicate that attention towards a certain stock plays a vital role when deciding which stock to purchase. This is especially true for individual investors that face relatively more severe difficulties to select stocks from the entire investment universe.

In a related study, Seasholes and Wu (2007) confirm the results of Barber and Odean (2008) concerning the attention-based buying behaviour of individual investors in an out-of-sample test. In particular, Seasholes and Wu (2007) study investors' trading behaviour and its implication for stock return performances using upper price limits of the Shanghai Stock Exchange as a proxy for attention grabbing events. They find that attention strongly affects investment decisions, which translates into return predictability. Not only show individual investors net buy-sell imbalances following attention grabbing events, also net buy-sell imbalances appear to be more positive when only a few stocks hit their upper price limit on the

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<sup>174</sup> Hou and Moskowitz (2005, p. 982).

<sup>175</sup> Barber and Odean (2008, p. 788).

<sup>176</sup> Barber and Odean (2008, p. 787).

same day.<sup>177</sup> Furthermore, attention events attract new investors to purchase the underlying security. This evidence lends support to Merton (1987), who argues that attention enhances an assets overall breadth of ownership. Seasholes and Wu (2007) demonstrate that this attention-based buying behaviour has an impact on stock prices. On the day after an attention grabbing event, stock prices are pushed upwards.<sup>178</sup> However, the price increase is only temporary, resolving in a negative return over the next few trading days. The documented price mean reversion indicates that investment decisions of individual investors are mainly driven by behavioural factors, and not necessarily well-informed trades.

Yuan (2009) investigates the effects of attention on investors' trading behaviour and asset pricing dynamics. Using record levels of the Dow index and coverage of the stock market on front pages of prominent newspapers as a proxy for market wide attention, the author examines the trading behaviour of individual as well as institutional investors and its implications for market return performances. Similar to the evidence provided by Barber and Odean (2008), Yuan (2009) finds that attention-grabbing events have a strong influence on the trading behaviour of individual investors. In periods of high attention, individual investors liquidate their stock positions after the Dow index has passed record levels. Conversely, when the Dow index is relatively low, investors appear moderately increase stock market exposure. Furthermore, market wide attention predicts the stock market performances. The NYSE-Amex index decreases, on average, by 19 basis points over a one day period after Dow index record events.<sup>179</sup> The result clearly suggests that market wide attention affects the trading behaviour of investors and generates return predictability.

Hou, Peng and Xiong (2008) examine the relation between the profitability of price and earnings momentum trading strategies and investor attention. The authors use trading volume and market state as a proxy for investor attention and hypothesize that investor attention has a dual role in explaining market anomalies and return predictability.<sup>180</sup> While observed under reactions to relevant information such as earnings news stem from low investor attention, high investor attention causes overreactions to information such as price histories. In line with their hypothesis, Hou, Peng and Xiong (2009) find that the profits to price momentum strategies are

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<sup>177</sup> Seasholes and Wu (2007, p. 592-594).

<sup>178</sup> Seasholes and Wu (2007, p. 593).

<sup>179</sup> Yuan (2009), p. 11.

<sup>180</sup> The use of up and down markets as a proxy for investor attention is motivated by the work of Karlsson, Loewenstein, and Seppi (2005) who point out that investors more closely follow the developments of stock markets in good states

substantially larger in times of high investor attention as measured by high trading volume and up markets. In contrast, profits to earnings momentum strategies are larger in times of low investor attention, that is low trading volume and down markets. Hence, the degree of investor attention appears to play a role in explaining the documented return patterns related to investors' under- and overreactions to relevant information.

Chemmanur and Yan (2009) examine the short-term and long-term effects of advertising on the cross-section of stock returns and find that high levels of advertising are associated with higher stock returns in the short-term, but decreased return in the long term. The authors argue that the observed return pattern is a result of investor attention. Firms that heavily advertise attract the attention of investors. Once attention has been attracted, investors begin to heavily purchase the underlying stocks generating superior returns. In the long-term, the effects of advertising wears out, resulting in declining return performances. Using trading volume and the number of analysts as a proxy for investor attention, Chemmanur and Yan (2009) provide consistent evidence for an investor attention-based explanation of the documented return pattern. Specifically, they show that advertising increases the visibility of stocks among investors. Also, the documented decreased future returns of high advertising firms are only observable if advertising is significantly reduced in later periods. Thus, the level of advertising affects investors' attention and this, in turn, generates return predictability.

Da, Engelberg and Gao (2009) argue that a stock's search frequency in Google (SVI) is a direct measure of investor attention. They show that even though the SVI is positively correlated with traditional proxies of investor attention, it clearly captures different information. Specifically, the SVI tends to lead alternative measures of investor attention such as news or extreme returns.<sup>181</sup> Thus, the SVI appears to capture investor attention in a more timely fashion. Moreover, the SVI measure appears to capture the information on attention of individual and retail investors, rather than professional money managers.<sup>182</sup> Da et al. (2009) examine the relationship between SVI and the cross-section of stock returns and find that the SVI measure predicts stock returns. In particular, an increase in SVI causes stock prices to increase within the next two weeks with an eventual return reversal effect over the following year.

Loh (2009) examines whether the under reaction of investors to security analyst stock recommendation is related to investor attention. Using trading volume as a proxy for investor

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<sup>181</sup> Da et al. (2009, p. 2).

<sup>182</sup> Da et al. (2009, p. 1).



attention, the author shows that investors' reaction to stock recommendation differs substantially between low- and high-attention stocks. Specifically, unattended stocks exhibit a lower reaction around a three day event window.<sup>183</sup> Also, the subsequent price drift is larger for those stocks, suggesting that investor inattention plays a vital role in explaining the return predictability following the publication of analyst recommendations.<sup>184</sup> For unattended stocks, the information is impounded only gradually into stock prices.

### 2.2.3. Section Summary

Evidence from the psychological literature suggests that individuals are limited in their capacity to perform many tasks at the same time. Given a constrained cognitive capacity, investors may fail to impound all relevant information into asset prices. This has led to the limited investor attention hypothesis. Merton (1987) was among the first to put forward a theoretical model which acknowledges that investors optimize their portfolio based only on a limited set of securities which they know about. Regardless of the all the securities in the investment universe, investors purchase only known securities. Intuitively, this has severe implications for asset pricing dynamics causing prices to deviate from their fundamental values.

Hong and Stein (1999) develop a model that helps in explaining return predictability associated with investors' under- and overreaction. Modelling a world in which investors are "boundedly" rational in that they are only able to adequately process a limited amount of information, they show that agents will underreact in the short-run, but overreact in the long run, given that information diffuses slowly.

Hirschleifer and Teoh (2003) show that investor face difficulties in processing non-salient information. In their model, investors do not pay attention to information that is not readily observable, but rather has to be derived. They provide evidence for inattentive investor to use only a subset of available information and demonstrate that return patterns related under-and overreactions to e.g. public announcements generate return predictability.

There is a growing body of research that tests the implications of the limited attention hypothesis on asset prices empirically. This section has provided an overview. The studies discussed in the section are categorized by the proxy used to capture the degree of investor

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<sup>183</sup> Loh (2009, p. 1223).

<sup>184</sup> Loh (2009), p. 1223).

attention: Competing stimuli, information salience and ease of processing and other proxies. The studies unanimously suggest that investors' attention constraints lead to return predictability. The results of the empirical investigations are summarized in Table 3 below:

**Table 3: Summary of the Literature on Investor Attention**

This table summarizes the findings of the studies that empirically investigate the effects of investor attention on stock returns. The studies are listed according to a chronological order.

Author	Year	Proxy / Setting	Sample		Findings
			Time	Data	
Pagach and Stephan	1992	Trading and non-trading hours	1982 - 1986	US	<ul style="list-style-type: none"> <li>• Reaction to earnings announcements during non-trading hours is substantially weaker</li> <li>• Information is not fully impounded: Investors are distracted by the arrival of competing signals</li> </ul>
Gervais et al.	2001	Trading volume	1963 - 1996	US	<ul style="list-style-type: none"> <li>• Stocks with high trading volume over a day or week exhibit higher returns in the following month</li> <li>• High volume premium is caused by enhanced visibility</li> </ul>
Hou and Moskowitz	2005	Price delay	1963 - 2001	US	<ul style="list-style-type: none"> <li>• Measures of price delay reliably predict stock returns</li> <li>• Return premium is driven by investor recognition of the stocks</li> </ul>
Bagnoli et al.	2006	Trading and non-trading hours	2000 - 2003	US	<ul style="list-style-type: none"> <li>• Sluggish reaction to earnings announcements during non-trading hours</li> <li>• Under reaction due to clustered arrival of stimuli when the market opens</li> </ul>
Menzly and Ozbas	2006	Related industries	1963 - 2002	US	<ul style="list-style-type: none"> <li>• Industries related through the supply chain (both, up- and downstream) predict each other's returns</li> <li>• Information diffuses slowly across industries</li> <li>•</li> </ul>
DellaVigna and Pollet	2007	Demo-graphic trends	1939 - 2003	US	<ul style="list-style-type: none"> <li>• Impact of demographic trends is not priced in stocks producing age-sensitive goods</li> <li>• Long-term demand growth is ignored, while short-term growth is impounded into asset prices</li> </ul>
Hong et al.	2007	Related industries	1946 - 2002	US	<ul style="list-style-type: none"> <li>• Certain industries forecasts stock market performances by up to two months</li> <li>• Slow information diffusion causes return predictability</li> </ul>
Seasholes and Wu	2007	Upper price limits	2001 - 2003	China	<ul style="list-style-type: none"> <li>• Individual investors exhibit net buy-sell imbalances following attention grabbing events</li> <li>• Attention attract new investors to purchase a security</li> </ul>

Cohen and Frazzini	2008	Economic linkages	1980 - 2004	US	<ul style="list-style-type: none"> <li>• Investors fail to incorporate information of related firms into stock prices</li> <li>• Return predictability across the supply chain</li> </ul>
Engelberg	2008	Salient versus non-salient earnings	1999 - 2005	US	<ul style="list-style-type: none"> <li>• Non-salient news are more difficult for investors to decipher: Increased return predictability for hard-to-process earnings</li> </ul>
Peress	2008	Media coverage	1993 - 2002	US	<ul style="list-style-type: none"> <li>• More comprehensive media coverage is associated with a stronger earnings announcement reaction from investors</li> <li>• PEAD is weaker for firms covered in the press</li> </ul>
Barber and Odean	2008	Trading volume, returns, media	1987 - 1996	US	<ul style="list-style-type: none"> <li>• Individual investors are net buyers in periods of high attention</li> <li>• Individual investors face difficulties in absorbing information on all available stocks</li> </ul>
Della Vigna and Pollet	2009	Friday Earning Announcements	1984 - 2006	US	<ul style="list-style-type: none"> <li>• Response to earnings announcements is weaker in terms of trading volume and stock returns on Friday announcements</li> <li>• More significant PEAD for Friday announcements</li> </ul>
Hirshleifer et al.	2009	Multiple Earnings Announcement	1995 - 2004	US	<ul style="list-style-type: none"> <li>• Trading volume and returns response weaker on days with earnings announcements of multiple firms</li> <li>• Stronger PEAD for firms announcing on busy days</li> </ul>
Hou et al.	2009	Trading volume, market state	1964 - 2005	US	<ul style="list-style-type: none"> <li>• Profits to price momentum strategies are larger in times of high investor attention</li> <li>• Profits to earnings momentum strategies are larger in times of low investor attention</li> </ul>
Chemmanur and Yan	2011	Product marketing	1996 - 2005	US	<ul style="list-style-type: none"> <li>• Advertising increases the visibility of stocks among investors</li> <li>• High advertising is associated with higher stock returns</li> </ul>
Da et al.	2009	Google search frequency (SVI)	2004 - 2008	US	<ul style="list-style-type: none"> <li>• SVI is a direct measure of individual investor attention, leading alternative measures</li> <li>• SVI predicts stock returns: Higher SVI translate into higher stock returns</li> </ul>

Loh	2009	Trading volume	1993 - 2006	US	<ul style="list-style-type: none"> <li>• Investors' reaction to stock recommendation differs with the degree of investor attention</li> <li>• Unattended stocks show lower reaction, and a stronger PEAD</li> </ul>
Yuan*	2011	Index record levels	1983 - 2005	US	<ul style="list-style-type: none"> <li>• Attention-grabbing events affect the trading behavior of individual investors</li> <li>• Market wide attention affects stock market performances</li> </ul>
Cohen and Lou	2011	Complex versus easy firms	1997 - 2009	US	<ul style="list-style-type: none"> <li>• Investor impound industry-wide information only gradually into more complex firms</li> <li>• Easy-to-process firms lead complex firms</li> </ul>
Belo et al.	2013	Presidency cycles	1939 - 2011	US	<ul style="list-style-type: none"> <li>• Firms with more exposure to government spending produce superior return performances</li> <li>• Investors underreact to variation in government spending</li> </ul>

This section has provided comprehensive evidence of the inability of investors to fully incorporate relevant information into the stock prices. In addition to reviewing the literature regarding the questions of how to measure financial distress and whether it is priced, it is relevant for this study to understand the mechanics of financial contagion. The next section reviews the literature on the contagious nature of bankruptcy-related distress. First, the channels through which distress can be transmitted from one firm to another are presented. Second, empirical studies that examine the extent of distress contagion is discussed.

### 2.3. Literature on Contagion

There is little consensus about the precise definition of financial contagion in the economic or financial literature.<sup>185</sup> Generally, the term “contagion” has its root meaning in the field of epidemiology describing a disease that transmits from one subject to another by direct or indirect contact.<sup>186</sup> Based on this broad understanding, financial contagion can then be defined as “the spread of financial distress from one firm, market, asset class, nation, or geographical

<sup>185</sup> See Kolb (2011) or Pericolli and Sbrazia (2003) for a detailed discussion of the definition of financial contagion. Also, Dornbusch et al. (2000) provides an overview of the breadth of definitions.

<sup>186</sup> The American Heritage Dictionary defines contagion as “(a) Disease transmission by direct or indirect contact; (b) A disease that is or may be transmitted by direct or indirect contact; a contagious disease. (c) The direct cause, such as a bacterium or virus, of a communicable disease. Psychology: The spread of a behavior pattern, attitude, or emotion from person to person or group to group through suggestion, propaganda, rumor, or imitation. A harmful, corrupting influence: feared that violence on television was a contagion affecting young viewers The tendency to spread, as of a doctrine, influence, or emotional state”

region to others”.<sup>187</sup> As this particular definition already indicates, research directions related to financial contagion are rather broad. For example, financial contagion can be investigated in the context of a financial crisis, across countries or financial systems. Given the focus of this study however, only literature that examines the effects associated with credit contagion will be discussed. Credit contagion can be defined as “the propagation of [...] distress from one firm to another.”<sup>188</sup>

Credit contagion can generally take two different forms: information contagion and counterparty contagion. The information transmission hypothesis suggests that a firm’s bankruptcy induces investors to update their beliefs and expectations about the prospects of other firms, even in the absence of a direct exposure to the distressed firm.<sup>189</sup> Information contagion can then be defined as “the information that one [...] firm is troubled results in negative shocks at other [...] institutions largely because the firms share common risk factors”.<sup>190</sup> The counterparty contagion hypothesis posits that firms with direct exposure to the distressed firm will experience adverse developments due to their fundamental business linkages.<sup>191</sup> The definition of counterparty contagion is “one important [...] institution’s collapse leads directly to problems at other creditor firms, whose trouble snowball and drive other firms into distress”.<sup>192</sup>

Related to the concepts of information and counterparty contagion, there are several ways through which financial distress can spread among firms. Figure 2 provides an overview of the channels associated with credit contagion.

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<sup>187</sup> Kolb (2011, p. 3)

<sup>188</sup> Giesecke and Weber (2005, p. 741)

<sup>189</sup> See e.g. Collin-Dufresne et al. (2003)

<sup>190</sup> Helwege (2010, p. 260)

<sup>191</sup> Davis and Lo (2001)

<sup>192</sup> Helwege (2010, p. 260)

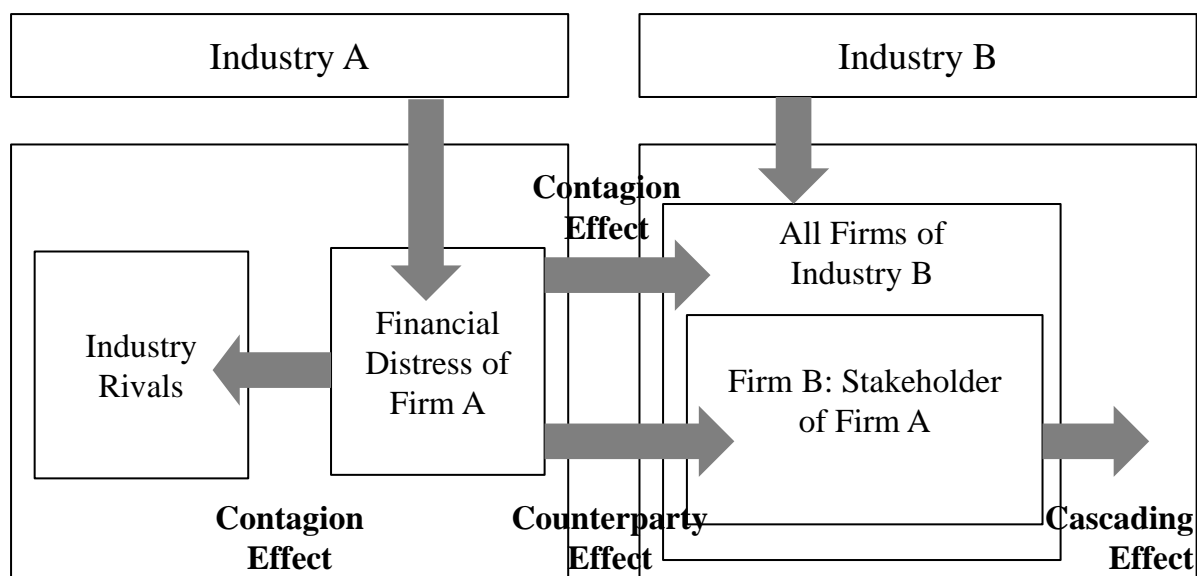


Figure 2: Channels of Credit Contagion<sup>193</sup>

Figure 2 shows that a bankruptcy and inherent financial distress of Firm A in Industry A may have valuation implications for all other firms in the same industry. Here, the spill-over effects for the firm’s immediate competitors can be of “contagious” and “competitive” nature, depending on the corresponding default correlations.<sup>194</sup> In general, “contagious effects” are associated with positive default correlations.<sup>195</sup> That is, the distress experienced by one firm translates into distress of its direct competitors. By intuition, positive default correlations can be a result of customers and suppliers who become wary of the future profitability of all firms in an industry. Negative default correlations or “competitive effects” arise when a firm’s bankruptcy results in market power gains for the remaining firms.<sup>196</sup> Given a fixed demand, rival firms may be able to capture new clients from the bankrupt firm. These competitive effects may also occur prior to the actual liquidation. For example, customers, becoming wary of their reputation, may refrain from doing business with the financially distressed firm. While contagious and competitive effects may coexist, the net of it is generally referred to as intra-industry contagion.

Contagious effects of financial distress may also transmit across industries. For example, when Industry A is a major client of Industry B, a firm bankruptcy in Industry A may disclose new

<sup>193</sup> Adapted from Jorian and Zhang (2009, p. 2057)

<sup>194</sup> Lang and Stulz (1992), p. 47-49.

<sup>195</sup> Lang and Stulz (1992), p. 47.

<sup>196</sup> Lang and Stulz (1992), p. 48.

information to the market concerning the cash-flow components that are common to all firms within one industry and hence decrease profitability expectations.

A further channel through which financial distress can spill-over from one firm to another is direct counterparty exposure. Suppose that Firm A is a stakeholder of firm B, either through real or financial linkages. Real linkages may comprise direct economic relationships in the form of customer and supplier linkages, while financial linkages may consist of granted trade credit for industrial firms or bonds and loans for the financial service industry. Financial distress or bankruptcy of Firm A will then inevitably translate into immediate consequences for Firm B: Losses of trade credit or loans repayments may cause financial distress for linked partners. Furthermore, this may have cascading effects for all stakeholders of Firm B.

This section provides an overview of the empirical findings related to credit contagion. Section 2.1.1 presents the results with respect to intra-industry contagion. Section 2.1.2 discusses studies that specifically focus on contagious effects transmitted through counterparty exposure. Within these sections, studies are described according to a chronological order.

### 2.3.1. Literature on Intra-industry Contagious Effects of Firm Bankruptcies

Lang and Stulz (1992) are among the first to directly test for potential intra-industry contagious effects of firm failures.<sup>197</sup> The common view is that a firm's bankruptcy makes the suppliers and customers suspicious about the economic health of all other firms in the same industry. Hence, a bankruptcy of a firm should lead to negative externalities, that is, decreases in firm value, of all other firms with similar business activities. On the other hand, a bankruptcy may also increase the competitive position of the remaining firms in the market. Potential redistribution of wealth from the bankrupt firm to rivals will then increase corresponding firm values. Using a sample of firms with liabilities in excess of \$120 million that filed for bankruptcy in the time period between 1970 and 1989, Lang and Stulz (1992) test both lines of reasoning. They show that the market value of a rival firm plummets on average by 1% at the time of the bankruptcy announcement.<sup>198</sup> The contagious effects are more pronounced in highly leveraged industries.<sup>199</sup> Here, the average wealth drop of competitor firms is as large as 3% of

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<sup>197</sup> In an earlier study, Gruber and Warner (1977) find no contagious effects within industries. They show that monthly competitor firm returns are not substantially influenced when a firm goes bankrupt. The sample of the study includes railroad bankruptcies between 1930 and 1959.

<sup>198</sup> Lang and Stulz (1992, p. 59).

<sup>199</sup> Highly leveraged industries are defined as industries with a debt-to-asset ratio that exceeds the sample median.



the market value.<sup>200</sup> In more concentrated industries, the rival firms' market value increases by 2.2% at the time of the bankruptcy announcement.<sup>201,202</sup> Thus, a bankruptcy announcement has both, a significant contagion effect as well as a significant competitive effect on the remaining firms within an industry, depending on the level of market concentration.

In a related study, Ferris, Jayaraman and Makhija (1997) find support for contagious effects in an intra-industry setting. The authors study bankruptcy announcements in the time period between 1979 and 1989 and show that rivals to large bankrupt firms experience a significant return decrease of 0.56% around the three days of the Chapter 11 announcement. Similarly, small firm bankruptcies trigger financial contagion, however, only among smaller sized rival firms. However, the effect is considerably less pronounced: Small rivals exhibit a loss of only 0.12% around the time of bankruptcy announcement.<sup>203</sup> In a more detailed analysis, Ferris et al. (1997) distinguish between contagious and competitive effects of bankruptcy announcements. Specifically, a competitor firm that enters Chapter 11 within three years after the original bankruptcy announcement is assumed to experience contagious effects. Conversely, rival firms that do not file for bankruptcy are assumed to experience competitive effects. The authors demonstrate that candidates for contagious effects earn a return of -4.68% at the original bankruptcy announcements. Contrary to expectations, candidates for competitive effects also earn a negative, albeit weaker return response. This is counterintuitive as competitive effects should increase the market share and profit potential for the remaining firms in an industry. Ferris et al. (1997) suggest that the market is generally able to anticipate the Chapter 11 filings and that the competitive effects have already been incorporated into the stock prices before the actual bankruptcy announcement. A test reveals that candidates for competitive effects experience a positive return in the 100 days before the bankruptcy announcement. This finding supports the abovementioned hypothesis.<sup>204</sup>

Jorion and Zhang (2007) investigate how financial distress can be transmitted within an industry using three different credit events. Chapter 7 filings, chapter 11 filings and 'jumps' in a firm's credit default spread (CDS). Generally, a Chapter 7 filing enforces a firm to complete liquidation, while a Chapter 11 filing protects the firm from creditors and allows for

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<sup>200</sup> Lang and Stulz (1992, p. 60).

<sup>201</sup> Lang and Stulz (1992, p. 60).

<sup>202</sup> Industry concentration is represented by the Herfindahl index.

