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ANALYSIS OF DISTRESS RISK PREMIUM ANOMALY: THE CASE OF U.S. INTERNET AND SOFTWARE FIRMS

Master's Thesis by the 2nd year student Vitalii V. Gabaidulin

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ЗАЯВЛЕНИЕ О САМОСТОЯТЕЛЬНОМ ХАРАКТЕРЕ ВЫПОЛНЕНИЯ ВЫПУСКНОЙ КВАЛИФИКАЦИОННОЙ РАБОТЫ

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АННОТАЦИЯ

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Описание цели, задач и основных результатов	В процессе исследования мы проводим эмпирический эконометрический анализ и следуем подходу Кэмпбелла, Хильшера и Сзилажи (2008) для определения премии за риск несостоятельности (кризисности) компаний интернет, программного обеспечения, а также компьютерных услуг. Мы предполагаем, что индустрия компаний интернет, программного обеспечения, а также компьютерных услуг характеризуется другой структурой каналов распространения информации, а следовательно объяснение аномалии несостоятельности через неправильное ценообразование можем быть слабее для этого типа фирм. Мы проводим анализ двумя способами. В первом мы накладываем эмпирическую меру финансового стресса определённых фирм на совокупную доходность их акций к определенной дате, выбранной до наступления ситуации вхождения в стадию несостоятельности, и сортируем эти фирмы в квантили. Затем мы анализируем среднюю совокупную доходность каждого квантиля. Во втором способе мы составляем два портфеля акций, отобранных посредством сортировки компаний по квантилям эмпирической меры несостоятельности, в котором первый содержит акции высокого риска кризисности, а второй низкого. Затем мы анализируем среднюю доходность этих портфелей. В результате обоих способов мы находим доказательства положительной связи между риском несостоятельности (кризисности) и доходностью акций – то, что пытались найти исследователи в предыдущих работах. Мы предлагаем возможные причины такой связи, а также широко раскрываем статистические различия между нашими результатами и результатами, полученными в предыдущих исследованиях. Наши наблюдения помогают лучше понять корни кризиса доткомов и вносят дополнительную ценность в литературу, посвященную предсказанию несостоятельности фирм, а также предлагают эмпирические наблюдения, обращенные в сторону смещенного

	фокуса инвесторов на определённые особенности фирм интернет и программного обеспечения.
Ключевые слова	Аномалия несостоятельности (кризисности), риск финансовой несостоятельности, премия за риск, компании интернет и программного обеспечения, модель выживаемости, портфельный анализ, доходности акций, кризис доткомов.

ABSTRACT

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INTRODUCTION

The interrelation of stock returns and distress risk has important implications for risk-premium trade-off in the world of financial markets. The market pricing of distress risk has attracted a lot of academic scrutiny beginning with Chan and Chen (1991) and Fama and French (1996) who at their time attributed higher returns to the firms that they named as relatively distressed. Generally, if the distress risk can be considered as systematic, investors should demand the premium for bearing such risk. The implementation of usual specification of capital asset pricing model (CAPM) fails to capture the distress risk-premium if corporate failures are correlated with deteriorating investment opportunities (Merton, 1973), or unmeasured components of wealth such as human capital (Fama and French, 1996), or debt securities (Ferguson and Shockley, 2003). A number of recent articles including Agarlwal and Taffler (2008), Campbell et al (2008), Chava and Purnanandam (2010), Garlappi and Yan (2011), O'Doherty (2012) find out that the stocks with elevated probabilities of financial distress in various forms (bankruptcy, default or delisting) earn anomalously low returns, compared with the intuitive rationale for risk-reward relation. In the academic literature this condition has received an informal name of "distress puzzle" or distress anomaly, which up to the best of our knowledge had not been explained empirically. The answer that had gained the biggest authority amongst the academicians is that market misprices the distressed firms. It can happen either by not considering possible positive future results due to limited information about the distressed firms (they are usually small and lack analyst coverage), or by noisy environment surrounding the firm.

However, more recent studies suggest that not all distressed firms exhibit the same results. Walker and Wu (2019) show that the distress anomaly is weaker among firms that have institutional investors in their capital structure, which is in line with the idea that investment and hedge funds apply some efforts into understanding the future prospects of the firm before investing in it.

Gopalan and Xie (2011) investigate if different industries experience the same or not impact of financial distress. Their findings provide two major points to consider: (1) conglomeration weakens the effect of financial distress in the overall industry, primarily due to the internal capital market (ICM) and more constructive information spread between the market players. These industries during distress have higher sales growth and higher investments in research and development, compared with single-segment industry; (2) industries that are characterised with higher past performance and that are more competitive experience less negativity in financial results even when in distress. This suggests that some industries naturally are less prone to distress, and some are more prone.

Lastly, Kolay, Lemmon and Tashjian (2016) study either financial distress can be spread along the value chain. The authors' results exhibit that working with economically distressed firms greatly negatively influences their suppliers, creating higher selling, general and administrative (SG&A) expenses and decreasing their margins due to the replacement of contactors. These findings reflect that, intuitively, sectors and industries that are less burdened by the bargaining power of their suppliers or are less linked to the asset specificity may experience less distress when the overall industry goes downward, because distress firm being independent would not significantly harm other external stakeholders other than its customers.

If we would look at the composition of the industries in the United States, we would suggest that technological sector, namely internet, software and computer services companies' subset of technological sector complies to the most extent for the description of being (1) relatively independent (supply chain is not as long as in, e.g. oil and gas industry), (2) conglomerate industry with high competition (historically, the technological sector is a mixture of hardware and software companies with infrastructure and equipment providers that surround the firms). Technological firms are often associated with venture capital (as opposed to institutional investments), that shows similar traits as in Walker and Wu (2019), according to Megginson et al. (2016) that find that VC-backed IPOs experience less financial distress risk post-offering than do comparable non-VC-backed IPOs companies. Moreover, companies backed by more reputable venture capitalists exhibit higher levels of financial distress risk even when they show superior operating performance, due to their highly levered capital structure and investment in relatively illiquid assets (Megginson et al, 2016).

Based on this rational we would suppose that internet, software and computer services companies' might be characterised by the decreased extent of mispricing, due to the decreased informational asymmetry circulating within this subsector. If the mentioned parameters are applicable for technological industry, we may perceive the information dissemination channels to differ from other sectors, and contain more complete information for market to correct, fully or partially, pricing inefficiency.

Considering that, I define the research questions of the paper as: do the mispricing explanation is weaker for distressed subset of technological firms represented by internet, software and computer services companies? Can we identify the positive relation between distress and risk premium for them? How can we differentiate empirical measure of distress of technological firms from other firms?

Answering these questions would shed a new light to the topic of distress risk anomaly into several directions. Mainly, we can differentiate them as academic implications and managerial implications.

In terms of academic, we would observe either the equity market consistently misprices the distressed firms on the industrial scale, to say either we can observe the similar anomalously low returns for both accentuated by the paper subsector of technological firms and non-technological firms. To accomplish that we would compare the results of the analysis with the previous papers' findings following the same approach to discriminate distressed firms and for their subsequent returns calculations. We would discuss these issues in-depth in the methodology section of the paper.

Another point for academic considerations includes empirically observing the phenomenon of distress risk premium for the mentioned firms. The major implication in this field would contain the answer for the question: can we observe the positive relation between distress characteristic and return, measured as realized returns? This is a fundamental question for the previous research, which would be put from the industrial perspective of specified sample.

The managerial implications would include, again, two central points. The first influences the financial and credit risk analysts within institutional and non-institutional financial organisations, which could apply the findings of the paper for the future development of empirical approaches for distress risk measurement and connected to it pricing options.

The second point could provide a soil for elaborating on new investment strategies for both institutional and non-institutional investors, particularly interested in distress investing.

LITERATURE REVIEW

1. Outline of the problematic of financial distress

To begin with we shall outline what we would understand as the financial distress and how should we define the key terms that surround its notion.

Generally, by the financial distress we consider a situation when a firm has a trouble meeting its debt obligations. This idea is quite simple and naturally leads to the assumption that the higher leverage the firm possesses, the greater are the chances for it to become financially distressed one. At this point we can recall the conventional trade-off theory (Figure 1), postulating that there is a maximum of the function that represent the relationship between the value of the levered firm and value of its debt – up to the maximum point (D^*) the value of the firm increases with the increase of value of its debt, and after some maximum point, with increase of the debt on the balance, the value of the firm starts to decrease.

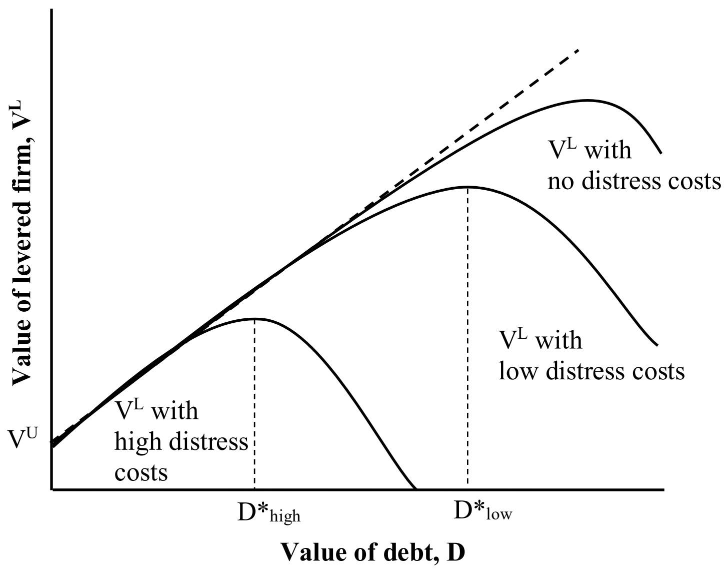

Figure 1. Optimal Leverage with financial distress costs

Linking this theory with the suggestion that the leverage normally increases the risk of financial distress, we can speak about some sort of cost of distress. In fact, the cost of financial distress reduces the value of the levered firm. The amount of this reduction increases with probability of default, which in turn increases with the level of debt, again see Figure 1. This rule works with any kind of firms, however high distressed firms experience the maximum point earlier than low distressed ones, and indeed much earlier than firms with no distress whatsoever.

In the opposition to this basic view on how we can measure the level of financial distress, we can underpin the signalling theory of the debt, which had been explained in the following manner. In some cases, firms use leverage-taking as a way to signal good information to the investors. This phenomenon has been studied in-depth from the position of behavioural economics and it has some reflection in the adverse behaviour theory, majorly pointing out that if the firm's management understands that taking leverage in the context of potential failure increases the chances of its default, it would not do it, otherwise we can say that the management is convinced that this leverage-taking would improve the firm's position. Thus, investors seeing increased leverage would associate it with future positive results, because the firm would not behave harmful for itself. Put in another way, with the same inputs, when a firm faces financial distress by increasing its leverage, shareholders can gain sufficiently from decisions that increase the risk of the firm, even if they have negative Net Present Value (NPV).

This example helps to demonstrate the basic concept, which has been tremendously studied in the following years, the concept of financial anomaly. In general, anomaly can be attributed to the market inefficiency, as opposed to the market efficiency theory, which assumes that the market fully consumes all the inputs it gets and instantaneously reflects it in the market signals – most intuitively in stock prices. In this regard, when talking about anomaly we would understand anomaly in stock returns. The nature of anomaly is what keeps the academic researchers in distress from ceasing to exist and cannot be formulated easily.

The quintessence of financial distress is the bankruptcy; however, it is not limited to it. The bankruptcy can be referred to as an event, however in reality for the company to reach the point of becoming bankrupt it takes much more time and resources than simple one-phase event. Bankruptcy in turn is rather complicated and time-consuming process which imposes direct and indirect costs for numerous stakeholders of the company, the main of which are investors, creditors and owners. As we are focusing in this paper on the U.S. market, we shall give an account on what are the major phases a firm can go through when experiencing distress.

The U.S. bankruptcy code was established for the purpose of organizing the process of bankrupting the entity so that creditors would be treated fairly. 1978 Bankruptcy Reform Act had stated that firms can file into two forms of bankruptcy protection: Chapter 7 Liquidation and Chapter 11 Reorganization. Chapter 7 implies the selling of firm's assets through an auction. The proceeds from the sale are used to pay the creditors in the end of which firm ceases to exist. Chapter 11, in contrast, works through a different process as can be viewed from its name. When large corporation files into Chapter 11 reorganisation, all its pending interest collection suspends, while the management board is given a chance to come up with rescue plan, or reorganisation. At the same time the corporation continues to operate, while management develops a plan on how to treat each creditor. The resulting plan may introduce more debt or equity to the particular creditor, as well as the simple cash payment. Corporation also tries to negotiate with creditors to avoid filling for any other chapters. The final decision is taken by the voting of the creditors, which is monitored by the bankruptcy court. In circumstances when the reorganization plan is not confirmed, the court may ultimately force the corporation for Chapter 7 liquidation. On the other hand, if the financially distressed firm successfully manages to negotiate the reorganization plan with the creditors, it mitigates the bankruptcy. This situation is usually called as workout. Another approach, which is known to be the quickest and with minimal direct losses (Tashjian et al., 1996) to re-emerge from bankruptcy is called prepackaged bankruptcy (or "prepack"). In a prepack, a firm develops a reorganization plan before it files to Chapter 11, agrees upon the terms with all major creditors and then files the Chapter 11 to implement the plan. It is assumed that the positive consequence of Chapter 11 in any approach is firm that continues to operate.

