# PREDICTING FINANCIAL DISTRESS OF TURKISH NON-FINANCIAL FIRMS: EVIDENCE FROM MICRO DATA

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## ABSTRACT

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In this thesis, determinants of financial distress probabilities are analyzed for the period over 2006-2016 by utilizing firm-level and loan-level data sets. Based on the financial distress definition constructed from the existence of non-performing loans, univariate tests indicate that financially problematic Turkish corporates have lower liquidity, profitability and asset turnover, while they are also the ones with inferior short and long-term debt paying ability. To form multivariate specifications, variable selection techniques such as univariate logit, principal components analysis and bootstrap stepwise logit estimations are applied on a broad set of financial ratios. Multivariate logit and panel logit models indicate that stronger liquidity buffers, abundant profits and improved asset turnover decrease the probability of financial distress. On the other hand, rising interest expenses and considerable debt burden increase the likelihood of facing financial problems. The informative nature of multivariate models are evaluated for in-sample predictions and out-of-sample forecasts. Survival analysis is also performed to assess the time to financial distress. It is found that firm size, profitability, liquidity and operational performance lengthen the period until the occurence of financial problems, while leverage significantly shortens it.



**Keywords:** Financial Distress, Logit Model, Variable Selection, Survival Analysis

# ÖZ

TÜRK REEL SEKTÖR FİRMALARININ FİNANSAL STRES OLASILIKLARININ TAHMİNİ: MİKRO VERİ ÜZERİNDEN BULGULAR

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Bu tezde, 2006-2016 dönemine ait firma ve kredi seviyesinde veriler kullanılarak Türk reel sektör firmalarının finansal stres yaşama olasılıklarının belirleyicileri araştırılmıştır. Takibe girmiş alacak niteliğindeki kredi bakiyesine göre oluşturulan finansal stres göstergesiyle gerçekleştirilen tek değişkenli istatistiki testler finansal stres yaşayan firmaların düşük likidite, karlılık ve iş hacmine sahip olduğunu göstermektedir. Finansal stres durumundaki firmaların aynı zamanda görece kötü kısa ve uzun vadeli borç ödeme performansına sahip olduğu anlaşılmaktadır. Çok değişkenli analiz modellerinin kurulması için ise geniş bir finansal rasyo listesine tek değişkenli lojistik regresyon, temel bileşenler analizi ve bootstrap aşamalı lojistik regresyon gibi değişken seçimi yöntemleri uygulanmıştır. Çok değişkenli lojistik model tahminleri likidite, karlılık ve iş hacminin artmasının finansal stres olasılıklarını düşürdüğüne, faiz maliyetleri ve borç yükünün artmasının ise olasılıkları yükselttiğine işaret etmektedir. Söz konusu modellerin örneklem içi ve dışı öngörü performansları da karşılaştırılmıştır. Ek olarak, finansal stresin gerçekleşmesine kadar olan süreyi etkileyen faktörler incelenmiştir. Firma büyüklüğü, karlılık, likidite ve operasyonel performanstaki iyileşmelerin ilgili süreyi uzattığı, borç yükündeki artışların ise süreyi kısalttığı bulgulanmıştır.

**Anahtar Kelimeler:** Finansal Stres, Lojistik Regresyon, Değişken Seçimi, Sağkalım Analizi

To My Family

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| | |
|---|---|
| Fed | Federal Reserve |
| ECB | European Central Bank |
| FX | Foreign Currency |
| TOBB | Turkish Union of Chambers |
| CBRT | Central Bank of Turkey |
| NPL | Non-Performing Loans |
| BIST | Borsa Istanbul |
| SME | Small and Medium Enterprises |
| MDA | Multivariate Discriminant Analysis |
| US | United States |
| EBITDA | Earnings Before Interest, Tax, Depreciation and Amortization |
| NYSE | New York Stock Exchange |
| GFC | Global Financial Crisis |
| EM | Emerging Markets |
| S&P | Standard and Poor's |
| UK | United Kingdom |
| FDI | Foreign Direct Investment |
| TRY | Turkish Lira |
| ROC | Receiver Operating Characteristics |
| PCA | Principal Component Analysis |
| MLE | Maximum-Likelihood Estimation |
| AFT | Accelerated Failure Time |
| CPI | Consumer Price Index |
| NWC | Net Working Capital |
| EBIT | Earnings Before Interest and Tax |
| COGS | Cost of Goods Sold |

# CHAPTER 1

# INTRODUCTION AND MOTIVATION

With the ongoing financial liberalization, global integration of markets, and the sophistication of financial products, the operational success of businesses have become more dependent on financial health. In this regard, there is a vast amount of studies in corporate finance literature investigating the bankruptcy, business failure, and financial distress prediction (Wu et al., 2010).[1] As expected, the definition of bankruptcy is varied given country dynamics, economic structure and legal framework.

One common way of classifying problematic firms is using legal status. For studies conducted in developed country cases, researchers can evaluate the legal bankruptcy filings to construct a sample of troubled firms. Especially for the studies focusing on US case, firms which are assessed under Chapter 7 or 11 bankruptcy codes are considered in predictive analyses (Zmijewski, 1984; Altman and Sabato, 2007; Gupta and Gregoriou, 2018). In the Finnish case, for instance, Laitinen and Laitinen (1998) select the failed firms if they previously made a legal bankruptcy declaration specified by Finnish commercial law. Similarly, Rıfqı and Kanazaki (2016) collect bankruptcy filings in legal court decisions to come up with bankrupt sub-sample in Indonesia. However, from an empirical perspective, some issues are restricting the use of legal bankruptcy definition. Due to the inefficiency of legal systems, bankruptcy filing processes in developing countries can typically take many years to be completed given the issues like restructuring, liquidation etc. This inevitably creates a significant time lag between deterioration in financial soundness and accounting data capitalized to explain it (Gupta et al., 2018). More importantly, comprehensive legal bankruptcy

[1] Throughout this thesis, concepts akin to bankruptcy such as firm failure, financial soundness, firm health, and financial distress are used interchangeably.

data that can properly be matched with financial information is unfortunately scarce in emerging economies, which makes it impossible to empirically analyze the issue. Given these deficiencies, as literature has evolved, many studies choose to work on a broader concept of financial distress with other definitions. Given the fact that capital markets stand among the major sources of obtaining finance for businesses in relatively advanced economies, being continued to be traded in stock markets is preferred as an indicator of financial health (Altman, 2010; Okay, 2015). Fitzpatrick and Ogden (2011) handle the issue of defining failed firms by involving the ones which are delisted from the stock exchange. Luciana (2006) choose financially troubled firms from the subgroup delisted as a consequence of carrying negative income and equity in the income statement and balance sheet, respectively. As a study deciphering the determinants of financial distress in Malaysia, Yap et al. (2012) take companies in Bursa Malaysia for which transactions on shares are frozen, due to dissolving of equity capital.

Alternatively, as the financial structure of business entities get more and more complicated, multi-faceted qualitative definitions have emerged in studies. The ability of firms to generate operational earnings to cover interest expenses or to purvey market-based worth exceeding financial debt is frequently used. In fact, Pindado et al. (2008) and Keasey et al. (2014) name financially problematic firms if they record income less than interest expenses for consecutive years or if they experience shrinking income in sequential time periods. Having elevated leverage and witnessing disturbances in cash flow expectations are also relevant to financial distress as they can lead to a higher likelihood of default (Chan and Chen, 1991). In some cases, researchers decide to quantify the degree of deterioration in financial data by putting concrete thresholds in a multi-dimensional framework. To exemplify, Bhattacharjee and Han (2014) select Chinese firms which either face with interest coverage ratio being less than 0.7 or attain decline in fixed assets or see a slowdown in equity capital formation. Available market measures can be further benefited. Lau (1987) inspect the quoted companies whenever they omit or decrease the dividend payments to its shareholders, whereas Manzaneque et al. (2016) seek to disentangle

whether or not a decline in market capitalization occurs in two consecutive fiscal periods.

In this study, while we aim to understand the factors contributing business failure and conduct empirical predictions about financial distress, an innovative definition is constructed for Turkish firms by exploiting micro-level data sets describing the loan repayment ability and details are provided in the following chapters.

Regardless of how one defines financial distress, the implications have plainly made it worthwhile to analyze. Corporate finance theory hypothesizes such essential consequences. As argued by Warner (1977), the market value of distressed companies can be subject to sizeable erosions. This could harm the existing shareholders and prevent the firm to issue new shares to raise capital at a lower cost. If the situation becomes epidemic or systematically influences other firms, it could lead to downturns in general market outlook taking the prominent concurrent contagion mechanism in emerging market stock exchanges (Dungey and Gajurel, 2014; Abdennadher and Hellara, 2018).

As surveyed by Kumar and Ravi (2007), starting from the earlier works of Miller and Modigliani (1958) and Myers and Majluf (1984), capital structure theory has mentioned about direct costs of bankruptcy including legal and administrative expenses, profit erosion and fire sales of assets at less than fair value all incurred once bankruptcy is declared which can result in substantial losses. Furthermore, there are indirect costs of financial distress, causing even more enormous burden. As emphasized by Chancharat et al. (2007), financially distressed firms may be subject to external examination processes via voluntary administration and arrangement schemes. This inevitably distorts the regular course of business operations. Financial troubles also lead to debt restructuring and possible violations of debt covenants which can affect debtholders (Flagg et al., 1991). Notably, the firms operating in emerging markets are known to be financially restricted. In other words, their access to finance is limited when the financial sector is bank oriented and other sources of

obtaining funds are widely infeasible. In countries like Turkey, firms even face obstacles to get bank loans, given the fact that collateral values are either non-existent or not enough (Beck et al., 2008). Banks tend to charge higher premiums for interests on borrowing in the form of loans once financial distress is observed. On the top of this, as another side effect of financial unsoundness regarding capital markets, analysts are inclined to discount expected future cash flows more and tend to come up with lower fair values to analogize with the current market price to make buy, sell or hold recommendations (Gepp and Kumar, 2008). Inefficiencies of supply-chain structure, eradication of existing market share and customer base as well as ultimate downward pressure on economic activity can be counted among other indirect costs of financial distress.

In addition to these general reasons for the importance of quantitatively assessing financial distress given costs to be encountered, there exist some particular motives for emerging markets in general and Turkish case in specific from financial stability and economic growth perspectives. The first motive can be defined over the ongoing transformation of emerging market economies. Timely monitoring of firms' financial well-being has become critical, particularly in emerging economies, given the immense level of debt and relatively immature deleveraging efforts in those counties. Economic agents in those markets have benefitted from the abundance of global liquidity and accompanying sizeable capital flows caused by the unconventional monetary policies and return-seeking behavior of global investors (Dedola et al., 2013; Ramirez and Gonzalez, 2017). Costs of financing and improvements of collateral values resulted from inflows to local financial assets as well as the banking sector. They have been assuming a historically high level of debt in the form of bond securities and credit extensions leading to rises in firm leverage (Figure 1).

As the impact of the crisis started to phase out, there are signs of coincided monetary policy normalization around the prominent monetary authorities like Fed and ECB (Figure 2). Recent studies have empirically shown that, given the high degree of co-movements across countries' asset prices and interest rates, this policy normalization

might have repercussions on domestic financial conditions of emerging markets through cross-border lending relations and interest rate pass-through (Curcuru et al., 2018; Lavigne et al., 2014). The extent of spillover, functioning through channels like portfolio, signaling, exchange rate, and trade flows, seems to depend on structural characteristics of individual economies such as capital account openness, exchange rate regime, the autonomy of monetary policies, dollarization etc. (Caceres et al., 2016).

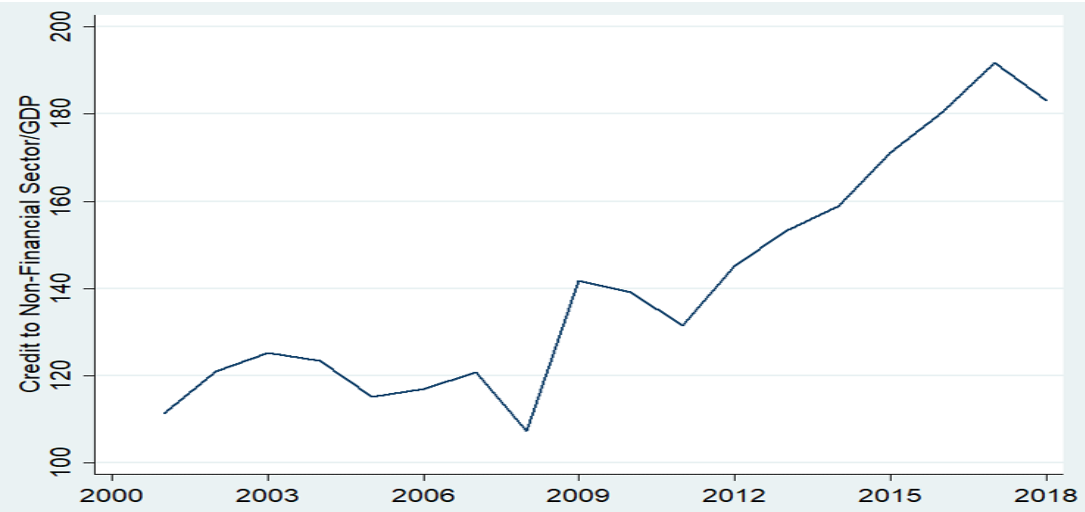



***Figure 1.*** Credit to Non-Financial Sector in Developing Countries (As a Share of GDP)


***Figure 2.*** Policy Rate of Developed Countries (Percentage)

In this context, abrupt shifts in global risk appetite, drastic changes in capital flows to emerging economies, rising trend of interest rates, downward outlook in global economic activity and weakening in external demand all have contributed to the riskiness of real sector firms. In terms of financial conditions, such impacts are transformed into tightening in borrowing conditions and increases in cost of financing (Chen and Semmler, 2018). In fact, monetary policy easing is related to relatively lower level of credit risk premium which is a part of yields on bond issuances (Gertler and Karadi, 2013). Moreover, together with rising interest burden, currency movements might cause the leverage position to further deteriorate. The unsustainability of financial health would inevitably result in widespread bankruptcies. Given the network channels between local firms and banks in terms of lending relationships, worsening financial health of companies can be transmitted to asset quality of banks, causing further disturbances in financial stability (De Bock and Demyanets, 2012). Turning to the case of Turkey, the episodes during which real sector experiences financial problems are also characterized with deterioration in asset quality of banking sector. The fact that bank loans constitutes most important financing source in Turkish firms, the situation is exacerbated (Figure 3 and 4).

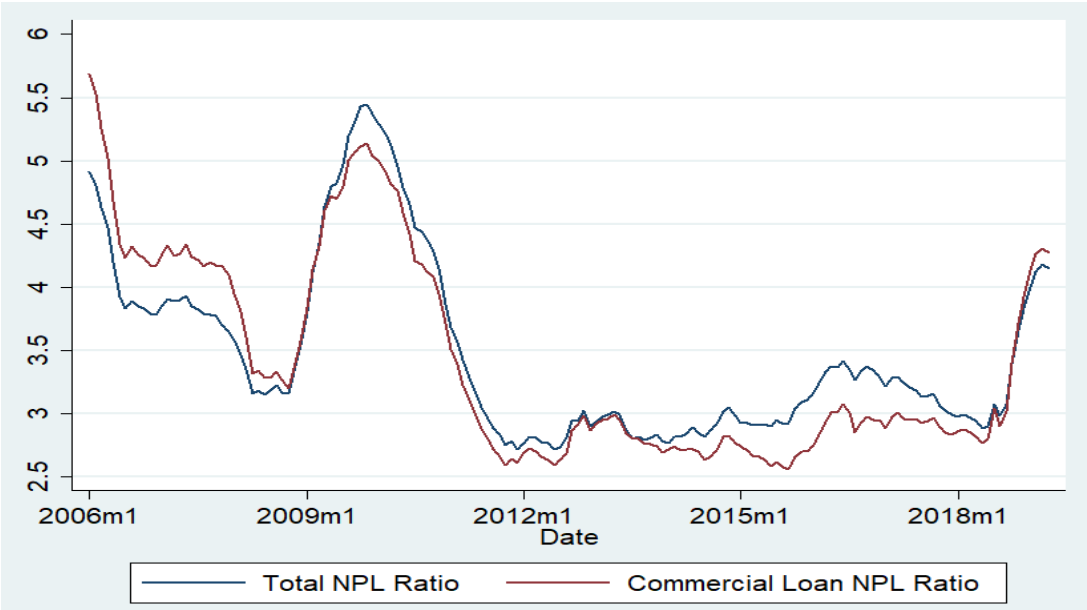



***Figure 3.*** Non-Performing Loan (NPL) Ratio (Percentage)

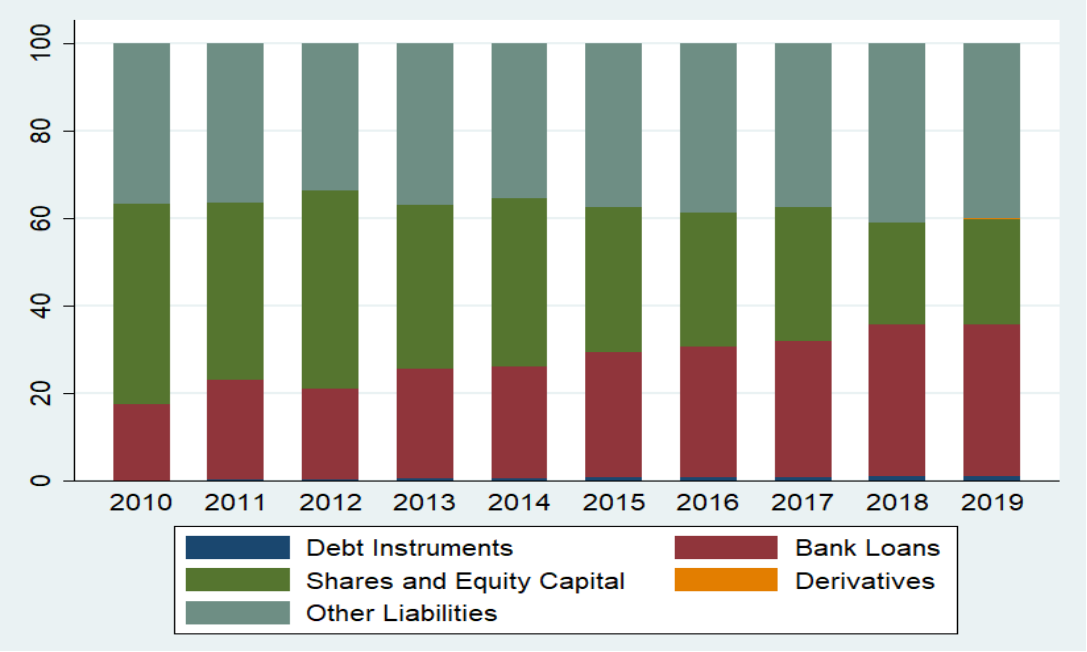



***Figure 4.*** Liability Structure of Turkish Real Sector Firms (Shares, Percentage)

Therefore, the financial soundness of firms constitutes an indicator of financial stability which is one of the main policy goals of monetary authorities after the Global Financial Crisis. In this context, the non-financial sector is considered to be one of the areas in financial stability monitoring from policymakers' perspective (Adrian et al., 2015). As recent crisis has shaken up the view that macroeconomic policies suffice in stabilizing the economy, some started to argue that monetary policy authorities should also focus on financial stability as it can have negative feedbacks on price stability as well (Smets, 2014). In this sense, variables related to leverage, FX mismatch, interest coverage, etc. needs to be timely monitored. This increases the importance of methodologies and techniques utilized in predicting business failure.

Apart from financial stability and monitoring perspective, given the structure of the Turkish economy, firm dynamics are also critical in determining the overall growth performance of the country, especially gross capital formation tendencies. It is widely seen that financial constraints can be a vital obstacle affecting investment decisions for Turkish firms. Yeşiltaş (2009) and Gül and Taştan (2018) work on firm-level investment-cash flow sensitivity of Turkish firms, and they identify that firms are

financially constrained. Thus, any shock coming to financial conditions of firms would have immediate and lagged impacts on investments, and eventually on overall productivity and economic growth potential. Figure 6 depicts the high degree of co-movement between financial conditions and economic growth. Examining the aggregate macro-level data published by Turkish Union of Chambers (TOBB) historically yields that episodes with the high number of closed firms are also somewhat associated with depression in investment growth tendencies, particularly after 2012 (Figure 5).

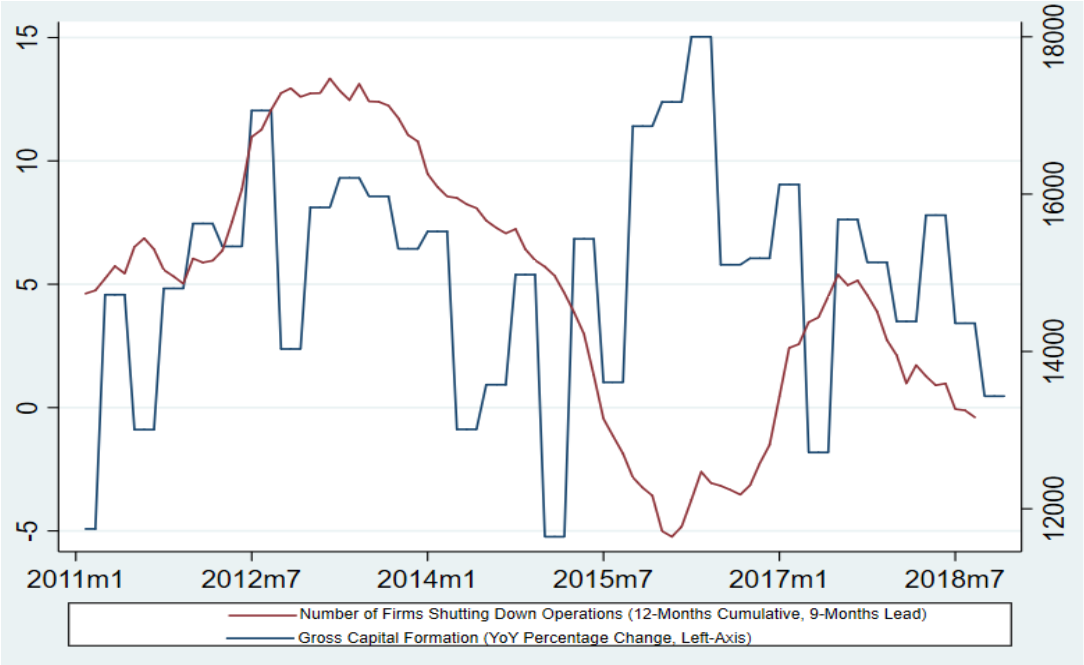



***Figure 5.*** Firm Failure and Investment Growth

In this thesis, we utilize annual financial statement information of Turkish non-financial firms derived from micro-level data set available at CBRT named Real Sector Company Accounts to assess the determinants of financial distress over the period 2006-2016. The definition of financial distress is also modified suitably to Turkish case where bank-based financing has become the dominant channel of obtaining funds. In this regard, another micro-level data set (Credit Registry available at CBRT) used to extract the information about NPLs taken as a criterion of

occurrence of financial distress. By employing binary outcome models, we do not only assess the contribution of each financial ratio describing different dimensions of firm operations/financing, we also come up with a scoring mechanism that can be applied to cases for which financial statement data is available in quarterly frequencies to monitor financial stability (such as BIST-quoted manufacturing firms). To complement this analysis, our methodology also includes duration analysis to predict the time to firm failure.

