International Review of Economics and Finance 76 (2021) 952–987

Contents lists available at ScienceDirect

International Review of Economics and Finance

journal homepage: www.elsevier.com/locate/iref

Financial crises, bank efficiency and survival: Theory, literature and emerging market evidence

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ARTICLE INFO

JEL classification:
C67
D2
E32
G21
G28
G33
H12

Keywords:
Financial stability
Crisis
Efficiency
Default
Failure
DEA
SFA
Probit
Early warning system
Turkish banks

ABSTRACT

The finance literature on *efficiency* and *crisis* at the macro-level and *efficiency* and *default* at the micro-level has hitherto grown surely but distinctly. In this comprehensive paper, we globally review and theoretically unify these two strands of research in studying the record level of bank failures and the deepest financial crisis of an emerging market, Turkey, with sixteen distinct measures of efficiency, stemming from two alternative methods, stochastic frontier analysis (SFA) and data envelopment analysis (DEA). The results show that efficiency scores tend to deteriorate gradually before crisis, hit bottom during crisis, and rebound after crisis. Inelastic inputs and elastic outputs seem to produce this pattern. The efficient banks have the highest survival rates. Managers of survivor banks are evidently better at controlling costs and scales, utilizing and allocating resources, generating assets, revenues and profits. Demotion to a lower efficiency class is a rare event in normal times but widespread during crises. The least efficient banks are the least likely to be acquired by private bidders. Default prediction models notably improve with DEA scores, off-balance sheet items, definition of failure with "*factual insolvency*", deciles of efficiency, changes in some key variables, homogenous dataset, and efficiency scores based on quantities of inputs and outputs rather than their noisy prices.

1. Introduction

The IMF reported about 150 banking crises from 100 different countries over the period 1970–2011 (Laeven and Valencia, 2012). Social, political and economic costs of such crises are enormous as banks still dominate finance virtually everywhere. They are the repositories of a nation's savings, conduits of its financial payments, managers of its risky assets, monitors of its businesses, and financiers of its economic growth. Banks, the main trustees of our savings, are charged with safeguarding and investing these funds. If they can allocate these funds to their most productive uses, the resulting *value creating* loans and projects that cover their costs and risks healthily enrich both financial and real sectors. However, if banks misallocate their funds, then not only banks but also the families, industries and economies that they support eventually collapse.[1] Thus, it becomes critical to understand if the recent distresses

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[1] Illustratively, the 2008 global recession left in its wake a worldwide rise of thirty million in the number of people unemployed.

https://doi.org/10.1016/j.iref.2021.07.016
Received 13 April 2020; Received in revised form 5 March 2021; Accepted 29 July 2021
Available online 5 August 2021
1059-0560/Published by Elsevier Inc.

observed in banking around the world was a sign of bank extinction or adaptation in response to changing business environment. The existence of large loan losses, often preceding crises by months or years (Beim & Calomiris, 2001; Berger & DeYoung, 1997) might be *prima facie* evidence for declining profitable opportunities for *all* banks. On the other hand, the fact that not all banks performed poorly in these turbulent times (Barr et al., 1994; Isik and Folkinshteyn, 2017; Wheelock and Wilson, 1995, 2000) might indicate that not all but *some* banks are unfit to manage the new challenges. More plainly, is banking (as a business) dying as Gorton and Rosen (1995) prophesized not long ago? Or, are the least efficient banks or banking systems being weeded out by natural selection as Jovanovic (1982) advocated earlier?

Because an efficient, deep and sound banking system is a *sine qua non* for sustainable economic growth, policymakers, regulators, bankers and researchers need to gain further insights into banking crises and failures that keep haunting national and global economies again and again in recent times. In this paper, by drawing on the case of Turkey, we turn the attention to the experience of emerging markets, where the crises are not only more frequent but also more costly to resolve given the limited resources of these economies (Demirguc-Kunt & Detragiache, 1998, 2005; Brown & Dinc, 2009; Laeven and Valencia, 2012).[2] Turkey serves as an ideal setting for this purpose. Afflicted with notorious "boom and bust" cycles in its economic trajectory, nearly every decade before the turn of the millennium ended with a major crisis accompanied by bank failures in Turkey. When politics, regulation, business, and banking converge and intertwine too closely, as they often do in developing countries, both public (regulatory) and private (managerial) decisions are likely to be made inefficiently and the subsequent crises become inevitable. Without creating the infrastructure needed for an efficient financial system, the liberalization experience of Turkey in the 1980s turned out to be a catalyst for ruinous bank failures. Out of the 44 *commercial* bank failures observed between 1970 & 2003, 39 happened after liberalization. More strikingly, while just 25 banks (*commercial* or *non-commercial*) failed in 60 years prior to liberalization (1920–1980), 50 banks failed in just 20 years after liberalization (1981–2003), of which most (about 60%) happened during the most recent and severest crisis of Turkey in 2001 (see Fig. 1). Concerns over the weakening banking sector and slow reforms prior to the crisis, together with a surge in capital flight, triggered both a banking and a currency crisis (typical *twin crises*), which reached its peak in February 2001. In its aftermath, interest rates skyrocketed, several banks had to be rescued, and the IMF assisted Turkey with thirty billion dollars in total. As a result, the Turkish economy shrunk by about 10% on a lira basis and 24% on a dollar basis, a record in the country's modern history (see Table 1), which wiped out one third of personal incomes and led to the failure of nearly half of the banks in the industry. The resolution cost was a staggering $53.6 billion (34% of GDP), of which $47 billion had to be borne by the Treasury (ultimately ordinary taxpayers).

