BANKING FAILURES IN TURKEY: AN ECONOMETRIC ANALYSIS

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ABSTRACT

BANK FAILURES IN TURKEY: AN ECONOMETRIC ANALYSIS

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This study investigates the factors that were important in the failure of 36 banks in 1997-2006. The study uses cross-section time series data from 81 banks and employs limited dependent variable models, a duration model and a dynamic panel data model in the analysis. The major concerns are to examine the determinants of banking failures by explaining the contribution of microeconomic and macroeconomic factors in Turkish banking system, to estimate the likelihood of banking failure and timing of failure, to analyze survival time path of failed and non-failed banks separately and to construct the degree of fragility of overall banking system.

Furthermore, the determinants of bank profitability and the effects of bank-specific factors and macroeconomic conditions on bank profitability are analyzed by using dynamic panel data model.

Keywords: Bank Failures, Banking Sector, Fragility, Profitability, Turkey.

ÖZ

TÜRKİYE'DE BATIK BANKALAR: EKONOMETRİK BİR ÇÖZÜMLEME

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Bu çalışma, 1997-2006 yılları arasında Türkiye'de 36 banka batışına ilişkin faktörleri incelemektedir. Çalışma, 81 bankanın akış kesiti zaman serisi verlerini kullanarak limitli bağımlı değişken modeli, süre modeli ve dinamik panel data modeli ile incelemektedir. Bu çalışmada, banka batışlarını belirleyen faktörlerden banka-özel ve makroekonomik değişkenlerin katkılarını değerlendirmek, banka batış olasılıklarını ve zamanını tahmin etmek, batık ve sağlam bankaların yaşam sürelerini analiz etmek ve bankacılık sisteminin kırılganlığını belirlemek ele alınması gereken

başlıca konulardır. Ayrıca, banka karlılığının belirleyicileri ve banka-özel ve makroekonomik değişkenlerin banka karlılığı üzerine etkileri dinamik panel data modeli kullanılarak araştırılmaktadır.

Anahtar Kelimeler: Batık Bankalar, Bankacılık Sektörü, Kırılganlık, Karlılık, Türkiye.

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TABLE OF CONTENTS

LIST OF TABLES

TABLES

LIST OF FIGURES

FIGURES

CHAPTER 1

INTRODUCTION

During the recent decades of trade and financial liberalization, the frequency of financial sector problems has risen both in developed and emerging market economies (Brown and Dinc, 2005). In Latin America, severe banking crises occurred in Chile and Colombia during the 1980s and in Mexico and Venezuela during the first half of the 1990s. The Turkish cases in 2000 and 2001 represent the most recent crises in an emerging market economy. The banking system problems that have occurred in Japan during the mid-1990s, in UK in early 1990s, in US during the mid-1980s and early 1990s and in the Nordic countries during the early 1990s have widely discussed in empirical literature, that are mentioned in literature survey chapter.

Despite the difficulties in identifying and measuring the magnitude of banking crises, several common features of countries experiencing banking crises emerge from the literature. *World*

Economic Outlook (IMF, 1998) identified 54 banking crises in both industrial and developing countries between 1975 and 1997. Most of these crises were experienced in the second half of the sample period, and the incidence was greater among the developing countries (42 crises) than the industrial countries (12 crises).

The IMF (1998) report identifies several general categories of problems, which are frequently associated with financial crises (both banking and currency crises): unsustainable macroeconomic policies, weaknesses in financial structure, global financial conditions, exchange rate misalignments, and political instability. Moreover, Ozkan-Gunay and Tektas (2006) pointed out that poor banking practices, capital inadequacy, poor credit evaluation process, lack of revenue diversification, connected lending, maturity and currency mismatches, rapid increase in non-performing loans are the main causes of severe banking crises (Ozkan-Gunay and Tektas, 2006). Furthermore, for the political reasons, preemptive actions regarding large bank failures are not taken by the governments at the periods just preceding the elections. This can be considered as one of the major reason for severe banking crises at least from emerging market economies (Brown and Dinc, 2005).

According to the IMF (1998) report the cost of banking crises is on average 14 -15 % of GDP. This cost combined with currency crises rises to 17-19 % of GDP. The fiscal and quasi-fiscal cost of restructuring financial institutions to resolve the banking crises has often been large, reaching over 40 % of GDP in some cases (Argentina and Chile in the early 1980s). The real output cost is also substantial as financial institutions and markets fail to function effectively. Recovery usually takes 3-5 years (Davis, 1999). Hence, more attention has been given to the question of bank failures and banking crises in the literature.

The current literature on explaining bank failures and banking crises is mostly divided into two types of studies: those that analyze bank-specific data to explain why the banks have failed, and those that examine how changes in various macroeconomic variables have contributed to banking crises. Microeconomic approach uses different empirical methods such as discrete choice models and duration model with cross-section, micro-level data. On the other hand, in the macroeconomic approach, the role of macroeconomic conditions on banking crises such as interest rates, inflation rates etc, is examined (Gonzales-Hermosillo, 1999). These studies use cross-country and time-series macroeconomic data. The main motivation of all these studies is to enhance the role of the regulation and supervision authorities in preventing bank failures and minimizing the cost of crisis by utilizing these bank failure prediction models.

This thesis investigates the main factors associated with 36 failures in Turkey in 1997-2006. The study uses cross-section time series data from 81 banks and employs limited dependent variable models, a duration model and a dynamic panel data model in the analysis. The major objectives are to examine the determinants of banking failures by explaining the contribution of microeconomic and macroeconomic factors in Turkish banking system, to estimate the likelihood of banking failure and timing of failure, to analyze survival time path of failed and non-failed banks separately and to construct the estimated degree of fragility of overall banking system. Furthermore, the determinants of bank profitability and the effects of bank-specific factors and macroeconomic conditions on bank profitability are analyzed by using dynamic panel data model.

Firstly, in order to predict the probability of banking failures and determine the factors of bank failures, both binary and multinomial logit estimation techniques are applied to the whole data set. The multinomial logit model adds the mergers/acquisitions to the failed and non-failed outcomes of the binary logit model. Moreover, the models also test empirically the proposition that banking sector failures are determined by both bank-specific factors and macroeconomic variables. Thus, the aim of this study is to define the nature and the patterns of these banking crises and to determine the different characteristics between failed and non-failed banks. This study also attempts to evaluate the economic indicators and the causes of banking sector weaknesses econometrically. This analysis can lead to a better understanding of the crises and to predict further failures.

Secondly, duration model deals with the time to failure instead of predicting the probability of banking failures. It aims to take a closer look at the duration until bank failure. It also allows measuring the effect of bank specific variables using balance sheet of the banks, tries to construct models for the determination and prediction of timing of failure and examines survival time path of failed and non-failed banks. Moreover, it tries to institute a pattern concerning characteristics that distinguish the survived banks from the failed banks for regulation and supervision agencies. It focuses on examination of survival time path of failed and non-failed banks separately and construction of the degree of fragility of banking system as being different from discrete choice models.

Lastly, by using dynamic panel data models, the main indicators related to the bank profitability are determined for the sample period. The main motivation of this chapter is to examine the determinants of bank performance that can be another tool for preventing bank failures, suggesting optimal policies for bank management and promoting sound banking system. This is because of the fact that a strong and profitable banking sector supports broader financial stability (Goddard et al, 2004). This provides that preemptive actions regarding problematic banks are taken by the regulation and supervision institutions before bank failures actually occur.

Similarly, Goddard et al (2004), Bourke (1989), Rhoades (1985), Molyneux and Thornton (1992), Athanasoglu et al (2005) and Gerlach et al (2004) attempted to determine the profitability and performance of banking sectors by using dynamic panel data models. Applying GMM technique to a panel of banks of Turkish banking system, the effects of both bank specific variables from balance sheet of the banks and macroeconomic conditions on bank profitability are examined.

This study is organized as follows: The empirical literature on bank failures and banking crises is given in chapter 2. There are microeconomic, macroeconomic and mixed approaches in the literature. Independent variables that were found to be significant and estimation techniques in selected studies are surveyed. Chapter 3 briefly analyzes overview of Turkish banking sector. At the first glance, it gives historical background of the sector. Then it reviews the 2000-2001 Turkish banking crises in conjunction with the motivation of this study.

Chapter 4 describes data set used through the analysis and presents the principal component analysis to determine the eigenvectors and variables that are used in empirical analysis. Then, it gives the descriptive statistics of the selected variables by using principal component analysis. Chapter 5 explains the classification of failed and non-failed banks based on prediction of the probability of banking failures and the factors of bank failures by using binary and multinomial logit models. Chapter 6 represents estimation results of duration model. It examines survival time path of failed and non-failed banks separately and estimated degree of fragility of overall banking system by using duration model. Chapter 7 analyzes the determinants of bank profitability by using dynamic panel data model. Chapter 8 concludes.

CHAPTER 2

LITERATURE SURVEY

The empirical literature on the determinants of bank failures and banking crises is large. Mainly, the empirical literature can be divided into three different approaches: microeconomic, macroeconomic and mixed approaches. Microeconomic studies on banking failures are mainly based on the bank specific variables used in CAMEL rating categories[1], which are taken from financial statements of the banks. These studies use different empirical methodologies such as limited dependent variable model and duration model with cross-section, micro-level data of specific countries or regions data. On the other hand, in the macroeconomic approach, the role of macroeconomic conditions on banking crises such as interest rates, inflation rates, Central Bank foreign exchange

[1] CAMEL is a rating system for evaluating financial condition of the banks for supervisory purposes. It has five categories; capital adequacy, asset quality, management quality, earnings and profitability and liquidity. It was developed by US regulators. Variations of this framework are widely used by regulatory and supervisory agencies in a number of countries to evaluate the state of banks.

reserves and credit expansion etc, as well as the role of institutional variables such as central bank independence, explicit deposit insurance, financial liberalization proxies etc, are examined (Gonzales-Hermosillo, 1999). These studies use cross-country and time-series macroeconomic data.

2.1. MICROECONOMIC APPROACH

The earliest studies of individual bank failures started in mid-1970s. Most of these studies examined bank failures in the United States (Bell and Pain, 2000). In 1970s and 1980s, the studies tried to discriminate between closed and non-closed or problem and non-problem banks by using only bank specific variables (Demirguc-Kunt, 1989). Sinkey (1975) and Altman (1977) used discriminant analysis, which was a classification technique. The analysis was based on financial ratios from US banks over the period of 1969 and 1972 and the period of 1966 and 1977, respectively to discriminate between problem and non-problem banks. In these studies, capital adequacy, asset quality and earnings proxies were found significantly. Sinkey (1975) found that the ratio of loan to revenue, which was a proxy of asset quality, was the best discriminator. Altman (1977) concluded that operating income, the proxy of earnings, was the most important discriminator (Demirguc-Kunt, 1989).

More recently, Thomson (1991) estimated the logit model by using only financial statements of U.S. banks operating from 1982 to 1989 to predict the probability of bank failures. Thomson (1991) found the CAMEL - motivated proxy variables to determine bank condition such as book equity capital, the loans to assets ratio, overhead to total assets ratio, deposits per branch and size in terms of assets significantly by using logit model. In a similar study, Logan (2001) used a logit model for examining the balance sheet characteristics of the small and medium-sized UK banks and identified leading indicators of bank failures over the period of 1989 and 1991. Logan (2001) found that the most important indicators in determining future failure was high dependence on net interest income, low profitability, low loan growth and low short-term assets relative liabilities (see table 2.1).

All these studies try to explain the probability of failure in a specified period. However, in the earlier studies, Lane et al (1986) and Whalen (1991) tried to explain the timing of failure by using duration models. With pioneering of these two studies, the duration models have been widely used to explain and predict bank failures in the last decade. Most of the studies used semi-parametric model which was known as Cox proportional hazards model since it has the advantage of getting rid of the strong distributional assumptions associated with parametric survival models (Cole and Gunther, 1995).

Lane et al (1986) and Whalen (1991) used a proportional hazard model to determine the financial indicators that could have predicted the US banking failures over the period of 1979 and 1983 and the period of 1987 and 1990. Lane et al (1986) found that capital to assets ratio as capital adequacy proxy, commercial loans to total loans ratio as loan composition proxy, operating expenses to operating income ratio as earnings proxy and loans to deposits ratio as liquidity proxy were significant in the duration model. Whalen (1991) studied proportional hazard model with a small number of explanatory variables constructed from publicly available data. Furthermore, Whalen (1991) found that the survival banks had lower ratio of loans to assets, ratio of deposits to assets and ratio of operating expenses to assets and higher the ratio of net income to assets and capital to assets ratio than failed banks.

In the same manner, Wheelock and Wilson (1994) employed Cox proportional hazard model to investigate the deposit insurance and bank failures of Kansas banks in the US in 1910 and 1928. Accordingly, it was found that deposit insurance related to moral hazard had a negative relationship with survival of banks. Another study of Wheelock and Wilson (2000) examined bank failures and acquisitions in US during 1984-1993 by using only microeconomic variables.

Table 2.1: Independent Microeconomic Variables Found Significant in Selected Studies

Selected Studies	Bank-specific Variables (CAMEL)				
	Capital Adequacy	Asset Quality	Management Quality	Earnings	Liquidity
Sinkey (1975)	X	X	X	X	
Altman (1977)	X	X		X	
Thomson (1991)	X	X	X		X
Logan (2001)	X	X	X		X
Cole and Gunther (1995)	X	X		X	
Dabos and Escudero (2000)	X	X		X	X
De Young et al 2000	X	X			X
Lane et al (1986)	X		X	X	X
Molina (2002)	X	X		X	X
Whalen (19991)	X	X	X	X	
Wheelock and Wilson (1994)	X			X	X
Wheelock and Wilson (2000)	X	X		X	X
Bernhardsen (2001)	X			X	X
Sales (2005)		X	X		
Gonzales-Hermosillo (1999)	X	X			
Gonzales-Hermosillo et al (1997)	X	X		X	X

Dabos and Escudero (2004) studied several bank specific variables in determining Argentinean bank failures during 1994 - 1996. Molina (2002) also used a proportional hazard model with bank-specific variables to determine the financial indicators that could have predicted the bank failures during the 1994 and 1995 Venezuelan banking crisis. The findings of Wheelock and Wilson (2000), Logan (2001) and Molina (2002) are consistent with each other though the studies cover the different time span and different countries; US, UK and Venezuela. According to this, failed banks had lower profits, less liquid and weaker asset quality than the survival banks.

Cole and Gunther (1995) used a split-population survival time model to examine the determinants of bank survival and bank survival time. The split-population model separates the determinants of bank failure from the determinants of survival time of failing banks. The results of study of Cole and Gunther (1995) showed that a selected group of explanatory variables extensively used to predict bank failure by discrete choice model helped explain survival time of the banks. According to this, the main determinants of the soundness of banks such as capital, troubled assets and profit were related to the survival time of failing banks. Moreover, liquidity proxies and size of banks in terms of assets, which were used commonly in predicting the likelihood of bank failures, were not found significant.

De Young et al (2000) also estimated a 'split-population' duration model for 656 commercial banks chartered in 1984 and 1985 to investigate the long-run financial viability of newly chartered banks, and tested whether the determinants of survival of bank failures differed from new banks that were established banks during the specified period. De Young et al (2000) found that the risk factors such as risky and illiquid investments, excess overhead costs, rapid asset growth and low capital ratios at both sets of banks were similar.

2.2. MACROECONOMIC APPROACH

Another strand of literature studies on banking crises used cross-country time-series macroeconomic data. In explaining cross-country comparisons in banking crisis, Demirguc-Kunt and Detragiache (1999) and Hardy and Pazarbasioglu (1998) tried to utilize only macroeconomic variables to monitor banking sector fragility in a large sample of countries. Before analyzing these studies, it is useful to distinguish between the bank failures and banking crises.

Banks, like other firms, are likely to encounter financial difficulties when the difference between the value of their assets and the value of their liabilities is negative (i.e. technical insolvency) (Demirguc-Kunt, 1989). A problem at a bank may be associated with failure of other banks, if each bank is simultaneously affected by the same shock. This would suggest that banking system problems are more likely if the banks have similar fundamental characteristics. The banking crises in the Nordic countries (Finland, Norway and Sweden) during the early 1990s are an example of this (Bell and Pain, 2000).

Demirguc-Kunt and Detragiache (1999) emphasized that low GDP growth rate, high real interest rate, high inflation, high M2 to Central Bank foreign exchange reserves ratio and high growth of real private credit significantly increase the likelihood of systemic problems. Moreover, unstable macroeconomic environment was not the sole factor, but also institutional characteristics had a role in systemic problems. Demirguc-Kunt and Detragiache (1999) also constructed a rating system for bank fragility by using estimated crisis probabilities from logit model. The similar study from Hardy and Pazarbasioglu (1998) suggested that systemic problems were related to fall in real GDP growth, fluctuations in inflation, credit expansion, increase in real interest rates, decline in real exchange rate and adverse trade shock (see table 2.2).

Santor (2003) used limited dependent variable model to examine contagion across banking systems in developed and developing countries; over 90 countries during 1975-1998 by using only macroeconomic variables. Santor (2003) found that the probability of banking crises increases as countries have slow economic growth, high inflation and high real interest rates. Besides, information contagion plays a significant role in predicting future banking crises.

Hutchison and McDill (1999) also used multivariate probit model to examine banking distress for a large sample of developed and developing countries (65 countries) in 1975-1997. In their study, banking distress was defined as the ratio of capital equity minus non-performing loans to total assets. According to this, decreases in GDP and asset prices and institutional factors such as Central Bank independence, explicit deposit insurance and financial liberalization increased the probability of banking sector distress in sample countries and in Japan.

Table 2.2: Independent Macroeconomic Variables Found Significant in Selected Studies of Banking Crises

Selected Studies	Macroeconomic Variables							
	Inflation	GDP Growth	M2/Reserves	Imports/Reserves	Credit/GDP	Credit Growth	Real Int. Rate	Depreciation
Santor (2003)	X	X					X	
Hardy and Pazarbasioglu (1998)		X	X			X	X	X
Hutchison and McDill (1999)		X						
Demirguc-Kunt and Detragiache (1999)		X					X	X
Bernhardsen (2001)	X	X			X			
Sales (2005)				X				
Gonzales-Hermosillo (1999)		X					X	
Gonzales-Hermosillo et al (1997)	X	X					X	X

2.3. MIXED APPROACH

Gonzales-Hermosillo, et al. (1997) and Gonzales-Hermosillo (1999) used both bank-specific and macroeconomic variables to determine bank fragility and the factors of bank failures for Mexico, Columbia and US banking systems. Gonzales-Hermosillo (1999) analyzed the probability of crises and their timing of the crises by using the definition of severe distress, which was the same in the study of Hutchison and McDill (1999) and the definition of failure, which was considered the period before government intervention.

Gonzales-Hermosillo (1999) found that the banking distress index tended to overstate the number of occurrences of banking problems. The results of this study showed that capital equity to total assets ratio and non-performing to total assets ratio which was the proxy of fragility, were the main indicators of banking problems. The availability of quarterly data[2] improved the performance of the use of the limited dependent regression model so that it can give the possibility to monitor the evolution of the failure probability and to take preventive action before the failure (Gaytan and Johnson, 2002).

Bernhardsen (2001) has followed Gonzales-Hermosillo (1999) to predict the likelihood of bank failures and used a random-effects probit model to predict bankruptcies in Norway. Sales (2005)

[2] In banking crises studies, annual data was used commonly due to unavailability of quarterly or monthly data for less developed countries. Naturally, the performance of the model of the early warning of financial problems that uses annual data may be poor.

investigated the determinants of bank failure and bank unsoundness in Brazil by applying both proportional hazard and parametric method during 1994-1998. Sales (2005) found that the survival banks had lower credit risk, higher efficiency and lower spreads than failed banks. Among the macroeconomic variables, the ratio of total imports to international reserves as liquidity indicator and among contagion variables percentage change of loans per month as lending booms indicator were found significant. Sales (2005) also estimated the mean and median survival times of each bank and found that failed banks exhibited long survival times before the failure. Thus, Sales (2005) concluded that the survival times of each banks allows the regulator to oversee the survival time path and to detect outliers so that it becomes possible to take a corrective action.

Furthermore, Sales (2005) and Gonzales-Hermosillo et al. (1997) provide a financial fragility index for each bank, which was based on the probability of failure of banks. This index suggested that both Mexican and Brazilian banking systems showed signs of fragility before the crises. In this thesis, the effects of both microeconomic and macroeconomic approaches are examined and also these applications based on the predictions of the probability of failure and timing of failure are analyzed.

In either the microeconomic or the macroeconomic approach, a critical issue is to define banking failure or insolvency. However, in the literature, there is a difference between insolvency and failure.

Accordingly, insolvency exists when market value of the bank or market value of capital of the bank or institution turns out to be negative. Nevertheless, failure can be seen as the legal recognition of a bank's preexisting economic insolvency. In fact it is a choice that supervisory or regulatory institution may put into operation or not (Demirguc-Kunt, 1989).

In assessing the definition of banking failures, two kinds of banking failures can be seen; de jure and de facto failure (Demirguc-Kunt, 1989). Accordingly, de jure failure takes place as economic insolvency is judged officially and the bank is closed or involuntarily merged out of existence. On the other hand, de facto failure occurs when any regulatory authority cancelled the bank's license (Demirguc-Kunt, 1989). As a result, the bank regulatory authority can be considered as the only determinant of both types of failure. In this thesis, de facto and de jure failures are attempted to explain statistically. The model recognizes financial factors that influence the probability of de facto and de jure bank failures.

Table 2.3 presents countries covered and econometric methods for explaining banking failures in selected studies. Both microeconomic and macroeconomic studies used either limited dependent variable model; binary and multinomial logit or probit or duration model; the proportional models or parametric models. In the empirical literature, due to the difficulties in defining banking crises and banking failures there is no use of dynamic panel data for econometric tool to examine the determinants of banking failures. In this thesis, dynamic panel data is used for investigating the determinants of bank profitability.

Moreover, dynamic panel data methods are used to determine the causes of bank runs, to examine the costs of banking crises, and the indicators of banking performance such as bank profitability in the literature. Burdisso et al (2003) and McCandless et al (2003) investigated the determinants of the causes of bank runs during Argentine banking crisis and exchange rate crisis of 2001 by using the behavior of individual deposits as dependent variable in dynamic panel data models. The different studies from determining causes of bank runs or banking performance were presented by Hutchison and Neuberger (2005) and Loayza (2006). While Hutchison and Neuberger (2005) examined the output effects of banking crises in emerging markets, Loayza (2006) analyzed the dynamics of output growth and financial intermediation around systemic crises.

Table 2.3: Country Coverage and Methodology of Selected Studies on Banking Crises or Failures

Selected Studies	Country Coverage	Discriminant Analysis	Discrete Choice Models	Duration Model
Sinkey (1975)	US (1969-1972)	X		
Altman (1977)	US (1966-1977)	X		
Thomson (1991)	US (1982-1989)		Logit	
Logan (2001)	UK (1990-1994)		Logit	
Cole and Gunther (1995)	US (1986-1992)			Cox Proportional Hazard
Dabos and Escudero (2000)	Argentina (1994 -1996)			Cox Proportional Hazard
De Young et al, 2000	US (1984-1985)			Split-population log-logistic
Lane et al (1986)	US (1979-1983)			Cox Proportional Hazard
Molina (2002)	Venezuela (1994 -1995)			Cox Proportional Hazard
Whalen (19991)	US (1987-1990)			Cox Proportional Hazard
Wheelock and Wilson (1994)	US (1910 -1926)			Cox Proportional Hazard
Wheelock and Wilson (2000)	US (1984-1993)			Cox Proportional Hazard
Santor (2003)	90 countries (1975-1998)		Probit	
Hardy and Pazarbasioglu (1998)	50 countries (1975-1997)		Logit	
Hutchison and Mcdill (1998)	97 countries (1975-1997)		Probit	
Demirguc-Kunt and Detragiache (1999)	65 countries (1980-1995)		Logit	Cox Proportional Hazard
Bernhardsen (2001)	Norway (1988-1999)		Probit	
Sales (2005)	Brazil (1994-1998)			Cox Proportional Hazard
Gonzales-Hermosillo (1999)	5 countries (1982-1995)		Logit	Cox Proportional Hazard
Gonzales-Hermosillo et al (1997)	Mexico (1994-1995)			Split-population log-logistic
Matthews and Whitfield (2005)	Jamaica (1992-1998)		Multinomial Logit	Split-population log-logistic

Goddard et al (2004), Bourke (1989), Rhoades (1985), Molyneux and Thornton (1992), Athanasoglu et al (2005) and Gerlach et al (2004) tried to determine the profitability and performance of the banking sector by using dynamic panel data models. In these studies, bank profitability is determined by bank-specific factors and overall banking sector conditions. However, Rhoades (1985), Bourke (1989) and Goddard et al. (2004) consider determinants of profitability with only bank-specific variables hence, there is no analysis of the effect of macroeconomic conditions. The empirical literature recognizes various determinants of bank profitability. However some of the variables such as capital adequacy and liquidity proxies are common. In Rhoades (1985), Bourke (1989), Molyneux and Thornton (1992) and Goddard et al. (2004), both these proxies are found positively related to profitability. Moreover, Molyneux and Thornton (1992), Rhoades (1985) and Bourke (1989) found a positive relationship between credit risk and profit.

To summarize, there are two different approaches in examining the empirical literature on banking failure models; microeconomic and macroeconomic approaches. In this thesis, both bank-specific and macroeconomic variables are used for all empirical specification due to performance of classification accuracy. The studies which used microeconomic variables or macroeconomic variables or that are a combination of two strands used either limited dependent variable model; logit or probit or duration model; the proportional models or parametric models. The choice of bank failure definition is based on both de facto and de jure failures. In this thesis, both bank-specific and macroeconomic variables are examined by using both limited discrete choice model and duration model to predict the probability of failures of banks and timing of bank failures. Moreover, dynamic panel data is used in investigating the determinants of bank profitability.

CHAPTER 3

TURKISH BANKING SYSTEM: OVERVIEW

This chapter briefly exposes relevant structural changes in the Turkish banking sector. Afterwards, it reviews historical background of the Turkish banking sector and gives a short overview of financial crises on the banking system that occurred in November 2000 and February 2001. As discussed in the literature survey chapter, there are common characteristics of the bank failures such as the actions taken by supervisory institutions after the crisis and the changing of the existing institutional setup. These policy actions taken by supervisory institutions after the crises changed the overall structure of the banking system. These actions can be summarized as follows: strengthening supervisory and regulatory structure, promoting mergers, liquidating, closing of the banks and easing the entry of foreign capital (Ozkan-Gunay and Tektas, 2006). Before reviewing historical background of Turkish banking sector and the effects of financial crises, dealing with the changes in the number of banks before and after the crises and the situation of banking sector in the economy will contribute to the understanding of the rest of the study.

Firstly, before the crisis period, in the early 1980s, liberalization and global integration efforts took effect. Turkish banking system has developed significantly in those years. In the financial liberalization process; the entry of new banks to the sector were eased and interest rates were liberalized (Alper and Onis, 2002). The main goals of this process were to enhance competition and reduce inefficiencies in the financial system. By allowing new entries, while there were 43 banks of which four were foreign banks in Turkey in 1980, over the past two decades, the number of banks about doubled. This increasing trend has been ceased by the financial crises. In the 1994 crisis, the operations of three middle-sized banks were suspended. Between 1999 and 2006, total number of banks in the system diminished from 81 to 47 sharply due to the withdrawals of permission for carrying out banking operations and mergers and takeovers by Savings Deposit Insurance Fund (SDIF). Therefore, as of 2006, the Turkish banking sector consists of 47 banks[3] of which 34 are deposit-taking institutions and the remaining are investment and development banks (Banks Association of Turkey, 2006).

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[3] In addition, as of end of 2006, there were 4 Special Finance Institutions, 58 Insurance Companies, 92 Factoring, 81 Leasing, 7 Consumer Finance Institutions and 151 Intermediary Institutions operating in the financial sector. Roughly, 9.6 % of financial sector assets consist of non-bank financial institutions' assets. The banks also had insignificant share of non-bank financial institutions in financial system. As a result, there has been almost no competitive pressure from non-bank financial institutions.

Secondly, from the point of view of the situation of Turkish banking system in the economy, the size of Turkish banking system relative to the economy has grown the 1980s. This was caused by increased after the liberalization of interest rates and easing entry requirements to the banking system. Accordingly, total assets of the banks increased from 31 % of the GNP to 93 % of the GNP over 20 years. Nevertheless, the overall size of banking system has contracted from 92 % to 82 % during 1999 - 2005 due to the financial crisis in 2000 and 2001. As of the end of 2005, total asset size of the banking sector was 82 % of GNP (Banks of Association of Turkey, 2006).

The ratio of total loans to GNP ratio which is about 31 % by the end of 2005 can be viewed as credit activity of the banking system and the level of financial intermediation between lenders and borrowers. In 2003, it was about 20 % of GDP thus, the deposit-taking institutions could not finance firms sufficiently compared to developed countries[4] due to the high interest rates. Under these circumstances, it is hard to mention that banking sector could contribute to sustainable economic growth due to high and volatile interest rate environment, chronically high inflation and large public sector borrowing requirements.

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[4] For instance, in EU-15 countries, the ratio of total loans to GDP was 117 % in 2005. Similarly, in Switzerland and Japan with major international banking sectors, the ratios were 165 % and 117 % of GDP respectively.

3.1. HISTORICAL BACKGROUND OF THE TURKISH BANKING SECTOR

Turkish banking sector has developed considerably in the liberalization era of the 1980s. Introducing uniform accounting principles, allowing to borrow directly from abroad by syndicated loans, establishing an interbank money market (Istanbul Stock Exchange and Capital Markets Board), starting T-bills and government bonds auctions and also technological and human resources improvements in the sector has helped in the growth of the banking sector in Turkey (Ozkan-Gunay and Tektas, 2006).

After these encouraging developments in the banking sector, in the last decade, many emerging countries have had financial crises. These crises drove home the point of the significance of a sound banking system in achieving macroeconomic stability. After financial liberalization, Turkey experienced three serious crises in April 1994, November 2000 and February 2001 (Alper and Onis, 2002). Turkish financial system suffered accordingly. Alper and Onis (2002) stated the major reasons of emerging market financial crises, especially in Turkey, as; a) macroeconomic imbalances; high and rising fiscal deficits, high inflation and high real interest rates, b) the distortions created by state owned banks, c) full deposit insurance scheme, d) connected lending, e) high exposure concentrations and large foreign exchange positions and f) weakness of regulation and supervision in the banking system (Alper and Onis, 2002).

During the 1990s, Turkish economy experienced high political instability. There were four elections and nine governments. Brown and Dinc (2005) write that politicians had a motivation to take the costly action of postponement of severe regulatory intervention in bank failures until after the elections. This is because of the fact that failures of large banks may have an adverse effect on the economy at least in the short run (Rogoff and Sibert, 1988). Therefore, takeover or closing of failing banks naturally necessitates large funds by taxpayers. Politicians will always choose not to handle such issues before the elections (Brown and Dinc, 2005). In 1990s, the political instability in Turkey delayed the regulations in banking sector as theory suggested.