Main contributions of this study to empirical literature are threefold. Firstly, previous studies for Turkish firms had to use data of companies whose shares are traded in BIST, given the inability to reach micro-level data sets. Although these firms are comparatively large and important, financial risk analysis should also focus on small and medium enterprises (SMEs) as their role in employment creation, investments and exports are prominent.[2] Unlike our setup in which a relatively larger number of firm/year observations are available, working with publically traded firms would excessively restrict the size of the sample with few bankruptcies.

Secondly, when financial distress is defined by the shutdown of firm operations, identification can get somewhat complicated. Apart from working with the finite number of observations in the cases of stock market delisting or legal bankruptcy filings (regarding BIST firms), due to the restructuring and merger/acquisition activities, the inferences that can be derived from accounting information about financial soundness may not be definite. Furthermore, the inability of paying bank loans back seems to be more informative for firm failure taking bank-dependent financial architecture into consideration. Hence, our way of defining financially problematic firms by using micro-level credit data for NPLs has the potential to enhance the identification process. Thirdly, while multivariate discriminant analysis (MDA) is widely preferred in Turkish studies, binary outcome models are not

[2] According to information provided by TOBB, SMEs constitute almost 75% of total employment, 53% of all investments on fixed assets and 60% of all exporting activities in the Turkish economy. http://www.kobi.org.tr/index.php/bilgibankasi/statistikler

frequently utilized in studies. Thus, in this study, logit and duration models are considered.

The structure of this thesis is as follows. Chapter 2 presents the existing empirical literature in detail with particular focus on methodological aspects. Chapter 3 initially describes the micro-level data sets and how we merge them to create the sample. In the former part of same section, methodological aspects of variable selection, univariate analysis and logit models are provided. In the following part, empirical results for the estimation of financial distress are presented. The last chapter concludes the discussion.

# CHAPTER 2

# LITERATURE REVIEW

The efforts made to differentiate financially problematic firms from others traced back to Beaver (1966). In that study, author checks 158 US manufacturing firms in a matched sample setting with 79 failed and 79 non-failed firms in the context of 14 financial ratios employed based on cut-off scores to minimize misclassification. Putting it differently, a dichotomous classification based on a simple t-test of mean differences is conducted to detect the error rates experienced by a potential hypothetical creditor if companies are grouped as financially distressed or not in the light of individual financial ratios. His analysis displays the usefulness of ratios such as “cash flow to total debt”, “total debt to total assets” and “net income to total sales” with varied level of predictive power. However, certain criticisms are directed to this method as sole differentiation criteria. As argued by Altman (1968), univariate analysis involving single ratios at a time would result in misinterpretation and confusion. In fact, different ratios might suggest conflicting results for the very same company. Lin and Piesse (2001) further claim that it is vastly dependent upon single ratio rather than benefiting from the joint effect of multiple factors that can together point out corporate failure.

Since a single indicator can not capture all the dimensions of firms’ financial situation, subsequent studies highlight the need for composite indicators to assess to which extent firms are closer to bankruptcy. Seminal work of Altman (1968) addresses inconsistency problem related to the univariate approach and introduces a scoring tool, which has been widely used in the literature since then. Here, a statistical technique called multivariate discriminant analysis (MDA) is chosen to combine several financial ratios. MDA is a way of deriving an index score which can distinguish two sub-groups with the same number of members. In other words, an

index score is created through the weighted sum of individual indicators such that differential between mean index score of failed and healthy company groups are maximized (Johnson and Wichern, 1982). Similarly, the loadings of individual financial ratios in scoring mechanism are obtained such that inter-group variance is maximized, while within-group variability is minimized (Kocisova and Misankova, 2014). This method also reduces the analysts' space dimensionality with the help of given cut-off points.

Altman (1968) aim to discriminate 33 bankrupted firms from 33 solvent counterparties which are all listed in the New York Stock Exchange (NYSE) for the period covering 1946-1965. Starting from initial class of 22 financial ratios and market-based data, that paper suggests the linear combination of five ratios describing liquidity, profitability, sales turnover, and leverage. In particular, specific coefficients are assigned to "working capital to total assets", "retained earnings to total assets", "Earnings Before Interest, Tax, Depreciation and Amortization (EBITDA) to total assets", "market value of equities to book value of total liabilities", and "net sales to total assets" to calculate Z-score for which values lower than 1.8 is interpreted as a sign for financial distress and convergence towards bankruptcy. Altman (1968) also show that his model has almost 94% predictive power in detecting the bankruptcy for US firms.

While the methodological aspect remains mostly same throughout the historical formation of the empirical literature, some improvements are made in the MDA approach. While the original version is assuming a linear formation of ultimate score within a bottom-up approach, this entails the assumption that financially problematic and healthy firms happen to have same variance-covariance structure. Altman et al. (1977) try to overcome this issue by introducing a quadratic discriminant model as a natural consequence of incorporating the inequality of variance-covariance matrices, whereas this improvement brings some complexity into the estimation process, as argued by Eisenbeis (1977). By also using log-transformation of explanatory financial information, they define what is termed as ZETA model involving seven financial

variables for 111 manufacturing and retail/wholesale firms over the period 1969-1975. While in the original MDA framework, arbitrary matched samples are chosen to detect the variability between bankrupt and non-bankrupt firms, Altman et al. (1995) choose to employ a simulation selection technique in sampling procedure. Altman and Sabato (2007) further extend the scoring formation to SMEs instead of relatively large and publically traded firms. For the US firms during the period from 1994 to 2002, that work calibrates the individual financial ratio loadings for the case of SMEs.

Thanks to its more straightforward applicability and interpretation, MDA method has constituted the methodological foundation of several bankruptcy prediction studies, not only in the case of advanced economies but also for emerging market studies such as Greece, Israel, Malaysia and Turkey among many others (Gerantonis et al., 2009; Lifschutz and Jacobi, 2010; Çolak, 2019). However, there are some severe drawbacks of MDA models. First of all, as stated by Ohlson (1980), MDA is simply an ordinal ranking tool lacking strong intuition. Secondly, the MDA model works with a matched-sample setup, which is infeasible to be used in micro-level data sets and might cause the self-selection problems. In particular, observing the bankrupt firms and composing the dependent variable in the first step and then creating the remaining sample based on that knowledge will violate random-sampling design (Zmijewski, 1984). Thus, a researcher using the MDA model would have to make estimations on non-random samples whose features are so different than corresponding populations. As a third weakness, on the top the assumption requiring proportionality of samples, the multivariate scoring technique also makes a zero-intercept assumption which is deemed to be somewhat unrealistic (Keasey and Watson, 1991).

Furthermore, MDA models assume that group dispersion matrices are equal across failed and non-failed firm groups, which is something regularly violated in the real-life data (Barnes, 1982; McLeay and Omar, 2000). More importantly, MDA model assumes that explanatory variables are multivariate normally distributed and its coefficients, unfortunately, can not be interpreted as traditional slope values in the

regression-type analysis displaying the relative importance of each of the individual financial ratios. As other flaws of MDA method in relation to emerging market studies, one can argue that utilization of Altman (1968)'s original variables and coefficient values might be misleading and they can not capture firm dynamics well. Due to the lack of developed capital markets in EM countries, for instance, financial ratios extracting information from the market value of equities can not provide accurate picture given inefficient pricing formation and shallow liquidity of traded instruments (Çolak, 2019). Moreover, earnings generated by firms in EM countries are known to be severely volatile. They are also subject to various country-specific shocks apart from industrial dynamics. When weighted with original Z-score coefficients derived from US case, "retained earnings to total assets" can bring unreliable profitability information.

To immunize the empirical results from the deficiencies of MDA model described above which are paired-sample structure, normal distribution pre-supposition, zero-intercept assumption, inability to reveal the relative importance of individual ratios and misleading nature of original Z-score coefficients, later studies in the literature employ binary outcome models and maximum-likelihood estimations. As mentioned by Mensah (1984) and Charitou et al. (2004), this modeling approach does not put forward restrictive assumptions about prior probabilities of firm failure and distribution of financial ratios. The use of binary outcome models also allows one to assess the statistical significance of individual independent variables. Even, diagnostic measures similar to the ones in regression models can be used to evaluate the overall quality of fit in considered specifications (Neophytou and Molinero, 2004). More importantly, this group of models can directly approximate the weights with which each coefficient contributes to the ultimate prediction of financial distress. Hence, it is capable of producing a simple final probability score (Nam and Jinn, 2000). From an empirical perspective, binary outcome models seem to perform better than MDA specifications in out-of-sample forecasting practices (Gepp and Kumar, 2008).

Ohlson (1980) is the pioneering work aiming to overcome statistical violations of MDA method by using conditional logit model on a relatively larger sample including 2000 financially healthy and 105 financially problematic US manufacturing firms over the period 1970-1976 without having to create a matched-sample. Measures describing firm size, leverage, operational performance, and liquidity are found to be statistically significant predictors. Predictive performance of the model is checked through Type I and Type II errors. Assuming the 0.5 cut-off point implying the symmetric loss function across two types of classification errors, the author predicts one and two-year ahead failure. It is seen that their estimation yields 96-97% of correct prediction.

Zmijewski (1984) is another earlier study laying the foundation for this branch of literature. The sample of this study is drawn from firms traded in US stock exchanges for the period that covers the 1972-1978 interval. By collecting information from different qualitative sources, financially distressed firms are identified from bankruptcy filings. A probit model is estimated through weighted exogenous sample maximum likelihood to assess the impact of profitability, leverage, and liquidity on the probability of facing bankruptcy.

Aftermath, these methodologies have been applied to individual country cases and cross-country setups with several firm-level and economy-wide covariates. Altman and Sabato (2007) choose the logit model along with MDA to examine the bankruptcy tendencies of 2000 US firms for the period 1994-2002 covering 120 default incidents. They pre-determine financial ratios under five different categories corresponding to dimensions of firm outlook. After applying variable selection techniques, they narrow down possible covariates to 10 financial ratios and implement logit models to predict binary dependent variable defined from Chapter 11 bankruptcies. They find that logistic models outperform MDA specification for the holdout samples for the years 2003 and 2004.

Brezigar-Masten et al. (2018) work with Slovenian micro-credit data and aim to model whether or not firms can pay back their bank loans in the sample period from 2007 to 2014. In their paper, they do not only predict the binary variable indicating the existence of non-completed loan payments with static and dynamic probit models, but they also focus on estimating the number of days past due via static and dynamic versions of tobit models as the variable of interest is censored at zero from below. Their empirical results show that the lag of dependent variable is highly significant, pointing out the existence of high persistence in financial distress. Dynamic tobit model appears to be the best-performing model accompanied with an overall accuracy rate of 97%.

The empirical analysis of Baggs et al. (2009) has the goal of testing the impact of exchange rate movements on firm survival and entry rates, which is known to be related to the extensive margin in industrial organization literature. By employing a detailed data set belonging to Canadian firms for the period 1986-1997, probit model estimations report that coefficient on the industry-specific trade-weighted real exchange rate displays that an appreciation of local currency would decrease the probability of survival for Canadian firms. This negative effect seems to be less profound for more productive entities.

Laitinen and Laitinen (1998) focus on 41 bankrupt Finnish firms to evaluate the hypothesis that, in the case of financially distressed firms, the absolute values of the elasticity terms of cash balance carried by the firm to motive factors are expected to be much smaller than financially sound ones. They estimate a group of equations describing cash management behavior of non-financial firms, one of which defines the bankruptcy prediction via stepwise logistic model. They conclude that variables such as “cash flow to net sales”, “cash flow to debt capital”, “sales growth” and “return on investment” have predictive power.

Although it ignores the time-series dimension, the work of Foreman (2003) focuses on the cross-section of 77 firms in US telecommunication industry in 1999. The

binomial logit model is estimated to predict the firms' bankruptcy probabilities in a two-year interval. They detect the significance of variables covering areas such as profitability, asset utilization, firm size, market-to-book ratio, and liquidity in explaining the probability of bankruptcy to occur. Logit regression results also show that the percentage of correctly classifying bankrupt and non-bankrupt firms are 86% and 98%, respectively.

Lin and Piesse (2001) try to explain the factors contributing to the firm failure for 904 UK companies over the period 1985-1994. Apart from the univariate analysis involving with traditional t-test for mean differences regarding financial ratios across failed and non-failed companies, this study uses conditional maximum likelihood estimate via modified logit model as specified by Maddala (1983). As a first step, univariate logit models are run for individual ratios stemming from five different dimensions which are management inefficiency, capital structure, insolvency, general economic outlook, and profitability. They report that univariate models do not discriminate failed firms well as they have relatively lower accuracy rates being closer to 50%. However, they find that once the methodology is moved into multivariate logit estimations, the accuracy rate is improved in an important manner.

Neophytou et al. (2000) is another study examining UK firms. They choose to model the financial soundness of UK firms for the period over 1988-1997 by using different methodologies, including MDA and logit models. After presenting univariate results (some of which bring good prediction performance like accuracy rates reaching to 80%), they see that predictor variables such as "cash flow from operations to total liabilities", "EBIT to total liabilities" and "total liabilities to total assets" turn out to be statistically significant. In fact, the overall classification power of multivariate logit model within one-year prior to encountering financial trouble is found to be almost 94%.

Fitzpatrick and Ogden (2011), on the other hand, investigate the role of risk proxies obtained from asset pricing and corporate finance literature on the firm failure in the

US case. By collecting a sample comprising 14358 firm years within the period 1983-1998, they estimate a logit model to associate risk proxies such as stock return volatility, profitability, leverage, book-to-market ratio, and firm size with bankruptcy. Since Standard and Poor's (S&P) credit ratings are available for some of the sample companies, they compare logit regression results with those credit risk measurements. They find that among the firms estimated to be in a failed category depending on the chosen cut-off point, almost 90% belongs to speculative investment-grade category of S&P criterion.

As a study involving different countries' firms in Europe, Tykvova and Borell (2012) analyze financial distress risk and bankruptcy rates for European firms during the period preceding GFC. Logit model estimations are performed on the data of privately held firms from 15 countries for the period from 2000 to 2008. Here, financial ratios from five different sub-groups, including liquidity, profitability, operating efficiency, market dimension and sales turnover are considered. Logit model estimations have resulted in a successful identification of problematic firms and further examination reveals that buyout investors tend to select companies to acquire when distress score is considerably high. The measures also suggest that financial distress risk is distinctly elevated, especially three years after the buyout transactions are completed.

Moving into other individual country studies, Nam and Jinn (2000) work with non-financial listed Korean firms around the episode of Asian Crisis and a bailout of the Korean economy by IMF, precisely during the period 1997-1998. After choosing an initial candidate list for determinants involving 33 ratios, they implement univariate logit regressions to assess the significance and predictive power. In line with the findings of the first step, in the following step, they estimate multivariate logit models. Their findings are compatible with the expectations that distressed firms are the ones producing a lower level of profit to cover the debt, incurring a higher level of interest expenses and facing with a weaker level of receivables turnover.

Yap et al. (2012) attempt to develop bankruptcy prediction framework for Malaysian firms. In addition to other methods, they also use a logit model for the period between 1996 and 2005. By choosing 16 financial ratios based on the arguments of previous literature and relative predictive performance, they are able to construct an ultimate logistic regression model including ratios such as "cash flow to total debt", "total debt to total assets", "retained earnings to total assets" and "cash to current liabilities", for which significance is retained and signs of coefficients are in line with hypothesized arguments. In-sample and holdout sample classification success of final model within 5-years horizon are determined to be 88% and 92%, respectively.

Manzaneque et al. (2016) take a different path and aim to assess the role of corporate governance on financial distress for the period covering 2007-2012. They follow the Mangena and Chamisa (2008) and use conditional logit model to reveal the impact of board ownership, independent directors and board size on financial distress, while controlling for profitability, financial expenses and retained earnings.

Among more recent studies, Gupta and Gregoriou (2018) assess bankruptcies and financial distress situations of US listed and non-listed SMEs by extracting predictive information from 12 accounting and five market-based indicators. Their univariate logit regressions provide insightful results such that default and financial distress likelihood of listed SMEs are less influenced by one unit change in chosen covariates.

Some other studies still choose to use logit-type frameworks but extend them to a longitudinal form of the data sets. McGuinness et al. (2018) specifically analyze the effect of trade credit on the financial distress of European firms. Although their initial modeling attempt includes MDA analysis as well, they estimate fixed-effects panel logit model which provide the results such that companies receiving a higher level of short-term financing through trade credit are subject to a significantly lower level of bankruptcy probability. Concerning other controls, it is determined that larger, older and more liquid firms are less likely to experience financial distress during the sample period in the post-GFC era. Iwanicz-Drozdowska et al. (2018) are also counted among

the empirical works utilizing a panel form of logit models. Actually, this study examines how the presence of local banks influence the future prospects of firms which are already faced with financial problems. In particular, authors consider data of Polish SMEs as input for the period between 2006 and 2015 with the final sample comprising more than 40000 companies. While different models are employed to empirically test a variety of hypotheses of paper, in one specific part of the study, authors analyze the drivers of legal bankruptcies and economically defined financial distress consequences. They try to predict the one year ahead bankruptcy formations by using random-effects panel logit model. Their results have important implications as they describe the improvement of financial distress probabilities in the presence of secure local bank networks. It is also found that elevated stocks of liquid assets, high profitability, greater firm size, solid equity capital base, and corporate governance practices significantly provide SMEs an immunity against bankruptcy.

Even though it is not a static technique like logit models, duration analysis is also preferred as an underlying framework in bankruptcy prediction studies. As explained by Gepp and Kumar (2008), survival analysis reckons failure prediction as a timeline representing the lifetime distributions of firms in the form of a random variable. This branch of the literature is known to contain descriptor functions characterizing the time-wise nature of financial distress, when it also does not make the time-wise stability assumption for the failure process. Two such functions are survival function, which defines the probability of a firm to survive within the arbitrary upcoming time period given that it did not encounter financial distress until time t, and hazard function, which describes the instantaneous risk that financial distress event will occur at time t given that the firm survives until time t.

As superiorities over other modeling ways, durations models are also able to deal with delayed entry/exit of firms in the sample as well as censored observations (Gepp and Kumar, 2008). This is against other traditional studies for which censored observations are not incorporated (Allison, 1995). Apart from containing more

abundant information, survival analysis for firm bankruptcy is also found to perform well in out-of-sample forecasting, as mentioned by Shumway (2001).

One group of studies exercise non-parametric techniques to obtain hazard rates and survival functions. Gupta et al. (2018) draw on popular Kaplan-Meier estimator to produce hazard curves, not only for legal bankruptcies, but also for financially distressed firms in the US. In a similar vein, Gepp and Kumar (2008) analyze Australian case for a relatively long time interval covering the period 1974-1991. Again, Kaplan-Meier methodology is embraced for the creation of survival and hazard function. Gupta and Gregoriou (2018) utilize rather a recent sample period of UK firms to construct survival curves of financially distressed firms via the Kaplan-Meier method. It is determined that at any given firm age, the survival curve of listed SMEs stands above those of unlisted firms.

For more advanced duration settings, semi-parametric methods are preferred. Continous time Cox proportional hazards model based on the seminal work of Cox (1972) stands as the most favored one in the empirical literature. It is indeed semi-parametric in the sense that no limiting assumption is made about the shape of the hazard function (Gupta et al., 2018). In this model, the hazard rate is specified as a multiplicative combination of baseline hazard function and vector of explanatory variables. In detail, while baseline function determines the non-parametric component of the model, remaining part is parametric and it defines how the hazard function is shaped by the firm-level explanatory variables (Gepp and Kumar, 2008). Coefficient vector is estimated via partial maximum likelihood technique.

Lane et al. (1986) is the pioneer study for the application of survival analysis on business failure prediction. By working with the successful and failed US banks over the period 1979-1983, they establish a Cox proportional hazards model. Laitinen and Laitinen (1991) again apply the Cox model to business failure using 36 failed and 36 non-failed Finnish limited companies. Kaufman and Wang (2008) use the Cox model to explore the relative strength of firm features on failure tendencies of Internet-based

businesses for dot-com bubble period in US. One of the modeling choices of Bhattacharjee and Han (2014) in examining the determinants of bankruptcy probability for Chinese firms is again seen to be the Cox proportional hazards model. Partington et al. (2006) utilize a Cox proportional hazards model to predict the duration of Chapter 11 bankruptcy and the payoff to shareholders. Similarly, Chancharat et al. (2007) identify the probability of Australian corporate survival in a given time interval with the help of the Cox model. Their findings also point out the fact that size of the company has an amplifying influence on the likelihood of facing financial distress. Iwanicz-Drozdowska et al. (2018) choose to implement Cox model for Polish firms. Their results implicate that liquidity, profitability, and leverage deepen the worsening in financial outlook.

Although they are encountered not frequently, as a further component of duration setting in bankruptcy prediction, discrete-time and parametric survival techniques are opted for. Gupta et al. (2018) state that expressing the time to default event naturally leads to dealing with data expressed in discrete-time terms. Hence, the authors argue that parametric discrete-time survival model framework might be more suitable for failure prediction. Their results show that, in fact, discrete-time model with logit/cloglog links appear to perform better than semi-parametric models like Cox specification. As suggested by Shumway (2001), multi-period logit model can be regarded as equivalent to discrete-time hazard model when the variable of interest is categorized as a discrete random variable. Stemming from this analogy, Filipe et al. (2016) utilize a multi-period logit model in the context of the assumption that marginal probability of experiencing the distress situation (in other words, hazard rate) is shaped by logistic distribution. Similarly, Gupta and Gregoriou (2018) complement non-parametric duration analysis with discrete-time hazard model to predict firm failure. As another study employing parametric survival framework is Buehler et al. (2006) in which how the baseline hazard rate differs depending on firm age is determined by distributional assumptions. Then, hazard ratios indicating the change in hazard ratio caused by variations in covariates are examined. It is specifically emphasized that strengthening in economic activity measured by

increases in GDP growth rate is creating a downward impact on the probability of firm bankruptcy.

When we examine the existing empirical works done for the Turkish case, it turns out that, due to unavailability of proper micro-level data set, inferences have been based on data belonging to firms quoted in BIST with considerably few bankruptcy instances. Hence, studies directly focusing on explaining the motives of legal bankruptcy and/or stock market delisting had to proceed with MDA techniques for most of the time.

Selimoğlu and Orhan (2015) conduct univariate tests to identify the differentiation of financial ratios between bankrupt and non-bankrupt Turkish real sector companies. Among others, Yılmaz and Yıldıran (2015), Kulalı (2016), Zeytinoğlu and Akarım (2013) choose to implement original Altman's Z-score on BIST firms. On the other hand, Terzi (2011) also follow the MDA method, but the framework is calibrated specifically to the Turkish case by considering 19 financial ratios. Vuran (2009) and Baş and Çakmak (2012) utilize logit model similar to our methodology, but as stated above, they are limited with few bankruptcy observations and their inferences are not based on contemporary data. As an exciting work, Okay (2015) implement different models such as MDA, logit, neural networks, and decision tree to predict delisting behavior of Turkish non-financial firms. It is concluded that holdout sample prediction results have revealed the superiority of neural networks and quadratic discriminant methods.

As a recent and well-designed contribution to the existing literature for the case of Turkey, Çolak (2019) modify MDA model to Turkish case and come up with a scoring mechanism providing best identification performance across different sample choices. The empirical results of that study conclude so-called MFA score getting input from seven financial ratios representing liquidity, leverage, profitability, and financial expenses. Extracted indicator for BIST firms is also found to display strong co-movements with macroeconomic outcomes such as economic growth and

exchange rate. When BIST firms are categorized into different tranches based on the degree of financial distress implied by MFA-score, the distribution of credit debt and open FX positions across these tranches are investigated to detect any possible risk accumulation from a financial stability perspective.

# CHAPTER 3

# DATA AND METHODOLOGY

In the first part of this chapter, we introduce two separate micro-level data sets encapsulating both the criteria for financial distress and the accounting information about firm financials and performance. In the second section, methodological foundations of univariate analysis, variable selection, logit model, and survival analysis are explained.