In the course of this paper the notion of financial distress would be used in a broader way, such as in Campbell et al. (2008) and others. In an even more generic way, financial distress refers to the public recognition of firm's inability to operate its business normally. This recognition is defined either by firm's own decision, or by public monitoring. Own decision includes announcement of firm's default on obligations. Public monitoring, in turn, refers to (1) financial delisting from a stock exchange (when firm fails to comply with obligatory requirements of e.g., stock price level is lower than required by the exchange) and (2) receiving D (default) credit rating by one of reputable credit rating agencies, such as S&P, Moody's or Fitch.

The following sections of literature review would be structured as follows. First, I shall give an explicit overview of the history of bankruptcy prediction techniques, as one of the main stages of subsequent data analysis would rely on the prediction of indicator of financial distress, hence it is important to explain to what extent the academic literature had studied the topic and discuss the applicability of the model in each particular situation. Second, I am going to give an explicit account on the history of financial distress anomaly, since the very first concepts and hypotheses of distress risk premium existence until the most recent implications in this field. Finally, it is worth mentioning that in the context of this paper we are going to use the words distress, default, fail, insolvency and bankruptcy in application to their corresponding risk interchangeably.

2. The financial distress prediction approaches

2.1 The classical approach for distress studies

The interest in distress studies from the very first publications was concentrated around the value of predicting the bankruptcy for credit issuance. In 1930's, the main reason for assessing distress firms was to understand either particular firm has any of prospects for future growth. (Smith and Winakor, 1935) If it was clear that firm experiences some output contraction, or it doesn't have the proper amount of cash to cover its losses and obligations, the interest in studying the firm would shift for bankruptcy prediction (Foulke, 1961). Before quantitative methods, bankers and analysts were using personal professional judgement and some financial statements inferences, e.g. accounting ratios and the quality of financial information, to conclude either the company should be given with loan or credit. As can be also seen from these facts, there would normally be cases, when the company would take the credit with overreacted interest rate, or the sum of credit cash would not be sufficient for the company. These were the crucial disadvantages of paper-based credit issuance decisions.

However, there were attempts to create new theory of credit risk modelling before, E. Altman (1968) had managed to successfully implement the previous ideas into single paper, which later became the central point of reference for multiple studies. The key value captured by Altman, was the implication of traditional accounting ratios into more data-driven decision making, whereas the data was still very limited. Classification of ratios by profitability, liquidity, and solvency nature and significance choice of the most applicable variables within these categories, allowed the author to build, for that time, rather robust model for predicting bankruptcy. The results, as a product, were considered as the so-called Z-Score approach (1), being the simple scoring system for predicting default. Particularly, the Z-Score looks the following way:

$$Z = 0.012X1 + 0.014X2 + 0.033X3 + 0.006X4 + 0.999X5 \tag{1}$$

where Z defined as overall index; X1 – Working capital/Total assets; X2 – Retained Earnings/Total assets; X3 – EBIT/Total assets; X4 – Market value equity/Book value of total debt; X5 – Sales/Total assets.

The approach for constructing the model was specifically MDA (Multiple Discriminant Analysis). As a conclusion, the lower the discriminant score (Z-Score), the bigger is the probability for firm's bankruptcy. Based on a sample of both bankrupt and non-bankrupt firms, in a 1-year timeframe, the Z-Score managed to predict 94 percent of bankrupts correctly. Prolonging the timeframe to two years prior to the bankruptcy, decreased the predicting ability to 72 percent, which is still a rather solid result. Three years period would decrease the predicting ability sufficiently, making it of no use (Altman, 1968).

What is significant to underpin in the case of Altman's Z-Score is that the equation that he had received was based only on the sample of companies, that were bankrupt for the particular bank. The data provided by that bank was a closed information, and academic society typically was not allowed for the data like this at that time. The uniqueness of the dataset, basically, doesn't correspond with the wideness of conclusions made upon it. If we would redo the same iterations that were done by Altman for another sample, we would receive absolutely different results, however at that time as was said it was relatively impossible for common academicians. Moreover, later tests had proved inconsistency of the Z-Score to predict universally out-of-sample bankruptcies (e.g., Shumway, 2001)

2.2 Primary attempts to link distress and financial performance measures

In the following years, Altman et al. (1977) and in his other studies, tried to modify the Z-Score, in his ZETA score, and industrial implications, mentioning that each iteration would produce more convincing results and would widen the scope of applicability of ratio analysis for prediction of defaults and distress, rather than simple bankruptcy.

In 1990's the spotlight of distress research shifts towards considering indirect measures and significance of particular measures in analysis the financial performance of the distress firms. Previously financial economics would portray distress as costly event which influences capital structure because it creates a tendency for firms to do things that are harmful to debtholders and nonfinancial stakeholders (Opler and Titman, 1994). In contrast, Jensen (1989) and Wruck (1990) individually show that distress could improve firm values by forcing executives to make difficult value-maximizing choices, which they would otherwise avoid. Following the up-to-date stream of researching activity, Opler and Titman (1994) link firm's leverage to losses in sales and market value of equity. The more relatively distressed firm is, classified by leverage deciles, the bigger the losses in sales it has in the distress industry situation, defined as output contraction. The same situation happens in the market value of equity. The authors results comply with the view that indirect costs of distress are significant and positive (Opler and Titman, 1994). This line of thought would be in-depth discussed in the second section of the literature review.

By the same time, the number of studies related to credit default predictions have been classified and overviewed by Altman and Saunders (1998) over the 20-year timeframe. Generally, we may now speak about four central methodologies for predicting defaults. These include (1) MDA and its alterations, (2) logit and probit models, such as in Martin (1977), Ohlson (1980), Platt and Platt (1991), Shumway (2001), Campbell et al. (2008) and later studies, (3) real-options approach, like those in Kealhofer (1996), Kahl (2002), Rhodes-Kropf, Robinson, and Viswanathan (2005) and (4) simple assets over debt classification, as in (Wilcox, 1973; Scott, 1981; Santomero and Vinso, 1977). The last methodology should not be related to as the methodology in its general sense, as the probability of bankruptcy in this case is seen only through one lens: the possibility of failing to pay for debts measured as the ratio of leverage. Later studies had proved the inefficacy of this method.

Interestingly, Altman and Saunders (1998) mention the applicability of neural networks for predicting defaults, as they would implicate tacit correlations amongst predictive variables which are then entered as additional explanatory variables in the non-linear bankruptcy prediction function. Exceptionally, this approach is now used by most of the banks in their credit-scoring algorithms.

2.3 Hazard models

The most important critique that is faced toward the simple ratio models, such as equations described above, is that they tend to ignore the fact that firm is set within dynamic environment, and it is changing over time. Because of this, static models produce bankruptcy probabilities that are biased (Shumway, 2001), while the models' estimates are inconsistent. In the majority of studies connected to bankruptcy probabilities, authors apply the data on bankrupt firms of a year before the event occurs. As proposed by Shumway (2001) these researchers ignore the data on solvent firms that eventually go bankrupt. By making this choice arbitrarily, authors make unnecessary selection bias. In contrast, hazard models solve this issue simply by accounting for the time factor, because the distress probability in a static model does not vary with time. As explicitly explained by Shumway (2001) there are three major arguments to choose hazard model instead of static one:

1. Static models do not control for company's period at risk. There are circumstances, especially with long sampling periods, when some companies experience bankruptcy risk for a long number of years and file for it only in the latest year, whereas there are firms filing for bankruptcy during their very first year on the market.
2. Hazard models incorporate time-varying independent variables, in other words, we can observe dynamically how firms deteriorates, as financial data reveals it. Moreover, hazard models can use the same macroeconomic data for each of the firms in a sample for a given point in time. For example, hazard models had been tested for the firms age to be one of the significant explanatory variables. This procedure could not be easily done with static model.
3. Hazard models can produce much better out-of-sample prediction by using much more data (Shumway, 2001). It is reached via the fact that in a hazard models understands a particular firm-year as a separate observation. In this case, a model is represented as binary regression, where one corresponds to the dependent

observation in which period the bankruptcy (or distress) had occurred, and zero in any other observation of firm's existence. This opens up an opportunity for dynamic studies utilizing tens-times more observations by accounting for monthly data in a long timeframe.

The most recent studies that academic literature on financial distress anomaly portrays all concentrate on utilizing hazard family of models in their probabilities of distress implication. Obviously, we should not neglect the other modern approaches of estimating bankruptcy and credit risk, such as neural networks and machine learning, taught on the big data massive. These models utilise different approach and apply multitude of variables, requiring data processing much more complex than logit and probit regressions on the limited datasets. Liu and Wu (2017) discuss the hybrid use of incremental bagging and genetic algorithm in their dynamic forecasting of financial distress, however we shall not deepen for this line of techniques in this paper, and hence we shall leave this topic outside of the scope of the study.

In the following subsection of literature review we shall discuss the historical background of distress anomaly research.

3. Distress anomaly

The concept of financial distress had been promoted in the asset-pricing literature to explain the anomalous patterns in the cross-section of stock returns (Chan and Chen (1991) and Fama and French (1991, 1996)). Some firms, which are characterized by elevated probability of failure, can be considered as financially distressed. Chan and Chen (1991) explain these firms as "marginal firms", whilst Fama and French (1996) in a similar manner call them "relatively distressed". The volatility of the stocks of these firms cannot be diversified away, thus investors charge a premium for bearing this risk (Campbell et al, 2008). The general Capital Asset Pricing Model (CAPM), being a theorem-based model, cannot capture the distress risk premium in each given circumstance correctly, as it is usually associated with some sort of behavioural patterns in the trading strategies if present. The distress anomaly arises in a way, that one empirically cannot clearly observe risk-reward relationships between distress risk and risk premium, generally measured in higher-than-average returns. For some reason, highly financially distressed firms exhibit lower than expected returns, and even anomalously low in certain probability of default quintiles. Fama and French (1993, 1996) had proposed a hypothesis that size and value effects can be used as a proxy for financial distress, leading from a logic that usually high book-to-market firms had lost their market capitalization because of poor performance, and this effect is usually observed among small caps. Being the risky firms to invest to, investors should bear an elevated risk premium for them, proposing that distress risk has to be rewarded with premia as well.

In the following subsections of the background review, we shall outlook why these hypotheses historically had not been empirically confirmed to the most extent and provide some discussion on what we can find different when considering technological firms for the analysis afterwards.

3.1 Score-based studies of distress anomaly

In the section 2.2 we shortly touched upon the topic of other factors that may produce distress, which are does not necessarily arise within organisation. The first major attempt to link market conjuncture in explaining the failing of firms was proposed by Opler and Titman (1994). Authors had suggested that there are 3 major potential causes that may lead to declines in performance of firms, excluding internal factors, when the entire industry faces downturn (economic distress).

1. Customer-driven explanation – customers and, in general, external stakeholders disregard the firm, switching to other market player for non-competitive reasons.
2. Competitor-driven explanation – that promotes the idea that more solid competitors exploit the weaker bargaining power of other firms by decreasing prices, to capture bigger market share.
3. Manager-driven explanation – managers voluntarily perform some expansion-preventing actions (for instance, divestments of assets, closing of manufacturing facilities, cutting HR resource etc.) that decrease sales revenues.

At the same time, authors highlight the idea that is frequently neglected – the loss in sale must not be necessarily explained by the fact that firm had entered financial distress, in turn the case of financial distress might appear because of some unpredictable decline in sales. For a remark, hazard model account for these events unlike static models, as exhibited in the previous paragraphs.

In the course of the paper, Opler and Titman (1994) test the idea about the positive distress risk-reward relation in consideration of financial discipline. This idea partially collides with the signalling theory of debt and is represented as follows. In the occurrence of industry downturn, a firm should start increased scrutiny on its operating issues, or in other words, financial distress should increase the attentiveness of a firm to its own operations and, in consequence, debt maintenance. If this logic works, the highly leveraged firms should perform better than their more conservatively financed competitors. If this improved performance increases competitive abilities of some sort of firms, these highly levered firms should gain in value relative to their less levered peers. Unfortunately, the empirical evidence showed by the authors corresponds to the opposite effects. To add, authors conclude that more specialised firms (that have larger expenses on R&D) and firms in more concentrated industries, experience this adverse effect of leverage stronger.

The paper of Lasfer et al. (1996) observes the 3rd explanation of Opler and Titman (1994) from the different angle. The authors find that the mentioned expansion-preventing measure such as divestments, sufficiently improves stock prices of distressed firms. It goes along the idea that distressed firm reduced the distress by divesting of unproductive or risky assets. Unlike fire sales, divestment represents the weighted decision of a firm's management to improve fit or focus (John and Ofek, 1995), which should be evaluated by the market as a positive move, and it does, as showed by empirical results. The main benefit of divestment comes from the resolution of financial distress (Lasfer et al., 1996).