<sup>203</sup> Ferris et al. (1997, p. 367)

<sup>204</sup> Ferris et al. (1997), p. 370.

reorganizations.<sup>205</sup> The authors argue that the forced exit of a firm under Chapter 7 should be associated with competitive effects as industry related overcapacity problem are resolved. In contrast, Chapter 11 bankruptcies should lead to contagious effects since the restructured firm potentially re-emerges as a 'new' competitor. Consistent with this line of argumentation, Jorion and Zhang (2007) find that industry rivals exhibit positive (negative) stock market reaction and narrower (wider) CDS spreads following Chapter 7 (Chapter 11) filings. While a bankruptcy filing may (at least) partly be anticipated by the market, a jump event “represents a purely unanticipated credit shock”.<sup>206</sup> Collin-Dufresne, Goldstein, and Helwege (2003) note that “many corporate bonds experience a large jump in their yield spreads without ever defaulting (e.g., the RJR LBO).<sup>207</sup> Thus, CDS spread jumps should be associated with contagious, rather than competitive effects since the firm continues to exist in the market. In line with this hypothesis, Jorion and Zhang (2007) find evidence for strong intra-industry contagious effects following jumps in a firm’s CDS spread. The observation of contagious versus competitive effects is depended on the type of credit events.

Hertzel and Officer (2012) study potential intra-industry contagious effects by investigating the impact of a firm's bankruptcy on the terms and conditions of loan contracts to industry rivals. The authors demonstrate that the average spread on loans to industry competitors is significantly higher when at least one bankruptcy occurred around the origination or renegotiation of the loan agreement. In addition, the non-price terms in a credit agreement appear to be stricter around industry bankruptcies. Specifically, loans tend to be shorter in maturity, have more covenants and collateral. Consistent with the evidence provided by Lang and Stulz (1992), the documented contagious effects differ with industry concentration. Hertzel and Officer (2012) show that industry contagion in loan spreads "is mitigated in concentrated industries".<sup>208</sup> While previous research has put emphasis on the short-term effects of financial distress contagion, this study provides evidence for contagious effects to have long-term consequences for a firm’s financing and investment policies.

### 2.3.2. Literature on Stakeholder Contagious Effects of Firm Bankruptcies

Hertzel, Lo, Officer and Rodgers (2008) are among the first to study how contagious effects of bankruptcy-related financial distress can extend beyond industry competitors to a firm’s

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<sup>205</sup> Jorion and Zhang (2007, p. 863).

<sup>206</sup> Jorion and Zhang (2007, p. 865).

<sup>207</sup> Collin-Dufresne, Goldstein, and Helwege (2003, p. 28)

<sup>208</sup> Hertzel and Officer (2012, p. 494)

economically linked partners. The authors examine the effects of bankruptcy events on a firm's customers and suppliers. They find that suppliers to bankrupt firms experience significant negative stock price reactions on the distress date and the bankruptcy announcement date.<sup>209</sup> The documented contagious effect of financial distress among suppliers appear to be stronger when the filing firm's industry experiences horizontal contagious effects. This suggests that suppliers find it more difficult to switch to other customer or have economic relations with other competitors of the filing firm. Hertz et al. (2008) further show that financial distress contagion not only affects the filing firm's immediate suppliers, but also their respective industries. In the presence of horizontal contagion effects, industry portfolios of the filing firm's suppliers exhibit a negative returns prior to and on the actual bankruptcy filing date. For customers, no significant contagious effects of financial distress can be observed.<sup>210</sup>

Jorion and Zhang (2009) investigate the extent to which bankruptcy-related financial distress can be transmitted across firms through the channel of counterparty risk. In particular, they examine how a bankruptcy event causes adverse effects to the filing firm's creditors. For industrial firms, exposure to counterparty risk comes in the form of trade credit. Trade credit represents an important part of a firm's financing activities, amounting to approximately 20% of a firm's assets.<sup>211</sup> In case of a debtor bankruptcy, the creditor may be faced with severe difficulties, dependent on the size of the exposure. Also, to the extent that trade credit is granted by the major customer and used to finance the operating activities, a creditor's ongoing business may be impaired by the bankruptcy. For financial service firms, exposure to counterparty risk stems from loans or bonds. Here, potential contagious effects on creditor firm should be less severe. This is due to a number of reasons: First, the lending amount to a particular firm is limited and financial institutions are compelled to diversify their risk. Second, banks voluntarily choose their borrowing partners, oftentimes under thorough scrutiny. Third, loans tend to be secured by other assets of the borrowing firm. Consequently, Jorion and Zhang (2009) hypothesize that the effects of a firm's default may be spilled-over to its creditors. Consistent with this, they find a negative stock price reaction and increasing CDS spreads for creditor firms following a bankruptcy event. The effect is stronger for the industrial firm

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<sup>209</sup> The distress date is defined as the date with "the most significant abnormal drop in market value of the filing firm" (Hertz et al. (2008, p. 379)

<sup>210</sup> Hertz et al. (2008) attribute the lack of statistical significance to the possibility that no economically relevant customer was identified. Also, customers may be the reason for the filing firm's financial distress indicating that potential demand shifts are already reflected in their stock prices.

<sup>211</sup> See e.g. Cunat (2007). In addition, Boissay (2006) reports that the average trade debt of S&P 500 firms is equal to around 30% to 40% of quarterly sales

sample. While the abnormal creditor return around the bankruptcy is -0.93% for industrial firm, the financial creditor firm sample experiences a return drop of 0.74%.<sup>212</sup> These contagious effects are also documented in the creditors' CDS spreads.

Kolay and Lemmon (2012) extend the work of Hertzel et al. (2008), using a similar dataset of firm failures and customer-supplier relationships the authors show that contagious effects (partly) depend on the type of distress that leads to bankruptcy. Specifically, contagious effects are stronger if the filing firm experiences pure economic distress, as compared to pure financial distress. While pure financial distress can be viewed as a firm having problems to repay their debt obligations but has an otherwise sound business model, pure economically distressed firms exhibit both, difficulties to meet existing debt obligations and poor operating performances.<sup>213</sup> Kolay and Lemmon (2011) show that suppliers to an economically distressed firms experience statistically significant returns of approximately -8% around distress date.<sup>214</sup> Suppliers to financially distressed firms, in contrast, have statistically insignificant returns in on the distress date. On the filing date, no significant wealth effects can be observed. In contrast to the findings of Hertzel et al. (2008), Kolay and Lemmon (2012) provide evidence for customers to suffer from contagious effects: Overall, customers to the filing firm exhibit a negative return of 1.87% around the distress date.<sup>215</sup> For subsamples based on pure economic and financial distress, however, the contagious effects of distress appear negligible. This is also true for the bankruptcy announcement period. Customers show no statistically significant abnormal returns around the date when the bankruptcy is announced.<sup>216</sup>

Boone and Ivanov (2012) study the contagious nature of firm failures in a different setting. The authors measure the wealth effects of firm bankruptcies on the partners to long-term collaborative agreements such as strategic alliances and joint ventures. For strategic alliances, strong evidence for negative spill-over effects of financial distress from the bankrupt to the non-bankrupt partner is provided. Specifically, non-bankrupt partner firms experiences, on average, statistically significant negative returns of 1.12% around the time of the bankruptcy announcement.<sup>217</sup> The spill-over effects are more pronounced for long-term partnerships and

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<sup>212</sup> Jorion and Zhang (2009, p. 2066).

<sup>213</sup> Kolay and Lemmon (2012, p. 3).

<sup>214</sup> The identification of the distress date involves a hand collection of news articles. The distress date is then defined as the "a date on which relevant news about the distressed firm first arrived in the market" (Kolay and Lemmon (2012, p. 3)

<sup>215</sup> Kolay and Lemmon (2011, p. 30).

<sup>216</sup> Kolay and Lemmon (2011, p. 49-55).

<sup>217</sup> Boone and Ivanov (2011, p. 558).

among partners that operate in declining industries.<sup>218</sup> Furthermore, the authors show that the operating performance and investment levels of non-bankrupt partners in strategic alliances are adversely affected by the bankruptcy event. For agreements that are structured as a joint venture, no significant wealth effects can be observed when one partners files for bankruptcy.<sup>219</sup>

In addition, a body of research has examined the spill-over effects of financial distress using the collapse of Lehman Brother as a case study. Work by Aragon and Strahan (2012), Fernando, May and Megginson (2012), Jorion and Zhang (2011) and Chakrabarty and Zhang (2012) unanimously show that firms with direct ties to the investment bank suffered severe adverse consequences, irrespective of the type linkages (e.g. prime brokerage for hedge funds, underwriting services for nonfinancial firms or derivatives exposures).

### 2.3.3. Section Summary

Section 2.1 provides an overview of the empirical studies that investigate the effects related to credit contagion. A number of studies have provided evidence for financial distress to cause both, competitive as well as contagious effects for industry rivals, depending on the level of industry concentration. However, the question of whether financial distress impacts industry rivals in a causal manner or whether the observed contagious effects are a result of an information release remains largely unanswered. Only Benmelech and Bergman (2011) make an attempt to provide insights on this issue by showing that competitors in the airline industry are affected by financial distress through the collateral channel. Furthermore, empirical studies have demonstrated that spill-over effects of financial distress can extend beyond industries affecting economically linked partners, such as suppliers, customers, and creditors of the troubled firm. Here, the effects vary with the level of exposure to the distressed firm. Table 4 provides a summary of empirical findings related to the contagious effects of firm bankruptcies.

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<sup>218</sup> Boone and Ivanov (2011, p. 559).

<sup>219</sup> Boone and Ivanov (2011, p. 568).

**Table 4: Overview of the Literature on Financial Contagion**

This table summarizes the findings of the studies that empirically investigate the contagious effects of financial distress. The studies are listed according to a chronological order.

Author	Year	Contagion Effects	Sample Time	Data	Findings
Lang and Stulz	1992	Industry contagion	1970 - 1989	US	<ul style="list-style-type: none"> <li>• Rival firms experience contagious effects when a firm files for bankruptcy</li> <li>• Contagious effects are more pronounced in highly levered industries</li> <li>• In concentrated industries, competitive effects dominate</li> </ul>
Ferris et al.	1997	Industry contagion	1979 - 1989	US	<ul style="list-style-type: none"> <li>• Rivals experience significant contagious effects when large firms file for bankruptcy</li> <li>• Small firm bankruptcies trigger contagious effects only among smaller sized firms</li> <li>• Candidates for competitive effects earn a positive cumulative return 100 before the bankruptcy announcement suggesting market anticipation</li> </ul>
Jorion and Zhang	2007	Industry Contagion	2001 - 2004	US	<ul style="list-style-type: none"> <li>• Industry rivals positive (negative) stock market reaction and narrower (wider) CDS spreads following Chapter 7 (Chapter 11) filings</li> <li>• Strong intra-industry contagious effects following unanticipated jumps in a firm's CDS spread</li> </ul>
Hertzel et al.	2008	Firm-level Contagion	1989 - 2007	US	<ul style="list-style-type: none"> <li>• Suppliers to bankrupt firms experience significant negative stock price reactions on the distress date and the bankruptcy announcement date</li> <li>• For customers, no significant contagious effects of financial distress can be observed</li> </ul>
Jorion and Zhang	2009	Firm-level Contagion	1999 - 2005	US	<ul style="list-style-type: none"> <li>• Negative stock price reaction and increasing CDS spreads for creditor firms following a bankruptcy event</li> <li>• The effect is stronger among industrial firms</li> </ul>
Kolay and Lemmon	2012	Firm-level Contagion	1980 - 2009	US	<ul style="list-style-type: none"> <li>• Contagious effects between customers and suppliers depend on the type of distress: financial and economic distress</li> <li>• Only suppliers to an economically distressed firms experience significant contagious effects</li> </ul>
Boone and Ivanov	2012	Firm-level Contagion	1989 - 2007	US	<ul style="list-style-type: none"> <li>• Contagious effects among partners in long-term collaborative agreements</li> <li>• Spill-over effects are more pronounced for long-term partnerships and among partners that operate in declining industries</li> <li>• Operating performance and investment levels are negatively affected</li> </ul>
Hertzel and Officer	2012	Industry Contagion	1980 - 2007	US	<ul style="list-style-type: none"> <li>• Average spread on loans to industry competitors is higher when at least one bankruptcy occurred around loan origination</li> <li>• Non-price term are more stringent around industry bankruptcies: shorter maturity, more covenants and collateral</li> </ul>

### 3. Data and Methodology

#### 3.1. Measurement of Distress Risk

This investigation uses a firm's expected default frequency (EDF) based on the distance-to-default measure of Merton's (1974) option pricing model to proxy for financial distress. In the Merton (1974) model, a firm's equity can be viewed in an option-based framework: Shareholders are residual claimants on the firm's assets in that they are only entitled to the cash flows that remain after all debt obligations have been fulfilled. The option's strike price is equal to the book value of debt. Consequently, the value of the equity is equal to zero if the value of the firm's liabilities exceeds the value of its assets.

The finance literature has put forward several alternative models to measure the degree to which firms are in financial distress.<sup>220</sup> Many of the existing models draw on accounting data retrieved from a firm's financial statements. The major concern using accounting data to predict corporate failure is that this type of information is inherently backward-looking, and thus disregards essential information about the future prospects of a firm.<sup>221</sup> In contrast, the EDF measure is computed using the theoretical underpinnings of the Merton (1974) model and thus includes investors' expectations about future performances. Financial distress is estimated using the market value of equity and debt. More importantly, the model takes the volatility of a firm's assets into account when estimating default risk. Particularly, the volatility of assets provides crucial information about a firm's probability to default. Accounting-based variables lack this sort of information.

##### 3.1.1. Expected Default Frequency

I closely follow Bharath and Shumway (2008) and Vassalou and Xing (2004) in computing the EDF measure for my sample of US firms.<sup>222</sup> I make a number of critical assumptions: First, I assume that the firm's assets consist of debt and equity only and that the value of the assets follows a geometric Brownian motion. This can be depicted mathematically as shown in the subsequent equation:

$$dV_A = \mu V_A dt + \sigma_A V_A dW \quad (22)$$

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<sup>220</sup> See Section 2.2.1 for an overview

<sup>221</sup> See Section 2.2.1 for a detailed discussion of the advantages of market-based distress risk models over accounting-based models.

<sup>222</sup> This approach is very similar to the one outlined in Crosbie (1999)

where,  $V_A$  represents the market value of the firm's assets,  $\mu$  is the continuously compounded expected return,  $\sigma_A$  is the instantaneous volatility of the firm's total assets and  $dW$  is a standard Wiener process.

Second, I assume that the firm has only one discount bond with maturity  $T$ . The strike price is equal to the face value of the firm's liabilities with a time to expiration of  $T$ . These assumptions make it possible to regard the equity value of the firm as a call option on the underlying assets. Applying the Black and Scholes (1973) formula, the value of the equity is then given by the following equation:

$$V_E = V_A N(d_1) - Fe^{-rT} N(d_2) \quad (23)$$

where,  $d_1$  and  $d_2$  are defined as follows.

$$d_1 = \frac{\ln\left(\frac{V_A}{F}\right) + \left(r + \frac{1}{2\sigma_A^2}\right)T}{\sigma_A\sqrt{T}}, \quad \text{and} \quad d_2 = d_1 - \sigma_A\sqrt{T} = \frac{\ln\left(\frac{V_A}{F}\right) + \left(r - \frac{1}{2\sigma_A^2}\right)T}{\sigma_A\sqrt{T}}$$

$V_E$  represents the market value of the equity and  $V_A$  is the market value of the total assets,  $F$  is denoted the face value of debt with time to maturity  $T$ ,  $r$  is the risk-free rate,  $\sigma_A$  is the asset's volatility, and  $N(\cdot)$  is the cumulative density function.

In order to derive the EDF measure, two important equations are required. The first is simply the Black and Scholes (1973) formula. The second puts the volatility of a firm's total value into a relation with the volatility of a firm's equity value. Specifically, on the ground that the equity value is a direct function of the total firm value and time, I can use Ito's Lemma to show that the volatility of the firm's equity and the volatility of the total firm value are related:

$$\sigma_E = \left(\frac{V_A}{V_E}\right) \times \frac{\partial V_E}{\partial V_{EA}} \times \sigma_A \quad (24)$$

Using the Black and Scholes (1973) model, it can be shown that  $\frac{\partial V_E}{\partial V_{EA}}$  is equal to  $N(d_1)$ . Thus, the volatility of the firm's assets and the volatility of the firm's equity are related according to the following form:

$$\sigma_E = \left(\frac{V_A}{V_E}\right) \times N(d_1) \times \sigma_A \quad (25)$$

Equation 23 and Equation 24 can then be used to estimate a firm's implied probability of default. Most of the various parameters required for solving the two equations are readily



available. Following Bharath and Shumway (2008), I estimate the volatility of equity ( $\sigma_E$ ) from historical stock returns over the last 12 months. The book value of a firm's debt is assumed to be equal to the face value of debt consisting of the current debt outstanding plus half of the long-term debt.<sup>223</sup> Vassalou and Xing (2004) argue that the inclusion of long-term debt is crucial as firms are required to pay interest payments which are part of the short-term liabilities. Also, the size of the long-term debt critically influences the firm's ability to roll over its short term debt. The time to maturity of the debt is assumed to equal one year. The market value of the firm's equity is simply the product of its share price times the number of shares outstanding. Estimates of the risk-free rate are obtained from the Federal Reserve Board of Governors.

I follow Vassalou and Xing (2004) and Crosbie and Bohn (2002) in implementing an iterative procedure to find the value of firm's assets. This involves several steps: I start by proposing an initial value of the firm's volatility of assets ( $\sigma_A$ ). This is equal to the historically estimated measure of the volatility of the firm's equity value ( $\sigma_E$ ) scaled by equity ratio. I then use this approximation in conjunction with Equation 23 to find the market value of the firm's assets for each day in the previous year. The next step is to estimate volatility of these values, which I use as an approximation for the next iteration. I repeat this procedure as long as the values of two consecutive iterations have converged to being smaller than 10E-10. Then, I use the estimate of the volatility of assets ( $\sigma_A$ ) to solve for the value of the firm's assets ( $V_A$ ) in Equation 23.

Once the solution is found, I use the following formula to compute the distance-to-default (DD) measure:

$$DD = \frac{\ln\left(\frac{V_A}{F}\right) + \left(\mu + \frac{1}{2\sigma_A^2}\right)T}{\sigma_A\sqrt{T}} \quad (26)$$

where  $\mu$  is the expected annual rate of return on assets. The expected default frequency (implied probability of default) is then computed in the following way:

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<sup>223</sup> The question of how much of a firm's long-term debt to include into the model is somewhat arbitrarily as actual interest payments cannot be estimated reliably. However, KMV uses this 50% arguing that "it captures adequately the financing constraints of firms" (Vassalou and Xing, 2004, p.837)

$$EDF_t = N \left( - \left( \frac{\ln \left( \frac{V_{A,t}}{X_t} \right) + \left( r - \frac{1}{2} \sigma_A^2 \right) T}{\sigma_A \sqrt{T}} \right) \right) = N(-DD) \quad (27)$$

This estimation process is repeated at the end of every month, resulting in monthly EDF values for each firm in my sample. A higher EDF indicates a higher probability of default.

### 3.1.2. Ohlson's (1980) O-Score

Even though the EDF measures based on Merton's (1974) model appears superior to accounting-based models on theoretical grounds, I also perform part of the analysis with Ohlson's (1980) O-Score model as a robustness check.<sup>224</sup> Potentially, the O-Score may provide further insights into the relationship between a firm's distress risk and the performance of its economically linked partners. I follow Griffin and Lemmon (2002) in construction the O-Score measure. I collect relevant data from the firm's financial statements using the Compustat quarterly tape. I then compute quarterly measures of the O-Score for each firm in my sample using the following equation:

$$\begin{aligned} O - Score = & -1.32 - 0.407(SIZE) + 6.03(TLTA) - 1.43(WCTA) \\ & + 0.076(CLCA) - 1.72(OENEG) - 2.37(NITA) - 1.83(FUTL) \\ & + 0.285(INTWO) - 0.521(CHIN)^{225} \end{aligned} \quad (28)$$

where,

- SIZE = Log (total assets divided by GNP price-level index)
- TLTA = Total liabilities divided by total assets
- WCTA = Working capital divided by total assets
- CLCA = Current liabilities divided by current assets
- OENEG = One if total liabilities exceeds total assets, zero otherwise
- NITA = Net income divided by total assets
- FUTL = Funds provided by operations divided by total liabilities
- INTWO = One if net income was negative for the last two years, zero otherwise

<sup>224</sup> See Section 2.2.1 for a detailed discussion of the flaws of accounting-based distress models

<sup>225</sup> The model depicted above is the Model 1, which shows the highest accuracy compared to different alternatives. In total, Ohlson (1980) establishes three different models: Model 1 is calibrated to predict default within one year, while Model 2 within two years, given that no default occurred in the first year. Model 3 is calibrated to predict default within one or two years.

- CHIN =  $(NI_t - NI_{t-1})$  divided by  $(|NI_t| + |NI_{t-1}|)$ , where NI is net income

In constructing the O-Score measure, I impose a lack of six month on the accounting variables to ensure that relevant information to compute the O-Score is available to market participants.

### 3.2. Data Sources

In order to empirically test the relationship between customer financial distress and supplier performances, I retrieve relevant data from multiple sources. This section outlines the data sources used in this investigation and explains corresponding matching procedures. While Section 3.2.1 provides information on databases that have become standard in empirical financial research, Section 3.2.2 gives a detailed overview of the dataset on customer-supplier relationships. Section 3.2.3 provides information on data sources used to implement the EDF measure of the Merton (1974) model.

#### 3.2.1. Traditional Data Sources

I collect stock trading information such as stock prices, returns, trading volume, and shares outstanding as well other firm level data from the Centre for Research on Security Prices (CRSP). Accounting data such as book value of equity and debt as well as other data from financial statements is retrieved from the Compustat database. For the stock return analysis, all accounting data is lagged by six months to ensure that the information is known to the general public. Information on institutional holdings is retrieved from Thomson 13F filings database. Analyst forecasts are retrieved from Institutional Broker Estimate System (I/B/E/S).

Given the necessity of using different databases to examine the relation between distress risk and performance of economically linked partners, I match the available data across all databases. I start with merging CRSP and Compustat. This involves a number of steps. First, I download the original CRSP and Compustat files. Second, I retrieve CRSP's merged linking table "cstlink2", a cross-reference file that includes a firm's historical CRSP Permno as well as the Compustat's corresponding Gvkey.<sup>226</sup> I use this table to link information provided by CRSP to the information contained in the Compustat database. For the purpose of illustration,

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<sup>226</sup> Beaver, McNichols and Price (2007) point out that the use of CRSP's reference table "cstlink2" may not be optimal as up to half of the delistings are excluded from the sample because the effective dates ranges of the links in the merged CRSP/Compustat database end before the actual delisting of a security occurs. This can produce a high degree of sample noise clouding inferences from the empirical analysis. To take of this potential problem, I conduct all the tests based on database matches using their proposed linking table. The results are not sensitive to this treatment.

Figure 3 shows an extract of the “cstlink2” reference table for the firm “Cabot Microelectronics Corporation”.

Observations	Standard and Poor's Identifier (Gvkey)	Historical CRSP PERMNO Link to COMPUSTAT Record	Historical CRSP PERMCO Link to COMPUSTAT Record	Link Type Code	Link Flag	First Effective Date of Link	Last Effective Date of Link	Used flag
1	133726	0	0	NR	XXX	19951001	20000403	0
2	133726	88152	37148	LC	BBB	20000404	E	1

Figure 3: Illustration of CRSP’s “cstlink2” File

As shown in the figure, the firm’s unique identifier provided by Compustat (Gvkey) is 133726 and its unique identifier provided by CRSP (Permno) is 88152. The link type code specifies the nature of the link. In the example, only the second observation is retained as the link type code “LC” indicates a complete link.<sup>227</sup> The used flag is set equal to one to indicate that this is the primary link.<sup>228</sup> In my study, I use the links that are designated with the link type code “LC” and “LU”. The “E” indicates that the link is effective up to the date on which the data has been downloaded.

After merging CRSP and Compustat, I use a firm’s CUSIP to link the information provided by Thomson Reuters Institutional Holdings (13F) Database to my sample.<sup>229</sup> Due to the fact that the CUSIP may change overtime, I rely on CRSP’s Permno-Historical CUSIP map to ensure that each CUSIP is matched with the corresponding Permno in the same time period.

In a last step, I match firm observations with the data provided by the I/B/ES database. While I/B/E/S provides for each firm a single primary identifier (IBES Ticker), this identifier is not

<sup>227</sup> The CRSP/Compustat merged database guide states that “Link type code. Each link is given a code describing the connection between the CRSP and Compustat data. Values are: LC – Link research complete. Standard connection between databases, LU – Unresearched link to issue by CUSIP, LX – Link to a security that trades on another exchange system not included in CRSP data, LD – Duplicate Link to a security. Another GVKEY/IID is a better link to that CRSP record, LS – Link valid for this security only. Other CRSP PERMNOs with the same PERMCO will link to other GVKEYS, LN – Primary link exists but Compustat does not have prices, NR – No link available, confirmed by research, NU – No link available, not yet confirmed” (CRSP, 2011 p. 5)

<sup>228</sup> Due to a number of reasons including the fact that CRSP focuses on stocks and Compustat on firms, mergers and acquisitions or delistings, a Permno – Gvkey link is not a one-to-one link during a period. Instead, one Permno may be linked to multiple Gvkeys and vice versa. The primary link indicates the best link as researched by CRSP.