## 3.1 Data

First micro-level data set in this study is Company Accounts compiled by CBRT. This set of statistics has been compiled by CBRT to monitor the sectoral developments with the help of financial statement information of real sector enterprises. In addition to the balance sheet and income statement items described under Turkish Accounting System (Tek Düzen Hesap Planı), it also stores non-financial information such as sectoral classification in which companies are operating. It is an unbalanced longitudinal data because of the shifts in firm coverage and issues like restructuring, the partition of operations, bankruptcies, mergers, and acquisitions. Hence, to some extent, the number of firm observations available in a selected year follows a volatile course (Figure 6).

Although, the scope of data covers relatively earlier periods and embodies information for the time interval between 1989 and 2016, when evaluated in detail, periods preceding 2000s are found to contain fewer firms. Furthermore, episodes posterior to 2001 crisis are characterized with sizeable disinflation, a considerable decline in the budget deficit, launched financial deepening, accelerated foreign direct investment (FDI) inflows, diversified exporting activities and ultimately strong rebound in growth and firm investment. Hence, it is assessed to be more informative

in examining firm-level phenomena during a period with abovementioned characteristics. More importantly, as described by Gül (2017), certain changes in accounting regulations have been legislated in 2004, which make it difficult to put forward an analysis comparable to earlier periods. Thus, we specify our sample period as the 2006-2016 interval.


Source: CBRT.

***Figure 6***. Number of Firm Observations per Year in Company Accounts

Other micro-level data set utilized in this thesis is Credit Registry provided by the Bank Association of Turkey (BAT). It encompasses firm-level loan information including a variety of information such as lender, borrower, currency of denomination, maturity, sector, and financing issue. In other words, it embodies all the commercial loans extended to non-financial firms in a given time period. It is available for the 2006-2019 period, with no earlier observations like Company Accounts.

We have performed a multi-step data processing task before the empirical analysis. In the first step, since financial and non-financial information is retrieved from different sources within Company Accounts, merging procedures are completed. We benefit from the cross-section identification termed as "IGSNO" in the data set, which

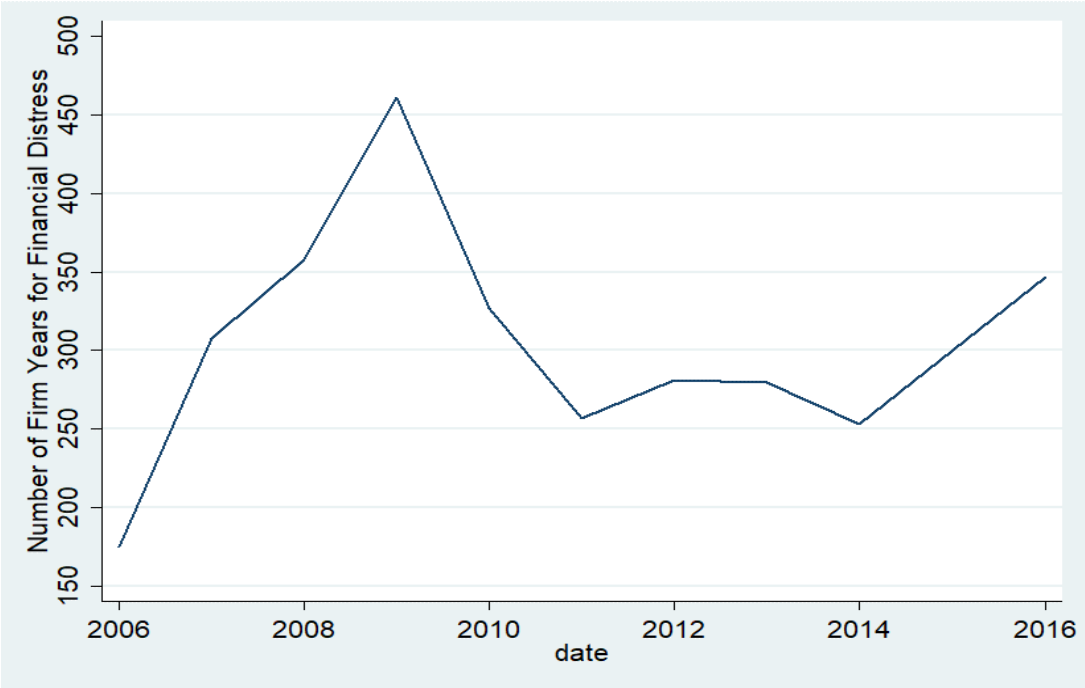
stands for masked firm id codes, to conduct one-to-one merge between balance sheet and income statement information[3]. Then, industry information is merged with this set. As briefly mentioned in the Introduction chapter and described in detail in the upcoming Methodology chapter, our empirical design defines the event of financial distress with the existence of NPL for non-financial firms. We have gathered this input from the Credit Registry data as follows. Loan-level data is aggregated on the firm and year dimensions. Afterward, the following items (in bank balance sheets) and firm identification codes are retained to describe NPLs and which companies they belong to:

- 300-TL Tasfiye Olunacak Alacaklar (Dissolved Receivables in TRY)
- 301-TL Tahsili Şüpheli Ücret, Komisyon ve Diğer Alacaklar (Doubtful Fees, Commissions and Other Receivables in TRY)
- 302-TL Zarar Niteliğindeki Krediler ve Diğer Alacaklar (Defaulted Loans and Other Receivables in TRY)
- 350-YP Tasfiye Olunacak Alacaklar (Dissolved Receivables in FX)
- 351-YP Tahsili Şüpheli Ücret, Komisyon ve Diğer Alacaklar (Doubtful Fees, Commissions and Other Receivables in FX)
- 352-YP Zarar Niteliğindeki Krediler ve Diğer Alacaklar (Defaulted Loans and Other Receivables in FX)

As the next step in data processing, these items are being summed to form the eventual NPL balances to be matched with financial information retrieved from Company Accounts. These two sources are again one-to-one matched concerning firm identification codes in a way that financial statement data is kept as “master” file, while NPL balances is taken as “using” file, according to the syntax of Stata package. By assigning a dummy variable named “Distress” which takes the value of one given the existence of non-zero NPL balance (and zero otherwise), we separate financially-distressed firms in our data set from healthy ones. As depicted in Figure 7, as

[3] Ignorably low number of observations are missed in this step.

expected, observations corresponding to financial distress are relatively rare and fluctuate over the years. Total number of firm years over the sample period is found to be 3347. Given the implications of GFC in terms of financial turbulence and economic fluctuations across EM countries, as expected, our distress indicator is attached with considerably more observations during the time spanning the GFC era.




Source: CBRT, Bank Association of Turkey, Author's Calculations.

***Figure 7.*** Financial Distress Observations

Since data set also includes sector information described by NACE Rev.2 classification framework, sectoral distribution of financially distressed firms can be reported alongside time-series properties. When we examine the number of firm years and how they distribute across industries, it seems that sectors like manufacturing, wholesale/retail trade, construction, transportation, and tourism comprise the majority of the financially distressed firm dynamics (Figure 8). On the other hand, since absolute values alone might not inform adequately about the financial risks of the sectors, it would be more appropriate to look at financial distress rates which are basically the share of firm failure observations in the total number of firm years of specific sectors. Figure 9 presents financial distress rate and it can be seen that apart

from unidentified firms with no sector information, companies operating in construction, professional services, transportation, and manufacturing are detected to be the riskier ones for the sample period.

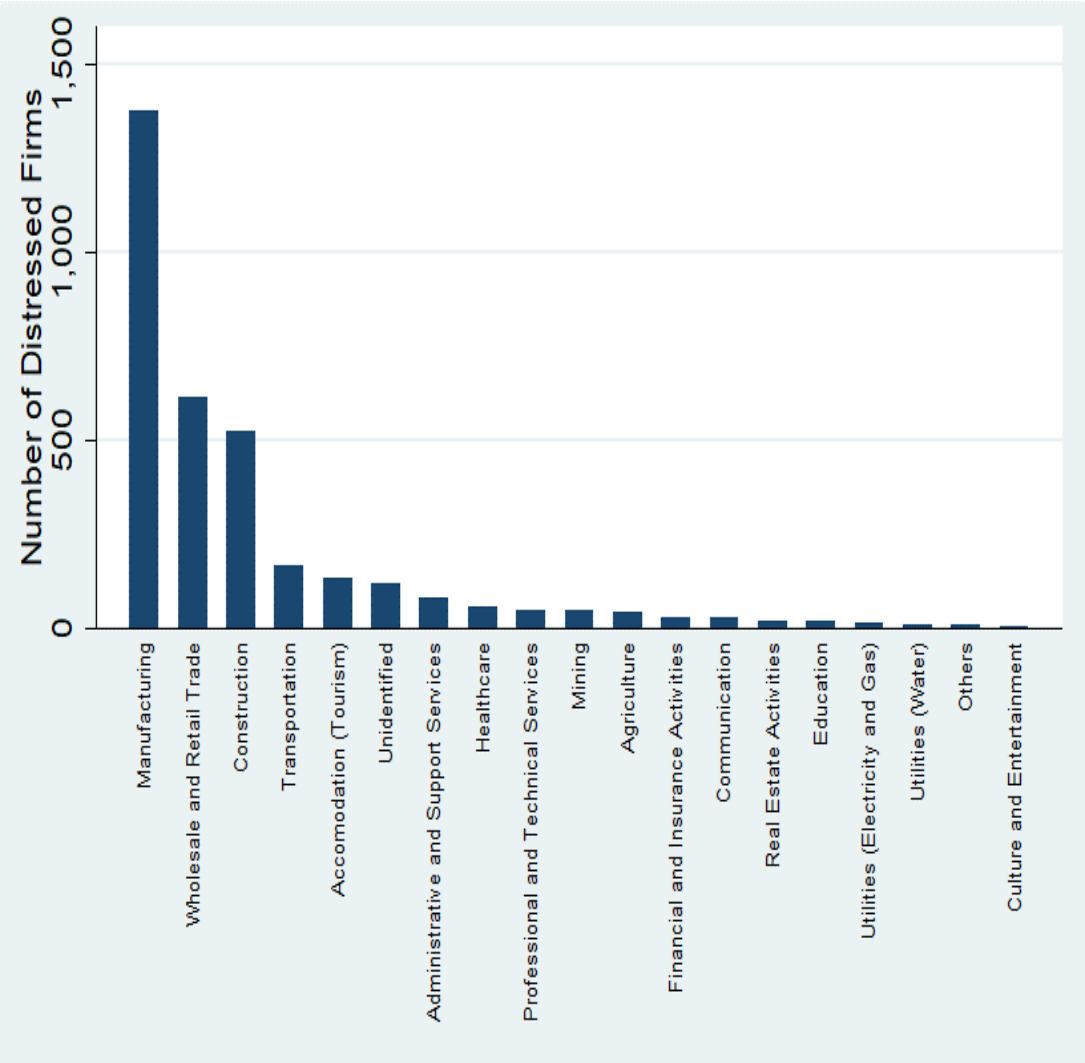



***Figure 8.*** Sectoral Distribution of Financially Distressed Firms (Number of Firm-Years)

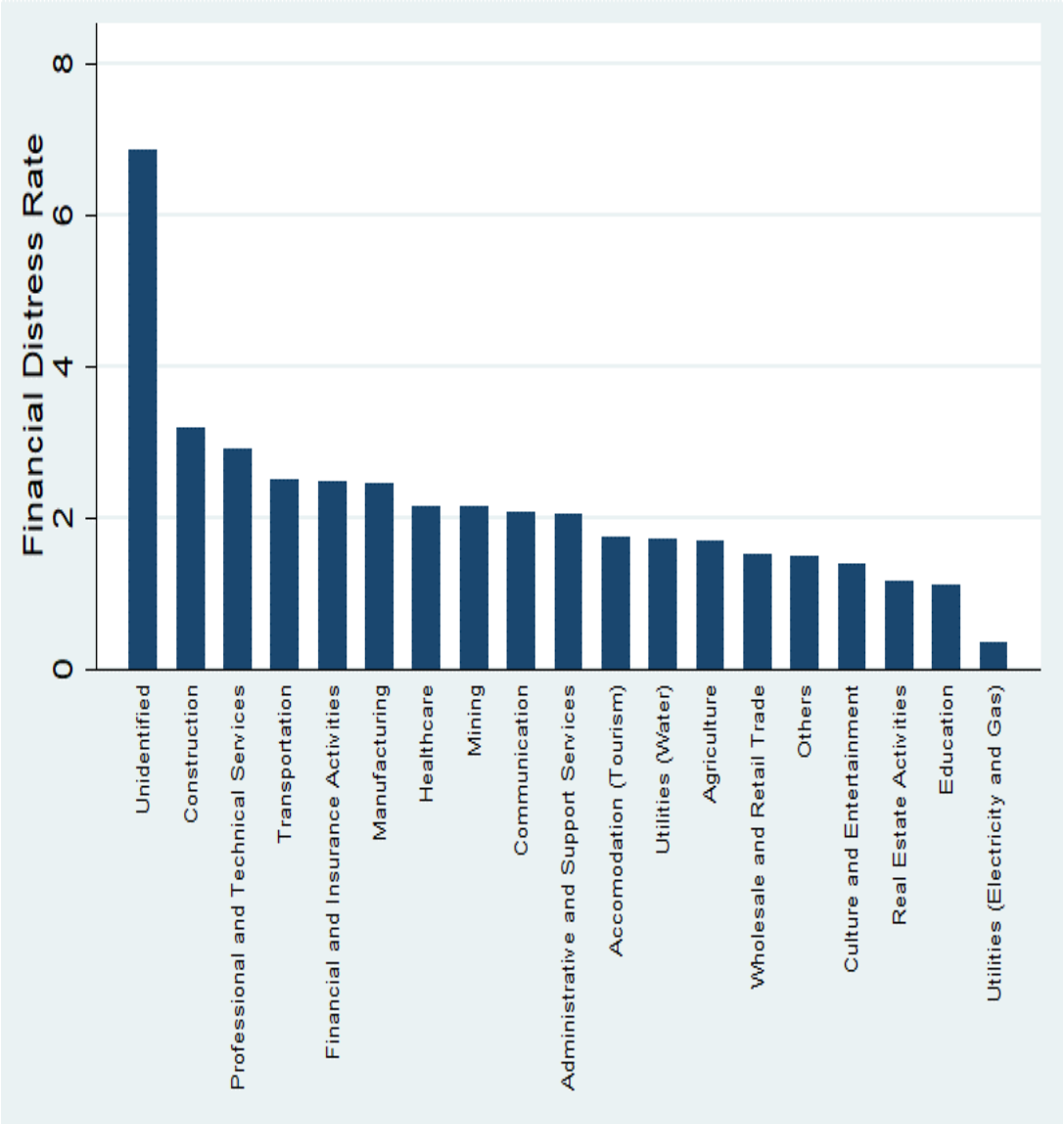



***Figure 9.*** Sectoral Distribution of Financially Distressed Firms (Financial Distress Rate)

To provide input in the firm failure prediction process, further modifications are done by utilizing this derived data set. To be used in univariate analysis and logit regressions, financial ratios are calculated. Considering the fact that the choice of explanatory variables holds importance for the predictive ability and estimation of financial distress models, we undertake additional literature review about the type and definitions of financial ratios used in other studies. In this context, after the examination of 60 studies, as a general finding, existing studies are observed to

associate corporate bankruptcy with accounting-based financial ratios, market data and non-financial corporate governance characteristics. Since an important portion of sample firms are not publically traded, market data does not turn out to be a feasible input. This type of consideration and detailed analysis finally have yielded 42 different financial ratios under six different dimensions of firm financials and operating structure.

- Firm Size
- Liquidity
- Profitability
- Interest Coverage
- Leverage
- Turnover

After the creation of financial ratios, the last step before econometric estimation involves the handling of outliers and extreme values. Due to misreporting and other reasons, our financial ratios are found to contain some outliers which are known to have an influence on estimation results and inferences. Primarily, in the firm failure prediction literature, studies engaging with micro-level data and financial ratios are known to apply specific techniques to handle this issue. Shumway (2001) utilize truncation of the data at $1^{st}$ and $99^{th}$ percentiles. However, truncating observations might cause the loss of valuable information and it is more likely to diminish the number of available observations, particularly for unbalanced data like ours. Another method is winsorizing, which is basically replacing excessive observations with certain percentile values. In fact, Filipe et al. (2016) prefer to use bottom and top 1% tranches for winsorizing. Similarly, Gupta and Gregoriou (2018) conduct winsorizing with the help of $5^{th}$ and $95^{th}$ percentiles. Although, there is no consensus about the degree of winsorizing in the empirical literature, by also considering the large number of observations and micro-level nature of the data, winsorizing is performed with $2^{nd}$ and $98^{th}$ percentiles.

## 3.2 Methodology

### 3.2.1 Univariate Analysis

Before implementing a multivariate analysis, to gain initial insight about the characteristics of financially distressed firms, a univariate investigation is conducted. In terms of bankruptcy prediction studies, Lin and Peese (2001) examine the differentiation of the behavior of their accounting ratios around financial trouble episodes from financially sound firm years by utilizing simple t-test of mean differences. The t-test is also widely preferred in studies like Nam and Jinn (2000) and Nam et al. (2008) for an initial step of the variable selection procedure.

Instead of the traditional paired sample or equal variances t-test setup, our empirical strategy seems to be more suitable with Welch's t-test method. The study of Welch (1947) proposes an adjustment to original t-test setting to account for potential bias in Type I error arisen from the distinctness among sample sizes and variances of different sub-groups. Ruxton (2006) state that Welch's t-test should be the preferred method in evaluating the central tendencies of two non-overlapping samples. Similarly, Overall et al. (1995) oversee the power of Welch's t-test in an experimental setting and validate its acceptability.

The test statistic for assessing the equality of group means ( $\mu_{distressed} = \mu_{non-distressed}$), when group variances $\sigma_{distressed}$ and $\sigma_{non-distressed}$ are assumed to be unknown and unequal, can be described as follows:

$$t = \frac{\bar{x}_{distressed} - \bar{x}_{non-distressed}}{\left(\frac{S_{distressed}^{2}}{n_{distressed}} - \frac{S_{non-distressed}^{2}}{n_{distressed}}\right)^{1/2}} \tag{1}$$

where $\bar{x}$ stands for sample mean, $S$ represents sample variance and $n$ symbolizes the number of observations. Resulting test statistic is distributed as Student's t with degrees of freedom ($v$) adjusted by Welch (1947)'s formula as expressed as follows:

$$v = -2 + \frac{\left(\frac{S_{distressed}}{n_{distressed}}^2 + \frac{S_{non-distressed}}{n_{non-distressed}}^2\right)^2}{\frac{\left(\frac{S_{distressed}}{n_{distressed}}^2\right)^2}{n_{distressed}+1} + \frac{\left(\frac{S_{non-distressed}}{n_{non-distressed}}^2\right)^2}{n_{non-distressed}+1}} \tag{2}$$

As argued by Bhattacharyya and Johnson (1977), a simple t-test procedure is subject to some flaws. In this context, we also apply the Wilcoxon rank-sum test to test the equality of median values belonging to two subgroups defined over our financial distress criteria. It is a non-parametric alternative technique to assess differences in terms of central tendencies. It is valid for data from other distributions, which is something that can not be mentioned for t-test due to dependence normal distribution assumption. It is also deemed to be less sensitive to the existence of outliers and it can capture differences in terms of the shape of the distribution, in addition to central tendency. Studies like Nam et al. (2008) utilize this test complementing simple t-test, especially in univariate analysis and variable selection.

Assuming that data consists of two different groups, in the initial step of Wilcoxon rank-sum test, data is ranked without considering sub-sample structure. Hence, the test statistic depicted by Wilcoxon (1945) is equal to the sum of the ranks coming from the first sub-group observations. Assuming that the first group in our case is distressed firms and number of observations for that group is denoted by $n_{distressed}$:

$$T = \sum_{i=1}^{n_{distressed}} R_{distressed,i} \tag{3}$$

In a similar vein, Mann and Whitney (1947) propose another test statistic which only differs by a constant term that is specified as follows:

$$U = T - \frac{n_{distressed}(n_{distressed} + 1)}{2} \tag{4}$$

In this context, Fisher's principle of randomization is accepted as a common method to calculate the distribution of this test statistic. In detail, randomization process includes $\binom{n}{n_{distressed}}$ ways to select $n_{distressed}$ number of ranks among the set of all ranks ($n$) to be assigned to the first sample. Here, equations (5) and (6) hold for mean and variance of test statistic, respectively:

$$E(T) = \frac{n_{distressed}(n + 1)}{2} \tag{5}$$

$$Var(T) = \frac{n_{distressed} n_{non-distressed} s^2}{n} \tag{6}$$

where $s$ stands for the standard deviation of combined ranks for both subgroups to be examined within whole sample data. Finaly, applying the normal approximation would bring test statistic, expressed in equation (7):

$$z = \frac{T - E(T)}{\sqrt{Var(T)}} \tag{7}$$

### 3.2.2 Variable Selection Methods

To build a parsimonious model in multivariate estimations, we implement three different variable selection techniques by using our broad variable set. The literature review conducted in Chapter 2 has revealed several variable selection methods employed in firm failure prediction studies.

Gupta et al. (2018) choose to run univariate logit regressions and evaluate candidate financial ratios based on average marginal effects and p-value realizations. Filipe et al. (2016) exploit the informative nature of area under receiver operating characteristics (ROC) curve approach as a graphical analysis comparing sensitivity (which is the fraction of correctly specified positive outcome cases) and specificity (which is the fraction of correctly specified negative outcome cases), as explained by Peterson et al. (1954) and Green and Swets (1966). Filipe et al. (2016) also consider correlation analysis and forward stepwise selection procedure to narrow down the candidate list of financial ratios. Altman and Sabato (2007) is another study focusing on the stepwise selection technique based on pre-determined significance level for each variable to satisfy to be included in the ultimate bankruptcy prediction specification. Lin and Peese (2001) apply univariate logit estimations and they report the accuracy rate of individual ratios as additional inputs in the variable selection process. Neophytou et al. (2000) prefer to use a combination of forwards and backward univariate logistic regressions and they assess the statistical significance as well as whether or not signs of coefficients are in line with theoretical and empirical arguments. Rıfqı and Kanazaki (2016) benefit from stepwise logit and MDA analysis to construct ultimate prediction models. Lastly, Nam et al. (2008) proceed with univariate statistical tests of mean/median differences to eliminate some of the financial information.

In line with the literature, the first method we choose is univariate logit regressions. However, in our case, univariate logit estimations are performed for each ratio group separately, while we always proxy firm size with the natural logarithm of total assets in a multivariate setting. For instance, to determine which ratio will be chosen to represent liquidity, 11 financial ratios in our list relevant to liquidity position are evaluated as a first step. Then, the same procedure is applied to ratios belonging to profitability dimensions. Similar statistical analysis is done for five ratios in interest coverage group, seven ratios in leverage group, and four ratios in turnover group. In all of the univariate logit estimations, we check the sign and significance of coefficient, area under ROC curve and log-likelihood values. Then, based on this

criterion, one ratio from each group is selected to be utilized in the multivariate logit model.

The second method to form the multivariate model is using principal component analysis (PCA). It is the most popular multivariate statistical method utilized for data reduction and size compression. It aims to extract the critical information from a comprehensive data set by expressing it as a set of new orthogonal variables called principal components. In this context, the factor representing the highest proportion of the total variation across variables is termed as the first principal component, which embodies the common movements. Technically, in PCA method, we identify the directions in the data with most variation (which are called eigenvectors) and project the data onto these directions.