In addition to this political economy concerns regarding bank failures, there were high chronic inflation and high public sector borrowing because of the expansionary fiscal policies after the 1980s and loose monetary policies in the early 1990s. Furthermore, private commercial banks invested in government securities that issued short-term debt at high interest rates, by opening longer term foreign exchange (FX) positions.

These open positions made the banks susceptible to financial failure in case of large-scale defaults as a result of financial crises. An unsustainable fiscal deficit, monetary expansion through short-term advances from the Central Bank to the Treasury and loss of credibility in both domestic and foreign markets prepared the ground for the exchange rate crisis of 1994 (Ozkan-Gunay and Tektas (2006). Furthermore, at the beginning of 1994, the Central Bank increased the interest rates and the Turkish lira was devalued by 60 %. The overnight interest rates peaked to 1000 %, resulting in panic in the financial system (Ozkan-Gunay and Tektas (2006).

With liquidity problems of the banks in conjunction with the depositor runs in the spring of 1994, the currency crisis resulted in the withdrawal of permission for carrying out banking operations of three medium-sized banks. In April 1994, the stabilization, structural adjustment policies and full coverage of insurance scheme for bank deposits were introduced (Ertugrul and Selcuk, 2001).

Despite those measures, the vulnerability of the banking system could not be prevented and the effect of the 1994 crisis on commercial banks was very destructive. In 1994, the total assets of the banking system decreased from USD 72.5 billion to USD 52.7 billion, while equity capital fell to USD 4.3 billion from USD 6.6 billion. The ratio of networking capital to total assets decreased from 2.2 % to 0.5 %, while for foreign banks it increased from 8.6 % to 14.4 %, for the state-owned banks it diminished substantially 3.2 in percentage terms (Bank Association of Turkey, 1999).

Accordingly, the incentive structure for banks has been distorted by high inflation rates, large public sector borrowing requirements, short-term borrowing-based financing policies

(Ertugrul and Selcuk, 2001). After 1994 crisis, in Turkish banking system, there were three main problems related to the above distorted incentives: opening foreign exchange positions, a large number of weak banks providing connected lending and banking supervision by Treasury which had borrowing needs from banks (Rijckeghem and Ucer, 2005).

Firstly, Rijckeghem and Ucer (2005) write that "the open foreign exchange positions of the banking sector widened after 1994 crisis. In order to invest in Treasury bonds with high real interest rates, banks borrowed from abroad in the form of syndicated loans or collect foreign exchange deposits. This process combined with adopting accommodative monetary policy by Central Bank. The necessary liquidity was provided by Central Bank through open market operations. Until November 2000, banks earned high profits; Treasury rolled over debt and large public sector borrowing requirement was met" (Rijckeghem and Ucer, 2005).

Secondly, the full deposit insurance coverage[5] caused some imprudent banking practices and competitive distortions as a result of moral hazard. It encouraged weaker banks to expand their deposit base by offering above market interest rates. The full deposit

[5] Deposit insurance scheme, was first introduced in 1933 and redesigned in 1983 with the establishment of the Savings Deposit Insurance Fund. A partial deposit insurance application, which was in effect following the 1982 financial crisis, was rearranged as full deposit insurance in 1994 with the aim of protecting depositor against the risk of failure of the banks and maintaining public confidence despite increasing banks' risks and loosing market discipline.

insurance coverage helps a large number of these banks to survive (Lindgren et al, 1996).

Lastly, after the 1985 law on banking regulations, in Turkish banking system, Treasury held the supervisory responsibilities for banks (Alper and Onis, 2002). With these responsibilities, Treasury tried to roll over the debt by selling Treasury bills to the banks in the market. This created conflict of interest between Treasury's supervisory responsibilities and the borrowing needs. Therefore Treasury had a temptation to examine banks' financial standing tolerantly (Rijckeghem and Ucer, 2005).

3.2. A SHORT OVERVIEW OF THE TWIN FINANCIAL CRISES IN 2000-2001

In December 1999, Turkey adopted an IMF program, which sought to ensure debt sustainability, to reduce chronic and high inflation with the use of foreign exchange as a nominal anchor, fiscal adjustment and several structural measures. The 1999 IMF program also aimed to reform banking sector by forming independent supervisory and to rehabilitate state banks and improve the performance of banking sector (Alper and Onis, 2002). Thus, the new banking law was enacted in the year of 1999 establishing of independent Banking Regulation and Supervision Agency (BRSA)[6] compatible with the regulation and supervision standards of the

[6] BRSA was in full operation by September 2000.

Basel committee, removing the distortions created by the state owned banks and setting the appropriate prudential requirements in line with international standards.

Before the November 2000 crisis, the Banking Regulatory and Supervisory Authority (BRSA) has encouraged merger of the banks to eliminate the weaknesses of the system. A lower inflation rate and lower interest rate environment would remove the foreign exchange and interest rate arbitrage and the gains from investing in Treasury bonds. Because Turkey had many banks (82 banks in 1999), the concentration ratios in terms of total assets were very low compared to the other emerging market economies. Some of small and weak banks had difficulties in adapting to the new environment (Rijckeghem and Ucer, 2005).

As discussed in the previous section, state-owned banks have distorted incentives in the banking sector notably in the 1994 crisis due to their quasi-fiscal activities (Alper and Onis, 2002). The total burden of preferential and subsidized credit and agricultural support programs and quasi-fiscal activities of state-owned banks, called duty losses of the state-owned banks[7], reached USD 20 billion which were above 10 % of GDP and 14 % of the total assets of the banking system at the end of year 2000 (Ertugrul and Selcuk, 2001). This led state-owned banks to increase interest rate and interbank borrowing

[7] The concept of duty losses of the state-owned banks can be considered as the quasi-fiscal losses incurred through directed lending, which the Treasury recognizes as an obligation (Alper and Onis, 2002).

and deterioration of capital adequacy ratios of banks. In addition, the demand deposits and large part of the time deposits were directed to overnight repo offering high interest rate (Bank Association of Turkey, 1999). Rijckeghem and Ucer (2005) also points out that state banks had serious liquidity problems and had to roll over about USD 4-5 billion daily by deposits and money markets by offering higher interest rates than private banks in the late 1999 due to the opaque relationship between state banks and Treasury.

Nevertheless, after the summer of 2000, the devaluation expectations arose and capital outflow due to the instability in the market caused an increase in interest rates, excess demand for foreign currency and a decrease in the Central Bank reserves. The dramatic increase in interest rates created liquidity pressure on the banking sector. Some commercial banks[8] with liquidity problems tried to sell their holdings of government bonds.

In December 2000, this liquidity crisis ended with the IMF-led additional financial support which helped to reverse capital flow, to raise the Central Bank reserves to the pre-crisis level, to drop interest rates and to succeed in normalizing the situation for a while (Ozkan, 2005). The dependency on the capital flows and the vulnerability of

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[8] Especially, Demirbank had a substantial government securities portfolio, which was financed through short term borrowing from the money market. It is estimated that Demirbank (paid capital USD 300 millions) had approximately USD 7.5 billion of government securities (almost 15 % of the total domestic debt stock) (Ertugrul and Selcuk, 2001).

the banking sector signaled the possibility of a new crisis (Ertugrul and Selcuk, 2001). After two months, the fragility of economic environment coupled with the political dispute caused massive attacks on the currency. Thus, in February 2001, the currency peg had to be abandoned and replaced by free-floating regime.

Turkish economy and its banking system were hit hard by the crises of 2000 and 2001. Thus, the size of banking system in terms of assets contracted by 17 % of GDP and 35 % of banks was eliminated from the system. Turkish financial system suffered accordingly. The resulting output loss of the twin crises was substantial and the economy contracted by over 9 % in 2001, which was the nation's most severe recession since 1945 (Alper and Onis, 2002).

The design of 1999 IMF program did not provide measures on foreign exchange risks and liquidity risks in the banking sector. Although there was legislation about restrictions on open foreign exchange positions, widening open foreign exchange positions was ignored in order to meet large public sector borrowing requirements (Rijckeghem and Ucer, 2005). Despite liquidity risks, there were excessive restrictions on the Central Bank's ability to be Lender of the Last Resort in the design of the program, since the IMF program eliminated the Central Bank's facility of implementing implicit insurance mechanism against systemic risks involving interbank deposits by specifying a ceiling on its Net Domestic Assets as a performance criteria (Alper and Onis, 2002).

Another issue is that the number of weak banks in the banking sector was underestimated though five private banks were taken under Saving Deposit Insurance Fund at the beginning of the IMF program (Ertugrul and Selcuk, 2001). The last issue is that the short-term borrowing and lending operations of state banks related to duty losses were also neglected in the design of the IMF program, creating vulnerability to the shocks in the banking system.

To recapitulate, the following factors led the Turkish financial system to experience a crisis in November 2000: First, there were the problematic issues in sustaining capital inflows. Second, despite of the existence of an exchange rate risk and financial need of Treasury, there was not sufficient support by the IMF. Third, as a result of widening open foreign exchange positions, large amount of duty losses of state banks, connected lending of weak banks under full deposit insurance scheme, weak implementation of supervision by Treasury due to conflict of interest of Treasury, a large number of weak banks and the unfavorable external conditions, the banking system was highly fragile.

The crises of November 2000 and February 2001 stemmed primarily from the fragility of the banking sector. The Turkish experience shows that both public and private banks contributed significantly to the outbreak of economic crises. In retrospect, it can be expressed that private commercial banks played an instrumental role in the November 2000, while public banks emerged as the central actors in the context of the subsequent crisis of February 2001 (Alper and Onis, 2002). As discussed throughout this chapter, all distorted incentives in Turkish banking sector such as opening foreign exchange positions, liquidity problems, poor asset quality and capital inadequacy due to weakness of regulation and supervision in the banking system is analyzed in conjunction with empirical specifications in the next chapters.

In the empirical part of the thesis, high levels of liquidity and asset quality, good management conditions of banks are found as the determinants of survival of banks. Furthermore, as a supervisory tool, estimated degree of fragility of individual banks and overall banking system presents the fluctuations before the failure quarters. These findings may help institutions like Banks Association of Turkey and Banking Supervision and Regulation Agency to devise or fine-tune their procedures in detecting banking sector fragilities. The main drivers of the failures in Turkey, which are discussed in this chapter, are analyzed econometrically. For this, discrete choice models, a duration model and a dynamic panel data model are used.

CHAPTER 4

DATA

The data set used in the analysis comprises financial information about banks in the Turkish banking system. The data are publicly available from the Banks Association of Turkey[9]. Macroeconomic variables for Turkey are taken from the IMF International Financial Statistics (IFS[10]) publication.

The quarterly data for bank-specific variables are drawn from the financial statements: The balance sheet and income statements, which are used to compute financial ratios for both failed and non-failed banks. These financial statements are collected from the quarterly reports of The Banks Association of Turkey for 1997 through

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[9] http://www.tbb.org.tr/net/donemsel/default.aspx?dil=EN

[10] http://ifs.apdi.net/imf/ifsbrowser.aspx?branch=ROOT

2006[11]. Moreover, the quarterly macroeconomic data are obtained from IFS for the same period.

Microeconomic variables are mainly based on the bank specific variables used in CAMEL rating categories (capital adequacy, asset quality, management quality, earnings and profitability and liquidity), which are taken from financial statements of the banks. Besides, by using macroeconomic variables, the role of macroeconomic conditions on banking crises such as interest rates, inflation rates, Central Bank foreign exchange reserves and credit expansion etc, are examined (Gonzales-Hermosillo, 1999). Both microeconomic and macroeconomic variables those appeared in the previous studies and with few exceptions have been identified as good indicators of failures.

Over the period of December 1997-June 2006, there were 36 failed banks, of which 8 are mergers and acquisitions, and 45[12] non-failed banks were in the Turkish banking system (see table A.1 in the appendix). In fact, in this period, there were 37 failed banks including Türk Ticaret Bankası, which was taken under Saving Deposit Insurance Fund in November 6, 1997. Thus, its observations

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[11] The first electronically available data set is dated 1997.

[12] Total number of banks in the banking system (except participation banks) is 46 excluding Birleşik Fon Bankası which is in the group of banks in Saving Deposit Insurance Fund as of June 2006. Moreover, 89.34 % of paid-in capital of Türk Dış Ticaret Bankası A.Ş. was transferred to Fortis Bank in July 2005. However, Fortis Bank was not included in the sample due to its lack of data.

have only one quarter in the specified period and the bank is not included in the sample due to the limited data. Moreover, there is another point in clarifying dataset issue. It is found that there is a difference between the date of last financial statements issued and the date of failure for some of the failed banks (see figure A.1 in Appendix A section). Therefore, in the estimation process, the date of last financial statements is taken as the date of failure as in Molina (2002).

4.1 PRINCIPAL COMPONENT ANALYSIS

Principal component analysis is a multivariate statistical technique. Principal components are linear combinations of the variables that explain variance-covariance properties of the variables. Direct uses of principal component analysis are the identification of groups of inter-related variables, the reduction of number of variables and a method of transformation of data (Anderson, 2003). Principal component analysis is a technique of categorizing patterns in data and expressing the data in such a way to highlight their similarities and differences. The main advantage of principal component analysis is to compress the data by reducing the dimension without loss of information (Anderson, 2003).

From the point of view of statistical theory, Anderson (2003) argued that the set of principal components yields a convenient set of coordinates, and the accompanying variances of the components characterize their statistical properties. In statistical practice, the method of principal components is used to find the linear combinations with large variance (Anderson, 2003). Therefore, principal component analysis yields orthogonal explanatory variables and eigenvectors and removes collinearity in the estimation.

The motivation in using principal component analysis is to identify highly correlated variables. This is done so that later econometric analysis will suffer less in accuracy and reliability. It is more likely to have highly correlated subsets of variables when there are a large number of variables in the database as in here. The objective of principal component analysis is to reduce the dimensionality (number of variables) of the dataset but retain most of the original variability in the data (Anderson, 2003). The first principal component accounts for as much of the variability in the data as possible, and each succeeding component accounts for as much of the remaining variability as possible.

In this study, both microeconomic variables and macroeconomic variables are separately subjected to principal component analysis. In the first step, the factors whose eigenvalues are greater than one, should be retained for both microeconomic and macroeconomic variables separately. The first principal component is the eigenvector with the highest eigenvalue. If the eigenvalues are so small, the loss of information will be less. Then, the first p eigenvectors having eigenvalues greater than one, are classified based on CAMEL categories and macroeconomic conditions. Principal component analysis is utilized to classify eigenvectors and to determine proxy variables and corresponding eigenvectors for each CAMEL category from the pool of independent variables, which summarized the financial information of the banks and macroeconomic conditions.

Table 4.1 presents the eigenvalues of factors for both microeconomic and macroeconomic variables. Based on the results of principal component analysis, the first eight eigenvectors whose eigenvalues are greater than one for microeconomic variables and the first three eigenvectors whose eigenvalues are greater than one for macroeconomic variables are chosen.

Table 4.1: Eigenvalues of Factors for Microeconomic and Macroeconomic Variables

Components	Eigenvalues	Proportion of Explained Variance	Cumulative Explained Variance
Microeconomic Components			
1	3.81	0.20	0.20
2	2.75	0.14	0.35
3	2.07	0.11	0.45
4	1.81	0.10	0.55
5	1.69	0.09	0.64
6	1.51	0.08	0.72
7	1.02	0.05	0.77
8	1.00	0.05	0.82
Macroeconomic Components			
1	4.98	0.50	0.50
2	2.54	0.25	0.75
3	1.04	0.10	0.86

Accordingly, the first eight eigenvectors for microeconomic variables explain 82 percent of total variance and the first three eigenvectors for macroeconomic variables explain 86 percent of total variance (see Table 4.1). Tables A.2 and A.3 in Appendix A section present the variables that have the highest factor scores related these eigenvectors. The classifications of eigenvectors are based on these scores. However, there are very close scores to each other in a single eigenvector. Principal component analysis is again applied to those variables that have close eigenvalues to determine the selected variables in such a situation.

Based on the classification of eigenvectors, the first eigenvector is named as size category for share in sector in terms of assets.[13] The classifications of other seven eigenvectors are named as; earning category for the ratio of income before tax to total assets, liquidity category for the ratio of liquid assets to total assets[14], asset quality category for the ratio of permanent assets to total assets[15],

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[13] Share in sector in terms of loans has greater factor score than that of share in sector in terms of assets. In the second application of principal component analysis with four variables - share in sector in terms of loans, assets, deposits and logarithmic value of assets - share in sector in terms of assets has the greatest score with 0.53.

[14] In spite of the ratio of total loans to total assets has the greatest score in the first step, in the second application of principal component analysis with four variables - the ratio of loans to assets, the ratio of liquid assets to assets the ratio of FX liquid assets to FX liabilities, the ratio of total deposits to number of branches - share in sector in terms of assets has the greatest score with 0.61.

[15] In the second application of principal component analysis with four variables - the ratio of permanent assets to total assets, the ratio of FX deposits to number of branches, the ratio of total deposits to number of branches and the ratio of

earnings category for the ratio of net income to shareholder equity, management category for the ratio of total deposits to number of branches[16], liquidity category for the ratio of foreign exchange liquid assets to foreign exchange liabilities and asset quality category for the ratio of total loans to net working capital, respectively. This set of microeconomic eigenvectors and variables based on principal component analysis that is utilized in the next two chapters.

The variables and eigenvectors selection procedure based on principal component analysis is also applied to ten macroeconomic variables in table A.3 in Appendix A section, covering macroeconomic conditions of the country. Among macroeconomic variables, the first three eigenvectors can be named as credit channel category for credit growth[17], real costs category for real interest rate variable and real effect category for GDP growth. This set of macroeconomic eigenvectors and variables based on principal component analysis that is utilized in the next three chapters including dynamic panel data model.

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permanent assets to liquid assets - the ratio of permanent assets to total assets has the greatest score with 0.66.

[16] In the second application of principal component analysis with three variables - the ratio of total deposits to number of branches, the ratio of permanent assets to liquid assets and the ratio of FX deposits to number of branches - the ratio of total deposits to number of branches has the greatest score with 0.69.

[17] In the second application of principal component analysis with four variables - credit growth, the ratio of credit to private sector to GDP, the ratio of domestic credit to GDP and inflation rate - credit growth has the greatest score with 0.51.

Turning to the microeconomic variables again, there is need to prepare new microeconomic set of eigenvectors and variables to use in dynamic panel data model to analyze bank profitability in the last chapter. As preparing a set of eigenvectors and variables for the analysis of bank profitability, earning category should be extracted from the data set. Therefore the last application of principal component analysis is used to prepare a set of eigenvectors and variables for using in dynamic panel data model in the last chapter due to question of endogenity. Tables A.4 and A.5 in Appendix A section reports the repetition of principal component analysis for excluding earning category from data set. Accordingly, the first eight components explain 85 percent of total variation (see table A.4 in Appendix A section).

Based on the classification of eigenvectors for bank profitability analysis, the first eight eigenvectors can be named as follows; the first eigenvector is named as size for share in sector in terms of assets as in the first case. The other eigenvectors are named as; asset quality category for the ratio of permanent assets to total assets and for the ratio of total loans to total assets, management category for the ratio of total deposits to number of branches and the ratio of foreign exchange deposits to number of branches, asset quality category for the ratio of total loans to net working capital, liquidity category for the ratio of foreign exchange liquid assets to foreign exchange liabilities and asset quality category for the ratio of total loans to shareholders equity, respectively. This set of eigenvectors and variables based on principal component analysis that is utilized in the last chapter for dynamic panel data model to determine the main factors of bank profitability in Turkish banking system. The final set of eigenvectors and variables are listed at the end of the chapter (see table 4.3).

4.2. DESCRIPTIVE STATISTICS

The selection of explanatory variables depends on both bank-specific and macroeconomic variables to predict bank failures that have been mentioned in the previous chapters. As a preliminary check, a test of mean difference is done as Hutchison and McDill (1999). This can describe different movements in microeconomic variables for the failed banks and the non-failed banks separately. For failed banks, one quarter before the failure was excluded from the data in order to assess the pattern of explanatory variables for failed banks before crisis. Therefore, this test reports differences between the failed banks and the non-failed banks during non-failure periods.

The mean differences of the microeconomic eigenvalues and variables for both non-failed and failed banks are given in table 4.2. In the first and second column, the mean values for both failed and non-failed banks are shown[18] and the last column illustrates the

[18] The standard deviations are shown in parentheses.

p-value of mean difference tests[19]. According to mean difference test, all variables are found significantly higher in non-failed banks than in failed banks. If mean values for non-failed banks are higher (lower) than that of failed banks then, the sign of estimated coefficients can be expected to be negative (positive) in line with t-test results.

Table 4.2 Mean Difference Test[20] for Selected Eigenvectors and Variables

Variables / Eigenvectors	Mean Values For Non-failed Banks	Mean Values For Failed Banks	Differences in Mean Values (P > |t|)
Share in Sector (T. Assets)	1.93 (3.68)	0.88 (1.14)	0.00
Size Category	0.10 (2.11)	-0.28 (1.40)	0.00
Income Before Tax/T. Assets	3.43 (8.88)	-0.03 (25.54)	0.00
Earnings Category	0.13 (1.33)	-0.37 (2.29)	0.00
Liquid Assets/T. Assets	44.53 (23.12)	45.81 (22.98)	0.27
Liquidity Category	-0.01 (1.47)	0.00 (1.34)	0.97
Permanent Assets/T. Assets	12.88 (12.75)	15.04 (14.48)	0.86
Asset Quality Category	0.14 (1.20)	-0.38 (1.64)	0.00
Net Income/S. Equity	0.10 (1.00)	0.06 (2.77)	0.05
Earnings Category	0.05 (0.74)	-0.14 (2.19)	0.00
T. Deposits/No. of Branches	16.14 (35.87)	18.37 (31.44)	0.20
Management Category	-0.02 (1.08)	0.07 (1.56)	0.14
FX Liquid Assets/FX Liabilities	47.80 (54.76)	36.65 (24.86)	0.00
Liquidity Category	0.01 (0.91)	-0.01 (1.23)	0.03
T. Loans/Net Working Capital	-0.07 (2.22)	0.01 (0.30)	0.38
Asset Quality Category	-0.01 (1.16)	0.01 (0.22)	0.69

[19] The two-sample t-test is used to determine if two population means are equal.

[20] Ho: Mean (Exp. var. for failed banks) – Mean (Exp. var. for non-failed banks) = 0

Share in sector in terms of total assets, the size of banks in terms of assets, can be negatively related to the likelihood of failure since relatively large banks may diversify risks subject to small banks. Besides "too large to fail" policies can help decreasing the failure probability for relatively large banks (Gonzales-Hermosillo et al, 1997). The ratio of foreign exchange liquid assets to foreign exchange liabilities reflects liquidity structure and foreign exchange exposure risk. Again, the ratio is expected to be negatively related to the probability of bank failure. The expected signs of these selected eigenvector and related variables based on t-test are consistent with the theoretical view.

From the income-expenditure side of the banks, the ratio of total deposits to the number of branches can be assessed in terms of efficiency. It is assumed that managerial ability can be measured to the extent that it can be a sign of explicit managerial decisions. Within the same context, the ratio of income before tax to total assets and the ratio of net income to shareholders' equity reflect the earnings condition of the banks.

As expected, earnings and management quality proxy variables would be negatively related to the probability of bank failure. However, the sign of earnings proxy may be positive since riskier investments are more profitable depending on the condition of the banks. Furthermore, the ratio of total loans to net working capital and the ratio of permanent assets to total assets can be assessed in the asset quality category. Banks that failed during the sample period had higher ratio of total loans to net working capital and ratio of permanent assets to total assets. The interpretation of this is straightforward: A high level of the ratio of total loans to net working capital indicates a high level of credit risk of the banks.

Based on t-test results, except for the eigenvectors related to liquidity category, management category and asset quality category, the eigenvectors related to other CAMEL categories including size category are significant at one percent significance level. Similarly, except for the ratio of liquid assets to total assets, the ratio of permanent assets to total assets, the ratio of total deposits to number of branches and the ratio of total loans to net working capital, other variables are again significant at one percent significance level based on mean difference test results. Therefore, the mean values of selected explanatory variables and eigenvectors for non-failed banks are different from those for failed banks. This provides preliminary evidence that motivates further analysis.

This chapter prepared a set of eigenvectors and variables based in principal component analysis that will be utilized in the empirical specifications, discrete choice models, a duration model and a dynamic panel data model, respectively in the next chapters (see table 4.3). Multinomial and binary logit model are used by comparing the predictive accuracy of the models in order to capture the different outcomes of failure with the same selected eigenvectors and related variables, separately.

Table 4.3 List of Selected Eigenvectors and Variables for Empirical Specifications

Estimation Technique	Thesis Section	Selected Variables	Categories related to Selected Eigenvectors
Discrete Choice Models & Duration Models	Section 5.2 & Section 6.2	Share in Sector (T. Assets)	Size
		Income Before Tax/T. Assets	Earnings
		Liquid Assets/T. Assets	Liquidity
		Permanent Assets/T. Assets	Asset Quality
		Net Income/S. Equity	Earnings
		T. Deposits/No. of Branches	Management
		FX Liquid Assets/FX Liabilities	Liquidity
		T. Loans/Net Working Capital	Asset Quality
		Credit Growth	Credit Channel
		Real Interest Rate	Real Cost
		GDP Growth	Real Effect
Dynamic Panel Data Model	Section 7.2	Share in Sector (T. Asset)	Size
		Permanent Assets/T. Asset	Asset Quality
		Total Loans/T. Asset	Asset Quality
		T. Deposits/No. of Branch.	Management
		FX Deposits/No. of Branch.	Management
		T. Loans/Net Working Cap.	Asset Quality
		FX Liquid Assets/FX Liab.	Liquidity
		T. Loans/ Equity	Asset Quality
		Credit Growth	Credit Channel
		Real Interest Rate	Real Cost
		GDP Growth	Real Effect

Afterwards, duration model deals with the time to failure instead of predicting the probability of banking failures. Moreover, using the same eigenvectors and variables, it is possible to compare the prediction results of duration model with that of discrete choice models in the next two chapters. However, in the last chapter, the same eigenvectors and variables cannot be used in dynamic panel data model to analyze bank profitability because of endogeneity question. In dynamic panel data model, size, asset quality, liquidity and management categories and related variables will be used as independent variables.

CHAPTER 5

THE EMPIRICAL SPECIFICATION I: DISCRETE CHOICE MODELS

This chapter analyzes the main factors that were crucial in the bank failures with 36 banks in 1997-2006 by using limited dependent variables models. Both multinomial logit model and traditional binary model are applied to the selected eigenvectors and variables based on principal component analysis in order to predict the probability of bank failures and determine the factors of bank failures. This chapter also analyzes econometrically the bank-specific and macroeconomic determinants of bank failures.

In this chapter, the primary objective is to distinguish the state of problematic banks as failure and mergers/acquisition; by using multinomial logit model. Since a multinomial model discriminates between two failure outcomes and uses more information (i.e., failed banks versus mergers/acquisition), it is likely to be a better predictor of bank failures (Matthews and Whitfield, 2006). The other objectives are to examine the determinants of banking failures, to estimate the likelihood of banking failure, to analyze the contribution of microeconomic and macroeconomic factors in banking system problems in Turkey and to identify leading indicators of banking failures in Turkey.

5.1. THE MODEL

In binary choice models, the dependent variable should be dichotomous. In each quarter, the bank is either failed (de facto and de jure failures as mentioned in chapter 2) or not failed. Multinomial logit model proposes the possibility to evaluate the third alternative outcome, the mergers/acquisition alternative, which is concerned with identifying the factors that distinguish the banks bailed out by a mergers/acquisition. It is also concerned with identifying the ability of statistical models to differentiate between distressed banks that had different outcomes. Moreover, multinomial logit model that has potential to differentiate between these outcomes might be superior to binary choice model that accepts merged/acquired banks and failed banks as a common group (Matthews and Whitfield, 2006).

The traditional logit model for panel data is used to explain the probability of bank failure. In each quarter, the bank is either experiencing a failure or not. Accordingly, dependent variable is a binary outcome taking the values of 0 when it fails or 1 when it survives. Let $i = 1,2,..,81$ denote the banks and $t = 1,2,\ldots,35$ denote the quarters for the i^{th} bank. The conventional function, which indicates the cumulative standard logistic probability distribution function, is described as follows:

$$\text{Prob (Failure}_{it} = 1) = \exp(X_{it}\beta) / (1 + X_{it}\beta) \qquad (5.1)$$

Equation (5.1) is estimated using maximum likelihood procedure. Moreover the probability of bank failures that will occur at a particular time in a particular bank is hypothesized to be a function of a vector of n explanatory variables X_{it} and β is a vector of n unknown coefficients[21] (Greene, 1997).

A multinomial logit model, which is used to differentiate between bank failure, mergers/acquisitions and non-failed outcomes, is estimated by maximum likelihood. Again, let i = 1,2,..,81 denote the banks and t = 1,2,…,35 denote the quarters for the i^{th} bank. The conventional function is described as follows:

$$\text{Prob } (Y_{it} = j) = \exp(X_{it}\beta_j) / (\sum_{k=0}^{2} X_{it}\beta_k) \qquad \text{for } j = 0,1 \text{ or } 2 \qquad (5.2)$$

where Y_{it} is a random variable indicating the state of the banks in each quarter. This can take a value of j = 0, 1 or 2, which represents non-failed, failure and mergers/acquisition, respectively. The vector X_{it} represents a set of exogenous variables and β represents regression parameters to be estimated. The estimated equations above provide a set of probabilities for the j + 1 choices for an individual with characteristics X_{it} (Greene, 1997). Equation (5.2) is estimated again using the maximum likelihood procedure.

[21] See Greene (1997) for a full exposition of the derivations.

Moreover, the multinomial logit model assumes independence of odd ratios of different alternatives, therefore the model requires that the assumption of 'independence of irrelevant alternatives (IIA)' be satisfied (Greene 1997). In order to validate this assumption, the Hausman specification test as well as the Small-Hsiao IIA test is presented in table A.6 in Appendix A section.

5.2. ESTIMATION RESULTS

This section presents both multinomial logit models, which jointly determine failure, merger/acquisition and non-failure and standard binary logit models in which merger/acquisition and failure outcomes are pooled. Tables 5.1 - 5.4 illustrate the specifications for binary and multinomial logit models. The first three columns for each model illustrate the estimated coefficients, the relevant statistics of significance (z) and the p-value respectively. The first model specification includes only bank-specific eigenvectors and variables and the second one combines both microeconomic and macroeconomic eigenvectors and variables for both models.