In the finance literature, the utilization of efficiency indexes in understanding financial crises and bank defaults has been gaining some momentum lately, especially after the 2008 global financial crisis. In order to contribute to this burgeoning literature, this paper has the following five major goals: 1) at the theoretical level, to link operational efficiency to financial stability (crisis and default), which has not been fully addressed yet in the literature; 2) at the macro level, to examine the behavior of a number of efficiency measures at the turning points of business cycles, 3) at the micro level, to explore what kind of banks are more likely to pass the survival test of a major crisis, 4) at the methodological level, to determine which of the available efficiency measures (cost, allocative, technical, scale, profit, or revenue), which banking technology (modern or traditional) and what frontier methods [Data Envelopment Analysis (DEA) or Stochastic Frontier Analysis (SFA)], perform better in understanding phenomena like crisis and default, and finally 5) at the literature level, with a global review, to offer some promising avenues for future research. We picked the 2001 crisis episode of Turkey to put efficiency measures to a test for a number of reasons. First, we need a strong force to check the resilience of banks and the usefulness of efficiency estimates. This crisis meets the requisite conditions set by Lindgren et al. (1996), Caprio and Klingebiel (1996), Kaminsky and Reinhart (1999), Demirguc-Kunt and Detragiache (2005), and Laeven and Valencia (2012) to be considered a full-fledged banking crisis. Earlier episodes of Turkey were not as systemic as the 2001 crisis; they were relatively mild, partial and short-lived (Isik and Hassan, 2003a; Isik and Folkinshteyn, 2017).[3] In addition, the highest number of banks failed during the 2001 crisis, while its predecessors had three casualties at most (see Fig. 1). Third, the data on off-balance sheet activities and foreign exchange denominated assets and liabilities, which occupy a critical role in the design of our inquiry, have not been collected yet during the earlier episodes by the Banks Association of Turkey (BAT) (the primary source of banking data in Turkey). Fourth, the BAT has changed the format of bank financial statements with inflation accounting, different definitions, and aggregations after 2002, making it very challenging, if not impossible, to keep consistency across preceding and succeeding periods. Moreover, the country, conciliatorily, has experienced neither a banking crisis nor a *commercial* bank failure yet since the 2001 crisis. Finally, although the 2001 crisis of Turkey was a unique learning opportunity for researchers to understand the dynamics of financial crises, it has not been the focus of studies as much as it would warrant, especially in terms of efficiency.

Isik and Hassan (2003a) is credited for being the first to investigate the association of bank efficiency/productivity with a financial crisis (e.g., Sufian, 2009b, p. 344; Sufian 2010, p. 870; Sufian and Habibullah, 2010, p. 338; Gulati and Kumar, 2016, p. 169; Andrieș & Ursu, 2016, p. 486; Tanna et al., 2017, p. 68; Iosifidi et al., 2021, p. 7, among others), while Barr et al. (1994) is considered to be the

[2] Of the 31 systemic banking crises identified between 1980 and 1994 by Demirguc-Kunt and Detragiache (1998), 23 took place in emerging countries and 8 in advanced countries. Demirguc –Kunt and Detragiache (2005) also find that the level of development as measured by GDP per capita is negatively correlated with systemic banking crises, indicating that developing countries are more vulnerable to bank fragility. Moreover, Laeven and Valencia (2012) report that monetary and fiscal policies are used more extensively during banking crises in advanced economies than in emerging and developing countries. The implication is that advanced economies have more resources, better financing options to use countercyclical fiscal policy and generally have more space to use monetary policy.

[3] As a matter of fact, since 1982, only the 2001 crisis of Turkey qualifies for inclusion in the database of systemic banking crises of IMF and 1982 and 2001 crises since 1970 (Laeven and Valencia, 2012).

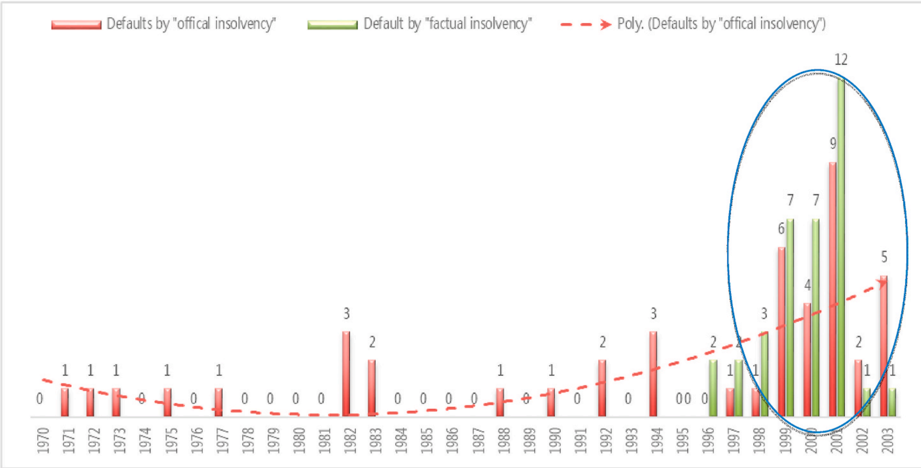

Fig. 1. The number of commercial bank defaults in Turkey by "official insolvency" [1970–2003] and "factual insolvency" [1995–2003].

Table 1
Key economic and financial indicators of Turkey: 1994–2002.