PCA method handles this issue by conducting spectral decomposition of the correlation (or covariance) matrix of the data. Let D represent the (pxp) correlation matrix to be analyzed. The eigen-decomposition of D can be illustrated as follows in which $k_i$ terms represent eigenvectors (principal components):

$$D = K\Lambda K' = \sum_{i=1}^{p} \lambda_i k_i k_i' \tag{8}$$

$$k_i' k_j = \delta_{ij} \tag{9}$$

$$\lambda_1 \geq \lambda_2 \geq \cdots \geq \lambda_p \geq 0 \tag{10}$$

The widespread use of PCA method in financial economics and forecasting practices is discussed in Stock and Watson (2002), Bai and Ng (2003), Diebold and Li (2006) and Ludvigson and Ng (2009). In fact, similar to first variable selection technique, we implement PCA on each financial ratio category from our data to obtain the first principal component which is known to explain the most of the variation embedded in financial ratios. However, in this way, we are still able to retain the information derived from non-included financial ratios compared to the first selection method.

The third variable selection method is stepwise logistic regression. For this part, we have used the Stata command "swboot" developed by Garrett (2000). It simply composes bootstrapped samples with sizes being equal to the number of non-missing observations so as to validate the choice of candidate variables in the stepwise framework. In other words, one can draw pre-determined bootstrapped samples to conduct backward and forwards stepwise selection concerning pre-specified cut-off significance levels. We utilize this command to perform both backwards and forwards selection procedure on each one of the financial ratio categories separately with 100 drawn samples, and we evaluate the number of times each particular variable is selected under all estimations. As the last step, if the number of times chosen is equal for multiple variables, the correlation matrix among the remaining ones are reviewed to choose the specific ratio with the lowest level of correlations with others. A particular caveat here is that ratios, which included in the first variable selection strategy are not chosen to be included in cases for which stepwise procedure point out those ratios. This precaution is taken to ensure the existence of differed specification within this empirical strategy.

### 3.2.3 Logit Model

After forming specifications, predicting financial failure is estimated with multivariate logit models combining inputs from several financial ratios. Since, discrete choice model is structured with a binary outcome dependent variable defined over whether or not a firm has positive NPL balance, following representation can be presented:

$$Distress_{it} = \begin{cases} 1, & NPL_{it} > 0 \\ 0, & NPL_{it} \leq 0 \end{cases} \tag{11}$$

where dummy variable $Distress_{it} \in \{0,1\}$ governs the firm behavior showing whether or not a firm is encountered financial distress situation for firm i at year t. Thus, the probability of bankruptcy can be formulated as follows:

$$\Pr(Distress_{it} = 1|X_{it}, \alpha) = \Pr(NPL_{it} > 0|X_{it}, \alpha) = \Phi(X_{it}{}'\beta + \alpha) \quad (12)$$

$$\begin{aligned}\Phi(X_{it}{}'\beta + \alpha) = \Phi(\alpha &+ \beta_1 Firm\ Size_{it} + \beta_2 Liquidity_{it} \\ &+ \beta_3 Profitability_{it} + \beta_4 Interest\ Coverage_{it} \\ &+ \beta_5 Leverage_{it} + \beta_6 Turnover_{it})\end{aligned} \quad (13)$$

Here, $\alpha$ stands for the intercept term and $\beta_k$ for k=1 to 6 represent coefficients measuring the effects of firm characteristics of financial distress. In this modeling framework, $\Phi(.)$ is defined as the cumulative distribution function of the logistic distribution. Hence, specification can be represented as the following:

$$\begin{aligned}NPL_{it} = \alpha &+ \beta_1 Firm\ Size_{it} + \beta_2 Liquidity_{it} + \beta_3 Profitability_{it} \\ &+ \beta_4 Interest\ Coverage_{it} + \beta_5 Leverage_{it} \\ &+ \beta_6 Turnover_{it} + \varepsilon_{it} \quad where \quad \varepsilon_{it} \sim^d Logistic\end{aligned} \quad (14)$$

As widely discussed in Cameron and Trivedi (2005), estimation is conducted with a method called maximum-likelihood estimation (MLE). In this context, outcome is governed by Bernoulli distribution, which is the binomial distribution within one-trial setup. A compact notation for density of $Distress_i$ is termed as probability mass function specified as follows:

$$\mathrm{f}(Distress_i|X_i) = p_i^{Distress_i}(1 - p_i)^{1-Distress_i}\ for\ \ Distress_i = 0,1 \quad (15)$$

where $p_i = F(X_i{}'\beta)$, and this equality will yield probabilities $p_i$ and $(1 - p_i)$ considering the fact that $f(1) = p^1(1-p)^0 = p$ as well as $f(0) = p^0(1-p)^1 = 1 - p$. Thus, this density definition will ensure that log density is defined as $\ln f(Distress_i) = Disress_i lnp_i + (1 - Disress_i)\ln(1 - p_i)$. This framework will result in the following log-likelihood function:

$$L(\beta) = \sum_{i=1}^{N}\{Distress_i lnF(X_i{}'\beta) + (1 - Distress_i)\ln(1 - F(X_i{}'\beta))\} \quad (16)$$

When this function is differentiated with respect to $\beta$ and then set it equal to zero, we will obtain MLE estimates of coefficients ($\hat{\beta}_{MLE}$) which satistify the following:

$$\sum_{i=1}^{N}\left\{\frac{Distress_i}{F_i}F_i{}'X_i - \frac{1-Distress_i}{1-F_i}F_i{}'X_i\right\} = 0 \tag{17}$$

Here, $F'(z) = \partial F(z)/\partial z$. Mathematical simplification will create MLE first-order conditions:

$$\sum_{i=1}^{N}\frac{Distress_i - F(X_i{}'\beta)}{F(X_i{}'\beta)\big(1-F(X_i{}'\beta)\big)}F'(X_i{}'\beta)X_i = 0 \tag{18}$$

As explained by Cameron and Trivedi (2005), no explicit solution is available for $\hat{\beta}_{MLE}$. On the other hand, in practice Newton-Raphson iterative algorithm available in econometrics package programs like Stata has resulted in convergence for logit models[4].

Since logistic model has the approach of applying logistic cumulative distribution on probability, MLE condition in equation (18) is transformed into following expression:

$$p = \Lambda(X_i{}'\beta) = \frac{e^{(X_i{}'\beta)}}{1+e^{(X_i{}'\beta)}} \tag{19}$$

$$\sum_{i=1}^{N}\{Distress_i - \Lambda(X_i{}'\beta)\}X_i = 0 \tag{20}$$

where $\Lambda(.)$ defines the logistic cumulative distribution function.

[4] In the context of this thesis, we utilize "logit" and "xtlogit" commands in Stata to obtain estimates.

In addition to the logit model, to account for unobserved heterogeneity across firms and to exploit the longitudinal feature of the data set, we implement panel logit estimations. We prefer to proceed with random-effects panel logit specifications because of some concerns. Firstly, using panel logit embedded with fixed effects would exclude cross-sections for which dependent variable stay the same across all years. In other words, we will not be able to make inferences for firm years which correspond to "all distressed" or "all non-distressed" observations over the course of the sample period. Hence, the majority of our sample will be lost due to the high persistence feature of financial distress. Secondly, it would be infeasible to contain time-invariant variables like industry information in fixed-effects estimation.

Lastly, after estimating multivariate logit models, a quantitative scoring tool to monitor the financial stability of real sector firms are obtained in the following way. Linear prediction derived from the logit model as a weighted sum of parameter estimates and covariate realizations will be equal to what is called "logit". This concept is equivalent of the logarithm of the odds ratio that is the division of the "probability of experiencing financial distress" to the "one minus same probability value". From this equivalence, probability values can be derived, as demonstrated in equation (21):

$$\begin{aligned} logit = \log(Odds\ Ratio) &= \log\left({p_{it}}/{1 - p_{it}}\right) \\ &= \hat{\alpha} + \hat{\beta}_1 Firm\ Size_{it} + \hat{\beta}_2 Liquidity_{it} + \hat{\beta}_3 Profitability_{it} \\ &+ \hat{\beta}_4 Interest\ Coverage_{it} + \hat{\beta}_5 Leverage_{it} \\ &+ \hat{\beta}_6 Turnover_{it} \end{aligned} \tag{21}$$

### 3.2.4 Survival Analysis

To further understand the dynamics of time to firm bankruptcy and the impact of firm financials on the period till encountering financial distress, as the last component of empirical estimations, we conduct survival analysis. As argued by Cameron and

Trivedi (2005) and Cleves et al. (2010), parametric survival models are appropriate for data structure displaying features like delayed entry, gaps, time-varying explanatory variables as well as multiple-failure cases. Thus, they are implemented in our setting. Especially, because our micro-level data set is unbalanced, covered firms sometimes have multiple NPL observations, and covariates (firm financials) are changing over the course of the sample period, parametric models are assessed to be more suitable for inference purposes. After declaring the survival-time structure of our data set, we proceed by estimating accelerated failure time (AFT) models with two different parametric survival distributions, which are exponential and Weibull[5]. Here, the natural logarithm of survival duration is specified as a linear function of explanatory variables bringing the following representation:

$$log\ t_j = X_j{}'\beta + z_j \tag{22}$$

In this context, $X_j$ refers to the vector of covariates, which cover the same dimensions as univariate and logit analysis. In other words, we are testing the impact of firm size, liquidity, profitability, interest coverage, leverage and turnover on survival time. $\beta$ and $z_j$ stand for vector of regression coefficients and error term, respectively. Here, error term is assumed to have density function $f(.)$ being shaped by extreme value density to yield exponential and Weibull models.

Weibull hazard and survivor functions can be described as in equation (23) and (24). On the other hand, when shape parameter $p$ is being equated to 1, then hazard and survivor functions of exponential model are derived.

$$h(t) = p\lambda t^{p-1} \tag{23}$$

$$S(t) = \exp(-\lambda t^{p}) \tag{24}$$

[5] "stset" command in Stata is used to declare the survival-time nature of data set by taking our financial distress variable (defined over NPL data) as failure indicator and firm codes (IGSNO) as id indicator.

On the other hand, the parameterization of AFT model estimaton and ancillary parameters are listed in the Table 1.

**Table 1.**

Survival Model Parameterization

| Distribution | Survivor Function | Parameterization | Ancillary Parameter |
|---|---|---|---|
| Exponential | $\exp(-\lambda_j t_j)$ | $\lambda_j = \exp(-X_j{}'\beta)$ | |
| Weibull | $\exp(-\lambda_j {t_j}^p)$ | $\lambda_j = \exp(-pX_j{}'\beta)$ | $p$ |

# CHAPTER 4

# EMPIRICAL RESULTS

This chapter initially presents the empirical results of univariate analysis and variable selection process. In the upcoming parts, multivariate logistic regressions results for selected specifications are evaluated and discussed. In the following section of this chapter, in-sample and holdout sample predictive power of constructed models are investigated as well. While fourth sub-section provides survival analysis results, last part conducts a general discussion about empirical results.

## 4.1 Univariate Results

Table 2 presents results supporting the differentiation of firm size proxy and liquidity indicators as we move from financially distressed firms to healthier ones. As indicated in the previous chapter in which data descriptions are provided, the natural logarithm of total assets has been chosen to measure firm size, while we also adjust for the effect of price changes as well by dividing total assets with consumer price index (CPI) realizations of the Turkish economy. When we examine the mean and median values within two sub-group of our sample, firms facing with financial troubles (selected via the existence of NPL in our empirical strategy) appear to be very similar to financially sound ones regarding the size and scope of firm operations.

However, liquidity ratios with varied definitions point out substantial discrepancies among two sub-group. First three ratios are very similar to each other in gauging to what extent short-term and more liquid assets can cover fund outflows if there exists a need to pay back entire current liabilities. They only differ in terms of which current assets items are included in that kind of analysis. While cash ratio is only involved with cash, cash equivalents and marketable securities; quick ratio incorporates

accounts receivables; whereas current ratio has the broadest specification in which even inventories are covered. For these ratios, without exception, it can be inferred that bankrupt firms have a lower level of liquidity buffers compared to their financially healthy counterparts. T-test and Wilcoxon rank-sum test results display the statistical significance of this divergence.

In addition to these three traditional ratios, the existence of liquid assets in firms' balance sheets are also examined with ratios embodying net working capital (NWC), which can be calculated as the difference between current assets and current liabilities. When this capital is normalized with financial information in a stock form such as total assets and liabilities, obtained central tendency measures and univariate testing procedures turn out to be in line with our expectations drawing a frame for more liquid structures. Albeit this finding, when a flow variable of total sales is utilized for normalization, results are found to be somewhat mixed. We also review other, more specific liquidity ratios available in our master variable set. Firm failure incidents are also determined as cases in which less cash is held and less trade credit is obtained.

**Table 2.**

Test Results for Mean and Median Differences
(Firm Size and Liquidity Ratios)

| Variable | Mean (Distressed) | Mean (Non-Distressed) | Median (Distressed) | Median (Non-Distressed) | t-test | Wilcoxon Rank-Sum Test |
|---|---|---|---|---|---|---|
| Firm Size | 11.556 | 11.537 | 11.486 | 11.468 | -0.714 | -0.442 |
| Current Ratio | 1.625 | 2.293 | 1.062 | 1.293 | 14.925*** | 21.446*** |
| Quick Ratio | 1.096 | 1.591 | 0.725 | 0.889 | 15.587*** | 17.488*** |
| Cash Ratio | 0.164 | 0.454 | 0.018 | 0.104 | 29.620*** | 34.852*** |
| Inventory/NWC | 0.039 | 0.768 | 0.515 | 0.402 | 4.285*** | 14.168*** |
| NWC/Total Assets | 0.029 | 0.145 | 0.035 | 0.139 | 20.501*** | 21.364*** |
| NWC/Total Liabilities | 0.226 | 0.586 | 0.044 | 0.208 | 20.047*** | 22.954*** |
| NWC/Total Sales | 0.279 | 0.263 | 0.054 | 0.116 | -0.302 | 10.340*** |
| Cash/Total Assets | 0.053 | 0.100 | 0.009 | 0.042 | 25.156*** | 31.851*** |
| AR/Total Liabilities | 0.319 | 0.426 | 0.201 | 0.300 | 16.296*** | 13.098*** |
| NWC/Operating Expenses | 3.678 | 3.848 | 0.539 | 1.417 | 0.408 | 11.880*** |
| Current Assets/Total Assets | 0.604 | 0.627 | 0.655 | 0.681 | 4.695*** | 4.532*** |

Another dimension of our variable list aims to monitor firms' ability to generate earnings from the operations for sustainable growth and prospects. In fact, Earnings Before Interest and Tax (EBIT) is an item in the income statement directly quantifying the income generation of operating activities as we only deduce overhead, management, operating and marketing expenses to reach the EBIT figures in financial statements. Hence, the ratio of EBIT to total assets is widely used as an indicator of profitability. Mean and median values for this ratio clearly shows that distressed firm/year observations seem to be much less profitable (Table 3). When one wants to improve profitability analysis from the static framework, cumulative profitability of a firm can be observed from retained earnings account in equity part of the balance sheet, which does not only involve the current earnings but also past non-reinvested ones. Here, univariate test results also validate the argument that financially healthy firms have better profitability positions. As our variable list permits, we also check the univariate results belonging to ratios including bottom-line profitability i.e., net income, normalized with financial statement aggregates. The superiority of the profitability outlook for financially sound firms is also confirmed by t-test and Wilcoxon rank-sum test results.

Gross profit represents the operational income generation by deducting the Cost of Goods Sold (COGS) for manufacturing firms. Its division by total sales would create the gross margin indicator. When we resolve this ratio, it is ascertained that failed firms are working with much narrower margins compared to non-failed companies. As a different representation of margin structure, the ratio of COGS to total sales emerges to be larger for failed firms indicating more costly production processes and eroded profitability.

**Table 3.**

Test Results for Mean and Median Differences (Profitability Ratios)

| Variable | Mean (Distressed) | Mean (Non-Distressed) | Median (Distressed) | Median (Non-Distressed) | t-test | Wilcoxon Rank-Sum Test |
|---|---|---|---|---|---|---|
| EBIT/Total Assets | 0.007 | 0.050 | 0.004 | 0.043 | 29.129*** | 31.956*** |
| Retained Earnigs/Total Assets | -0.150 | -0.013 | -0.023 | 0.001 | 24.751*** | 26.552*** |
| Net Income/Total Sales | -0.324 | -0.098 | -0.013 | 0.013 | 14.255*** | 27.827*** |
| Net Income/Total Assets | -0.037 | 0.014 | -0.004 | 0.014 | 26.264*** | 32.872*** |
| Net Income/Fixed Assets | -0.340 | 0.367 | -0.024 | 0.071 | 14.230*** | 31.729*** |
| Net Income/Total Equity | 0.048 | 0.071 | 0.016 | 0.064 | 1.915* | 13.930*** |
| Gross Profit/Total Sales | 0.172 | 0.196 | 0.117 | 0.142 | 5.221*** | 11.881*** |
| Gross Profit/Total Assets | 0.087 | 0.167 | 0.046 | 0.129 | 35.887*** | 35.167*** |
| EBIT/Total Liabilities | 0.022 | 0.117 | 0.005 | 0.064 | 29.361*** | 32.792*** |
| Net Income/Total Liabilities | -0.023 | 0.080 | -0.005 | 0.020 | 27.660*** | 32.629*** |
| Net Income/Net Sales | -0.334 | -0.101 | -0.013 | 0.014 | 14.287*** | 27.759*** |
| EBIT/Current Liabilities | 0.032 | 0.177 | 0.008 | 0.089 | 25.433*** | 31.209*** |
| Net Income/Current Liabilities | -0.058 | 0.093 | -0.007 | 0.028 | 21.095*** | 31.167*** |
| COGS/Total Sales | 0.804 | 0.781 | 0.862 | 0.837 | -4.923*** | -10.232*** |

As a next step, we inspect the characteristics of failed companies in terms of short-term debt-paying ability. In this context, interest coverage ratios are used as important indicators. The most popular one is EBIT to financial expenses ratio which shows that to what extent operational profits are proportionate to financial expenses incurred including interest paid on outstanding bank loans, dividends distributed by firm management and bond coupon payments made to debtholders if any exists. Although the overall debt level of a company may not hint any unbalances for the medium or longer-term horizon, the inability to undertake immediate payments to cover shorter-term financing expenses would seriously impair financial health and cause firm failure. Our univariate test results provided in Table 4 suggest that non-distressed firms have comparably robust EBIT to financial expenses ratio, while distressed firms carry lower coverage ratios. Except for the financial expenses to total liabilities ratio, all other interest coverage ratios applying some normalization to financing expenses

would also result in statistically significant differences among financially healthy and unhealthy companies.

**Table 4.**

Test Results for Mean and Median Differences (Interest Coverage Ratios)

| Variable | Mean (Distressed) | Mean (Non-Distressed) | Median (Distressed) | Median (Non-Distressed) | t-test | Wilcoxon Rank-Sum Test |
|---|---|---|---|---|---|---|
| EBIT/Financial Expenses | 3.191 | 10.198 | 0.311 | 1.504 | 11.107*** | 29.320*** |
| Financial Expenses/Total Assets | 0.038 | 0.031 | 0.022 | 0.021 | -9.995*** | -4.932*** |
| Financial Expenses/Total Sales | 0.148 | 0.072 | 0.044 | 0.021 | -15.718*** | -20.455*** |
| Financial Expenses/Total Liabilities | 0.049 | 0.047 | 0.030 | 0.034 | -2.570** | 1.553 |
| Financial Expenses/Net Sales | 0.152 | 0.073 | 0.045 | 0.021 | -15.908*** | -20.497*** |

Leverage ratios contain information about the long-term debt-paying ability of examined companies. More specifically, the more the degree of debt financing against internally generated sources or equity-type funds is inflated, the more amplified the possibility to experience financial instability. Two traditional ratios representing the leverage position are equity to liabilities and equity to assets ratios, both of which are higher for non-distressed firm/year observations emphasizing that their leverage risks are lower (Table 5). On the other hand, when common equity is considered as sole shareholders' fund item in the calculation of leverage ratio, results are not compatible with intuition. However, when alternative definitions are chosen to construct leverage ratios such as the share of total liabilities and long-term liabilities in "credit" side of the balance-sheet, financially distressed firms appear to carry a high level of debt. These findings stay same for ratios displaying the financial debt by excluding other types of liabilities.

Lastly, the dissimilarity between failed and non-failed observations are analyzed in terms of operational performance by evaluating the univariate results for turnover ratios (Table 6). These measures are designed to monitor how well companies are utilizing their assets and resources to generate sales and potential income stream. T-

test and Wilcoxon rank-sum test results show that asset utilization is relatively better for financially healthy firms as proxied by four selected financial ratios.

**Table 5.**

Test Results for Mean and Median Differences (Leverage Ratios)

| Variable | Mean (Distressed) | Mean (Non-Distressed) | Median (Distressed) | Median (Non-Distressed) | t-test | Wilcoxon Rank-Sum Test |
|---|---|---|---|---|---|---|
| Total Equity/Total Liabilities | 0.756 | 1.361 | 0.211 | 0.429 | 15.825*** | 26.442*** |
| Total Equity/Total Assets | 0.207 | 0.340 | 0.174 | 0.301 | 25.980*** | 26.445*** |
| Common Equity/Total Assets | 0.338 | 0.274 | 0.247 | 0.207 | -12.410*** | -13.136*** |
| Total Liabilities/Total Assets | 0.792 | 0.659 | 0.825 | 0.699 | -25.980*** | -26.445*** |
| Long-Term Liabilities/Total Assets | 0.226 | 0.177 | 0.144 | 0.080 | -11.283*** | -12.841*** |
| Financial Debt/Total Assets | 0.327 | 0.309 | 0.278 | 0.284 | -3.887** | -3.293** |
| Long-Term Financial Debt/Total Assets | 0.210 | 0.198 | 0.114 | 0.064 | -2.929** | -7.278** |

**Table 6.**

Test Results for Mean and Median Differences (Turnover Ratios)

| Variable | Mean (Distressed) | Mean (Non-Distressed) | Median (Distressed) | Median (Non-Distressed) | t-test | Wilcoxon Rank-Sum Test |
|---|---|---|---|---|---|---|
| Total Sales/Total Assets | 0.757 | 1.244 | 0.506 | 0.974 | 30.735*** | 30.135*** |
| Receivables Turnover Ratio | 0.747 | 0.323 | 0.280 | 0.178 | -23.091*** | -23.158*** |
| COGS/Inventory | 18.26 | 25.950 | 2.960 | 4.951 | 6.48*** | 19.814*** |
| Net Sales/NWC | 1.425 | 4.615 | 0.110 | 2.506 | 10.231*** | 22.530*** |

## 4.2 Variable Selection Results

As outlined before, the first method used to extract financial information in the initial variable list is to assess the diagnostics and statistical significance of univariate logit regressions. In Table 7, we present findings related to liquidity ratios. First inputs to be examined are the sign and statistical significance of coefficients in logit regressions

with one-variable specifications. It seems that current, quick and cash ratios have coefficients accompanied with negative coefficients, which is compatible with expectations claiming that stronger liquidity buffers would evaporate the high probability of experiencing financial distress. Similar findings are seen for liquidity ratios using NWC as a numerator and denominator in liquidity ratios, except for NWC to total sales ratio, which has positive and insignificant coefficient contracting with postulations and existing literature. The ratio of NWC to operating expenses also lacks statistical significance.

In addition to this criterion, we further investigate the predictive power of individual liquidity ratios measured by area under the ROC curve. It is known that the ROC curve for an empirical binary outcome model without any predictive ability is featured with $45^0$ line. Thus, as the area beneath the curve is enlarged, more inference is made from utilized models. In other cases, predictive power is thought to underperform. For instance, Lin and Piesse (2001) report that their univariate logit estimations have resulted in area values, which either stay below 50% or hover around that threshold. They argue that this finding validates the inability of univariate setting in evaluating bankruptcy and financial distress.