<sup>229</sup> This database was formerly known as CDA / Spectrum 3 4 database

contained in the CRSP database. Therefore, I again rely on a firm's CUSIP to link information across databases.

### 3.2.2. Customer-Supplier Data

The Statement of Financial Accounting Standards No. 14 (SFAS No. 14 – “Financial Reporting for Segments of Business Enterprise”) of the Financial Accounting Standard Board (FASB) establishes the standards for public business enterprises regarding the disclosure of financial information on operating segments in their financial reports. According to SFAS No. 14, firms must report financial information for any industry segment that accounted for more than 10% of consolidated yearly sales, assets, or profits. Most importantly for my study, SFAS No. 14 requires public firms to report the identities of and the sales to their major customers if the revenue generated by a single customer is equal to or more than 10 % of the firm's total sales.<sup>230</sup> This regulation, being effective as of 1977, was replaced in 1998 by the Statement of Financial Accounting Standards No. 131 (SFAS No. 131), which imposes similar disclosure requirements on publically traded firms.<sup>231</sup>

Compustat collects the information published by firms in accordance with SFAS No. 131 in their industry segment files. This allows me to retrieve information on important and oftentimes longstanding customer-supplier relationships between firms. However, the data in the segment files are not listed in a usable format. While reporting firms are listed in the database with a unique identifier (Gvkey), customer identities are generally tabulated as company names or company name abbreviations. Here, the information on company names may vary across years. For example, the mining company Cliff Natural Resources Inc. reports their customer AK Steel Corporation as “AK STL HLD” in 1998 and as “AK Steel Holding Corp” in 1999. In addition, company names may also vary across firms. For example, in 1987, Armtek Corporation lists its customer Chrysler Corporation as “CHRYSLER CORP”, while Acme Precision Products

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<sup>230</sup> Paragraph 39 of SFAS No. 14 addresses the rules for disclosing information on major customers. Specifically, it states that “If 10 percent or more of the revenue of an enterprise is derived from sales to any single customer, that fact and the amount of revenue from each such customer shall be disclosed. (For this purpose, a group of customers under common control shall be regarded as a single customer.) Similarly, if 10 percent or more of the revenue of an enterprise is derived from sales to domestic government agencies in the aggregate or to foreign governments in the aggregate, that fact and the amount of revenue shall be disclosed. The identity of the industry segment or segments making the sales shall be disclosed. The disclosures required by this paragraph shall be made even if the enterprise is not required by this Statement to report information about operations in different industries or foreign operations” (Statement of Financial Accounting Standards No. 14, 1976).

<sup>231</sup> Even though SFAS No. 131 no longer requires firms to disclose the identity of their major customers, a large number of firms continued to provide this information in their annual reports.

Inc. lists Chrysler Inc. as “CHRYSLER CP”. Given the lack of a set pattern in the Compustat industry segment files, customer names cannot be readily matched with other firm information.

I follow the procedure as outlined in Fee and Thomas (2004) to link the customer names with full company data. This involves a number of steps: First, I employ a string matching algorithm that compares the order and number of letters of the customer names as listed in the segment files to the company names as reported in the CRSP historical company names file. The algorithm produces a list of preliminary matches by generating the three company names that are most similar to the abbreviation. I then visually inspect the list to verify the list of potential matches. In cases where a certain, distinct match can be determined, I link the customer abbreviation to the permanent identification number (Permno) as listed in the CRSP company names file. In some cases, the program generates multiple potential matches. Following Banerjee, Dasgupta and Kim (2008) I examine the business description of the respective industry segment to correctly identify the customer firm.<sup>232</sup> I eliminate all matches that do not appear to be related to the product of the industry segment. In addition, I exclude all customers from the sample where only a probable match can be established to ensure that my dataset contains only actual customer-supplier relationships. This involves a certain degree of discretion. However, I am deliberately conservative in matching company abbreviation with company names. I believe that the costs of including false customers exceed the costs of failing to identify a constrained number of true customers. My final sample has 15,797 unique customer-supplier relationships with 49,020 distinct annual customer-supplier relationships.<sup>233</sup> Table 5 presents the summary statistics for my sample of customers and suppliers.

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<sup>232</sup> Fee and Thomas (2004) provide an example of how the information on industry segments can be used to identify customer firms. My inspection procedure exactly follows their line of argumentation.

<sup>233</sup> My sample approximately corresponds to the sample used by Cohen and Frazzini (2008), who report 30,622 distinct firm-year relationships and a total of 11,484 unique supplier–customer relationships in the time period between 1980 and 2004.

**Table 5: Descriptive Statistics Customer-Supplier Sample**

This table shows the descriptive statistics of my customer-supplier sample used in this study. Coverage of stocks (EW) is the number of firms in the sample with a valid customer-supplier link divided by the total number of firms in the CRSP stock universe. Coverage of stocks (VW) is the total market capitalization of firms in the sample with a valid customer-supplier link divided by the total market capitalization of all stocks in the CRSP universe. Size is the market value of equity.

	Min	Max	Mean	SD	Median
<b>Panel A: Time Series (30 Annual Observations, 1981-2010)</b>					
Number of suppliers per year	573	1,427	1,062	236	1,054
Number of customers per year	281	749	529	129	509
Full sample coverage of stocks (EW)	17.58%	34.54%	25.75%	4.02%	25.46%
Full sample coverage of stocks (VW)	38.48%	74.64%	59.37%	8.82%	58.53%
Supplier coverage of stocks (EW)	11.80%	22.12%	17.15%	2.35%	16.83%
Supplier coverage of stocks (VW)	4.46%	17.35%	11.52%	3.23%	11.47%
Customer coverage of stocks (EW)	5.79%	12.76%	8.60%	1.78%	8.25%
Customer coverage of stocks (VW)	33.99%	60.27%	47.86%	6.71%	47.11%
<b>Panel B: Firms (Pooled Firm-Year Observations)</b>					
Supplier size percentile	0.01	0.99	40.32	0.62	39.50
Customer size percentile	0.01	0.99	78.64	2.99	98.00
Supplier Market-to-book percentile	0.01	0.99	39.40	0.88	36.50
Customer Market-to-book percentile	0.01	0.99	44.64	3.50	46.00
Number of firms per customer	1.00	14.00	1.51	0.95	1.00
Percentage sales to customer	0.00	100.00	19.80	17.04	14.38

Table 5 summarizes the descriptive statistics of my sample. The table shows the coverage of the firms in my sample as a fraction of the entire CRSP common stocks universe. For the supplier firms, my sample approximately mimics the size distributions of the CRSP universe. The mean supplier size percentile is equal to 40%. In contrast, the customer size distribution is. The customer size percentile is equal to 79%, and thus skewed towards large capitalization securities. This is intuitive given the fact that firms are required to report the identity of customers making up more than 10% of their sales. Intuitively, larger firms are more likely to be above the 10% sale cut-off.

### 3.2.3. Data Sources for Computing Expected Default Frequencies (EDF)

As described in the previous section, the Merton (1974) model requires a battery of input variables to compute monthly values of expected default frequencies. The first is the market value of equity that I use as a proxy for an initial value of the volatility of a firm's assets. I retrieve the information of the market value of a firm's equity by multiplying the shares outstanding with the share price. This information is retrieved from the daily file of the CRSP database. The second input variable of the Merton (1974) model is the book value of the firms'

long-term debt and short-term liabilities. I collect this information from the COMPUSTAT quarterly tape and convert it into monthly values.<sup>234</sup> The last information required for measuring a firm's expected default frequency is the risk-free rate. I download the relevant data from the website of the Federal Reserve Board of Governors. Specifically, the risk free rate used in this study is the 1-year Treasury Constant Maturity Rate, obtained from the Board of Governors of the Federal Reserve System.<sup>235</sup> Table 6 illustrates the EDF distribution of all firms in the sample by year.

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<sup>234</sup> CRSP's unique identifiers are different from COMPUSTAT's unique firm identifiers. I match the data from the two databases using the linking table as provided by WRDS. The detailed matching procedure is described in Section 3.2.3.

<sup>235</sup> The risk free rate can be found on <http://research.stlouisfed.org/fred2/series/DGS1/>



**Table 6: Descriptive Statistics EDF**

This table reports the mean, standard deviation, and the quartiles of the expected default frequency (EDF) distribution of firms in my sample per year. The sample period spans from 1980 to 2010. EDF quantities are reported in percentage terms.

Year	Mean	SD	25%	50%	75%
1980	6.691	18.291	0.000	0.001	0.928
1981	10.376	22.686	0.000	0.008	5.483
1982	4.915	15.763	0.000	0.000	0.198
1983	9.519	22.786	0.000	0.000	2.525
1984	9.165	22.585	0.000	0.000	1.916
1985	9.539	23.406	0.000	0.000	1.888
1986	10.872	23.749	0.000	0.008	5.430
1987	15.538	27.670	0.000	0.317	16.946
1988	11.543	25.049	0.000	0.002	5.557
1989	18.475	31.018	0.000	0.163	24.654
1990	17.439	30.272	0.000	0.115	20.850
1991	12.521	25.921	0.000	0.008	7.424
1992	11.368	25.046	0.000	0.002	4.853
1993	9.969	23.011	0.000	0.003	3.769
1994	10.398	23.850	0.000	0.002	3.557
1995	8.465	21.519	0.000	0.000	1.641
1996	9.370	23.223	0.000	0.000	1.666
1997	12.302	26.383	0.000	0.003	5.623
1998	16.190	28.774	0.000	0.283	17.619
1999	16.340	28.713	0.000	0.359	18.245
2000	22.093	34.008	0.000	0.678	35.964
2001	17.496	31.337	0.000	0.066	17.662
2002	13.217	27.644	0.000	0.005	6.454
2003	5.259	17.704	0.000	0.000	0.035
2004	6.354	19.652	0.000	0.000	0.071
2005	5.695	18.736	0.000	0.000	0.021
2006	5.763	18.556	0.000	0.000	0.040
2007	17.820	30.864	0.000	0.166	20.636
2008	28.913	35.652	0.030	8.053	57.254
2009	9.178	22.564	0.000	0.000	1.865
2010	6.691	18.291	0.000	0.001	0.928

Figure 4 below shows the relation between an aggregate measure of EDF, an aggregate measure of the O-Score and recession periods.<sup>236</sup> It can be verified that both the EDF measure as well as Ohlson's (1980) O-Score increase in periods of economic recessions. This clearly underlines the relationship between market downturns and default risk estimates.

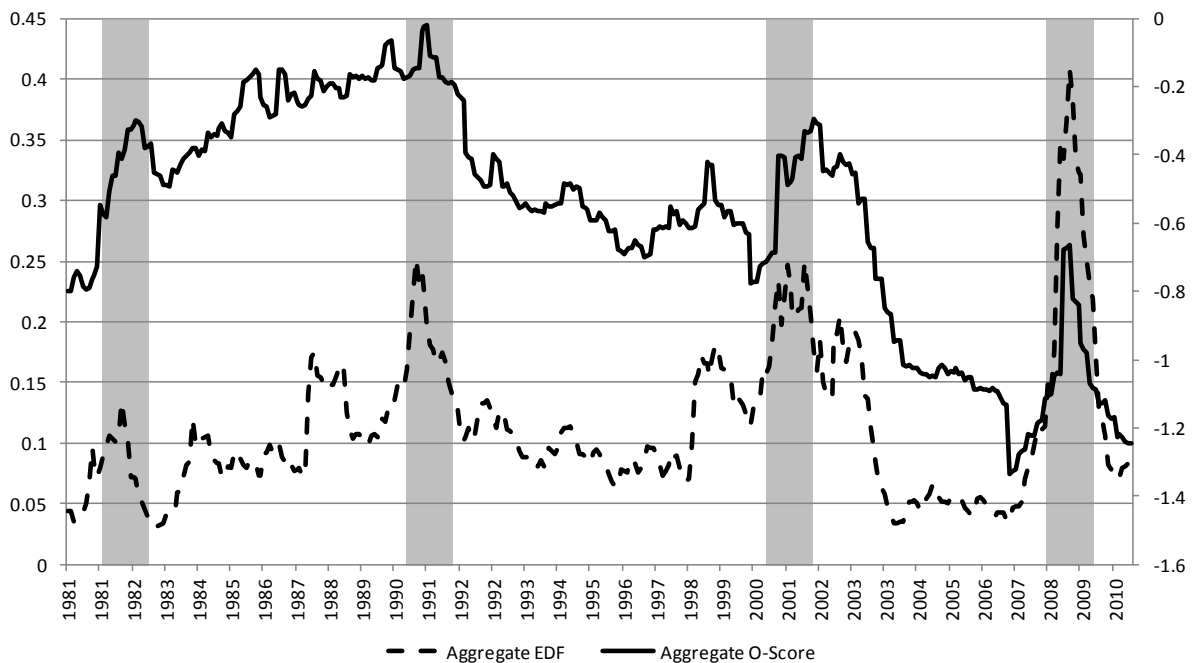


Figure 4: Aggregate EDF and O-Score Over Time

#### 4. Empirical Investigation

This section presents the empirical investigation concerning the contagious nature of financial distress. In the first subsection, the return and operating performance of suppliers to under-pressure customers is investigated. Next, the determinants of financial distress contagion are addressed. The last subsection presents the results concerning the question of whether investors are able to price the information on customer distress across the supply chain.

<sup>236</sup> The aggregate EDF is simply the average of all EDF values for the sample of CRSP/Compustat merged firms. Similarly, the aggregate O-Score is equal to the average O-Score for all firms with available data. Both measures are trimmed at the 1% and 99% level. Information on recession periods is available on <http://www.nber.org/cycles.html>

## 4.1. Performance of Suppliers to Under-pressure Customers

### 4.1.1. Stock Return Analysis

This section examines the performance of suppliers to distressed customers on the stock return level. First, unadjusted stock returns are presented. Second, returns are adjusted using the DGTW approach as well as industry portfolios.

#### 4.1.1.1. Stock Returns of Suppliers to Under-pressure Customers

This section shows the results of the empirical investigation for different weighting schemes of supplier portfolio returns. First, equally-weighted portfolios are examined. Second, sales-weighted portfolio returns are presented.

##### 4.1.1.1.1. Equally-weighted Portfolio Sorting

Table 7 shows the main results of this investigation. Each month from January 1981 to January 2011, I form quintile portfolios by sorting suppliers on their customers' EDF measure in the previous month. To be included in the portfolio, the firms must have non-missing customer distance-to-default values at the end of the previous month. Generally, low price stocks tend to have increased transaction costs, making it more difficult for investors to trade them. Following Garlappi et al. (2008), I exclude securities with a stock price smaller than 2\$ at the time of portfolio formation.<sup>237</sup> This restriction ensures that portfolio returns are not driven by illiquid micro-capitalization stocks.

Several firms in my sample have multiple customers at a given point in time. In that case, I use the average distance-to-default measure in my calculation.<sup>238</sup> For example, if two customers are identified for one supplier, the average of the two customers' EDF values is used in assigning the supplier into one of the quintiles.

Table 7 reports mean excess returns over the risk-free rate in monthly percentage points, with t-statistics in parentheses. Following Vassalou and Xing (2004), I use equal weights in computing average portfolio returns.<sup>239</sup> Furthermore, the table depicts alphas with respect to

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<sup>237</sup> Results remain qualitatively and quantitatively unchanged if I relax the liquidity threshold to 5\$.

<sup>238</sup> I also tried alternative ways to deal with multiple customers. For example, I used the highest (lowest) customer EDF values for assigning stocks into quintile portfolios. Results are not tabulated, however, remain unchanged.

<sup>239</sup> Results remain qualitatively the same when I use market value weights.

the CAPM, the three-factor model of Fama and French (1993). These models are estimated using the standard mimicking portfolios available on Professor Kenneth French's website.

The results in Panel A of Table 7 draw a clear picture: Suppliers to under-pressure customers underperform suppliers to non-distressed customers. The average excess return of suppliers in the highest customer default risk quintile is a low 0.18% per month, or approximately 2.2% per annum, and the average excess return of suppliers to the lowest customer default risk quintile is 0.73% per month or approximately 8.7% per annum. The difference is statistically significant at the 1% significance level. A zero-cost, long-short strategy that shorts suppliers to distressed customers and goes long suppliers to non-distressed customers yields an average excess return over the risk-free rate of 0.55% per month or 6.6% per year.

**Table 7: Supplier Returns to Under-Pressure Customers**

This table shows calendar-time supplier portfolio abnormal returns. At the beginning of each calendar month in the observation period from 1981 to 2010, stocks are ranked in ascending order according to their major customer's EDF measure in the previous month. The ranked stocks are assigned to one of five quintile portfolios (quintile 1: low customer risk portfolio, quintile 5: high customer risk portfolio). All stocks are equally-weighted within a given portfolio. I rebalance the portfolios every month to maintain the equal weights. The portfolios in the table include all stocks that have a share price larger than 2\$ at the time of portfolio formation. Panel A reports the mean excess returns over the risk-free rate and intercepts (alphas) from a rolling regression of monthly excess returns. Explanatory variables include the market factor and Fama and French factors (small minus big and high BM minus low BM). The factors are retrieved from the mimicking portfolios available on Professors Kenneth French's website. L/S is a rolling, zero-cost strategy that purchases the lowest 20% customer default risk suppliers and sells short the top 20% customer default risk suppliers. All returns and alphas are in monthly percent. Panel B reports corresponding factor loadings of the three-factor model regressions. Panel C presents portfolio characteristics. T-statistics are reported in italics. \*\*\*, \*\* and \* denote the statistical significance at the 1%, 5% and 10% level, respectively.

	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	L/S
<b>Panel A</b>						
Mean excess return	<b>0.73%</b>	<b>0.66%</b>	<b>0.70%</b>	<b>0.43%</b>	<b>0.18%</b>	<b>0.55%</b>
	<i>2.02**</i>	<i>1.92*</i>	<i>1.89*</i>	<i>1.17</i>	<i>0.47</i>	<i>2.95**</i>
CAPM alpha	<b>0.07%</b>	<b>0.01%</b>	<b>0.01%</b>	<b>-0.27%</b>	<b>-0.54%</b>	<b>0.61%</b>
	<i>0.32</i>	<i>0.05</i>	<i>0.03</i>	<i>-1.32</i>	<i>-2.45**</i>	<i>3.28***</i>
Three-factor alpha	<b>0.12%</b>	<b>-0.03%</b>	<b>0.01%</b>	<b>-0.28%</b>	<b>-0.61%</b>	<b>0.74%</b>
	<i>0.94</i>	<i>-0.25</i>	<i>0.08</i>	<i>-2.05</i>	<i>-4.01***</i>	<i>3.97***</i>
<b>Panel B</b>						
Market	<b>1.03</b>	<b>1.01</b>	<b>1.07</b>	<b>1.05</b>	<b>1.09</b>	<b>-0.06</b>
	<i>33.14***</i>	<i>37.99***</i>	<i>36.17***</i>	<i>35.96***</i>	<i>35.20***</i>	<i>-1.65</i>
SMB	<b>0.96</b>	<b>0.91</b>	<b>0.98</b>	<b>0.89</b>	<b>1.01</b>	<b>-0.05</b>
	<i>22.02***</i>	<i>24.24***</i>	<i>23.47***</i>	<i>21.72***</i>	<i>23.08***</i>	<i>-0.85</i>
HML	<b>-0.20</b>	<b>-0.07</b>	<b>-0.16</b>	<b>-0.15</b>	<b>-0.08</b>	<b>-0.12</b>
	<i>-4.33**</i>	<i>-1.77*</i>	<i>-3.52***</i>	<i>-3.43***</i>	<i>-1.75**</i>	<i>-2.08**</i>
Adjusted R <sup>2</sup>	0.87	0.90	0.90	0.89	0.89	0.27
<b>Panel C</b>						
Median Size	201,739	211,054	188,730	180,211	160,777	
Average Customer EDF	0.00	0.00	0.03	0.79	17.38	
Average Supplier EDF	4.18	4.84	4.90	5.39	6.82	
Portfolio SD	6.86	6.52	7.04	6.94	7.34	

Correcting for firm specific risks using standard asset pricing models does not alter the overall picture. In fact, it only worsens the performance of suppliers to customers in the highest default risk quintile. Suppliers to distressed stocks have a negative CAPM alpha of -0.54% per month, with a t-statistic of -2.45. A zero-cost long short strategy yields a monthly CAPM alpha of 0.61%, which is statistically significant at the 1% level.

In further tests, I add the book-to-market and small firm factors to the CAPM model. Similarly to the market factor in the CAPM model, the additional risk factors cannot explain the poor performance of suppliers to distressed customers. The Fama-French alpha of suppliers in the highest customer risk quintile is -0.61% per month, which is statistically significant at the 1% significance level. A zero cost, long-short strategy even yields a monthly alpha of 0.74%, translating into a return of approximately 8.88% per year. It is important to note that the return differential in the cross-section of supplier returns stems mainly from the high customer default risk leg. The computed alphas of suppliers to non-distressed supplier stocks are statistically indifferent from zero. Obviously, supplier returns suffer from the difficulties due to the increased distress risk of their respective customers.

In summary, Panel A of Table 7 provides robust evidence for supplier stocks to experience adverse developments when their respective customers become financially distressed. More importantly, rational asset pricing models do not appear to be able to fully capture these effects. This indicates that the information on the level of distress risks of economically linked partners is not priced by investors. I call this phenomenon the under-pressure customer anomaly.

Panel B of Table 7 presents the loadings of the three-factor model regression for the estimated calendar time portfolios. For the market (RM) and size (SMB) factors, no significant difference can be observed. The portfolios have similar exposure to these traded factors: While the loading of the market factor is equal to 1.03 (1.09) for the low (high) customer distress supplier portfolio, the loading of the size factor is equal 0.96 and 1.01 for the high and low customer distress portfolios, respectively. The loadings of the book-to-market factor (BM) differ to some extent across supplier portfolios. Here, low customer distress suppliers exhibit a factor loading of -0.2, while high customer distress suppliers have a factor loading of only -0.08. This suggests that supplier portfolios are rather dominated by low BM firms, as opposed to high BM firms. A similar picture can be drawn for the long-short portfolios. While the market and size factor do not capture the returns differentials, the book-to-market factor is partly able to explain the observed return patterns.

Panel C of Table 7 reports a selection of portfolio characteristics such as the median firm size, average customer EDF, supplier EDF and portfolio standard deviation. The median size firm declines across the supplier portfolios of customer distress risk. However, the differences are rather small. The median firm size decreases by approximately one quarter from the most to the least customer distress risk portfolio. Customer EDF differs significantly across portfolios. While customers in the lowest distress risk quintile have an EDF of 0.00% on average, the customers in the highest risk deciles have an EDF of 17.38%. Interestingly, the estimated EDF quantities for the supplier firms in the respective customer risk quintiles do not differ significantly. Suppliers to low distressed customers have an average EDF of 4.18%, while suppliers to highly distressed customers have an average EDF of 6.82%. This suggests that even though the return performance of the suppliers are significantly influenced by customer distress risk, the distress risk of the suppliers itself are not impacted. A similar picture can be drawn from the portfolios standard deviation. No significant differences across the customer distress risk portfolios can be documented.

This section provides evidence for a negative relationship between the extent to which a firm suffers from financial distress and the return performance of its economically linked partners. Traditional asset pricing model are not able to capture the return differences, suggesting that factors unrelated to systematic risk play a role. The results indicate that investors have difficulties in processing the information on financial distress across firms. In the next section, I examine whether the under-pressure customer anomaly is sensitive to using sales-weighted instead of equal-weighted sorting mechanisms.

#### 4.1.1.1.2. Sales-weighted Portfolio Sorting

In addition to using equally-weighted supplier portfolio returns in our analysis, I also conduct the same test as outlined above with the only difference being that I weigh the returns in the supplier portfolios by their sales weight to the respective customers. The results are presented in Table 8 below.

**Table 8: Sales-weighted Supplier Returns to Under-pressure Customers**

This table shows calendar-time supplier portfolio abnormal returns. At the beginning of each calendar month in the observation period from 1981 to 2010, stocks are ranked in ascending order according to their major customer's EDF measure in the previous month. Portfolio returns are weighted by the percentage of supplier total sales (PERSALES) that are generated by the respective customer. The ranked stocks are assigned to one of five quintile portfolios (quintile 1: low customer risk portfolio, quintile 5: high customer risk portfolio). The portfolios in the table include all stocks that have a share price larger than 2\$ at the time of portfolio formation. Panel A reports the mean excess return over the risk-free rate and intercepts (alphas) from a rolling regression of monthly excess returns. Explanatory variables include the market factor and Fama and French factors (small minus big and high BM minus low BM). The factors are retrieved from the mimicking portfolios available on Professors Kenneth French's website. L/S is a rolling, zero-cost strategy that purchases the lowest 20% customer default risk suppliers and sells short the top 20% customer default risk suppliers. Panel B reports portfolio characteristics. All returns and alphas are in monthly percent. T-statistics are reported in italics. \*\*\*, \*\* and \* denote the statistical significance at the 1%, 5% and 10% level, respectively.