Indicators	Unit	1994	1995	1996	1997	1998	1999	2000	2001	2002
GDP growth	%	−6.1	8.1	7.5	8.0	3.8	−6.4	6.30	−9.40	7.9
Income per capita	$US	2,161	2,835	3,000	3,105	3,213	2,912	2,986	2,101	2,609
Inflation-Wholesale	%	149.6	65.6	85.0	91.0	54.0	63	33	89	31
Inflation-Consumer	%	125.5	79.0	79.6	99.0	70.0	69	39	70	30
PSBR	% GNP	8.1	5.2	8.8	8.0	10.0	15.4	11.90	16.50	12.8
Domestic debt	$ mil	26.42	1422	3199	6,257	11,612	22,921	36,411	122,517	149,870
External debt	$ mil	64.4	73.3	79.6	84.3	96.9	103.1	36.30	32.10	37.8
Interest Rate-T-Bond	%	137	107.0	116.0	96.0	112.0	108.0	102.00	770.00	63.0
Interest Rate-T-Bill	%	190	125.0	132.0	108.0	116.0	104.0	40.00	97.00	65.0
FOREX (TL/$US)	TL	29,670	45,679	83,043	151,428	264,600	426,681	671,765	1,446,638	1,639,745
Fixed Capital Outlay	% Chg	−15.7	9.6	12.1	7.9	−1.7	−7.6	22.60	19.00	17.4
Total Consumption	% Chg	−3.1	6.1	7.7	5.3	0.6	2.2	81.85	82.58	81.0
Exports	$ bil	18.1	21.7	23.1	26.2	26.9	26.6	27.80	31.30	34.5
Imports	$ bil	23.3	35.7	42.4	48.1	45.9	40.1	54.50	40.40	45.7
Trade Balance	$ bil	−4	−13.2	−10.6	−15.4	−14.4	−10.4	−22.3	−4.50	−8.6
Current Account	$ bil	2.6	−2.3	−2.4	−2.7	1.9	−1.4	−9.8	3.40	−1.8
Capital Account	$ bil	−4.2	4.7	8.8	8.6	0.4	4.7	9.4	−14.2	1.8
Borsa Istanbul Ind.	$	413	383	534	982	484	1654	817	558	368
Total bank assets[a]	$ mil	51,630	68,397	83,337	94,645	117,399	133,533	155,237	116,976	129,700
Total bank loans[a]	$ mil	20,278	29,072	35,906	43,037	45,019	40,206	50,931	25,636	34,377
Total bank deposits[a]	$ mil	32,665	44,431	57,165	61,273	77,097	89,361	101,884	80,633	86,835
Total bank equity[1]	$ mil	3,200	4,187	5,028	6,121	6,786	3,644	8,152	10,150	15,672

[a] The financial sector statistics are total values and not averages, and they belong to all types of banks operating in Turkey (development and investment banks as well as commercial banks). Source: State Institute of Statistics; State Planning Organization; Banks Association of Turkey (BAT).

first *published* study that examined the linkage between bank efficiency and failure in the literature (e.g., Wheelock and Wilson, 1995; Berger & DeYoung, 1997; Berger & Humphrey, 1997; Isik and Hassan, 2003a). The researchers afterwards have followed either the *efficiency-crisis* strand of Isik and Hassan (2003a) or the *efficiency-failure* strand of Barr et al. (1994) by replicating their studies for different countries and institutions. This study differs fundamentally from these original and application papers because unlike them, we study the association of bank efficiency with both a major crisis and the chance of survival in one place. Also, in contrast to our sixteen distinct efficiency scores, earlier papers employed usually one or two efficiency measures in their analyses.[4] Hence, unlike our predecessors, the current study conducts a 360-degree performance analysis, so to speak, by tracking the mistakes done by banks on both input side and output side of banking operations during crises and defaults by means of various efficiency measures, considering not only the amount (technical and scale efficiencies) or mix (allocative efficiency) of these operational variables but also their contributions to the banks' cost (cost efficiency), revenue (revenue efficiency) and the bottom-line (profit efficiency). This paper will

[4] Exceptions are Luo (2003), Sufian (2009a and 2010) and Alvarez-Franco and Restrepo-Tobón (2016) who utilized three efficiency indices. Luo (2003) uses technical, pure technical and scale efficiency measures in his analysis but with two variants where bank inputs are modeled to maximize profitability (revenue and profit) and marketability (market value, EPS and stock price) outputs.

be also the first that employs *revenue efficiency* in studying both failure and crisis in the literature. Furthermore, unlike most efficiency studies, we utilize two competing frontier approaches in predicting efficiency estimates, non-parametric DEA and parametric SFA, to test and demonstrate their methodological usefulness in explaining major financial events. Also, the current paper studies the *universe* of banks in an emerging market, while some earlier studies focused only on small (e.g.; Siems, 1992; Barr et al., 1994), or large (e.g., Luo, 2003; Mehdian et al., 2019), or regional (e.g., Miller and Noulas, 1996; Wheelock and Wilson, 1995) American or other advanced country banks (e.g., Vu and Turnell, 2011; Alzubaidi & Bougheas, 2012; Andrieș & Ursu, 2016). Moreover, the current paper is the first paper that investigates the *efficiency mobility* of banks to see if there is a stark difference in the movements of banks towards the frontier during crisis. Furthermore, this paper explores for the first time the relationship between efficiency and *resolution forms* of failed banks by regulators.