In our case, for the overwhelming majority of individual logit regressions, areas under the ROC curve indicate the improvement derived from using liquidity ratios regarding empirical classification power. When these ratios are ranked according to this measure, the cash ratio is chosen as the ratio representing the liquidity position of real sector firms. It is also seen that this ratio also produces comparably higher log-likelihood value.

The abovementioned procedure is repeated for 14 profitability ratios in our data set (Table 8). Signs of coefficients obtained from univariate logit models are broadly in line with our presupposition that strengthened profitability creation would contribute to decreasing probability of entering into the phase of financial distress. The coefficient for COGS to sales ratio is positive, but it is not a contradiction, given the

fact that the construction of this ratio is different from others in the sense that any increase in the ratio corresponds to weakening in profitability. Statistical significance is also retained across all profitability ratios. Hence, similar to the previous group, variable selection is based on area under ROC curve. The gross profit to total assets ratio is found to carry higher predictive power measured by this indicator.

**Table 7.**

Diagnostics of Univariate Logit Estimations (Liquidity Ratios)

| Variable | Sign | Significance | Area Under ROC Curve | Log-Likelihood |
|---|---|---|---|---|
| Current Ratio | - | *** | 0.6082 | -16094.312 |
| Quick Ratio | - | *** | 0.5884 | -16050.032 |
| **Cash Ratio** | **-** | ***** | **0.6782** | **-15562.053** |
| Inventory/NWC | - | *** | 0.5716 | -16136.152 |
| NWC/Total Assets | - | *** | 0.6078 | -15944.483 |
| NWC/Total Liabilities | - | *** | 0.6158 | -16030.826 |
| NWC/Total Sales | + | | 0.4467 | -15526.155 |
| Cash/Total Assets | - | *** | 0.6628 | -15557.273 |
| AR/Total Liabilities | - | *** | 0.5661 | -16064.337 |
| NWC/Operating Expenses | - | | 0.5605 | -15884.261 |
| Current Assets/Total Assets | - | *** | 0.5229 | -16180.042 |

**Table 8.**

Diagnostics of Univariate Logit Estimations (Profitability Ratios)

| Variable | Sign | Significance | Area Under ROC Curve | Log-Likelihood |
|---|---|---|---|---|
| EBIT/Total Assets | - | *** | 0.6612 | -15802.185 |
| Retained Earnigs/Total Assets | - | *** | 0.6348 | -15487.260 |
| Net Income/Total Sales | - | *** | 0.6434 | -15388.013 |
| Net Income/Total Assets | - | *** | 0.6658 | -15750.704 |
| Net Income/Fixed Assets | - | *** | 0.6609 | -15852.129 |
| Net Income/Total Equity | - | ** | 0.5703 | -16187.186 |
| Gross Profit/Total Sales | - | *** | 0.5612 | -15505.455 |
| **Gross Profit/Total Assets** | **-** | ***** | **0.6774** | **-15647.839** |
| EBIT/Total Liabilities | - | *** | 0.6654 | -15934.647 |
| Net Income/Total Liabilities | - | *** | 0.6646 | -15889.054 |
| Net Income/Net Sales | - | *** | 0.6434 | -15388.013 |
| EBIT/Current Liabilities | - | *** | 0.6575 | -16007.829 |
| Net Income/Current Liabilities | - | *** | 0.6572 | -16021.253 |
| COGS/Sales | + | *** | 0.5528 | -15472.354 |

To come up with specific ratio proxying short-term debt-paying ability, univariate logistic regressions are run for interest coverage ratios (Table 9). EBIT to financial expenses ratio has a positive and significant coefficient suitable for ratio definition and expectations. Other four ratios incorporating financial expenses in the numerator and normalize it with the different balance sheet and income statement items have resulted in positive and significant coefficients, which also validate the contribution of large financial costs incurred to the likelihood of financial distress. However, are under the ROC curve measures show a distinctive performance favoring the first ratio. Hence, EBIT to financial expenses ratio is chosen to represent interest coverage in the multivariate specification.

**Table 9.**

Diagnostics of Univariate Logit Estimations (Interest Coverage Ratios)

| Variable | Sign | Significance | Area Under ROC Curve | Log-Likelihood |
|---|---|---|---|---|
| **EBIT/Financial Expenses** | **-** | ******* | **0.6586** | **-14084.817** |
| Financial Expenses/Total Assets | + | *** | 0.5249 | -16033.722 |
| Financial Expenses/Total Sales | + | *** | 0.6057 | -15267.084 |
| Financial Expenses/Total Liabilities | + | *** | 0.4921 | -16097.758 |
| Financial Expenses/Net Sales | + | *** | 0.6059 | -15262.592 |

Since they are essential indicators for debt burden carried by firms, leverage ratios are expected to have massive statistical significance which is verified by the results in Table 10. While the first three ratios embody the capital held by the firms, we expect these ratios to have positive coefficients. While it is valid for equity to liabilities and equity to assets ratios, common equity to assets ratio turns out to have a positive coefficient. Hence, we discard this ratio in the variable selection process. Remaining ratios are direct measurements of leverage, so they have expected negative coefficients and statistical significance yielding the conclusion that sizeable liabilities and financial debt are associated with inflated probability of bankruptcy. Again, area under the ROC curve is utilized in combination with log-likelihood as a ranking criterion, which suggests the use of total liabilities to total assets ratio.

**Table 10.**

Diagnostics of Univariate Logit Estimations (Leverage Ratios)

| Variable | Sign | Significance | Area Under ROC Curve | Log-Likelihood |
|---|---|---|---|---|
| Total Equity/Total Liabilities | - | *** | 0.6334 | -16091.766 |
| Total Equity/Total Assets | - | *** | 0.6334 | -15772.946 |
| Common Equity/Total Assets | + | *** | 0.5663 | -16098.968 |
| **Total Liabilities/Total Assets** | **+** | ***** | **0.6334** | **-15772.934** |
| Long-Term Liabilities/Total Assets | + | *** | 0.5641 | -16120.463 |
| Financial Debt/Total Assets | + | *** | 0.5167 | -15976.866 |
| Long-Term Financial Debt/Total Assets | + | *** | 0.5359 | -16017.659 |

As the last component of our multivariate framework, asset utilization and performance ratios are examined by referring to univariate logit regression diagnostics. In this context, sign, significance and ROC curve criterion reveal the predictive power of sales to assets ratio as an ultimate indicator of operational performance. In this regard, the increases in turnover record seem to decrease the likelihood of firm failure.

**Table 11.**

Diagnostics of Univariate Logit Estimations (Turnover Ratios)

| Variable | Sign | Significance | Area Under ROC Curve | Log-Likelihood |
|---|---|---|---|---|
| **Total Sales/Total Assets** | **-** | ***** | **0.6521** | **-15779.873** |
| Receivables Turnover Ratio | + | *** | 0.6194 | -14991.342 |
| COGS/Inventory | - | *** | 0.6038 | -14991.249 |
| Net Sales/NWC | - | *** | 0.6136 | -16156.713 |

As described in the previous chapter, the variable selection process is further augmented with the use of PCA as a data compression method. Instead of choosing one ratio from each group based on logit regression diagnostics and predictive power, we try to summarize the informative content of all ratios in sub-groups. Thus, we implement the PCA analysis incrementally on all dimensions of firm financials/operations. In this context, we select the first principal component obtained from PCA applications. Table 12 presents the informative nature of those components

by reporting the percentage of total variance explained by selected static factors to be added to multivariate logit models. Highest successes in summarizing total variation are obtained for interest coverage and leverage ratios.

**Table 12.**

PCA Results

| Ratio Group | Percentage of Total Variance Explained by First Component |
|---|---|
| Liquidity | 41.19% |
| Profitability | 39.71% |
| Interest Coverage | 50.00% |
| Leverage | 53.15% |
| Turnover | 36.23% |

The third variable selection method is termed as bootstrap stepwise logistic regressions. We repeat stepwise estimations for 100 drawn samples for both backward and forwards selection[6]. Then, the number of times a particular financial ratio is chosen in these repetitive exercises are reported. The ratios which are found to be always included in estimations with drawn samples are initially separated.

In the following step, the correlation matrix for the ratios are examined. The ones with a lower level of correlation with others are chosen. In the last step, in order to establish a multivariate specification differing from the one derived in the first variable selection technique, we tend to exclude ratios selected in that method. Hence, the ultimate specification is constructed with highlighted ratios in upcoming tables (Table 13 to 17).

[6] The p-value criteria for the inclusion of financial ratios is specified as 0.005, whereas the p-value criteria for the exclusion of financial ratios is specified as 0.01.

**Table 13.**

Number of Times of Inclusion in Bootstrap Stepwise Estimations
(Liquidity Ratios)

| Variable | Backward Selection | Forwards Selection |
|---|---|---|
| Current Ratio | 36 | 20 |
| Quick Ratio | 94 | 79 |
| Cash Ratio | 100 | 85 |
| Inventory/NWC | 83 | 75 |
| NWC/Total Assets | 100 | 100 |
| NWC/Total Liabilities | 36 | 28 |
| NWC/Total Sales | 100 | 100 |
| **Cash/Total Assets** | **100** | **100** |
| AR/Total Liabilities | 100 | 100 |
| NWC/Operating Expenses | 98 | 100 |
| Current Assets/Total Assets | 100 | 100 |

**Table 14.**

Number of Times of Inclusion in Bootstrap Stepwise Estimations
(Profitability Ratios)

| Variable | Backward Selection | Forwards Selection |
|---|---|---|
| EBIT/Total Assets | 73 | 84 |
| Retained Earnigs/Total Assets | 100 | 100 |
| Net Income/Total Sales | 0 | 1 |
| **Net Income/Total Assets** | **100** | **100** |
| Net Income/Fixed Assets | 4 | 3 |
| Net Income/Total Equity | 49 | 38 |
| Gross Profit/Total Sales | 98 | 71 |
| Gross Profit/Total Assets | 100 | 100 |
| EBIT/Total Liabilities | 95 | 29 |
| Net Income/Total Liabilities | 100 | 69 |
| Net Income/Net Sales | 3 | 3 |
| EBIT/Current Liabilities | 93 | 32 |
| Net Income/Current Liabilities | 100 | 70 |
| COGS/Sales | 99 | 74 |

**Table 15.**

Number of Times of Inclusion in Bootstrap Stepwise Estimations
(Interest Coverage Ratios)

| Variable | Backward Selection | Forwards Selection |
|---|---|---|
| EBIT/Financial Expenses | 100 | 100 |
| **Financial Expenses/Total Assets** | **100** | **100** |
| Financial Expenses/Total Sales | 41 | 28 |
| Financial Expenses/Total Liabilities | 100 | 100 |
| Financial Expenses/Net Sales | 99 | 98 |

**Table 16.**

Number of Times of Inclusion in Bootstrap Stepwise Estimations
(Leverage Ratios)

| Variable | Backward Selection | Forwards Selection |
|---|---|---|
| Total Equity/Total Liabilities | 100 | 100 |
| Total Equity/Total Assets | 100 | 100 |
| Common Equity/Total Assets | 100 | 100 |
| Total Liabilities/Total Assets | 100 | 100 |
| Long-Term Liabilities/Total Assets | 100 | 100 |
| **Financial Debt/Total Assets** | **100** | **100** |
| Long-Term Financial Debt/Total Assets | 100 | 100 |

**Table 17.**

Number of Times of Inclusion in Bootstrap Stepwise Estimations
(Turnover Ratios)

| Variable | Backward Selection | Forwards Selection |
|---|---|---|
| Total Sales/Total Assets | 100 | 100 |
| **Accounts Receivables/Total Sales** | **100** | **100** |
| COGS/Inventory | 23 | 14 |
| Net Sales/NWC | 96 | 95 |

### 4.3 Logit Model Results

Although, univariate analysis can produce descriptive insight about the relationship between bankruptcy and firm characteristics, multivariate models allow us to interpret the impact of one particular variable on firm failure, while controlling for the influence of other variables. More crucially, multivariate models are designed for prediction and forecasting tasks. Thus, our process of creating a quantitative scoring tool for real sector financial distress is based on results provided in this part.

By using the specifications retrieved from three different variable selection procedure, logit and panel logit models are estimated to predict a dichotomous dependent variable of financial distress[7]. As it may be recalled, in the first specification, cash ratio, gross profit to assets ratio, EBIT to financial expenses ratio, liabilities to assets ratio and total sales to assets ratio are chosen to deputize for financial outlook dimensions. In the first numbered column of Table 18, most basic model results are provided. In the second and third columns, logit models controlling for time effects and industry effects are presented. In the last column, estimation results belonging to random-effects panel logit model are given.

We find mixed results about the explanatory power of firm size. It is not found to have a statistically significant effect on the probability of experiencing financial distress revealed by baseline logit model and augmented versions with different controls. However, when panel logit estimation is applied for inference, the negative and significant coefficient is encountered hinting that, as the firm size gets larger, the likelihood of having financial distress might decrease. Regarding the cash ratio indicator, estimation results show that more liquid companies are also the ones with a lower level of likelihood to face with unhealthy financial outlook. Findings are robust to the use of dummy variables to account for the cross-section-invariant macroeconomic effects and industrial characteristics. Moreover, when firm-level

[7] Correlation matrices of these coefficients are provided in the Appendix to assess any possible multicollinearity issues.

unobserved heterogeneity is controlled by panel logit method, the coefficient is still determined to be negative, suggesting the contribution of liquidity buffers to cope with firm failure. In this specification, profitability is proxied by gross profit to assets ratio and the coefficient on that variable is found to be negative across all modeling choices in a significant manner. In other words, more profitable firms are less likely to experience firm failure. This validates the previous empirical literature and hypothesis of this study, claiming that profit generation is an important input for financial distress prediction.

As another component of financial outlook, EBIT to financial expenses ratio has been chosen to stand for short-term debt-paying ability. Due to structure of this ratio designed to serve as an indirect representation of interest coverage (compared to other ratios in that sub-group), we expect this ratio to have negative coefficient as higher EBIT compared to financial costs would improve the interest coverage and contribute to the financial health. However, as seen in Table 18, this variable has an insignificant and positive coefficient. On the other hand, we choose to keep this variable in the model specification since omitting it might decrease the accuracy level of the model, which will be relevant to the next tasks in the empirical analysis. When results for leverage is examined, it is seen that higher liabilities to assets ratio inflates the probability of facing financial distress, as expected. This finding is robust across different models. Lastly, the turnover ratio has a significant and negative coefficient implying that operational performance and asset utilization can mitigate the higher risk of being confronted with financial distress. Robustness of these analyses is further evaluated with a specification in which both time and industry effects are controlled. Results provided in the Appendix show that the direction of the relations between financial distress and explanatory variables as well as the significance stay broadly similar.

**Table 18.**

Logit Regression Results (Variable Selection: Univariate Logit)

| | (1)<br>Logit | (2)<br>Logit | (3)<br>Logit | (4)<br>Panel Logit |
|---|---|---|---|---|
| Firm Size | 0.0017<br>(0.0150) | 0.0045<br>(0.0148) | 0.0137<br>(0.0158) | -0.2099***<br>(0.0317) |
| Liquidity | -0.7253***<br>(0.1099) | -0.7075***<br>(0.1086) | -0.6892***<br>(0.1125) | -0.5797***<br>(0.0750) |
| Profitability | -3.0171***<br>(0.2702) | -3.0148***<br>(0.2656) | -3.3936***<br>(0.2985) | -4.3912***<br>(0.3380) |
| Interest Coverage | 0.0002<br>(0.0005) | 0.0002<br>(0.0005) | 0.0003<br>(0.0006) | 0.0010<br>(0.0008) |
| Leverage | 1.5709***<br>(0.1008) | 1.7385***<br>(0.1004) | 1.8092***<br>(0.1071) | 2.4737***<br>(0.1512) |
| Turnover | -0.3331***<br>(0.0309) | -0.3471***<br>(0.0311) | -0.4102***<br>(0.0383) | -0.5353***<br>(0.0470) |
| Time Effects | No | Yes | No | No |
| Industry Effects | No | No | Yes | No |
| No. of Observations | 137743 | 137743 | 137711 | 137743 |
| McFadden's Adj. R-square | 0.068 | 0.080 | 0.085 | |
| LR Test for Rho | | | | 4434.93*** |
| Log-Likelihood | -12874.116 | -12698.165 | -12626.196 | -10656.651 |

Constant term is included in the regressions. Robust standard errors are provided in the parantheses. ***, ** and * represent statistical significance at 1%, 5% and 10%, respectively.

Same logit and panel logit estimations are also repeated for the specification constructed with second variable selection technique (Table 19). In this case, explanatory variables are simply the first principal components obtained from ratio groups. Similar to the first set of multivariate estimations results, the impact of firm size is again found to be vague given the fact that three logit models yield positive coefficient with inferior significance level, whereas panel logit model suggests negative and highly significant coefficient. Thus, a cautionary approach should be embraced in interpreting the role of firm size. As expected, the static factor representing liquidity turns out to be significantly and inversely related to the probability of bankruptcy. The direction of the relation, magnitude of the coefficient and statistical significance of the impact are not subject to substantial alterations as dummy variables are included and estimation technique is switched to panel logit.

In line with the hypothesis and previous works, improvements in firm profitability, represented by rises in the first principal component derived from that group, decreases the likelihood of financial distress. On the other hand, considering the fact that only one ratio in interest coverage group (EBIT to financial expenses ratio) has indirect representation while other three has direct compositions, one would expect the increases in this factor should represent improvements regarding short-term debt-paying ability. Hence, positive coefficient is anticipated in this case, which is somewhat different from the interpretation in first set of multivariate estimations. However, while coefficients are found to be positive, only the one retrieved from panel logit estimation is significant, suggesting the diminishing role of improved interest coverage on financial distress probability. Furthermore, high leverage is found to induce more probability of bankruptcy, as demonstrated by the positive and significant coefficients in Table 19. Lastly, the static factor representing the turnover dimension is determined to decrease the likelihood of having financial distress. When both time and industry dummies are introduced to the baseline logit specification, results appear to be robust for which no significant deviation from the estimated coefficients of the baseline model is observed (see the Appendix). From PCA analysis, it is inferred that second principal components in each of the financial ratio categories can also be derived.[8] The results belonging to logit estimations embedded with second static factors are presented in the Appendix.

[8] In this context, second static factors in liquidity, profitability, interest coverage, leverage and turnover categories explain 14.76%, 16.73%, 18.63%, 22.90% and 24.49% of the total variation, respectively.

**Table 19.**

Logit Regression Results (Variable Selection: PCA)

| | (1)<br>Logit | (2)<br>Logit | (3)<br>Logit | (4)<br>Panel Logit |
|---|---|---|---|---|
| Firm Size | 0.0298*<br>(0.0155) | 0.0298*<br>(0.0154) | 0.0412**<br>(0.0163) | -0.1382***<br>(0.0316) |
| Liquidity | -0.1433***<br>(0.0127) | -0.1417***<br>(0.0128) | -0.1627***<br>(0.0146) | -0.1615***<br>(0.0217) |
| Profitability | -0.2025***<br>(0.0112) | -0.2001***<br>(0.0112) | -0.2117***<br>(0.0118) | -0.2714***<br>(0.0178) |
| Interest Coverage | 0.0002<br>(0.0121) | 0.0134<br>(0.0121) | 0.0140<br>(0.0127) | 0.0384**<br>(0.0190) |
| Leverage | 0.0804***<br>(0.0124) | 0.1164***<br>(0.0128) | 0.1153***<br>(0.0138) | 0.1273***<br>(0.0227) |
| Turnover | -0.4298***<br>(0.0180) | -0.4498***<br>(0.0179) | -0.4380***<br>(0.0205) | -0.6250***<br>(0.0284) |
| Time Effects | No | Yes | No | No |
| Industry Effects | No | No | Yes | No |
| No. of Observations | 126920 | 126920 | 126897 | 126920 |
| McFadden's Adj. R-square | 0.078 | 0.089 | 0.092 | |
| LR Test for Rho | | | | 3855.450*** |
| Log-Likelihood | -11631.182 | -11487.490 | -11433.984 | -9703.4564 |

Constant term is included in the regressions. Robust standard errors are provided in the parantheses. ***, ** and * represent statistical significance at 1%, 5% and 10%, respectively.

The last set of multivariate estimations is done for the specification with stepwise variable selection method (Table 20). In this context, cash to assets ratio, net income to assets ratio, financial expenses to assets ratio, financial debt to assets ratio, and accounts receivables to sales ratio describe multiple dimensions of financial outlook. Mixed results for firm size variable are observed in these estimations. On the other hand, firms' tendency to hold more cash reserves normalized by firm assets seem to decrease the probability of bankruptcy. Superior ability of profit generation stemming from rises in net income to asset ratio is also determined to reduce the probability of firm failure.

More strikingly, in contrast to previous sets of multivariate estimations, increases in financial expenses are found to harm the financial health and inflate the likelihood of financial distress. Moreover, if firms carry more massive financial debt in their balance sheets, the probability of facing financial distress is more pronounced. Lastly,

the turnover ratio turns out to have a significant and positive coefficient. This finding is also compatible with expectations and previous results. Since ratio for this dimension is chosen to be accounts receivables to sales ratio, increases in this indicator would mean that more sales are made on trade credit terms which are not directly channeled into profitability and equity capital items of firm financials. Hence, rises in this ratio are associated with deterioration of operational productivity and performance, thus ultimately leading to propagated financial distress. Results do not change when both time and industry controls are integrated into model specifications (see the Appendix).

**Table 20.**

Logit Regression Results (Variable Selection: Bootstrap Stepwise)

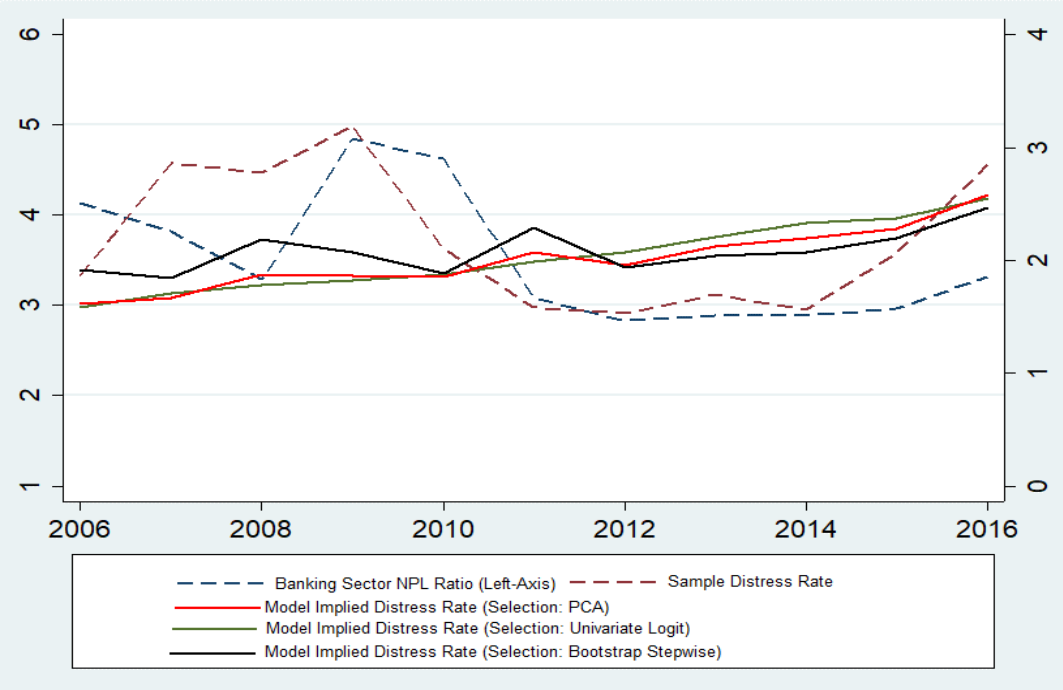
| | (1)<br>Logit | (2)<br>Logit | (3)<br>Logit | (4)<br>Panel Logit |
|---|---|---|---|---|
| Firm Size | 0.0242*<br>(0.0136) | 0.0278**<br>(0.0136) | 0.0348**<br>(0.0142) | -0.0852***<br>(0.0269) |
| Liquidity | -2.8073***<br>(0.2623) | -2.8220***<br>(0.2640) | -2.8128***<br>(0.2683) | -2.8314***<br>(0.2934) |
| Profitability | -4.4586***<br>(0.1872) | -4.5730***<br>(0.1900) | -4.6178***<br>(0.1925) | -5.8568***<br>(0.2887) |
| Interest Coverage | 4.2937***<br>(0.5915) | 3.3905***<br>(0.5962) | 3.7458***<br>(0.6099) | 4.0047***<br>(0.8718) |
| Leverage | 0.4338***<br>(0.0837) | 0.2698***<br>(0.0856) | 0.2660***<br>(0.0873) | 0.4318***<br>(0.1384) |
| Turnover | 0.5743***<br>(0.0175) | 0.5788***<br>(0.0175) | 0.5861***<br>(0.0200) | 0.8682***<br>(0.0340) |
| Time Effects | No | Yes | No | No |
| Industry Effects | No | No | Yes | No |
| No. of Observations | 149332 | 149332 | 149295 | 149332 |
| McFadden's Adj. R-square | 0.068 | 0.075 | 0.079 | |
| LR Test for Rho | | | | 4982.21*** |
| Log-Likelihood | -14100.834 | -13987.574 | -13914.674 | -11609.729 |

Constant term is included in the regressions. Robust standard errors are provided in the parantheses. ***, ** and * represent statistical significance at 1%, 5% and 10%, respectively.