In 1998 Ilia Dichev had attempted to rationalise the current observations in the field of distress risk anomaly by asking one key question: is the risk of bankruptcy a systematic risk? If the answer to the question is "yes", one should expect positive relation between the risk of bankruptcy and realized returns. Dichev (1998) had become one of the first authors who decided to summarise up to that date studies on the nature of distress risk premium and distress anomaly, as the evidence on the actual existence of this phenomenon was fragmented. Shumway (1996) found that firms with high probability of being delisted from NYSE and AMEX for performance reasons earned higher than average returns, proposing that distress risk is a systematic risk. In contrast, already mentioned study by Opler and Titman (1994), as well as Asquith, Gertner, and Sharfstein (1994) provide empirical evidence of idiosyncrasy in the nature of distress factors, hence distress should not be associated with systematic risk. Another line of thoughts adds Altman (1993) who shows that high-yielding bonds, namely bonds of distressed firms, exhibit low, not high, returns. This suggests negative risk-reward relation. Dichev (1998) findings go along with Altman, resulting in bankruptcy firms possessing anomalously low return. The rationale for that Dichev saw as mispricing.

It should be pointed out that, Dichev (1998), as well as others, in their modelling of distress had been using score-based approaches (Z or O-Score of Ohlson (1980)). As we mentioned before, these approaches are characterised as being static and inefficient, that is why the next chapter in the distress anomaly studies had been started after hazard models took widespread in the literature, presumably in 2000s.

Despite that fact, another important study by Griffin and Lemmon (2002) had been performed by using O-Score of Ohlson. Authors had attempted to look at distressed firms and high book-to-market firms as they are separate entities that should behave differently in terms of stocks returns. This goal was driven by inconsistency of Dichev's (1998) results, in the view that high B/M firm earn high returns as a distress risk premium. Proxying distress by O-Score, however, authors find that firms in the highest O-Score quintile (representing highest probability for distress) which have high B/M earn returns almost the same as other high B/M firms. This suggested that O-Score does not actually contain information on distress risk other than that captured in high B/M ratios of those firms. At the same time, highest O-Score quintile firms with low B/M did not exhibit characteristics related to distress firms, unlike high B/M firms in this quintile. This inconsistency is explained by the authors as that low B/M firms are overpriced, while high B/M firms are under-priced. Consisted with idea that mispricing usually occurs in situation of high informational asymmetry, authors observe that highest O-Score quintile firms are usually small firms with low analyst coverage. They also possess weak current fundamentals that make them harder to value correctly (Griffin and Lemmon, 2002). Authors attribute all of these factors to be the main explanations for the abnormally low returns of small firms with low analyst coverage.

3.2 Variation in research questions and approaches for distress studies

Elaborating on the idea that size and value effects produce mispricing, Vassalou and Xing (2004) suggest different approach for the empirical study of distress anomaly. The approach that had been chosen defines the probability of default by using DD (distance-to-default) model, that is naturally based on Merton's (1974) option pricing model. The way the DD is calculated is comprised of usage of DLI (default likelihood indicators) that, in turn, are calculated using the contingent claims methodology of Black and Scholes (1973) and Merton (1974). As was later showed by the authors, this approach contains very different information from the commonly used aggregate default spreads (Vassalou and Xing, 2004). Strictly speaking, because of much more limited data, than in the more pronounced papers that were using the DD approach, the authors do not call their distribution of default probability as the real probability, instead they refer to default likelihood, which claims some important limitation to the interpretation of the results.

Nevertheless, the findings of the authors can be structured as follows:

1. Authors claim that default risk is a systematic risk
2. Size and value effects are closely related to the default risk
3. The size effect exists only in the high-default risk quintile.
4. The smallest firms amongst the most probable for the default typically have the highest B/M loadings.

5. Within the high default risk quintile, small firms have much higher default probability than big firms. The default risk decreases monotonically as size increases.
6. Lastly, high-default risk firms earn higher returns, than low risk firms, however only to the extent that they are small and have high B/M. It is vital to say, that if these two criteria are not met, there is no evidence of higher return, even if the risk of default is high (Vassalou and Xing, 2004).

In the following years, preceding the Great Depression of 2008, the focus of academicians has been circulating around different ways of understanding of distress anomaly, namely finding factors that can influence the distress to sustain even when there are no rational and clear explanations. Almeida and Philippon (2007) identify that NPV of distress (both direct and indirect costs), calculated as the difference between pre-distress and distress value of the firm, is 4.5% of pre-distressed value. In comparison, ignoring the distress risk premium in changing of firm's value generates only 1.4% NPV of pre-distressed conditions. This finding suggests that there are tacit changes in pricing of distress that is incorporated within the firm's value.

At the same time Franzen et al. (2007) document that accounting reporting standards and the way corporations use accounting principles in their income statements and balance sheets can significantly distort the distress risk attribution and classify the firm to be high or low distress risk incorrectly. The authors results, in the general sense, can question any distress identification model based on static accounting-based information.

Particularly, the authors provide the evidence that higher research and development (R&D) spending increases the likelihood of misclassifying the solvent firms into insolvent, using O-Score. Then, if we adjust firms' R&D accounting to united conservative way in the sample, it will significantly improve the number of correctly identified distressed firms (Franzen et al., 2007). To clarify, the authors understand "conservative" way of accounting R&D as described in Financial Accounting Standards No.2 (FAS No. 2), so that R&D are to be expensed as incurred costs, with the exception for software development companies. After such adjustment authors document alleviation of previously observed anomalously low returns of large, low B/M, high-distressed corporations.

3.3 Intensification of distress puzzle research

The central study for this paper, as well as for the number of studies that were focused on more advanced approaches to the search of distress risk, had become the paper by Campbell, Hilscher and Szilagyi (2008) (later Campbell et al., 2008). The paper had received an eminent place in the field of distress anomaly, primarily because of the depth of modelling for distress prediction, namely with application of two most accurate prediction models (excluding machines learning and neural networks that were receiving more and more attention that time). In short, authors applied dynamic logit model (as in Shumway (2001) and Chava and Jarrow (2004)) and DD (distance-to-default) approach (as in Crosbie and Bohn, 2001) and received very similar conceptual results – even though the most distressed firms attained all the required loadings on size, value, beta and standard deviation of stocks, that naturally should have led to the higher returns, these firms had been showing anomalously low returns, after the number of robustness tests. This outcome had led the authors to still consider that the market misprices the distress risk.

The novelty in the Campbell et al. (2008) approach is primarily concentrated in the dynamic logit panel model specification and the consequent application of it to the large sample of more than 1 million firm-months, which predicted the distress quite precisely. Similar to the other studies that used hazard family of models (logit and probit models that identify the probability/factor of bankruptcy/distress), namely Shumway (2001) and Chava and Jarrow (2004), Campbell et al. (2008) first build their own measure of financial distress and, second, estimate the realized returns on the portfolios sorted by empirical probability of distress. The authors managed to estimate very effective, but still not perfect, models specification of distress probability using wider notion of distress, namely bankruptcy occurrence, financial delisting, D credit rating.

The paper makes a number of important implications for the future works and provides empirical evidence for the previous works. By saying so, authors confirm the previously found evidence that distress anomaly is stronger in stocks with low analyst coverage, institutional presence, price per share and liquidity. This idea leads to the adoption of fact that distress anomaly is concentrated amongst stocks that are expensive for institutional investors to arbitrage (Campbell et al., 2008). Other observation includes the fact that momentum in stock returns of small loser firms does not correspond to the anomaly, as well as the low returns to highly volatile stocks. All of mentioned evidence adds more complexity to the view on intuitive positive distress risk–return relation in the financial markets.

Agarwal and Taffler (2008) continued the momentum-explanation of distress risk anomaly view, providing the evidence that the mid-term momentum (the continuation of low returns of firm into some years into the future) can be a proxy for distress risk. As with Campbell et al. (2008), they find that size and value effects are not linked to distress. Barberis, Shleifer, and Vishny (1998) propose that the existence of momentum anomaly can be explained by the fact that investors are not agile to change their beliefs in response to new information. Jegadeesh and Titman (1993, 2001) and Daniel and Titman, 1999; Hong, Lim, and Stein, (2000) also argue that momentum is driven by underreaction for the market to information. The problematic being well-established Fama (1998) suggests that the momentum anomaly is the most challenging of all anomalies. Using the Z-Score approach, Agarwal and Taffler (2008) find that for the sample of UK publicly traded distressed firms, the distress risk has negative premium, the momentum effect is subsumed by the distress factor and size and value factors do not capture distress risk.

Up to the beginning of the second decade of 2000s, the focal point of academicians was concentrated on the application of the novel well-established prediction models (primarily logit and option-based models) to the different circumstances. In the majority of cases, it was empirically proven that anomaly pertains to the low returns of distress firm and cannot be explained uniformly. This conjuncture had provided the soil for alternative uses of models, as well proving previous approaches under in-depth scrutiny.

Advocating that in previous distress risk researches the usage of noisy ex post realised returns could produce biases, Chava and Purnanandam (2010) use ex ante estimates that are based on implied cost of capital (ICC). As a result, they find positive cross-sectional relationship between expected stocks return, calculated with ICC, and distress risk, calculated as in Shumway (2001), Chava and Jarrow (2004) and Campbell et al. (2008), and, alternatively using Merton's (1974) approach of option pricing, as in Duffie et al. (2007) and Bharath and Shumway (2008). Although the results show positive relation, the actual realised returns represent the opposite situation.

Another variation used in distress studies was propound by Garlappi and Yan (2011), who explicitly consider financial leverage in their equity valuation model. Authors focus on how shareholders can win in value when a firm resolves its financial distress in the cross-section. Calculating distress using more mathematical than econometrical approach in modification to MKMV (Moody's KMV), authors explicitly show how their model can predict a hump-shaped relationship between value premium and default probability (similar to Figure 1.), and stronger momentum profits for nearly distressed firms, that are characterised by elevated potential for recovery from distress.

One of the last papers significant in terms of variation in research design has become Friewald et al. (2014), who measured the distress risk as a credit risk, estimated from credit default swap (CDS) spreads, namely CDS forward curve following Cochrane and Piazzesi (2005). Then, following the well-established sequence, the authors sort portfolios by estimated risk premia and document strong positive relation between credit risk premium and consequent excess returns.

Mentioned excess returns were calculated by buying high and selling low credit risk firm. Testing the factors with Fama and French (1993) three-factor model and Carhart (1997) with momentum reflect factor loading being not significantly different from zero, which means, in authors view, that CDS-implied risk premium contains information that is priced in stocks prices, which at the same time is ignored by other common measures of distress risk or by traditional risk factors (Friewald et al., 2014).

3.4 Suggestions for distress risk in internet, software and computer services firms

The past decade of 21st century had been admitted with the rise of technological companies becoming public like never before. Even though dotcom crisis of yearly 2000s had left its mark on investors beliefs about investing in technological firms, the regulatory field of U.S. and increased scrutiny into compliance to Securities and Exchange Commission (SEC) had improved the overall market confidence about the technological sector as a reliable niche for investing. However, this fact is not propelled only be the means of legal authorities. Increased ownership of institutional investors, as well as the rise of successful venture capitalists had ameliorated the technological sector with better analyst coverage, consulting services and improved fit of firms.

In response, the distress anomaly studies had found new motives for developments in the field. Megginson et al. (2016) study the effect of venture capital (VC) in the capital structure of new IPOs on the sample of around 1600 IPOs in from 1990 to 2007. The major findings are represented as follows:

1. VC-backed IPOs experience less financial distress risk in periods after becoming public, comparable with non-VC-backed IPOs. The major suggestions on the explanation of that: (1) venture capitalists are effective screeners on the future of a firm; (2) VCs financing is effective to low distress risks.
2. Firms that are financed by more reputable VCs exhibit higher level of financial distress (calculated as Z-Score of Altman (1995)), despite being very effective in terms of their operating performance, due to highly levered capital structure and investments in relatively illiquid assets.

The latter observation suggests that from the point of idiosyncratic risk, there could be cases of technological firms that are highly distressed, from the position of accounting variables, but produce higher returns from the position of market variables. This fact is a matter of more in-depth analysis in the next sections. In the majority of previous papers, these observations were not directly found, rather there were a lot of case when high distress in accounting measures accompanied poor performance on the market side measures. However, the goal of this paper is to provide the evidence that these (point 2) idiosyncratic situations might be explained from the view of systematic risk.

Continuing the topic, institutional presence in the capital structure in Walker and Wu (2019) is viewed as the linkage between growth prospects of a firm (distressed or non-distressed) and its abnormal returns. Giving more detail, the authors try to classify the firms by their propensity to grow with accounting values and meta-data, and then test whether distressed firms show better abnormal returns in the presence of their growth potential. Authors use three dimensions for doing that. First is concerning firm as a growth if we observe positive growth of R&D expenditures (as well as ΔR&D). High levels, or increases in R&D, suggest that these firms have increasing financing needs for potential growth (Walker and Wu, 2019). The second dimension is so-called portion of book-to-market ratio, as in Rhodes-Kropf, Robinson, and Viswanathan's (2005), used as a proxy for the difference between long-run value and book value (LRVTB). The third dimension is considering either the firms possess any institutional presence in its capital structure as in Aghion, Van Reenen, and Zingales (2013). The mentioned authors find positive relation between institutional ownership and valuable innovation, as usually institutional investors e.g., hedge funds, investments funds etc., have an exceptional expertise and tackle each company to invest in with high scrutiny. In other words, one institutional investor would not invest in a firm with too high risks, or with no clear vision of firm's prospect. Therefore, high institutional ownership, or an increase in institutional ownership, is likely an indicator of quality growth opportunities observed by these sophisticated investors (Walker and Wu, 2019).

The empirical evidence promotes the idea of growth as factor of abnormal returns for distressed firms. So, the authors find that ΔR&D and ΔLRVTB are associated with better abnormal announcement returns for distressed SEO companies yet with higher extent to that than for non-distressed ones. Institutional investments parameter is positive in all type of firms, but better abnormal returns are associated with distress ones. The changes in measures (deltas) also reflect the empirical evidence of dynamic nature of better explanations for distress firms returns.