The results[22] in binary model in table 5.1 shows that all bank-specific eigenvectors except for size category, liquidity categories and one of asset quality categories are significant at one percent significance level. Moreover, for joint-significance of variables, the

[22] These results based on panel data in which the observations responding from the failure quarter onwards are excluded for both models.

Wald and LR[23] tests are applied and in both model specifications, the null hypothesis of zero coefficients of explanatory variables is rejected at one percent significance level (see table 5.1).

Table 5.1: Estimation Results of Binary Logit Model for Selected Eigenvectors[24]

Variables / Models	Model 1			Model 2		
	Coef.	z	P>z	Coef.	z	P>z
Microeconomic Variables						
Size Category	-0.24	-0.89	0.38	-0.13	-0.72	0.47
Earnings Category	-0.80	-4.64	0.00	-0.49	-4.93	0.00
Liquidity Category	-0.37	-1.44	0.15	-0.15	-0.97	0.33
Asset Quality Category	-0.51	-2.87	0.00	-0.47	-3.73	0.00
Earnings Category	-0.40	-2.48	0.01	-0.28	-2.43	0.02
Management Category	0.37	2.00	0.05	0.16	1.26	0.21
Liquidity Category	0.32	1.11	0.27	0.25	0.94	0.35
Asset Quality Category	0.02	0.04	0.97	0.03	0.10	0.92
Intercept Dummy	2.09	2.26	0.02	2.26	3.54	0.00
Constant	-6.94	-5.70	0.00	-6.13	-12.1	0.00
Macroeconomic Variables						
Credit Channel	-	-	-	0.41	2.68	0.01
Real Cost	-	-	-	0.27	2.44	0.02
Real Effect	-	-	-	-0.05	-0.27	0.79
Model Fit						
AIC	234.50			217.90		
Pseudo R^2	0.233			0.247		
Diagnostic Test of Validity of Regressors						
LR	100.38			136.95		
Wald	31.91			72.34		

[23] LR test statistics is equal to the difference between log likelihood values of the model in the first iteration and the last iteration, which is multiplied by minus 2 (Gonzales-Hermosillo, 1999).

[24] Eigenvectors selection procedure based on principal component analysis is explained in detail in section 4.1.

Table 5.2 reports that all selected bank-specific variables except for share in sector in terms of assets the ratio of liquid asset to asset, the ratio of net income to equity, deposits per branch and the ratio of loans to net working capital are significant at one percent significance level. These results are consistent with the results of binary logit model with selected eigenvectors. Moreover, for joint-significance of variables, the Wald and LR[25] tests are applied and in both model specifications, the null hypothesis of zero coefficients of explanatory variables is rejected at one percent significance level (see tables 5.1 and 5.2).

Tables 5.1 and 5.2 also show the overall model selection criteria with Akaike' information criteria (AIC)[26] and Pseudo R^2 [27]. According to both criteria, the estimates in the full model specification, which uses both microeconomic and macroeconomic variables, provide higher Pseudo R^2 and lower AIC values than that of the former one which uses only microeconomic variables.

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[25] LR test statistics is equal to the difference between log likelihood values of the model in the first iteration and the last iteration, which is multiplied by minus 2 (Gonzales-Hermosillo, 1999).

[26] AIC can be used for the model with having different number of variables. It can be defined as the sum of log likelihood value and number of explanatory variables, which is multiplied by minus 2.

[27] Pseudo R^2 can be used for comparing the fit of different models for the same dependent variable. It is equal to one minus the ratio of log likelihood value of the model in the first iteration to log likelihood value in the last iteration (Gonzales-Hermosillo, 1999).

Table 5.2: Estimation Results of Binary Logit Model for Selected Variables[28]

Variables / Models	Model 1			Model 2		
	Coef.	z	P>z	Coef.	z	P>z
Microeconomic Variables						
Share in Sector (T. Assets)	-0.21	-1.16	0.25	-0.13	-0.99	0.32
Income Before Tax/T. Assets	-0.05	-5.52	0.00	-0.05	-6.07	0.00
Liquid Assets/T. Assets	0.01	0.62	0.53	0.01	1.25	0.21
Permanent Assets/T. Assets	0.03	2.42	0.02	0.01	1.19	0.24
Net Income/S. Equity	0.05	0.68	0.50	0.02	0.28	0.78
T. Deposits/No. of Branches	0.00	0.03	0.98	0.00	0.64	0.52
FX Liquid Assets/FX Liabilities	-0.04	-2.86	0.00	-0.03	-3.05	0.00
T. Loans/Net Working Capital	0.07	0.23	0.82	0.05	0.18	0.85
Intercept Dummy	1.97	2.48	0.01	3.58	4.14	0.00
Constant	-5.36	-5.87	0.00	-3.93	-5.68	0.00
Macroeconomic Variables						
Credit Growth	-	-	-	-0.04	-2.75	0.01
Real Interest Rate	-	-	-	0.02	2.52	0.01
GDP Growth	-	-	-	-0.06	-2.03	0.04
Model Fit						
AIC	248.29			222.34		
Pseudo R^2	0.215			0.254		
Diagnostic Test of Validity of Regressors						
LR	96.07			116.03		
Wald	43.49			76.72		

For the second quarter of 2001, a crisis dummy variable[29] is included in both model specifications for each model and it is found positive and statistically significant. From tables 5.1 and 5.2, the full specification of the models, earning categories and asset quality

[28] Variables selection procedure based on principal component analysis is explained in detail in section 4.1.

[29] The effect of the crisis that occurred in February 2001 can be seen from the financial reports of the banks, which were published in the second quarter of 2001. Therefore, dummy variable is included to both model specifications per model. It takes the value 1 from 2001.q2 to 2006.q2 but 0 elsewhere.

category are found negative and statistically significant, as expected (see table 5.1). This means that the said categories are negatively related bank failures. As considered the estimation with variables, the ratio of income before tax to total assets and the ratio of foreign exchange liquid assets to foreign exchange liabilities are negative, as expected. They have a negative effect on the probability of failure (see table 5.2). The results of two different estimations have consistency in terms of significance of the independent variables.

From the macroeconomic perspective, in most studies, there is evidence that if there is credit expansion in economy, banking sector problem can be expected (Demirguc-Kunt and Detragiache, 1997). In this study, credit growth is likely to be positively associated with the likelihood of failure. Lower GDP growth rate or adverse developments in the real side of the economy can be a main source of banking sector problems (Demirguc-Kunt and Detragiache, 1997). Real interest rate is likely to be related to the proxy of macroeconomic mismanagement, which adversely affects the economy and the banking system through various channels. Therefore, the sign of the estimated coefficient of real interest rate turns out to be positive. In this study, except for credit growth variable, other macroeconomic variables have expected signs. Only the eigenvector related to macroeconomic real effect is statistically insignificant. There is no additional proper information on banking failure in the estimation with eigenvectors. This is because of the fact that ingredients of the said eigenvector have the composition of the other variables (see Chapter 4).

Tables 5.3 and 5.4 report the results of the re-estimation of two specifications of both selected eigenvectors and variables using multinomial logit model. Again, all banks and all periods are included in the pooled sample. The coefficients that affect the probability of merger/acquisition positively also affect the probability of failure positively and vice versa. The coefficients differ largely across the probabilities of merger/acquisition and failure in both specifications of multinomial logit model. However, the estimated coefficients in both binary and multinomial logit models are close to each other for the failed banks. Moreover, dummy variable for is found statistically insignificant which is different from that of binary logit model. There is no effect of financial crisis on the probability of merger/acquisition.

In table 5.4, the sign of net income to shareholders' equity to total assets have positive sign, unexpectedly. However, the sign of earnings proxy is not clear "a priori". Although profitability can signal a well-functioning bank, excessively risky projects can be very profitable for a while before the failure. In this study, profitability proxy variable has positive impact on hazard rate. In other words, profitability of the banks has a negative impact on the survival of the banks.

Table 5.3: Estimation Results of Multinomial Logit Model for Selected Eigenvectors[30]

Variables / Models	1 (Failed)			2 (Merger/Acquisition)			1 (Failed)			2 (Merger/Acquisition)		
	Coef.	z	P>z	Coef.	z	P>z	Coef.	z	P>z	Coef.	z	P>z
Microeconomic Variables												
Size Category	-0.05	-0.40	0.69	-0.07	-0.18	0.86	-0.08	-0.56	0.58	-0.13	-0.32	0.75
Earnings Category	-0.64	-5.22	0.00	-0.46	-3.84	0.00	-0.54	-3.73	0.00	-0.30	-2.38	0.02
Liquidity Category	-0.05	-0.29	0.78	-0.34	-1.21	0.23	-0.09	-0.50	0.61	-0.32	-1.16	0.25
Asset Quality Category	-0.35	-2.70	0.01	-0.22	-1.59	0.11	-0.43	-3.02	0.00	-0.33	-2.36	0.02
Earnings Category	-0.23	-2.59	0.01	-0.06	-0.42	0.67	-0.25	-2.87	0.00	-0.08	-0.56	0.58
Management Category	0.01	0.08	0.94	0.63	2.76	0.01	-0.05	-0.27	0.79	0.53	2.49	0.01
Liquidity Category	0.47	3.06	0.00	-0.01	-0.06	0.95	0.35	2.12	0.03	-0.06	-0.35	0.72
Asset Quality Category	0.03	0.80	0.42	0.28	1.95	0.05	0.00	0.03	0.98	0.30	1.79	0.07
Intercept Dummy	0.68	1.48	0.14	1.77	1.65	0.10	2.26	2.41	0.02	3.08	1.49	0.14
Constant	-5.42	-13.48	0.00	-7.61	-7.47	0.00	-6.37	-9.01	0.00	-8.86	-5.52	0.00
Macroeconomic Variables												
Credit Channel	-	-	-	-	-	-	0.47	2.23	0.03	0.19	0.52	0.60
Real Cost	-	-	-	-	-	-	0.22	2.03	0.04	0.61	1.97	0.05
Real Effect	-	-	-	-	-	-	0.07	0.44	0.66	-0.39	-0.74	0.46
Model Fit												
AIC	259.86						237.58					
Pseudo R2	0.284						0.326					
Diagnostic Test of Validity of Regressors												
LR	110.06						126.33					
Wald	106.29						121.52					

[30] Eigenvectors (also used in binary models) selection procedure based on principal component analysis is explained in detail in section 4.1.

Table 5.4: Estimation Results of Multinomial Logit Model for Selected Variables[31]

Variables / Models	1 (Failed)			2 (Merger/Acquisition)			1 (Failed)			2 (Merger/Acquisition)		
	Coef.	z	P>z	Coef.	z	P>z	Coef.	z	P>z	Coef.	z	P>z
Microeconomic Variables												
Share in Sector (T. Assets)	-0.13	-1.24	0.22	-0.04	-0.37	0.71	-0.16	-1.45	0.15	-0.05	-0.36	0.72
Income Before Tax/T. Assets	-0.06	-4.99	0.00	0.03	2.66	0.01	-0.06	-4.61	0.00	0.02	2.08	0.04
Liquid Assets/T. Assets	0.01	0.88	0.38	0.02	0.63	0.53	0.01	1.04	0.30	0.01	0.51	0.61
Permanent Assets/T. Assets	0.02	1.81	0.07	0.04	3.36	0.00	0.01	0.78	0.43	0.03	2.08	0.04
Net Income/S. Equity	0.07	2.96	0.00	-0.16	-2.62	0.01	0.05	2.08	0.04	-0.11	-1.55	0.12
T. Deposits/No. of Branches	0.00	0.62	0.54	0.00	0.34	0.73	0.00	0.22	0.83	0.01	1.20	0.23
FX Liquid Assets/FX Liabilities	-0.03	-2.28	0.02	-0.03	-1.40	0.16	-0.03	-2.46	0.01	-0.03	-1.64	0.10
T. Loans/Net Working Capital	0.00	0.20	0.84	0.17	2.38	0.02	-0.01	-0.24	0.81	0.19	2.26	0.02
Intercept Dummy	0.78	1.71	0.09	2.07	1.87	0.06	3.91	3.01	0.00	3.64	1.27	0.21
Constant	-4.79	-7.19	0.00	-7.74	-4.41	0.00	-3.90	-5.98	0.00	-7.19	-4.25	0.00
Macroeconomic Variables												
Credit Growth	-	-	-	-	-	-	-0.06	-2.17	0.03	-0.02	-0.51	0.61
Real Interest Rate	-	-	-	-	-	-	0.03	2.31	0.02	0.02	1.46	0.15
GDP Growth	-	-	-	-	-	-	-0.03	-0.83	0.40	-0.11	-1.67	0.10
Model Fit												
AIC	268.18						238.60					
Pseudo R2	0.285						0.344					
Diagnostic Test of Validity of Regressors												
LR	114.18						137.76					
Wald	120.66						134.66					

[31] Variables (also used in binary models) selection procedure based on principal component analysis is explained in detail in section 4.1.

It is also tested that whether the binary models are valid restrictions of the multinomial models. Table 5.2 reports the likelihood based on Pseudo R^2 statistics and a statistical test that discriminates formally between the binary and multinomial specifications. With regard to the former one, the estimates in multinomial logit model provide higher pseudo R^2 values than binary model in each specification.

Furthermore, table A.6 in Appendix A section indicates that both model specifications with selected eigenvectors and variables confirm the validity of IIA assumption based on both Hausman and Small-Hsiao specification tests. Moreover, in Wald tests for combining outcomes, the null hypothesis - namely, that the categories can be collapsed - is strongly rejected for both specifications in multinomial logit model[32].

[32] For the first model specification with selected eigenvectors, which uses only microeconomic variables, test statistics for all categories failed–merger/acquisition, failed–non-failed and merger/acquisition–non-failed are 46.97 (sign level 0.00), 40.60 (sign level 0.00) and 69.08 (sign level 0.00) with 9 degrees of freedom, respectively. For the full specification with selected eigenvectors, test statistics are 38.70 (sign level 0.00), 57.18 (sign level 0.00) and 64.94 (sign level 0.00) with 12 degrees of freedom, respectively. For the first specification with selected variables, test statistics are 69.83 (sign level 0.00), 48.03 (sign level 0.00) and 66.19 (sign level 0.00) with 9 degrees of freedom, respectively. Lastly, for the full specification with selected variables, test statistics are 47.72 (sign level 0.00), 63.56 (sign level 0.00) and 75.66 (sign level 0.00) with 12 degrees of freedom, respectively.

5.3. PREDICTION

Thomson (1991) pointed out that the discrete choice models order a bank as failed if the predicted value of the dependent variable exceeds an exogenously set cut-off probability. Cut-off probability is set typically, at 0.5. However, as unsatisfactory results are obtained using a cut-off probability, 0.5, it is suggested that the cut-off probabilities should be corrected by using the mean of predicted values of the dependent variable. In addition, if type I error[33] is regarded to be more costly than type II error, a lower value for the cut-off probability can be adjusted (Thomson, 1991).

In examining both binary and multinomial logit models from tables A.7 - A.10 in Appendix A section, the prediction results for cut-off probability as being 0.5 are not satisfactory. Accordingly, only 9 banks for binary logit model estimated with both selected eigenvectors and related variables out of all failed banks are correctly classified as failed bank in any quarters of the sample period. Moreover, only 7 and 9 banks for multinomial logit model estimated with both selected eigenvectors and related variables out of all failed banks are correctly classified as failed bank in any quarters of the sample period, respectively. Based on the mean of predicted values, the predictive accuracy jumped from 20 % to 75 % in the category of predicted as a failure in the quarter of failure in both binary and

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[33] Type I error occurs when a failed bank is incorrectly classified as a non-failed bank and type II error occurs when a non-failed bank is incorrectly classified as a failed bank (Thomson, 1991).

multinomial logit model estimated with both selected eigenvectors and related variables. Further, for the other categories, the results are more satisfactory than that of former one (see tables A.7 - A.10 in Appendix A section).

In the last column of tables A.7 - A.10, the third alternative of cut-off probability is given. It reports that the calculated percentage of predictive accuracy is based on different cut-off probabilities for each quarter that is they vary with mean of predicted values of dependent variable quarter by quarter. In binary models, with different cut-off probabilities, overall prediction varies between 89 % and 45 % for estimated with eigenvectors and 92 % and 34 % for estimated with variables, respectively. In the multinomial models, giving almost the same result, overall prediction varies between 89 % and 44 % for estimated with eigenvectors and 94 % and 33 % for estimated with variables, respectively. Naturally, models with higher cut-off probabilities present more accurate results in non-failed observations correctly classified than in failed observations correctly classified. This adjustment provides minimization of failure costs.

Detailed prediction results of failed banks for both models that are given in tables 5.5 and 5.6 are constructed based on different cut-off probabilities for each quarter. Binary logit models correctly classifies 88 % of all the failures in any quarters for estimated with eigenvectors and 92 % of all the failures in any quarters for estimated with variables; in the quarter of failure, 83 % of the failures for estimated with eigenvectors and 78 % of the failures for estimated with variables and at least four quarters before the failure 89 % of the failures for estimated with eigenvectors and variables.

Moreover, multinomial logit model gives almost the same results with binary logit model. Accordingly, in tables 5.7 and 5.8, it correctly classifies 89 % of the failed banks as a failure in any quarters for estimated with eigenvectors and 94 % of all the failures in any quarters for estimated with variables. The rates in the quarter of failure are 81 % of the failures for estimated with eigenvectors and 79 % of the failures for estimated with variables. The rates in the category of at least four quarters before the failure are 89 % of the cases for estimated with eigenvectors and 92 % of the cases for estimated with variables. These results suggest that the elements that contribute to banking failure may be in place for four quarters or more before the failure. According to both models, banks in difficulties one year before the failure should have been failed; however, political reasons or the weakness in regulation and supervision can retard the failure process.

Table 5.5: Prediction Results for Binary Logit Model for Selected Eigenvectors

Failed Banks	Not Predicted as a Failure	Predicted as a Failure in the Quarter of the Failure	Predicted as a Failure 4 Quarters Before
Atlas Yatırım Bankası A.Ş.	NO	YES	YES
Bank Ekspres A.Ş.	NO	YES	YES
Bank Kapital Türk A.Ş.	NO	YES	YES
Bayındırbank A.Ş.	NO	YES	YES
Birleşik Türk Körfez Bankası A.Ş.	NO	YES	YES
Ak Uluslararası Bankası A.Ş.	NO	YES	YES
Credit Lyonnais Turkey	NO	YES	YES
Credit Suisse First Boston	NO	YES	YES
Demirbank T.A.Ş.	YES	NO	NO
EGS Bankası A.Ş.	NO	YES	YES
Egebank A.Ş.	NO	YES	YES
Eskişehir Bankası T.A.Ş.	NO	YES	YES
Etibank A.Ş.	NO	YES	YES
Fiba Bank A.Ş.	NO	YES	YES
İktisat Bankası T.A.Ş.	NO	YES	YES
ING Bank N.V.	YES	NO	NO
Interbank	NO	YES	YES
Kentbank A.Ş.	NO	YES	YES
Milli Aydın Bankası T.A.Ş.	NO	YES	YES
Morgan Guaranty Trust Co.	YES	NO	NO
Okan Yatırım Bankası A.Ş.	NO	YES	YES
Osmanlı Bankası A.Ş.	NO	NO	YES
Pamukbank T.A.Ş.	NO	YES	YES
Park Yatırım Bankası A.Ş.	NO	NO	YES
Rabobank Nederland	YES	NO	NO
Sınai Yatırım Bankası A.Ş.	NO	YES	YES
Sitebank A.Ş.	NO	YES	YES
Sümerbank A.Ş.	NO	YES	YES
Tekfen Yat. Ve Fin. Bankası A.Ş.	NO	YES	YES
Toprakbank A.Ş.	NO	YES	YES
Türk Dış Ticaret Bankası	NO	NO	YES
Türkiye Emlak Bankası A.Ş.	NO	YES	YES
TTB Yaşarbank A.Ş.	NO	YES	YES
Türkiye İmar Bankası T.A.Ş.	NO	YES	YES
Ulusal Bank T.A.Ş.	NO	YES	YES
Yurt Ticaret ve Kredi Bankası A.Ş.	NO	YES	YES
Number of incorrectly classified	4	6	4
Percentage of incorrectly classified	11.11	16.67	11.11

Table 5.6: Prediction Results for Binary Logit Model for Selected Variables

Failed Banks	Not Predicted as a Failure	Predicted as a Failure in the Quarter of the Failure	Predicted as a Failure 4 Quarters Before
Atlas Yatırım Bankası A.Ş.	NO	YES	YES
Bank Ekspres A.Ş.	NO	YES	YES
Bank Kapital Türk A.Ş.	NO	NO	YES
Bayındırbank A.Ş.	NO	YES	YES
Birleşik Türk Körfez Bankası A.Ş.	NO	YES	YES
Ak Uluslararası Bankası A.Ş.	NO	NO	YES
Credit Lyonnais Turkey	YES	NO	NO
Credit Suisse First Boston	NO	NO	YES
Demirbank T.A.Ş.	YES	NO	NO
EGS Bankası A.Ş.	NO	YES	YES
Egebank A.Ş.	NO	YES	YES
Eskişehir Bankası T.A.Ş.	NO	YES	NO
Etibank A.Ş.	NO	YES	YES
Fiba Bank A.Ş.	NO	YES	YES
İktisat Bankası T.A.Ş.	NO	YES	YES
ING Bank N.V.	NO	YES	YES
Interbank	NO	YES	YES
Kentbank A.Ş.	NO	YES	YES
Milli Aydın Bankası T.A.Ş.	NO	YES	YES
Morgan Guaranty Trust Co.	NO	NO	YES
Okan Yatırım Bankası A.Ş.	NO	YES	YES
Osmanlı Bankası A.Ş.	YES	NO	NO
Pamukbank T.A.Ş.	NO	YES	YES
Park Yatırım Bankası A.Ş.	NO	YES	YES
Rabobank Nederland	NO	YES	YES
Sınai Yatırım Bankası A.Ş.	NO	YES	YES
Sitebank A.Ş.	NO	YES	YES
Sümerbank A.Ş.	NO	YES	YES
Tekfen Yat. Ve Fin. Bankası A.Ş.	NO	YES	YES
Toprakbank A.Ş.	NO	YES	YES
Türk Dış Ticaret Bankası	NO	YES	YES
Türkiye Emlak Bankası A.Ş.	NO	YES	YES
TTB Yaşarbank A.Ş.	NO	YES	YES
Türkiye İmar Bankası T.A.Ş.	NO	YES	YES
Ulusal Bank T.A.Ş.	NO	NO	YES
Yurt Ticaret ve Kredi Bankası A.Ş.	NO	YES	YES
Number of incorrectly classified	3	8	4
Percentage of incorrectly classified	8.33	22.22	11.11

Table 5.7: Prediction Results for Multinomial Logit Model for Selected Eigenvectors

Failed Banks	Not Predicted as a Failure	Predicted as a Failure in the Quarter of the Failure	Predicted as a Failure 4 Quarters Before
Atlas Yatırım Bankası A.Ş.	NO	YES	YES
Bank Ekspres A.Ş.	NO	YES	YES
Bank Kapital Türk A.Ş.	NO	YES	YES
Bayındırbank A.Ş.	NO	YES	YES
Birleşik Türk Körfez Bankası A.Ş.	NO	NO	YES
Ak Uluslararası Bankası A.Ş.	NO	NO	YES
Credit Lyonnais Turkey	NO	YES	YES
Credit Suisse First Boston	NO	NO	YES
Demirbank T.A.Ş.	YES	NO	NO
EGS Bankası A.Ş.	NO	YES	YES
Egebank A.Ş.	NO	YES	YES
Eskişehir Bankası T.A.Ş.	NO	YES	YES
Etibank A.Ş.	NO	YES	YES
Fiba Bank A.Ş.	NO	YES	YES
İktisat Bankası T.A.Ş.	NO	YES	YES
ING Bank N.V.	YES	NO	NO
Interbank	NO	YES	YES
Kentbank A.Ş.	NO	YES	YES
Milli Aydın Bankası T.A.Ş.	NO	YES	YES
Morgan Guaranty Trust Co.	YES	NO	NO
Okan Yatırım Bankası A.Ş.	NO	YES	YES
Osmanlı Bankası A.Ş.	YES	NO	NO
Pamukbank T.A.Ş.	NO	YES	YES
Park Yatırım Bankası A.Ş.	NO	YES	YES
Rabobank Nederland	NO	YES	YES
Sınai Yatırım Bankası A.Ş.	NO	YES	YES
Sitebank A.Ş.	NO	YES	YES
Sümerbank A.Ş.	NO	YES	YES
Tekfen Yat. Ve Fin. Bankası A.Ş.	NO	YES	YES
Toprakbank A.Ş.	NO	YES	YES
Türk Dış Ticaret Bankası	NO	YES	YES
Türkiye Emlak Bankası A.Ş.	NO	YES	YES
TTB Yaşarbank A.Ş.	NO	YES	YES
Türkiye İmar Bankası T.A.Ş.	NO	YES	YES
Ulusal Bank T.A.Ş.	NO	YES	YES
Yurt Ticaret ve Kredi Bankası A.Ş.	NO	YES	YES
Number of incorrectly classified	4	7	4
Percentage of incorrectly classified	11.11	19.44	11.11

Table 5.8 Prediction Results for Multinomial Logit Model for Selected Variables

Failed Banks	Not Predicted as a Failure	Predicted as a Failure in the Quarter of the Failure	Predicted as a Failure 4 Quarters Before
Atlas Yatırım Bankası A.Ş.	NO	NO	YES
Bank Ekspres A.Ş.	NO	YES	YES
Bank Kapital Türk A.Ş.	NO	NO	YES
Bayındırbank A.Ş.	NO	YES	YES
Birleşik Türk Körfez Bankası A.Ş.	NO	NO	YES
Ak Uluslararası Bankası A.Ş.	NO	NO	YES
Credit Lyonnais Turkey	NO	YES	YES
Credit Suisse First Boston	NO	NO	YES
Demirbank T.A.Ş.	YES	NO	NO
EGS Bankası A.Ş.	NO	YES	YES
Egebank A.Ş.	NO	YES	YES
Eskişehir Bankası T.A.Ş.	NO	YES	NO
Etibank A.Ş.	NO	YES	YES
Fiba Bank A.Ş.	NO	YES	YES
İktisat Bankası T.A.Ş.	NO	YES	YES
ING Bank N.V.	NO	YES	YES
Interbank	NO	YES	YES
Kentbank A.Ş.	NO	YES	YES
Milli Aydın Bankası T.A.Ş.	NO	YES	YES
Morgan Guaranty Trust Co.	NO	YES	YES
Okan Yatırım Bankası A.Ş.	NO	YES	YES
Osmanlı Bankası A.Ş.	YES	NO	NO
Pamukbank T.A.Ş.	NO	YES	YES
Park Yatırım Bankası A.Ş.	NO	YES	YES
Rabobank Nederland	NO	YES	YES
Sınai Yatırım Bankası A.Ş.	NO	YES	YES
Sitebank A.Ş.	NO	YES	YES
Sümerbank A.Ş.	NO	YES	YES
Tekfen Yat. Ve Fin. Bankası A.Ş.	NO	YES	YES
Toprakbank A.Ş.	NO	YES	YES
Türk Dış Ticaret Bankası	NO	YES	YES
Türkiye Emlak Bankası A.Ş.	NO	YES	YES
TTB Yaşarbank A.Ş.	NO	YES	YES
Türkiye İmar Bankası T.A.Ş.	NO	YES	YES
Ulusal Bank T.A.Ş.	NO	NO	YES
Yurt Ticaret ve Kredi Bankası A.Ş.	NO	YES	YES
Number of incorrectly classified	2	8	3
Percentage of incorrectly classified	5.56	22.22	8.33

This chapter attempts to reflect the probability of banking failures, which is a function of both bank-specific and macroeconomic eigenvectors and corresponding variables by estimating both binary and multinomial models. Banks with strong liquidity state in terms of foreign exchange, higher earnings and asset quality has a role to decrease the likelihood of banking failures.

From the macroeconomic perspective, higher credit growth and real interest rates are associated with the higher probability of banking failures. The results are consistent with the findings of Wheelock and Wilson (2000), Logan (2001) and Molina (2002) in samples of US, UK and Venezuelan banks respectively. The significance of macroeconomic variables is also consistent with the studies of Demirguc-Kunt and Detragiache (1997) and Hutchison and McDill (1999).

However, the aim of this chapter is not to construct a manual for bank failures for supervisory institutions. The findings of this chapter can be interpreted as the microeconomic and macroeconomic determinants of the failure probabilities of Turkish banking system with different models. According to prediction results, the multinomial logit model with estimated variables gives slightly more accurate results than that of other three specifications.

The findings in this chapter may help decision makers in supervisory institutions in terms of the determinants of bank failures in Turkish banking system. Moreover, this chapter provides a motivation for developing duration model for the determination and prediction of timing of failures since the discrete choice models do not use the information concerning how long banks survive.

CHAPTER 6

THE EMPIRICAL SPECIFICATION II: DURATION MODEL

This chapter analyzes the main factors that were important in survival of the banks in 1997-2006 by using duration model with the selected eigenvectors and variables[34] in chapter 4. Instead of predicting the probability of banking failures, this chapter deals with the timing of failure. It aims to take a closer look at timing of bank failure comparing with discrete choice models on bank failures. It also allows measuring the effect of bank specific variables. Moreover, it tries to construct models for the determination and prediction of timing of failure and examines survival time path of failed and non-failed banks.

The main motivation of this chapter is to institute a pattern concerning characteristics that distinguish the survived banks from the failed banks for regulation and supervision agencies. This

[34] The data set used in this chapter is the same as which was described and used in the previous chapter.

chapter focuses on especially examining survival time path of failed and non-failed banks separately, identifying breaks of survival time of the banks and the estimated degree of banking sector fragility as being different from discrete choice model.

6.1. THE MODEL

Duration models, unlike binary and multinomial logit models discussed in the previous chapter, utilize information concerning how long banks survive. Estimated coefficients show whether an increase in the value of a bank specific explanatory variable will decrease or increase the expected time until failure occurs (Wheelock and Wilson, 1994). Nevertheless, logit models typically ignore information on the timing of failures, and provide an estimate only of the probability of failure within a given interval of time (Wheelock and Wilson, 1994). Discrete choice models compared with duration models on bank failures can be seen as preliminary analysis. In these types of models, there is no difference between a bank that failed in the first quarter of the sample period and a bank that failed in the last quarter of the sample, however, duration models explicitly comprise this type of information (Wheelock and Wilson, 1994).

In duration analysis, there are two types of data (also called "spells"): known length of spell and unknown length of spell. This latter type of data is said to be "censored". An observation is said to be left-censored, if the event of interest has already occurred when observation begins, and right-censored if the observation begins at the defined time and terminates before the outcome of interest is observed (Kiefer, 1988). Another right-censored data type occurs if the survival time of the event is not observed due to the end of the study. The observation for some banks in the sample will be both left and right censored if the establishment date and the failure date of the banks do not cover the sample period. By contrast, the observation for some banks will be uncensored if the establishment date and the failure date of the banks cover the sample period.