As a matter of fact, we not only distinguish among alternative types of efficiency, but also definitions of failure and crisis. Unlike our predecessors that typically adopted *official (de jure) insolvency* as bank default, we opted for *factual (de facto) insolvency* in our *efficiency-default* investigation, where default occurs when equity is lost regardless of regulatory closure. Likewise, when conducting our *efficiency-crisis* analysis, unlike earlier studies, we define crisis as a year in which at least three banks default [*factual (de facto) crisis*] instead of government admission [*official (de jure) crisis*].[5] Factual failure or crisis is a *de facto* or market-determined event. In contrast, official failure or crisis results from conscious decisions by government authorities to acknowledge the weakened financial condition of an institution (default) or industry (crisis). Hence, official insolvency or crisis is an administrative option that the government may or may not exercise despite the strong evidence from markets. According to the *public choice theory*, there exist conflicts of interests between the public officials (regulators and politicians) and taxpayers that often lead to the adoption of such forbearance policies (Demirguc-Kunt, 1989). These conflicts may allow political, bureaucratic, economic pressures and career-oriented incentives of the public officials to shape failure and crisis decisions.[6] Clearly, in a realistic econometric analysis, *de facto* and *de jure* failures and crises should be distinguished, but studied simultaneously. To further enrich the analysis, we also experiment with both *traditional banking technology*, where banks are defined as the intermediaries that channel funds into various earning assets, as well as with *modern banking technology*, where banks are defined as the intermediaries that convert their funds into both interest earning on-balance sheet (*traditional*) and fee generating off-balance sheet (*modern*) outputs. Overall, with the sixteen alternative efficiency indexes, a plethora of models, tests, and robustness checks, this study aims to be an important guide on crisis, efficiency, and survival for regulators and policymakers in understanding the impact of a major shock on the efficiency and survival of banks, in mobilizing their limited resources to where they are most needed and in safeguarding financial stability from any potential crisis.

This paper is structured as follows. Following the introduction in section 1, section 2 discusses the conditions that led to the 2001 financial crisis; section 3 reviews the methodology, theory, and evidence on the linkage of efficiency with financial stability; section 4 elaborates data set and empirical design; section 5 assesses the empirical findings; and section 6 finally concludes the study.

2. An overview of the preconditions of the 2001 financial crisis

There exist several political and regulatory distortions that culminated in the 2001 financial crisis of Turkey. Particularly, the pre-liberalization era of the new republic (1923–1980) characterizes a textbook case of *financially repressed market*: directly setting or imposing ceilings on interest rates (from 1940s to 1986); imposing high reserve (RR) and liquidity (LR) requirements on banks (RR = 16% and LR = 20% in the 1980s); directing bank loans to favorite parties (almost 75% of the loans by 1980); owning and/or micromanaging banks (the largest bank is still state-owned; until the late 1990s, 8 state banks controlled 50%, and now the remaining 3 about 30% of industry assets) (Isik, 2007); restricting entry into the financial system, especially by foreigners (between 1960 and 1980, there were only 3 domestic but no foreign entries); and controlling the capital account (restrictions on personal holdings of foreign currency until 1984 and international capital flows until 1989). All these policies were *extractive* in nature and to the detriment of savers and/or efficient allocation of funds, but to the benefit of government and its few close allies. With a series of financial reforms, Turkey started to liberalize its repressed economy and markets in the 1980s by deregulating interest and FX rates, lifting entry barriers, cutting directed lending, developing new money, equity and bond markets, allowing new institutions and instruments and opening the capital account (Isik and Hassan, 2002a, 2003c; Isik and Uysal, 2006; Isik, 2007). However, Turkey has embarked on this new journey with less regard to the fact that financial liberalization is a kind of balancing act, striving to get the benefits while avoiding the possible instabilities. According to Beim and Calomiris (2001), "sequencing certainly matters; financial deregulation cannot occur in a vacuum. It works best when accompanied by fiscal reform, the privatization of state-owned enterprises (SOEs), discontinuation of state subsidies, and taxation reforms that enable the government to end its fiscal dependence on the taxation of the financial sector. If a government still has uncovered fiscal deficits that could raise inflationary pressures, it will prove a hardship to give up capital controls, domestic interest rate interventions, and high reserve requirements. Thus, a rational system of bank regulation should be in effect before banks are turned loose". A financial liberalization in the absence of appropriate law and regulation may give rise to chaos, which

[5] Given the dominance of the financial markets by banks around the world, our crisis definition is obviously bank centered. Many emerging markets have limited number of banks, thus, failure of three banks is a serious financial shock.

[6] Regulators may be reluctant to admit their failures in the areas of prudent regulation and effective supervision or too optimistic and hopeful of an immediate recovery, or too close to their regulatory clientele due to past or future employment, or may face pressures from politicians that appropriate their budgets and decide their appointments, or may simply lack resources to deal with an imminent default or crisis. Politicians may also face lobbying from bankers, may be unwilling to admit their failures, especially if elections are near and critical, may wish to gain time, and may incur budgetary constraints in dealing with troubled banks or crises.

is epitomized by a well-known study by Diaz-Alejandro (1985) "*Good-bye financial repression, hello financial crash*". Financial liberalization, in the absence of prudential regulation and supervision, may indeed increase banking fragility due to increased opportunities for excessive risk taking and fraud. Evidently, Kaminsky and Reinhart (1999) showed that a financial liberalization dummy variable tends to predict the occurrence of banking crises in a sample of 20 countries. Furthermore, using a larger dataset from 53 countries between 1980 and 1995, Demirguc-Kunt and Detragiache (1998) found that banking crises are indeed more likely to happen in liberalized financial systems. They also noted that the adverse impact of deregulation on banking sector fragility is stronger where the institutional environment is weaker, i.e., where there is little respect for the rule of law, high levels of corruption, and poor contract enforcement.