Indeed, the presence of institutional investors in the capital structure of distressed firm intuitively provides some credential for a firm's prospects. Unlike with Megginson et al. (2016), the case of better results of distressed firms due to institutional presence is weighting more towards systematic effect, rather than idiosyncratic, but still does not answer the question if the institutions are the only factor that may produce positive distress risk-reward relation for insolvent firms.

Another angle at which we can question technological sector' specificity has been elaborated by Gopalan and Xie (2011), who demonstrate the difference between industries' distress characteristics during economy downturn. Basing their general theory on resource allocation principles, once for all suggested by Ronald Coase (1937), the authors study how different distressed segments of the market react to economic distress, and in particular how the firm level in an industry influences in turn its level of financial distress. The authors compare concentrated or conglomerate industries with single-segment ones. As the central finding that authors suggest – the conglomeration of industry decreases the level of financial constraints within this distressed industry.

Moreover, concentrated distressed industries maintain higher sales growth, cash flows and expenditures to R&D than their single-segment counterparts. Especially this is true for industries with high past performance, and for those that are very competitive. Because of that, as Gopalan and Xie (2011) propound, firms with high past performance easier acquire their rivals, while low past performers quit the industry.

In this light, we can underpin the similar nature of conglomeration for technological firm, namely those studied in this paper – internet, software and computer services – which are (1) historically under two sides: hardware and software giants, (2) supported by infrastructure providers (datacentres, cloud-services providers, equipment and peripherals providers and so on). We cannot directly define whether internet, software and computer services subsector is a conglomerate industry, however, the description provided can help explain some findings discussed in the next sections of this paper

4. Conclusion on background review

In the previous paragraphs we discussed two most important sides relevant to the topic of the research, first being the evolution of distress prediction models and second being the timeline of distress anomaly studies. In the former, we explicitly overviewed what distress identification models were the central for number of papers connected to distress anomaly, starting from the very basic concepts of static ratios-based scorings, ending in dynamic non-linear panel models, that forecast distress very effectively from the position of large out-of-sample tests. The latter had been the in-depth analysis and overview on how the distress anomaly study developed, what were the major milestones and which papers became central for the majority of other publications on the topic. In the following section we are going to discuss the research design and approach for the research, the use of models and the way they are applied in the data-analysis process.

METHODOLOGY

In this section of the paper, we would explicitly describe the research design. We ought to start with the data description, indicating the data gathering process and summary statistics for all of the constructed variables. We would also outline the formulas used to construct each variable and comment on the reason of including any particular explanatory variable in the sample.

After that, we would consider the modelling approach for the logit specification used in the paper, compare the regressions on different timescales for distress prediction similar to other authors in the field. We would also attract attention to the two views on how to observe distress risk premium used in the paper: (1) the total return to the stock of a firm and (2) portfolio returns. We would widely describe how we implement the models into the dataset and focus on the differences between the current and previous results.

In the process of the data research, we would closely follow the approach of Campbell, Hilscher, and Szilagyi (2008) in the model building sequence. We will also adopt the general idea of sorting firms based on their empirical distress indicator to estimate the average returns on their stock portfolios.

The research would be structured into two parts, similar to Shumway (2001), Chava and Jarrow (2004), Campbell et al (2008), which all start by constructing the empirical measure of financial distress as a step one. The process is iterative and requires finding the best specification for the predicting model. After that as a step two, I am going to calculate the average returns on distressed stocks portfolios, classified by various levels of relative (fitted) distress probability into quintiles, adjusting for various trading strategies, in order to then relate the distress risk with the returns that these sorted portfolios create. I would also assess the total return a firm generates and relate it to the distress risk as an initial sequence for distress premium search.

1. Data description

In order to estimate the hazard model as in Shumway (2001), Chava and Jarrow (2004) and Campbell et al. (2008) we require an indicator of financial distress that is to work as a dependant variable, and a set of explanatory variables. The indicator that we are going to use consists of three major subsets: the financial delisting subset, the bankruptcy subset, and a default subset. We start by considering all internet, software and computer services companies from Thompson Reuters's Eikon Datastream that are traded on both Nasdaq and New York Stock Exchange (NYSE). It yields about 1500 firm-information entries, that include both active companies and dead companies. The time frame for the firms spans from the 1973 to the latest publication of 2021. Then, we separate active firms from dead ones, that yields us 1063 dead firms, which in turns contain firms that were delisted for various reasons: mergers, acquisitions, bankruptcies and financial delisting. The Eikon data does not discriminate the bankruptcy and financial delisting from each other, though does so for the rest of reasons for the firm stocks to become dead. We exclude these firms from the sample and receive 316 firms that were delisted either by bankruptcy reasons or due to financial delisting due to incompliance to the exchange terms.

We do understand that software firms in 1973 were not even similar to those that emerged after the PC or Mac had been introduced. Before and during early 1970s, the major focus of any computer was located within the national defence systems, which is accurate for e.g., the U.S and U.S.S.R. In fact, in 1973 the prototype of Xerox Alto – first ancestor of the modern PCs – was manufactured in few thousand copies. In 1976 the Apple I was introduced to the society, but the real boom of personal computers had started with the 1981 introduction of IBM PC, according to sales of which IBM claimed the successful fulfilling of the half-year plan in just one month.

For this reason, we exclude the software and computer firms before 1980. After this step, we receive 303 firms spanning from 01.01.1980 to the 01.03.2021, that make up our delisting subset of the final dataset.

Next, we use Orbis Bureau van Djik to locate the bankrupt and default firms, that represent internet, software and computer services companies and were traded or are still listed on either Nasdaq or NYSE. Default firms filter in Orbis refers to either Chapter 11 Reorganization plan, rescue plan or default state of the firms. Usually, these firms are still counted as active in the Eikon Datastream, that is why they were disregarded by us in the first iteration of the data gathering. In terms of bankrupt firms, Orbis claims that the firms came through Chapter 7 Liquidation. We merge these firms with the delisted subset, by applying to the database of Eikon. If any bankrupt firm from Orbis was not added to the delisted sample already, we add it manually by search for financials tool in Eikon.

After the merge of data samples, we receive 336 firms that had entered delisting for financial reason, are bankrupt or are in the default stage as for 01.04.2021. Each of the firm in the dataset contains information about the date of failure event – the date of filing for Chapter 7 or 11, the date of delisting or becoming defaulted. Later we refer to these dates as the monthly indicator of distress that is to become the dependent variable. To maintain the initial equality of the number of observations for all 336 firms we take into the panel the entire set for each particular firm, which yields us about 160,000 firm months. To produce the complete dataset, we exclude all observations that contain missing values for the variables. The majority of the cut in a sample is due to the low number of failed internets, software and computer services firms in early 1980s, whilst the number of them grows proportionately as the distance to the major economic crises decreases.

Overall, after the exclusion of missing values in variables, we receive 35,696 firm-months considered as separate observations. Table 1 summarises all failure cases and is represented as follows.

Year	Delisted firms (Eikon)	Bankrupt firms (Orbis)	Defaulted firms (Orbis)
1997	1	-	-
1998	2	-	-
1999	3	-	-
2000	9	4	3
2001	10	0	1
2002	1	2	-
2003	16	2	-
2004	24	2	-
2005	25	-	-
2006	24	1	-
2007	17	2	-
2008	22	-	-
2009	16	-	-
2010	17	1	-
2011	6	-	2
2012	12	-	2
2013	10	-	3
2014	16	-	-
2015	20	-	1
2016	13	-	-
2017	16	-	-
2018	14	-	-
2019	11	-	-
2020	5	-	-
Total observations:		35,696	

Table 1. The distress indicators included into the final dataset

From Table I it is immediately seen that before 1997 the Eikon or Orbis does not contain any information on the failures of firms from internet, software and computer services industry, so that we do not list the cases before this year. It is also apparent that the largest number of cases is distributed between the dotcom crisis of early 2000s and the Great Recession of 2007-2009. Though we may conclude that the number of cases does not seem to be vast in terms of failures frequency in comparison to the destructive effect of global financial crises, it is useful to recall that usually industrial distress to the most extent hurts the smaller, non-public firms, that could not enter the initial dataset. Second, the wave of mergers had been realised as the consequence of crises, when potentially successful companies were acquired by their peers of out-of-industry counterparts. Third, the conglomeration of technological industry involves the great number of hardware firms, apart from solely software, that were harmed to the same or even bigger extent as their software peers. All in all, the internet, software and computer services firms included in the dataset are strictly added only by the means of being distressed. Although there might be cases when a well-established software firm enters distress during the dotcom crisis and then gets acquired by some bigger player, we cannot statistically differentiate them from a successful software firm being acquired by takeover, that is why the sample might be decreased involuntarily, however the ending dataset is crystallised in the sense of pure financial distress indication.

In order to construct explanatory variables, following Campbell et al. (2008) we collect the number of firm-level financial indicators from Eikon, representing both accounting and market variables, as well as the general market indicators. We start by collecting monthly values for each particular firm including its market capitalization, close price of its stocks, net income, total assets, total liabilities, cash and short-term investments, market-to-book ratio (MB) (2). Then, for each month of a firm's life, we add the respective amount capitalization of S&P500 index at that particular month.

This allows us to calculate the monthly return of S&P500 and monthly return of firm's stocks. The calculations are done on the simple basis (1) and are as follows:

$$Return_{i,t} = \frac{Value_{i,t+1} - Value_{i,t}}{Value_{i,t}} \tag{1}$$

$$MB\ (Market\text{–}\ to\text{–}\ book\ ratio)_{i,t} = \frac{Market\ price\ per\ share_{i,t}}{Book\ price\ per\ share_{i,t}} \tag{2}$$

Following Campbell et al. (2008), we then calculate the respective ratios, that characterise each particular firm-month from the positions of: profitability, leverage and liquidity of a firm. Before calculating the final specifications of variables as in Campbell et al., we construct the ratios of Shumway (2001) and Chava and Jarrow (2004), based on profitability and leverage principles of firms' characteristics. These include the log of relative size of a firm (*RSIZE*), compared with the size of S&P500 (3); profitability ratio of Net income divided by total assets (*NITA*) (4); leverage ratio of total liabilities divided by total assets (*TLTA*) (5); the log excess return of a firm relative to the log of return of S&P500 (*EXRET*) (6); finally, volatility of firm's stock returns, calculated as the annualized 3-month rolling sample standard deviation (*SIGMA*) (7).

$$RSIZE_{i,t} = \log\left(\frac{Firm\ Market\ Equity_{i,t}}{Total\ S\&P500\ Market\ Value_t}\right) \tag{3}$$

$$NITA_{i,t} = \frac{Net\ Income_{i,t}}{Total\ Assets_{i,t}} \tag{4}$$

$$TLTA_{i,t} = \frac{Total\ Liabilities_{i,t}}{Total\ Assets_{i,t}} \tag{5}$$

$$EXRET_{i,t} = \log\left(1 + R_{i,t}\right) - \log\left(1 + R_{S\&P500,t}\right) \tag{6}$$

$$SIGMA_{i,t-1,t-3} = \left(252 * \frac{1}{N-1} \sum_{k\in\{t-1,t-2,t-3\}} r_{i,k}^2\right)^{\frac{1}{2}} \tag{7}$$

where *i* stands for particular firm, and *t* stands for particular month.

In their final model specification, Campbell et al. (2008) add adjusted versions of accounting variables above, as well as the measure of liquidity, market-to-book parameter and the log of price of stock at particular month.

The authors ended their best variable specification up to considering the market-value adjusted parameters. For instance, in order to capture how the market looks at the firm's total assets, they add value of market to capitalisation to the total liabilities. In this way, the authors adjusted *TLTA*, *NITA* to be *TLMTA* and *NIMTA*, which both stand for total liabilities over market-valued total assets (8) and net income over market-valued total assets (9). As a ratio of liquidity, the authors calculate cash and short-term investments over market-valued total assets (*CASHMTA*) (10).

$$TLMTA_{i,t} = \frac{Total\ Liabilities_{i,t}}{Firm\ Market\ Equity_{i,t} + Total\ Liabilities_{i,t}} \tag{8}$$

$$NIMTA_{i,t} = \frac{Net\ Income_{i,t}}{Firm\ Market\ Equity_{i,t} + Total\ Liabilities_{i,t}} \tag{9}$$

$$CASHMTA_{i,t} = \frac{Cash\ and\ short\text{–}\ term\ investments_{i,t}}{Firm\ Market\ Equity_{i,t} + Total\ Liabilities_{i,t}} \tag{10}$$

Lastly, the authors add the log of price of firm's stock in a particular month (*PRICE*) (11) and the market-to-book value (2) a separate variable.

$$PRICE_{i,t} = \log\left(Price_{i,t}\right) \tag{11}$$

For the reasons of our approach to distress risk premium analysis, we also calculate the total return for the firm to the particular month. The total return is measured as the ratio between the month of distress indicator stock price and first complete data month stock price. For instance, if the firm claims financial delisting at the month t and the first month the firm had stock information for is $t - n$, then the total return for month t is calculated as in (12):

$$Total\ Return_{i,t} = \frac{Stock\ price_{i,t}}{Stock\ price_{i,t-n}} \tag{12}$$

This variable does not go into the logit model to predict the distress; however, it would be used to measure the return for the firm in a lagged distress indicator. For each of the variables above, except for *Total Return,* we do not make any adjustments or winsorization. We would make 1/99 percentile adjustment for *Total Return* on the later stages of data analysis to exclude the outliers from the sample.