	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	L/S
<b>Panel A</b>						
Mean excess return	<b>0.62%</b>	<b>0.54%</b>	<b>0.64%</b>	<b>0.43%</b>	<b>0.05%</b>	<b>0.57%</b>
	<i>1.52</i>	<i>1.44</i>	<i>1.66*</i>	<i>1.13</i>	<i>0.11</i>	<i>2.62***</i>
CAPM alpha	<b>0.01%</b>	<b>-0.01%</b>	<b>0.08%</b>	<b>-0.14%</b>	<b>-0.54%</b>	<b>0.55%</b>
	<i>0.06</i>	<i>-0.06</i>	<i>0.35</i>	<i>-0.64</i>	<i>-2.19**</i>	<i>2.51**</i>
Three-factor alpha	<b>-0.03%</b>	<b>-0.07%</b>	<b>0.03%</b>	<b>-0.15%</b>	<b>-0.68%</b>	<b>0.64%</b>
	<i>-0.20</i>	<i>-0.48</i>	<i>0.21</i>	<i>-0.99</i>	<i>-3.61***</i>	<i>2.93***</i>
Adjusted R <sup>2</sup>	0.85	0.85	0.83	0.86	0.84	0.12
<b>Panel B</b>						
PERSALES	15.69	18.42	20.34	20.72	21.97	
Median Size	764,338	944,368	1,209,342	797,276	429,948	
Average Customer EDF	1.06	0.54	0.05	0.45	15.10	
Average Supplier EDF	5.70	5.45	5.02	5.83	6.36	
Portfolio SD	6.99	6.49	6.59	6.61	7.02	

The results in Panel A of Table 8 are very similar to the results in Table 7. Suppliers to under-pressure customers underperform suppliers to financially healthy customers. The excess return differential between suppliers in the lowest customer distress risk quintile and suppliers in the highest customer risk quintile is equal to 0.57% per month, corresponding to approximately 6.84 per year. This difference is statistically significant at the 1% significance level. Using the CAPM model to correct for risk worsens the performance of suppliers to under-pressure customers. Specifically, the CAPM alpha of suppliers in the highest customer distress risk quintile is equal to -0.54% per month, statistically significant at the 5% level. A zero-cost, long-short strategy yields a CAPM alpha of 0.55% at the 5% significance level. Adding more factors to explain the return of supplier portfolios yields similar results. The Fama and French (1993)



three-factor alpha for suppliers in quintile 5 is -0.68% per month, which is statistically significant at the 1% level. The corresponding alpha of the long-short investment strategy is equal to 0.64% per month. This translates into an annual risk-adjusted return of approximately 7.68%.

Panel B reports various portfolio characteristics. The average sales percentage going to the customers increases slightly from the low customer risk portfolio to the high customer risk portfolio. In quintile 1, around 15% of the suppliers' total sales are generated by the customer firms, while in quintile 5 this number increases to approximately 22%. Supplier firm in quintile 5 appear to be smaller in market capitalization compared to suppliers in quintile 1. The standard deviations of portfolio returns as well as the supplier EDFs do not appear to vary substantially across the different customer risk quintiles of supplier firms.

Overall, the results in Table 8 suggest that the under-pressure customer anomaly is not affected by a change in the portfolio weighting procedure. A significant return differential between suppliers to low distress customers and high distress customers can be documented.

#### 4.1.1.2. Return Adjustments

##### 4.1.1.2.1. DGTW-adjusted Returns

Daniel et al. (1997) argue that characteristics-based benchmark portfolios provide a better ex-ante forecasts of the cross sectional pattern of future returns. Also, Cremers et al. (2012) show that Fama & French (1993) mimicking portfolios have a methodological bias as they put too much weight on small-value firms. To check for the possibility that abnormal returns are driven by errors in the underlying methodology of the mimicking portfolios, I apply a characteristic-based benchmark portfolio approach to adjust for risk differences among the supplier firms. I follow Daniel et al. (1997) in estimating benchmark portfolios.<sup>240</sup> Specifically, I subtract the return on a portfolio of firms matched with respect to size, BM and 1-year return momentum from the supplier stocks' returns. This sorting procedure results in a total of 125 matching portfolios. The DGTW quintile portfolios are constructed using the entire CRSP stock universe with available data in that month. The portfolios are restructured every month. Table 9 reports the results of this test.

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<sup>240</sup> A number of papers have also used DGTW adjusted returns. See e.g. Campbell et al. (2008)

**Table 9: DGTW-adjusted Returns of Suppliers to Under-pressure Customers**

This table shows calendar-time supplier portfolio abnormal returns. At the beginning of each calendar month in the observation period from 1981 to 2010, stocks are ranked in ascending order according to their major customer's EDF measure in the previous month. The ranked stocks are assigned to one of five quintile portfolios (quintile 1: low customer risk portfolio, quintile 5: high customer risk portfolio). All stocks are equally-weighted within a given portfolio. I rebalance the portfolios every month to maintain the equal weights. The portfolios in the table include all stocks that have a share price larger than 2\$ at the time of portfolio formation. Panel A reports DGTW adjusted returns. DGTW-adjusted returns are defined as raw monthly returns minus the returns on an equally weighted portfolio of all CRSP firms in the same size, market-book and 1-year momentum quintile. L/S is a rolling, zero-cost strategy that purchases the lowest 20% customer default risk suppliers and sells short the top 20% customer default risk suppliers. Panel B reports portfolio characteristics including average customer EDF and average supplier EDF. All returns are in monthly percent. T-statistics are reported in italics. \*\*\*, \*\* and \* denote the statistical significance at the 1%, 5% and 10% level, respectively.

	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	L/S
<b>Panel A</b>						
DGTW Returns	<b>0.22%</b>	<b>0.04%</b>	<b>0.14%</b>	<b>-0.13%</b>	<b>-0.29%</b>	<b>0.51%</b>
	<i>1.64</i>	<i>0.40</i>	<i>1.23</i>	<i>-1.24</i>	<i>-2.71**</i>	<i>3.03***</i>
<b>Panel B</b>						
Average Customer EDF	0.00%	0.00%	0.03%	0.80%	17.76%	0.00%
Average Supplier EDF	6.90%	8.15%	7.93%	8.87%	11.08%	6.90%

Panel A of Table 9 presents the returns to equally-weighted supplier portfolios sorted based on the previous month customer EDF measure. The results indicate that the under-pressure anomaly is not due to methodological bias in the Fama and French (1993) mimicking portfolios. Suppliers to high default risk customers (quintile 5) earn an average size, value and momentum adjusted excess return of -0.29%, which is statistically significant at the 1% level. In contrast, suppliers to non-distressed customer (quintile 1) earn a statistically insignificant positive excess return of 0.22%, on average. The difference in returns of suppliers to high and low customer default risk is 0.51% per month and statistically significant at the 1% level. Using DGTW-adjusted returns even increases the returns generated by the long-short strategy. Hence, the under-pressure customer anomaly cannot be traced back to methodological issues concerning Fama and French (1993) mimicking portfolios.

Panel B of Table 9 reports average customer EDF and average supplier EDF quantities. The customer EDF values are fairly similar to the ones reported in Table 7. While the lowest customer distress portfolios exhibit EDF measures close to zero, the highest customer distress

risk portfolio has an average EDF of 17.76%.<sup>241</sup> The same is true for the portfolios' average supplier EDF measure. A slight increase of supplier EDF can be observed as I move from low customer distress risk portfolios to high customer distress risk portfolios.

#### 4.1.1.2.2. Industry-adjusted Returns

The under-pressure customer anomaly could well be a result of industry-related effects, rather than true contagious effects across contractually linked partners. For example, the decreased returns of suppliers to distressed customers could stem from overall negative developments in their specific industry and not from the poor performance of the customers. I account for this possibility by measuring the under-pressure customer anomaly using industry-adjusted returns. Industry-adjusted returns are computed by deducting the returns on industry-matched portfolios from monthly supplier returns. Industries are defined according to Fama and French (1997) 48 industry portfolios.<sup>242</sup> Table 10 presents the industry-adjusted return performances of supplier portfolios.

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<sup>241</sup> In my main investigation, this measure is equal to 17.38%.

<sup>242</sup> The results in this paper are robust to different industry classifications

**Table 10: Industry-adjusted Returns of Suppliers to Under-pressure Customers**

This table shows calendar-time supplier portfolio abnormal returns. At the beginning of each calendar month in the observation period from 1981 to 2010, stocks are ranked in ascending order according to their major customer's EDF measure in the previous month. The ranked stocks are assigned to one of five quintile portfolios (quintile 1: low customer risk portfolio, quintile 5: high customer risk portfolio). All stocks are equally-weighted within a given portfolio. I rebalance the portfolios every month to maintain the equal weights. The portfolios in the table include all stocks that have a share price larger than 2\$ at the time of portfolio formation. Industry adjusted returns are defined as raw returns minus the returns of the corresponding industry portfolios. Panel A reports the industry-adjusted returns of the supplier portfolios. Industry-adjusted returns are computed by deducting the returns on industry-matched portfolios from monthly supplier returns. Industries are defined according to Fama and French (1997) 48 industry portfolios. L/S is a rolling, zero-cost strategy that purchases the lowest 20% customer default risk suppliers and sells short the top 20% customer default risk suppliers. All returns are in monthly percent. Panel B reports corresponding portfolio average customer EDF and portfolio average supplier EDF. T-statistics are reported in italics. \*\*\*, \*\* and \* denote the statistical significance at the 1%, 5% and 10% level, respectively.

	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	L/S
<b>Panel A</b>						
Industry-adjusted returns	<b>-0.08%</b>	<b>-0.22%</b>	<b>-0.11%</b>	<b>-0.26%</b>	<b>-0.54%</b>	<b>0.46%</b>
	<i>-0.68</i>	<i>-2.08**</i>	<i>-1.10</i>	<i>-2.58**</i>	<i>-5.35***</i>	<i>4.66***</i>
<b>Panel B</b>						
Average Customer EDF	0.00%	0.00%	0.03%	0.79%	17.38%	
Average Supplier EDF	4.18%	4.84%	4.90%	5.39%	6.82%	

The table clearly shows that the under-pressure customer anomaly is not caused by industry-related effects. Even though the suppliers in the different customer distress portfolios appear to underperform their industry on average, the suppliers to the most distressed customers show the worst performance.<sup>243</sup> The monthly return difference between suppliers in the lowest customer distress risk quintile and suppliers in the highest customer risk quintile is equal to 0.46% and statistically significant at the 1% level. The strategy's profitability can be attributed to the short leg, with a highly statistically significant return of -0.54%.

#### 4.1.1.3. Section Summary

This section shows that supplier returns are affected by customer default risk. Using equally-weighted quintile portfolios, I provide evidence for suppliers to distressed customers to underperform significantly. The negative returns cannot be fully explained by conventional asset pricing models. This already indicates that investors may not be able to process the

<sup>243</sup> A potential explanation for the overall underperformance of US suppliers may include increased competition from international suppliers squeezing their US based peers.

information on customer distress risk and pricing respective supplier stocks. Furthermore, the observed under-pressure customer anomaly is robust to return adjustments. In a test, I have used DGTW-adjusted returns to check for the possibility that the Fama and French mimicking portfolios do not effectively capture the fundamental risks in the cross-section of stock returns. The results indicate that this has no effect on the persistence of the under-pressure customer anomaly. Moreover, I used industry-adjusted return instead of excess returns over the risk-free rate to investigate whether the under-pressure customer anomaly is related to industry effects, rather than true contagious effects of financial distress. The results show that the anomaly is robust to this possibility as well.

#### 4.1.2. Under-pressure Customers and Real Effects of Suppliers

This section examines the real effects of customer distress on supplier firms. Section 4.1.2.1 investigates the operating performances of suppliers to under-pressure customers, while Section 4.1.2.2 focuses on the effects on trade credits.

##### 4.1.2.1. Operating Performance

Potential strategic or operational measures undertaken by distressed customers should not only be reflected in the supplier firm stock returns, but may also be visible in their books. For instance, Hertz et al. (2004) cite the example of US Airways, which announced flight cuts while experiencing financial difficulties in the time period from 2001 to 2002. Possibly, these measures will translate into adverse effects of its suppliers causing the operating performances to deteriorate. This section examines how the operating performance of suppliers to distressed customers is affected. I use data from the Compustat quarterly tape to derive a number of widely used operating ratios. These ratios include operating margin (EBITDA / Sales), pretax profit margin (Pre-tax profit / Sales), return on assets (Profit / Assets) and returns on sales (Profit / Sales). Supplier stocks are sorted into quintile portfolios according to their major customers' previous month EDF values. Table 11 reports the results of the tests.

**Table 11: Operating Performance of Suppliers to Under-pressure Customers**

This table shows the operating performance of suppliers to distressed customers. Each quarter, stocks are ranked in ascending order according to their major customer's EDF measure in the previous month. The ranked stocks are assigned to one of five quintile portfolios (quintile 1: low customer risk portfolio, quintile 5: high customer risk portfolio). Operating profit margin is a firm's EBITDA divided by the sales. Pre-tax profit margin is a Firm's pre-tax profit scaled by sales. Return on assets and return on sales is a firm's net profit divided by the assets and sales, respectively. Panel A shows the median unadjusted operating ratios for supplier stocks. Panel B reports the industry adjusted median operating performance ratios. Firms are assigned to the Fama and French 48 industry portfolios and the median operating performance measure is computed. Industry adjusted operating performance is computed by subtracting the median industry operating performance from the supplier firm's operating performance. All stocks are equally weighted within a given portfolio. The portfolios in the table include all stocks that have a share price larger than 2\$ at the time of portfolio formation. T-statistics are reported in italics. \*\*\*, \*\* and \* denote the statistical significance at the 1%, 5% and 10% level, respectively.

	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	Q1-Q5
<b>Panel A: Raw Operating Performance Ratios</b>						
Operating profit margin	3.77%	3.82%	3.67%	3.64%	3.58%	0.18% 2.84***
Pretax-profit margin	5.65%	5.50%	5.32%	5.12%	4.31%	1.34% 4.72***
Return on assets	1.64%	1.60%	1.56%	1.53%	1.39%	0.24% 4.98***
Return on sales	3.73%	3.62%	3.53%	3.33%	2.80%	0.93% 4.75***
<b>Panel B: Industry-adjusted Operating Performance Ratios</b>						
Operating profit margin	0.37%	0.45%	0.34%	0.23%	0.14%	0.23% 4.89***
Pretax-profit margin	1.06%	1.35%	1.03%	0.49%	-0.14%	1.20% 5.15***
Return on assets	0.27%	0.25%	0.19%	0.12%	0.02%	0.25% 7.08***
Return on sales	0.72%	0.86%	0.66%	0.31%	-0.06%	0.78% 5.01***

Panel A of Table 11 shows several key operating performance measures for the quintile portfolios formed in a similar fashion to the return analysis. Every quarter I sort supplier stocks according to their customers' distress risk in the previous month. For each portfolio, I compute the average median operating performance measures. The results in Table 11 show that all listed operating performance measures are significantly lower for suppliers to under-pressure customers (quintile 5) as compared to suppliers to non-distressed customers (quintile 1). These differences are all statistically significant at the 1% level. Suppliers to distressed customers earn an operating profit margin that is approximately 0.18% lower than the operating margin

of suppliers to non-distressed customer firms. This picture is even more severe for the pre-tax margin and return on sales: suppliers to under-pressure customers have a pre-tax profit margin and a return on sales of 4.31% and 2.80%, respectively. This is almost two-thirds of what suppliers to non-distressed customers are able to generate, specifically 5.65% and 3.73% for the pre-tax profit margin and return on sales, respectively.

Panel B of Table 11 replicates the results in Panel A using industry-adjusted median operating performance measures. I compute the industry medians using Fama and French 48 industry classifications and deduct the estimated industry medians from the supplier firm's corresponding operating performance measures. The adjustment generates a consistent picture: Suppliers to distressed customers exhibit a lower operating performance throughout all listed performance measures. The operating profit margin of suppliers in quintile 5 is 0.23% lower compared to suppliers in the lowest customer distress quintile. For the pre-tax profit margin and the return on sales, suppliers to under-pressure customers show negative operating performance measures, suggesting that these firms even underperform their industry. Suppliers to high distress customers generate a return on asset that is close to zero.

The results in Table 11 unanimously suggest that the operating performance of suppliers is affected by the degree of customer financial distress.<sup>244</sup> Supplier firms are impacted by the consequences of the financial difficulties experienced by their respective major customers.

#### 4.1.2.2. Trade Credits

I also examine whether suppliers change their trade credit policy when their major customers become financially under pressure. As outlined in Ng, Smith and Smith (1999), a trade credit contract in its simplest form spell outs that full payment is due in a certain period of time after product delivery. Hence, trade credit can be regarded as a type of short term financing granted by the selling firm. It is important to note that under chapter 11 regulation, trade credit is treated as an unsecured claim, that is, trade credit has the lowest priority for payment. Hence, the suppliers who fear that their major customer will file for bankruptcy have two opposite incentives: On the one hand, suppliers may become wary of trade credit claims and consequently reduce it in the wake of customer financial distress substantially. On the other hand, suppliers to distressed customers may extend trade credit to prevent liquidation of the

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<sup>244</sup> In unreported results, I examine the operating performance of suppliers for more extreme percentiles of the customer distress risk distribution. The results indicate a strong negative relation between customer distress risk and supplier operating performance

customer firm. That is, they trade-off the loss of existing trade credit with the loss of future sales generated by the customers. In this section, I investigate the response of suppliers to distressed customer with respect to their trade credit policies. Following Kolay and Lemmon (2012) I measure supplier trade credit as the trade receivables outstanding divided by the total assets. Data on trade receivables is retrieved from the Compustat annual file.<sup>245</sup> Given that the data is only available in annual format, I diverge from the monthly sorting procedure. Instead, I measure the average customer EDF in year  $t$  and investigate corresponding effects of supplier trade credit policies in year  $t+1$ . Also, since changes in trade credit policies may be more relevant for suppliers to close-to-bankruptcy customers, I use more extreme customer distress percentiles in the analysis. Specifically, I compare suppliers in the lowest five percent customer distress percentile to suppliers in the highest five percent customer distress percentile. Table 12 reports the sorting results.

**Table 12: Trade Credits of Suppliers to Under-pressure Customers**

This table shows the operating performance of suppliers to distressed customers. Each quarter, stocks are ranked in ascending order according to their major customer's EDF measure in the previous month. The ranked stocks are assigned to one of five quintile portfolios (quintile 1: low customer risk portfolio, quintile 5: high customer risk portfolio). Trade credit is measured as the trade receivables outstanding divided by the total assets. Panel A shows the median level of trade credit outstanding. Panel B reports the change in trade credits form year  $t$  to year  $t-1$ . Firms are assigned to the Fama and French 48 industry portfolios. All stocks are equally weighted within a given portfolio. The portfolios in the table include all stocks that have a share price larger than 2\$ at the time of portfolio formation. T-statistics are reported in italics. \*\*\*, \*\* and \* denote the statistical significance at the 1%, 5% and 10% level, respectively.

	00-05	06-95	95-100	H-L
<b>Panel A: Median Level of Supplier Trade Receivables</b>				
Trade	14.23%	15.59%	15.88%	1.65
<b>Panel B: Percentage Change in Supplier Trade Receivables</b>				
% Change in	0.41%	-0.16%	-3.37%	-3.78

Panel A of Table 12 presents the median level of trade receivables outstanding of suppliers sorted according to the previous year customer EDF quantities. It is observable that suppliers to under-pressure customers have slightly higher trade receivables in their books. This may indicate that suppliers, becoming wary of future cash-flows generated by their customers, rather extend trade credit lines to existing customers. On the other hand, the higher level of trade credit for suppliers in quintile 5 may indicate that customers simply delay product

<sup>245</sup> Compustat does not report trade receivables in the quarterly file.



payment. This leads to swelling trade receivables. To further investigate this issue, I compute the annual change in supplier trade receivables, reporting the results in Panel B.

Panel B clearly shows that suppliers to highly distressed customers decrease their trade receivables by 3.37% in the year after the customer becomes financially under pressure. In contrast, suppliers to financially healthy customers show a median change that is close to zero. This result suggests that suppliers indeed change their trade credit policies in the wake of customer distress. Potentially, they become wary of the outstanding claims and decrease trade receivables to prevent further losses.

#### 4.1.2.3. Section Summary

This section examines the real effects of customer distress on respective supplier firms. I use four different, widely used operating ratios to measure the effect of customer distress on the operating performance of suppliers. The results suggest that suppliers to distressed customers experience significantly lower performances compared to suppliers to non-distressed customers. This relationship holds across all used measures of operating performance and even if I adjust for industry differences. Furthermore, suppliers to highly distressed customers decrease their trade receivables in the wake of customer financial distress. This implies that supplier firms favour outstanding claims over the possibility to generate future revenue with the customer.

### 4.2. Robustness Tests of the Under-pressure Customer Anomaly

The results in Section 4.1 and 4.2 draw a consistent picture: Supplier firms show a significant underperformance when their major customers suffer from financial distress. However, a number of alternative explanations of the return patterns may also be plausible. In this section, I perform a battery of robustness checks to examine whether I observed true contagious effects of financial distress or not.

#### 4.2.1. Ohlson's (1980) O-Score

The first robustness test involves the use of an alternative model to estimate the level of customer default risk. I select Ohlson's (1980) O-Score model as it is widely used in other studies that examine the cross sectional relation between distress risk and stock returns.<sup>246</sup> The O-Score model is based on accounting data as opposed to the EDF measure of the Merton

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<sup>246</sup> See e.g. Griffin and Lemmon (2004)

model (1974). Whereas proponents of market-based default models claim that there is no insightful information in accounting data, there are studies suggesting that accounting information can be incrementally informative, even if markets are efficient.<sup>247</sup> I define the O-Score variable as outlined in Griffin and Lemon (2002). I use quarterly data to compute the O-scores for each customer in the sample. The relevant accounting data is lagged by six month. The sorting procedure follows the guidelines as described in Section 4.1.

**Table 13: Supplier Returns to Under-Pressure Customers using Ohlson’s O-Score Model**

This table shows calendar-time supplier portfolio abnormal returns. At the beginning of each calendar month in the observation period from 1981 to 2010, stocks are ranked in ascending order according to their major customer’s O-Score measure in the previous month. O-Score is defined as in Griffin and Lemmon (2004). The ranked stocks are assigned to one of five quintile portfolios (quintile 1: low customer risk portfolio, quintile 5: high customer risk portfolio). All stocks are equally-weighted within a given portfolio. I rebalance the portfolios every month to maintain the equal weights. The portfolios in the table include all stocks that have a share price larger than 2\$ at the time of portfolio formation. Panel A reports the intercepts (alphas) from a rolling regression of monthly excess returns. Explanatory variables include the market factor and Fama and French factors (small minus big and high BM minus low BM). The factors are retrieved from the mimicking portfolios available on Professors Kenneth French’s website. L/S is a rolling, zero-cost strategy that purchases the lowest 20% customer default risk suppliers and sells short the top 20% customer default risk suppliers. All returns and alphas are in monthly percent. Panel B reports corresponding portfolio average customer O-Scores and portfolio average supplier O-Scores. T-statistics are reported in italics. \*\*\*, \*\* and \* denote the statistical significance at the 1%, 5% and 10% level, respectively.