Demonstratively, the "quasi-liberalization experience" of Turkey, where regulations were loosened under weak regulatory and legal infrastructure, ended up with a marked increase in the number of crises, which paved the way for the epic 2001 systemic crisis. As Fig. 1 depicts, roughly two thirds of the failures in Turkey happened in the more deregulated environment (including development and investment banks). Turkish banks had entered this neo-liberal era under an overprotective government. In fact, such patronage that substantially boosted the profitability of all Turkish banks, whether managed well or poorly, had created important franchise value for them. However, this franchise was based on government protected rents rather than innovation and efficiency. After liberalization, these franchise values tended to gradually evaporate because banks' monopolistic powers were eroded and some perks were taken away, which naturally hurt banks. This sort of *creative destruction* is actually appropriate, as it forces banks to create economic value or die. However, the liberal reforms in Turkey that were undertaken in a highly distorted environment, where banks' profits were privatized while losses were socialized, proved to be more dangerous than no liberalization. As also observed in the transition phases of the former command economies in the early 1990s and the quasi-liberalized Asian economies in the late 1990s, the newly privatized or created Turkish banks became the political and economic "piggybanks" of industrial empires. They became involved in excessive growth and insider lending, held little equity, and undertook negative NPV projects, ultimately gambled and failed (Isik, 2008).

Especially in the 1990s as portrayed in Table 1, ambitious growth and extravagant welfare policies of Turkey's weak and inefficient governments coupled with the limited tax base and underdeveloped financial markets were the major source of its large fiscal deficits. The constant need of the state to finance its deficits by expropriating resources from the central bank, domestic banks and international markets were the catalysts of the subsequent anomalies: high and unstable inflation, dependent and clumsy banks, and deep and sharp currency devaluations (50% and 30% during the 1994 and 2001 crises, respectively). The increased borrowing need of the public sector eventually resulted in the crowding out and drying up of capital flows to the private sector, because no investment in Turkey was as profitable as financing the government (Isik and Hassan, 2002a, 2003b). Banks stopped doing real banking and firms stopped doing real business in pursuit of easy money under this lucrative arbitrage opportunity. The 1997 Asian and 1998 Russian crises did not help Turkey, either. As can be seen in Table 1, nervous international investors sharply reduced their exposure to Turkey, which reduced the economic growth from 8% in 1997 to 3.8% in 1998. The strong fall in capital inflows and a devastating earthquake that hit the industrial heartland of Turkey in August 1999 pushed the economy into a deep recession in 1999, shrinking the gross domestic product (GDP) by 6.4%. As a result, the budget deficit reached 12% of GDP and public debt rose to 40% of GDP. During the 1999 recession, thirteen banks were taken under the full control of the Savings Deposit Insurance Fund (SDIF). Legislation on the privatization of state banks was repeatedly delayed due to political filibuster throughout 2000 (Isik, 2007). Given the weakness of the banking system, this increased tensions in the markets. In 2000, criminal investigations into fraud at ten private banks taken over by the SDIF were commenced. These developments exacerbated the suspicion about the fragility of the banking system. As a result, banks shut down their interbank credit lines to weak banks, and foreign investors ran for the exit, triggering the banking crisis. Interbank rates that skyrocketed during the crisis (rising from 50% to 8,000%) affected especially illiquid banks. In 2001, particularly private banks faced large losses following the devaluation of the Turkish lira by 30%. The contraction in economy resulted in a sharp deterioration in loan quality, as the ratio of non-performing loans reached 19% in 2001. Consequently, during 1997–2003, the SDIF had to rescue or close twenty-eight banks in total, together holding about a quarter of total assets in the banking sector.

3. The review of theory and evidence on efficiency, crisis and survival

Despite the numerous survey studies on crises and defaults, there is no dedicated review of the association of efficiency with bank failures and crises. Demirguc-Kunt (1989) that surveys deposit-institution failures and Demirguc-Kunt and Detragiache (2005) that reviews cross-country studies of systemic bank distresses do not cite any efficiency study. Cielen et al. (2004) is the only efficiency study in the Kumar and Ravi (2007)'s survey that presents a comprehensive review of the application of statistical and intelligent techniques to solve the bankruptcy prediction problem faced by banks and firms during 1968–2005. Fethi and Pasiouras (2010) review 196 operational research and artificial intelligence studies between 1998 and 2009. Of these, 16 employ classification models used in the prediction of bank failure (10), bank underperformance (2), and credit ratings (4). However, none of them, except for Wheelock and Wilson (2000), dwell on the relationship between efficiency and default. Demyanyk and Hasan (2010) surveys econometrics and operations research methods used in the empirical literature to describe, predict, and remedy financial crises and defaults. Of the 5 DEA efficiency studies they summarize, only 3, Luo (2003), Kao and Liu (2004) and Cielen et al. (2004), are directly linking efficiency to bankruptcy. Thus, one goal of this paper is to fill this void in the literature, to an extent, by theoretically linking efficiency with bank defaults and crises and summarizing the general findings of the selected empirical studies in these areas. The *theory of the firm* assumes that managers (agents) are hired by owners (principals) to maximize their wealth by operating in the most efficient way possible. However, internal or external factors may cause bank managers to deviate from this objective. Sinkey (1975) in his problem-bank study, one of the earliest on this topic, suggested that quality and honesty of management are the most important factors leading to bank failures. Graham and Homer (1988), after studying the factors contributing to bank failures in the U.S., confirmed that main difference between the failed and survived banks was indeed the caliber of management. Miller (1995) also found that management driven weaknesses played a critical role in determining 90% of bank failures in the U.S. Seballos and Thomson (1990) maintained that the ultimate determinant of whether or not a bank fails is the ability of its management to operate the institutions efficiently and to evaluate and manage business risks. It is obvious that the *quality of management* is critical in deciding the survival of institutions. However, what is not obvious is how to objectively measure it. Bank examiners assess management quality as part of their CAMELS rating system but such evaluation is qualitative and hence often requires professional analysis of nonpublic data.[7] Barr and Siems (1991) were the first to propose that the efficiency indexes could serve as quantitative and objective measures to proxy management quality in banking. DeYoung (1998) verified that this proxy works well: higher efficiency is not only positively related to management quality, as measured by bank examiners, but also leads to fewer problem loans. Mathematically, the relative efficiency is defined simply as the ratio of the weighted sum of multiple outputs and the weighted sum of multiple inputs:

$$EFFICIENCY_b = \sum_{y=1}^{n} u_{yb} OUTPUT_{yb} \Big/ \sum_{x=1}^{m} v_{xb} INPUT_{xb} \tag{1}$$

where u_{yb} is the unit weight assigned to output y; v_{xb} is the unit weight assigned to input x by the bth bank in a population of banks; and n and m represent the number of output and input variables, respectively. The weights are selected to attain Pareto optimality for each decision making unit (DMU). By identifying multiple outputs and inputs, this model captures increasingly diverse role of modern management better than single traditional performance indicators such as financial ratios. In a competitive environment, bank managers that cannot generate as many (and profitable) outputs as their rivals and/or that employ more and costly bank inputs than their competitors are destined to record losses, erode capital, and eventually fail. Barr et al. (1994) were the first to empirically explore the relationship between *bank efficiency* and *failure* in a systematic manner.[8] The hypothesis of their empirical study is that efficiency measures, as ideal proxies for *management quality*, can statistically discriminate between problem and non-problem institutions.[9] They found evidence that banks with low efficiency failed at greater rates and this relationship was evident a number of years ahead of eventual failure (Berger & Humphrey, 1997; Isik and Hassan, 2003a; Wheelock and Wilson, 1995, 2000).

After studying 77 crisis episodes, Demirguc-Kunt and Detragiache (2005) conclude that banking crises tend to manifest themselves during the periods of weak economic growth. Investigating 26 banking crises, Kaminsky and Reinhart (1999) find that real output growth falls below trend about eight months before the peak of the banking crisis, suggesting that banking crises are preceded by a cyclical downturn. The *theory of noisy market selection* developed by Jovanovic (1982) maintains that inefficiently run firms would face hardship and eventually be either taken over or pushed away from the market by more efficient ones. Cross-country studies such as Sachs et al. (1996) and Demirguc-Kunt and Detragiache (1998, 2005), indeed indicate that most bank defaults happen during turbulent times. Apparently, financial crises exacerbate the fragility of already weak banks and serve as a litmus test to separate "good" managers from "bad" managers by subjecting them to a survival test. Perhaps, a fragile banking industry is one with a large proportion of low quality ("bad") managers. Bongini et al. (1999) reports that there were significant prior weaknesses at the individual bank level that contributed to the Asian crisis in 1997. These studies also demonstrate that *credit growth* is a significant crisis indicator. We may utilize the *agency theory*, the economic analysis of the effects of *adverse selection* and *moral hazard*, to help understand the theoretical relationship between financial stability and bank efficiency. According to Mishkin (1991), financial crises happen when a disruption in the financial system causes a sharp increase in asymmetric information problems in markets, which inhibits their ability to channel savings efficiently to those with productive investment opportunities. According to Demirguc-Kunt and Detragiache (1998, 2002), the existence of explicit or implicit government safety net, particularly deposit insurance, is a trigger to worsen such problems. The most serious drawback results from *moral hazard*, the incentives of one party to a transaction to engage in activities detrimental to the other party. In a normal risk decision, the agent making the decision bears the full weight of its consequences. With a safety net, depositors know that they will not suffer from losses if a bank fails, so they do not impose market discipline on banks by withdrawing deposits when they suspect that the bank is taking on too much risk. Consequently, banks with deposit insurance have an incentive to take on greater risks than they otherwise would, with taxpayers paying the bill if the bank subsequently fails. A further problem with deposit insurance arises due to *adverse selection*, the fact that the people who are most likely to produce the adverse outcome are those who are most likely to be selected. Since fully protected depositors have little reason to discipline banks, such system might lure especially

[7] According to Demirguc-Kunt (1989), DeYoung (1998) and Isik and Folkinshteyn (2017), the determination of management quality by bank examiners is very subjective. Examiners simply decide on the competence of management based on the bank's performance in the other four CAMEL categories.