Table 2 exhibits the summary statistics for the constructed variables for each firm-month of 35,696 observations.

Variable	*NITA*	*NIMTA*	*TLTA*	*TLMTA*	*EXRET*	*RSIZE*	*SIGMA*	*CASHMTA*	*MB*	*PRICE*
Mean	-0.166	-0.082	0.509	0.274	-0.007	-4.057	1.512	0.267	3.288	2.261
Std. Dev.	2.807	5.141	2.088	0.245	0.226	2.685	6.138	1.339	67.02	1.337
Min	-63.91	-132.1	-0.086	-0.326	-4.156	-19.40	0	0.002	-4181	-4.605
Max	107.3	244.2	65.44	0.999	4.548	2.583	536.7	64.81	1847	19.719
Observations: 35,696										

Table 2. Summary statistics

We shall highlight some of the most important differences and particularities associated with our sample as well as in comparison to Campbell et al. (2008), whose sample although being 44 times higher than ours (1.6 million observations), spans the data from 1963 to 2003, taking the half of our sample period.

The first observation we may consider is the mean excess return which is to be higher than of Campbell et al. – negative 0.7% per month in our sample over the negative 1.1% per month for the authors. Generally speaking, this corresponds to the average underperformance of internet, software and computer services companies in comparison to the market benchmark. However, what differentiates our sample from Campbell et al. significantly is the fact that history of the sector we investigate is covered by the crises almost in half. It means that the rise of the computer era in the early 1990s had been almost always distorted by the financial crises happening on the market: the crisis of 1997-1998, the dotcom crises and the Great Recession. For almost 15 years the market had been experiencing shocks, which would ultimately affect the average conditions of return relative to the market. The graphical representation of the excess returns of firms in the sample can be seen on the Figure 2.

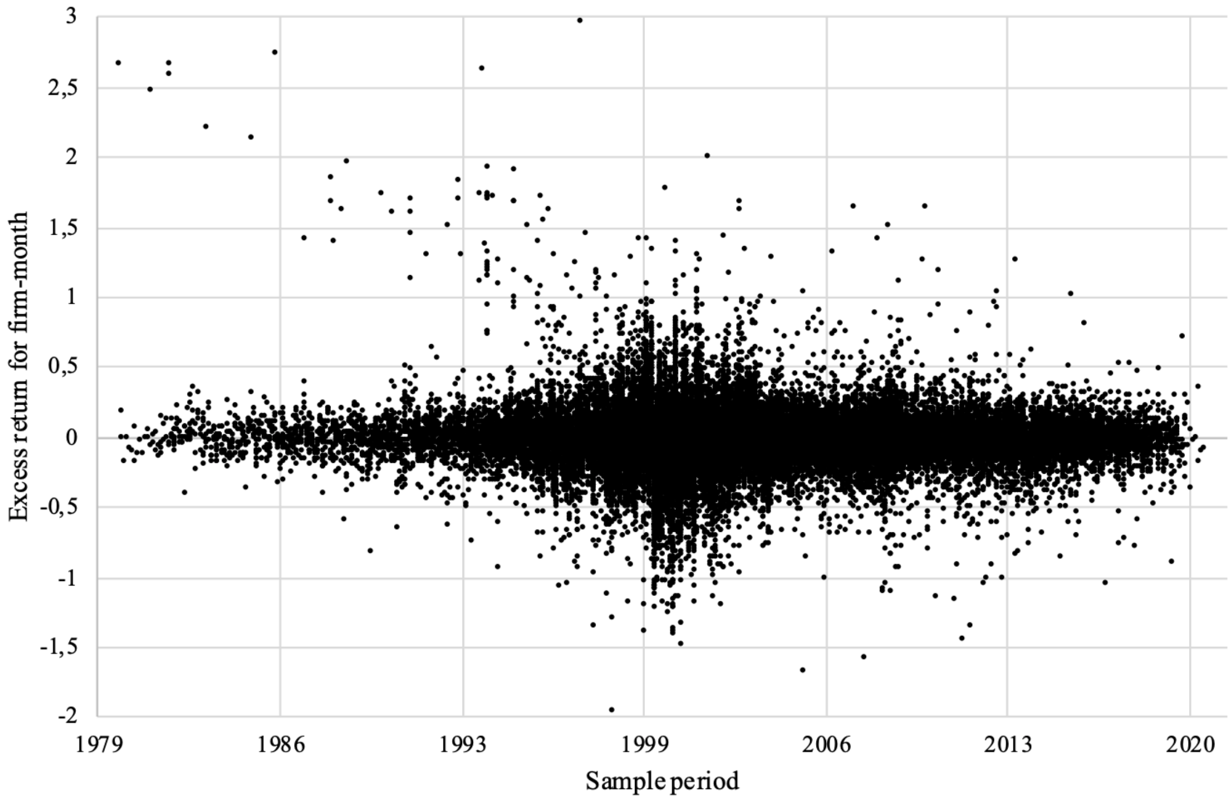

Figure 2. Excess returns distribution over sample timeframe

Basically, we can observe how the negative excess returns overall increase around the dotcom crisis of 2000-2004 is backed by the positive excess returns to the same extent. This empirical observation suggests that although the mean can be -0.7%, we cannot make any preliminary conclusions on either the sample contains some distress risk premium.

The next issue that should be underpinned in the 156% average *SIGMA*, that corresponds to the fact that the stocks are extremely volatile. In contrast Campbell et al. had 56% average volatility, that authors had explained by the great number of small firms entering the dataset in the later years of the sample (late 1990s and early 2003), that are exactly the centre of our dataset. This strong volatility can be also explained by the fact that dotcom crisis is a specific crisis that harmed particularly internet, software and computer services firms to the most extent.

The other point of contrast in our sample is the difference between the average *TLTA* and *TLMTA* values. The average *TLTA* in our case is 0.509, in Campbell et al. this figure is almost absolutely the same – 0.506, that is consistent with intuition that in the normally distributed sample, the debt to assets structure would be built around the mean of 50%. The loading on *TLMTA* in Campbell et al. is offset towards the higher total assets, as the market value of equity is on average higher than the book value, specifically 5.5% higher, and it is 0.445. Unlike that, our sample exhibits very different picture. The loading on *TLMTA* is calculated to be 27% on average. This means that on average the market estimated the total assets of a particular firm to be 23% higher. This is a significant indicator, that investors perceive the potential of the internet, software and computer services firms much higher than in general for any other sector company.

Last but least, if we consider the average loadings on profitability ratios of *NITA* and *NIMTA*, we will observe much higher negative values in comparison to Campbell et al. (2008). The values for the same ratios in their paper are -0.001 and 0.000 (almost zero, very slightly negative) respectively. This corresponds to the fact that in their sample was the prevalence of small unprofitable companies in the later years. What we observe in our case is significantly different. We acquired -17% and -8% for *NITA* and *NIMTA* respectively. This can be explained by the prevalence of unprofitable firms in the centre of industrial crisis, but at the same time if we look at the standard deviation, we will see the 280% interval, that suggests that there might be cases when firm does earn negative profits, but still manages to stay solvent and produces positive excess returns.

The rest of critical value can be explained simply by the factors of increase in overpriced firms. This trend in the recent years is specifically relevant for the internet companies, however it produced much higher offsets in the summary statistics due to the bubble shape of dotcom crisis that naturally led to inflated loadings on *MB* and *RSIZE* factors.

2. The logit model of distress prediction

In order to construct the logit panel model following Shumway (2001), Chava and Jarrow (2004) and Campbell et al. (2008) we need an indicator of financial distress. As was discussed in the beginning of paragraph 1 of this section, for each of 336 firms in our sample, we possess the date on event that led to distress, namely the date of being delisted for financial reasons, the date of filing for Chapter 7 or 11, or recognising itself as being in default. Based on that, the distress indicator equals one in a month the firm fails, otherwise it equals zero.

In the course of the model building, I am assuming that the marginal "probability" of failure or becoming bankrupt over the next period follows logistic distribution and is given by (13):

$$P_{t-1}(Y_{it} = 1) = \frac{1}{1 + \exp\left(-\alpha - \beta x_{i,t-1}\right)} \tag{13}$$

where Y_{it} is an indicator that equals to 1, if the firm becomes bankrupt or fails in time-period t, and $x_{i,t-1}$ is a vector of explanatory variables, known at the end of the previous time-period. Elevated value for $\alpha + \beta x_{i,t-1}$ implies higher "probability" for bankruptcy or failure consequently. The term probability in this case is used to ease the understanding of prediction properties of the model. In fact, the probability should follow the distribution between zero and one. The hazard logit model allows us to retain the basic meaning of probability but reaching values out of 0 to 1 interval. In more general terms, we can observe the hazard logit model as a way to score the firm for potential failure, calculate the empirical measure of distress by the potential of failure and analyse the specific characteristic the firm possesses according to its firm-months.

Estimating the best specification of a distress prediction requires testing the predicting ability of the model to reflect failure possibility into future periods. As in Chava and Jarrow (2004), Campbell et al. (2008) replicate the logit specifications for the period adjustments, particularly for *j* months before the failure coincides. The timeframes usually are taken in half-year periods, so to say that the models are tested for 6 months, 12 months, 18 months, or 1, 2 or 3 years depending on the approach. In the process of the research, it is one of the tasks to investigate which time horizon is best, moderate and weakest suited for predicting of failure. The logistic regression for probability of failure in j months, conditional on survival in the dataset for $j - 1$ months appears to be as:

$$P_{t-1}\left(Y_{i,t-1+j} = 1 | Y_{i,t-2+j} = 0\right) = \frac{1}{1 + \exp\left(-\alpha - \beta x_{i,t-1}\right)} \tag{14}$$

In our research we compare the predicting ability of the model 6 months prior to failure happens, 12 months, 18 months, 24 months and 36 months. We start from estimating the regressions from 6 months horizon, as this lag allows the company to season for the distress indication well-enough. If the firm displays any evidence of "relative distress", as formulated by Fama and French (1992), we expect that the firm would already exhibit the distress risk premium. This would not be applicable for firms with life of less than 6 months, but we do not have any case of this firm in our sample. Moreover, we go in line with the Campbell et al. (2008) idea that it has no economic sense to estimate the actual day/month of distress to get the premium, as it would not be meaningful to predict the heart attack of a person, who lie on ground clutching his chest. The authors eventually use the 12 months ahead model for their premium search. Unlike that, we begin by estimating half a year distress prior to the actual case to capture the premium, if it is evident, that would be well-assessed by investors. In order to construct the lagged distress indicator, we program each actual distress indicator with the simple logic formula: "if month t equals 1, then month $t - 6 \ldots to\ t - 36$ equals 1".

RESULTS

1. Construction of regressions

We start by estimating the basic specification of Chava and Jarrow (2004) that predict failure using 5 explanatory variables: *NITA*, *TLTA*, *EXRET*, *SIGMA* and *RSIZE*. We copy the model by switching between the lagged distress indicators. Afterwards, we construct the explicit final model of Campbell et al., that contains the following explanatory variables: *NIMTA*, *TLMTA*, *EXRET*, *SIGMA*, *RSIZE, CASHMTA, MB, PRICE.* We again copy the same lagged indicators for each model estimation. Overall, we estimate 10 logit regressions. The outlook on the models' coefficients and significance of the model is represented in the Table 3 and Table 4 for basic specification and final specification respectively.

	Chava and Jarrow (2004) Basic model				
Lags	6 months	12 months	18 months	24 months	36 months
NITA	-0.0046	-0.0074	-0.0040	-0.0028	-0.0262
TLTA	-0.0176	-0.0126	-0.0226	-0.0256	-0.0726
EXRET	-0.2520	-0.0368	-0.3804	-0.1747	0.2445
SIGMA	-0.0062	-0.0654	0.1201	-0.0634	-0.0265
RSIZE	-0.0817	-0.0627	-0.0475	-0.0461	-0.0354
Constant	-6.8661	-6.4550	-6.0323	-5.9723	-5.7316
P-value	0.0016	0.0152	0.014	0.1125	0.1907
Significance level	***	**	**	-	-

Note: '***' for significance on 1% level, '**' for 5% level, '*' for 10% level.

Table 3. Basic logit regression specification with lags

	Campbell, Hilscher, and Szilagyi (2008) model				
Lags	6 months	12 months	18 months	24 months	36 months
NIMTA	-0.0079	-0.0067	-0.0027	-0.0024	-0.0028
TLMTA	0.0193	0.2549	-0.0122	0.1260	-0.0910
CASHMTA	0.0095	0.0032	0.0095	0.0035	0.0135
SIGMA	-0.0135	-0.0683	-0.1221	-0.0608	-0.0257
RSIZE	-0.0295	-0.0166	-0.0318	-0.0300	-0.0410
EXRET	-0.2363	0.0081	-0.3748	-0.1605	0.2385
PRICE	-0.1634	-0.1032	-0.0521	-0.0213	0.0096
MB	-0.0005	-0.0009	0.0002	0.0004	0.0020
Constant	-6.3194	-6.1283	-5.8654	-5.9143	-5.7971
P-value	0.0003	0.0009	0.0648	0.3416	0.2600
Significance	***	***	*	-	-

Note: '***' for significance on 1% level, '**' for 5% level, '*' for 10% level.