	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	L/S
<b>Panel A</b>						
Mean excess return	<b>0.81%</b>	<b>0.50%</b>	<b>0.66%</b>	<b>0.52%</b>	<b>0.50%</b>	<b>0.31%</b>
	<i>1.78*</i>	<i>1.43</i>	<i>1.90*</i>	<i>1.50</i>	<i>1.46</i>	<i>1.46</i>
Three-factor alpha	<b>0.16%</b>	<b>-0.12%</b>	<b>-0.07%</b>	<b>-0.21%</b>	<b>-0.22%</b>	<b>0.38%</b>
	<i>0.93</i>	<i>-0.82</i>	<i>-0.56</i>	<i>-1.76*</i>	<i>-1.72*</i>	<i>2.14**</i>
Adjusted R <sup>2</sup>	<i>0,87</i>	<i>0,83</i>	<i>0,88</i>	<i>0,89</i>	<i>0,86</i>	<i>0,36</i>
<b>Panel B</b>						
Average Customer O-Score	-3.55	-2.48	-1.96	-1.35	-0.06	
Average Supplier O-Score	-1.84	-1.08	-1.08	-1.40	-1.21	

Panel A of Table 13 presents portfolio mean excess returns and three-factor alphas. Qualitatively, I can document a return pattern consistent with the existence of an under-pressure customer anomaly: While suppliers in quintile 1 earn monthly excess returns of 0.81%, suppliers in quintile 5 realize monthly excess returns of only 0.5%, on average. The difference, however, is not statistically significant at conventional levels. The picture changes when I correct for risks using the Fama and French (1993) three-factor model. Suppliers to low

<sup>247</sup> See e.g. Core and Schrand (1999) and Duffie and Lando (2001).

distress customers show a statistically insignificant alpha of 0.16%, while suppliers to high distress customer earn a negative alpha of 0.22%, which is significant at the 10% level. The long-short strategy generates a significant alpha equal to 0.38%. Thus, the observed relationship between under-pressure customers and their respective suppliers does not depend on the model used for estimating customer default risk. However, it is less pronounced compared to the results when I use the Merton (1974) model to proxy for customer distress risk. I attribute this to the noise generated by using accounting variables instead of market data.

#### 4.2.2. Lead-lag Effects and the Under-pressure Customer Anomaly

##### 4.2.2.1. Lead-lag Effects in Market Capitalization

Lo and Mackinley (1990) provide evidence for stocks to exhibit positive cross-autocorrelation. The authors show that the returns of large firms lead the returns of small firms. Potentially, the under-pressure customer anomaly can be a cause of such lead-lag effects, rather than true contagious effects of financial distress. For my sample, these effects may particularly become severe as the customers are, on average, larger in market capitalization than their suppliers.<sup>248</sup> In order to test for this hypothesis, I conduct the an analysis as outlined in Section 4.1, only that I exclude all suppliers that are smaller than their customers at the time of portfolio formation. If the under-pressure customer anomaly is a result of the contagious nature of financial distress, and not size-related lead-lag effects, the negative relationship between customer distress and supplier performance should hold. Table 14 presents the results.

#### **Table 14: Lead-lag Effects – Market Capitalization**

This table shows calendar-time supplier portfolio abnormal returns. At the beginning of each calendar, stocks are ranked in ascending order according to their major customer's EDF measure in the previous month. The ranked stocks are assigned to one of five quintile portfolios (quintile 1: low customer risk portfolio, quintile 5: high customer risk portfolio). All stocks are equally-weighted within a given

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<sup>248</sup> See the descriptive statistics (Table 5)

portfolio. I rebalance the portfolios every month to maintain the equal weights. The portfolios in the table include all stocks that have a share price larger than 2\$ at the time of portfolio formation. All supplier stocks are excluded that have a market capitalization smaller than their major customer. The table reports excess returns and the intercepts (alphas) from a rolling regression of monthly excess returns as well as average customer EDF and supplier EDF. Explanatory variables include the market factor and Fama and French factors (small minus big and high BM minus low BM). The factors are retrieved from the mimicking portfolios available on Professors Kenneth French's website. L/S is a rolling, zero-cost strategy that purchases the lowest 20% customer default risk suppliers and sells short the top 20% customer default risk suppliers. All returns and alphas are in monthly percent. T-statistics are reported in italics. \*\*\*, \*\* and \* denote the statistical significance at the 1%, 5% and 10% level, respectively. Panel A presents the results for the time period from 1981 to 1995. Panel B reports the results for the time period from 1996 to 2010.

	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	L/S
<b>Panel A: Returns</b>						
Excess Returns	<b>0.98%</b>	<b>0.36%</b>	<b>0.81%</b>	<b>0.35%</b>	<b>-0.09%</b>	<b>1.06%</b>
	<i>2.04**</i>	<i>0.85</i>	<i>1.72*</i>	<i>0.67</i>	<i>-0.15</i>	<i>1.98*</i>
Three-factor alpha	<b>0.32%</b>	<b>-0.15%</b>	<b>0.19%</b>	<b>-0.35%</b>	<b>-0.98%</b>	<b>1.30%</b>
	<i>1.04</i>	<i>-0.49</i>	<i>0.57</i>	<i>-1.05</i>	<i>-2.28**</i>	<i>2.41**</i>
R2	0,59	0,51	0,51	0,61	0,47	0,02
<b>Panel B: Portfolio</b>						
Average Customer EDF	0.00%	0.06%	1.62%	11.25%	43.90%	
Average Supplier EDF	0.53%	0.58%	0.95%	2.05%	5.15%	

Panel A of Table 14 presents the excess returns and three-factor alphas of supplier portfolios. Suppliers to distressed customers clearly underperform suppliers to non-distressed customers. While suppliers in quintile 1 earn an average excess return of 0.98% per month, suppliers in quintile 5 produce mean excess returns equal to -0.09% per month. The difference is statistically significant at the 10% level. The extent of the under-pressure customer anomaly is more pronounced if I correct for risk using the Fama and French (1993) three-factor model. Here, differences in alpha between quintile 1 and quintile 5 amounts to 1.30% per month, which is statistically significant at the 5% level.

The customer EDF values increase sharply across supplier portfolios. In quintile 1, the average customer EDF value is close to zero, while the average EDF measure in quintile 5 is equal to 43.90%, more than twice as large as compared to the average EDF values in Table 7 in Section 4.1. The considerable differences in the portfolio's average customer EDF quantities is intuitive, given the fact that only the smallest customers are retained in the sample. Conceptually, smaller firms are more likely to suffer from financial distress than larger firms.

#### 4.2.2.2. Lead-lag Effects in Trading Volume

Chordia and Swaminathan (2000) find that trading volume is an important determinant of the lead-lag pattern in stock returns. The authors show stocks with high trading volume lead the returns of stocks with low trading volume.<sup>249</sup> In this section, I test whether the observed underperformance of suppliers to under-pressure customers is caused by lead-lag effects related to trading volume. For that, I exclude all suppliers from the sample that have lower trading volume than their respective customers. Trading volume is measured as monthly trading volume scaled by the number of shares outstanding. Table 15 reports the results of the analysis.

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<sup>249</sup> Specifically, the authors show that low volume stocks respond rather sluggish to new information as compared to high trading volume stocks.

**Table 15: Lead-lag Effects – Trading Volume**

This table shows calendar-time supplier portfolio abnormal returns. At the beginning of each calendar, stocks are ranked in ascending order according to their major customer's EDF measure in the previous month. The ranked stocks are assigned to one of five quintile portfolios (quintile 1: low customer risk portfolio, quintile 5: high customer risk portfolio). All stocks are equally-weighted within a given portfolio. I rebalance the portfolios every month to maintain the equal weights. The portfolios in the table include all stocks that have a share price larger than 2\$ at the time of portfolio formation. All supplier stocks are excluded that have a monthly trading volume smaller than their major customer. The table reports excess returns and the intercepts (alphas) from a rolling regression of monthly excess returns as well as average customer EDF and supplier EDF. Explanatory variables include the market factor and Fama and French factors (small minus big and high BM minus low BM). The factors are retrieved from the mimicking portfolios available on Professors Kenneth French's website. L/S is a rolling, zero-cost strategy that purchases the lowest 20% customer default risk suppliers and sells short the top 20% customer default risk suppliers. All returns and alphas are in monthly percent. T-statistics are reported in italics. \*\*\*, \*\* and \* denote the statistical significance at the 1%, 5% and 10% level, respectively. Panel A presents the results for the time period from 1981 to 1995. Panel B reports the results for the time period from 1996 to 2010.

	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	L/S
<b>Panel A: Returns</b>						
Excess Returns	<b>0.83%</b>	<b>0.57%</b>	<b>0.59%</b>	<b>0.72%</b>	<b>0.41%</b>	<b>0.41%</b>
	<i>1.88*</i>	<i>1.51</i>	<i>1.46</i>	<i>1.62</i>	<i>0.91</i>	<i>1.75*</i>
Three-factor alpha	<b>0.22%</b>	<b>0.00%</b>	<b>-0.06%</b>	<b>0.09%</b>	<b>-0.32%</b>	<b>0.54%</b>
	<i>1.15</i>	<i>-0.02</i>	<i>-0.35</i>	<i>0.48</i>	<i>-1.71*</i>	<i>2.25**</i>
R2	0.82	0.83	0.81	0.84	0.84	0.02
<b>Panel B: Portfolio</b>						
Average Customer EDF	0.00%	0.00%	0.00%	0.15%	9.87%	
Average Supplier EDF	3.29%	3.81%	4.04%	3.73%	5.20%	

Panel A of Table 15 reports average portfolio excess returns and three-factors alphas. The results draw a consistent picture: Suppliers to distressed customers underperform suppliers to non-distressed customers. For the mean excess returns, the differential between quintile 1 and quintile 5 is equal to 0.41% per month, which is statistically significant at the 10% level. Correcting for risk only increases the extent of the under-pressure customer anomaly. The difference between three-factor alphas of suppliers to high distress customer and suppliers to low distress customers is 0.54% per month, and is statistically significant at the 5% level. Thus, the well-documented lead-lag effect with respect to trading volume does not account for the observed return pattern as caused by the under-pressure customer anomaly.

Panel B shows portfolio characteristics with respect to the average customer and supplier EDF measures. The average customer EDF in quintile 5 is considerably lower compared to former

tests. The average supplier EDF value ranges from 3.29% to 5.20%, a pattern similar to what I observed in Section 4.1.

#### 4.2.2.3. Lead-lag Effects in Institutional Ownership

While extant research has provided evidence for lead-lag effects to exist between large and small capitalization firms, there are also studies documenting positive return correlations for stocks with a high number of institutional investors and a high number of retail investors. For example, Badrinath, Kale and Noe (1995) show that the level of institutional ownership plays a significant role in asset pricing dynamics. Specifically, the authors demonstrate that stocks with a high fraction of institutional investors lead the stocks with a low number of institutional investors. I test whether the under-pressure customer anomaly is robust to this type of lead-lag effect. I exclude all suppliers that have a lower fraction of institutional investors than their customers. The fraction of institutional investors is computed as the number of stocks held by institutional investors divided by the total number of shares outstanding. Table 16 presents the results.

**Table 16: Lead-lag Effects – Institutional Ownership**

This table shows calendar-time supplier portfolio abnormal returns. At the beginning of each calendar, stocks are ranked in ascending order according to their major customer's EDF measure in the previous month. The ranked stocks are assigned to one of five quintile portfolios (quintile 1: low customer risk portfolio, quintile 5: high customer risk portfolio). All stocks are equally-weighted within a given portfolio. I rebalance the portfolios every month to maintain the equal weights. The portfolios in the table include all stocks that have a share price larger than 2\$ at the time of portfolio formation. All supplier stocks are excluded that have a lower fraction of institutional investors than their major customer. The table reports excess returns and the intercepts (alphas) from a rolling regression of monthly excess returns as well as average customer EDF and supplier EDF. Explanatory variables include the market factor and Fama and French factors (small minus big and high BM minus low BM). The factors are retrieved from the mimicking portfolios available on Professors Kenneth French's website. L/S is a rolling, zero-cost strategy that purchases the lowest 20% customer default risk suppliers and sells short the top 20% customer default risk suppliers. All returns and alphas are in monthly percent. T-statistics are reported in italics. \*\*\*, \*\* and \* denote the statistical significance at the 1%, 5% and 10% level, respectively. Panel A presents the results for the time period from 1981 to 1995. Panel B reports the results for the time period from 1996 to 2010.

	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	L/S
<b>Panel A: Returns</b>						
Excess Returns	<b>0.52%</b>	<b>0.78%</b>	<b>0.43%</b>	<b>0.49%</b>	<b>0.22%</b>	<b>0.30%</b>
	<i>1.35</i>	<i>2.32**</i>	<i>1.14</i>	<i>1.24</i>	<i>0.52</i>	<i>1.06</i>
Three-factor alpha	<b>-0.07%</b>	<b>0.13%</b>	<b>-0.25%</b>	<b>-0.14%</b>	<b>-0.51%</b>	<b>0.44%</b>
	<i>-0.38</i>	<i>0.81</i>	<i>-1.44</i>	<i>-0.91</i>	<i>-2.49**</i>	<i>1.54</i>
R2	0.78	0.76	0.80	0.85	0.78	0.04
<b>Panel B: Portfolio</b>						
Average Customer EDF	0.00%	0.00%	0.02%	0.75%	19.45%	
Average Supplier EDF	1.80%	2.75%	2.62%	2.16%	4.29%	

Panel A of Table 16 shows mean excess returns alphas with respect to the three-factor model. While the under-pressure customer anomaly is qualitatively existent, I can document a slight decrease in statistical significance. Suppliers to low distressed customers exhibit an average excess return of 0.52% per month. Suppliers to high distress customers show a monthly excess return performance of 0.22%. The difference is not statistically significant at conventional levels. Principally the same is true when I correct for risk using the three-factor model. Here, suppliers to distressed customers underperform suppliers to non-distressed customers. However, the alpha difference is not statistically significant. It should be noted, however, that suppliers in quintile 5 earn a negative alpha of -0.51% per month, which is statistically significant at the 5% level. Thus, the effect of customer distress on supplier returns still remains present.



Panel B presents portfolio characteristics with respect to average customer EDF and average supplier EDF. These values are comparable to the ones reported in the analysis using the complete sample.

#### 4.2.2.4. Lead-lag Effects in Analyst Coverage

Brennan, Jegadeesh and Swaminathan (1993) provide evidence for the existence of lead-lag effects depending on the number of analyst following a specific stock. They argue that a security's analyst coverage can be seen as a proxy for the speed with which information is incorporated into stock prices. Thus, stocks with a high number of analysts have the tendency to lead stocks with a low number of analysts. I test whether these analyst driven lead-lag effects account for the observed return pattern of the under-pressure customer anomaly. I exclude all supplier firms for which the number of analyst following the stock is lower than the number of analysts following their customers. Table 17 reports the results.

**Table 17: Lead-lag Effects – Analyst Coverage**

This table shows calendar-time supplier portfolio abnormal returns. At the beginning of each calendar, stocks are ranked in ascending order according to their major customer's EDF measure in the previous month. The ranked stocks are assigned to one of five quintile portfolios (quintile 1: low customer risk portfolio, quintile 5: high customer risk portfolio). All stocks are equally-weighted within a given portfolio. I rebalance the portfolios every month to maintain the equal weights. The portfolios in the table include all stocks that have a share price larger than 2\$ at the time of portfolio formation. All supplier stocks are excluded that have a lower number of analysts following the stock than their major customer. The table reports excess returns and the intercepts (alphas) from a rolling regression of monthly excess returns as well as average customer EDF and supplier EDF. Explanatory variables include the market factor and Fama and French factors (small minus big and high BM minus low BM). The factors are retrieved from the mimicking portfolios available on Professors Kenneth French's website. L/S is a rolling, zero-cost strategy that purchases the lowest 20% customer default risk suppliers and sells short the top 20% customer default risk suppliers. All returns and alphas are in monthly percent. T-statistics are reported in italics. \*\*\*, \*\* and \* denote the statistical significance at the 1%, 5% and 10% level, respectively. Panel A presents the results for the time period from 1981 to 1995. Panel B reports the results for the time period from 1996 to 2010.

	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	L/S
<b>Panel A: Returns</b>						
Excess Returns	<b>1.03%</b>	<b>0.21%</b>	<b>0.22%</b>	<b>0.38%</b>	<b>0.26%</b>	<b>0.77%</b>
	<i>1.92*</i>	<i>0.43</i>	<i>0.34</i>	<i>0.68</i>	<i>0.38</i>	<i>1.35</i>
Three-factor alpha	<b>0.34%</b>	<b>-0.44%</b>	<b>-0.63%</b>	<b>-0.64%</b>	<b>-0.95%</b>	<b>1.29%</b>
	<i>0.94</i>	<i>-1.26</i>	<i>-1.36</i>	<i>-1.74</i>	<i>-2.06**</i>	<i>2.27**</i>
R2	0.55	0.53	0.50	0.59	0.55	0.07
<b>Panel B: Portfolio</b>						
Average Customer EDF	0.00%	0.02%	0.48%	4.73%	28.39%	
Average Supplier EDF	0.78%	1.36%	1.88%	2.70%	3.88%	

Panel A of Table 17 reports portfolio mean excess returns and three-factor alphas for supplier portfolios sorted according to previous month customer EDF values. The under-pressure customer anomaly is existent with respect to both excess returns and three-factor alphas. While suppliers in quintile 1 earn an average excess return of 1.03% per month, suppliers in quintile 5 produce monthly excess returns of only 0.26% per month. However, the difference in excess returns is not statistically significant at conventional levels. This changes when I correct for risk using the three-factor model. The zero-cost, long-short strategy generates risk-adjusted returns of 1.29% per month, which is statistically significant at the 5% level. Hence, the under-pressure customer anomaly does not appear to be caused by lead-lag effects related to analyst coverage.

Panel B presents portfolio characteristics. Albeit somewhat higher, the average customer EDF and average supplier EDF values do not diverge considerable from the values as observed in the full sample analysis in Section 4.1.

#### 4.2.2.5. Lead-lag Effects in Industries

Hou (2006) documents a lead-lag effect in an intra-industry setting. Specifically, the author shows that large firms lead small firms, value firms lead growth firms, and low volatility firms lead firms with high idiosyncratic volatility, within the same industry. To account for these effects, I build two subsamples based on industry classifications and test for the existence of an under-pressure customer anomaly. The first subsample excludes all customer-supplier links that operate in the same industry. The second subsample excludes all customer-supplier links that operate in different industries. I use 48 different industries classifications to determine a firm's industry.<sup>250</sup> The results are reported in Table 18.

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<sup>250</sup> Industries are defined as in Fama and French (1997)

**Table 18: Lead-lag Effects – Industries**

This table shows calendar-time supplier portfolio abnormal returns. At the beginning of each calendar, stocks are ranked in ascending order according to their major customer's EDF measure in the previous month. The ranked stocks are assigned to one of five quintile portfolios (quintile 1: low customer risk portfolio, quintile 5: high customer risk portfolio). All stocks are equally-weighted within a given portfolio. I rebalance the portfolios every month to maintain the equal weights. The portfolios in the table include all stocks that have a share price larger than 2\$ at the time of portfolio formation. I use Fama and French 48 industry portfolios to classify stocks to a certain industry. In Panel A, I exclude all customer and suppliers that operate in the same industry. Panel A reports excess returns and the intercepts (alphas) from a rolling regression of monthly excess returns for as well as average customer EDF and supplier EDF. In Panel B, I exclude all customer and suppliers that operate in different industries and report excess returns as well as the intercepts (alphas) from a rolling regression of monthly excess returns for as well as average customer EDF and supplier EDF. Explanatory variables include the market factor and Fama and French factors (small minus big and high BM minus low BM). The factors are retrieved from the mimicking portfolios available on Professors Kenneth French's website. L/S is a rolling, zero-cost strategy that purchases the lowest 20% customer default risk suppliers and sells short the top 20% customer default risk suppliers. All returns and alphas are in monthly percent. T-statistics are reported in italics. \*\*\*, \*\* and \* denote the statistical significance at the 1%, 5% and 10% level, respectively.

	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	L/S
<b>Panel A: Different Industries</b>						
Mean excess return	<b>0,69%</b> <i>1,96**</i>	<b>0,60%</b> <i>1,72*</i>	<b>0,68%</b> <i>1,83*</i>	<b>0,41%</b> <i>1,13</i>	<b>0,27%</b> <i>0,70</i>	<b>0,42%</b> <i>2,31**</i>
Three-factor alpha	<b>0,08%</b> <i>0,61</i>	<b>-0,10%</b> <i>-0,76</i>	<b>0,01%</b> <i>0,05</i>	<b>-0,30%</b> <i>-2,13**</i>	<b>-0,53%</b> <i>-3,52***</i>	<b>0,61%</b> <i>3,35***</i>
Adjusted R <sup>2</sup>	0.86	0.87	0.88	0.86	0.86	0.06
<b>Panel B: Same Industries</b>						
Mean excess return	<b>0,85%</b> <i>1,86*</i>	<b>0,99%</b> <i>2,38**</i>	<b>0,56%</b> <i>1,35</i>	<b>0,52%</b> <i>1,23</i>	<b>0,16%</b> <i>0,33</i>	<b>0,70%</b> <i>1,93*</i>
Three-factor alpha	<b>0,21%</b> <i>0,93</i>	<b>0,33%</b> <i>1,62</i>	<b>-0,18%</b> <i>-0,76</i>	<b>-0,18%</b> <i>-0,76</i>	<b>-0,66%</b> <i>-2,17**</i>	<b>0,87%</b> <i>2,40**</i>
Adjusted R <sup>2</sup>	0.76	0.77	0.70	0.71	0.60	0.04

Panel A of Table 18 presents the sorting results for customers and suppliers operating in different industries. Suppliers to distressed customers clearly underperform suppliers to non-distressed customers. The monthly excess return difference between quintile 1 and quintile 5 is equal to 0.42% and statistically significant at the 5% level. The three-factor alphas exhibit a similar pattern: Suppliers in quintile 5 underperform suppliers in quintile 1 by 0.61%. This difference is statistically significant at the 1% level. Thus, the under-pressure customer anomaly is not driven by industry-related lead-lag effects a la Hou (2006).

Panel B of Table 18 shows the mean excess returns and three-factor alphas for customers and suppliers that operate in the same industry. Here, the under-pressure customer anomaly also holds: Suppliers to distressed customers earn an excess return and three-factor alpha of 0.16% and -0.66% per month, respectively. The return performance of suppliers to non-distressed customers is considerably higher. The difference is large and statistically significant at conventional levels.

#### 4.2.3. Financial Contagion in Different Time Periods

In a further robustness test, I examine whether the under-pressure customer anomaly is restricted to a specific time period. Potentially, investors may become aware of the customer-supplier relationship over time and may arbitrage the existing returns differentials away. To investigate whether the under-pressure customer anomaly has diminished over time, I split the total observation period of customer-supplier relationships in half and measure excess returns and three-factor alphas of the supplier portfolios for each of the two sub-periods. Specifically, the earlier time period is defined to range from 1981 to 1995, while the later time period extends from 1996 through 2010. The portfolio construction procedure is identical to the one as detailed in Section 4.1. Table 19 presents the results.

**Table 19: Supplier Returns to Under-Pressure Customers in Different Time Periods**

This table shows calendar-time supplier portfolio abnormal returns. At the beginning of each calendar, stocks are ranked in ascending order according to their major customer's EDF measure in the previous month. The ranked stocks are assigned to one of five quintile portfolios (quintile 1: low customer risk portfolio, quintile 5: high customer risk portfolio). All stocks are equally-weighted within a given portfolio. I rebalance the portfolios every month to maintain the equal weights. The portfolios in the table include all stocks that have a share price larger than 2\$ at the time of portfolio formation. The table reports excess returns and the intercepts (alphas) from a rolling regression of monthly excess returns as well as average customer EDF and supplier EDF. Explanatory variables include the market factor and Fama and French factors (small minus big and high BM minus low BM). The factors are retrieved from the mimicking portfolios available on Professors Kenneth French's website. L/S is a rolling, zero-cost strategy that purchases the lowest 20% customer default risk suppliers and sells short the top 20% customer default risk suppliers. All returns and alphas are in monthly percent. T-statistics are reported in italics. \*\*\*, \*\* and \* denote the statistical significance at the 1%, 5% and 10% level, respectively. Panel A presents the results for the time period from 1981 to 1995. Panel B reports the results for the time period from 1996 to 2010.