[8] Siems (1992) is credited by Luo (2003) as the first study that established an association between bank efficiency and default. However, Siems's study is preliminary and exploratory in nature, just testing the mean efficiency difference in the efficiency scores of failed and survived banks. However, Barr, Seiford and Siems (1994) are the first who employed the efficiency scores in predicting bank defaults. In identifying troubled institutions, their model was superior to all other early warning models that used no efficiency predictors. Isik and Folkinshteyn (2017) also falsely credit Wheelock and Wilson (1995) as the pioneers of bank efficiency and default literature. Berger and DeYoung (1997) also cite Berger and Humphrey (1992) and DeYoung and Whalen (1994) in addition to Barr et al. (1994) and Wheelock and Wilson (1995) as the researchers who first found that failing banks tend to be located far from the best practice frontier but these studies do not have the failure of institutions as their main research question.

[9] Actually, Sinkey (1975) had used two *proxy* (non-frontier) *measures of efficiency*, the ratios of 1) other expenses/total revenue and 2) operating expense/operating income, as proxies for management quality in his multiple discriminant model. These ratios were the second-best discriminators between problem and nonproblem banks after the loan revenue to total revenue ratio, an indicator of asset quality.

risk-loving entrepreneurs into banking. Even worse, if there are weak or no screening process, "outright crooks" (in Mishkin's words) might be tempted to enter banking because it is easy for them to get away with fraud and embezzlement. The effects of such information problems should be negligible when banking is tightly regulated. However, when financial liberalization takes place – as it has been in many countries since the 1980s – the opportunities for risk taking rise substantially. A growing economy also reduces risk premiums and inflames risk appetite. Due to declining franchise value in a competitive and liberal environment, banks seek out new and potentially risky ventures to keep profits up, such as extending to marginal loans, real estate, leveraged buyouts, junk bonds, private equity, hedge funds, derivatives, etc. By placing a greater percentage of their funds in such risky on- and off-balance sheet activities, banks ultimately lead to dangerous credit and asset booms, because a generously designed government safety net in a deregulated market gives banks a sure bet: "heads they win, tails the taxpayer loses".

Increases in interest rates, a sharp decline in stock markets, government imbalances, and increased uncertainty, by intensifying moral hazard and adverse selection problems, e.g., inability to distinguish between "bad credit" and "good credit" clients or subsidized gambling and looting opportunities at the expense of depositors and taxpayers, may lead to credit crunch, lower investment, contractions in economic activity, and ultimately banking fragility (Isik and Hassan, 2003a; Kaminsky and Reinhart, 1999; Mishkin, 1991). Consequently, *bank outputs* such as on- and off-balance sheet assets (credit, investment and derivatives) should dramatically shrink during economic downturns. Whereas, *bank inputs* such as deposits, fixed assets and labor, might be less affected since they are either invariable in the short run or stabilized due to blanket government guarantees during crises. As a matter of fact, strategies like large lay-offs of personnel or branch closings or liquidation of properties could be tried in response to the sharp fall in the volume of outputs in order to remain efficient during crisis times. However, such reactions entail considerable costs, both monetarily and in terms of reputation. Moreover, such factors, especially physical capital (properties) input, are long-term assets, hence, may not be variable in the short run. If the management thinks that crisis will last short, then, they may be reluctant to let their staff go, as well. Also, rigid labor laws and regulations may prevent or make such short-notice large lay-offs prohibitively expensive. Isik and Hassan (2003a), acknowledging this, hypothesized that "by limiting the general economic activity and suppressing the production of bank loans and other bank services, a financial disruption can bring about a decline in bank productivity and efficiency" (page 293). More plainly, a crisis may lead to lower *technical* and *pure technical efficiency* because of diminished outputs and relatively stable inputs, lower *scale efficiency* due to asset downsizing (credit crunch, loan charge-offs or security defaults), lower *cost efficiency* because of increased funding and operational costs owing to rising risks and loan problems, lower *allocative efficiency* stemming from volatile and uncertain prices, lower *revenue efficiency* because of fewer opportunities, and lower *profit efficiency* as a result of lower cost and/or revenue efficiency.