Table 4. Final logit regression specification with lags

In order to assess the models, we would start by describing, first, the significance of the models. Based on that, we will disregard the insignificant regressions and focus on describing the coefficients of the significant models. We then choose two most significant regression for the further interpretation and application for distress risk premium estimation.

It is apparent that the basic specification of Chava and Jarrow (2004) although contains the important explanatory information, has higher values for the p-value of each exact regression. The most significant regression of 6 months predicting the distress is almost five times worse explains the variance in comparison to the final regression of Campbell, Hilscher, and Szilagyi (2008). P-value also exhibits sudden weakening of prediction power when distress is estimated 2 and 3 years prior the actual event. The models of 24 and 36 months appear to be insignificant. For these reasons, we choose the former family of regressions for the further analysis.

Similar to the Campbell et al., we find that the 1.5 years ahead model (18 months) has the last regression that theoretically could be used to estimate the distress more or less effectively. The next two regressions for predicting the distress on 2- and 3-years horizons become insignificant with p-values of 34% and 26% respectively. We do not consider this uplift in the p-value for the last regression to be meaningful for the future study. What we should focus on is the 6- and 12-months ahead regressions. These estimations of regressions are both significant on 1% level and possess the majority of individually significant predictors. As the research is empirical and is built upon the highly effective model provided by Campbell et al. (2008), we do not provide the explicit information on the individual significance of each variable in the later research, though we would observe the predicting ability visually in the next section of this research.

In the Table 5 we display the regression coefficients for 6- and 12-month ahead models we received with the Campbell et al. coefficients, received by applying the exact same regressions on the sample of 1.6 million observations.

Campbell, Hilscher, and Szilagyi (2008) denoted as *CHS*

Lags	6 months	6 months *CHS*	12 months	12 months *CHS*
NIMTA	-0.0079	-23.92	-0.0067	-20.26
TLMTA	0.0193	2.06	0.2549	1.42
CASHMTA	0.0095	-2.40	0.0032	-2.13
SIGMA	-0.0135	1.27	-0.0683	1.41
RSIZE	-0.0295	0.047	-0.0166	-0.045
EXRET	-0.2363	-7.79	0.0081	-7.13
PRICE	-0.1634	-0.468	-0.1032	-0.058
MB	-0.0005	0.047	-0.0009	0.075
Constant	-6.3194	-8.07	-6.1283	-9.16
Failure cases	336	2,008	335	1,968

Table 5. Comparison between the regressions of Campbell et al. (2008) and the empirical results received on the sample of internet, software and computer services firms

The first observation that we can make by comparing two models is that the coefficients do not show consistency of the sign with which they enter the model between themselves. For instance, the leverage and profitability ratios of *TLMTA* and *NIMTA* enter the model with the same signs between the models, however liquidity ratio of *CASHMTA* differ the sign in both regressions. The same applies for *SIGMA* and *MB* coefficients. The size of loadings on parameters is the other difference between our results and previous, however it is explained by the structure of Campbell et al (2008) sample, that contains multitude of industries in it that retain significantly different financials.

We shall focus on the sign of coefficients first in our comparison. Campbell et al. (2008) in their paper claim that the new variables of their model as compared with the basic of Chava and Jarrow (2004) enter the logit regression with the expected sign, however they do not explain what distribution the fitted distress prediction follow. Moreover, they do not explain how we should interpret the signs of the coefficients in general. Intuitively, we can expect that the increase in leverage (*TLMTA*) should increase the level of possible distress, as the positive sign on the coefficient is multiplied by always positive leverage ratio. In the same manner, we can expect the coefficient of profitability ratio (*NIMTA)* to be negative, as the negative net income would suggest that the firm bears losses: negative NIMTA multiplied by the negative coefficient would again rise the final score of the firm, recalling that the higher is the score – the higher is the probability of distress.

Unlike this logic, the $x_{i,t-1}$ that represent the vector of explanatory variables in the logit distribution (13) enters the model with the negative sign. That is why the eventual score for distress prediction is concentrated in the negative intervals around the constant. Empirically, there are no cases of positive fitted values of distress prediction, primarily due to the fact that there are no purely solvent firms that cannot enter the distress in any circumstance. The existence of such firm is out of the scope of this paper in any case.

This explanation allows us now to concentrate not on the sign of coefficients per se, but on the size of their loadings, for both positive and negative coefficients. Referring to the Table 5, on the 6 months predicting horizon the most significant variable that predicts the distress is the excess returns over S&P500; the next variable in the order is the price of a firm's stock. Campbell et al. at the same time founds net income over market-valued total assets to be the most significant variable, while excess return holds the second position. This difference has important implication for the technological industry and particularly our subset of software and internet firms. The possible explanation for it is that the market assesses the price of a firm stocks and its return over the benchmark as the main signal of firm's success (or unsuccess) if the firm is software/internet service provider. It is negotiable then, that the market evaluates the quality of IT firm prospects simply by the price it holds against other industries. If the price is lower than some overall sentiment for what it should be, then the market consciously underestimates it, thus considers to be “relatively distressed”. Next, as with the Campbell et al. case of *EXRET* being in top-2 of significance, internet, software and computer services firms are evaluated by the market through the prism of the return it should provide. If the return of a firm fails to be close to, or moves away from the benchmark, the market considers the firm to be unsuccessful, that leads to the distress eventually. It should be again emphasized that the following significance pertains to the 6-month firm conditions prior to the distress occurrence. 6 months distance to failure allows to foresee it, basing the bigger portion of predicting ability onto price and excess return indicators.

12-month lag varies the coefficients significantly. Unlike in Campbell et al., that report similar coefficients’ predicting power, our empirical evidence suggests that on the one-year horizon prior to the distress, the leverage becomes the most important factor for failure prediction. This finding is noticeable. Basically, one year prior to distress is long enough distance for the sudden distress occurrence, so that usually the “relatively distressed” firm has to deteriorate to the stage when the distress is clearly visible. That is why the distress potential of the IT firm is assessed through the simple leverage. As this firm deteriorates in financial terms in the next 6 months, the leverage cease to predict the approximating failure, and the market looks at the price and return indicators of this firm to figure out the distress is close enough. This actually proposes that software and internet firms are evaluated differently from any overall firm. Leverage indicator significantly loses its predicting value towards the distress, because leverage of IT firm may suppose something other than deteriorating opportunities for it e.g., increase in leverage may support the will of a firm to improve its performance. At the same time, the excess return remains to be in the top-2 most powerful predictors. The fact that excess return factor stays significant for 6- and 12-months lags (and in 18 and 24 as well, Table 4), whereas other factors vary their power, suggests that even if the firm deteriorates significantly the market sentiment still tracks the returns. It can happen, for instance, if investors wait for large premium until the actual failure emerges and disregard firm’s fundamentals. This idea is in line with Chava and Purnanandam (2010), who report that investors await the higher returns for distressed firms (as they measure it by implied cost of capital), but eventually receive lower than expected returns. Another view that can explain this evidence, is supported by the dotcom bubble nature. Investors were obsessed with the internet revolution, that they strongly disregarded the true fundamentals of such firms, even if they were highly distressed.

12-month lag also exhibits 6 times higher loading on stock returns volatility than in 6 months. This evidence supports the idea that the stability (instability) of returns plays important role for investors that buys software and internet stocks.

2. Distress risk and stock returns

In this section of the paper, we would turn our attention to the distress risk premium search associated with the internet, software and computer services firms. We measure the premium for financial distress in two different approaches. In the first, we construct the empirical measure of financial distress by scoring each firm-month with the fitted prediction of distress using 6- and 12-months lagged logit regressions, following Campbell et al. (2008) approach. After that we sort the firm months by the predicted distress and choose only those firm-months that are directly 6 and 12 months prior to the failure. It yields us 336 and 335 firms respectively. We then winsorize these firms by 1 and 99 percentiles to exclude the extreme outliers in the sample and at the same time save as much observations as possible. It yields us 330 and 329 firms respectively.

After that we construct 10 quintiles sorted by the predicted distress scores: 0 to 10, 10 to 20, 20 to 30, 30 to 40, 40 to 50, 50 to 60, 60 to 70, 70 to 80, 80 to 90 and 90 to 100 percentiles. Using our total return variable calculated previously, we then calculate the average total return of each quintile to observe if the higher (lower) distressed quintile would earn higher (lower) average total returns. This approach has a very important limitation. The quintiles are sorted only by the indicator of predicted distress. It means that we are not controlling for the same date of quintile formation. For example, there could be cases when two the most distressed firms 6-months prior to their failure situate in the same quintile, but the first had bankrupted in 2001, and the second had been delisted in 2014. That is why the first approach does not consider any portfolio construction, as this situation is not usually possible in the real investments. It is potential, however very improbable.

For this reason, the second approach considers the portfolio formation as done in Campbell et al. (2008) and other later studies that seek to relate distress risk with its premium. We construct 10 quintiles sorted by the predicted distress scores: 0 to 10 to 90 to 100 percentiles, however this time we control for the portfolio formation date. As our sample does not allow us to rebalance the portfolios each year effectively, we build out of 10 quantiles two portfolios: first contains the firms from the highest distress prediction intervals – 80 to 90 (9^{th} quantile) and 90 to 100 percentiles (10^{th} quantile), and the second one from 0 to 10 (1^{st} quantile) and 10 to 20 (2^{nd} quantile). We will in-depth describe the portfolio formation sequence and its results in the section 2.2.

2.1 Total returns and distress risk premium

We start by estimating the empirical measure of financial distress for each firm month. The resulting distribution of distress prediction for 6-month logit model is reported on the Figure 3, for the 12-month logit model predictions please refer to the Figure 4.

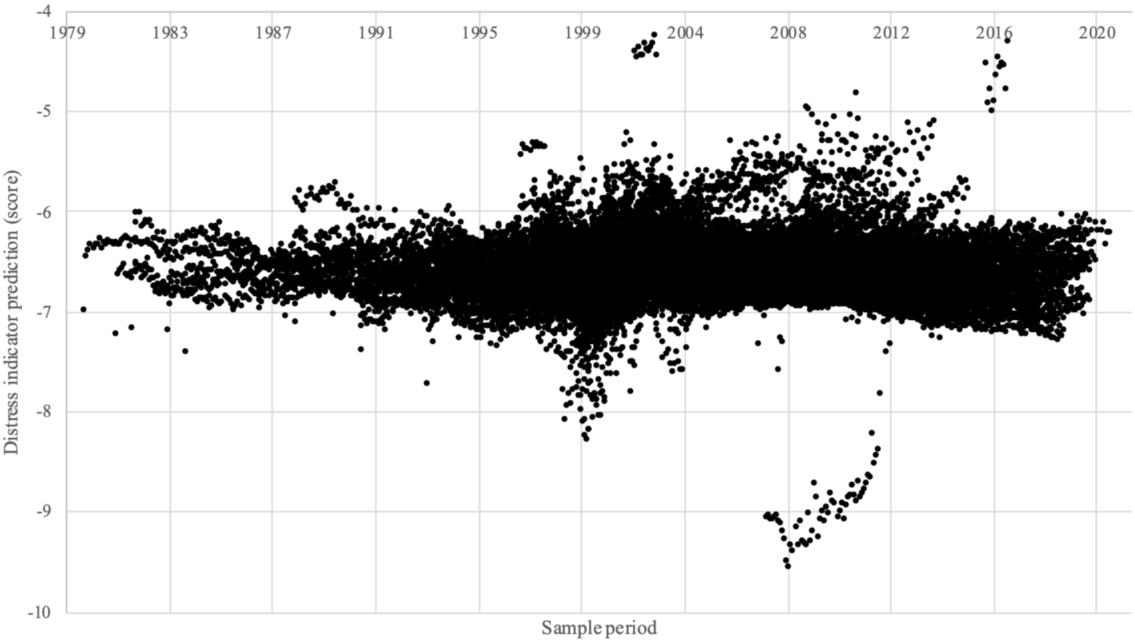

Figure 3. The distress prediction distribution (6-month model)

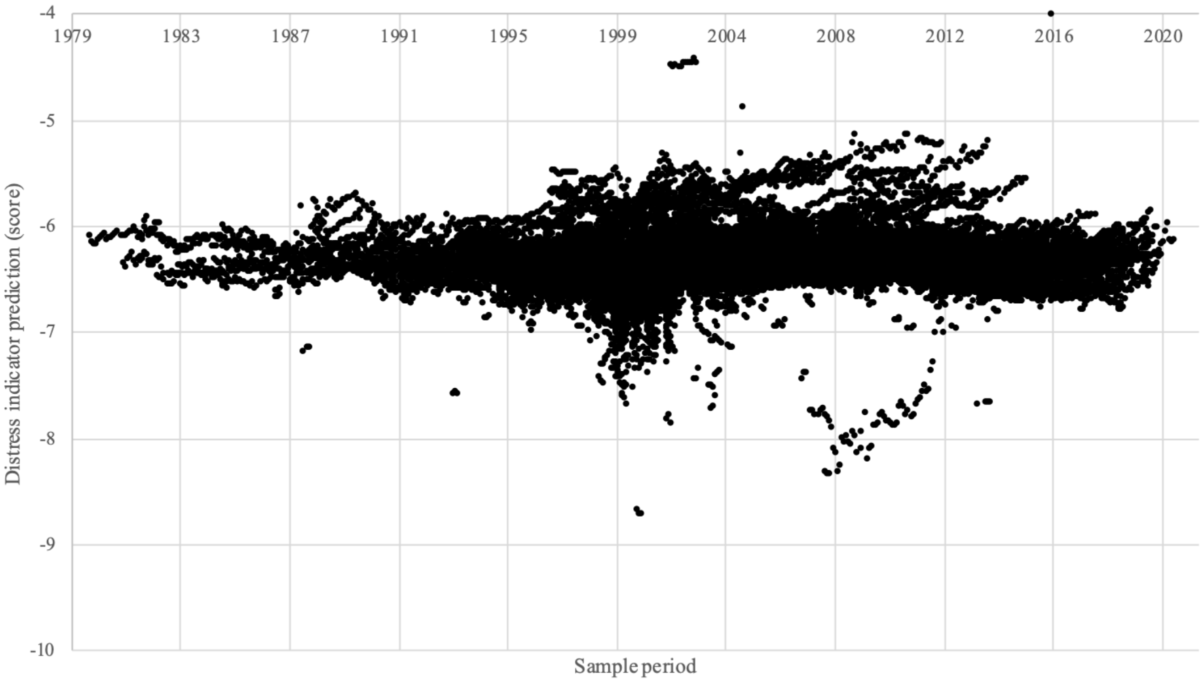

Figure 4. The distress prediction distribution (12-month model)

It is apparent that the 6-month logit model (Figure 3) is less dense, that signalises about higher detailing of predictions. We can also outlook some of the outliers around the central density on the 12-month model (Figure 4), that are not present on the previous picture. This indicates about the possible mispredictions of distress.