	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	L/S
<b>Panel A: 1981-1995</b>						
Mean excess return	<b>0.51%</b>	<b>0.34%</b>	<b>0.48%</b>	<b>0.30%</b>	<b>0.15%</b>	<b>0.36%</b>
	<i>1.07</i>	<i>0.79</i>	<i>1.14</i>	<i>0.74</i>	<i>0.37</i>	<i>1.78*</i>
Three-factor alpha	<b>-0.02%</b>	<b>-0.21%</b>	<b>-0.09%</b>	<b>-0.27%</b>	<b>-0.47%</b>	<b>0.45%</b>
	<i>-0.09</i>	<i>-1.43</i>	<i>-0.59</i>	<i>-1.71</i>	<i>-3.14***</i>	<i>2.36**</i>
Adjusted R <sup>2</sup>	0.88	0.90	0.87	0.87	0.88	0.22
Average Customer EDF	0.00%	0.00%	0.00%	0.12%	13.65%	
Average Supplier EDF	3.89%	4.11%	4.28%	4.61%	5.53%	
<b>Panel B: 1996-2010</b>						
Mean excess return	<b>0.95%</b>	<b>0.98%</b>	<b>0.93%</b>	<b>0.55%</b>	<b>0.24%</b>	<b>0.71%</b>
	<i>1.72*</i>	<i>1.82*</i>	<i>1.50</i>	<i>0.91</i>	<i>0.35</i>	<i>2.27**</i>
Three-factor alpha	<b>0.26%</b>	<b>0.22%</b>	<b>0.13%</b>	<b>-0.24%</b>	<b>-0.65%</b>	<b>0.91%</b>
	<i>1.33</i>	<i>1.21</i>	<i>0.67</i>	<i>-1.05</i>	<i>-2.62***</i>	<i>3.20***</i>
Adjusted R <sup>2</sup>	0.87	0.90	0.91	0.90	0.91	0.47
Average Customer EDF	0.00%	0.00%	0.06%	1.46%	21.16%	
Average Supplier EDF	4.48%	5.59%	5.51%	6.17%	8.12%	

Panel A of Table 19 shows the excess returns and Fama and French (1993) three-factor alphas for the supplier portfolios in the earlier time period. While suppliers to low distress customers (quintile 1) earn a monthly excess return of 0.51%, suppliers to distressed customers (quintile 5) produce monthly excess return of only 0.15%, on average. The excess return of the long-short strategy is equal to 0.36% per month and statistically significant only at the 10% level.

However, if I correct for risks using the Fama and French (1993) three-factor model, the returns to the long-short strategy increases to 0.45% and a statistical significance of 5%. The majority of the strategy's profitability stems from its short leg, which shows a statistically significant alpha of -0.42%. Thus, the under-pressure customer anomaly is existent in the earlier time period, even though its magnitude is slightly less pronounced compared to the overall results as reported in Table 7.

Panel B of Table 19 presents the sorting results for the later time period. Overall, the results suggest that the under-pressure customer anomaly has increased over time, rather than decreased. In fact, the magnitude of the long-short strategy based on mean excess returns has doubled to 0.71% per month, which is statistically significant at the 5% level. Similarly, the three-factor alpha has increased to approximately 0.91% per month, with a significance level of 1%. Two-thirds of the difference between the alphas of suppliers to low distress customers and suppliers to high distressed customers can be attributed to the short leg. It is interesting to note that the three-factor alpha of the later time period slightly exceeds the alpha of the entire observation period.<sup>251</sup>

An examination of the portfolios' average customer EDF value reveals that the observed increase in the extent of the under-pressure customer anomaly can potentially be attributed to increased customer EDF values. While customers in the highest distress quintile have an average EDF quantity of 13.65% in the earlier period, an average customer EDF value of 21.16% can be observed for the high customer distress quintile in the later period. This suggests that an increase in customer distress directly translates into a higher underperformance of respective suppliers.<sup>252</sup>

#### 4.2.4. Financial Contagion in Different Economic Cycles

A further robustness tests involves the examination of the under-pressure customer anomaly in different economic cycles. Potentially, the effect of customer distress on supplier performances may be larger during times of economic downturns when overall output is significantly reduced. More importantly, the results of the analysis using the entire sample may be driven by a few month observations in down markets. I test for this possibility in this section. For that,

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<sup>251</sup> The three-factor alpha of the long-short strategy over the entire observation period is equal to 0.74% per month.

<sup>252</sup> In fact, untabulated results show that the under-pressure customer anomaly is stronger if I use decile portfolio sorts instead of quintiles.

I split the sample into two subsamples: One that examines the under-pressure customer anomaly in times of down markets, and one in up-markets. I use NBER definitions of US economic cycles.<sup>253</sup> Table 20 reports the results.

**Table 20: Supplier Returns to Under-Pressure Customers Across Economic Cycles**

This table shows calendar-time supplier portfolio abnormal returns. At the beginning of each calendar, stocks are ranked in ascending order according to their major customer's EDF measure in the previous month. The ranked stocks are assigned to one of five quintile portfolios (quintile 1: low customer risk portfolio, quintile 5: high customer risk portfolio). All stocks are equally-weighted within a given portfolio. I rebalance the portfolios every month to maintain the equal weights. The portfolios in the table include all stocks that have a share price larger than 2\$ at the time of portfolio formation. The table reports excess returns and the intercepts (alphas) from a rolling regression of monthly excess returns as well as average customer EDF and supplier EDF. Explanatory variables include the market factor and Fama and French factors (small minus big and high BM minus low BM). The factors are retrieved from the mimicking portfolios available on Professors Kenneth French's website. L/S is a rolling, zero-cost strategy that purchases the lowest 20% customer default risk suppliers and sells short the top 20% customer default risk suppliers. All returns and alphas are in monthly percent. T-statistics are reported in italics. \*\*\*, \*\* and \* denote the statistical significance at the 1%, 5% and 10% level, respectively. Panel A presents the results for the down market. Panel B reports the results for the up-market. Up- and down-markets are defined according to NBER

	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	L/S
<b>Panel A: Down Market</b>						
Mean excess return	<b>-0.95%</b> <i>-0.79</i>	<b>-0.91%</b> <i>-0.76</i>	<b>-0.99%</b> <i>-0.79</i>	<b>-1.09%</b> <i>-0.83</i>	<b>-2.09%</b> <i>-1.48</i>	<b>1.14%</b> <i>1.88*</i>
Three-factor alpha	<b>0.17%</b> <i>0.47</i>	<b>0.01%</b> <i>0.02</i>	<b>0.26%</b> <i>0.66</i>	<b>0.20%</b> <i>0.50</i>	<b>-0.88%</b> <i>-1.87*</i>	<b>1.05%</b> <i>1.78*</i>
Adjusted R <sup>2</sup>	<i>0.91</i>	<i>0.91</i>	<i>0.91</i>	<i>0.91</i>	<i>0.90</i>	<i>0.12</i>
Average Customer EDF	0.00%	0.00%	0.18%	3.40%	33.68%	0.00%
Average Supplier EDF	6.44%	7.46%	7.48%	9.51%	11.70%	6.44%
<b>Panel B: Up-Market</b>						
Mean excess return	<b>1.03%</b> <i>2.76***</i>	<b>0.94%</b> <i>2.69**</i>	<b>0.95%</b> <i>2.51**</i>	<b>0.74%</b> <i>1.99**</i>	<b>0.64%</b> <i>1.64</i>	<b>0.39%</b> <i>2.01**</i>
Three-factor alpha	<b>0.16%</b> <i>1.07</i>	<b>-0.09%</b> <i>-0.68</i>	<b>-0.05%</b> <i>-0.36</i>	<b>-0.29%</b> <i>-1.87*</i>	<b>-0.44%</b> <i>-2.59***</i>	<b>0.59%</b> <i>2.93***</i>
Adjusted R <sup>2</sup>	<i>0.86</i>	<i>0.88</i>	<i>0.88</i>	<i>0.84</i>	<i>0.83</i>	<i>0.03</i>
Average Customer EDF	0.00%	0.00%	0.01%	0.34%	14.67%	
Average Supplier EDF	3.80%	4.41%	4.47%	4.68%	5.99%	

Panel A of Table 20 reports mean excess returns and three-factor alphas of supplier portfolios for the down-market period. The average monthly excess return is negative across all supplier

<sup>253</sup> www.nber.com

portfolios of customer distress. This is intuitive, given that only periods of economic turmoil are included in this subsample. Suppliers in the least customer distress quintile earn monthly excess returns of -0.95%, while suppliers to the most distressed customer produce returns of -2.09% per month. The difference is significant at the 10% level. A similar picture can be drawn when I correct for risk using the three-factor model. Suppliers in quintile 5 underperform suppliers in quintile 1 by 1.05% per month. This is statistically significant at the 10% level. Thus, the under-pressure customer anomaly appears to persist through periods of economic recessions. I can attribute the decreased statistical significance to the decreased sample size of only 39 months. The average customer EFD and average supplier EDF values are naturally higher compared to the full sample analysis.

Panel B of Table 20 shows the results for the up-market sub-period. Here, excess returns and three-factor alphas exhibit a return pattern consistent with the under pressure-customer anomaly. The underperformance of suppliers to highly distressed customers is statistically significant at the 1% level. Economic cycles do not appear to have a considerable influence on the persistence of the under-pressure customer anomaly.

#### 4.2.5. Section Summary

This section performs a series of robustness test to separate the true effects of the contagious nature of customer financial distress on suppliers from other plausible explanations of the data.

In a first test, I have used Ohlson's (1980) O-Score model as an alternative to the EDF measure based on Merton (1974) model to assess the extent to which customers suffer from financial distress. Even though the results indicate a reduced statistical significance, I can safely reject the hypothesis that the observed return pattern is exclusive to the EDF measure of Merton's (1974) model. Second, I examined whether the observed return pattern is caused by positive cross-autocorrelations of stocks. I excluded all observation for which potential lead-lag effects related to size, institutional holdings, industry, analyst coverage, and trading volume. None of these effects appear to significantly impact the under pressure customer anomaly. Last, I examined whether the under-pressure customer anomaly is restricted to a certain time period, or to economic cycles. Suppliers to distressed customers underperform suppliers to non-distressed customers throughout all time sub-period of time and economic conditions. Overall, there appears to be a true relationship between customer distress and supplier return performances.



### 4.3. Determinants of Financial Distress Contagion

Extant theory on contagious effects of financial distress suggests several factors that might lead to a cross-sectional variation of how financial distress spills over from one firm to another (e.g. Hertz et al (2008)). In this section, I test a number of these factors and their underlying hypotheses. Specifically, I analyse the effects of revenue dependency, industry concentration and product specificity on the nature and extent of supplier contagion.

#### 4.3.1. Financial Contagion and Percentage of Customer Sales

In order to gain insights into the relationship between the contagious effects of financial distress and the magnitude of customer reliance, I perform double-sorts based on the percentage sales to the customers and customer EDF values. First, I sort supplier stocks into tercile portfolios according to the percentage of sales to the customers. For each tercile portfolio, I generate quintile portfolios of supplier stocks based on customer EDF. Thus, 15 portfolios are produced in total. Table 21 reports excess returns and Fama and French (1993) three-factor alphas of the supplier portfolios.

**Table 21: Under-pressure Customer and Percentage of Customer Sales**

This table shows calendar-time supplier portfolio abnormal returns. At the beginning of each calendar month in the observation period from January 1980 to November 2010, stocks are double-sorted first on percentage of sales to the customers (terciles), then on customer default risk (quintiles). All stocks are equally weighted within a given portfolio. I rebalance the portfolios every month to maintain the equal weights. The portfolios in the table include all stocks that have a share price larger than 2\$ at the time of portfolio formation. The alphas presented are the intercepts from a rolling regression of monthly excess returns. Explanatory variables include the market factor and Fama and French factors (small minus big and high BM minus low BM). The factors are retrieved from the mimicking portfolios available on Professors Kenneth French's website. L/S is a rolling, zero-cost strategy that purchases the lowest 20% customer default risk suppliers and sells short the top 20% customer default risk suppliers. All returns and alphas are in monthly percent, t-statistics are reported in italics. \*\*\*, \*\* and \* denote the statistical significance at the 1%, 5% and 10% level, respectively

	Low	Medium	High
Panel A: Returns			
Q1 (Low Distress)	<b>0.68%</b> <i>1.73*</i>	<b>0.70%</b> <i>1.85*</i>	<b>0.93%</b> <i>2.09**</i>
Q2	<b>0.61%</b> <i>1.60</i>	<b>0.75%</b> <i>2.09*</i>	<b>0.97%</b> <i>2.24**</i>
Q3	<b>0.58%</b> <i>1.44</i>	<b>0.85%</b> <i>2.28**</i>	<b>0.47%</b> <i>1.21</i>
Q4	<b>0.43%</b> <i>1.04</i>	<b>0.69%</b> <i>1.76*</i>	<b>0.46%</b> <i>1.13</i>
Q5 (High Distress)	<b>0.46%</b> <i>1.09</i>	<b>0.18%</b> <i>0.45</i>	<b>0.11%</b> <i>0.26</i>
Q1-Q5	<b>0.22%</b> <i>0.72</i>	<b>0.52%</b> <i>1.92*</i>	<b>0.82%</b> <i>2.60**</i>
Panel B: Three-factor			
Q1 (Low Distress)	<b>-0.13%</b> <i>-0.63</i>	<b>-0.06%</b> <i>-0.29</i>	<b>0.09%</b> <i>0.34</i>
Q2	<b>-0.14%</b> <i>-0.60</i>	<b>-0.06%</b> <i>-0.34</i>	<b>0.00%</b> <i>-0.02</i>
Q3	<b>-0.17%</b> <i>-0.73</i>	<b>0.06%</b> <i>0.32</i>	<b>-0.21%</b> <i>-0.88</i>
Q4	<b>-0.30%</b> <i>-1.21</i>	<b>-0.04%</b> <i>-0.18</i>	<b>-0.27%</b> <i>-1.17</i>
Q5 (High Distress)	<b>-0.35%</b> <i>-1.40</i>	<b>-0.75%</b> <i>-3.46***</i>	<b>-0.79%</b> <i>-3.11***</i>
Q1-Q5	<b>0.21%</b> <i>0.66</i>	<b>0.69%</b> <i>2.41**</i>	<b>0.88%</b> <i>2.64**</i>
PERSALES	0.0424	0.1345	0.3357

Panel A of Table 21 presents the supplier excess returns over the risk-free rate. Overall, the results provide evidence for a positive relation between the dependence on customers and contagious effects of financial distress. The under-pressure customer anomaly disappears in the lowest PERSALES tercile. Suppliers to the least distressed customers earn an excess return of 0.68% per month, while suppliers to the most distressed customers produce excess returns equal to 0.46%. The difference is not statistically significant at conventional levels. The picture slightly changes when I turn to the medium PERSALES portfolios. Here, suppliers to highly distressed customers underperform suppliers to non-distressed customers by 0.52% per month. The difference is significant at the 10% level. In the highest PERSALES tercile, I can document a return pattern strongly in line with the under-pressure customer anomaly. Suppliers in quintile 5 produce monthly excess returns of only 0.11%, while suppliers in quintile 1 generate monthly excess returns equal to 0.93%. The difference is statistically significant at the 1% level. Thus, the under-pressure customer anomaly depends on the magnitude of the customer-supplier link. In fact, a closer look at the returns reveals that the under-pressure customer anomaly monotonically increases across the tercile portfolios of percentage customer sales.

A similar picture emerges when I correct for risk using the Fama and French (1993) three-factor model. Panel B reports respective supplier alphas. While the under-pressure customer anomaly is statistically insignificant in the lowest PERSALES tercile, it is strong and significant in the medium and highest PERSALES tercile. Again, an almost monotonic increase of the under-pressure customer anomaly can be observed as I move across PERSALES terciles. The return differential between suppliers stocks of low and high customer distress can be mainly attributed to the short leg. This is consistent with the results as reported in Section 4.1.

#### 4.3.2. Financial Contagion and Industry Concentration

Supplier contagion effects may also be stronger among firms that operate in a concentrated industry. Presumably, these firms may have fewer switching alternatives for re-routing their output leading to a higher dependence on their major customers. I test this hypothesis in this section. I sort supplier stocks based on a measure of industry concentration, then on distress risk. The results are presented in Table 22. I compute industry concentration using the Herfindahl index. Following Lang and Stulz (1992) and Hertz et al. (2008), I compute the Herfindahl indices using the firm's SIC code. In line with my hypothesis, contagious effects of financial distress are more pronounced for supplier firms in concentrated industries.

Panel A reports the mean excess returns of supplier portfolios. The under-pressure customer anomaly is much stronger in the high industry concentration subsample. Suppliers to high distress customers clearly underperform supplier to non-distressed customers in the concentrated industries.

Panel B shows the three-factor alphas of supplier portfolios. Supplier to distressed customers with relatively high Herfindahl indices exhibit negative three-factor alphas, which are large and statistically significant at the 1% level. Suppliers to distressed customers in less concentrated industries show insignificant negative alphas. Therefore, the level of industry concentration appears to have an effect on the extent of supplier contagion.

**Table 22: Under-pressure Customer Anomaly and Industry Concentration**

This table shows calendar time three-factor alphas. At the beginning of each calendar month in the observation period from 1980 to 2010, stocks are divided into two subsamples based on industry concentration, and then sorted on customer default risk (terciles). Industry concentration is measured using the Herfindahl index. Herfindahl indices are computed using a firm's SIC codes. All stocks are equally weighted within a given portfolio. I rebalance the portfolios every month to maintain the equal weights. The portfolios in the table include all stocks that have a share price larger than 2\$ at the time of portfolio formation. The alphas presented are the intercepts from a rolling regression of monthly excess returns. Explanatory variables include the market factor and Fama and French factors (small minus big and high BM minus low BM). The factors are retrieved from the mimicking portfolios available on Professors Kenneth French's website. High-Low is a rolling, zero-cost strategy that purchases the lowest 30% customer default risk suppliers and sells short the top 30% customer default risk suppliers. All returns and alphas are in monthly percent, t-statistics are reported in italics. \*\*\*, \*\* and \* denote the statistical significance at the 1%, 5% and 10% level, respectively.

	T1	T2	T3	High-Low
Panel A: Portfolio Excess Returns				
Low industry concentration	<b>0.84%</b>	<b>0.72%</b>	<b>0.53%</b>	<b>0.30%</b>
	<i>2.42**</i>	<i>2.11*</i>	<i>1.46</i>	<i>1.67*</i>
High industry concentration	<b>0.83%</b>	<b>0.75%</b>	<b>0.37%</b>	<b>0.46%</b>
	<i>2.46**</i>	<i>2.24**</i>	<i>1.03</i>	<i>2.38**</i>
Panel B: Portfolio Three-factor Alphas				
Low industry concentration	<b>0.23%</b>	<b>-0.03%</b>	<b>-0.24%</b>	<b>0.47%</b>
	<i>1.60</i>	<i>-0.25</i>	<i>-1.56</i>	<i>2.59**</i>
High industry concentration	<b>0.20%</b>	<b>0.07%</b>	<b>-0.45%</b>	<b>0.65%</b>
	<i>1.49</i>	<i>0.54</i>	<i>-2.94***</i>	<i>3.38***</i>

#### 4.3.3. Financial Contagion and Product Specificity

The uniqueness of a product may intensify the dependencies among contractually linked partners. On the one hand, firms that sell a specialized product may experience difficulties to find alternative customers, and thus experience greater contagion. On the other hand, these suppliers may be of such an importance to their customers to run their business that customer

firms refrain from taking strategic measures that adversely affect their suppliers. This may particularly be the case when the firm has still not filed for bankruptcy. I test these hypotheses in Table 23. Following Titman and Wessels (1988), I use a firm's R&D intensity to proxy for the specificity of a product. R&D intensity is computed by scaling a firm's research and development expense by the total assets.

Panel A reports mean excess returns of supplier portfolios. Clearly, suppliers to under-pressure customers in the high R&D subsample show the worst performance. In fact, these suppliers earn excess returns that are almost half of what suppliers to distressed customer generate in the low R&D subsample.

I report three-factor alphas in Panel B. Here, suppliers to under-pressure customer selling a specialized product exhibit a negative three-factor alpha of 0.34%. Similarly, suppliers to non-distressed customers with high R&D intensity show a negative alpha of 0.38%. Both alphas are statistically significant at conventional levels; albeit the former is slightly more significant. Thus, product specificity does not seem to be an influential factor when deciding over the strategic and operational measures taken by customer firms.

**Table 23: Under-pressure Customer Anomaly and Product Specificity**

This table shows calendar time three-factor alphas. At the beginning of each calendar month in the observation period from 1980 to 2010, stocks are divided into two subsamples based on product specificity, and then sorted on customer default risk (terciles). Product specificity is proxied by R&D intensity. All stocks are equally weighted within a given portfolio. I rebalance the portfolios every month to maintain the equal weights. The portfolios in the table include all stocks that have a share price larger than 2\$ at the time of portfolio formation. The alphas presented are the intercepts from a rolling regression of monthly excess returns. Explanatory variables include the market factor and Fama and French factors (small minus big and high BM minus low BM). The factors are retrieved from the mimicking portfolios available on Professors Kenneth French's website. High-Low is a rolling, zero-cost strategy that purchases the lowest 30% customer default risk suppliers and sells short the top 30% customer default risk suppliers. All returns and alphas are in monthly percent, t-statistics are reported in italics. \*\*\*, \*\* and \* denote the statistical significance at the 1%, 5% and 10% level, respectively.

	T1	T2	T3	High-Low
Panel A: Portfolio Excess Returns				
Low Customer R&D	0.65%	0.89%	0.49%	0.16%
	<i>2.12**</i>	<i>2.73**</i>	<i>1.32</i>	<i>0.75</i>
High Customer R&D	0.87%	0.58%	0.28%	0.60%
	<i>1.69*</i>	<i>1.17</i>	<i>0.54</i>	<i>2.53**</i>
Panel B: Portfolio Three-factor Alphas				
Low Customer R&D	0.05%	0.15%	-0.34%	0.39%
	<i>0.37</i>	<i>1.20</i>	<i>-2.12**</i>	<i>1.91*</i>
High Customer R&D	0.31%	0.03%	-0.38%	0.69%
	<i>1.38</i>	<i>0.16</i>	<i>-1.67</i>	<i>2.87***</i>

#### 4.3.4. Section Summary

This section examines the potential variation in the contagious nature of financial distress. In sum, there seems to be a significant relationship between the magnitude of the dependence on customers and the under-pressure customer anomaly. This is intuitive. If a higher proportion of sales are generated by a customer, and this customer becomes distressed, corresponding suppliers will experience increased adverse effects. For weak links between customer and suppliers, almost no contagion effect of financial distress can be observed. Intuitively, supplier firms that are more dependent on their customers will be more adversely affected when their customers experience financial difficulties. I investigate whether industry concentration and product uniqueness affect the extent of financial contagion. The results suggest industry concentration and product specificity reinforce the effects of financial distress contagion. Suppliers to distressed customers that operate in concentrated industries exhibit substantially negative three-factor alphas. Similarly, suppliers producing highly specialized products earn negative monthly alphas.

#### 4.4. Financial Contagion and Proxies of Investor Attention

The anomalous return predictability as documented in the previous sections imply that market participants neglect the information on customer default risk when pricing the corresponding supplier stocks. A number of papers find that many anomalies are more pronounced for stocks that encounter the most severe information problems or are difficult to trade. The following sections examine the under-pressure anomaly for subsamples of firms based on variables that measure the ease of trading, the availability of information, and the tendency of institutional investors to hold them.

##### 4.4.1. Size

A natural starting point for investigating the relationship between the under-pressure anomaly and the degree of information dissemination is to use a security's size as a proxy variable. Plausibly, information about firms with smaller market capitalizations tend to spread more slowly. For example, if investors face fixed costs of acquiring information, they may devote more time and effort to gather and process information of stocks in which they can take larger positions, that is, stocks with larger market capitalizations. Hence, I examine whether the under-pressure anomaly and associated return predictability is more pronounced among small capitalization stocks. For that, I first group supplier portfolios into tercile portfolio based on

supplier firm size, and then into quintile portfolio according to customer EDF values. Table 24 presents the results of this test.

**Table 24: Financial Contagion and Market Capitalization**

This table shows calendar-time supplier portfolio abnormal returns. At the beginning of each calendar month in the observation period from January 1981 to November 2010, stocks are double-sorted first on firm characteristic (terciles), then on customer default risk (quintiles). Panel A reports the results of supplier returns for different market capitalization terciles and customer default risk quintiles. Market capitalization is a firm's number of shares outstanding multiplied with the share price. All stocks are equally weighted within a given portfolio. I rebalance the portfolios every month to maintain the equal weights. The portfolios in the table include all stocks that have a share price larger than 2\$ at the time of portfolio formation. The alphas presented are the intercepts from a rolling regression of monthly excess returns. Explanatory variables include the market factor and Fama and French factors (small minus big and high BM minus low BM). The factors are retrieved from the mimicking portfolios available on Professors Kenneth French's website. High-Low is a rolling, zero-cost strategy that purchases the lowest 20% customer default risk suppliers and sells short the top 20% customer default risk suppliers. All returns and alphas are in monthly percent, t-statistics are reported in italics. \*\*\*, \*\* and \* denote the statistical significance at the 1%, 5% and 10% level, respectively.