After forming and assessing these competing models, in-sample prediction and out-of-sample forecasting exercises are performed to gain more knowledge about the predictive ability of logit framework. To this end, as specified in the methodology part, baseline versions of logit models with varied variable selection techniques are utilized. In the first step, we obtain the predicted probabilities implied by these selected models. Then, graphical analysis is conducted for the averages of sample distress variable along with model-implied distress probabilities.

In Figure 10, the banking sector NPL ratio is also scattered with sample financial distress rate. Although there are some level differences obviously due to the formation of our sample and its differentiation from the whole population of troubled loans, we observe a close co-movement between sample distress rate and banking sector total NPL ratio, depicted by dark red and blue dotted lines. While both have increasing trend during GFC era and its implications on Turkish economy in the form of decline in domestic investments, deterioration in economic growth and downfall in exporting activities have all caused a surge in unpaid loans of manufacturing firms.

However, aftermath the GFC, rebound in economic activity coupled with the wave of macroprudential policies have created a downward trend in the sample-specific financial distress and banking sector aggregate NPL rate. Towards the end of our sample period, a rebound in financial distress is also observed measured by the increasing number of unpaid loans, possibly due to the geopolitical events and accompanied downward pressure in economic activity and financial stability. When we examine the average annual distressed rate composed of model-implied probabilities, it is seen that they are closely tracking the sample distress rate realizations during the investigated time period. However, in-sample predictive power turns out to be insufficient, especially for the respective hike in distress rate around GFC.




Source: BRSA, Author's Calculations.

***Figure 10***. Sample and Model-Implied Financial Distress Rates

Since abovementioned graphical analysis is based on average values of predicted probabilities, it can provide some initial insights, but formal in-sample analysis based on classification diagnostics of logit model should be performed for robust inferences on firm-level data. Threshold probability value to decide whether or not predicted probability for a particular firm-year observation implies financial distress situation is determined empirically from estimations themselves. To this end, Stata routine named "cutpt" developed by Clayton (2013) is implemented, based on the Liu (2012)'s non-parametric method searching for the optimal cut-off point maximizing the objective function, which is shown to perform well through simulation studies. In the context of failure prediction, utilized procedure oversees the maximization of the product of sensitivity (percentage of correctly classified distressed firms) and specificity (percentage of correctly classified non-distressed firms), so it helps to determine the optimal cut-off probability values for each of the multivariate logit estimations. By choosing these values, the in-sample predictive ability is investigated for the whole sample period covering 2006-2016 interval. In other words, cut-off probability values are basically obtained such that it maximizes following equality:

$$Liu\ Index = Sensitivity * Specificity \tag{25}$$

In addition to this, some of the studies in the literature is also analyzing the predictive power of models for pseudo-out-of-sample periods. In this context, logit models are initially run by using an estimation period from 2006 to 2014. Then, predicted probabilities from these estimations are created for the holdout (out-of-sample) period covering 2015-2016 interval. In the ultimate step, we manually categorize the observations within this interval by using the cut-off probability values obtained from in-sample analysis to determine the share of firms identified in a correct manner with respect to financial distress.

For the logit model established with the first variable selection procedure, the empirical optimal cut-off point is found to be 0.02149584. Graphical analysis for the determination of threshold probability is also provided in the Appendix. In this framework, the logit model seems to properly classify almost 71% of all financially distressed firms throughout the whole sample period (Table 21). For the correct identification of non-distressed companies, predictive power is found to be around 65%. Studies like Lin and Piesse (2001), Okay (2015), Brezigar-Masten et al. (2018), designate the overall accuracy rate as the simple average of predictive values exempted from type I and type II error, By following a similar method, total accuracy performance of the multivariate logit model created from first variable selection procedure (univariate logit) is determined to be 67%. On the other hand, when estimations are made for holdout sample, the ability to detect distressed firms in a correct manner has been increased to almost 74%, whereas exact identification of non-distressed firms has been mildly decreased to 56%. These findings add up total accuracy rate of 65% for the out-of-sample forecasting exercise.

As a complementary analysis, we implement prediction and forecasting exercises for the multivariate logit model designed with the inputs of the second variable selection method, which is PCA (Table 22). By considering Clayton (2013)'s empirical criteria, the optimal cut-off point is chosen to be 0.02185763. Here, the model underperforms

the first logit model since the percentage of correctly identified financially troubled firms is around 66% for in-sample analysis. On the other hand, 72% of all financially healthy firms are indeed detected as non-distressed in line with this logit model. However, when forecasting analysis is considered, the predictive performance of the model is slightly diminished given in-sample and out-of-sample accuracy rates are dropped to 63% and 68%, respectively.

Lastly, the logit model formed with third variable selection method (bootstrap stepwise) is investigated with respect to the cut-off point corresponding to 0.01966878 (Table 23). While approximately 65% of all distressed firms are confirmed to be financially problematic, 68% of all non-distressed firm years are determined to be financially healthy regarding in-sample prediction. Moreover, for forecasting ability, this logit model correctly sets 68% and 62% of all distressed firms and non-distressed firms, respectively. All in all, the logit model designed with the first variable selection procedure turns out to be the one with slightly better performance when prediction and forecasting results are reviewed.

**Table 21.**

Predictive Power of Logit Regression Model
(Variable Selection: Univariate Logit)

In-Sample Prediction

| | Distressed | Non-Distressed |
|---|---|---|
| Distressed | 70.79 | 35.75 |
| Non-Distressed | 29.21 | 64.25 |
| | Total Accuracy | 67.52 |

Out-of-Sample Forecasting

| | Distressed | Non-Distressed |
|---|---|---|
| Distressed | 73.72 | 44.11 |
| Non-Distressed | 26.28 | 55.89 |
| | Total Accuracy | 64.81 |

**Table 22.**

Predictive Power of Logit Regression Model (Variable Selection: PCA)

In-Sample Prediction

| | Distressed | Non-Distressed |
|---|---|---|
| Distressed | 66.38 | 27.96 |
| Non-Distressed | 33.62 | 72.04 |
| | Total Accuracy | 69.21 |

Out-of-Sample Forecasting

| | Distressed | Non-Distressed |
|---|---|---|
| Distressed | 63.21 | 31.96 |
| Non-Distressed | 36.79 | 68.04 |
| | Total Accuracy | 65.63 |

**Table 23.**

Predictive Power of Logit Regression Model
(Variable Selection: Bootstrap Stepwise)

In-Sample Prediction

| | Distressed | Non-Distressed |
|---|---|---|
| Distressed | 64.70 | 32.00 |
| Non-Distressed | 35.30 | 68.00 |
| | Total Accuracy | 66.35 |

Out-of-Sample Forecasting

| | Distressed | Non-Distressed |
|---|---|---|
| Distressed | 68.32 | 37.91 |
| Non-Distressed | 31.68 | 62.09 |
| | Total Accuracy | 65.20 |

## 4.4 Survival Analysis Results

Since first model specification derived from univariate logit variable selection methodology is found to perform better in terms of in-sample prediction and out-of-sample forecasting practices for financial distress, we choose to implement parametric survival regression with this particular specification. As it may be recalled from analyses above, it includes firm size, cash ratio, gross profit to assets ratio, EBIT to financial expenses ratio, liabilities to assets ratio, and sales to assets ratio.

Firstly, parametric survival model with Weibull distribution is estimated. Coefficients in terms of AFT metric are provided in Table 24. These coefficients can be interpreted in the sense that if sign attached to them is positive, then the time to financial distress is decelerated by an increase in respective covariate. In this case, firm size is found to have a positive coefficient pointing out the fact that as the firm size grows, it causes a delay in bankruptcy. Furthermore, companies with strong liquidity buffers and better performance of creating profits would end up with increased expected time until the occurrence of financial distress. Although, results display insignificant relation between interest coverage and bankruptcy for this specification, any increase in firm leverage seems to be transmitted to acceleration in time by shortening the time period till financial distress. Lastly, the significant decelerating impact of turnover in firm operations is evident from survival analysis with the Weibull regression model.

From another perspective, the same results can be interpreted through hazard ratios, which are also presented in Table 24. Here, whenever the hazard ratio stays above 1, the hazard rate for firm bankruptcy is increased given one unit rise in explanatory variables. Since hazard ratio values for firm size, liquidity and profitability are all less than 1, it can be said that hazard rate for financial distress will be decreased for larger firms with abundant liquid assets and voluminous profits. On the other hand, as the hazard ratio for leverage is far above the threshold of 1, any increase in leverage would result in an increase in hazard rate. As a last finding from this part, there exists a downward impact of better turnover rates for the hazard rate of firm bankruptcy.

This estimation can also produce survivor and cumulative hazard functions to describe the survival dynamics of financial distress (Figure 11). It is found that survival rate decreases steadily from earlier years towards year 11 (which marks the end of the sample period in this study). For instance, if a firm survives up to 10 years without encountering financial distress, the probability of going bankrupt decreases to almost 95%.

In the next step, the survival model is re-estimated with exponential distribution assumption (see the Appendix). In contrast to the Weibull model, the impact of firm size turns out to be insignificant. However, liquidity and profitability are still determined to be significant drivers of time to financial distress. In fact, both coefficients expressed in AFT metric and hazard ratio results are in line with the expectation that firms with stronger liquidity and profitability are characterized with a deceleration in time manifested in further delays in time to financial distress. Similar to Weibull results and logit model results in previous sections, this particular specification does not produce statistically significant relation between interest coverage and firm bankruptcy. Furthermore, coefficient and hazard ratio of firm leverage variable are found to support the hypothesis that higher leverage would shorten the time until financial distress events. As the last finding, improvements in turnover of firm operations are associated with increasing time to bankruptcy. Survivor and cumulative hazard functions for this estimation are presented in the Appendix.

**Table 24.**

Survival Analysis Results (Weibull)

| | Coefficient | Std. Error | Hazard Ratio |
|---|---|---|---|
| Firm Size | 0.0277** | 0.0141 | 0.9627 |
| Liquidity | 0.5239*** | 0.0958 | 0.4877 |
| Profitability | 2.2580*** | 0.2477 | 0.0453 |
| Interest Coverage | 0.0002 | 0.0005 | 0.9997 |
| Leverage | -0.9238*** | 0.0922 | 3.5461 |
| Turnover | 0.1374*** | 0.0243 | 0.8283 |
| No. of Observations | 134550 | | |
| Log Pseudo-Likelihood | -6460.587 | | |
| p (Shape Parameter) | 1.3702 | | |

Constant term is included in the regressions. Robust standard errors are provided in the parantheses. ***, ** and * represent statistical significance at 1%, 5% and 10%, respectively.

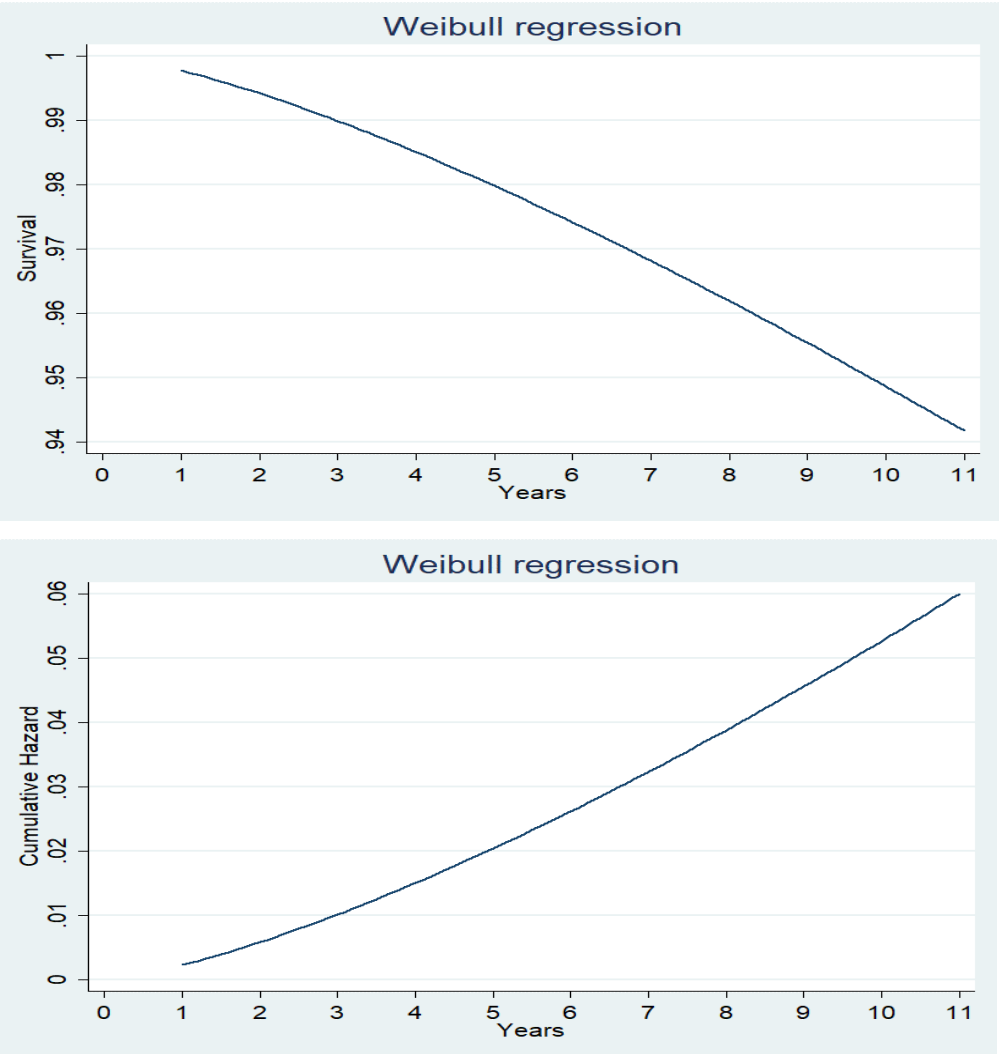



***Figure 11.*** Survivor and Cumulative Hazard Functions (Weibull)

## 4.5 General Discussion about Empirical Results

To generate a multivariate framework to be used in evaluating default risk, initial set of financial ratios is selected containing inputs from different dimensions of firm financials such as firm size, liquidity, profitability, interest coverage, leverage and turnover. Parametric and non-parametric univariate tests are used to analyze the differentiation between distressed and non-distressed firms with respect to firm features. Indeed, financially troubled firms appear to have low level of liquidity and less efficient profit generation process. Moreover, they are also associated with low interest coverage and considerably more debt burden, while they are utilized their assets in an inferior manner.

To perform more comprehensive analysis, our methodology includes multivariate logit estimations. However, since our initial ratio set is broad and varied, variable selection techniques such as univariate logit/area under the ROC curve, PCA and bootstrap stepwise logit are all applied to decide about competing ratio definitions and to form ultimate specifications. Logit and panel logit models estimated from these specifications show that likelihood of bankruptcy is negatively affected by strong liquidity buffers and ability to generate more profits. On the other hand, as expected, deterioration in short-term debt paying ability (interest coverage) and long-term debt paying ability (leverage) are found to increase the probability of financial distress, albeit slight differences are observed across specifications. Operational performance is detected as a factor which provides significant improvements on financial distress.

In addition to determining the statistical significance and model diagnostics of multivariate setting, both in-sample and out-of-sample exercises are performed to conclude whether or not abovementioned logit models can capture financial distress realizations based on threshold probability values obtained from empirical methods. It is determined that model specification whose covariates are chosen based on univariate logit has highest in-sample predictive power to detect financially distressed Turkish real sector firms covered in our micro-data. On the other hand, when

financially healthy firms are considered, model formed with PCA variable selection has the best-performing identification for in-sample investigation. The procedure with which estimation sample is narrowed down and forecasts are produced for holdout sample, model formulated with univariate logit estimations still turn out to be superior to other alternatives in identifying financially distressed firms, whereas model whose variable are determined by PCA is associated with lower level of errors in detecting non-distressed companies.

The insight brought by logit models is also supported with the help of survival analysis. By using parametric survival regression models specified with Weibull and exponential distribution, on the top of the probability of firm failure, the contribution of firm financials to time to bankruptcy is investigated. Working with the model specification produced by first variable selection technique (univariate logit), we have found robust results about the increasing impact of liquidity, profitability and turnover on the time to financial distress, wheras leverage significantly decrease it.

# CHAPTER 6

# CONCLUSIVE REMARKS

Anticipating the occurrence of financial instability have been relevant to several stakeholders including regulatory government agencies, commercial banks, equity analysts and academic parties. As non-financial business entities perform profound duties in the formation of economic activity, the creation of value added chain and the utilization of financing opportunities; any distrubances observed in the financial health of such firms should be closely monitored. Hence, a rich literature has been formed with varied methodologies and data sets to come up with a quantitative tool to approximate the factors contributing to the probability of financial distress. Although, this field had been widely dominated by multivariate scoring tools such as MDA, microeconometric models such as binary outcome specifications have also been utilized frequently.

This thesis aims to provide new approach in financial distress modelling on different perspectives. Firstly, data sets with larger number of observations are considered for more robust inference. Previous studies specifically focusing on Turkish real sector firms had to use publically traded firms quoted in BIST given the unavailability of firm-level micro data sets. This study exploits the financial information embedded in Company Accounts database compiled by CBRT, which allows considerably larger number of observations to be exploited.

Secondly, considering the importance of banking sector in financial intermediation activities and financial system formation in Turkey, our broad financial distress definition is different from other measures and it has been designed to reflect the credit risk of companies via NPLs. In other words, the information reflecting the deterioration in real sector firms' financial outlook through the existence of unpaid

loans is matched with balance sheet and income statement items, which are ultimately used to create financial ratios and explanatory variables. Another micro-level data set, called Credit Registry, is preferred to formulate financial distress definition.

Thirdly, this thesis aims to combine different empirical methodologies by including, not only the univariate tests and multivariate binary outcome models, but also multiple variable selection techniques and survival analysis. The top-to-bottom approach embraced with the use of multiple variable selection methods is thought to strengthen the robustness of the results. Additionally, on the top of the probability of engaging in financial distress situation, the time to firm failure is associated with financial ratio covariates via the parametric duration models.

All in all, this thesis undertakes a comprehensive empirical investigation for predicting firm failure. Although, several alternatives are available for modelling choices and variable selection, major findings indicate the informative nature of financial ratios derived from firm-level micro data set for the occurrence of distress events defined from the commercial loan data. Apart from validating the impact of firm financial outlook sub-components such as liquidity, profitability, interest coverage, leverage and turnover, ultimate product of our analysis is a quantitative tool including a scoring mechanism to monitor financial stability of real sector firms.

## REFERENCES


Abdennadher, E., & Hellara, S. (2018). Causality and contagion in emerging stock markets. *Borsa Istanbul Review*, 18(4), 300-311.

Adrian, T., Covitz, D., & Liang, N. (2015). Financial stability monitoring. *Annual Review of Financial Economics*, 7, 357-395.

Altman, E. I. (1968). Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance*, 23(4), 589-609.

Altman, E. I., Eom, Y. H., & Kim, D. W. (1995). Failure prediction: evidence from Korea. *Journal of International Financial Management and Accounting*, 6(3), 230-249.

Altman, E. I., Haldeman, R. G., & Narayanan, P. (1977). ZETATM analysis A new model to identify bankruptcy risk of corporations. *Journal of Banking and Finance*, 1(1), 29-54.

Altman, E. I., & Sabato, G. (2007). Modelling credit risk for SMEs: Evidence from the US market. *Abacus*, 43(3), 332-357.

Baggs, J., Beaulieu, E., & Fung, L. (2009). Firm survival, performance, and the exchange rate. *Canadian Journal of Economics/Revue canadienne d'économique*, 42(2), 393-421.

Bai, J., & Ng, S. (2007). Determining the number of primitive shocks in factor models. *Journal of Business and Economic Statistics*, 25(1), 52-60

Barnes, P. (1982). Methodological implications of non-normally distributed financial ratios. *Journal of Business Finance and Accounting*, 9(1), 51-62.

Baş, M., & Çakmak, Z. (2012). Gri ilişkisel analiz ve lojistik regresyon analizi ile işletmelerde finansal başarısızlığın belirlenmesi ve bir uygulama. *Anadolu Üniversitesi Sosyal Bilimler Dergisi*, 12(3), 63-82.

Beaver, W. H. (1966). Financial ratios as predictors of failure. *Journal of Accounting Research*, 71-111.

Beck, T., Klapper, L. F., & Mendoza, J. C. (2008). The typology of partial credit guarantee funds around the world. *The World Bank*.

Bhattacharjee, A., & Han, J. (2014). Financial distress of Chinese firms: Microeconomic, macroeconomic and institutional influences. *China Economic Review*, 30, 244-262.

Bhattacharyya, G. K., & Johnson, R. A. (1977). Statistical methods and concepts. *New York: Wiley Series in Probability and Statistics*.

Brezigar-Masten, A., Masten, I., & Volk, M. (2018). Evaluating the performance of dynamic and tobit models in predicting credit default. *Bank of Slovenia Working Papers*, 2018/1.

Buehler, S., Kaiser, C., & Jaeger, F. (2006). Merge or fail? The determinants of mergers and bankruptcies in Switzerland, 1995–2000. *Economics Letters*, 90(1), 88-95.

Caceres, C., Carriere-Swallow, M. Y., & Gruss, B. (2016). Global financial conditions and monetary policy autonomy. *International Monetary Fund*.

Cameron, A. C., & Trivedi, P. K. (2005). Microeconometrics: methods and applications. *Cambridge University Press*.

Chan, K. C., & Chen, N. F. (1991). Structural and return characteristics of small and large firms. *The Journal of Finance*, 46(4), 1467-1484.

Chancharat, N., Davy, P., McCrae, M. S., & Tian, G. G. (2007). Firms in financial distress, a survival model analysis. *In 20th Australasian Finance & Banking Conference*.