Overall, we can observe the highest density of distress predictions around and exactly within the 1999-2004 time period, that is usually associated with the dotcom crisis. At the same time, in 2004-2013 we can observe multiple scatters of firm-months towards the lesser distress probability. The 2010 to 2020 time period is characterised by curving downwards general pattern of distress factors, that can suggest the structural increase in distress probability across the entire software and computer industry, however we shall leave this discussion for the future studies.

The last visual fact that we can mention is that, obviously, 1980 to 1990 is characterised by lower number of firm months, simply by the means of lower number of existent firms in the industry. As was noted before, the 1990s had become the boom period for software and internet companies, that is why we display the widening array of firm-months in 1991 and straight until 2000, when the dotcom crisis had diminished the significant number of firms within the industry.

The sample distribution fits quite effectively the general pattern of the economic events that had been emerging throughout the time period of sample, still it has some outliers to fix for the subsequent analysis.

Now we shall consider the first approach to distress risk premium search. As we commented on before, we start the analysis by choosing specifically firm-months 6 and 12 lags prior to the failure event. We then winsorize the firms by 1 and 99 percentiles to exclude potential outliers, that could have emerged due to misclassification of firms or critical values in the dataset because of errors in the Eikon. These procedures yield us 330 and 329 firm respectively.

Then, we sort these firms by the predicted distress score using the corresponding logit model of Campbell et al. After doing so, we may construct 10 quantiles of firms sorted by the distress risk to detect the average total returns for these quantiles. We report the average total returns for 6- and 12-month predicted distress in Figure 5 and Figure 6 respectively.

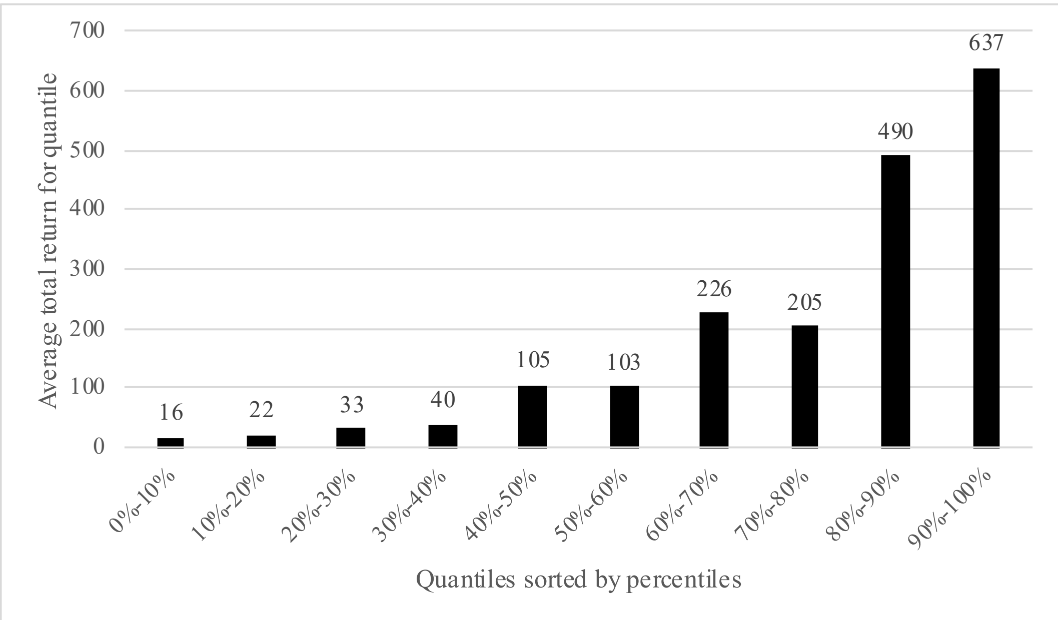

Figure 5. Average total return of distress sorted quantiles (6 months), %

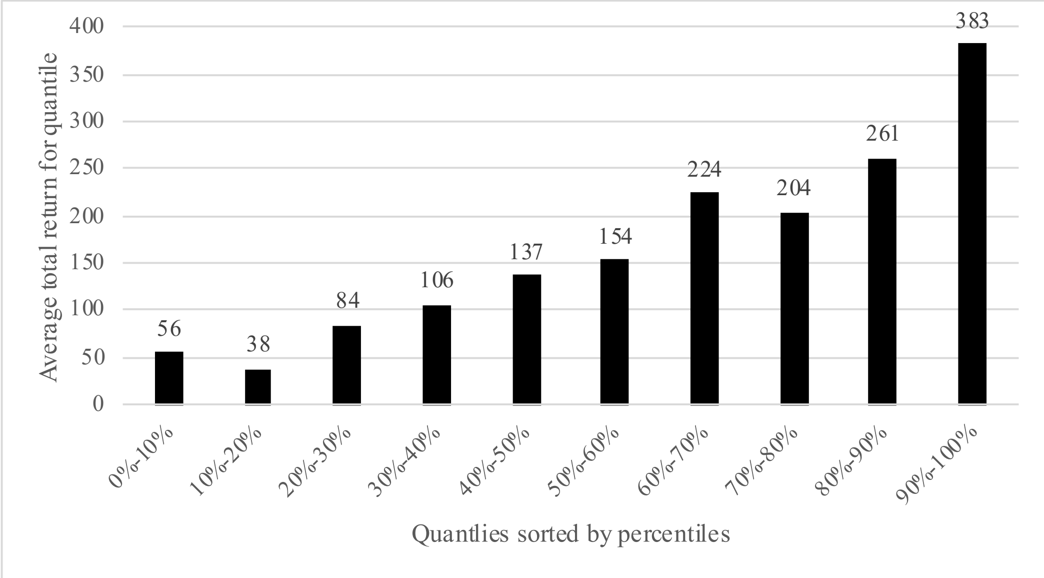

Figure 6. Average total return of distress sorted quantiles (12 months), %

As can be seen from the empirical results of the first approach, there is visible relation between the average total returns and the predicted distress "probability" (score). Please note that the average total returns are calculated by the average of total returns of quantiles sorted by distress factor and cannot be understood as portfolios. Nevertheless, our results contain some important new information.

First of all, our returns are calculated at the month exactly 6 and 12 months prior to the failure event. That means that the firms were sorted automatically and the possible manipulation (direct and indirect) with the data structure is minimised. Basically, the sorting of firms reflects the current state of any firm in terms of its total return. We perceive that there might be cases when a firm in one month experiences its stocks to skyrocket, however only if every second firm was like this, it would compromise the results significantly. We assume that in general the current state of firm's total returns displays the accumulated returns with bearing of some distress risk historically. This idea does not reject the inconsistency between total returns and the 6- or 12-month distress factor but takes the possible biases into consideration.

The next noticeable finding that our empirical evidence provides is the actual variation in total returns between the different distances to distress. 6 months ahead model captures much lower returns for low distressed firms and much critically larger for highly distressed ones in comparison to 12-month ahead model. This finding is consistent with the previous papers that indicate that firms experience the increased pace of deteriorating results closer to bankruptcy or failure. Figure 5 support this idea. In only 6 months, the total average returns for lowest distress quantile decreased in 4 times, suggesting that the market assessed the deteriorating financial conditions of a firm, that was reflected in lowered stock prices on average. Continuing this logic,

Figure 6 clearly portrays how distance to failure affects the total returns – we observe times higher returns in all quantiles 9-th and 10-th, that almost exactly two times lower that in the next 6 months. Figure 6 shows almost straight trend line between the distress risk and the total returns.

The most intriguing is the situation with the 9-th and 10-th quantiles in the 6-month ahead model. These quantiles demonstrate much higher total return than any other quantile taken together. The outlier's analysis had revealed no critical values within the quantiles, so the offset in data is not the explanation for extreme values of them. One possible explanation suggests that in 9-th and 10-th quantiles we collected the infamous firms that were in centre of dotcom crisis – their valuations and stock prices were extremely inflated, that if combined with the distress in fundamentals would produce this situation.

2.2 Portfolio analysis and distress risk premium

Next, we focus our attention at the second approach to study distress premium – the portfolio analysis. As we mentioned earlier, as our sample do not allow us to effectively rebalance firms for 10 portfolios linked to distress quantile, we construct two major portfolios – first containing firms from two highest distress portions – 9^{th} and 10^{th} quantiles, the second contains least distress firms – 1^{st} and 2^{nd} quantiles. We sort firms by quantiles only 6 months prior to distress occurrence, unlike in Campbell et al. (2008) who perform the analysis only 12 months prior.

In order to construct portfolios, we allocate the maximum possible number of firms into portfolios relative to the firm-survival interval. We adjust portfolios each year to compensate the delisted firms quitting portfolios and add firms that emerge on the stock-exchange retrospectively to their final 6 months distress prediction. We construct portfolios each year in the first months of the year and report return result in year-to-date period next year. The starting year for portfolios formation is 1987, because different quantiles contain firms with different distress prediction by time period, e.g., the lowest distress quantiles contain firms that exist only since 1987, and the highest quintiles since 1980. The final year for both portfolios to be computed is 2020. In order to fairly compare two sets, we choose a starting and ending year uniformly. During the analysis we compare the results with S&P500 benchmark to capture excess returns over it, similar to Campbell et al. (2008). The general outlook to the realized returns of portfolios is represented in the Table 6 below.

	9th and 10th quantiles	1st and 2nd quantiles	S&P500 reference
Return	12.31%	6.54%	9.83%
Value Per Stock	27.07	16.72	-
Excess Return	-3.18%	-9.12%	-

Table 6. Average annual values for sorted distress risk portfolios (1987-2020)

As can be seen from the Table 6, the highest distress risk portfolio had earned two times more than the lowest risk one (12.31 against 6.54 percent), and at the same time it had surpassed the average annual return of S&P500 (12.31 over 9.83 percent). The average value per stock resembles the value of total portfolio for each year divided by the number of firms that it contains. The predominance of higher distress over lower distress in this case is explained by on average higher value of portfolio accrued each year from *January t* to *January t+1*.

However, the average loadings for both portfolios on excess returns are negative, that is explained by, on average, worse results of portfolios in terms of their returns compared to S&P500. This finding is consistent with the summary statistics for the sample, that is represented by almost negative 1% of mean monthly returns, that is similar to Campbell et al. This fact also proposes the idea that if we long the portfolios for the entire timeframe we would earn losses, however the losses would be stronger for lowest risk portfolio (-9.12% of it against -3.18% of high distress predicted firms). In the figure 6 we show the dynamics of excess returns over the benchmark.

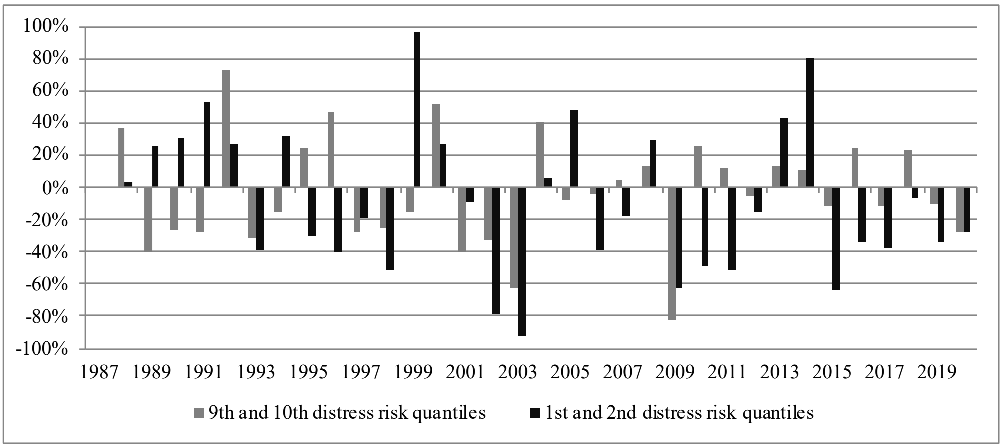

Figure 6. The excess returns of portfolios over the S&P500 annual returns, %

It can be immediately seen how more frequent the negative values of excess returns for both portfolios are. It also seen that the depth of negativity in values for 1st and 2nd distress risk portfolios is bigger. In general pattern, we can observe how often both portfolios are mirrored in terms of excess returns, to say that when one gets positive returns, the other is reversed to negative ones. There is only one cluster of observations that follows one-way dynamics for several periods in a row: 1999 to 2004 – the period of dotcom crisis. After the surge in annual excess returns of more than 50%, the value exhibit slips from -40% to -90% of excess returns in the three following years. This outlier is significant for mean values calculation, and if we disregard 2001-2003 years for mean excess returns calculations, we will receive positive 1.03% of excess returns for highest distress portfolio and negative -4.0% for mean excess returns of lowest distress portfolio. This is significant finding, however, makes only statistical importance, as the dotcom crisis is an event that could not be hedged due to its unsystematic economic nature.