Most of the literature (for example Lane et al., 1986; Gonzalez, 1999) that uses survival bank models impose sample period for the beginning of the analysis that does not coincide with calendar time that the banks are born. Furthermore, in the estimation process, as in the last chapter, the date of last financial statements is taken as the date of failure as in Molina (2002). One of the frequently cited disadvantages of hazard model is the difficulty of defining the failure event accurately. In this case, although the model failure does not exactly coincide with the actual failure event, taking the last quarter of financial statements publication by the failed bank as the failure event is a very reasonable assumption (Molina, 2002).

In estimation procedure, hazard function can be described as follows:

$$\lambda(t,X,\beta,\lambda_0)= \exp(X'\beta)\ \lambda_0(t) \tag{6.1}$$

where $\lambda_0(t)$ is a baseline hazard function, identical for all banks, X is covariate and β is parameter vector. The estimation is done after constructing the log likelihood function as;

$$L(\alpha,\beta)= \sum_{i=1}^{n} d_i \ln \lambda(t_i, X_i, \alpha, \beta) - \sum_{i=1}^{n} \Lambda(t_i, X_i, \alpha, \beta) \qquad (6.2)$$

where dummy variable d represents the state of banks; failure or survival and $\Lambda()$ is integrated hazard function.

Partial likelihood suggested by Cox (1972) provides a method to estimate β in the proportional hazard model without estimating baseline hazard function, λ_0 (Kiefer, 1988). If durations are ordered from smallest to largest with no censoring and no ties, log-likelihood function can be written as;

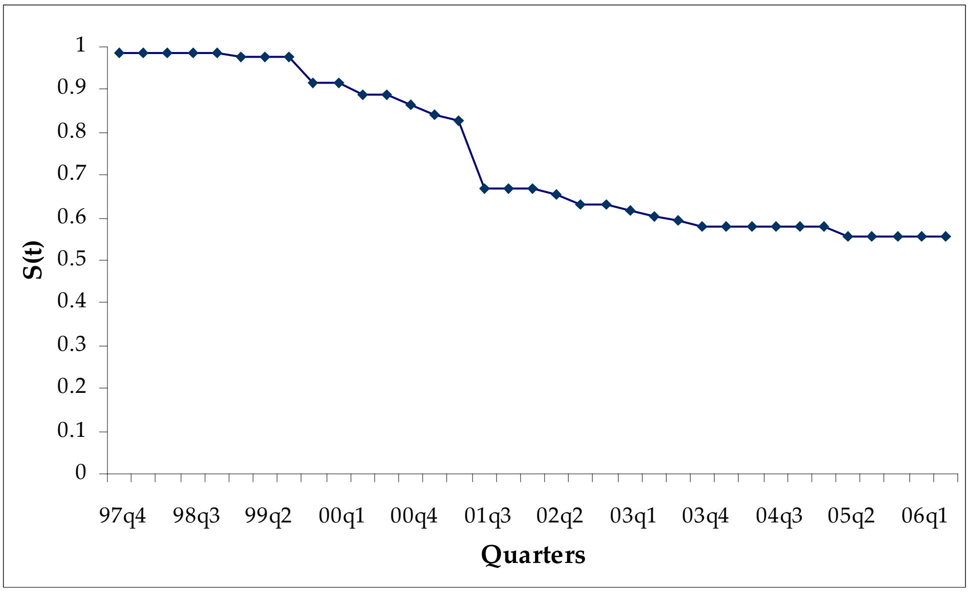
$$L(\beta)=\sum_{i=1}^{n} [\ln \exp(X_i\beta)- \ln[\sum_{i=1}^{n} \exp(X_i \beta)]] \qquad (6.3)$$

Estimating unknown coefficients is done by ordering durations without having information about baseline hazard. If there are censored observations, their contributions are seen in the second part of the log-likelihood function. They enter in to the second summation in Equation 6.3, not in the first summation part.

6.2. ESTIMATION RESULTS

The survival function was firstly estimated using the standard Kaplan-Meier non-parametric estimator based on study time, presented in figure 6.1, since applying wrong distribution may result in biased estimates when starting from directly parametric estimation. It reflects how many banks survive in the banking system as time goes (Serneels, 2004).

Figure 6.1: Kaplan- Meier Survival Function



From the figure of Kaplan-Meier survival function, two break points can be seen. The first one occurred in the fourth quarter of 1999. A series of amendments in the Banking Act were made in December 1999. The second one occurred in the third quarter of 2001, which is the consequence of February 2001 crisis. This survival function can be used in calculating the product-limit estimate of the hazard function. It reflects the number of banks failed at t, relative to the total number of banks in the banking system at t and is plotted in figure A.2 in Appendix A section.

The proportion of right-censored observations to the total observations is about 73.7 % and the proportion of right-censored banks to total banks is about 55.6 %. In table A.11 in Appendix A section, the second column is the total number of banks at risk of failure at the time shown in the first column. The third column shows the number of failures at each time. The estimates of the survivor function together with estimates of their statistical significance are shown in the remaining columns.

The table shows that 60 % of the sample remained non-failed up to 23rd quarter of study time (with a 95 percent confidence interval of 0.49, 0.70). Beginning from the second quarter of 2003, the survival rate decreases to 55 % and this rate seems to be fairly constant. As depicted in the figure A.2 in Appendix A section, the hazard rate does not exceed 20 % and stays mostly below 3 %. Moreover, the hazard rate rises initially, reaches a peak and then falls. Naturally, the consequences of February 2001 crisis can be observed at this peak point of the third quarter of 2001.

The commonly used specification in economics is the proportional hazard model, whereas the accelerated failure time model has been used less in economics (Kiefer, 1988). Kiefer also suggests that hazard function specification rather than densities in modeling duration may be easier to interpret economically. In this chapter, several different models are estimated. Model is estimated by Cox semi-parametric method, Exponential, Weibull and Gompertz parametric techniques.

Firstly, semi-parametric Cox PH model is estimated and tested whether the Cox PH assumption fits the data or not. The most important assumption of the Cox PH specification is that the hazard ratio is proportional over time. Test of Cox PH assumption is based on the scaled-Schoenfeld residuals. The test results of Cox PH assumption for both estimated with eigenvectors and variables are presented in the following tables 6.1 and 6.2. Accordingly, Cox PH assumption has been passed i.e., the global tests suggest the non-rejection of PH assumption at 1 % significance level.

Three asymptotically equivalent tests, Wald, Score (or Lagrange Multiplier-LM) and Likelihood Ratio (LR) can be used for the validity of regressors in the model (Kiefer, 1988). LR test is used in this study. As a model selection criterion, Akaike Information Criteria (AIC) can be used to select best fitting model among the said alternatives and among proportional hazard model.

Table 6.1: Test of Proportional Hazard Assumption for Selected Eigenvectors[35]

Variables	Rho		Chi-square		Prob > Chi2	
	M1	M2	M1	M2	M1	M2
Size Category	-0.01	-0.06	0.01	0.13	0.94	0.71
Earnings Category	-0.04	-0.08	0.06	0.19	0.81	0.66
Liquidity Category	-0.10	-0.11	0.41	0.35	0.52	0.56
Asset Quality Category	-0.09	-0.14	0.12	0.47	0.72	0.49
Earnings Category	-0.13	-0.12	0.47	0.37	0.49	0.54
Management Category	0.00	-0.06	0.00	0.13	0.99	0.72
Liquidity Category	0.03	0.08	0.02	0.15	0.89	0.69
Asset Quality Category	-0.02	-0.02	0.01	0.01	0.93	0.93
Intercept Dummy	0.01	-0.10	0.00	0.35	0.95	0.55
Credit Channel	-	-0.23	-	1.49	-	0.22
Real Cost	-	-0.07	-	0.18	-	0.68
Real Effect	-	-0.18	-	0.75	-	0.39
Global	-	-	1.92	4.73	0.99	0.97

Table 6.2: Test of Proportional Hazard Assumption for Selected Variables[35]

Variables	Rho		Chi-square		Prob > Chi2	
	M1	M2	M1	M2	M1	M2
Share in Sector (T. Assets)	-0.02	-0.20	0.00	0.53	0.95	0.47
Income Before Tax/T. Assets	-0.13	-0.17	2.14	2.87	0.14	0.09
Liquid Assets/T. Assets	0.05	0.05	0.11	0.10	0.74	0.75
Permanent Assets/T. Assets	0.13	0.06	0.32	0.08	0.57	0.77
Net Income/S. Equity	0.08	0.14	0.57	1.56	0.45	0.21
T. Deposits/No. of Branches	-0.05	-0.08	0.08	0.10	0.78	0.75
FX Liquid Assets/FX Liab.	-0.16	-0.06	1.29	0.12	0.26	0.73
T. Loans/Net Working Cap.	-0.05	-0.04	0.10	0.03	0.75	0.87
Intercept Dummy	-0.08	-0.31	0.20	2.92	0.66	0.09
Credit Growth	-	0.37	-	4.23	-	0.04
Real Interest Rate	-	-0.16	-	0.95	-	0.33
GDP Growth	-	0.07	-	0.15	-	0.70
Global	-	-	7.71	11.09	0.56	0.52

[35] Eigenvectors and variables (also used in Chapter 5) selection procedure based on principal component analysis is explained in detail in section 4.1.

Though passed the test of Cox-PH assumption for both specifications, three parametric survival models, i.e., Exponential, Weibull and Gompertz are also estimated. This is because of the fact that Cox-PH models limit the extensions of duration models such as Cox-PH models are not applicable with predicted survival time. Weibull model can be directly compared with exponential since these are nested models. Exponential model as a restriction of Weibull model can be tested as a formal procedure (Serneels, 2004). The hypothesis that ln (p) which is equal to zero, is rejected at 1 % significance level[36]. This indicates that the Weibull model fits better than exponential model for both model specifications estimated with eigenvector and variables.

When models are not nested, parametric survival distributions can be compared with AIC[37] values, such that the smallest AIC value gives the best fitting model. In tables A.12 and A.13 in Appendix A section AIC, log-likelihood values and likelihood ratio test statistics are given. The results indicate that Weibull model has the smallest AIC value for both estimated with eigenvectors and variables.

[36] The null hypothesis of p is equal to 1 which is equivalent to ln(p) is equal to zero (test statistics are 2.38 and 6.17 for both model specifications estimated with eigenvectors respectively with p>z 0.02 and 0.00) is rejected at 5 percent significance level. Moreover, the null hypothesis (test statistics are 1.73 and 5.44 for both model specifications estimated with eigenvectors respectively with p>z 0.04 and 0.00) is again rejected at 5 percent significance level.

[37] AIC=-2(log likelihood) + 2(c+p+1), where c is the number of model covariates excluding constant; p is the number of specific ancillary parameters. It is zero for exponential distribution and equals to one for Weibull and Gompertz distributions. Smallest AIC gives the preferred model.

Exponential and Gompertz models are eliminated according to this criterion.[38] Moreover, in all specifications, likelihood ratio (LR) test strongly indicates that the all coefficients are jointly equal to zero and is rejected at 1 % significance level.

Tables 6.3 - 6.6 represent both model specifications, which are estimated by Cox proportional hazard and Weibull models for estimated with both eigenvectors and variables, respectively. The first three columns of each model illustrate the estimated coefficients, the relevant statistics of significance (z) and the p-value respectively. As in the previous chapter, the first model specification includes only bank-specific variables and the second one comprises both microeconomic and macroeconomic variables.

Accordingly, for Cox-PH model estimated with eigenvectors, statistically significant variables are earnings category and real costs from macroeconomic side and crisis dummy variable with expected sign. Moreover, for Cox-PH model estimated with variables, statistically significant variables are the ratio of income before tax to total assets, the ratio of liquid assets to total assets a and the ratio of foreign exchange liquid assets to foreign exchange liabilities real interest rate and GDP growth from macroeconomic side and crisis dummy variable with expected sign. According to the results of Cox-PH estimation, estimated coefficients with variables give more

[38] The results of Exponential and Gompertz models will not be presented here.

Table 6.3: Estimation Results of Cox-PH Model for Selected Eigenvectors

Variables / Models	Model 1			Model 2		
	Coef.	z	P>z	Coef.	Z	P>z
Microeconomic Variables						
Size Category	-0.35	-1.33	0.18	-0.39	-1.40	0.16
Earnings Category	-0.29	-2.85	0.00	-0.21	-1.96	0.05
Liquidity Category	-0.05	-0.29	0.78	-0.12	-0.62	0.53
Asset Quality Category	-0.22	-1.39	0.17	-0.31	-1.69	0.09
Earnings Category	-0.12	-0.64	0.52	-0.16	-0.69	0.49
Management Category	0.17	1.17	0.24	0.10	0.72	0.47
Liquidity Category	0.61	1.22	0.22	0.75	1.53	0.13
Asset Quality Category	0.14	0.09	0.93	-0.06	-0.04	0.97
Intercept Dummy	0.70	1.48	0.14	1.60	2.27	0.02
Macroeconomic Variables						
Credit Channel	-	-	-	0.20	1.15	0.25
Real Cost	-	-	-	0.40	2.37	0.02
Real Effect	-	-	-	0.04	0.20	0.84
Diagnostic Test of Validity of Regressors						
LR	31.80			38.85		

Table 6.4: Estimation Results of Cox-PH Model for Selected Variables

Variables / Models	Model 1			Model 2		
	Coef.	z	P>z	Coef.	Z	P>z
Microeconomic Variables						
Share in Sector (T. Assets)	-0.13	-0.75	0.45	-0.19	-0.92	0.36
Income Before Tax/T. Assets	-0.02	-3.45	0.00	-0.02	-2.53	0.01
Liquid Assets/T. Assets	0.04	2.87	0.00	0.03	2.35	0.02
Permanent Assets/T. Assets	0.03	2.08	0.04	0.00	0.15	0.88
Net Income/S. Equity	-0.34	-1.09	0.28	-0.34	-1.03	0.31
T. Deposits/No. of Branches	0.00	-0.52	0.61	0.00	-0.43	0.66
FX Liquid Assets/FX Liabilities	-0.04	-3.61	0.00	-0.05	-3.56	0.00
T. Loans/Net Working Capital	-0.09	-0.10	0.92	-0.17	-0.23	0.82
Intercept Dummy	2.33	5.10	0.00	3.59	3.32	0.00
Macroeconomic Variables						
Credit Growth	-	-	-	-0.02	-1.10	0.27
Real Interest Rate	-	-	-	0.05	3.45	0.00
GDP Growth	-	-	-	-0.11	-3.18	0.00
Diagnostic Test of Validity of Regressors						
LR	110.06			134.95		

satisfactory results than that of eigenvectors (see tables 6.3 and 6.4). This is also the case for discrete choice models.

Turning to Weibull case, the results demonstrate that except for liquidity categories and size category all categories are significant individually. From macroeconomic perspective, only credit channel is significant with expected sign. Crisis dummy variable is statistically insignificant but with expected sign (see table 6.5). According to the estimation results of Weibull regression with selected variables, the results are consistent with the results of Cox-PH estimation. The ratio of income before tax to total assets, the ratio of the ratio of foreign exchange liquid assets to foreign exchange liabilities, credit growth and GDP growth are significant with expected sign (see table 6.6).

In both specifications of Cox- PH and Weibull regression, the sign of the ratio of income before tax to total assets, the ratio of foreign exchange liquid assets to foreign exchange liabilities and GDP growth are negative. The negative sign of estimated coefficients indicates that these variables have negative relationship with hazard rate of duration of banks and positive relationship with survival of banks. They coincide with the results of discrete choice models in the pervious chapter.

Table 6.5: Estimation Results of Weibull Model for Selected Eigenvectors

Variables / Models	Model 1			Model 2		
	Coef.	z	P>z	Coef.	z	P>z
Microeconomic Variables						
Size Category	-0.04	-0.34	0.74	-0.04	-0.34	0.74
Earnings Category	-0.28	-4.77	0.00	-0.15	-2.19	0.03
Liquidity Category	-0.11	-0.88	0.38	-0.15	-1.15	0.25
Asset Quality Category	-0.13	-1.36	0.17	-0.20	-1.95	0.05
Earnings Category	-0.16	-1.43	0.15	-0.19	-1.53	0.13
Management Category	0.27	2.39	0.02	0.23	1.98	0.05
Liquidity Category	0.35	2.17	0.03	0.23	1.62	0.11
Asset Quality Category	0.08	0.28	0.78	0.09	0.29	0.78
Intercept Dummy	-0.31	-0.60	0.55	-0.75	-0.97	0.33
Constant	-6.24	-5.53	0.00	-17.6	-4.33	0.00
Macroeconomic Variables						
Credit Channel	-	-	-	1.35	3.54	0.00
Real Cost	-	-	-	-0.19	-1.22	0.22
Real Effect	-	-	-	0.15	0.83	0.41
Diagnostic Test of Validity of Regressors						
LR	56.13			80.89		

Table 6.6: Estimation Results of Weibull Model for Selected Variables

Variables / Models	Model 1			Model 2		
	Coef.	z	P>z	Coef.	z	P>z
Microeconomic Variables						
Share in Sector (T. Assets)	-0.10	-0.96	0.34	-0.10	-0.96	0.34
Income Before Tax/T. Assets	-0.01	-6.35	0.00	-0.01	-4.12	0.00
Liquid Assets/T. Assets	0.00	0.41	0.68	0.00	0.35	0.73
Permanent Assets/T. Assets	0.02	2.00	0.05	0.01	0.82	0.41
Net Income/S. Equity	0.00	0.00	1.00	-0.01	-0.13	0.90
T. Deposits/No. of Branches	0.00	0.30	0.77	0.00	0.94	0.35
FX Liquid Assets/FX Liabilities	-0.02	-2.38	0.02	-0.02	-2.51	0.01
T. Loans/Net Working Capital	0.05	0.24	0.81	0.05	0.22	0.83
Intercept Dummy	-0.01	-0.01	0.99	1.08	1.41	0.16
Constant	-5.62	-4.68	0.00	-10.9	-4.22	0.00
Macroeconomic Variables						
Credit Growth	-	-	-	-0.07	-3.76	0.00
Real Interest Rate	-	-	-	0.01	1.18	0.24
GDP Growth	-	-	-	-0.09	-2.73	0.01
Diagnostic Test of Validity of Regressors						
LR	55.20			85.04		

6.3. PREDICTION

There are two applications of prediction section in this chapter. First, there is standard application for prediction of duration models. This is applied to both Cox-PH and Weibull models. Therefore, it can be compared with the predictive accuracy of two different estimation techniques fro both eigenvector and variables. This is based on the comparison between the predicted hazard of banks and pre-established cut-off value, bank-by-bank and quarter-by-quarter. For each period t, it is possible to obtain the predicted hazard. Then, banks are classified as "failed" if the estimated probability is higher than a set cut-off value. This exercise is done bank by bank, and then predicted survival status is compared to the observed one. According to this analysis, there may be two possible classification errors: predicting that a bank would survive until t when it did not, or predicting that the bank would not survive until t, when it did (Whalen, 1991).

Detailed prediction results for Cox-PH and Weibull models that are given in tables A.14 - A.17 in Appendix A section is constructed based on the mean of predicted hazard for each quarter as being cut-off probability. Accordingly, Cox-PH models correctly classifies 92 % of all the failures in any quarters for estimated with eigenvectors and 94 % of all the failures in any quarters for estimated with variables; in the quarter of failure, 75 % of the failures for estimated with eigenvectors and 69 % of the failures for estimated with variables and at least four quarters before the failure 89 % of the failures for estimated with eigenvectors and 78 % of the failures for estimated with variables (see tables A.14 and A.15 in Appendix A section).

Weibull models correctly classifies 92 % of all the failures in any quarters for estimated with eigenvectors and 94 % of all the failures in any quarters for estimated with variables; in the quarter of failure, 81 % of the failures for estimated with eigenvectors and 83 % of the failures for estimated with variables and at least four quarters before the failure 89 % of the failures for estimated with eigenvectors and 94 % of the failures for estimated with variables (see tables A.16 and A.17 in Appendix A section). When comparing the prediction results of duration model, Weibull models slightly gives more reliable results than that of Cox-PH models especially in the category of predicted failures in the quarter of failure.

According to Bell and Pain (2000), it is necessary to differentiate banking fragility and banking crises. Fragility related to the financial system's vulnerability to shocks and the structure of the financial system and crisis related to the interaction between fragility and some exogenous shocks. Most of the studies do not capture this distinction. The next logical step would be to obtain an indicator of the degree of fragility of the banking system and individual banks. This is related to survival model to construct bank's estimated degree of fragility, which is based on the estimated hazard function. The estimated degree of fragility of Turkish banking sector can be obtained from the predicted hazard of each bank for each quarter. As a first step, an individual bank's estimated degree of fragility, which is derived from survival model, is weighted by the market share of banks in terms of assets.

The estimated degree of fragility of overall banking system is derived from the summation of individual bank's estimated degree of fragility for each quarter (Gonzales-Hermosillo et al, 1997). Figure 6.2 represents degree of fragility of overall banking system based on Weibull model estimated with variables because of having more predictive accuracy. According to this, the degree of fragility of banking system was fairly stable until end of 1999 since five private banks were taken under Saving Deposit Insurance Fund at the beginning of the IMF program in 1999. Afterwards, it increased at the peak point until the third quarter of 2001 since structural weaknesses and the two crises increased the fragility of the banking system. The degree of fragility decreased immediately after several banks failed. Naturally, by definition of this specification of models, the last financial statements of failed banks were actually during 2001.

Table A.18 and A.19 give the figures of the degree of fragility of failed and selected non-failed banks respectively. The fragility of most of failed banks[39] can be easily seen in one or two quarters before

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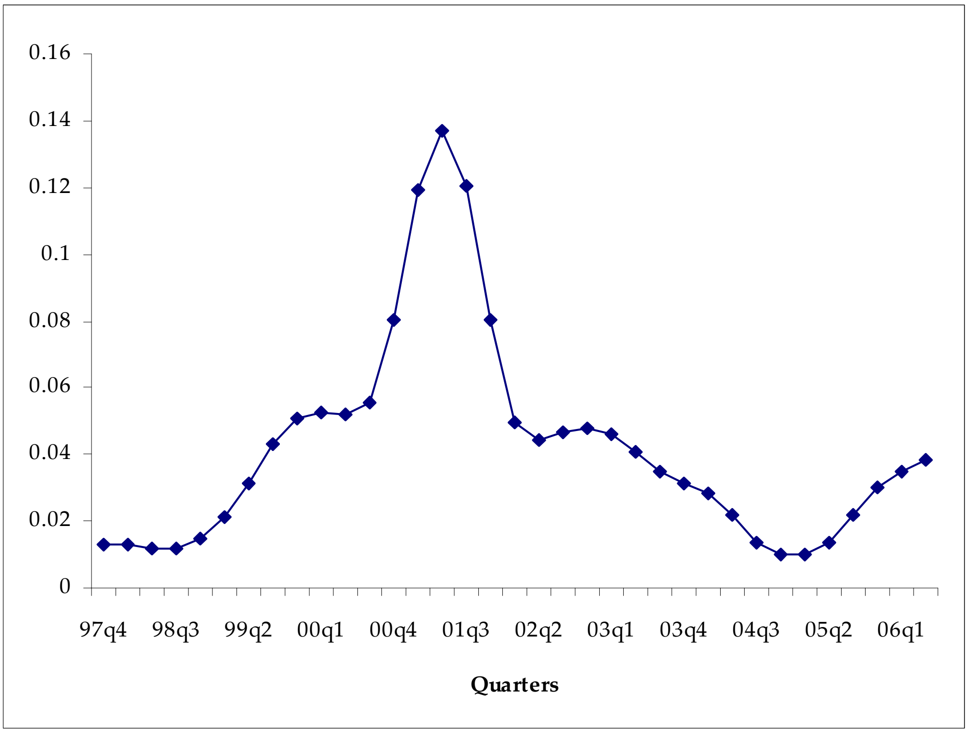
[39] 32 banks out of 36 failed banks reflect the high degree of fragility before the failure.

the failure in the graphs. The degree of fragility of selected non-failed banks – which were the four big banks in terms of assets, Oyakbank, HSBC Bank, Finansbank are fairly stable despite the fluctuations during 2001.

Figure 6.2: Estimated Degree of Fragility of the Overall Banking System[40]



To summarize, the consistent results with discrete choice models are that banks with strong liquidity state in terms of foreign

[40] The estimated degree of fragility of overall banking system is derived from the summation of individual bank's estimated degree of fragility (it is derived from the predicted hazard of each bank that is weighted by the market share of banks in terms of assets) for each quarter.

exchange, higher earnings and asset quality have a role in increasing the survival of the banks. From the macroeconomic perspective, higher credit growth and real interest rates are associated with the lower survival rates of the banks. Therefore, macroeconomic mismanagement and credit growth adversely affects the survival of the banks through various channels.

According to the results, in the category of predicted the failure in any quarters, duration models give more accurate results than both multinomial and binary logit models especially in the analysis of the comparison of the estimated predicted hazard and pre-established cut-off value. Moreover, the second contribution is the construction of degree of fragility for each bank and overall banking system. The fragility of failed banks and overall banking system can be extracted by using this approach. This can be the sign of the problem of the aforementioned banks for regulation and supervision agencies.

CHAPTER 7

THE EMPIRICAL SPECIFICATION III: DYNAMIC PANEL DATA MODEL

In the previous chapters, poor asset quality, low levels of liquidity, credit risk and mismanagement conditions of banks are found as the determinants of bank failures. Moreover, as a supervisory tool, the degree of fragility of individual banks and overall banking system is evaluated. At this point, by examining dynamic feature of the variables, there is need for analysis of bank profitability since; a strong and profitable banking sector supports broader financial stability.

The main motivation of this chapter is to examine the determinants of bank performance that can be another tool for preventing bank failures and promoting a sound banking system (Goddard et al, 2004). Moreover, most of the empirical literature, Rhoades (1985), Bourke (1989) and Goddard et al. (2004) consider determinants of profitability with only bank-specific variables as there is no investigation on the effect of macroeconomic conditions. However, this chapter analyzes the main determinants of bank profitability over the period of 1997 to 2006 in Turkey by using dynamic panel data models. Applying GMM technique to a panel of banks of the Turkish banking system, the effects of both bank specific variables from balance sheets of the banks and macroeconomic eigenvectors and variables on bank profitability are analyzed.

The measurements of profitability in the literature are the ratio of profit (net income) to total assets and the ratio of profit to shareholders' equity (Goddard et al, 2004). In most of the studies on banking profitability, the ratio of profits to total assets is preferred over the latter one. The idea behind selecting the ratio of profit to assets ratio is that it measures financial leverage. Banks with lower leverage (higher equity) will generally report higher ratio of profit to assets, but lower ratio of profit to equity. Therefore, using the ratio of profit to equity is likely to ignore capital inadequacy of banks (Athanasoglu et al., 2005). In this study, the dependent variable is the ratio of profits to total assets of the banks[41]. Figure A.2 in Appendix A section depicts both the ratio of profit to assets and equity for Turkish banking sector between 1997-2006 quarterly. Both ratios follow similar path after 2000-2001 crises, stable path over time.

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[41] The ratio of profit to shareholders' equity is also used as a dependent variable however; the estimation results based on this variable are not satisfactory in the context of coefficients and specification tests. Therefore the results are not reported in this study. Moreover, using of the ratio of profit to shareholders' equity as a dependent variable, capital adequacy – the ratio of shareholders' equity to total assets – cannot be used in the estimation as an independent variable.

The empirical literature recognizes various determinants of bank profitability. However, some of the variables are common, such as capital adequacy and liquidity proxies. In Rhoades (1985), Bourke (1989), Molyneux and Thornton (1992) and Goddard et al. (2004), both these proxies are found to be positively related to profitability (see chapter 2). In the majority of studies on bank profitability, the determinants of bank profitability are selected only from bank-specific variables. In this study, the effect of macroeconomic environment can be analyzed so, as in the previous chapters, the independent variables are selected based on principal component analysis in chapter 4. They are also consistent with the majority of bank profitability studies in the literature except for macroeconomic environment.

7.1. THE MODEL

The use of panel data, the dataset combining both cross-sections and time series, has advantage over only cross-section data in the context of the analysis of macroeconomic subjects with microeconomic dynamics (Bond, 2002). In static dynamic panel data models, there are two basic approaches; fixed-effects and random effects model. However, estimating a dynamic relationship with fixed or random effect model will cause biasedness and inconsistency problems due to inclusion of the lagged dependent variable, since, the lagged dependent variable is correlated with the disturbance term even it is assumed that it is not itself autocorrelated (Greene, 1997).

The proper estimation, which is the Generalized Method of Moments (GMM) estimation for dynamic panel data models, suggested by Arellano and Bond (1991), provides efficiency improvements by exploiting all the available moment conditions in the first difference transformation. Using the GMM estimation rather than the OLS estimation allows the control of unobserved heterogeneity and simultaneity in the panel data estimation. This estimation method can eliminate unobservable characteristics of banks by taking first differences and can produce more efficient estimators against the problem of the potential endogeneity of the explanatory variables (Greene, 1997).

First differences of the panel data are obtanied to remove the individual fixed effects as follows:

$$\Pi_{it} - \Pi_{i,\,t-1} = (X_{it} - X_{i,\,t-1})\beta + \delta\,(\Pi_{i,\,t-1} - \Pi_{i,\,t-2}) + (\varepsilon_{it} - \varepsilon_{i,\,t-1}) \qquad (7.1)$$

where Π_{it} is the profitability of a bank i at time t, with i=1,…81, t=1,…36, and X_{it} is a vector of n explanatory variables. However, there still remains a problem owing to the correlation between $(\Pi_{i,t-1}-\Pi_{i,t-2})$, the lagged dependent variables and $(\varepsilon_{it}-\varepsilon_{i,t-1})$, disturbances. Without the group effects, the dynamic model with instrumental variables estimator is estimated in order to solve this problem. It is proposed by Arellano and Bond (1991) as GMM type estimator. These additional instruments can be gained if all possible orthogonality conditions are used; i.e. $E(\Pi_{i,t-2}, \varepsilon_{it} - \varepsilon_{i,t-1}) = 0$, $E(\Pi_{i,t-3}, \varepsilon_{it} - \varepsilon_{i,t-1}) = 0$ etc., or in a more concrete term; $E(\Pi_{is}, \varepsilon_{it} - \varepsilon_{i,t-1}) = 0$ $s=0,\ldots, t-2$, $t=2,\ldots.T$. This shows that if the lagged observation $\Pi_{i,t-2}$ is not correlated with the error term $\varepsilon_{it} - \varepsilon_{i,t-1}$, any further lag $\Pi_{i,t-3}$, $\Pi_{i,t-4}$, etc. is not correlated with the error term $\varepsilon_{it} - \varepsilon_{i,t-1}$ and thus is a valid instrument. Therefore, all available lagged variables can be taken as instruments as suggested by Arellano and Bond (1991).