	Low	Medium	High
<b>Panel A: Returns</b>			
Q1 (Low Distress)	<b>0.88%</b> <i>2.18**</i>	<b>0.87%</b> <i>2.05**</i>	<b>0.55%</b> <i>1.46</i>
Q2	<b>0.74%</b> <i>1.74*</i>	<b>0.76%</b> <i>2.00**</i>	<b>0.62%</b> <i>1.83*</i>
Q3	<b>0.67%</b> <i>1.71*</i>	<b>0.81%</b> <i>1.98**</i>	<b>0.65%</b> <i>1.84*</i>
Q4	<b>0.41%</b> <i>1.03</i>	<b>0.40%</b> <i>0.97</i>	<b>0.46%</b> <i>1.21</i>
Q5 (High Distress)	<b>0.01%</b> <i>0.01</i>	<b>0.19%</b> <i>0.45</i>	<b>0.37%</b> <i>0.94</i>
Q1-Q5	<b>0.87%</b> <i>2.52**</i>	<b>0.67%</b> <i>2.93***</i>	<b>0.18%</b> <i>0.71</i>
<b>Panel B: Three-factor</b>			
Q1 (Low Distress)	<b>0.32%</b> <i>1.08</i>	<b>0.13%</b> <i>0.75</i>	<b>-0.02%</b> <i>-0.10</i>
Q2	<b>-0.03%</b> <i>-0.11</i>	<b>0.00%</b> <i>0.03</i>	<b>0.09%</b> <i>0.65</i>
Q3	<b>-0.04%</b> <i>-0.15</i>	<b>0.11%</b> <i>0.69</i>	<b>0.08%</b> <i>0.46</i>
Q4	<b>-0.27%</b> <i>-0.91</i>	<b>-0.44%</b> <i>-2.55**</i>	<b>-0.09%</b> <i>-0.54</i>
Q5 (High Distress)	<b>-0.66%</b> <i>-2.22**</i>	<b>-0.72%</b> <i>-3.86***</i>	<b>-0.30%</b> <i>-1.79*</i>
Q1-Q5	<b>0.99%</b> <i>2.81**</i>	<b>0.85%</b> <i>3.74***</i>	<b>0.28%</b> <i>1.14</i>
Size	24,687	173,361	4,085,685



Panel A of Table 24 shows the mean excess returns for the supplier portfolios. While the under-pressure customer anomaly is strong and significant in the lowest and medium size tercile, no reliable relationship between customer distress and supplier return performances can be established for firms in the largest size tercile. Specifically, suppliers to low distress customers in the lowest (medium) size tercile produce monthly excess returns of 0.88% (0.87%), while suppliers to highly distressed customers earn average excess returns of only 0.01% (0.19%). The differences are statistically significant at the 5% and 1% level, respectively. For larger capitalization firms, no statistically significant underperformance of suppliers to distressed firms can be documented.

Panel B of Table 24 presents three-factor alphas of supplier portfolios. Correcting for risk does not change the overall picture. Among the smallest and medium capitalization stocks, the under-pressure customer anomaly persists. On average, suppliers to highly distressed customers show a monthly return of -0.66% and -0.71% in the smallest and medium size terciles, respectively. These alphas are statistically significant at the 5% and 1% level. The long-short strategy is statistically significant at the 1% level for both, small and medium size terciles. Among the largest firms, the under-pressure customer anomaly is qualitatively present. However, it lacks statistical significance at conventional levels. Thus, for firms with a low and medium rate of information diffusion as proxied by market capitalizations, the return predictability among supplier stocks caused by customers' financial distress is strongest.

#### 4.4.2. Analyst Coverage

While a firm's market capitalization may in fact be a useful measure of the degree to which information disseminates, it is likely to capture other things as well. For example, Merton (1987) argue that size can be seen as a proxy for the capacity of arbitrage. Hong et al. (2000) point out that the number of analysts following a stock is an enhanced proxy for the rate of information diffusion. This is intuitive as a high number of analysts will be able to more thoroughly gather and process relevant stock information. Thus, I test whether the under-pressure anomaly is stronger among stocks that are followed by fewer analysts. Table 25 reports the test results when I sort supplier stocks into tercile portfolios based on the number of analyst, and then on customer default risk.

**Table 25: Financial Contagion and Analyst Coverage**

This table shows calendar-time supplier portfolio abnormal returns. At the beginning of each calendar month in the observation period from January 1981 to November 2010, stocks are double-sorted first on firm characteristic (terciles), then on customer default risk (quintiles). Panel A reports the results of supplier returns for different analyst coverage terciles and customer default risk quintiles. Analyst coverage is the number of analysts in the IBES database covering the stock. All stocks are equally weighted within a given portfolio. I rebalance the portfolios every month to maintain the equal weights. The portfolios in the table include all stocks that have a share price larger than 2\$ at the time of portfolio formation. The alphas presented are the intercepts from a rolling regression of monthly excess returns. Explanatory variables include the market factor and Fama and French factors (small minus big and high BM minus low BM). The factors are retrieved from the mimicking portfolios available on Professors Kenneth French's website. High-Low is a rolling, zero-cost strategy that purchases the lowest 20% customer default risk suppliers and sells short the top 20% customer default risk suppliers. All returns and alphas are in monthly percent, t-statistics are reported in italics. \*\*\*, \*\* and \* denote the statistical significance at the 1%, 5% and 10% level, respectively.

	Low	Medium	High
Panel A: Returns			
Q1 (Low Distress)	<b>0.92%</b> <i>1.95*</i>	<b>0.84%</b> <i>2.00**</i>	<b>0.45%</b> <i>1.21</i>
Q2	<b>0.47%</b> <i>1.09</i>	<b>0.65%</b> <i>1.61</i>	<b>0.74%</b> <i>2.00**</i>
Q3	<b>0.51%</b> <i>1.14</i>	<b>0.85%</b> <i>1.96**</i>	<b>0.81%</b> <i>1.98**</i>
Q4	<b>-0.02%</b> <i>-0.06</i>	<b>0.61%</b> <i>1.38</i>	<b>0.77%</b> <i>1.91*</i>
Q5 (High Distress)	<b>0.07%</b> <i>0.15</i>	<b>0.27%</b> <i>0.60</i>	<b>0.52%</b> <i>1.21</i>
Q1-Q5	<b>0.85%</b> <i>2.34**</i>	<b>0.57%</b> <i>1.88*</i>	<b>-0.07%</b> <i>-0.27</i>
Panel B: Three-factor			
Q1 (Low Distress)	<b>0.21%</b> <i>0.81</i>	<b>0.18%</b> <i>0.95</i>	<b>-0.06%</b> <i>-0.35</i>
Q2	<b>-0.38%</b> <i>-1.49</i>	<b>-0.01%</b> <i>-0.04</i>	<b>0.04%</b> <i>0.23</i>
Q3	<b>-0.30%</b> <i>-1.07</i>	<b>0.07%</b> <i>0.43</i>	<b>0.12%</b> <i>0.59</i>
Q4	<b>-0.82%</b> <i>-2.99***</i>	<b>-0.24%</b> <i>-1.22</i>	<b>0.15%</b> <i>0.72</i>
Q5 (High Distress)	<b>-0.74%</b> <i>-2.61**</i>	<b>-0.65%</b> <i>-2.88***</i>	<b>-0.20%</b> <i>-0.96</i>
Q1-Q5	<b>0.96%</b> <i>2.63***</i>	<b>0.83%</b> <i>2.73***</i>	<b>0.14%</b> <i>0.51</i>
Average AC	1.15	3.80	12.95

Panel A of Table 25 shows mean excess returns of supplier portfolios. I can document a return pattern consistent with the under-pressure customer anomaly for the lowest and medium analyst coverage tercile portfolios. Suppliers to non-distressed customers generate mean excess returns equal to 0.92% and 0.87% in the low and medium analyst coverage terciles, respectively. In contrast, suppliers to distressed customers earn mean excess returns of only 0.02% in the low analyst coverage tercile and 0.27% in the medium analyst coverage tercile, on average. The differences are statistically significant at conventional levels. It is interesting to note that the magnitude and statistical significance of the under-pressure customer anomaly decreases monotonically across the tercile portfolios. In the tercile of high analyst coverage, the under-pressure customer anomaly is only qualitatively existent.

Panel B of Table 25 reports alphas with respect to the three-factor model. In both, the smallest and medium analyst coverage terciles, suppliers to highly distressed customers earn statistically significant negative monthly alphas of -0.74% and -0.65%, respectively. Suppliers to non-distressed customer earn statistically insignificant alphas. The long-short strategy generates a monthly return of 0.96% (0.83%) in the tercile with the lowest (medium) analyst coverage. For firms followed by a high number of analysts, no significant underperformance of suppliers to distressed customers can be observed. Thus, the rate with which stock information spreads has clearly an impact on the degree of supplier return predictability caused by customers' default risk.

#### 4.4.3. Turnover

A number of papers find that asset mispricings are greater in illiquid markets.<sup>254</sup> I also examine the relationship between the liquidity of the supplier stocks and the under-pressure customer anomaly. Generally, illiquid assets are more difficult to trade as supply and demand for those stocks are rather low. Naturally, lower trading leads to less informationally efficient prices. Hence, the return predictability caused by the under-pressure customer anomaly may be more pronounced among stocks that are not traded frequently. Following Pastor and Stambaugh (2003), I use a stocks' turnover as a proxy for liquidity. A higher turnover is generally associated with an increased liquidity. Table 26 reports the results when I first group supplier

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<sup>254</sup> See for example Wurgler and Zhuravskaya (2002), Kumar and Lee (2006), and Chordia, Roll, and Subrahmanyam (2006) for empirical evidence supporting this view

stocks into tercile portfolios based on monthly turnover, and then into quintile portfolios using the customers' EDF values.

**Table 26: Financial Contagion and Trading Volume**

This table shows calendar-time supplier portfolio abnormal returns. At the beginning of each calendar month in the observation period from January 1981 to November 2010, stocks are double-sorted first on firm characteristic (terciles), then on customer default risk (quintiles). Panel A reports the results of supplier returns for different trading volume terciles and customer default risk quintiles. All stocks are equally weighted within a given portfolio. I rebalance the portfolios every month to maintain the equal weights. The portfolios in the table include all stocks that have a share price larger than 2\$ at the time of portfolio formation. The alphas presented are the intercepts from a rolling regression of monthly excess returns. Explanatory variables include the market factor and Fama and French factors (small minus big and high BM minus low BM). The factors are retrieved from the mimicking portfolios available on Professors Kenneth French's website. High-Low is a rolling, zero-cost strategy that purchases the lowest 20% customer default risk suppliers and sells short the top 20% customer default risk suppliers. All returns and alphas are in monthly percent, t-statistics are reported in italics. \*\*\*, \*\* and \* denote the statistical significance at the 1%, 5% and 10% level, respectively.

	Low	Medium	High
Panel A: Returns			
Q1 (Low Distress)	<b>0.84%</b> <i>2.57**</i>	<b>0.88%</b> <i>2.09**</i>	<b>0.72%</b> <i>1.45</i>
Q2	<b>0.55%</b> <i>1.76*</i>	<b>0.67%</b> <i>1.69*</i>	<b>0.60%</b> <i>1.24</i>
Q3	<b>0.60%</b> <i>1.92*</i>	<b>0.66%</b> <i>1.60</i>	<b>0.89%</b> <i>1.73*</i>
Q4	<b>0.29%</b> <i>0.94</i>	<b>0.41%</b> <i>0.98</i>	<b>0.66%</b> <i>1.61</i>
Q5 (High Distress)	<b>0.22%</b> <i>0.66</i>	<b>0.27%</b> <i>0.63</i>	<b>0.23%</b> <i>0.44</i>
Q1-Q5	<b>0.63%</b> <i>2.71***</i>	<b>0.61%</b> <i>2.49**</i>	<b>0.49%</b> <i>1.34</i>
Panel B: Three-factor			
Q1 (Low Distress)	<b>0.05%</b> <i>0.25</i>	<b>0.10%</b> <i>0.50</i>	<b>0.34%</b> <i>1.39</i>
Q2	<b>-0.34%</b> <i>-1.66*</i>	<b>-0.11%</b> <i>-0.60</i>	<b>0.06%</b> <i>0.28</i>
Q3	<b>-0.23%</b> <i>-1.05</i>	<b>-0.10%</b> <i>-0.53</i>	<b>0.37%</b> <i>1.57</i>
Q4	<b>-0.46%</b> <i>-2.14**</i>	<b>-0.38%</b> <i>-1.92*</i>	<b>0.18%</b> <i>0.72</i>
Q5 (High Distress)	<b>-0.56%</b> <i>-2.64**</i>	<b>-0.61%</b> <i>-3.08***</i>	<b>-0.47%</b> <i>-1.71*</i>
Q1-Q5	<b>0.62%</b> <i>2.55**</i>	<b>0.71%</b> <i>2.76***</i>	<b>0.81%</b> <i>2.12**</i>
MB	1.69	14.27	203.95

Panel A of Table 26 shows the mean excess returns of supplier portfolios. Across all turnover terciles, suppliers to distressed customers underperform. However, the differences between suppliers to high distress customers and suppliers to non-distressed customer are only statistically significant for the lowest and medium turnover terciles.

Panel B of Table 26 presents the alphas with respect to the three-factor model. Consistently, suppliers to under-pressure customers exhibit negative alphas. The statistical significance varies with the stock's turnover. While, the negative alphas of suppliers in quintile 5 are statistically significant at the 5% and 1% level for the lowest and medium turnover terciles, the suppliers with the highest turnover earn a negative alpha that is statistically significant at the 10% level. The long-short strategy generates large monthly alphas ranging from 0.65% to 0.81%, which are all statistically significant at conventional levels. Thus, the under-pressure customer anomaly is persistent across different liquidity levels, however more pronounced for illiquid stocks.

#### 4.4.4. Price

Similar to trading volume, the price of a security can be interpreted as a proxy for its underlying liquidity. More liquid stocks have generally higher prices. In this section, I test whether asset liquidity and the under-pressure customer anomaly are related. For that, I sort supplier stocks into tercile portfolios based on their one month lagged price, and then into quintile portfolios according to the previous month customer distress risk. Table 27 presents the results.

**Table 27: Financial Contagion and Price**

This table shows calendar-time supplier portfolio abnormal returns. At the beginning of each calendar month in the observation period from January 1981 to November 2010, stocks are double-sorted first on firm characteristic (terciles), then on customer default risk (quintiles). Panel A reports the results of supplier returns for different share price terciles and customer default risk quintiles. All stocks are equally weighted within a given portfolio. I rebalance the portfolios every month to maintain the equal weights. The portfolios in the table include all stocks that have a share price larger than 2\$ at the time of portfolio formation. The alphas presented are the intercepts from a rolling regression of monthly excess returns. Explanatory variables include the market factor and Fama and French factors (small minus big and high BM minus low BM). The factors are retrieved from the mimicking portfolios available on Professors Kenneth French's website. High-Low is a rolling, zero-cost strategy that purchases the lowest 20% customer default risk suppliers and sells short the top 20% customer default risk suppliers. All returns and alphas are in monthly percent, t-statistics are reported in italics. \*\*\*, \*\* and \* denote the statistical significance at the 1%, 5% and 10% level, respectively.

	Low	Medium	High
Panel A: Returns			
Q1 (Low Distress)	<b>1.07%</b> <i>2.45**</i>	<b>0.60%</b> <i>1.51</i>	<b>0.66%</b> <i>1.85*</i>
Q2	<b>0.64%</b> <i>1.57</i>	<b>0.55%</b> <i>1.43</i>	<b>0.88%</b> <i>2.73***</i>
Q3	<b>0.55%</b> <i>1.26</i>	<b>0.73%</b> <i>1.88*</i>	<b>0.71%</b> <i>2.05**</i>
Q4	<b>0.41%</b> <i>0.97</i>	<b>0.59%</b> <i>1.44</i>	<b>0.46%</b> <i>1.31</i>
Q5 (High Distress)	<b>-0.07%</b> <i>-0.15</i>	<b>0.25%</b> <i>0.61</i>	<b>0.27%</b> <i>0.78</i>
Q1-Q5	<b>1.14%</b> <i>4.04***</i>	<b>0.35%</b> <i>1.43</i>	<b>0.39%</b> <i>1.86*</i>
Panel B: Three-factor			
Q1 (Low Distress)	<b>0.32%</b> <i>1.23</i>	<b>-0.03%</b> <i>-0.18</i>	<b>0.19%</b> <i>1.16</i>
Q2	<b>-0.13%</b> <i>-0.59</i>	<b>-0.16%</b> <i>-1.00</i>	<b>0.42%</b> <i>2.90***</i>
Q3	<b>-0.25%</b> <i>-0.96</i>	<b>0.00%</b> <i>0.01</i>	<b>0.18%</b> <i>1.23</i>
Q4	<b>-0.35%</b> <i>-1.39</i>	<b>-0.19%</b> <i>-1.13</i>	<b>-0.04%</b> <i>-0.26</i>
Q5 (High Distress)	<b>-0.91%</b> <i>-3.25***</i>	<b>-0.59%</b> <i>-3.17***</i>	<b>-0.33%</b> <i>-2.40**</i>
Q1-Q5	<b>1.23%</b> <i>4.26***</i>	<b>0.56%</b> <i>2.31**</i>	<b>0.52%</b> <i>2.48**</i>
Price	5.70	12.12	35.97

Panel A of Table 27 presents the excess returns of supplier portfolios. The under-pressure customer anomaly is strong among suppliers in the lowest price tercile. Here, the mean excess return difference between suppliers to distressed customers and suppliers to non-distressed customers is equal to 1.14% per month and statistically significant at the 1% level. For the stocks in the medium and high price tercile, no highly significant difference between the returns of high customer distress and low customer distress can be documented. It should be noted however, that the under-pressure customer anomaly is still qualitatively existent.

Panel B of Table 27 shows the three-factor alphas. Throughout all price terciles, suppliers to high distress customer exhibit negative and statistically significant alphas. However, the extent of the under-pressure customer anomaly is slightly more pronounced in the medium and small price tercile. In fact, the long-short investment strategy in the lowest price tercile generates a return that is more than twice as high compared to the medium and high price tercile.

#### 4.4.5. Institutional Holdings

One important premise for anomalies to persist is a limited ability of investors to engage in arbitrage trading. Generally, arbitrage can involve a long and short position of a certain stock or a pair of stocks. If then the ability of short-selling is considerably constraint, arbitrageurs cannot profit from their underlying strategy. For the under-pressure customer anomaly this means the following: Even if a number of investors are aware of the negative relationship between customer distress and supplier return performances, they may not be able to trade on it due to limited arbitrage capabilities. This leads to a persistence of the anomalous return pattern. Nagel (2005) argues that the level of institutional ownership can be regarded as a useful proxy for the degree of a stock's short-sale constraints. In this section, I test whether the under-pressure customer anomaly is stronger among firms with a low number of institutions in their shareholder base.

Also, the sophistication of the investor base can be interpreted as a proxy for information completeness. For example, Nofsinger and Sias (1999) find a certain level of stock return predictability in the changes in institutional ownership. This suggests that institutional trading contains information about future returns. For my analysis, a larger base of institutional investors translates into a higher tendency that all available information is incorporated into the stock prices of the underlying security. I proxy the sophistication of the investor base by examining the number of shares held by institutional investors. Specifically, I compute an institutional holdings ratio by dividing the shares held by institutional investors by the total



shares outstanding at the end of a quarter.<sup>255</sup> Table 28 reports the test results when I sort supplier stocks into tercile portfolios based on the institutional holdings ratio, and then on customer default risk.

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<sup>255</sup> I also conduct the analysis with a Breath ratio of institutional holdings. Results are not reported, however, conclusions remain unchanged

**Table 28: Financial Contagion and Institutional Holdings**

This table shows calendar-time supplier portfolio abnormal returns. At the beginning of each calendar month in the observation period from January 1981 to November 2010, stocks are double-sorted first on firm characteristic (terciles), then on customer default risk (quintiles). Panel A reports the results of supplier returns for different institutional holdings terciles and customer default risk quintiles. All stocks are equally weighted within a given portfolio. I rebalance the portfolios every month to maintain the equal weights. The portfolios in the table include all stocks that have a share price larger than 2\$ at the time of portfolio formation. The alphas presented are the intercepts from a rolling regression of monthly excess returns. Explanatory variables include the market factor and Fama and French factors (small minus big and high BM minus low BM). The factors are retrieved from the mimicking portfolios available on Professors Kenneth French's website. High-Low is a rolling, zero-cost strategy that purchases the lowest 20% customer default risk suppliers and sells short the top 20% customer default risk suppliers. All returns and alphas are in monthly percent, t-statistics are reported in italics. \*\*\*, \*\* and \* denote the statistical significance at the 1%, 5% and 10% level, respectively.

	Low	Medium	High
Panel A: Returns			
Q1 (Low Distress)	<b>0.69%</b> <i>1.69*</i>	<b>0.77%</b> <i>1.92*</i>	<b>0.59%</b> <i>1.59</i>
Q2	<b>0.56%</b> <i>1.41</i>	<b>0.79%</b> <i>2.20**</i>	<b>0.85%</b> <i>2.34**</i>
Q3	<b>0.50%</b> <i>1.15</i>	<b>0.57%</b> <i>1.54</i>	<b>0.81%</b> <i>2.20**</i>
Q4	<b>0.01%</b> <i>0.03</i>	<b>0.61%</b> <i>1.56</i>	<b>0.68%</b> <i>1.82*</i>
Q5 (High Distress)	<b>-0.37%</b> <i>-0.88</i>	<b>0.29%</b> <i>0.71</i>	<b>0.53%</b> <i>1.29</i>
Q1-Q5	<b>1.06%</b> <i>3.85***</i>	<b>0.48%</b> <i>1.99**</i>	<b>0.06%</b> <i>0.23</i>
Panel B: Three-factor			
Q1 (Low Distress)	<b>0.07%</b> <i>0.28</i>	<b>0.13%</b> <i>0.75</i>	<b>-0.03%</b> <i>-0.20</i>
Q2	<b>-0.06%</b> <i>-0.26</i>	<b>0.10%</b> <i>0.70</i>	<b>0.17%</b> <i>1.06</i>
Q3	<b>-0.19%</b> <i>-0.72</i>	<b>-0.10%</b> <i>-0.64</i>	<b>0.08%</b> <i>0.53</i>
Q4	<b>-0.64%</b> <i>-2.50**</i>	<b>-0.16%</b> <i>-0.97</i>	<b>-0.03%</b> <i>-0.20</i>
Q5 (High Distress)	<b>-0.98%</b> <i>-3.91***</i>	<b>-0.52%</b> <i>-2.71***</i>	<b>-0.37%</b> <i>-2.05**</i>
Q1-Q5	<b>1.05%</b> <i>3.71***</i>	<b>0.65%</b> <i>2.69***</i>	<b>0.33%</b> <i>1.34</i>
Holdings	9.14%	33.63%	63.68%

Panel A of Table 28 presents the mean excess returns of supplier stocks. A return pattern consistent with the under-pressure customer can be detected in all terciles of institutional ownership. However, it is strongest and statistically significant only for supplier stocks in the low and medium institutional ownership terciles. Specifically, the difference between suppliers to high distress customers and suppliers to low distress customers is equal to 1.06% (0.48%) in the low (medium) institutional holdings terciles. Both differences are statistically significant at conventional levels.

The picture does not change significantly when I correct for risk using the three-factor model. Panel B of Table 28 shows the three-factor alphas of supplier firms. The supplier firms in quintile 5 exhibit negative alphas across all terciles of institutional ownership. The difference between suppliers to high customer distress and suppliers to low customer distress, however, is only significant for the lowest and medium institutional holdings groups. Thus, the under-pressure customer anomaly appears to vary with the level of sophisticated investors in the shareholder base.

#### 4.4.6. Market-to-Book Ratio

Campbell et al. (2008) find that the financial distress anomaly is stronger among stocks in the largest market-to-book ratio (MB) distribution. Potentially, the results presented in Table 7 could then be caused by extreme growth stocks, whose underperformance is not entirely captured by Fama and French (1992) three-factor model. I test for this possibility in this section. For that, I double sort suppliers, first into terciles portfolios on market-to-book ratios (MB), then into quintile portfolios on customers' EDF quantities. Table 29 presents the results.

**Table 29: Financial Contagion and Market-to-Book Ratio**

This table shows calendar-time supplier portfolio abnormal returns. At the beginning of each calendar month in the observation period from January 1981 to November 2010, stocks are double-sorted first on firm characteristic (terciles), then on customer default risk (quintiles). Panel A reports the results of supplier returns for different market-to-book terciles and customer default risk quintiles. I follow Fama & French (1992) in computing market-to-book ratios. All stocks are equally weighted within a given portfolio. I rebalance the portfolios every month to maintain the equal weights. The portfolios in the table include all stocks that have a share price larger than 2\$ at the time of portfolio formation. The alphas presented are the intercepts from a rolling regression of monthly excess returns. Explanatory variables include the market factor and Fama and French factors (small minus big and high BM minus low BM). The factors are retrieved from the mimicking portfolios available on Professors Kenneth French's website. High-Low is a rolling, zero-cost strategy that purchases the lowest 20% customer default risk suppliers and sells short the top 20% customer default risk suppliers. All returns and alphas are in monthly percent, t-statistics are reported in italics. \*\*\*, \*\* and \* denote the statistical significance at the 1%, 5% and 10% level, respectively.