Charitou, A., Neophytou, E., & Charalambous, C. (2004). Predicting corporate failure: empirical evidence for the UK. *European Accounting Review*, 13(3), 465-497.

Chen, P., & Semmler, W. (2018). Financial stress, regime switching and spillover effects: Evidence from a multi-regime global VAR model. *Journal of Economic Dynamics and Control*, 91, 318-348.

Clayton, P. (2013). Cutpt: Stata module for empirical estimation of cutpoint for a diagnostic test. *Statistical Software Components S457719, Boston College Department of Economics*.

Cleves, M. A., W. W. Gould, R. G. Gutierrez, and Y. V. Marchenko. (2010). An introduction to survival analysis using Stata. College Station, TX: Stata Pres.

Cox, D. R. (1972). Regression models and life-tables. *Journal of the Royal Statistical Society: Series B (Methodological)*, 34(2), 187-202.

Curcuru, S. E., Kamin, S. B., Li, C., & Rodriguez, M. (2018). International spillovers of monetary policy: Conventional policy vs. quantitative easing. *FRB International Finance Discussion Papers*, (1234).

Çolak, M. S. (2019). A New Index Score for the Assessment of Firm Financial Risks. *CBRT Working Papers*, No. 1904.

De Bock, R., & Demyanets, M. A. (2012). Bank asset quality in emerging markets: Determinants and spillovers (No. 12-71). *International Monetary Fund*.

Dedola, L., Karadi, P., & Lombardo, G. (2013). Global implications of national unconventional policies. *Journal of Monetary Economics*, 60(1), 66-85.

Diebold, F. X., & Li, C. (2006). Forecasting the term structure of government bond yields. *Journal of Econometrics*, 130(2), 337-364.

Dungey, M., & Gajurel, D. (2014). Equity market contagion during the global financial crisis: Evidence from the world's eight largest economies. *Economic Systems*, 38(2), 161-177.

Eisenbeis, R. A. (1977). Pitfalls in the application of discriminant analysis in business, finance, and economics. *The Journal of Finance*, 32(3), 875-900.

Filipe, S. F., Grammatikos, T., & Michala, D. (2016). Forecasting distress in European SME portfolios. *Journal of Banking and Finance*, 64, 112-135.

Fitzpatrick, J., & Ogden, J. P. (2011). The detection and dynamics of financial distress. *International Review of Finance*, 11(1), 87-121.

Flagg, J. C., Giroux, G. A., & Wiggins Jr, C. E. (1991). Predicting corporate bankruptcy using failing firms. *Review of Financial Economics*, 1(1), 67-75.

Foreman, R. D. (2003). A logistic analysis of bankruptcy within the US local telecommunications industry. *Journal of Economics and Business*, 55(2), 135-166.

Garrett, J. (2000). Swboot: Stata module to bootstrap stepwise linear or logistic regression models. *Statistical Software Components S415601, Boston College Department of Economics*.

Gepp, A., & Kumar, K. (2008). The role of survival analysis in financial distress prediction. *International Research Journal of Finance and Economics*, 16(2008), 13-34.

Gerantonis, N., Vergos, K., & Christopoulos, A. (2009). Can altman Z-score model predict business failures in Greece?. *In Proceedings of the 2nd International Conference: Quantitative and Qualitative Methodologies in the Economic and Administrative Sciences (p. 149)*. Christos Frangos.

Gertler, M., & Karadi, P. (2013). Qe 1 vs. 2 vs. 3...: A framework for analyzing large-scale asset purchases as a monetary policy tool. *International Journal of Central Banking*, 9(1), 5-53.

Green, D. M., & Swets, J. A. (1966). Signal detection theory and psychophysics (Vol. 1). *New York: Wiley*.

Gupta, J., & Gregoriou, A. (2018). Impact of market-based finance on SMEs failure. *Economic Modelling*, 69, 13-25.

Gupta, J., Gregoriou, A., & Ebrahimi, T. (2018). Empirical comparison of hazard models in predicting SMEs failure. *Quantitative Finance*, 18(3), 437-466.

Gül, S. (2017). Türkiye'de parasal aktarım kanallarının işleyişi: Bilanço kanalı. Doctoral Dissertation, Yıldız Technical University.

Gül, S., & Taştan, H. (2018). The impact of monetary policy stance, financial conditions, and the GFC on investment-cash flow sensitivity. *CBRT Working Papers*, No. 1811.

Iwanicz-Drozdowska, M., Jackowicz, K., & Kozłowski, Ł. (2018). SMEs' near-death experiences. Do local banks extend a helping hand?. *Emerging Markets Review*, 37, 47-65.

Johnson, R. A., & Wichern, D. W. (1982). Applied multivariate statistical analysis Prentice Hall. Inc.: Englewood Cliffs, NJ.

Kauffman, R. J., & Wang, B. (2008). Tuning into the digital channel: evaluating business model characteristics for Internet firm survival. *Information Technology and Management*, 9(3), 215-232.

Keasey, K., Pindado, J., & Rodrigues, L. (2014). The determinants of the costs of financial distress in SMEs. *International Small Business Journal*, 33(8), 862-881.

Keasey, K., & Watson, R. (1991). Financial distress prediction models: A review of their usefulness. *British Journal of Management*, 2(2), 89-102.

Kocisova, K., & Misankova, M. (2014). Discriminant analysis as a tool for forecasting company's financial health. *Procedia-Social and Behavioral Sciences*, 110, 1148-1157.

Kulalı, İ. (2016). Altman z-score modelinin bist şirketlerinin finansal başarısızlık riskinin tahmin edilmesinde uygulanması. *Uluslararası Yönetim, İktisat ve İşletme Dergisi*, 12(27), 283-292.

Kumar, P. R., & Ravi, V. (2007). Bankruptcy prediction in banks and firms via statistical and intelligent techniques: A review. *European Journal of Operational Research*, 180(1), 1-28.

Laitinen, E. K., & Laitinen, T. (1998). Cash management behavior and failure prediction. *Journal of Business Finance and Accounting*, 25(7-8), 893-919.

Lane, W. R., Looney, S. W., & Wansley, J. W. (1986). An application of the Cox proportional hazards model to bank failure. *Journal of Banking and Finance*, 10(4), 511-531.

Lau, A. H. L. (1987). A five-state financial distress prediction model. *Journal of Accounting Research*, 127-138.

Lavigne, R., Sarker, S., & Vasishtha, G. (2014). Spillover effects of quantitative easing on emerging-market economies. *Bank of Canada Review*, 2014(Autumn), 23-33.

Lifschutz, S., & Jacobi, A. (2010). Predicting bankruptcy: evidence from Israel. *International Journal of Business and Management*, 5(4), 133.

Lin, L., & Piesse, J. (2001). The identification of corporate distress: a conditional probability analysis approach. Birkbeck, University of London, School of Management and Organizational Psychology.

Ludvigson, S. C., & Ng, S. (2009). Macro factors in bond risk premia. *The Review of Financial Studies*, 22(12), 5027-5067.

Maddala, G.S. (1983). Limited-dependent and qualitative variables in econometrics. Cambridge, UK: Cambridge University Press.

Mangena, M., & Chamisa, E. (2008). Corporate governance and incidences of listing suspension by the JSE Securities Exchange of South Africa: An empirical analysis. *The International Journal of Accounting*, 43(1), 28-44.

Mann, H. B., & Whitney, D. R. (1947). On a test of whether one of two random variables is stochastically larger than the other. *The Annals of Mathematical Statistics*, 50-60.

Manzaneque, M., Priego, A. M., & Merino, E. (2016). Corporate governance effect on financial distress likelihood: Evidence from Spain. *Revista de Contabilidad*, 19(1), 111-121.

McGuinness, G., Hogan, T., & Powell, R. (2018). European trade credit use and SME survival. *Journal of Corporate Finance*, 49, 81-103.

McLeay, S., & Omar, A. (2000). The sensitivity of prediction models to the non-normality of bounded and unbounded financial ratios. *The British Accounting Review*, 32(2), 213-230.

Mensah, Y. M. (1984). An examination of the stationarity of multivariate bankruptcy prediction models: A methodological study. *Journal of Accounting Research*, 380-395.

Miller, M., & Modigliani, F. (1958). The cost of capital, corporate finance and the theory of investment. *American Economic Review*, 48, 261-297.

Myers, S. C., & Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of Financial Economics*, 13(2), 187-221.

Nam, C. W., Kim, T. S., Park, N. J., & Lee, H. K. (2008). Bankruptcy prediction using a discrete-time duration model incorporating temporal and macroeconomic dependencies. *Journal of Forecasting*, 27(6), 493-506.

Nam, J. H., & Jinn, T. (2000). Bankruptcy prediction: Evidence from Korean listed companies during the IMF crisis. *Journal of International Financial Management and Accounting*, 11(3), 178-197.

Neophytou, E., & Molinero, C. M. (2004). Predicting corporate failure in the UK: a multidimensional scaling approach. *Journal of Business Finance and Accounting*, 31(5-6), 677-710.

Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research*, 109-131.

Okay, K. (2015). Predicting business failures in non-financial Turkish companies. Master's Thesis, Bilkent University.

Partington, G., Stevenson, M., Torbey, V., & Wong, B. (2007). Surviving chapter 11 bankruptcies: Duration and payoff?. *Abacus*, 43(3), 363-387.

Peterson, W. W. T. G., Birdsall, T., & Fox, W. (1954). The theory of signal detectability. *Transactions of the IRE Professional Group on Information Theory*, 4(4), 171-212.

Pindado, J., Rodrigues, L., & de la Torre, C. (2008). Estimating financial distress likelihood. *Journal of Business Research*, 61(9), 995-1003.

Ramírez, C., & González, M. (2017). Have QE programs affected capital flows to emerging markets?: A Regional Analysis. *Investigación Conjunta-Joint Research*, 155-188.

Rifqi, M., & Kanazaki, Y. (2016). Predicting financial distress in Indonesian manufacturing industry (No. 62). Graduate School of Economics and Management, Tohoku University.

Ruxton, G. D. (2006). The unequal variance t-test is an underused alternative to Student's t-test and the Mann–Whitney U test. *Behavioral Ecology*, 17(4), 688-690.

Selimoğlu, S., & Orhan, A. (2015). Finansal başarısızlığın oran analizi ve diskriminant analizi kullanılarak ölçümlenmesi: BIST'te işlem gören dokuma, giyim eşyası ve deri işletmeleri üzerine bir araştırma. *Journal of Accounting and Finance*.

Shumway, T. (2001). Forecasting bankruptcy more accurately: A simple hazard model. *The Journal of Business*, 74(1), 101-124.

Smets, F. (2014). Financial stability and monetary policy: How closely interlinked?. *International Journal of Central Banking*, 10(2), 263-300.

Stock, J. H., & Watson, M. W. (2002). Forecasting using principal components from a large number of predictors. *Journal of the American Statistical Association*, 97(460), 1167-1179.

Terzi, S. (2011). Finansal rasyolar yardımıyla finansal başarısızlık tahmini: gıda sektöründe ampirik bir araştırma. *Çukurova Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*, 15(1).

Tykvová, T., & Borell, M. (2012). Do private equity owners increase risk of financial distress and bankruptcy?. *Journal of Corporate Finance*, 18(1), 138-150.

Vuran, B. (2009). Prediction of business failure: A comparison of discriminant and logistic regression analyses. *İstanbul Üniversitesi İşletme Fakültesi Dergisi*, 38(1), 47-63.

Warner, J. B. (1977). Bankruptcy costs: Some evidence. *The Journal of Finance*, 32(2), 337-347.

Welch, B. L. (1947). . The generalization of ‘student’s’ problem when several different population variances are involve. *Biometrika*, 34(1/2), 28-35.

Wilcoxon, F. 1945. Individual comparisons by ranking methods. *Biometrics*, 1: 80–83.

Wu, Y., Gaunt, C., & Gray, S. (2010). A comparison of alternative bankruptcy prediction models. *Journal of Contemporary Accounting and Economics*, 6(1), 34-45.

Yap, B. C. F., Munuswamy, S., & Mohamed, Z. (2012). Evaluating company failure in Malaysia using financial ratios and logistic regression. *Asian Journal of Finance and Accounting*, 4(1), 330-344.

Yeşiltaş, S. (2009). Financing Constraints and Investment: The Case for Manufacturing Firms. Master's Thesis, Bilkent University.

Yılmaz, H., & Yıldıran, M. (2015). Borsada işlem gören işletmelerde mali başarısızlık tahmini: altman modeli'nin BIST uygulaması. *Aksaray Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi*, 7(3), 43-49.

Zeytinoğlu, E., & Akarım, Y. D. (2013). Financial failure prediction using financial ratios: An empirical application on Istanbul Stock Exchange. *Journal of Applied Finance and Banking*, 3(3), 107.

Zmijewski, M. E. (1984). Methodological issues related to the estimation of financial distress prediction models. *Journal of Accounting Research*, 59-82.

# APPENDICES

## APPENDIX A: ADDITIONAL GRAPHS AND TABLES

**Table 25.**

Correlation Matrix (Variable Selection: Univariate Logit)

| | Firm Size | Cash Ratio | Gross Profit/Total Assets | EBIT/ Financial Expenses | Liabilities/ Assets | Sales/Total Assets |
|---|---|---|---|---|---|---|
| Firm Size | 1 | | | | | |
| Cash Ratio | 0.0187 | 1 | | | | |
| Gross Profit/Total Assets | -0.1036 | 0.0339 | 1 | | | |
| EBIT/ Financial Expenses | 0.0486 | 0.1449 | 0.2112 | 1 | | |
| Liabilities/ Assets | -0.0537 | -0.3167 | -0.1649 | -0.2326 | 1 | |
| Sales/Total Assets | -0.1319 | -0.0540 | 0.4130 | 0.0894 | 0.0023 | 1 |

**Table 26.**

Correlation Matrix (Variable Selection: PCA)

| | Firm Size_PCA | Liquidity_ PCA | Profitability _PCA | Interest Coverage_ PCA | Leverage_ PCA | Turnover_ PCA |
|---|---|---|---|---|---|---|
| Firm Size _PCA | 1 | | | | | |
| Liquidity _PCA | 0.0025 | 1 | | | | |
| Profitability _PCA | 0.0609 | 0.3066 | 1 | | | |
| Interest Coverage _PCA | 0.0094 | -0.1305 | -0.2647 | 1 | | |
| Leverage _PCA | 0.0183 | -0.4029 | -0.3750 | 0.2960 | 1 | |
| Turnover _PCA | -0.0848 | -0.0120 | 0.2123 | -0.02043 | -0.0738 | 1 |

**Table 27.**

Correlation Matrix (Variable Selection: Bootstrap Stepwise)

| | Firm Size | Cash/Total Assets | Net Income/ Total Assets | Financial Expenses/ Total Assets | Financial Debt/ Total Assets | AR/Total Sales |
|---|---|---|---|---|---|---|
| Firm Size | 1 | | | | | |
| Cash/Total Assets | 0.0025 | 1 | | | | |
| Net Income/ Total Assets | 0.0609 | | 1 | | | |
| Financial Expenses/ Total Assets | 0.0094 | 0.2766 | -0.2647 | 1 | | |
| Financial Debt/ Total Assets | 0.0183 | -0.1305 | -0.3750 | 0.2960 | 1 | |
| AR/Total Sales | -0.0848 | -0.4029 | 0.2123 | -0.2043 | -0.0738 | 1 |

**Table 28.**

Logit Regression Results with Time and Industry Effects
(Variable Selection: Univariate Logit)

| | (1)<br>Logit |
|---|---|
| Firm Size | 0.0153<br>(0.0157) |
| Liquidity | -0.6749***<br>(0.1116) |
| Profitability | -3.3576***<br>(0.2928) |
| Interest Coverage | 0.0004<br>(0.0006) |
| Leverage | 1.9387***<br>(0.1068) |
| Turnover | -0.4174***<br>(0.0309) |
| Time Effects | Yes |
| Industry Effects | Yes |
| No. of Observations | 137711 |
| McFadden's Adj. R-square | 0.097 |
| Log-Likelihood | -12484.694 |

Constant term is included in the regressions. Robust standard errors are provided in the parantheses. ***, ** and * represent statistical significance at 1%, 5% and 10%, respectively.

**Table 29.**

Logit Regression Results with Time and Industry Effects
(Variable Selection: PCA)

| | (1)<br>Logit |
|---|---|
| Firm Size | 0.0393**<br>(0.0162) |
| Liquidity | -0.1613***<br>(0.0146) |
| Profitability | -0.2088***<br>(0.0118) |
| Interest Coverage | 0.0011<br>(0.0127) |
| Leverage | 0.1432***<br>(0.0142) |
| Turnover | -0.4518***<br>(0.0204) |
| Time Effects | Yes |
| Industry Effects | Yes |
| No. of Observations | 126897 |
| McFadden's Adj. R-square | 0.1033 |
| Log-Likelihood | -11319.646 |

Constant term is included in the regressions. Robust standard errors are provided in the parantheses. ***, ** and * represent statistical significance at 1%, 5% and 10%, respectively.

**Table 30.**

Logit Regression Results
(Variable Selection: PCA, Second Principal Components)

| | (1)<br>Logit | (2)<br>Logit | (3)<br>Logit | (4)<br>Panel Logit |
|---|---|---|---|---|
| Firm Size | 0.0300*<br>(0.0155) | 0.0286*<br>(0.0155) | 0.0247<br>(0.0158) | -0.0768***<br>(0.0277) |
| Liquidity | -0.0728***<br>(0.0217) | -0.0681***<br>(0.0217) | -0.0952***<br>(0.0221) | -0.0357<br>(0.0278) |
| Profitability | -0.0270*<br>(0.0160) | -0.0200<br>(0.0160) | -0.0355**<br>(0.0163) | -0.0173<br>(0.0216) |
| Interest Coverage | 0.1385***<br>(0.0207) | 0.1571***<br>(0.0200) | 0.1364***<br>(0.0220) | 0.2230***<br>(0.0255) |
| Leverage | -0.0750***<br>(0.0198) | -0.0713***<br>(0.0199) | -0.0729***<br>(0.0205) | -0.0800***<br>(0.0267) |
| Turnover | 0.0698***<br>(0.0207) | 0.0702***<br>(0.0208) | 0.0644***<br>(0.0225) | 0.0416<br>(0.0307) |
| Time Effects | No | Yes | No | No |
| Industry Effects | No | No | Yes | No |
| No. of Observations | 126920 | 126920 | 126897 | 126920 |
| McFadden's Adj. R-square | 0.006 | 0.014 | 0.019 | |
| LR Test for Rho | | | | 4394.400*** |
| Log-Likelihood | -12550.491 | -12439.572 | -12383.772 | -10353.293 |

Constant term is included in the regressions. Robust standard errors are provided in the parantheses. ***, ** and * represent statistical significance at 1%, 5% and 10%, respectively.

**Table 31.**

Logit Regression Results with Time and Industry Effects
(Variable Selection: Bootstrap Stepwise)

| | (1)<br>Logit |
|---|---|
| Firm Size | 0.0356**<br>(0.0142) |
| Liquidity | -2.8227***<br>(0.2697) |
| Profitability | -4.7060***<br>(0.1958) |
| Interest Coverage | 3.0753***<br>(0.6167) |
| Leverage | 0.1491*<br>(0.0891) |
| Turnover | 0.5853***<br>(0.0199) |
| Time Effects | Yes |
| Industry Effects | Yes |
| No. of Observations | 149295 |
| McFadden's Adj. R-square | 0.0874 |
| Log-Likelihood | -13816.923 |

Constant term is included in the regressions. Robust standard errors are provided in the parantheses. ***, ** and * represent statistical significance at 1%, 5% and 10%, respectively.

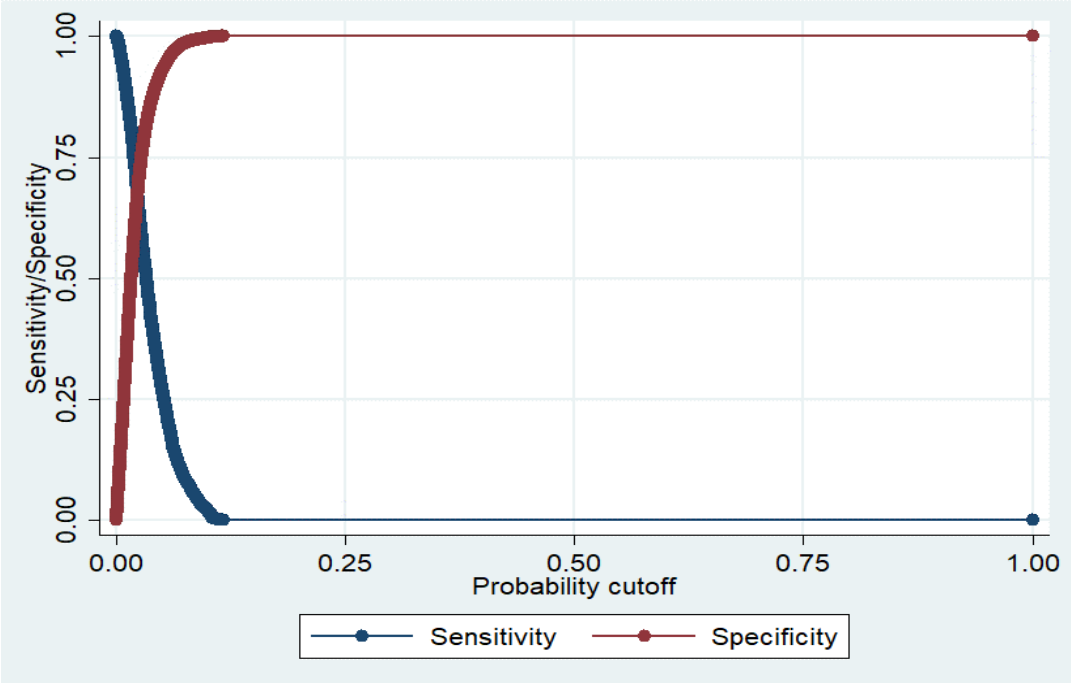



***Figure 12.*** Graphical Analysis for Optimal Cut-off Probability (Logit Model with First Variable Selection Method)

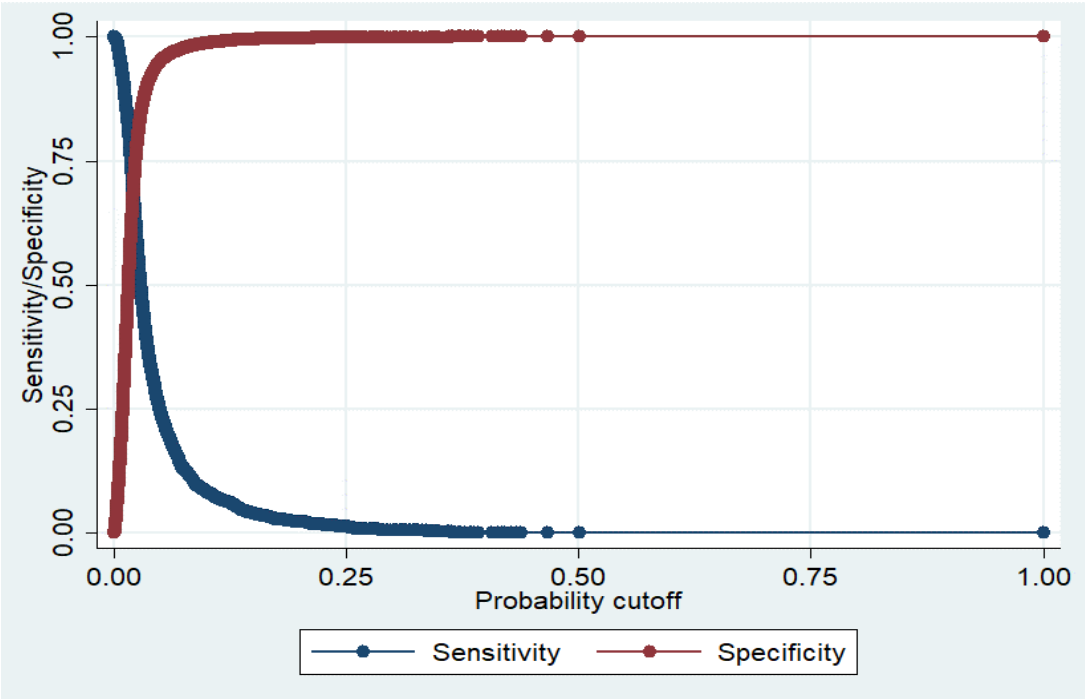



***Figure 13.*** Graphical Analysis for Optimal Cut-off Probability (Logit Model with Second Variable Selection Method)

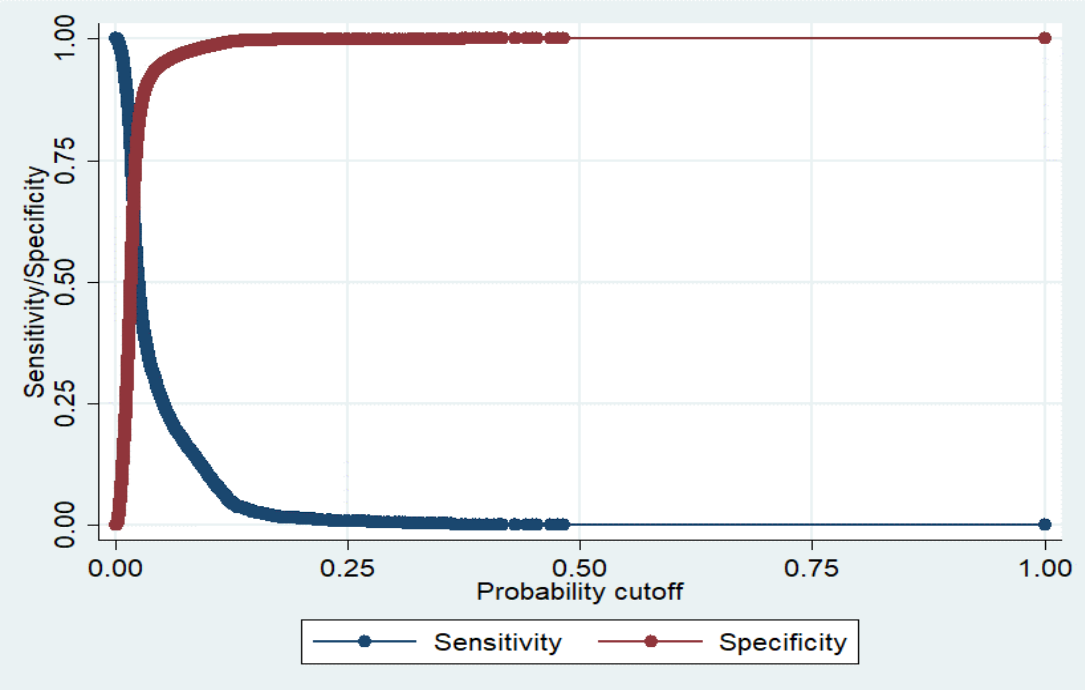



***Figure 14.*** Graphical Analysis for Optimal Cut-off Probability (Logit Model with Third Variable Selection Method)

**Table 32.**

Survival Analysis Results (Exponential)