Further, Arellano and Bover (1995) propose an extended GMM estimation in which additional moment conditions are imposed to gain more precision in estimations. In addition to the instruments available for the first-differenced equations, other valid instruments are specified for the equations in levels. In Blundell and Bond (1998), where the efficiency improvement of this extended GMM approach has been verified, the estimation performed with the instruments for both the first-differenced and levels equations is called the system GMM estimation and denoted by GMM-SYS, while that for only first-differenced equations is called the standard first-differenced GMM estimation and denoted by GMM-DIF.

Arellano and Bond (1991) provide diagnostic tests of the validity of the model specification in dynamic panel data estimations. The first test statistic is a Wald test that can be used for the validity of regressors in the model. The null hypothesis of the validity of the GMM instruments can be tested by a Sargan test of over-identifying restrictions. This test is asymptotically distributed as

Chi-square with a degrees of freedom computed with respect to the number of the over-identification restrictions. Similarly, a Difference-Sargan test statistic can be computed to test the validity of GMM-SYS estimates against GMM-DIF estimates, by testing the significance of the instruments used in levels equations as additional parameters. The statistic is simply the difference between the two Sargan test statistics computed with the GMM-SYS and GMM-DIF estimates respectively. The distribution of this statistic is Chi-square with the degrees of freedom equal to the number of instruments used in levels equations.

GMM estimates will be consistent when the error term does not have serial correlation. In this regard, two test statistics can be computed to test for the absence of first-order and second-order serial correlations in the first differenced residuals in the context of Arellano and Bond (1991). These two statistics have standard normal distributions asymptotically. Arellano and Bond (1991) also points out that second-order serial correlation in the first differenced residuals statistic is the indication of the absence of the serial correlation problem.

7.2. ESTIMATION RESULTS

As mentioned before, the dependent variable is the ratio of profit to total assets. Independent variables and eigenvectors are different from those used in discrete choice models and duration models. This set of eigenvectors and variables for the analysis of bank profitability by using dynamic panel data model are prepared by means of extracted earning category from the data set. Therefore, in this analysis, a different set of eigenvectors and variables are used to avoid endogeneity (see Section 4.1). Estimation results of bank profitability are given in tables 7.1 and 7.2. The first three columns for each estimation method illustrate the estimated coefficients, the relevant statistics of significance (z) and the p-value respectively. GMM-DIF and GMM-SYS estimation results are reported for two specifications.

Estimating a dynamic relationship with fixed or random effects model will cause biasedness and inconsistency problems due to inclusion of the lagged dependent variable. Therefore dynamic estimation method of GMM-DIF and GMM-SYS is used and the fixed-effects and random-effects model is not reported. The estimated models with GMM-DIF and GMM-SYS have passed the diagnostic test of validity of regressors, Wald test. All explanatory variables are jointly significant at one percent significance level (see tables 7.1 and 7.2).

According to GMM-DIF and GMM-SYS estimation results, the Sargan test statistics approve the validity of the GMM instruments.

According to AR (1) and AR (2)[42] test statistics, the consistency of the GMM estimators is verified, as there is evidence of first-order serial correlation and no evidence of second-order serial correlation in the differenced residuals of the model.

Further, according to GMM-DIF and GMM-SYS estimation results, the Sargan test statistics[43] approve the validity of the GMM instruments. According to the difference-Sargan test statistics[44], the null hypothesis of the validity of the additional instruments used in the GMM-SYS estimation rejected at one percent significance level. Therefore, the GMM-DIF parameter estimates appear to be reasonable (see tables 7.1 and 7.2).

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[42] Arellano-Bond test that average autocovariance in residuals of order 1 is 0: Ho: no autocorrelation. Arellano-Bond test that average autocovariance in residuals of order 2 is 0: Ho: no autocorrelation.

[43] The Sargan tests (over-identifying restrictions: Ho: the moment conditions are valid) presented in table 7.1 and 7.2 are based on the minimized values of the associated two-step GMM estimators. However, GMM results are one-step estimates with heteroscedasticity-consistent standard errors and test statistics (Bond, 2002).

[44] Difference Sargan test: Ho: the additional moment conditions are valid. Non-rejection of additional instruments indicates the use of GMM- SYS.

Table 7.1: Estimation Results of GMM-DIF and GMM-SYS with Selected Eigenvectors[45]

MODELS/ VARIABLES	GMM - DIF			GMM - SYS		
	Coef.	Z	P>z	Coef.	Z	P>z
Microeconomic Variables						
Lag (Net Income / T. Assets)	-3.02	-2.21	0.03	-1.26	-2.45	0.01
Size Category	0.08	1.87	0.06	0.43	0.13	0.89
Asset Quality Category	-2.55	-7.75	0.00	-2.26	-0.89	0.38
Asset Quality Category	2.62	5.05	0.00	2.49	0.79	0.43
Management Category	-2.61	-7.12	0.00	-1.37	-0.59	0.55
Management Category	5.43	14.12	0.00	7.84	1.45	0.15
Asset Quality Category	0.04	0.19	0.85	25.69	1.24	0.21
Liquidity Category	2.57	8.71	0.00	1.79	0.23	0.82
Asset Quality Category	3.63	12.44	0.00	10.44	1.00	0.32
Intercept Dummy	-5.00	-3.51	0.00	-24.5	-1.61	0.11
Macroeconomic Variable						
Credit Channel	-0.05	-0.11	0.92	-2.15	-0.81	0.42
Real Cost	-0.03	-0.16	0.87	-6.41	-1.42	0.16
Real Effect	0.14	0.62	0.53	0.45	0.15	0.88
Constant	0.28	2.19	0.03	11.23	1.47	0.14
Diagnostic Tests of Validity of Regressors						
Wald Test	X^2 (13) = 615.69 (0.00)			X^2 (13) = 272.66 (1.00)		
Specification Tests						
AR(1)	-2.97 (0.00)			-1.75 (0.08)		
AR(2)	1.11 (0.27)			1.11 (0.27)		
Sargan Test	X^2 (95) = 77.04 (0.91)			X^2 (123) = 27.31 (0.81)		
Difference Sargan Test	-			X^2 (28) = 49.73		

[45] The dependent variable is the ratio of profit to total assets. Eigenvectors (that are different from used in discrete choice models and duration model) selection procedure based on principal component analysis is explained in detail in section 4.1.

Table 7.2: Estimation Results of GMM-DIF and GMM-SYS with Selected Variables[46]

MODELS/ VARIABLES	GMM - DIF			GMM - SYS		
	Coef.	Z	P>z	Coef.	Z	P>z
Microeconomic Variables						
Lag (Net Income / T. Asset)	-5.30	-6.15	0.00	-2.50	-5.58	0.00
Share in Sector (T. Asset)	0.08	1.69	0.09	0.67	0.28	0.78
Permanent Assets/T. Asset	-0.09	-2.45	0.01	-0.13	-0.33	0.74
Total Loans/T. Asset	0.33	7.53	0.00	0.21	0.89	0.39
T. Deposits/No. of Branch.	-0.01	-0.86	0.39	-0.03	-0.59	0.56
FX Deposits/No. of Branch.	0.23	10.39	0.00	0.28	1.39	0.16
T. Loans/Net Working Cap.	0.00	0.00	1.00	7.53	0.61	0.54
FX Liquid Assets/FX Liab.	-0.01	-1.03	0.30	-0.07	-0.97	0.33
T. Loans/ Equity	0.03	0.71	0.48	2.32	0.71	0.48
Intercept Dummy	-5.57	-3.79	0.00	-53.41	-1.86	0.06
Macroeconomic Variable						
Credit Growth	-0.00	-0.23	0.82	-0.60	-1.90	0.06
Real Interest Rate	-0.01	-0.44	0.66	-0.19	-0.26	0.80
GDP Growth	0.08	1.43	0.15	0.43	0.60	0.55
Constant	0.50	5.66	0.00	66.62	2.09	0.04
Diagnostic Tests of Validity of Regressors						
Wald Test	(13) = 231.82 (0.00)			(13) = 220.33 (0.00)		
Specification Tests						
AR(1)	-2.58 (0.01)			-1.84 (0.07)		
AR(2)	0.30 (0.76)			0.35 (0.72)		
Sargan Test	X^2 (95) = 75.16 (0.93)			X^2 (123) = 29.33 (1.00)		
Difference Sargan Test	-			X^2 (28) = 45.83		

Overall, the models estimated with eigenvectors and variables seems to fit the panel data reasonably well, having quite stable coefficient estimates as the Wald test specifies goodness of fit and the

[46] The dependent variable is the ratio of profit to total assets. The independent variables (that are different from used in discrete choice models and duration model) selection procedure based on principal component analysis is explained in detail in section 4.1.

Sargan test indicates no evidence of over-identifying restrictions and there is no inconsistency since there is no second order autocorrelation even though negative first order autocorrelation is present as discussed in model section (Arellano and Bond, 1991).

Considering the explanatory variables, in all specifications coefficient estimates have the same sign. The estimated coefficients of eigenvectors are statistically significant except for size category and one of asset quality categories. Several studies use proxies for risk such as capital and liquidity ratios. A bank's capacity to absorb unexpected shocks determines its level of risk. A bank having higher liquid assets is associated with lower profits since in accordance with portfolio theory banks that have higher risks are likely to earn higher profits. The higher the ratio of liquid assets to total assets may cause higher possibility of ignoring profitable diversification or other opportunities (Goddard et al, 2004). However, the coefficient of liquidity category is positive and highly significant, reflecting the sound financial condition of Turkish banking sector.

A liquid bank is able to follow business opportunities more effectively and has more time and flexibility to deal with problems arising from unforeseen shocks, thus achieving increased profitability (Athanasoglu et al, 2005). This finding is consistent with that of Molyneux and Thornton (1992), Rhoades (1985) and Bourke (1989) who find a positive relationship between liquidity and profit. Further, inclusion of the first lagged dependent variables, as an independent variable is highly significant that also approves dynamic feature of the model specification for estimated with both eigenvectors and variables.

Moreover, higher the ratio of total loans to total assets ratio and corresponding to asset quality category can be associated with higher taking credit risks. A bank with holding these risky projects can earn more profits. Therefore, as expected, the ratio of loans to asset and related eigenvector is positively and significantly associated with bank profitability for estimated with both variables and eigenvectors. The sign of the estimated coefficient of the eigenvector related to management category turns out to be positive. This reflects that efficient management conditions of banks are positively related with bank profitability. This is the case for the coefficients estimated with variables. Finally, macroeconomic control variables such as credit growth, real interest rate and GDP growth are statistically insignificant. In estimation with eigenvectors, macroeconomic control variables are also statistically insignificant.

This chapter evaluated the determinants of profitability of banks by an empirical framework, dynamic panel data model, in terms of bank-specific and macroeconomic conditions. In addition to logit and duration estimation, the dynamic feature of the determinants is included by using dynamic panel data model. Unlike aforementioned estimation methods in finding the survival times of banks or the probability of bank failures, this chapter mainly focuses on the determinants of bank profitability. The approach pursued in this chapter may well have extensive potential as a tool for exploring bank profitability determinants with the purpose of suggesting optimal policies for bank management and preventing possible failure costs (Goddard et al, 2004).

CHAPTER 8

CONCLUSION

Banking sector problems have risen in all over the world since the early 1980s. This increase has led to the investigations for the connections between banking sector fragility and the overall economy. The Turkish experience, which stemmed primarily from the fragility of the banking sector, demonstrates that micro factors of both public and private banks and macroeconomic environment contributed significantly to the outbreak of economic crises. This study attempts to identify some of these factors by estimating discrete choice models and duration model. It also aims to examine fragility of the banking system by estimating a duration model and to analyze the determinants of bank profitability by using a dynamic panel data model with the same selected eigenvectors and variables based on principal component analysis.

In selecting proxy variables and eigenvectors for CAMEL categories, principal component analysis is employed in order to be consistent in all empirical specifications and assure the comparability of the prediction results. Accordingly, the following selected eigenvectors and variables are selected based on principal component analysis: the first eigenvector is named as size category for share in sector in terms of assets. The classifications of other seven eigenvectors are named as; earning category for the ratio of income before tax to total assets, liquidity category for the ratio of liquid assets to total assets, asset quality category for the ratio of permanent assets to total assets, earnings category for the ratio of net income to shareholder equity, management category for the ratio of total deposits to number of branches, liquidity category for the ratio of foreign exchange liquid assets to foreign exchange liabilities and asset quality category for the ratio of total loans to net working capital, respectively.

The variables and eigenvectors selection procedure based on principal component analysis is also applied to ten macroeconomic variables covering macroeconomic conditions of the country. Among macroeconomic variables, the first three eigenvectors can be named as credit channel category for credit growth, real costs category for real interest rate variable and real effect category for GDP growth.

After selection of the proxy eigenvectors and variables, both binary and multinomial logit estimation is employed to predict the probability of bank failures and to determine the factors of bank failures. Based on the results of both binary and multinomial logit estimation, all independent variables except for share in sector in terms of assets the ratio of liquid asset to asset, the ratio of net income to equity, deposits per branch and the ratio of loans to net working capital, are statistically significant. The correspondent eigenvectors related to these variables also turned out to be significant with the expected signs. Except for credit growth variable, other macroeconomic variables have expected signs. In the estimation with eigenvectors, only the eigenvector related to macroeconomic real effect is statistically insignificant.

Furthermore, to distinguish the state of problem banks as failure and merger/acquisition, multinomial logit model is employed. The test statistics concerning the validity of the different categories is confirmed using multinomial logit model that discriminates between two failure outcomes (i.e., failed banks versus merger/acquisition). Based on the prediction results, Binary logit models correctly classifies 88 % of all the failures in any quarters for estimated with eigenvectors and 92 % of all the failures in any quarters for estimated with variables; in the quarter of failure, 83 % of the failures for estimated with eigenvectors and 78 % of the failures for estimated with variables and at least four quarters before the failure 89 % of the failures for estimated with eigenvectors and variables. Moreover, multinomial logit model gives almost the same results with binary logit model.

The findings of discrete choice models may help decision makers in supervisory institutions in terms of the determinants of bank failures in Turkish banking system. As the discrete choice models are limited in terms of the determination and prediction of timing of failures, the use of duration model is required. This is because of the fact that the discrete choice models do not use the information concerning the length of the survival of the banks.

Using duration model, survival of banks is determined by both bank-specific factors and the macroeconomic condition with the same selected eigenvectors and variables based on principal component analysis as in discrete choice model. The results in duration model are consistent with the discrete choice models. The Cox-PH and Weibull models estimated with both eigenvectors and variables correctly classify 92 - 94 % of failures as a failure in any quarter. However, there is another improvement for the classification of predicted failures as a quarter that is four quarters before the failure compared with discrete choice models. Since, when the duration model correctly classifies 94 % of failures as a failure four quarters before the failure, binary and multinomial model correctly classifies 89 % of the failures. This shows that the use of duration model provides more time to take preventive actions before the failure than that of discrete choice models.

Another extension of the duration model gives the degree of fragility of the overall banking system and individual banks. The results based on duration model are satisfactory since they capture the fragility of the banking system before the crises or before the waves of failures. The individual analysis of banks of the degree of fragility exhibits a sharp increase in the degree of fragility before the failure for both failed and non-failed banks. Overall, the use of duration model provides useful extensions to take preemptive measures for fragile banks.

After analyzing the factors of the probability of failure, the timing of failure and the degree of fragility of individual banks and the overall banking system, using dynamic feature of the data set can be another tool for preventing bank failures and promoting a sound banking system, since a strong and profitable Turkish banking sector supports broader financial stability. To examine the determinants of bank performance, dynamic panel data is used. In the most of the studies on banking profitability, the ratio of profits to total assets is chosen. The same approach has been adopted here.

A bank with high liquidity level, good management in branches and asset quality increase the profitability of Turkish banking sector based on the results of the dynamic panel data estimation. Further, inclusion of the first lagged dependent variables also confirms the dynamic feature of the model specification. Moreover estimated with proxy variables, the ratio of total loans to total assets, the ratio of permanent assets to total assets, the ratio of foreign exchange deposits to number of branches are found statistically significant with expected signs.

As a limitation, the results and extensions of discrete choice models, duration model and dynamic panel data model are based on the financial information publicly available over the sample period. The motivation of this thesis stems from its quantitative neutrality and the possibility of observing assessable results of the microeconomic and macroeconomic indicators on bank failures in Turkey and determining the degree of fragility of overall banking and profitability of the Turkish banking sector.

The results presented in this thesis have important implications for regulatory and supervisory agencies in terms of the analysis of the probability of bank failure, the expected survival time of failed banks and degree of fragility of individual banks and the banking system. This can give an understanding of the factors that affect failure risks. Based upon the results, this thesis can provide corrective actions by regulatory and supervisory agencies for problematic banks before the failure.

Further research for Turkish case can apply to any framework, which are presented in chapters 5, 6 and 7 to help identify the determinants of bank soundness and profitability and to provide broader financial stability. The advantage of focusing on fragility or soundness of the banking system rather than bank failures is that the soundness of the banking system can be evaluated before bank failures actually occur. For regulatory and supervisory agencies, this can be a practical instrument.

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APPENDICIES

APPENDIX A: TABLES and FIGURES

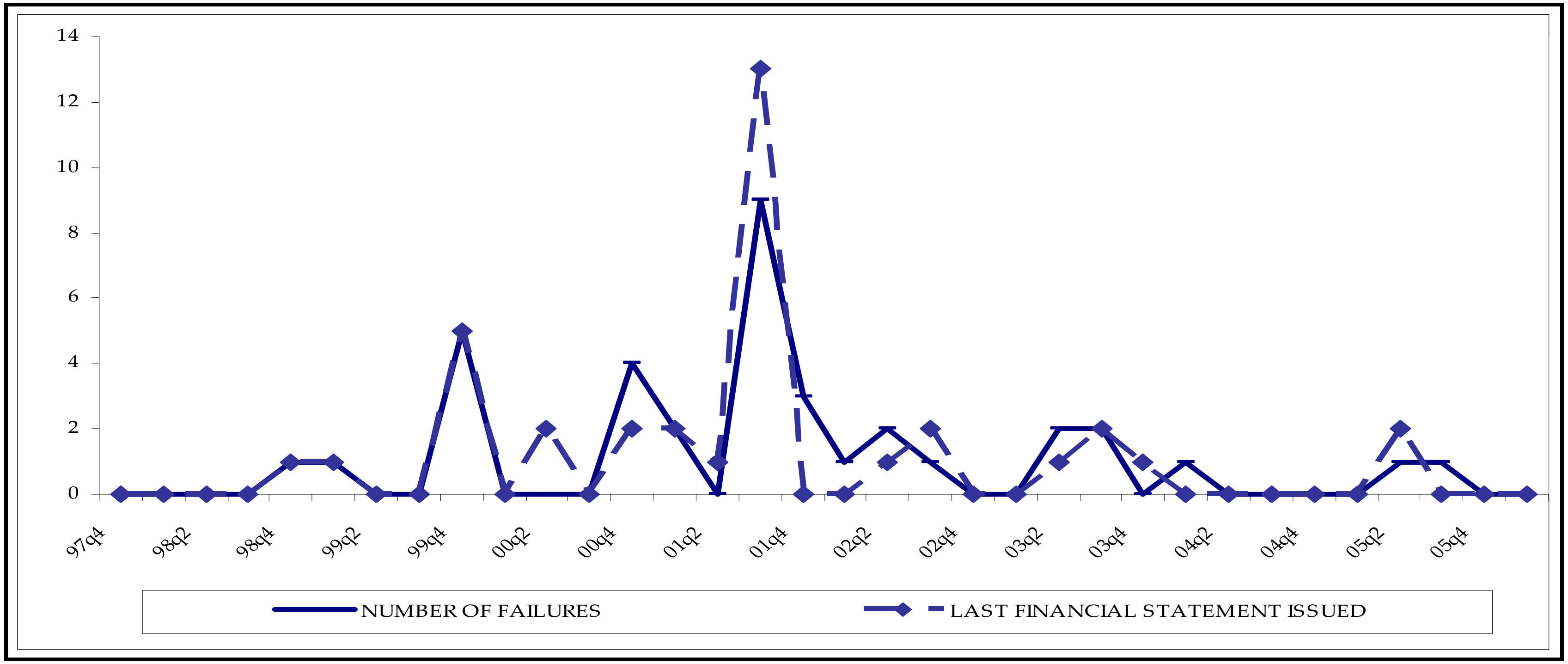
Table A.1: List of Failed Banks

Banks	Date of Failure	Type of Failure
Bank Ekspres A.Ş.	Dec 12, 1998	Taken under the SDIF
Interbank	Jan 7, 1999	Taken under the SDIF
Egebank A.Ş.	Dec 22, 1999	Taken under the SDIF
Eskişehir Bankası T.A.Ş.	Dec 22, 1999	Taken under the SDIF
Sümerbank A.Ş.	Dec 22, 1999	Taken under the SDIF
TTB Yaşarbank A.Ş.	Dec 22, 1999	Taken under the SDIF
Yurt Tic. ve Kredi Bankası	Dec 22, 1999	Taken under the SDIF
Bank Kapital Türk A.Ş.	Oct 27, 2000	Taken under the SDIF
Etibank A.Ş.	Oct 27, 2000	Taken under the SDIF
Demirbank T.A.Ş.	Dec 6, 2000	Taken under the SDIF
Park Yatırım Bankası A.Ş.	Dec 6, 2000	Withdrawal of permission
Ulusal Bank T.A.Ş.	Feb 28, 2001	Taken under the SDIF
İktisat Bankası T.A.Ş.	Mar 15, 2001	Taken under the SDIF
Türkiye Emlak Bankası A.Ş.	July 3, 2001	Merged under Ziraat Bank
EGS Bankası A.Ş.	July 9, 2001	Taken under the SDIF
Kentbank A.Ş.	July 9, 2001	Taken under the SDIF
Milli Aydın Bankası T.A.Ş.	July 9, 2001	Taken under the SDIF
Sitebank A.Ş.	July 9, 2001	Taken under the SDIF
Atlas Yatırım Bankası A.Ş.	July 10, 2001	Withdrawal of permission
Bayındırbank A.Ş.	July 10, 2001	Taken under the SDIF
Okan Yatırım Bankası A.Ş.	July 10, 2001	Withdrawal of permission

Table A.1: (Continued)

Banks	Date of Failure	Type of Failure
Birl. Türk Körfez Bank A.Ş.	Aug 31, 2001	Merged under Osmanlı Bankası
Tekfen Yatırım ve Fin. Bank	Oct 18, 2001	Withdrawal of permission
Morgan Guaranty Trust Co.	Nov 10, 2001	Merged under The Chase Manh. B.
Osmanlı Bankası A.Ş.	Dec 11, 2001	Merged under Garanti Bank
Sınai Yatırım Bankası A.Ş.	Mar 29, 2002	Merged under T. Sınai Kalkınma
Rabobank Nederland	Apr 2, 2002	Withdrawal of permission
Pamukbank T.A.Ş.	June 19, 2002	Taken under the SDIF
Toprakbank A.Ş.	Sept 30, 2002	Withdrawal of permission
Fiba Bank A.Ş.	Apr 3, 2003	Merged under Finans Bank
ING Bank N.V.	May 1, 2003	Withdrawal of permission
T. İmar Bankası T.A.Ş.	July 3, 2003	Withdrawal of permission
Credit Suisse First Boston	Sept 11, 2003	Withdrawal of permission
Credit Lyonnais Turkey	Mar 3, 2004	Withdrawal of permission
Türk Dış Ticaret Bankası	June 4, 2005	Merged under Fortis Bank
Ak Ulusl. Bankası A.Ş.	Sept 19, 2005	Merged under Akbank

Figure A.1: The Number of Failures between the 4th quarter of 1997 and the 1st quarter of 2006[47]



[47] There is difference between the date of last financial statements issued and the date of failure for some of the failed banks. For example, for Bank A, the date of last financial statements issued on the last quarter of 2003 however, Bank A failed on the first quarter of 2004. Therefore, in the estimation process, the date of last financial statements is taken as the date of failure (Molina, 2002).

Table A.2: The Scores of First Eight Factors with Microeconomic Variables

Variable	Classification	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8
Net Working Capital/ T. Assets	Capital Adequacy	-0.215	0.336	-0.092	0.256	0.132	-0.089	-0.056	0.020
S. Equity/FX Position	Capital Adequacy	-0.078	0.106	0.338	0.102	0.214	-0.250	-0.015	0.005
Permanent Assets/T. Assets	Asset Quality	0.014	-0.376	0.005	**0.324**	0.064	0.466	-0.007	0.011
T. Loans/T. Assets	Asset Quality	0.203	0.084	-0.514	-0.136	-0.219	0.020	0.042	0.017
T. Loans/S. Equity	Asset Quality	0.110	0.008	-0.245	-0.277	0.583	0.063	0.010	-0.008
T. Loans/Net Working Capital	Asset Quality	-0.020	0.000	0.008	-0.021	0.002	0.006	-0.119	**0.992**
Permanent Assets/Liquid Assets	Asset Quality	-0.073	-0.336	0.160	0.348	0.156	0.365	-0.055	-0.007
Net Income/No. of Branches	Management	-0.047	0.274	-0.185	0.007	-0.121	0.244	-0.175	-0.039
FX Deposits/No. of Branches	Management	-0.036	0.201	0.231	-0.362	-0.113	0.502	-0.002	-0.009
T. Deposits/No. of Branches	Management	-0.009	0.173	0.344	-0.416	-0.080	**0.349**	-0.011	-0.006
Income Before Tax/T. Assets	Earnings	-0.130	**0.455**	-0.077	0.282	0.107	0.208	0.094	0.009
Net Income/T. Assets	Earnings	-0.088	0.439	-0.107	0.284	0.104	0.161	0.114	0.013
Net Income/S. Equity	Earnings	-0.032	0.057	0.161	0.232	**-0.651**	-0.083	0.043	0.006
Liquid Assets/T. Assets	Liquidity	-0.256	0.129	**0.422**	-0.091	0.153	-0.244	-0.058	-0.027
FX Liquid Assets/FX Liabilities	Liquidity	0.015	-0.033	0.058	-0.025	0.021	0.013	**0.958**	0.112
Share in Sector in terms of T. Assets	Size	**0.453**	0.116	0.196	0.165	0.076	0.005	-0.028	0.004
Share in Sector in terms of T. Loans	Size	0.455	0.126	0.096	0.131	0.034	0.025	-0.035	0.011
Share in Sector in terms of T. Deposits	Size	0.443	0.100	0.217	0.158	0.083	-0.007	-0.019	0.003
Log(T. Assets)	Size	0.430	0.102	0.038	-0.077	-0.047	-0.074	-0.013	0.011

Table A.3: The Scores of First Three Factors with Macroeconomic Variables

Variable	Factor 1	Factor 2	Factor 3
GDP Growth	-0.228	-0.248	**0.603**
Depreciation	0.233	0.364	0.349
Real Interest Rate	-0.062	**0.556**	0.362
M2/CB Foreign Reserves	-0.243	0.373	-0.473
Credit Growth	**0.399**	0.105	-0.268
Credit to Private Sector/GDP	-0.398	0.027	0.041
Domestic Credit/GDP	-0.419	0.035	-0.044
Bank Liquid Assets/Bank Reserves	0.257	-0.407	0.176
Interbank Interest Rate	0.306	0.405	0.212
Inflation	0.423	-0.124	-0.087

Table A.4: Eigenvalues of Factors for Microeconomic Variables without Earnings Category for Dynamic Panel Data Model

Components	Eigenvalue	Difference	Proportion	Cumulative
Microeconomic Variables				
1	3.77	1.54	0.24	0.24
2	2.23	0.20	0.14	0.38
3	2.03	0.45	0.13	0.50
4	1.58	0.43	0.10	0.60
5	1.15	0.15	0.07	0.67
6	1.00	0.05	0.06	0.74
7	0.95	0.05	0.06	0.79
8	0.90	0.19	0.06	0.85

Table A.5: The Scores of First Eight Factors with Microeconomic Variables without Earnings Category for Dynamic Panel Data Model

Variable	Classification	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7	Factor 8
Net Working Capital/ T. Assets	Capital Adequacy	-0.172	0.180	-0.092	-0.345	0.408	0.019	0.146	0.271
S. Equity/FX Position	Capital Adequacy	-0.069	0.194	0.330	-0.315	-0.003	0.009	-0.031	0.243
Permanent Assets/T. Assets	Asset Quality	-0.014	**-0.528**	0.230	0.289	0.178	0.011	0.003	0.128
T. Loans/T. Assets	Asset Quality	0.212	-0.056	**-0.565**	0.089	-0.005	0.010	0.061	-0.025
T. Loans/S. Equity	Asset Quality	0.104	-0.001	-0.162	0.026	-0.336	0.017	-0.541	**0.729**
T. Loans/Net Working Capital	Asset Quality	-0.020	0.013	0.002	0.014	0.003	**0.999**	0.026	-0.002
Permanent Assets/Liquid Assets	Asset Quality	-0.099	-0.429	0.374	0.164	0.203	0.000	-0.036	0.188
Net Income/No. of Branches	Management	-0.016	0.174	-0.253	0.109	0.110	-0.030	0.213	0.360
FX Deposits/No. of Branches	Management	-0.019	0.360	0.088	0.581	**0.566**	-0.009	0.017	0.074
T. Deposits/No. of Branches	Management	0.001	0.411	0.183	**0.497**	-0.038	-0.002	-0.066	-0.026
Liquid Assets/T. Assets	Liquidity	-0.248	0.345	0.337	-0.200	-0.087	-0.016	-0.093	-0.037
FX Liquid Assets/FX Liabilities	Liquidity	0.012	-0.020	0.069	0.059	-0.499	-0.019	**0.782**	0.349
Share in Sector in terms of T. Assets	Size	**0.467**	0.047	0.222	-0.096	0.127	0.005	0.046	0.049
Share in Sector in terms of T. Loans	Size	0.470	0.036	0.112	-0.063	0.141	0.012	0.047	0.056
Share in Sector in terms of T. Deposits	Size	0.455	0.044	0.245	-0.097	0.098	0.003	0.037	0.037
Log(T. Assets)	Size	0.437	0.096	-0.008	-0.004	-0.105	0.015	-0.058	-0.136

Table A.6: Tests of Independent Irrelevant Alternative (IIA) Assumption[48]

Models	Model 1	Model 2
Tests of IIA for the Model with Selected Eigenvectors		
Hausman Tests of IIA assumption	omitted 1 $X^2(10) = 0.023$ (1.000)	omitted 1 $X^2(13) = 0.005$ (1.000)
	omitted 2 $X^2(10) = 0.002$ (1.000)	omitted 2 $X^2(13) = 0.052$ (1.000)
Small-Hsiao Tests of IIA assumption	omitted 1 $X^2(10) = 15.120$ (0.128)	omitted 1 $X^2(13) = 15.229$ (0.293)
	omitted 2 $X^2(10) = 13.185$ (0.213)	omitted 2 $X^2(13) = 12.202$ (0.511)
Tests of IIA for the Model with Selected Variables		
Hausman Tests of IIA assumption	omitted 1 $X^2(10) = 0.001$ (1.000)	omitted 1 $X^2(13) = 0.001$ (1.000)
	omitted 2 $X^2(10) = 0.003$ (1.000)	omitted 2 $X^2(13) = 0.003$ (1.000)
Small-Hsiao Tests of IIA assumption	omitted 1 $X^2(10) = 17.269$ (0.069)	omitted 1 $X^2(13) = 21.620$ (0.062)
	omitted 2 $X^2(10) = 8.947$ (0.537)	omitted 2 $X^2(13) = 9.684$ (0.720)

Table A.7: Predictive Accuracy for Binary Logit Model with Selected Eigenvectors[49]

Classification	Cut-off 0.50	Cut-off 0.017	Variation in Cut-off
Predicted as a failure (in any quarters) correctly	25.00	86.11	88.89
Predicted as a failure in the quarter of failure correctly	25.00	69.44	83.33
The percentage of non-failed observations that are correctly classified	100.00	85.87	68.12
The percentage of failed observations that are correctly classified (included all quarters before the failure)	2.03	16.21	44.57

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48 In the table, dummy variable d represents the state of banks (takes 0, 1 or 2); non-failed, failed and mergers/acquisitions banks, respectively.