	Low MB	Medium MB	High MB
Panel A: Returns			
Q1 (Low Distress)	<b>1.09%</b> <i>3.31***</i>	<b>0.89%</b> <i>2.52**</i>	<b>0.57%</b> <i>1.28</i>
Q2	<b>1.03%</b> <i>3.07***</i>	<b>0.90%</b> <i>2.58**</i>	<b>0.45%</b> <i>1.04</i>
Q3	<b>0.89%</b> <i>2.58**</i>	<b>0.73%</b> <i>2.03**</i>	<b>0.32%</b> <i>0.69</i>
Q4	<b>0.54%</b> <i>1.61</i>	<b>0.46%</b> <i>1.22</i>	<b>0.20%</b> <i>0.44</i>
Q5 (High Distress)	<b>0.42%</b> <i>1.08</i>	<b>0.45%</b> <i>1.14</i>	<b>-0.27%</b> <i>-0.58</i>
Q1-Q5	<b>0.67%</b> <i>2.61***</i>	<b>0.45%</b> <i>2.01**</i>	<b>0.83%</b> <i>3.17***</i>
Panel B: Three-factor			
Q1 (Low Distress)	<b>0.33%</b> <i>1.86*</i>	<b>0.25%</b> <i>1.52</i>	<b>0.03%</b> <i>0.16</i>
Q2	<b>0.13%</b> <i>0.72</i>	<b>0.23%</b> <i>1.50</i>	<b>-0.12%</b> <i>-0.66</i>
Q3	<b>0.04%</b> <i>0.20</i>	<b>-0.02%</b> <i>-0.14</i>	<b>-0.21%</b> <i>-1.08</i>
Q4	<b>-0.30%</b> <i>-1.47</i>	<b>-0.28%</b> <i>-1.68*</i>	<b>-0.41%</b> <i>-1.79*</i>
Q5 (High Distress)	<b>-0.53%</b> <i>-2.37**</i>	<b>-0.36%</b> <i>-1.95*</i>	<b>-0.90%</b> <i>-4.58***</i>
Q1-Q5	<b>0.87%</b> <i>3.33***</i>	<b>0.61%</b> <i>2.73***</i>	<b>0.94%</b> <i>3.51***</i>
MB	0.84	1.83	12.58

Panel A of Table 29 shows the mean excess returns of supplier portfolios. The results draw consistent picture: Across all tercile portfolios of MB ratios, the under-pressure customer anomaly is persists. For the lowest MB ratio tercile, suppliers to under-pressure customers underperform suppliers to non-distressed customer by 0.67% per month. This is statistically significant at the 1% level. For the highest MB tercile, the under-pressure customer anomaly is even stronger and statistically more significant: Suppliers to high distress customers produce a monthly excess return that is 83 basis points lower that the returns of suppliers to low distress customers. These results suggest that the under-pressure customer anomaly is not driven by extreme growth stocks, as I can document a persistence across all MB ratio terciles.

Similar inferences can be drawn from the three-factor alphas of supplier portfolios in Panel B of Table 29. Throughout all terciles of market-to-book ratios, the under-pressure customer anomaly is strong and statistically significant at the 1% level.

#### 4.4.7. Section Summary

This section examines the under-pressure customer anomaly for a number of subsamples based on firm characteristics that measure the ease of trading, liquidity and the level of information completeness. Specifically, firm characteristics include market capitalization, analyst coverage, trading volume, price, institutional ownership, and market-to-book ratios. I have grouped supplier firms first into three groups based on these supplier firm characteristic, then into five groups according to their respective customer EDF measure. Overall, the under-pressure customer anomaly appears to persist across all groups of different firm characteristics. However, it appears to be more pronounced among small stocks, stocks with low analyst coverage, institutional ownership, trading volume and price, a picture quite common to anomalies in the finance literature.

#### 4.5. Earnings Announcement Analysis

The stock return analysis has shown that suppliers to under-pressure customers generate abnormal negative returns even if I correct for firm-specific risks using standard asset pricing model such as Fama and French three-factor-model. This indicates that investors fail to price relevant information on customer distress risk into the stock prices of the corresponding suppliers. Furthermore, the analysis in the section above shows that the under-pressure customer anomaly is strongest among firms with low levels of information dissemination, an

unsophisticated investor base and low liquidity. In this section, I provide further evidence on the persistence of the under-pressure customer anomaly to stem from asset mispricing.

Chopra, Lakonishok, and Ritter (1992), and La Porta et al. (1997) provide evidence for low returns of growth stocks to stem from short periods of time around earnings announcements. Using this observation, the authors argue that investors are not fully aware of the earnings quality of growth firms and realize their mistake when earnings are announced. A similar test can be applied to the under-pressure customer anomaly: If investors are not aware of the customer-supplier relationships and suppliers experience adverse effects when their major customer becomes financially distressed, they will be negatively surprised when the actual earnings quality of supplier firms are made public. For example, customer XYZ experiences substantial financial distress resulting in deteriorating operating performances of supplier ABC.<sup>256</sup> If then investors are inattentive towards the contagious nature of financial distress, they only become aware of the supplier's true earnings quality around the publication of quarterly results. That is, they will be disappointed with the reported earnings and update their valuation accordingly. This, in turn, will produce negative earnings announcement returns of suppliers to under-pressure customers. In this section, I will apply this logic to the customer-supplier data used in this study.

In a further test, I estimate the standardized unexpected earnings (SUE) of suppliers to distressed customers. While the earnings announcement return analysis of suppliers to under-pressure customers provides an estimate of the market's expectation towards supplier earnings quality, the SUE directly measures the degree to which a firm's earnings results deviates from the "street view". Based on the logic as outlined in the paragraph above, I would expect an earnings measure that remains behind expectation for suppliers to distressed customers. In total, I use three different measures of SUEs: The first and second are based on the seasonal random walk model where the best estimate for an earnings figure is the earnings measure from the same quarter in the preceding year. I use one unadjusted SUE and one that adjusts for special items. The last SUE measure I use is based on the average forecasts of equity analysts covering the respective stock.

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<sup>256</sup> As shown in section 4.1.1

#### 4.5.1. Estimation Methodology

##### 4.5.1.1. Announcement Return Analysis

I use a similar event study methodology as detailed in La Port et al. (1997). Specifically, I sort supplier stocks into quintile portfolios based on their previous month EDF measure and estimate the cumulative average returns (CAR) around the five days  $[-2;+2]$  of the suppliers' earnings announcement dates. These CARs are then equally-weighted within each quintile portfolio. To compute abnormal average returns, I apply two different widely used methodologies:

First, I simply subtract the return on value-weighted CRSP market portfolio from the suppliers CARs around the earnings announcement dates. This methodology is also used by Hertzler et al. (2008).<sup>257</sup> Second, I compute Fama and French (1993) adjusted average returns to account for risk differences captured by the market, firm size and the book-to-market ratio. For that, I measure a stock's exposure to the market, SMB and BM factor in an estimation period of 80 days before the event until 10 days before the event  $[-80,-10]$ . This estimation methodology can be depicted graphically as shown in Figure 5.

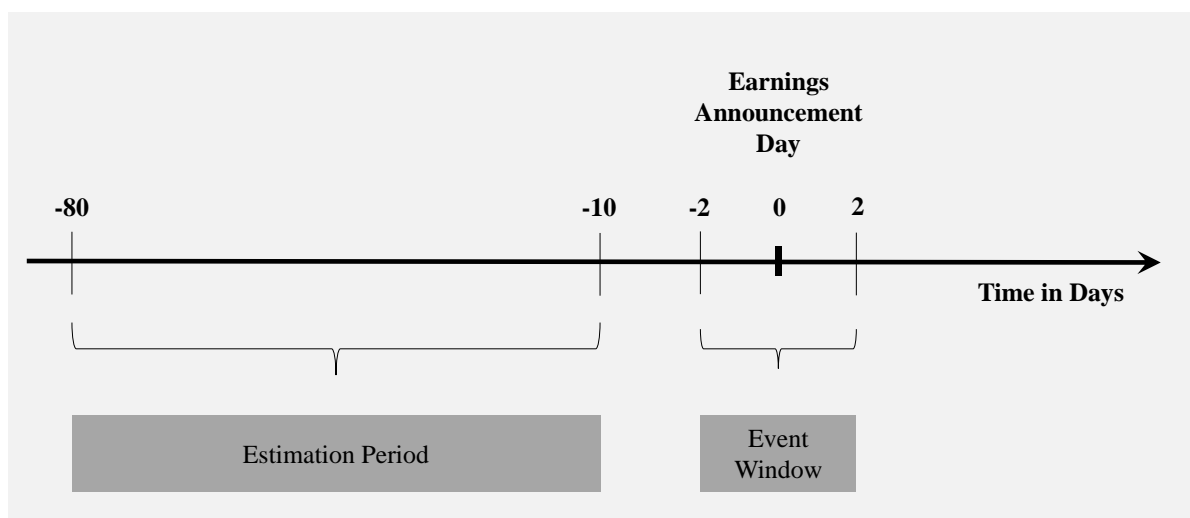


Figure 5: Overview of the Event Study Methodology

I use the mimicking portfolios made available on Professor Kenneth French's website to measure a stock's exposure to the market, SMB and HML factors. The Fama and French (1993) adjusted average announcement returns are computed as shown in Equation 29:

<sup>257</sup> The results remain unchanged if I use the return on the equally-weighted CRSP market portfolio

$$AR_{it} = R_{it} - \alpha - \beta R_M - \gamma SMB_{it} - \delta HML_{it} \quad (29)$$

where,  $AR_{it}$  is the abnormal return of stock  $i$  at time  $t$ ,  $R_{it}$  is the raw return around the five days of the earnings announcement date,  $R_M$  is a stock's exposure to the market factor,  $SMB$  the exposure to the size factor, and  $HML$  the exposure to the book-to-market factor. In sum, I adjust the returns generated over the event window of two days before the earnings announcements to the two days after the earnings announcement for the risk factors included in the Fama and French (1993) three-factor model.

#### 4.5.1.2. Standardized Unexpected Earnings

In order to compute the SUEs of supplier firms, I follow the methodology as detailed in Livnat and Mendenhall (2006). I define the SUE as actual earnings per share (AEPS) minus a measure of expected earnings per share (EEPS) scaled by the stock's share price.

In total, I use three different measures of SUEs. First, I compute the SUEs using a time-series measure of expected earnings. This measure is based on the seasonal random walk model. That is, I assume expected earnings to equal the firm's actual earnings in the same quarter of the last year. Equation 30 presents the first SUE measure mathematically:

$$SUE = \frac{X_{jt} - X_{jt-4}}{P_{jt}} \quad (30)$$

where  $X_{jt}$  is the actual earnings per share for firm  $I$  in quarter  $t$ , and  $P_{jt}$  is the firm's price per share at the end of quarter  $t$ . I do not adjust  $X_{jt}$  or  $P_{jt}$  for stock splits, but  $X_{jt-4}$  is adjusted for any stock splits or stock dividends that occurred in the time period from  $t$  to  $t-4$ .

My second measure of SUE differs from the first one only in the way that I use a firm's EPS estimate that excludes special items. Burgstahler, Jiambalvo, and Shevlin (2002) provide evidence for the market to under-react to earnings component such as special items. If, for example, suppliers to distressed customers have systematically higher measures of special items in their earnings report, inferences from the SUE analysis may be clouded.

The last variant of the applied SUE measure uses analysts' forecasts as a proxy for expected earnings. I retrieve analysts' forecasts from the I/B/E/S database. This SUE measure is calculated as indicated by Equation 30, only that I replace  $X_{jt-4}$  with the median analyst forecast in the time period of 90 days prior to actual earnings announcement date.



## 4.5.2. Results of the Earnings Announcement Analysis

### 4.5.2.1. Earnings Announcement Returns

Panel A of Table 30 shows the average raw earnings announcement returns for the supplier portfolios sorted by previous month's customer distress risk. Suppliers to under-pressure customers experience a raw earnings announcement return of -0.16% on average. In contrast, suppliers to non-distressed customers generate a positive average earnings announcement return of 0.48%. The difference of 0.64% is significant at the 5% level. In addition, I adjust the raw earnings announcement returns for firm specific risks. Panel B of Table 30 reports the results when using the market model to adjust for risks. I compute abnormal earnings announcement returns by subtracting the average return in the estimation period (-80, -10) from the earnings announcement return during the event window (-2, +2). The results show that the difference of the market-adjusted CAR of suppliers to non-distressed customers is significantly different from the market-adjusted CAR of suppliers to highly distressed customers around the respective earnings announcement dates. In fact, the difference is equal to 0.57% and statistically significant at conventional levels. Principally the same picture emerges when I use the Fama and French (1993) three-factor model to account for firm specific risk. Similar to the analysis using the market model, I measure factor exposure in the estimation period using the factor mimicking portfolios made available on Professor Kenneth French's website. The results remain consistent: Even if I adjust for risks, the earnings announcement returns of suppliers to under-pressure customers are significantly lower compared to the earnings announcement returns of suppliers to non-distressed customers. In the Fama and French (1993) three-factor model, the difference is equal to 0.58% and statistically significant at the 5% level.

**Table 30: Earnings Announcement Returns**

This table shows earnings announcement returns of supplier portfolios. Each quarter end, supplier stocks are ranked in ascending order according to their major customer's EDF measure in the previous month. The ranked stocks are assigned to one of five quintile portfolios (quintile 1: low customer risk portfolio, quintile 5: high customer risk portfolio). All stocks are equally weighted within a given portfolio. The portfolios in the table include all stocks that have a share price larger than 2\$ at the time of portfolio formation. Raw CAR is the raw cumulative average return over a five day window around the earnings announcement date (-2, +2). Market-adjusted CAR is defined as the raw returns around the earnings announcement date minus the return experienced in the estimation period (-80,-10). Three-factor adjusted CAR is the returns around earnings announcement taking the Fama and French (1992) factor exposure into account. Factor exposure is measured in the estimation period (-120,-10). The factors are retrieved from the mimicking portfolios available on Professors Kenneth French's website. High-Low is the difference in earnings announcement returns between high customer distress firms and low customer distress firms. T-statistics are reported in italics. \*\*\*, \*\* and \* denote the statistical significance at the 1%, 5% and 10% level, respectively.

	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	High-Low
<b>Panel A</b>						
Raw CAR	0.48%	0.50%	0.48%	0.23%	-0.16%	0.64% <i>2.37**</i>
<b>Panel B</b>						
Market-adjusted CAR	0.40%	0.43%	0.43%	0.13%	-0.17%	0.57% <i>2.16**</i>
<b>Panel C</b>						
Three-factor CAR	0.20%	0.20%	0.29%	0.04%	-0.38%	0.58% <i>2.00**</i>

According to the analysis above, investors do not seem to be able to price the information on customer default risk into the stock prices of their suppliers. Ignoring this relation, investors are negatively surprised when earnings are announced leading to a negative announcement returns as investors correct for their valuation mistakes.

#### 4.5.2.2. Standardized Unexpected Earnings

Table 31 reports the results of the SUE analysis. SUE 1 is computed using the seasonal random walk model including special items and presented in Panel A. According to this model, actual earnings of suppliers to high distress customers clearly remain behind their expectations. While the actual earnings of suppliers to low distress customers do not significantly deviate from their expected values, actual earnings and expected earnings for suppliers of distressed customers diverge considerably. In fact, suppliers in quintile 1 show a difference of actual and expected earnings of 0.01%, on average. In contrast, actual earnings of suppliers in quintile 1 are -0.5% below expectations. The difference between quintile 1 and quintile 5 is statistically significant at the 1% level.

Panel B shows the results when I exclude special items from the earnings per share estimate. Conclusion similar to the SUE1 analysis can be drawn. Suppliers to under-pressure customers report actual earnings that are significantly below expectations. The exclusion of special items in the EPS measure does not have a substantial effect on the analysis.

Panel C presents the results of the SUE3 analysis. SUE3 is computed by subtracting the median analyst forecast 90 prior to the announcement date from the actual reported earnings per share. Interestingly, the suppliers across all quintiles of customer default risk show negative SUEs. However, the effect of the under-pressure customer anomaly is still present. While actual earnings of suppliers in quintile 1 remain only around 0.12% behind analysts' forecasts, actual earnings of suppliers to highly distressed customers are 0.28% below expectations, on average. The difference between SUEs in quintile 1 and quintile 5 is still statistically significant at the 5% level.

**Table 31: Standardized Unexpected Earnings**

This table shows earnings announcement returns of supplier portfolios. Each quarter end, supplier stocks are ranked in ascending order according to their major customer's EDF measure in the previous month. The ranked stocks are assigned to one of five quintile portfolios (quintile 1: low customer risk portfolio, quintile 5: high customer risk portfolio). All stocks are equally weighted within a given portfolio. The portfolios in the table include all stocks that have a share price larger than 2\$ at the time of portfolio formation. SUE 1 is the standardized unexpected earnings following the methodology from Livnat and Mendenhall (2006). SUE 2 applies the same methodology and adjusts earnings for special items. SUE 3 is the standardized unexpected earnings using IBES analyst forecasts. High-Low is the difference standardized unexpected earnings between high customer distress firms and low customer distress firms. T-statistics are reported in italics. \*\*\*, \*\* and \* denote the statistical significance at the 1%, 5% and 10% level, respectively.

	Q1 (Low)	Q2	Q3	Q4	Q5 (High)	High-Low
<b>Panel A</b>						
SUE 1	<b>-0.03%</b>	<b>-0.09%</b>	<b>-0.13%</b>	<b>-0.26%</b>	<b>-0.50%</b>	<b>0.47%</b>
	<i>-0.28</i>	<i>-0.88</i>	<i>-0.90</i>	<i>-2.07**</i>	<i>-2.29**</i>	<i>3.09***</i>
<b>Panel B</b>						
SUE 2	<b>-0.01%</b>	<b>-0.07%</b>	<b>-0.06%</b>	<b>-0.18%</b>	<b>-0.43%</b>	<b>0.42%</b>
	<i>-0.11</i>	<i>-1.03</i>	<i>-0.67</i>	<i>-2.17**</i>	<i>-2.98***</i>	<i>3.68***</i>
<b>Panel C</b>						
SUE 3	<b>-0.12%</b>	<b>-0.24%</b>	<b>-0.32%</b>	<b>-0.17%</b>	<b>-0.28%</b>	<b>0.16%</b>
	<i>-2.21**</i>	<i>-2.08**</i>	<i>-1.34</i>	<i>-0.75</i>	<i>-5.03***</i>	<i>2.35**</i>

The results of all SUE analyses suggest that the suppliers to under-pressure customers report earnings that are consistently below of market expectations. This lends further support for a

mispricing story, in which the information on the relationship between customer distress and supplier performances is not adequately processed by market participants.

#### 4.5.3. Section Summary

This section tests whether the under-pressure customer anomaly is related to mispricing. For that, I conduct an event study return analysis around the earnings announcement of supplier firms for the different customer distress risk quintiles. This analysis reveals that suppliers to high distress customers experience, on average, a negative return around earnings announcement dates. This clearly suggests that investors are disappointed by the earnings quality when made public to the market. The differences between average abnormal returns of suppliers to distressed customers and suppliers to non-distressed customers is statistically significant at conventional level even if I adjust for risk using the Fama and French (1993) SMB and HML factors.

Moreover, I investigate whether actual earnings diverge from expectations in a SUE analysis. Using three different SUE models, I show that reported earnings remain behind expectations for supplier to under-pressure customers. In contrast, suppliers to low distressed customers appear to exhibit SUEs that are statistically indistinguishable from zero. This clearly suggests that the relationship between customer distress and supplier performance is not taken into account when pricing supplier stocks.

The results presented in this section strongly support the mispricing hypothesis. Investors fail to take the interconnection of customer-supplier relationships into account when predicting the earnings quality of suppliers to distressed customers. Ignoring this relation, investors are negatively surprised at the publication dates of supplier firm earnings and correct for their valuation mistakes accordingly.

## 5. Conclusion

In this study, I empirically examine the contagious effects of financial distress. Using a comprehensive sample of customer-supplier relationships between publically listed US firms, I specifically address three broad research questions: First, I examine whether financial distress at one firm is transmitted to economically linked partners. I measure financial distress using the expected default frequency as well as Ohlson's (1980) O-Score as a proxy. I then sort suppliers into quintile portfolios according to their customers' EDF (Ohlson O-Score) and measure subsequent performances. The results show that suppliers to financially distressed

customers underperform their peers on both the return as well as operating performance level. In fact, after correcting for risks using standard asset pricing models such as the Fama and French (1992) three-factor model, suppliers to under-pressure customers generate an alpha of -0.61% per month. A zero-cost, long-short strategy that purchases the suppliers to the least distressed customer quintile and sells short the suppliers in the highest distressed customer quintile generates a monthly return of approximately 0.74%, on average. A similar return pattern emerges when I use the Ohlson (1980) O-Score model to proxy for financial distress.

Second, I examine the determinants of financial distress contagion. Specifically, I investigate whether the magnitude of financial distress contagion varies with the level of industry concentration, product specificity and revenue intensity. The results indicate that contagious effects are stronger among suppliers that generate a higher percentage of sales with a distressed customer, sell a specialized product and operate in an overall concentrated industry.

Third, I investigate whether market participants use the information on customer distress when pricing corresponding supplier stocks. The fact that standard rational asset pricing models have difficulties to explain the return differentials between suppliers to non-distressed customers and suppliers to distressed customers already indicates an inadequate processing of available information. In an analysis, I show that this anomalous return pattern is stronger for stocks with relatively poor dissemination of information, an unsophisticated investor base and poor liquidity. These findings suggest that the under-pressure customer anomaly is driven by behavioural factors. An analysis of suppliers' earnings announcement returns as well as standardized unexpected earnings confirm this result. Suppliers to under-pressure customers show significantly lower returns when earnings are announced. This suggests that investors neglect the information on customer distress when pricing supplier stocks as they are negatively surprised when the true earnings quality is made public.

This work contributes to the existing body of research in several ways. First, I provide further evidence on the contagious nature of financial distress among contractually linked partners. So far, extant research has focused on distress related to bankruptcies exclusively. However, contagious distress effects may be relevant to firm's whose contractually linked partners did not file for bankruptcy, but are still financially under-pressure. With a sample of bankruptcy filings, only distress effects of firms that eventually fail to meet their debt obligations can be examined. I measure distress using a failure probability measure based on the distance-to-default variable of Merton's bond pricing model. This approach allows us to examine potential

distress spill-over effects for a much broader sample including all suppliers traded on major US stock exchanges between 1980 and 2010. Thus, my approach delivers a much more comprehensive picture of how distress at one firm can affect economically linked partners.

Second, I also examine the contagious effects of customer financial distress on the operating performance of corresponding suppliers. Measures undertaken by customers in distress to prevent insolvency may also be observable in the books of their suppliers. To the best of my knowledge, this is the first paper that uses the expected default frequencies derived from the Merton (1974) model to assess whether financial distress contagion also affects the operating performance of contractually linked partner firms.

Third, I present a battery of cross-sectional determinants of financial distress contagion. Specifically, I show that the contagious effects of financial distress vary with revenue dependency, product specificity and industry concentration. Given the much broader sample of this study, I am able to overcome the lack of statistical significance in the tests as encountered by Hertz et al. (2004).

Lastly, I provide further evidence on the lack of informational efficiency of equity capital markets. The under-pressure customer anomaly is more pronounced among stocks with information and liquidity problems. Furthermore, negative announcement returns and negative unexpected earnings surprises suggest that investors are not aware of the customer-supplier relationships and hence fail to price this information into supplier firm stock prices.

The implication of this work for further research are manifold. A natural point of departure is to investigate whether the under-pressure customer anomaly also holds across various capital markets. Potentially, the return pattern may also be present in other developed markets such as the UK, Germany or France. Furthermore, it would be interesting to investigate whether the magnitude of financial distress contagion is stronger in developing countries. Given the decreased level of information availability, the pricing of supplier stocks to distressed customers may be even more impeded.

A second interesting direction for further research is to investigate whether the contagious nature of financial distress extends beyond the pair-wise customer-supplier relationships to other related firms. That is, it would be interesting to examine potential cascading effects of financial distress contagion. For example, the decreased performance of suppliers to distressed customers may have an effect on the firms that are economically linked to this specific

supplier. Conceivably, this issue may be best addressed in a bankruptcy-related setting, where costs of financial distress are extremely high.

Last, it would be interesting to investigate whether customers also suffer from the financial condition of their respective suppliers. Thus, a further research direction could include redoing the analysis as described in this study only reversing the customer-supplier relationships. Given that customers tend to be larger and have a wide range of different suppliers, however, the contagious effects of financial distress may be significantly smaller.

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