| | Coefficient | Std. Error | Hazard Ratio |
|---|---|---|---|
| Firm Size | 0.0062 | 0.0184 | 0.9937 |
| Liquidity | 0.7073*** | 0.1277 | 0.4929 |
| Profitability | 3.0466*** | 0.3332 | 0.0475 |
| Interest Coverage | 0.0003 | 0.0006 | 0.9996 |
| Leverage | -1.3832*** | 0.1203 | 3.9876 |
| Turnover | 0.2052*** | 0.0332 | 0.8144 |
| No. of Observations | 134550 | | |
| Log Pseudo-Likelihood | -6533.684 | | |

Constant term is included in the regressions. Robust standard errors are provided in the parantheses. ***, ** and * represent statistical significance at 1%, 5% and 10%, respectively.

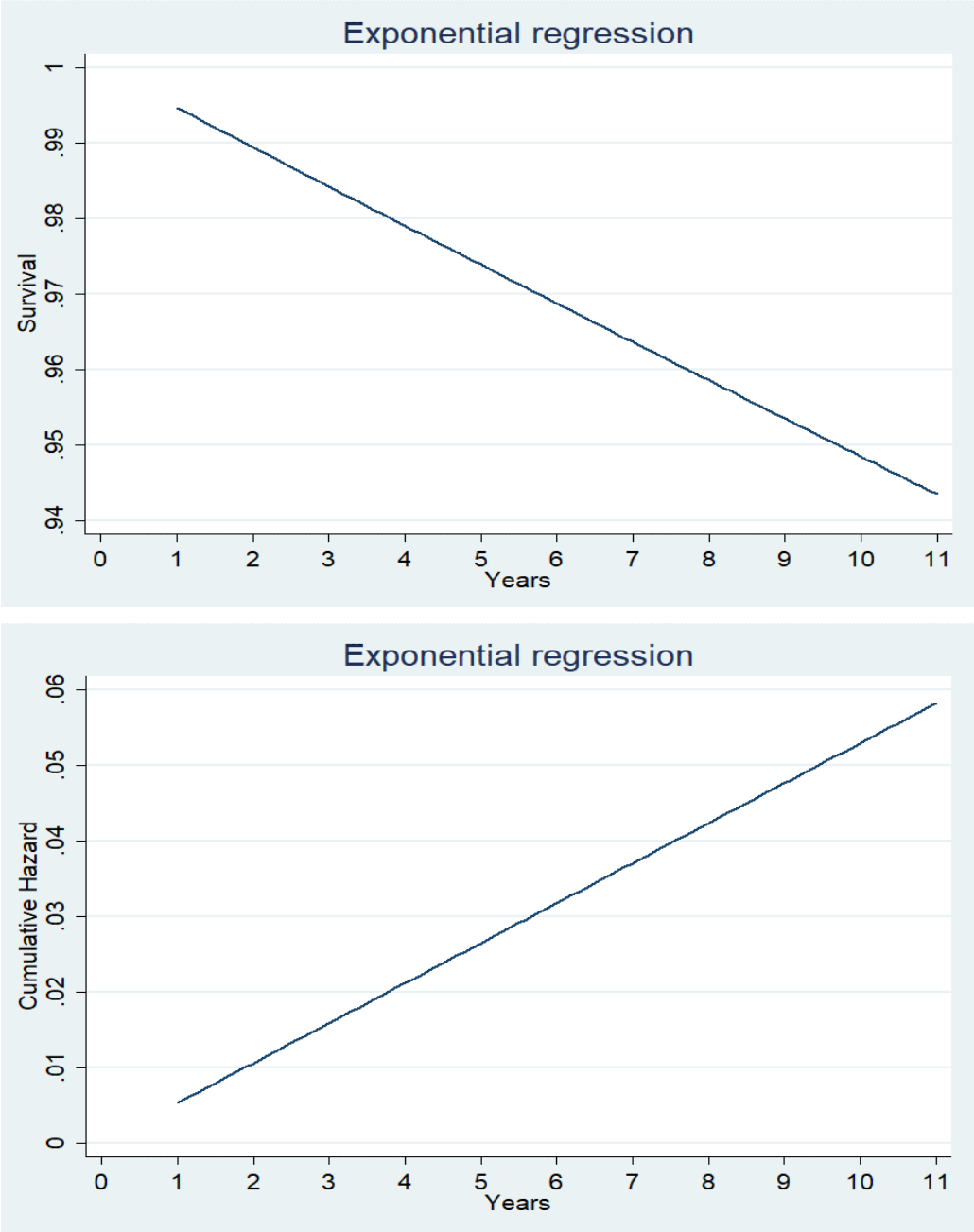



***Figure 15.*** Survivor and Cumulative Hazard Functions (Exponential)

## APPENDIX B: TURKISH SUMMARY / TÜRKÇE ÖZET

Firmaların finansal sağlamlığı faaliyet başarısı açısından önemli bir unsurdur. Literatürde finansal başarısızlığı ölçen erken dönem çalışmaları hukuki iflas durumlarını dikkate alırken, özellikle gelişmekte olan ülke (GOÜ) ekonomilerine odaklanan yakın dönem çalışmaları firmaların pay piyasasında işlem dışı kalması, negative kar açıklaması, finansal borç miktarının önemli ölçüde yükselmesi, faiz giderlerinden daha düşük kar elde edilmesi, temettü ödemelerinin durdurulması ve sabit varlıklardaki azalışlar gibi daha geniş kapsamlı finansal stres tanımları kullanılmaktadır.

Aşırı stres durumlarının yol açacağı firma iflaslarının doğrudan ve dolaylı maliyetleri olduğu bilinmektedir. İflas ve/veya yeniden çözümleme sürecinin idari masraflarına ek olarak kar marjındaki daralmalar, varlıkların piyasa değerinin altına satılması, borçların geri ödenememesi, müşteri tabanı ve piyasa payının kaybedilmesi ilgili maliyetler arasında sayılmaktadır. GOÜ özelinde bakıldığında, Küresel Finansal Kriz sonrası dönemde uygun maliyetleri fonlara erişim ve kredi aracılık faaliyetlerindeki güçlenmeyle beraber firma borçluluklarının arttığı bilinmektedir. Geleneksel olmayan para politikası uygulamalarından çıkışla birlikte küresel likiditenin daralması GOÜ yerel finansal koşullar üzerinde daraltıcı etki yapmaktadır. Bu bağlamda finansal istikrar kavramının başat unsuru olan reel sektör firma finasal durumunun sayısal araçlar vasıtasıyla takibi GOÜ özelinde önem taşımaktadır. Türkiye ekonomisinde faaliyet gösteren şirketler de benzer risklerle karşı karşıya kalmaktadır. Türkiye örneğinde firma yükümlülüklerinin önemli bir kısmının banka kredileri üzerinden sağlanması, Türkiye için yapılacak çalışmalarda finansal durum ile kredi riski arasında bir bağın kurulmasını gerekli kılmaktadır. Takibe girmiş alacaklar (TGA) olarak sınıflandırılan krediler oranının iktisadi faaliyetin ivme kaybettiği dönemlerde hızlı artışlar sergilemesi de bu ilişkiyi tanımsal olarak desteklemektedir. Yine Türkiye özelinde firma faaliyetleri ile yatırım oranının ters ilişkide olduğu gözlenmektedir.

Bu tezdeki ampirik çalışmalarda reel sektör firmalarının finansal stres yaşama olasılıklarını etkileyen firma-bazlı faktörler araştırılmaktadır. Yukarıda bahsedilen ilişkiler de göz önüne alınarak firmaların finansal stres durumları kredi riski üzerinden tanımlanmış ve TGA cinsinden sınıflandırılan kredi bakiyesinin tutar taşıyıp taşımadığına göre oluşturulan bir ikili bağımlı değişken (TGA varsa 1 yoksa 0 değerini alan) vasıtasıyla araştırılmıştır.

Kurumsal finans literatürü incelendiğinde, finansal olarak sorunlu firmaları diğerlerinden ayrıştırmaya yönelik ilk uygulamaların tek değişkenli istatistiki analzi yöntemlerini kullanan Beaver (1966) gibi çalışmalar tarafından yapıldığı anlaşılmaktadır. Fakat, bu yöntemin finansal rasyoları bir bütün olarak ele alamaması ve sağlam sonuçlar sunmaması dikkate alındığında çok değişkenli istatistiki analiz yöntemleri tercih edilmiştir. Altman (1968) çalışması tarafından ortaya koyulan bu metotta çoklu diskriminant analizi (ÇDA) kullanılarak firmalar için skorlama yapılmaktadır. Finansal olarak sağlıklı ve sağlıksız iki alt eşlenmiş örneklem üzerinden çalışan bu yöntemde, seçilen finansal rasyolardan faydalanılarak iki grup arasındaki skor farklılıklarının maksimize edilmesi amaçlanmıştır. Aynı model yapısında, finansal rasyoların toplam skorlamaya olan katkıları da gruplar arası varyansı en yüksek seviyeye çekecek şekilde elde edilmektedir. Bu yöntem Altman et al. (1977), Altman and Sabato (2007) gibi çalışmalarda metodolojik açıdan revise edilmiştir. Büyük ekonomilerdeki uygulamalara ek olarak Gerantonis ve diğ. (2009), Lifschutz ve Jacobi (2010), Çolak (2019) çalışmalarında olduğu gibi GOÜ örneklerinde kullanılmıştır.

Öte yandan, ÇDA yönteminin varsayımlarına getirilen eleştiriler (tesadüfi-örneklem kurgusunu bozması, sadece sıralamalı yorum gücü taşıması, finansal olarak sağlıklı ve sağlıksız firma gruplarının varyansını eşit kabul etmesi, finansal rasyoların ortak olarak normal dağıldığını varsayması gibi) Ohlson (1980) ve Zmijewski (1984) çalışmalarından itibaren mikroekonometrik tahmin yöntemlerinin finansal stres analizi için kullanılmasına yol açmıştır. Böylelikle ÇDA'nın kısıtlayıcı

varsayımlarına bağlı kalmadan doğrudan finansal iflas olasılıklarının modellenebildiği bir analiz aracı oluşturulmuştur. Brezigar-Masten ve diğ. (2018), Foreman (2003), Lin ve Piesse (2001), Fitzpatrick ve Ogden (2011), Gupta ve Gregoriou (2018) ikili bağımlı değişken modellerinin finansal stres modellemesinde kullanıldığı ülke çalışmalarına örnek oluşturmaktadır. Literatürün bu kısmında modellerin ima ettiği olasılık değerlerinden yararlanılarak örneklem içi ve dışı öngörü egzersizlerinin yapıldığı da gözlenmektedir.

Lojistik ve probit regresyon modellerini kullanan bazı çalışmalar örneklem verilerinin niteliğinde göre panel yapısını da dikkate alan analizler yapmışlardır (McGuinness ve diğ., 2018; Iwanicz-Drozdowska ve diğ. 2018). Ek olarak, iflas olasılığının dışında finansal stress durumlarının yaşanmasına kadar olan zaman boyutunu irdeleyen durasyon modelleri bulunmaktadır. Bu kapsamda, parametrik olmayan tekniklerle tehlike oranı ve hayatta kalma fonksiyonları türetilmekte, yarı-parametrik yöntemlerle firma bazlı özelliklerin stres yaşanmaya kalan süreye etkisi incelenmektedir (Shumway, 2001; Chancharat ve diğ., 2007; Gupta ve diğ., 2018).

Türkiye için yapılan ampirik çalışmalarda halka açık firmaların kullanılması örneklem boyutunu oldukça daraltmaktadır. Bu tezde ise iki ayrı mikro veri setinden faydalanılarak 2006-2016 dönemini kapsayan örneklem oluşturulmuştur. İlk aşamada TCMB bünyesindeki Sektör Bilançoları'ndan firmaların bilanço ve gelir tablosu kalemleri ile sektör bilgisi gibi girdiler alınmıştır. İkinci aşamada Risk Merkezi mikro verisinden TGA olarak sınıflanan krediler firma ve yıl boyutunda toplulaştırılarak çekilmiştir. İlerleyen aşamada bu iki veri seti firma kimlik kodu kullanılarak birleştirilmiştir. Bağımlı değişken tanımı ise TGA'ların varlığına göre 0-1 kodlaması yapılarak türetilmiştir. 2006-2016 dönemi için örneklem 3347 stres gözlemini kapsamaktadır. Metodolojinin bir sonraki aşamasında geniş bir literatür taraması yapılarak, 6 ayrı kategoride 42 farklı finansal rasyoyu içeren bir açıklayıcı değişken listesi belirlenmiştir. Gerçekleştirilen tek değişkenli istatistiki parametrik ve parametrik olmayan testler söz konusu rasyolar bağlamında finansal strese işaret eden ve etmeyen firma-yıl gözlemlerinin ortalama ve medyan değerleri arasındaki

farklılaşmayı tespit etmektedir. Bu kapsamda finansal stres yaşayan firmaların likidite tamponlarının, karlılık rasyolarının ve faiz karşılama oranlarının görece düşük olduğu anlaşılmaktadır. Öte yandan, finansal stres firma-yıl gözlemleri yüksek kaldıraç ve düşük operasyonel performansa denk geldiği görülmektedir.

Esas analizlerin gerçekleştirilmesinde girdi teşkil edecek model kurguları üç farklı değişken seçimi uygulanarak belirlenmiştir. Bu aşamada, ilk olarak tek değişkenli lojistik regresyonlar tahmin edilerek, her bir rasyo grubu altında katsayının istatistiki anlamlığı, katsayı işaretinin ekonomik anlamlılığı, log-olabilirlik değerleri ve işlem karakteristik eğrilerinin altında kalan alan raporlanmıştır. Bu yönteme göre likidite için nakit varlıklar/toplam yükümlülükler oranı (nakit rasyosu), karlılık için brüt kar/toplam varlıklar oranı, faiz karşılama için FAVÖK/finansman giderleri rasyosu, kaldıraç için toplam yükümlülükler/toplam varlıklar oranı, operasyonel performans için toplam satışlar/toplam varlıklar oranı seçilmiştir. İkinci değişken seçimi yöntemi olarak temel bileşenler analizi tercih edilmiştir. Bu bağlamda, bahse konu rasyo gruplarına ayrı ayrı temel bileşenler metodu uygulanmış, her gruptan birinci statik faktör açıklayıcı değişken olarak alınmıştır. Üçüncü değişken seçimi yönteminde ise Garrett (2000) çalışmasında geliştirilen yöntem vasıtasıyla bootstrap örneklemler üzerinden sıralı lojistik regresyon tahminleri yapılmıştır. Her bir rasyo grubu için tahminler 100'er kez tekrarlanarak, bu spesifikasyonlarda her rasyonun kaç kere içerildiği raporlanmıştır. Bu aşamada değişkenlerin aralarındaki korelasyon da dikkate alınarak üçüncü model yapısı kurulmuştur. Bu modelde likidite, karlılık, faiz karşılama, kaldıraç ve operasyonel performans özellikleri sırasıyla nakit varlıklar/toplam varlıklar, net kar/toplam varlıklar, finansman giderleri/toplam varlıklar, finansal borç/toplam varlıklar ve ticari alacaklar/toplam varlıklar oranlarıyla temsil edilmektedir.

Değişken seçimi yöntemleriyle oluşturulan spesifikasyonlar bir sonraki aşamada çok değişkenli lojistik ve tesadüfi etkiler panel lojistik regresyonlarla sınanmıştır. Ek olarak, zaman ve sektör etkileri kukla değişkenler kullanılarak kontrol edilmiştir. Birinci değişken seçimi yöntemiyle kurulan modelin tahmin sonuçları likidite ve

karlılık güçlendikçe finansal stres yaşama olasılığında düşüş gerçekleştiğini ortaya koymaktadır. Faiz karşılama değişkeni ve firma büyüklüğü anlamsız bulunurken, kaldıraç oranındaki yükselişler firma iflas olasılıklarını istatistiki olarak anlamlı bir biçimde yükseltmektedir. Öte yandan operasyonel performanstaki olumlu görünüm stres olasılıklarını düşürmektedir. Sonuçlar farklı controller kullanıldığında sağlamlığını korumaktadır. Benzer şekilde ikinci değişken seçimi yöntemiyle elde edilen model tahmin edilmiştir. Burada görece büyük firmalar daha fazla finansal stres olasılığı taşıdığı görülmüştür. Birinci modele benzer şekilde likidite ve karlılıktaki artışlar stres durumu yaşama olasılığını düşürürken, düşük kaldıraç ve yüksek performans stres olasılıklarını olumlu etkilemektedir. Son olarak üçüncü değişken seçimiyle üretilen model kullanılmıştır. Sonuçlar ilk iki modelle benzerlik taşırken ek olarak finansman giderlerinde firma ölçeğine göre yaşanan artışların finansal stresi beslediği bulgulanmaktadır.

Tahmin edilen çok değişkenli lojistik modeller örneklem içi ve dışı öngörü performansının belirlenmesinde de kullanılmıştır. Bu kapsamda örneklem içi analizde tüm dönemler için katsayıların ima ettiği olasılık değerleri elde edilmiştir. Ardından, Clayton (2013) çalışmasında öne sürülen yöntem kullanılarak eşik olasılık değerleri bulunmuştur. Bu eşik değerlerin aşılması halinde finansal stres durumunun yakalandığı varsayımı altında üç modelin sırasıyla %71, %66 ve %64 oranında doğru bilgi sağladığı tespit edilmektedir. İkinci aşamada modeller 2006-2014 aralığına tahmin edilerek 2015 ve 2016 dönemleri için ima edilen değerler hesaplanmıştır. Aynı olasılık eşikleri kullanılarak üç modelin sırasıyla %74, %63 ve % 68 oranında doğru bilgi sağladığı bulgulanmıştır.

Stres olasılığının dışında parametrik sağkalım modelleriyle stress durumuna kalan zaman boyutunu etkileyen faktörler de incelenmiştir. Bu aşamada, Weibull ve üssel model yapıları tahmin edilmiştir. Durasyon model sonuçları firma büyüklüğü, karlılık, likidite ve performanstaki artışların finansal stresin yaşanmasına kadar olan süreyi uzattığını, kaldıraç oranındaki yükselişlerin ise süreyi kısalttığını

göstermektedir. Bu analizle sağkalım ve birikimli tehlike fonksiyonları da tanımsal analiz için türetilmektedir.

Genel olarak tezdeki ampirik sonuçlar, kredi riski dikkate alındığında firma özelliklerinin finansal stres olasılıklarının dinamiklerini anlamakta önemli girdiler olduğuna işaret etmektedir. İlişkilerin yönüne dair ekonometrik çıkarımlara imkan sunmasının yanı sıra doğrudan olasılık skorlamasının yapılabilmesi ve zaman boyutunun analiz edilebilmesi, lojistik regresyon ve sağkalım yöntemlerinin önemli bilgi değeri taşıdığını göstermektedir.

## APPENDIX C: TEZ İZİN FORMU / THESIS PERMISSION FORM

**ENSTİTÜ** / INSTITUTE

**Fen Bilimleri Enstitüsü / Graduate School of Natural and Applied Sciences** ☐

**Sosyal Bilimler Enstitüsü** / Graduate School of Social Sciences ■

**Uygulamalı Matematik Enstitüsü** / Graduate School of Applied Mathematics ☐

**Enformatik Enstitüsü** / Graduate School of Informatics ☐

**Deniz Bilimleri Enstitüsü** / Graduate School of Marine Sciences ☐

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**Bölümü** / Department : İktisat

**TEZİN ADI** / TITLE OF THE THESIS (**İngilizce** / English) : Predicting Financial Distress of Turkish Non-Financial Firms: Evidence from Micro Data

**TEZİN TÜRÜ** / DEGREE: **Yüksek Lisans** / Master ■ **Doktora** / PhD ☐

1. **Tezin tamamı dünya çapında erişime açılacaktır. /** Release the entire work immediately for access worldwide. ■
2. **Tez iki yıl süreyle erişime kapalı olacaktır.** / Secure the entire work for patent and/or proprietary purposes for a period of **two years. *** ☐
3. **Tez altı ay süreyle erişime kapalı olacaktır.** / Secure the entire work for period of **six months**. * ☐

***** *Enstitü Yönetim Kurulu kararının basılı kopyası tezle birlikte kütüphaneye teslim edilecektir.*
*A copy of the decision of the Institute Administrative Committee will be delivered to the library together with the printed thesis.*

**Yazarın imzası** / Signature **Tarih** / Date