49 This table reports that cut-off probability in the second column is the mean of predictive values as 0.017 and in the third column; it is the mean of predicted values of dependent variable quarter by quarter.

Table A.8: Predictive Accuracy for Binary Logit Model with Selected Variables

Classification	Cut-off 0.50	Cut-off 0.018	Variation in Cut-off
Predicted as a failure (in any quarters) correctly	22.22	97.22	91.67
Predicted as a failure in the quarter of failure correctly	19.44	75.00	77.78
The percentage of non-failed observations that are correctly classified	100.00	83.23	70.36
The percentage of failed observations that are correctly classified (included all quarters before the failure)	1.66	20.44	34.44

Table A.9: Predictive Accuracy for Multinomial Logit Model with Selected Eigenvectors

Classification	Cut-off 0.50	Cut-off 0.014	Variation in Cut-off
Predicted as a failure (in any quarters) correctly	25.00	86.11	88.89
Predicted as a failure in the quarter of failure correctly	25.00	69.44	80.56
The percentage of non-failed observations that are correctly classified	100.00	88.05	66.73
The percentage of failed observations that are correctly classified (included all quarters before the failure)	2.03	15.84	44.20

Table A.10: Predictive Accuracy for Multinomial Logit Model with Selected Variables

Classification	Cut-off 0.50	Cut-off 0.014	Variation in Cut-off
Predicted as a failure (in any quarters) correctly	27.78	97.22	94.44
Predicted as a failure in the quarter of failure correctly	25.00	69.44	77.78
The percentage of non-failed observations that are correctly classified	100.00	87.06	70.23
The percentage of failed observations that are correctly classified (included all quarters before the failure)	2.03	19.15	32.97

Figure A.2: Hazard Rate Estimated from Kaplan-Meier Survival Function

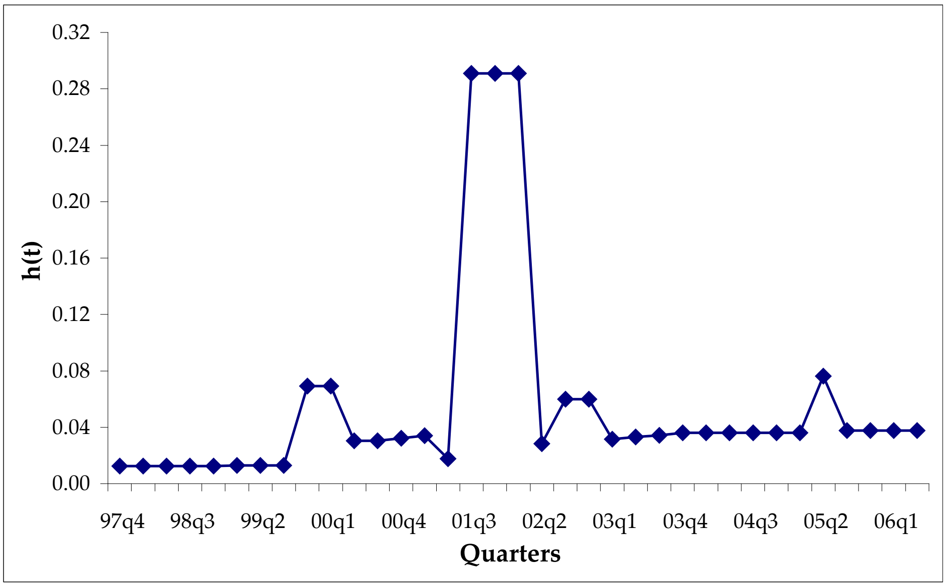


Table A.11: Survival Summary of the Banks

Time (quarters)	Number of Banks	Failures	Survivor Function	Standard Errors	95 % Confidence Interval	
5	81	1	0.988	0.012	0.916	0.998
6	80	1	0.975	0.017	0.905	0.994
9	79	5	0.914	0.031	0.827	0.958
11	74	2	0.889	0.035	0.797	0.941
13	72	2	0.864	0.038	0.768	0.922
14	70	2	0.840	0.041	0.740	0.904
15	68	1	0.827	0.042	0.726	0.894
16	67	13	0.667	0.052	0.553	0.758
19	54	1	0.654	0.053	0.540	0.747
20	53	2	0.630	0.054	0.515	0.724
22	51	1	0.617	0.054	0.502	0.713
23	50	1	0.605	0.054	0.490	0.702
24	49	1	0.593	0.055	0.478	0.690
25	48	1	0.580	0.055	0.465	0.679
31	47	2	0.556	0.055	0.441	0.656
35	45	0	0.556	0.055	0.441	0.656

Table A.12: AIC, Likelihood Values and LR Test Statistics for Selected Eigenvectors

Type of Distribution / Model		Model 1	Model 2
Weibull	Log-likelihood	-53.88	-41.50
	AIC	127.76	109.01
	LR	56.13	80.89
Gompertz	Log-likelihood	-55.25	-47.34
	AIC	130.51	120.68
	LR	56.79	72.62
Exponential	Log-likelihood	-55.29	-49.14
	AIC	128.58	122.29
	LR	56.79	69.08

Table A.13: AIC, Likelihood Values and LR Test Statistics for Selected Variables

Type of Distribution / Model		Model 1	Model 2
Weibull	Log-likelihood	-56.41	-41.49
	AIC	132.81	108.97
	LR	55.20	85.04
Gompertz	Log-likelihood	-57.24	-46.27
	AIC	134.48	118.55
	LR	57.50	79.43
Exponential	Log-likelihood	-57.58	-48.64
	AIC	133.16	121.29
	LR	56.95	74.82

Table A.14: Prediction Results of Cox-PH Model for Selected Eigenvectors

Failed Banks	Not Predicted as a Failure	Predicted as a Failure in the Quarter of the Failure	Predicted as a Failure 4 Quarters Before
Atlas Yatırım Bankası A.Ş.	NO	NO	YES
Bank Ekspres A.Ş.	NO	YES	YES
Bank Kapital Türk A.Ş.	NO	YES	YES
Bayındırbank A.Ş.	NO	NO	YES
Birleşik Türk Körfez Bankası A.Ş.	NO	NO	YES
Ak Uluslararası Bankası A.Ş.	NO	NO	YES
Credit Lyonnais Turkey	NO	YES	YES
Credit Suisse First Boston	NO	NO	YES
Demirbank T.A.Ş.	YES	NO	NO
EGS Bankası A.Ş.	NO	NO	YES
Egebank A.Ş.	NO	YES	YES
Eskişehir Bankası T.A.Ş.	NO	YES	NO
Etibank A.Ş.	NO	YES	YES
Fiba Bank A.Ş.	NO	YES	YES
İktisat Bankası T.A.Ş.	NO	YES	YES
ING Bank N.V.	NO	YES	YES
Interbank	NO	YES	YES
Kentbank A.Ş.	NO	YES	YES
Milli Aydın Bankası T.A.Ş.	NO	YES	YES
Morgan Guaranty Trust Co.	NO	YES	YES
Okan Yatırım Bankası A.Ş.	NO	YES	YES
Osmanlı Bankası A.Ş.	NO	YES	YES
Pamukbank T.A.Ş.	NO	YES	YES
Park Yatırım Bankası A.Ş.	NO	YES	YES
Rabobank Nederland	NO	YES	YES
Sınai Yatırım Bankası A.Ş.	NO	YES	YES
Sitebank A.Ş.	NO	YES	YES
Sümerbank A.Ş.	NO	YES	YES
Tekfen Yat. Ve Fin. Bankası A.Ş.	NO	YES	YES
Toprakbank A.Ş.	NO	YES	YES
Türk Dış Ticaret Bankası	NO	YES	YES
Türkiye Emlak Bankası A.Ş.	YES	NO	NO
TTB Yaşarbank A.Ş.	NO	YES	NO
Türkiye İmar Bankası T.A.Ş.	NO	YES	YES
Ulusal Bank T.A.Ş.	NO	NO	YES
Yurt Ticaret ve Kredi Bankası A.Ş.	NO	YES	YES
Number of incorrectly classified	2	9	4
Percentage of incorrectly classified	5.56	25.00	11.11

Table A.15: Prediction Results of Cox-PH Model for Selected Variables

Failed Banks	Not Predicted as a Failure	Predicted as a Failure in the Quarter of the Failure	Predicted as a Failure 4 Quarters Before
Atlas Yatırım Bankası A.Ş.	NO	YES	YES
Bank Ekspres A.Ş.	NO	YES	NO
Bank Kapital Türk A.Ş.	NO	NO	YES
Bayındırbank A.Ş.	NO	NO	YES
Birleşik Türk Körfez Bankası A.Ş.	NO	YES	YES
Ak Uluslararası Bankası A.Ş.	NO	NO	YES
Credit Lyonnais Turkey	NO	YES	YES
Credit Suisse First Boston	NO	YES	YES
Demirbank T.A.Ş.	YES	NO	NO
EGS Bankası A.Ş.	NO	NO	YES
Egebank A.Ş.	NO	YES	NO
Eskişehir Bankası T.A.Ş.	NO	YES	NO
Etibank A.Ş.	NO	YES	NO
Fiba Bank A.Ş.	NO	YES	YES
İktisat Bankası T.A.Ş.	NO	YES	YES
ING Bank N.V.	NO	YES	YES
Interbank	NO	NO	YES
Kentbank A.Ş.	NO	NO	YES
Milli Aydın Bankası T.A.Ş.	NO	YES	YES
Morgan Guaranty Trust Co.	NO	NO	YES
Okan Yatırım Bankası A.Ş.	NO	NO	YES
Osmanlı Bankası A.Ş.	NO	YES	NO
Pamukbank T.A.Ş.	NO	YES	YES
Park Yatırım Bankası A.Ş.	NO	YES	YES
Rabobank Nederland	NO	YES	YES
Sınai Yatırım Bankası A.Ş.	NO	YES	YES
Sitebank A.Ş.	NO	YES	YES
Sümerbank A.Ş.	NO	YES	YES
Tekfen Yat. Ve Fin. Bankası A.Ş.	NO	YES	YES
Toprakbank A.Ş.	NO	YES	YES
Türk Dış Ticaret Bankası	NO	YES	YES
Türkiye Emlak Bankası A.Ş.	NO	YES	YES
TTB Yaşarbank A.Ş.	YES	NO	NO
Türkiye İmar Bankası T.A.Ş.	NO	YES	YES
Ulusal Bank T.A.Ş.	NO	NO	YES
Yurt Ticaret ve Kredi Bankası A.Ş.	NO	YES	NO
Number of incorrectly classified	2	11	8
Percentage of incorrectly classified	5.56	30.56	22.22

Table A.16: Prediction Results of Weibull Model for Selected Eigenvectors

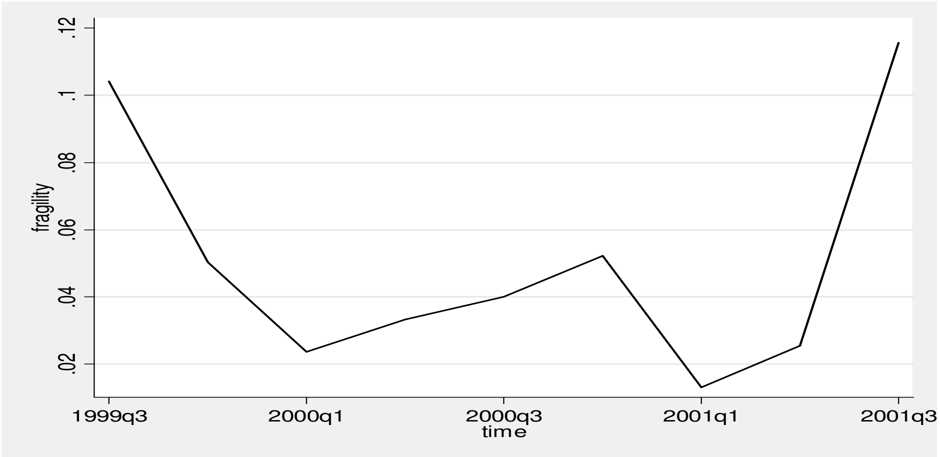
Failed Banks	Not Predicted as a Failure	Predicted as a Failure in the Quarter of the Failure	Predicted as a Failure 4 Quarters Before
Atlas Yatırım Bankası A.Ş.	NO	NO	YES
Bank Ekspres A.Ş.	NO	YES	YES
Bank Kapital Türk A.Ş.	NO	YES	YES
Bayındırbank A.Ş.	NO	YES	YES
Birleşik Türk Körfez Bankası A.Ş.	NO	YES	YES
Ak Uluslararası Bankası A.Ş.	NO	YES	YES
Credit Lyonnais Turkey	YES	NO	NO
Credit Suisse First Boston	NO	YES	YES
Demirbank T.A.Ş.	NO	YES	YES
EGS Bankası A.Ş.	NO	YES	YES
Egebank A.Ş.	NO	YES	YES
Eskişehir Bankası T.A.Ş.	NO	YES	YES
Etibank A.Ş.	NO	YES	YES
Fiba Bank A.Ş.	NO	YES	YES
İktisat Bankası T.A.Ş.	NO	YES	YES
ING Bank N.V.	YES	NO	NO
Interbank	NO	YES	YES
Kentbank A.Ş.	NO	YES	YES
Milli Aydın Bankası T.A.Ş.	NO	YES	YES
Morgan Guaranty Trust Co.	YES	NO	NO
Okan Yatırım Bankası A.Ş.	NO	YES	YES
Osmanlı Bankası A.Ş.	NO	NO	YES
Pamukbank T.A.Ş.	NO	YES	YES
Park Yatırım Bankası A.Ş.	NO	YES	YES
Rabobank Nederland	NO	YES	YES
Sınai Yatırım Bankası A.Ş.	YES	NO	NO
Sitebank A.Ş.	NO	YES	YES
Sümerbank A.Ş.	NO	YES	YES
Tekfen Yat. Ve Fin. Bankası A.Ş.	NO	YES	YES
Toprakbank A.Ş.	NO	YES	YES
Türk Dış Ticaret Bankası	NO	YES	YES
Türkiye Emlak Bankası A.Ş.	NO	YES	YES
TTB Yaşarbank A.Ş.	NO	YES	YES
Türkiye İmar Bankası T.A.Ş.	NO	YES	YES
Ulusal Bank T.A.Ş.	NO	NO	YES
Yurt Ticaret ve Kredi Bankası A.Ş.	NO	YES	YES
Number of incorrectly classified	3	7	4
Percentage of incorrectly classified	8.33	19.44	11.11

Table A.17: Prediction Results of Weibull Model for Selected Variables

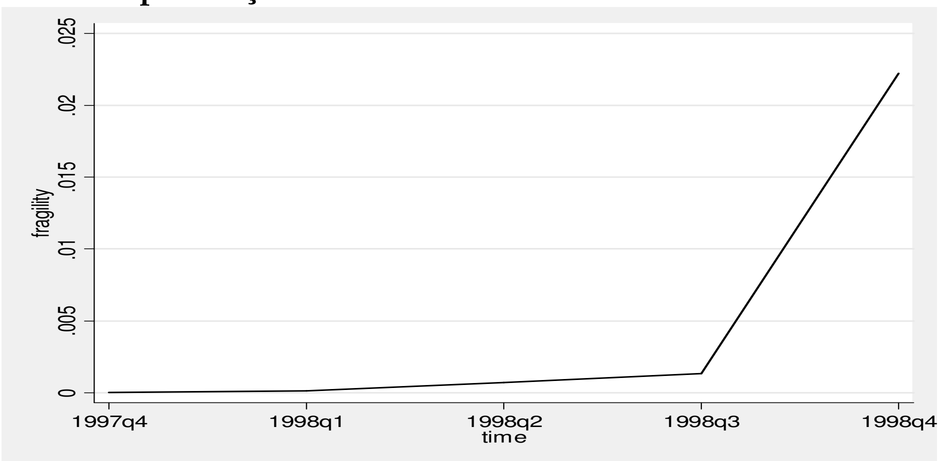
Failed Banks	Not Predicted as a Failure	Predicted as a Failure in the Quarter of the Failure	Predicted as a Failure 4 Quarters Before
Atlas Yatırım Bankası A.Ş.	NO	NO	YES
Bank Ekspres A.Ş.	NO	YES	YES
Bank Kapital Türk A.Ş.	NO	YES	YES
Bayındırbank A.Ş.	NO	YES	YES
Birleşik Türk Körfez Bankası A.Ş.	NO	YES	YES
Ak Uluslararası Bankası A.Ş.	NO	YES	YES
Credit Lyonnais Turkey	YES	NO	NO
Credit Suisse First Boston	NO	YES	YES
Demirbank T.A.Ş.	YES	NO	NO
EGS Bankası A.Ş.	NO	YES	YES
Egebank A.Ş.	NO	YES	YES
Eskişehir Bankası T.A.Ş.	NO	YES	YES
Etibank A.Ş.	NO	YES	YES
Fiba Bank A.Ş.	NO	YES	YES
İktisat Bankası T.A.Ş.	NO	YES	YES
ING Bank N.V.	NO	YES	YES
Interbank	NO	YES	YES
Kentbank A.Ş.	NO	YES	YES
Milli Aydın Bankası T.A.Ş.	NO	YES	YES
Morgan Guaranty Trust Co.	NO	YES	YES
Okan Yatırım Bankası A.Ş.	NO	YES	YES
Osmanlı Bankası A.Ş.	NO	NO	YES
Pamukbank T.A.Ş.	NO	YES	YES
Park Yatırım Bankası A.Ş.	NO	YES	YES
Rabobank Nederland	NO	NO	YES
Sınai Yatırım Bankası A.Ş.	NO	YES	YES
Sitebank A.Ş.	NO	YES	YES
Sümerbank A.Ş.	NO	YES	YES
Tekfen Yat. Ve Fin. Bankası A.Ş.	NO	YES	YES
Toprakbank A.Ş.	NO	YES	YES
Türk Dış Ticaret Bankası	NO	YES	YES
Türkiye Emlak Bankası A.Ş.	NO	YES	YES
TTB Yaşarbank A.Ş.	NO	YES	YES
Türkiye İmar Bankası T.A.Ş.	NO	YES	YES
Ulusal Bank T.A.Ş.	NO	NO	YES
Yurt Ticaret ve Kredi Bankası A.Ş.	NO	YES	YES
Number of incorrectly classified	2	6	2
Percentage of incorrectly classified	5.56	16.67	5.56

Table A.18: The Degree of Fragility of Failed Banks

Atlas Yatırım Bankası A.Ş.



Bank Ekspres A.Ş.



Bank Kapital Türk A.Ş.

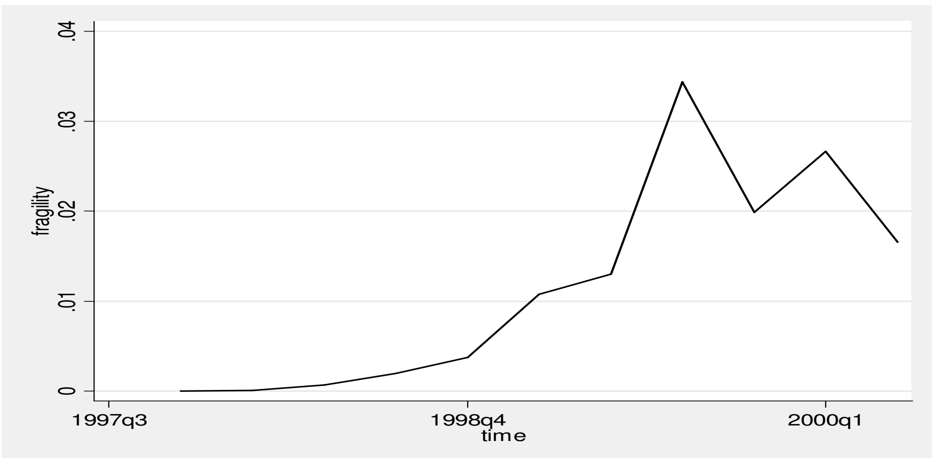
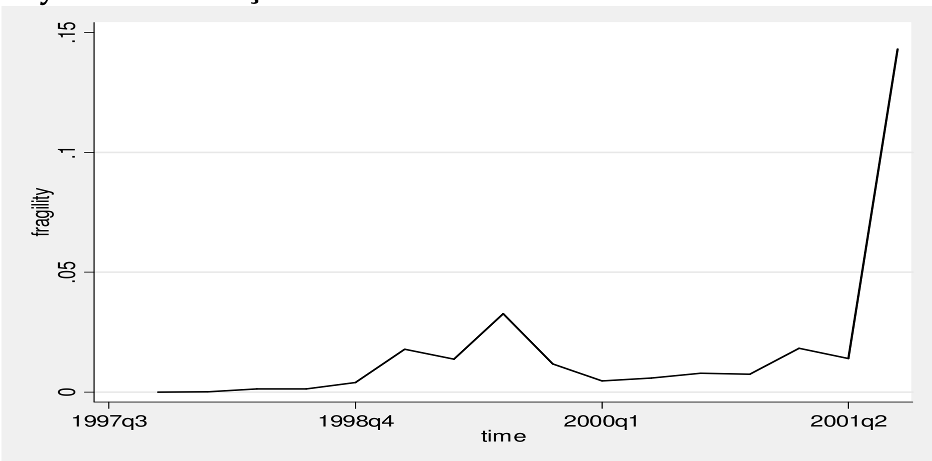
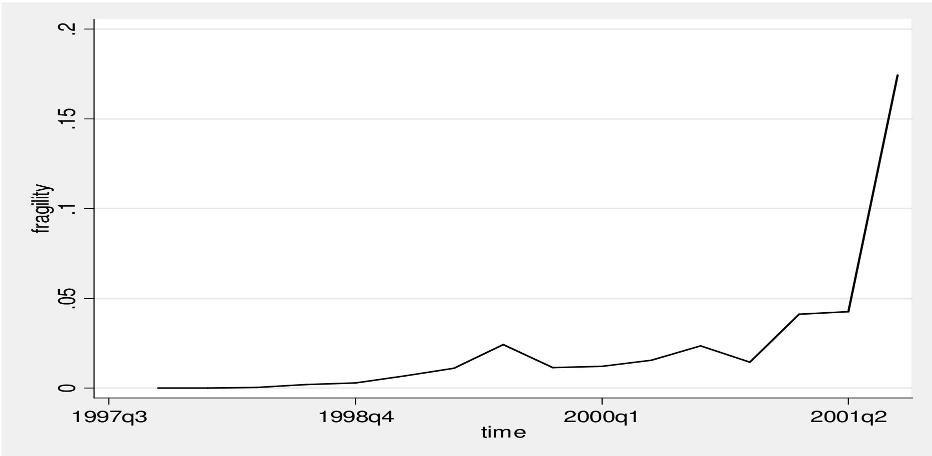


Table A.18: (Contiuned)

Bayındırbank A.Ş.



Birleşik Türk Körfez Bankası A.Ş.



Ak Uluslararası Bankası A.Ş.

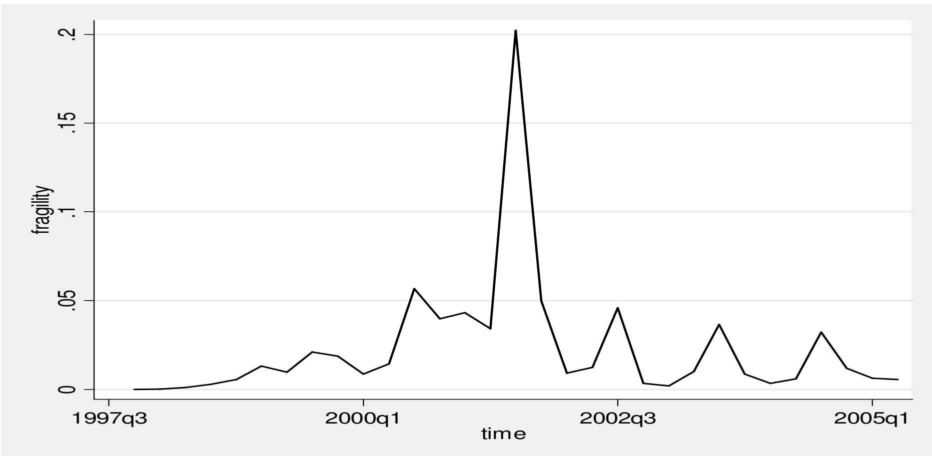
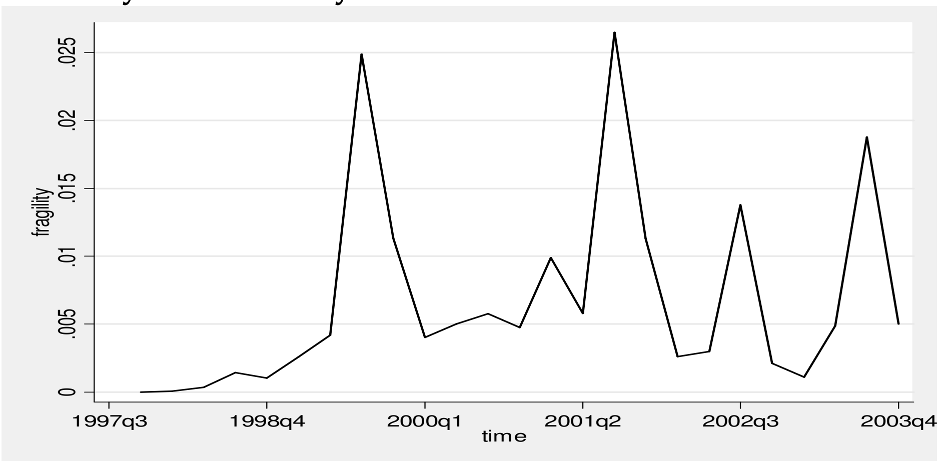
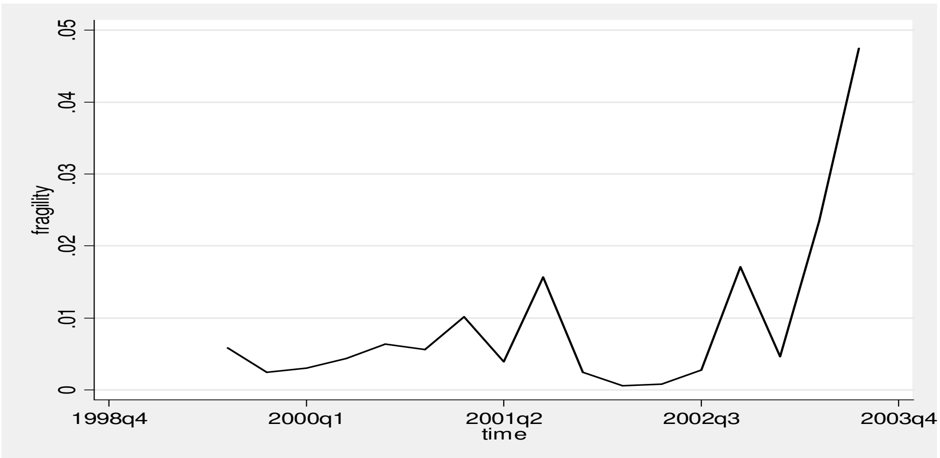


Table A.18: (Contiuned)

Credit Lyonnais Turkey



Credit Suisse First Boston



Demirbank T.A.Ş.

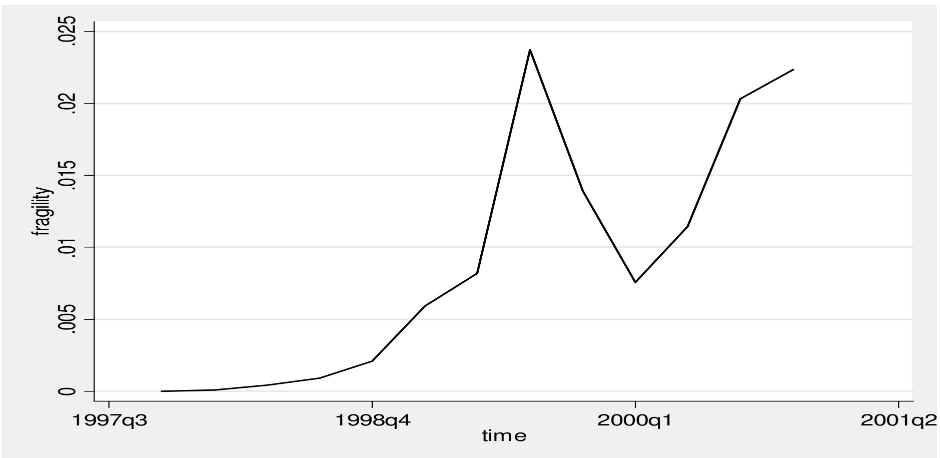
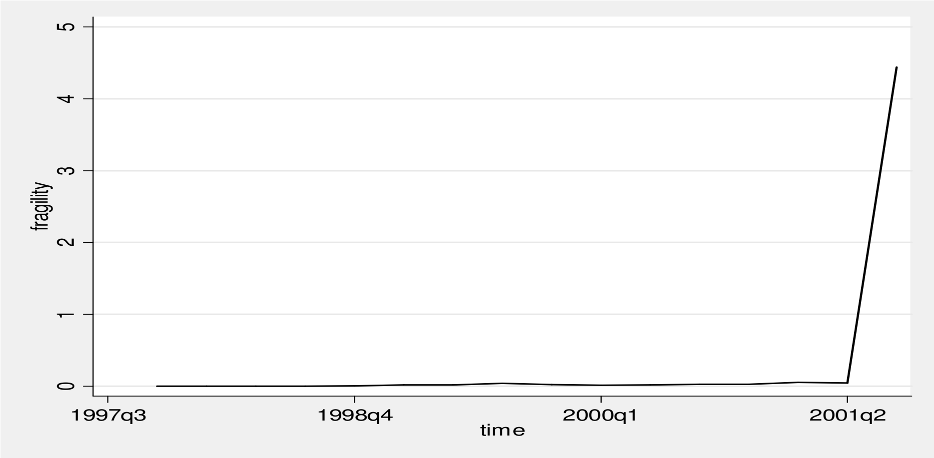
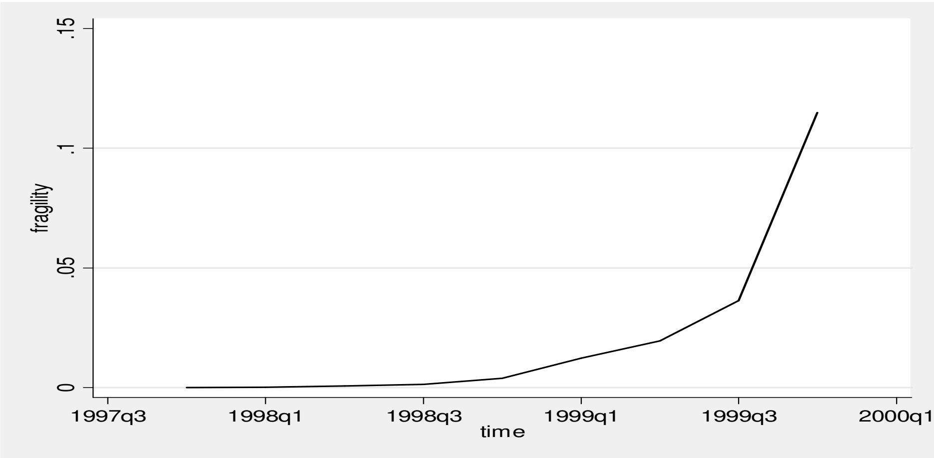


Table A.18: (Contiuned)

Ege Giyim Sanayicileri Bankası A.Ş.