Nevertheless, even with the inclusion of dotcom period into the portfolios, highest distress portfolios earn significantly higher returns, compared to the lowest risk firms, that is in line with the idea that distress risk may contain risk premium. On the sample of internet, software and computer services firms this suggestion had received an empirical confirmation to the extent of used instruments.

Despite the described numeric of results in terms of average values for realized returns, the period of portfolio construction retrospectively had played an important role as well, that contradicts partially to found results. To illustrate the notion, we refer to the Figure 7.

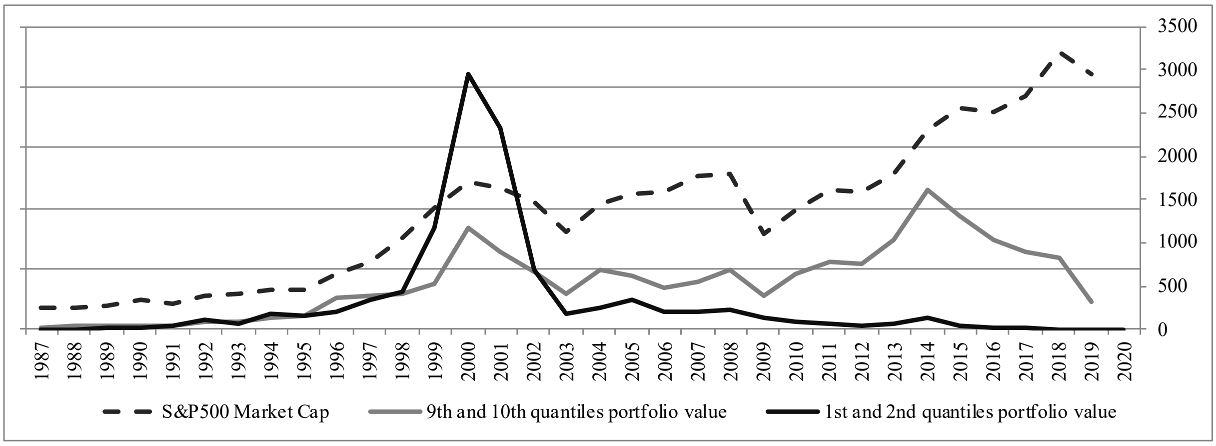

Figure 7. The total value of portfolios against the dynamics of S&P500, in USD
(The right axis is for portfolios values, the left axis is skipped, S&P500 line is indicative)

As we can observe, the lowest distress risk portfolios had surged dramatically during the dotcom crisis, intuitively, due to the nature of bubble of stocks prices. The extent to which it surpasses the highest risk portfolios is overcoming two times at the peak of year 2000. After that, the pace with which the low distress portfolio is slipping down is stronger than the highest distress one. That is a significant finding. The possible explanation to it is that market had some sentiment towards the highest distress firms, so that it was aware of potential losses if the bubble would occur, so it then changed its perspectives, focusing on the more stable (in terms of distress risk) firms, and explicitly invested in them, making their stocks rocket up. Reaching peak in 2000, there would only be one period of positive correction in 2005, after which the lowest risk portfolios would stably fall in its market value. In contrast, the highest risk portfolio had experienced much bigger volatility in the next years, experiencing phases of times higher market value than its counterpart since year 2008. The outliers of 1999-2003 are significant, that poses the question of why the highest distress risk portfolios earn higher returns than the lowest one. The answer to this question can be visualised on the Figure 8, which is to be found below.

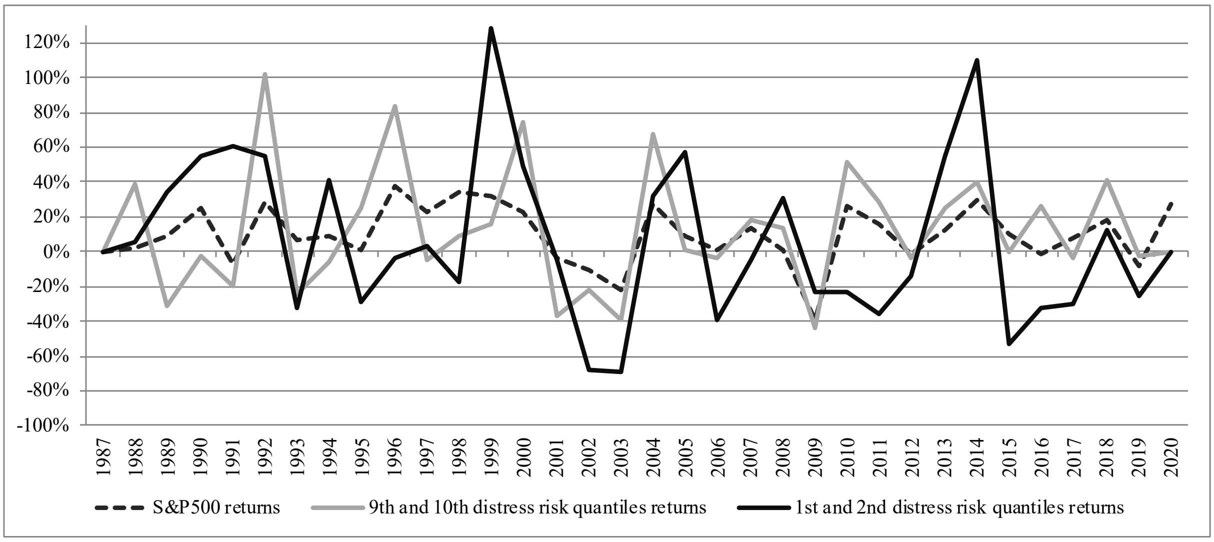

Figure 8. The annual returns of portfolios, %

The abovementioned figure stresses out the multitude of times when the highest distress risk portfolio outperformed the lowest one. Following some seasonality as it would seem visually by spikes of surged returns each 3-4 years, the highest risk portfolio consistently earns positive returns on a more frequent basis than its counterpart. It also essential to mention that the momentum of positive results is stronger than for negative. To put it another way, the cases when the highest risk portfolio is experiencing positive results in at least two consecutive years are more frequent than the reversed cases. Another point that highlights the mentioned portfolio is the pace with which it recovers from crisis and the depth of slips. We can more frequently observe the black line (resembling the 1st and 2nd quantiles of distress prediction) reaching the lowest value in comparable time period.

For these findings, we may suppose that investors consume the information about highly risky firms quicker than for low risky. Investors need to perform the actions faster in order to save their positions, that is why they may equity-research high distressed firms more closely, so that they could act accordingly in a timely manner. The lower level of interval deviation between the consecutive values for high-risk firms may suggest that investors perceive the internet, software and computer services firms to be a potentially good investment due to some behavioural factors (the uniqueness of technology, the global trend for digitization, etc.).

Eventually, considering all of the portfolio analysis we may conduct a number of conclusions to sum up the findings. First, firms that were predicted with highest distress risk earn on average two times higher returns than lowest risk firms, that supports positive distress risk premium hypotheses. Second, the relation between high and low distress firms is not positive amongst excess returns, and often is reversed. Third, dotcom crisis seems to be creating more opportunities for low stressed firms, however in the exact period of 2000-2004 the pace with which low stressed firms are recovered is slower. Lastly, statistically, if we neglect the effect of dotcom crisis on both portfolios, the high risk will become on average positive in excess returns, while the low risk one would stay negative.

3. Limitations of results

The received results although capture some credibility must be assessed with caution to important biases that may arise with direct interpretation. One of the biggest limitations of our findings lies in the field of data gathering and, consequently, the final sample. Campbell et al. (2008) had performed their analysis on the sample of almost 1.6 million firm-months to estimate the regressions, whilst receiving highest significance for each variable in their final logit specification. Our sample consists of only almost 36 thousand observations. It is a important difference that has to be taken into consideration first of all.

Next, we claim that we took all possible internet, software and computer services firms into the sample of delisted, bankrupt and defaulted firms, however, in reality we may miss some firms by the means of different coding of the primary firm activity. Sometimes a firm that had started its public trading with stating to be software developer changes its primary business activity to somewhat else. This case can happen in both ways. In this case we are facing mis-codification of a firm. Although this is a rare case for Nasdaq (that is centred around tech-firms) it may appear for NYSE (AMEX). Nevertheless, we reckon to not capturing significant number of such firms into the sample.

The last important limitation of the paper is the nature of being delisted for financial reasons. Thompson Reuters Eikon do not discriminate delisted firms only by the deterioration means from firm's own will to delist its stocks, excluding the case of M&A. It means that if a firm voluntarily delists its stocks from exchange, we would not in general understand it, as it would fall into financially delisted bucket. There is at least one case of such an event in our data sample, being company Dell to delist from stock exchange, due to going private. The firm is still active on the market and is part of the merger with EMC that occurred some years after going private by the former. We are acknowledged that we can have these case in our sample, although to the best of our knowledge each public-to-private actions are rare to occur, especially on the technological market.

CONCLUSION

This paper makes a number of small contributions to the financial distress literature and suggests unique ideas for trading strategies as well as for portfolio managers. First, we applied the approach that took high authority amongst academicians for the distinctive sample of internet, software and computer services companies that to the best of our knowledge were not studies in-depth. We collect the extensive sample of firms representing this industry in the search of specific results that would differentiate this subset of technological sector from other industries. We find a number of empirical evidences that support our idea: internet and software firms are assessed by the market differently – the distress prediction variables differ in their predicting power from other sectors in general; our sample shows that investors tend to neglect fundamentals and base their predictions on firms prospects based on their prices and excess returns over the benchmarks, suggesting that firms in our sample are expected to skyrocket at some point, even if fundamental suggest that the firm soon would become distressed. This logic helps to better understand the roots of dotcom crisis and adds some value to the distress prediction literature, as well as provides some empirical suggestions for the biased market sentiment towards internet and software firms.

Next, based on the previous literature approaches we construct our own measure of financial distress. We then apply this measure to sort firms by their marginal probability of becoming distressed. By doing so we were allowed to construct the quantiles firms sorted by financial distress factor and compare the distress with the total returns. We observe strong relation between distress factor and cumulated total return to the firm. These returns differ as the time distance to the failure diminishes; however, the general shape stays the same. Our results in this approach support the previous research that detected deteriorating results closer to the failure, however, display that these effects still allow our sample to form visible relation between total returns and distress risk indicator.

By constructing two portfolios sorted by the empirical measure of financial distress we were allowed to detect whether there is a difference in returns between portfolios that contains highest distress risk predicted firm and lowest. Our results exhibit similar evidence as in the total returns approach, providing example of higher average annual returns of more distressed portfolios of firms in comparison to the lower distress portfolios. The more explicit analysis of dynamics of market values, excess and annual returns suggests that investors take higher distress firms more accurate in terms of their valuations, still being effective to trade, especially in the pre- and post-crises time-periods. High distress firms also possess on average lower negativity in excess returns and were better to be used as a hedging instrument due to the fact that their market values decreased to the less extent that low-risk firms did.

Our findings may suggest a number of additives to the trading strategies of investors, institutional and non-institutional. Particularly, our results may adjust portfolio formation techniques and the choice of firms to include within – distress premium might be assessed when investing in internet and software firms, as well as when considering balancing returns. Horizon of investments may be corrected when investing is specific firms or industries, as well as the dates for rebalancing of portfolios, referring to the 6 months extremes in returns for the highest of 10 quantiles of our empirical measure of distress. Institutional and non-institutional investors may adjust their credit-scoring systems by means of industrial specificity of distress predictions. There may arise multitude of strategies that may be based solely on distress risk premium of IT firms. Large corporates may develop and apply machine learning systems that would predict market sentiment towards industries and base distress indicators on it.

As suggestions for future studies, we have to highlight the behavioural side of distress-risk premium explanation that has to be studied in depth. Based on our empirical results, there seems to be some bias towards some industries in terms of risk aversion and risk taking. Internet and software firms were already in the centre of such a bias but the current activities, especially on the crypto market provides some ideas on that this phenomenon still exists and has to be studied in advance. Producing renewed distress risk scoring systems for the new subindustries of technological companies is becoming more and more important and behavioural economics must play some important part in these endeavours.

It is wise to test whether if we shall take other industry, we would receive the similar or not results after the similar analysis. Technological industry, and especially software producing is a relatively young industry that may still work by other market rules if they are to be existing. The performed approach for industrial analysis of distress risk premium might be used on other sectors of U.S. and other economies.

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