Egebank A.Ş.



Eskişehir Bankası T.A.Ş.

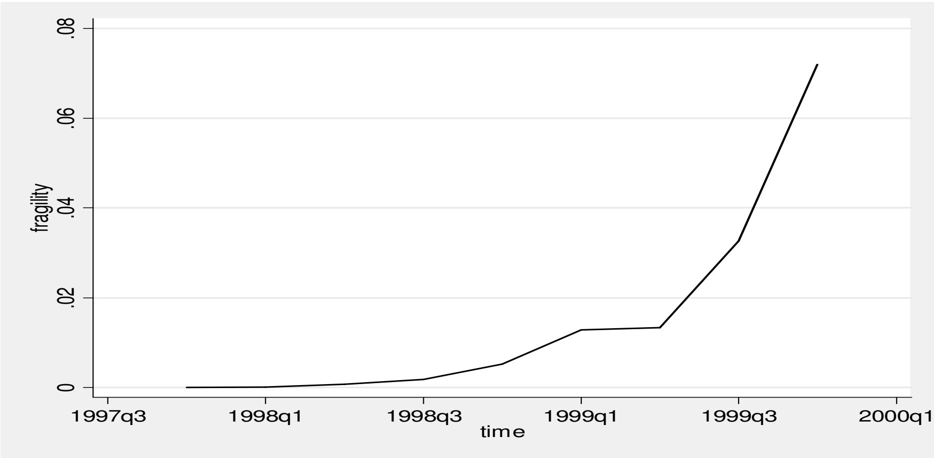
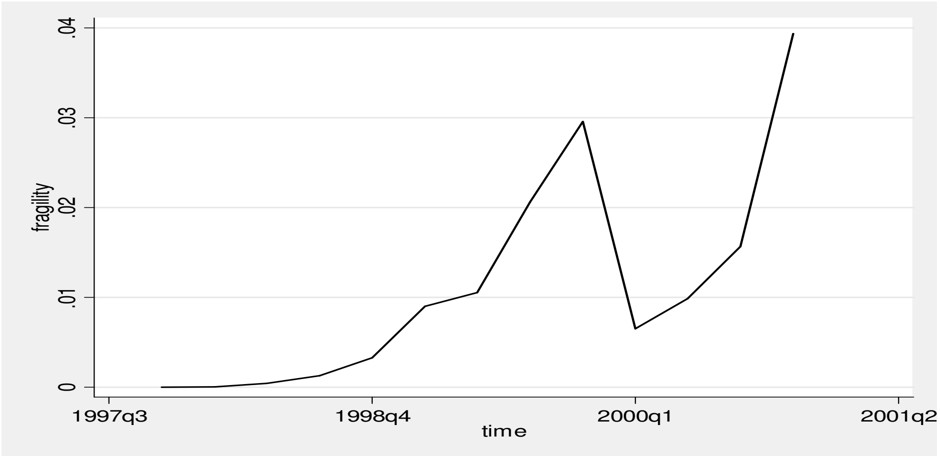
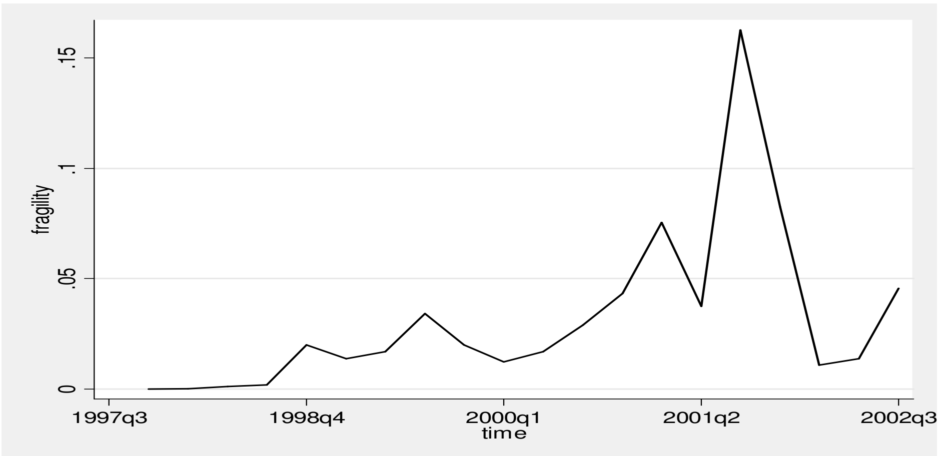


Table A.18: (Contiuned)

Etibank A.Ş.



Fiba Bank A.Ş.



İktisat Bankası T.A.Ş.

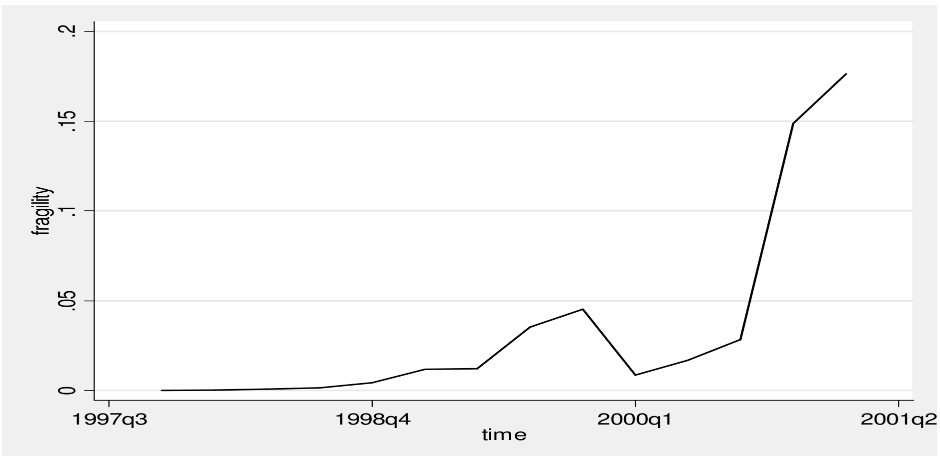
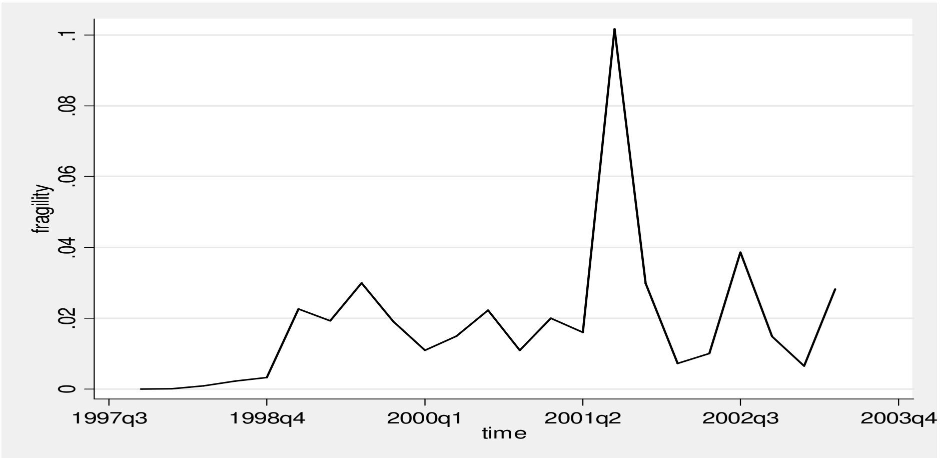
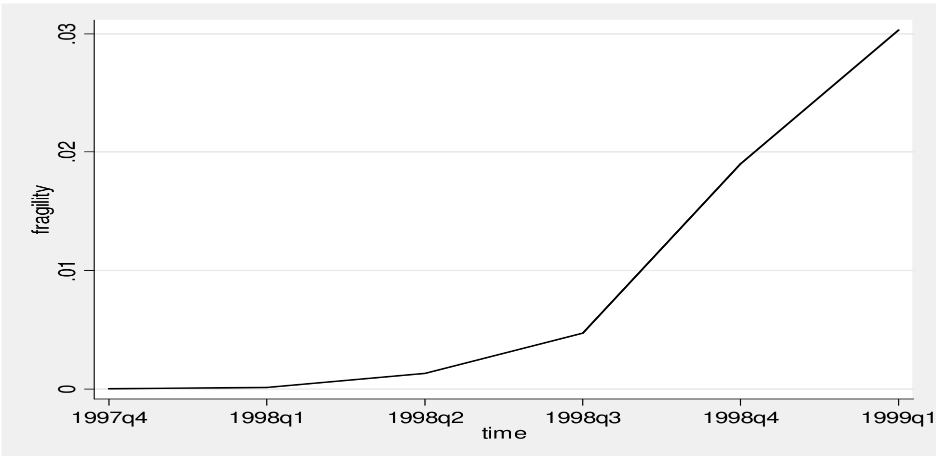


Table A.18: (Contiuned)

ING Bank N.V.



Interbank



Kentbank A.Ş.

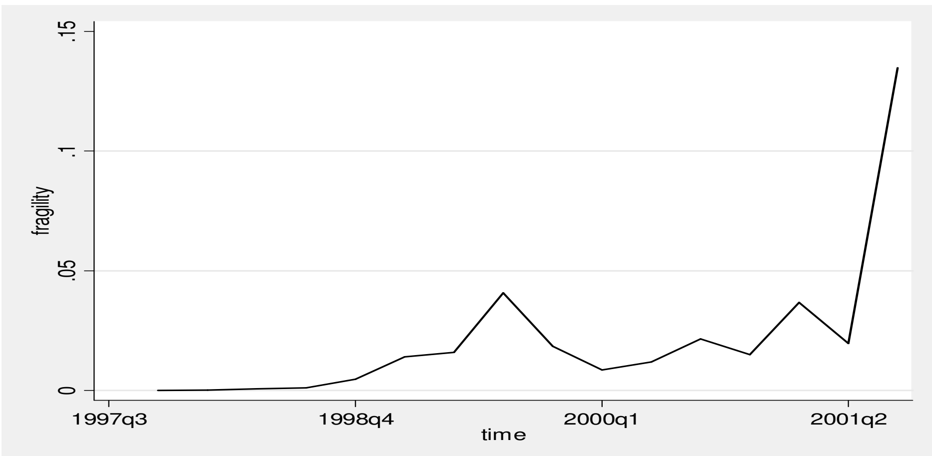
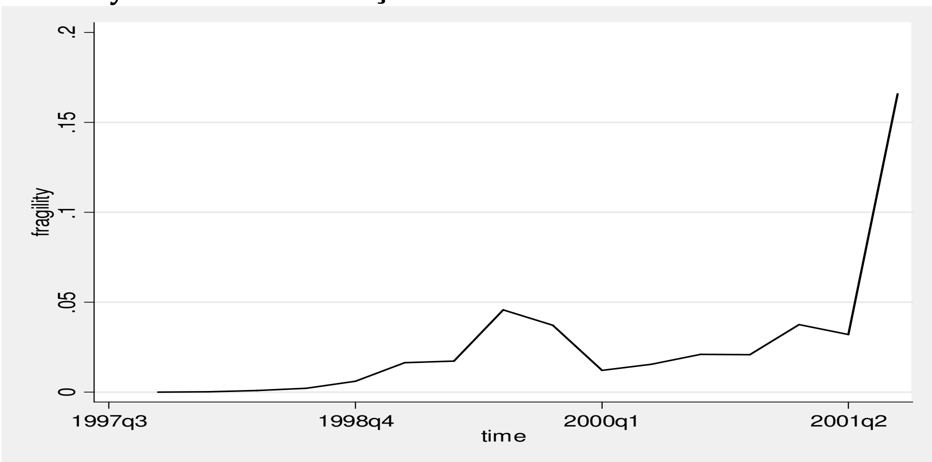
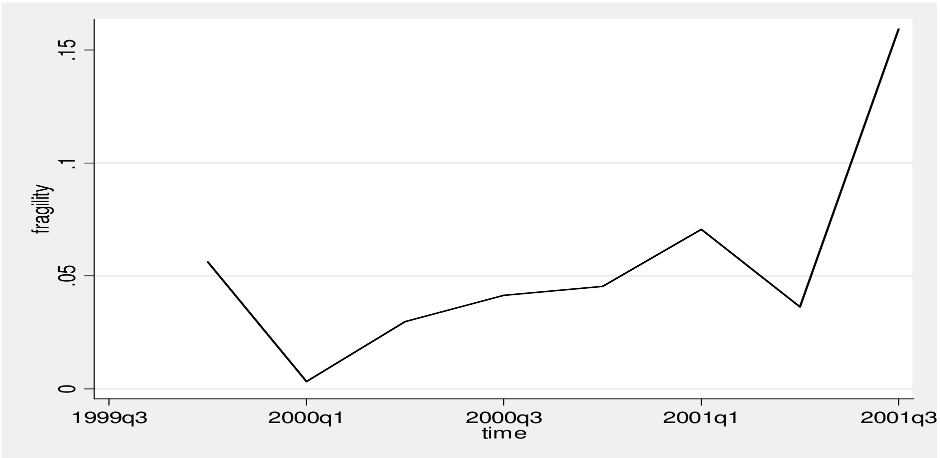


Table A.18: (Contiuned)

Milli Aydın Bankası T.A.Ş.



Morgan Guaranty Trust Co.



Okan Yatırım Bankası A.Ş.

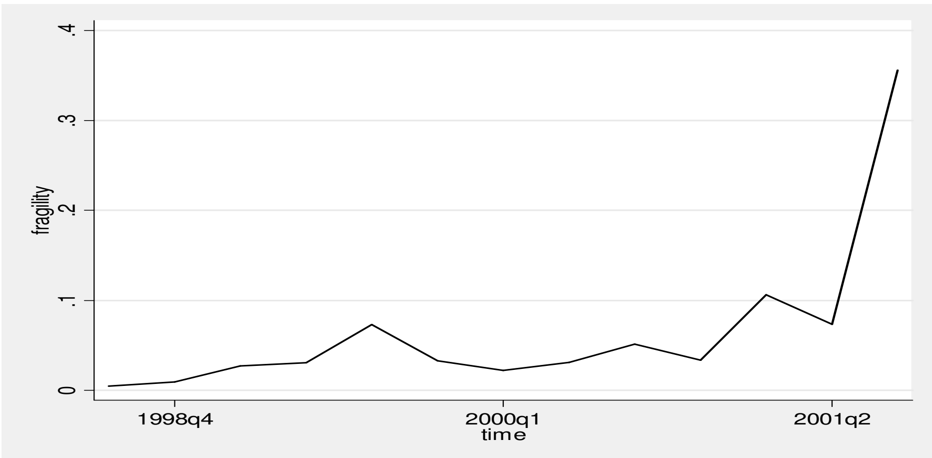
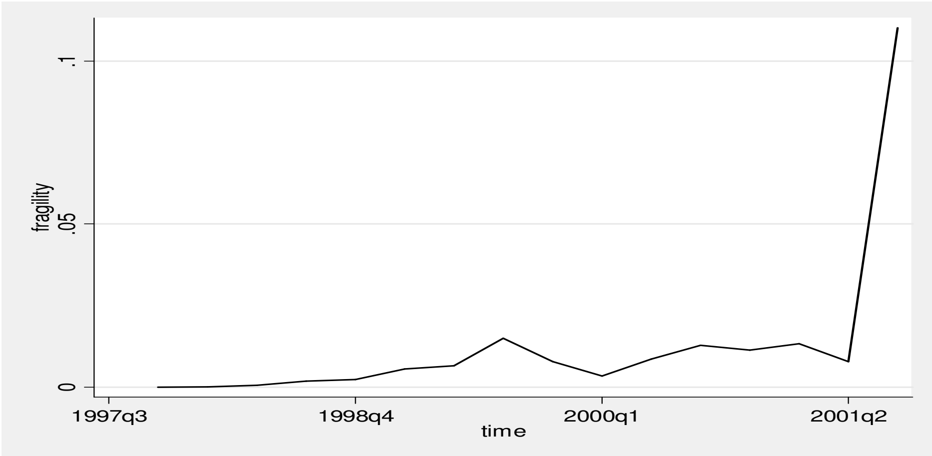
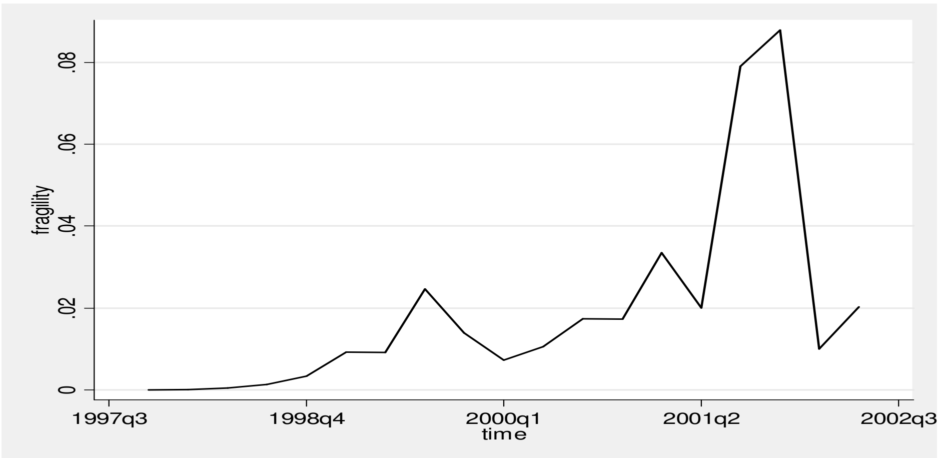


Table A.18: (Contiuned)

Osmanlı Bankası A.Ş.



Pamukbank T.A.Ş.



Park Yatırım Bankası A.Ş.

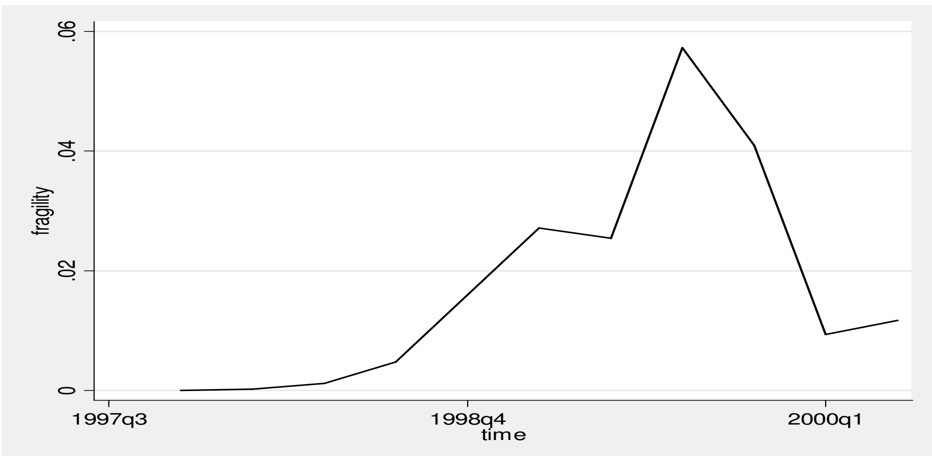
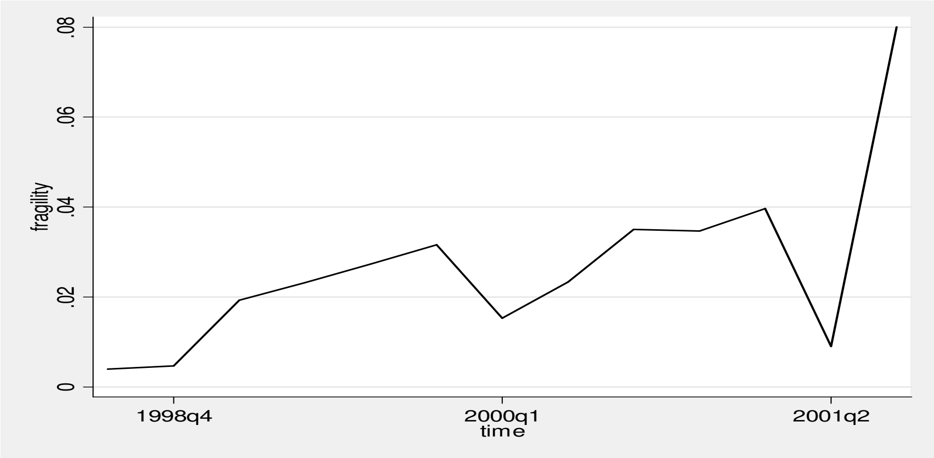
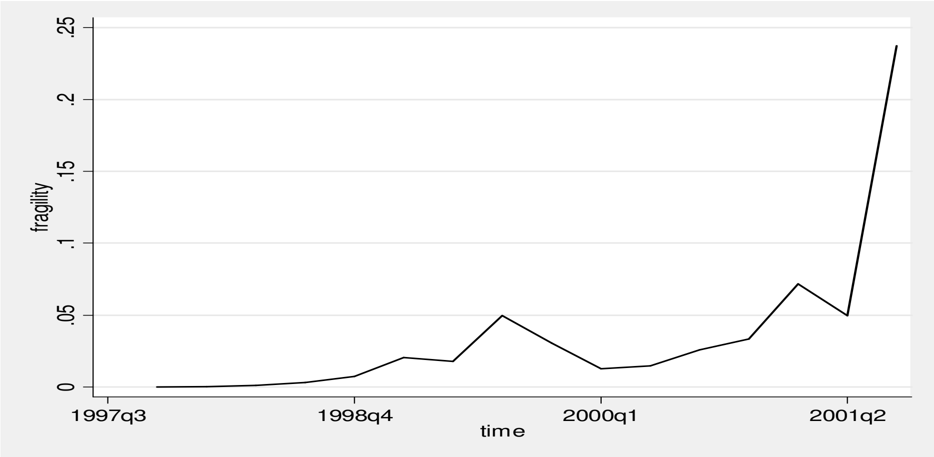


Table A.18: (Contiuned)

Rabobank Nederland



Sınai Yatırım Bankası A.Ş.



Sitebank A.Ş.

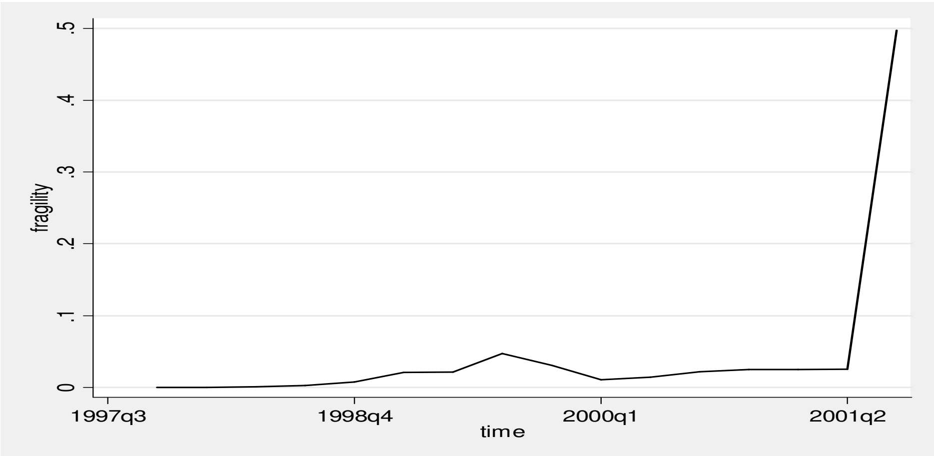
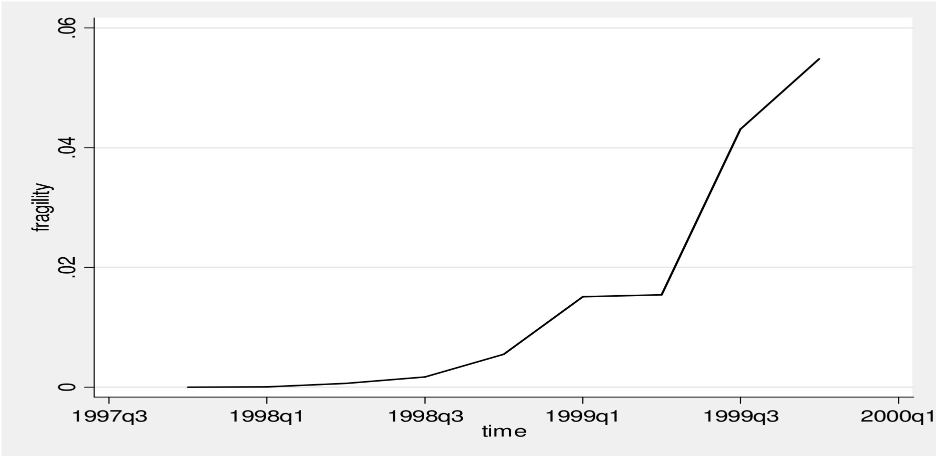
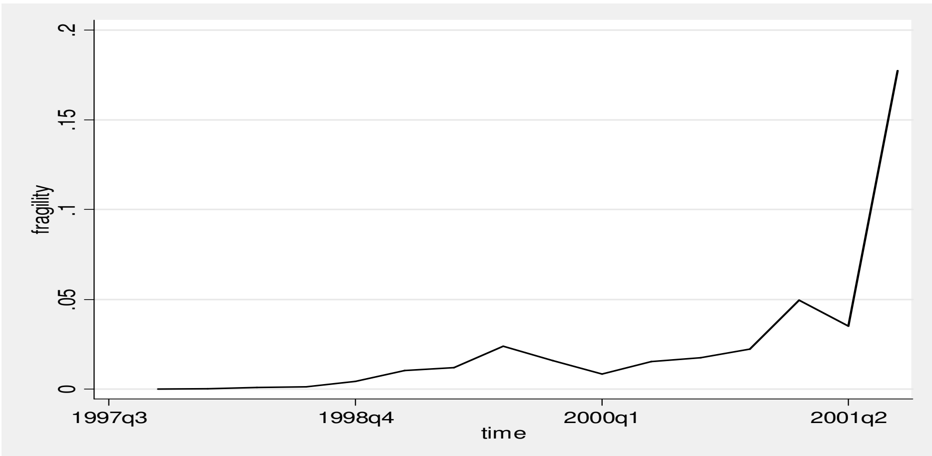


Table A.18: (Contiuned)

Sümerbank



Tekfen Yatırım ve Finansman Bankası A.Ş.



Toprakbank A.Ş.

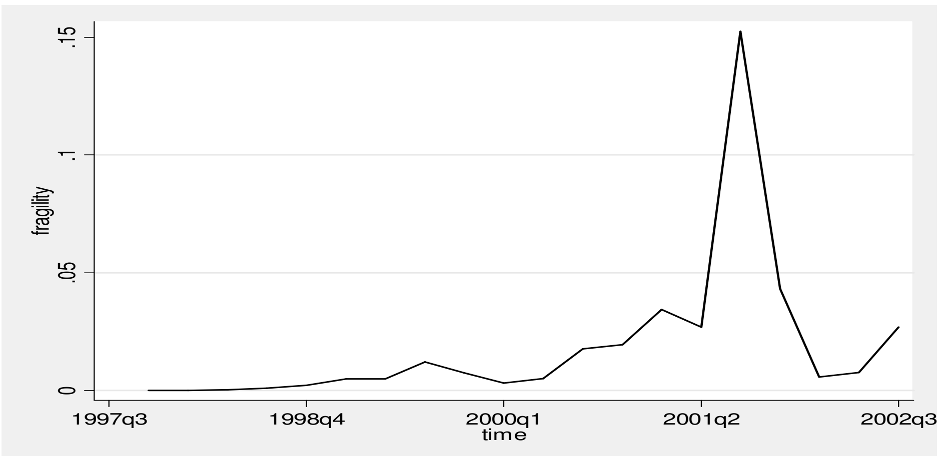
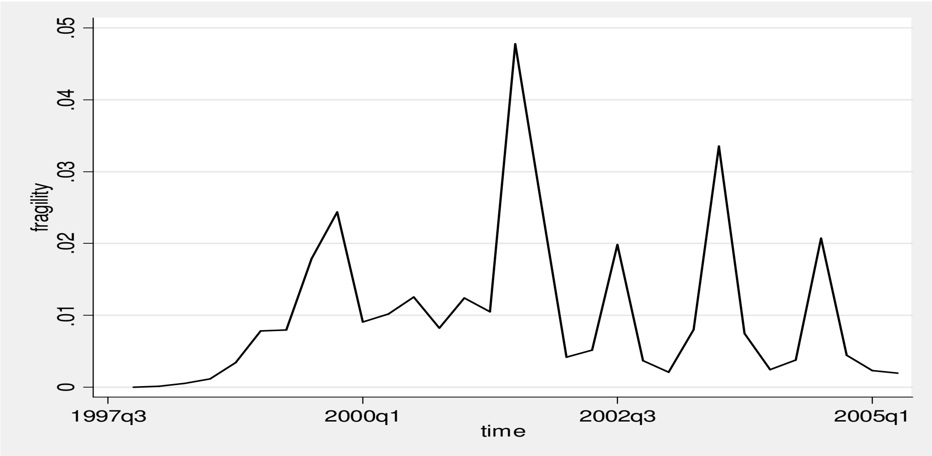
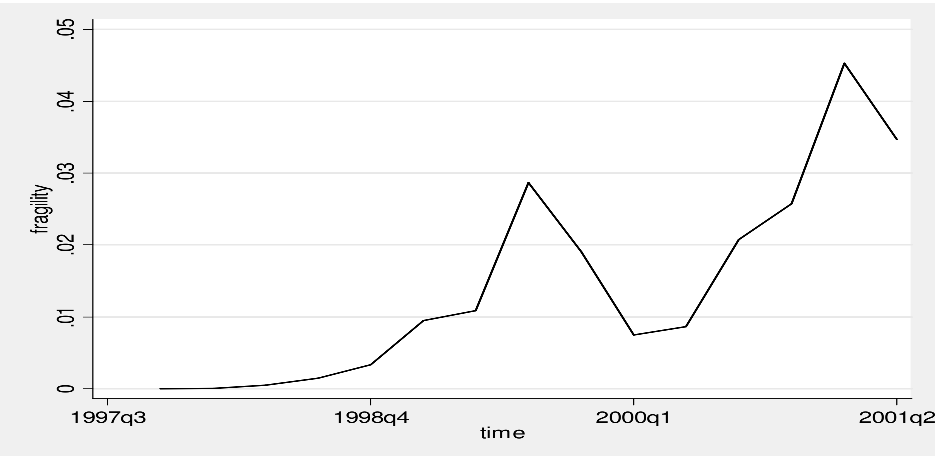


Table A.18: (Contiuned)

Türk Dış Ticaret Bankası



Türkiye Emlak Bankası A.Ş.



Türkiye Tütüncüler Bankası Yaşarbank A.Ş.

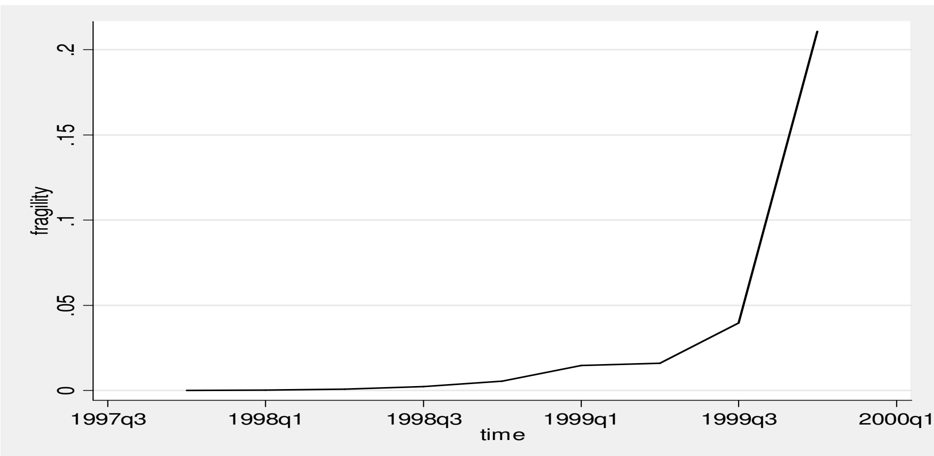
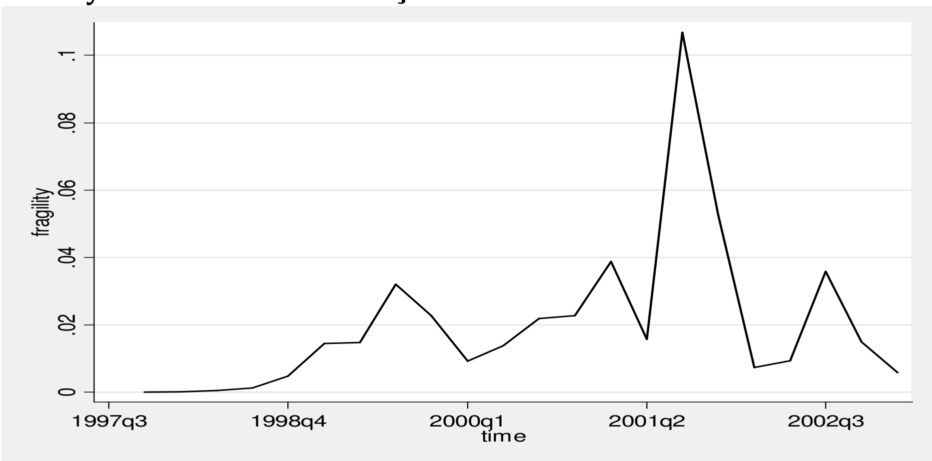
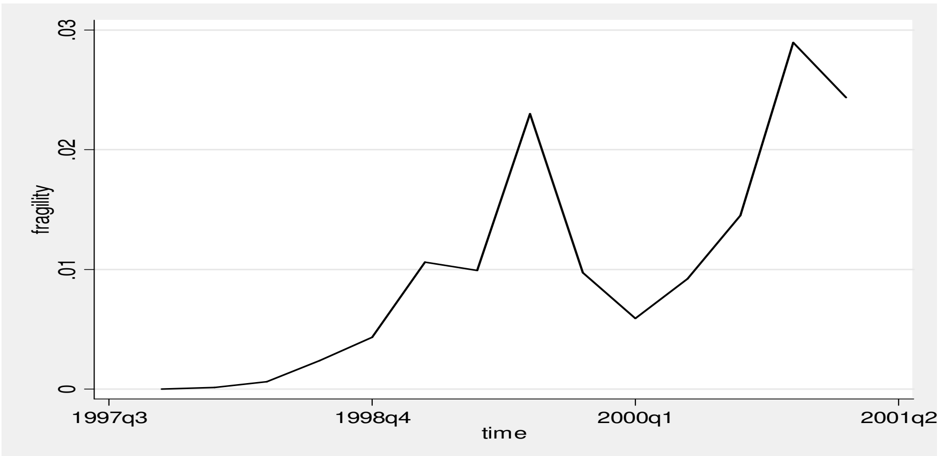


Table A.18: (Contiuned)

Türkiye İmar Bankası T.A.Ş.



Ulusal Bank T.A.Ş.



Yurt Ticaret ve Kredi Bankası A.Ş.

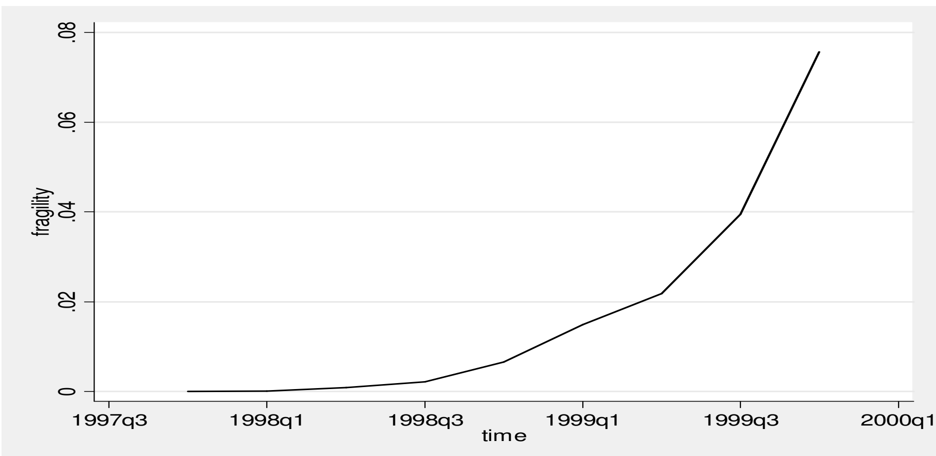
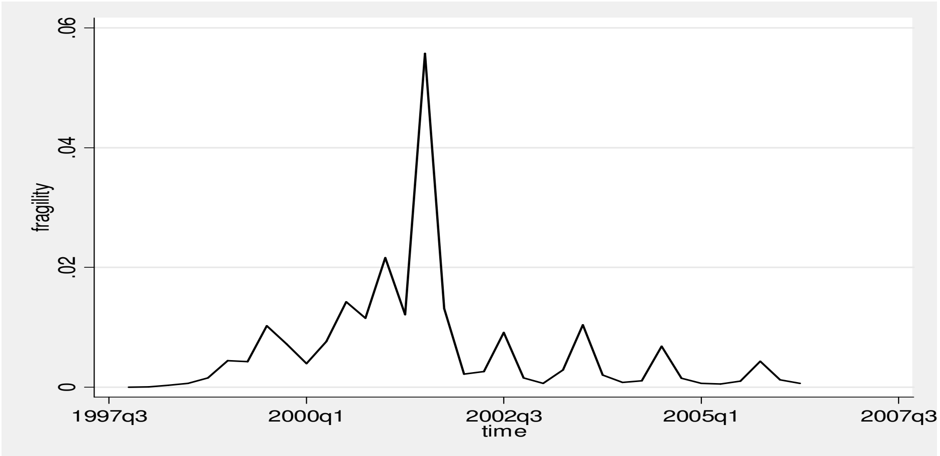
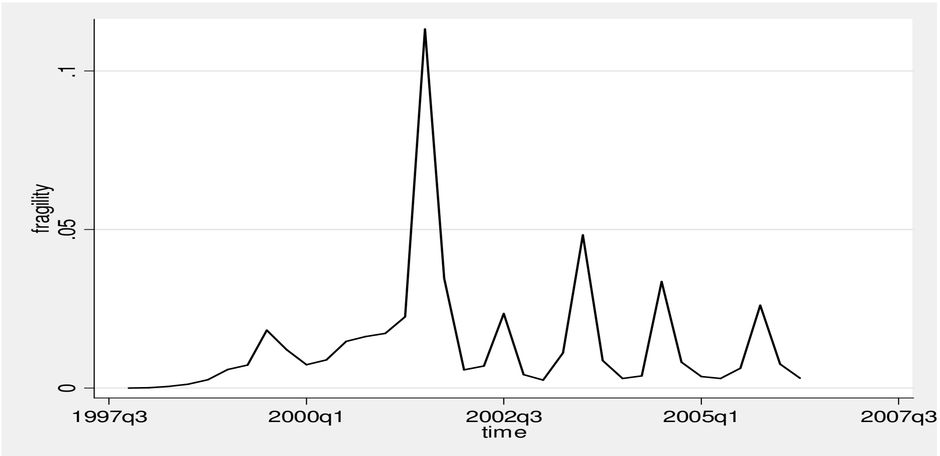


Table A.19: The Degree of Fragility of Selected Non-Failed Banks

Akbank T.A.Ş.



Finans Bank A.Ş.



HSBC Bank A.Ş.

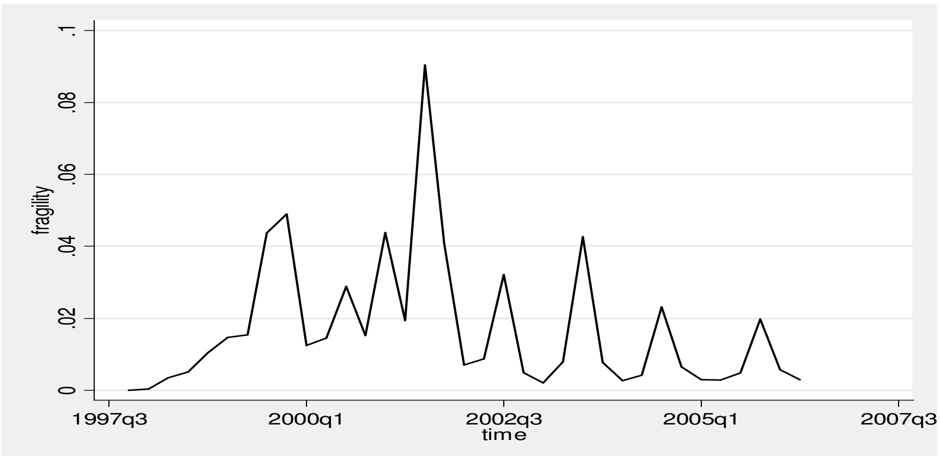
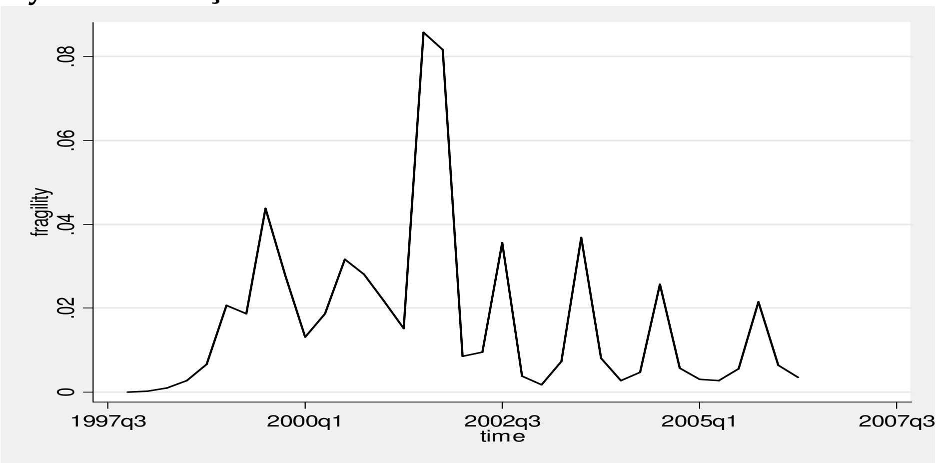
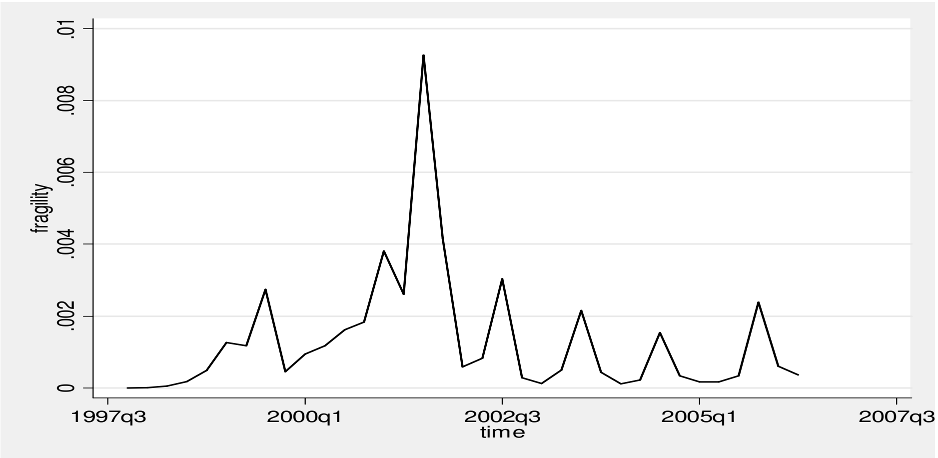


Table A.19: (Contiuned)

Oyak Bank A.Ş.



Türkiye Cumhuriyeti Ziraat Bankası



Türkiye Garanti Bankası A.Ş.

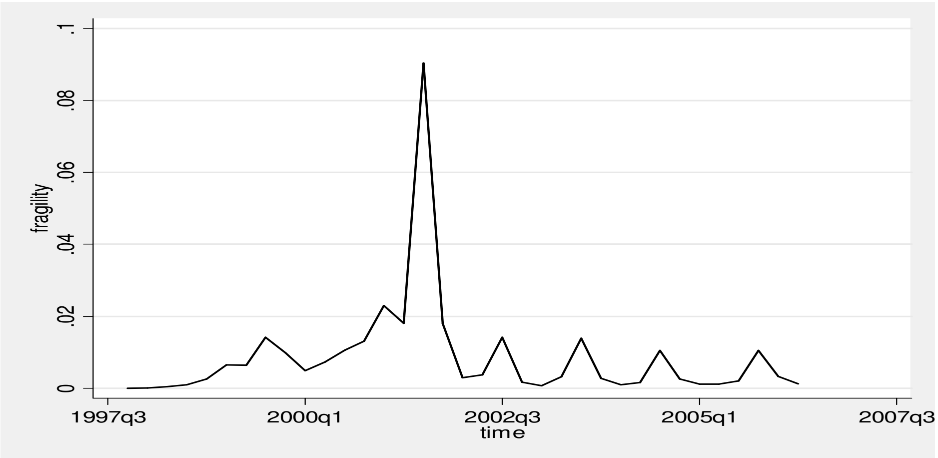
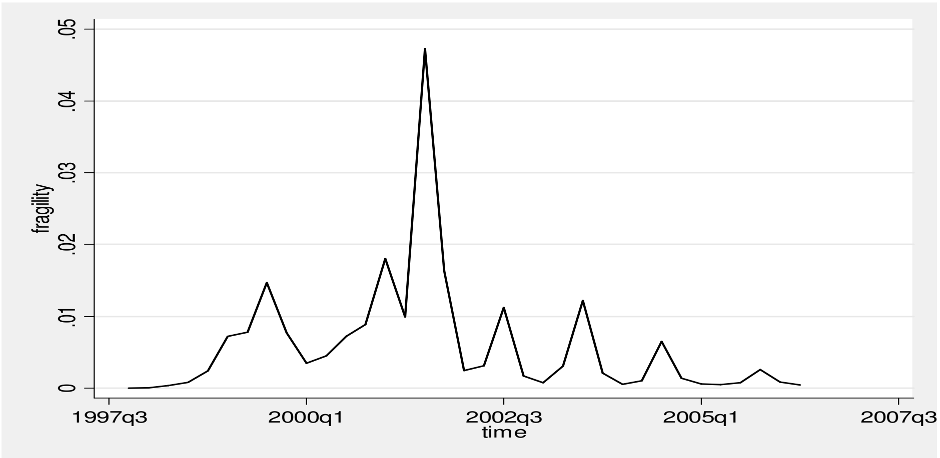


Table A.19: (Contiuned)

Türkiye İş Bankası A.Ş.



Türkiye Vakıflar Bankası T.A.O.

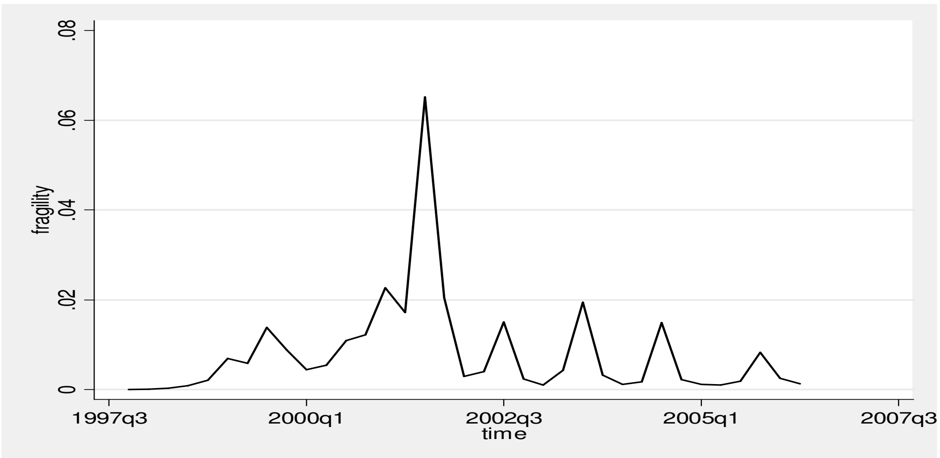
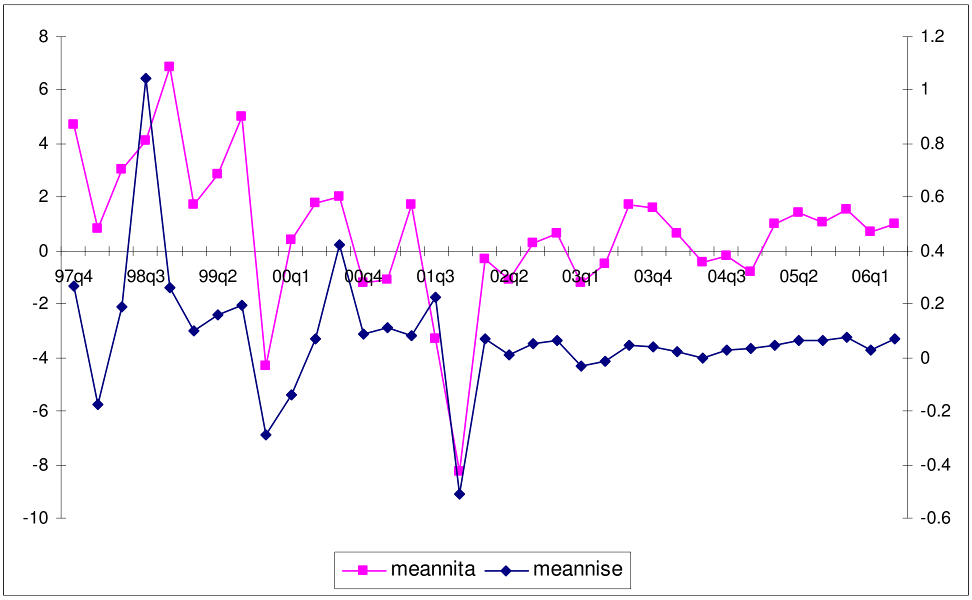


Figure A.2: The Figures of the Ratio of Net Income to Total Assets and the Ratio of Net Income to Shareholders' Equity of Turkish Banking Sector



APPENDIX B: TURKISH SUMMARY

1980'li yılların başından itibaren dünyada bankacılık sektörü problemleri artış göstermiştir. Bu artış, bankacılık sektörünün kırılganlığı ve genel ekonomi arasındaki bağlantılar üzerine çalışmalar yapılmasına neden olmuştur. Türkiye'de yaşanan kriz esas olarak bankacılık sektörünün kırılganlığından kaynaklanmıştır. Ayrıca, kamu ve özel bankalarına ilişkin mikroekonomik faktörler ve makroekonomik yapı yaşanan finansal krizlerde büyük rol oynamıştır.

Bu çalışma, 1997-2006 yılları arasında Türkiye'de 36 banka batışına ilişkin faktörleri incelemektedir. Çalışma, 81 bankanın akış kesiti zaman serisi verlerini kullanarak limitli bağımlı değişken modeli, süre modeli ve dinamik panel veri modeli ile incelemektedir. Bu çalışmada, banka batışlarını belirleyen faktörlerden banka-özel ve makroekonomik değişkenlerin katkılarını değerlendirmek, banka batış olasılıklarını ve zamanını tahmin etmek, batık ve sağlam bankaların yaşam sürelerini analiz etmek ve bankacılık sisteminin kırılganlığını belirlemek ele alınması gereken başlıca konulardır. Ayrıca, banka karlılığının belirleyicileri ve banka-özel ve makroekonomik değişkenler ve eigenvektörlerin banka karlılığı üzerine etkileri dinamik panel veri modeli kullanılarak araştırılmaktadır.

Öncelikle, temel bileşenler analizi CAMEL kategorilerin (Bankaların gözetim ve denetim aracı olarak kullanılan bu bileşik performans değerlendirme sistemi; sermaye yeterliliği (C), varlık kalitesi (A), yönetim yeterliliği (M), kazanç durumu (E) ve likiditenin (L) baş harflerini temsil etmektedir) herbiri için temsili değişken seçmek için kullanılmıştır. Buradaki amaç; yapılan ampirik çalışmalarda tutarlı olabilmek ve tahmin sonuçlarına karşılaştırabilirlik sağlamaktır.

Bu seçimler yapıldıktan sonra, batık banka olasıklarını tahmin etmek ve banka batışlarına ilişkin faktörleri belirlemek için ikili ve çoklu logit modeller kullanılmıştır. Alınan sonuçlara göre, varlıklar cinsinden sektör içinde banka payı, likit varlıkların varlıklara oranı, şube başına mevduat ve kredilerin çalışan sermayeye oranı değişkenleri dışında diğer tüm değişkenler istatiksel olarak belirli ve beklenen işarette çıkmıştır.

Ayrıca, sorunlu bankaların durumunu birleşme/satın alınma veya batık olarak ayırt edebilmek için çoklu logit modeli kullanılmıştır. Farklı kategorilere ilişkin çoklu logit modelin test sonucu, birleşme/satın alınma veya batık olarak ayırt edebilmesini onaylamıştır. Tahmin sonuçlarına göre, eigenvektörlerle tahmin edilen ikili logit model herhangi bir çeyrek dönemde batık bankaların yüzde 88'ini ve değişkenlerle tahmin edilen ikili logit model yüzde 92'sini doğru olarak tasniflemiştir. Banka batışının gerçekleştiği çeyrek dönemde ise batıkların sırasıyla yüzde 83'ü ve yüzde 78'i doğru olarak belirlenmiştir. Çoklu logit modelin tahmin sonuçları ikili logit modeline yakındır.

Biçimsel farklılaşma seçim modelinin bulguları Türk bankacılık sistemininde batık bankaların belirleyicileri açısından denetleme ve gözetim kuruluşlarına yardımcı olabilecek niteliktedir. Biçimsel farklılaşma seçim modelleri, teorik olarak, batıkların zamanlamasının tahmini ve belirlenmesi yönünden sınırlıdır. Bu durumda, süre modellerin kullanılması gerekli olmaktadır. Ayrıca, biçimsel farklılaşma seçim modelleri bankaların yaşam süreleri bilgisini kullanarak tahmin yapamamaktadır.

Biçimsel farklılaşma seçim modellerinde olduğu gibi süre modelinde de temel bileşenler analizine dayalı olarak seçilmiş temsili değişkenler ve eigenvektörler kullanılmıştır. Süre modelinin bulguları biçimsel farklılaşma seçim model bulgularıyla tutarlıdır. Biçimsel farklılaşma seçim modellerine benzer olarak süre modeli herhangi bir çeyrek dönemde batık bankaların yüzde 92-94 arasında doğru olarak tasniflemiştir.. However, there is another improvement for the classification of predicted failures as a quarter that is four quarters before the failure compared with discrete choice models. Since, when the duration model correctly classifies 94 % of failures as a failure four quarters before the failure, binary and multinomial model correctly classifies 89 % of the failures. This shows that the use of duration model provides more time to take preventive actions before the failure than that of discrete choice models.

Ancak, biçimsel farklılaşma seçim modellerine kıyasla süre modeli, banka batış tahminlerinde özellikle banka batışından dört çeyrek dönem önce banka batışları tahminlerinde gelişme göstermiştir. Süre modeli, banka batışlarını dört çeyrek dönem önce yüzde 94 oranında doğru olarak tasniflerken biçimsel farklılaşma seçim modelleri yüzde 89 oranında doğru olarak tasniflemiştir. Söz konusu durum, denetim ve gözetim kurumları tarafından biçimsel farklılaşma seçim modellerine kıyasla süre modeli kullanımının önleyici tedbir alma hususunda daha geniş bir zaman diliminde hareket kabiliyeti sağlamaktadır.

Süre modelinin bir diğer uzantısı bankacılık sisteminin ve bankaların kırılganlık düzeyini göstermesidir. Analizin, bankacılık sisteminin kırılganlığı hakkında banka batışlarından önce doğru bilgi vermesi nedeniyle süre modeline dayalı sonuçlar tatmin edicidir. Bankalar için bireysel olarak yapılan kırılganlık düzeyi analizinde ise, batık ve sağlam bankalar kriz öncesinde kırılganlık düzeylerinde keskin artışlar gözlemlenmektedir. Bu açıdan, süre modelinin kullanılması, kırılgan bankalara ilişkin önleyici tedbirler alınması hususunda yararlı olabilecektir.

Bankaların batma olasılıklarına, yaşam sürelerine ve bankacılık sisteminin kırılganlık düzeyine ilişkin faktörler biçimsel farklılaşma seçim modelleri ve süre modeli aracılığıyla belirlenmiştir. Güçlü ve karlı bir Türk bankacılık sektörünün finansal istikrarı desteklemesi nedeniyle bankacılık sistemi karlılık analizi veri setinin dinamik özelliğinin kullanılması ile mümkün olmaktadır. Banka karlılığının belirleyicileri dinamik panel veri modeli kullanılarak araştırılmaktadır. Banka karlılığının belirlenmesine ilişkin yapılan çalışmaların birçoğunda bağımlı değişken olarak karın varlıklara oranı kullanılmıştır. Bu çalışmada bağımlı değişken olarak karın varlıklara oranı kullanılmaktadır.

Dinamik panel veri modelinin bulgularına göre, yüksek likidite düzeyi, iyi yönetişim ve varlık kalitesi karlılığı olumlu yönde etkileyen faktörlerin başında gelmektedir. Ayrıca, birinci ve ikinci gecikmeli bağımlı değişkenin istatiksel belirliliği modelin dinamik yapısını doğrulamaktadır. Ayrıca, eigenvektörler yerine değişkenlerle tahmin edilen dinamik panel veri modelinin bulgularına göre ise, bankacılık sektörünün karlılığının kredilerin varlıklara oranı, donuk varlıkların toplam varlıklara oranı ve şube başına yabancı para mevduatı banka karlılığının temel belirleyicileri olmuştur.

Bir kısıt olarak, biçimsel farklılaşma seçim modelleri, süre modeli ve dinamik panel veri modeli sonuçları, örnek dönem için kamuya açık finansal veriler ile elde edilmiştir. Bu çalışma, banka batışlarını belirleyen banka-özel ve makroekonomik değişkenlerin katkılarını sayısal tarafsızlık bağlamında değerlendirmek kapsamında önem taşımaktadır. Bu çalışmadaki sonuçlar, banka batışlarının analizi, bankaların yaşam süreleri ve bankacılık sisteminin kırılganlık düzeyi hususlarında denetim ve gözetim kuruluşları için önem ifade etmektedir. Ayrıca, bu çalışma, banka batışlarını belirleyen faktörleri anlama imkanı verebilmekte ve söz konusu sonuçlara dayanarak; sorunlu bankalar için zamanında düzeltici tedbirlerin denetim ve gözetim kurumları tarafından alınmasının sağlamasına yardımcı olabilecektir.

Banka sağlamlığının ve karlılığının belirleyici faktörlerinin saptanmasına ve kapsamlı finansal istikrar sağlanmasına yardımcı olmak amacıyla beşinci, altıncı ve yedinci bölümlerde sunulan ampirik çözümlemeleri anılan çerçevede uygulanabilir. Banka batışlarını belirleyen faktörlerin belirlenmesine yönelik çalışmalar ile birlikte, özellikle bankacılık sisteminin kırılganlığı veya sağlamlığına ilişkin çalışmalar üzerine yoğunlaşmak; banka batışlarının gerçekleşmeden önce bankalara düzeltici yönde müdahale edilmesine yardımcı olabilecektir. Bu çalışmalar, denetim ve gözetim kuruluşları için pratik bir araç olarak kullanılabilecektir.

APPENDIX C: CURRICULUM VITAE

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BS	METU Economics	1997
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1998 - 2000	Ankara Unv, Department of Health Management	Research Assistant

FOREIGN LANGUAGES

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