The key findings of prominent empirical studies on crisis and efficiency are summarized in Appendix A. Using technical efficiency and productivity measures, Isik and Hassan (2003a) showed that Turkish banking industry indeed incurred a substantial productivity loss after the 1994 crisis (17%), which was partially caused by technical regress (10%) and partially by efficiency decrease (7%). Subsequently, some studies have examined the effect of the 1997 Asian crisis on bank efficiency with mixed results, such as Chen (2005) for Taiwanese banks (positive impact), Drake et al. (2006) for Hong Kong banks (no impact), Park and Weber (2006) and Sufian and Habibullah (2009) for Korean banks (no impact), Sufian (2009a,b) for Malaysian banks (negative impact), Sufian (2010) and Mahathanaseth and Tauer (2014) for Thai banks (no impact). On the other hand, Kyj and Isik (2008) and Isik et al. (2016) reported that the 1998 Russian debt crisis had a significant but short-lived *negative* impact on the technical efficiency of Ukrainian banks. After the eruption of 2008 global financial crisis, the researchers also explored its impact on the efficiency of banking systems. The studies that reported *negative* effects of global financial crisis on the efficiency of banking system contain Nitoi (2009) for Romanian banks, Sufian and Habibullah (2010) for Thai banks, Alzubaidi and Bougheas (2012) and Andrieș and Ursu (2016) for the E.U. banks, Zeitun and Benjelloun (2012) for Jordanian banks, Maredza and Ikhide (2013) for South African banks, Wolters et al. (2014) for Brazilian banks, Johnes et al. (2014) for Islamic banks, Park and Baek (2014) and Mehdian et al. (2019) for the U.S. banks, Stavarek and Řepkova (2014) for Czechian banks, Tzeremes (2015) for Indian banks, and Moradi-Motlagh and Babacan (2015) for Australian banks. However, the studies by Vu and Turnell (2011) for Australian banks, Luo et al. (2011, pp. 805–825) for Chinese banks, Ozkan-Gunay (2012) and Akin et al. (2013) for Turkish banks, Said (2012) and Rosman et al. (2014) for Islamic banks in the Middle East and Asia, Akhtar (2013) for Saudi banks, and Kumar and Charles (2012), Ramakrishna et al. (2016), Gulati and Kumar (2016) and Chesti and Khan (2018) for Indian banks found *no* material negative effects of global financial crisis on bank efficiency. As opposed to banking crisis and efficiency literature, there exist only a few studies that use efficiency measures to predict the risk of bank defaults. As briefly summarized in Appendix B, the notable *published* studies that showed that efficiency measures tend to be *negatively* associated with the probability of failures include Barr et al. (1994), Wheelock and Wilson (1995 and 2000), Luo (2003) and Alvarez-Franco and Restrepo-Tobón (2016) for the U.S. banks, Kao and Liu (2004) for Taiwanese banks, Kraft et al. (2006) for Croatian banks, Podpiera and Podpiera (2008) for Czechian banks and Isik and Folkinshteyn (2017) for Turkish banks. Some *working* papers (e.g., Miller, 1995 for Connecticut banks, Stryn, 2004 for Russian banks, and Wallace, 2009 for Jamaican banks) failed to observe the hypothesized *negative* association between efficiency and probability of default, i.e., managerial inefficiency did not provide significant information to explain bank failures in these episodes. In fact, there are only a few studies that relate the performance of Turkish banks to banking crises and failures. Notably, Canbas et al. (2005), Celik and Karatepe (2007), and Boyacioglu et al. (2008), using accounting ratios, tested the performance of statistical and artificial intelligence techniques in analyzing bank failures in Turkey. Yet, none of them used DEA (operational research) or SFA (econometrics) frontier methods and utilized any efficiency measure, an ideal proxy for management quality.[10] Ozkan-Gunay and Tektas (2006) detected a gradual decline in Turkish banking efficiency as a result of crises; however, their analysis reported the evolution of singular measure (DEA technical efficiency) over the years and did not relate it to crisis or failure or any control variable in a multivariate framework. Hence, they did not develop an early warning model for either crises or failures, and totally ignored the state-owned banks, which then accounted for about 50% of the industry assets. In terms of *default* and *efficiency* analysis, Isik and Folkinshteyn (2017) analyzed the linkage of bank efficiency with failure, but not with crisis, in Turkey. Their main focus was limited to the investigation of whether bank regulators or managers were the main suspects in causing bank failures. They mostly blamed the latter.

There are two dominant approaches used in practice to estimate efficiency in production, non-parametric DEA and parametric SFA. The former attributes all deviations from the best-practice frontier to managerial inefficiency, while the latter claims that such aberrations are partly due to managerial incompetence and partly due to pure luck and accounting error. Hitherto, no formulation has been devised yet that unifies these two competing technologies in a single analytical framework. Thus, in the spirit of Bauer et al. (1998) who advocated the methodological crosschecking of results that have policy importance, we estimated sixteen alternative efficiency scores utilizing both approaches. DEA is a mathematical programming technique that identifies the most efficient banks in a population (efficiency = 1) and provides a measure of inefficiency for all others (efficiency <1). Figs. 2 and 3 illustrate how to acquire the efficiency measures of a hypothetical bank, *b*, by estimating DEA frontiers. We first construct the frontiers *I–I*′ (Fig. 2) and *0n* (Fig. 3) by assuming constant returns to scale (CRS), and *prstuv* (Fig. 3) by assuming variable returns to scale (VRS). Then, we draw a line from the origin *0* to the point *b* (dotted line, *Ob*, in Fig. 2). Suppose that *I–I*′ and the zone above and to the northeast show all combinations of two inputs (*x1* and *x2*) that generate at least output level *y*. Cost minimization happens at point *e* given the current technology and input prices, represented by the slope of isocost line *c-c'*. Since point *b* illustrates a particular bank producing output *y*, overall DEA *cost efficiency* (CEd) for bank *b* is measured by the ratio *0g/0b,* which is a product of *technical efficiency* (TEd = *0f/0b*) and *allocative efficiency* (AEd = *0g/0f*). Fig. 3 illustrates the decomposition of TEd for a one input (*x1*) and one output (*y*) case with respect to *CRS* and *VRS* frontiers. Technical inefficiency is the distance *mb* under CRS frontier (TEd), and *sb* under VRS frontier (PTEd). The difference between them, *ms*, is attributed to scale inefficiency, implying that the bank can produce its current level of loans with fewer inputs if it attains *CRS*. Hence, the overall DEA *technical efficiency*, TEd = PTEd * SEd = *(ks/kb) * (km/ks) = km/kb*. Overall *cost efficiency* [CEd = AEd*TEd], the potential or efficient input usage to actual input employed, can be achieved by 1) *allocative efficiency (AEd)*, reduction in production costs using an optimal input mix given their prices, and 2) *technical efficiency (TEd)*, effectively utilizing inputs to maximize outputs. Whereas, overall *technical efficiency* [TEd = PTEd*SEd] can be attained by 1) *pure technical efficiency* (PTEd), managerial ability to utilize firms' given resources, and 2) *scale efficiency (*SEd*)*, exploiting economies of scale to minimize production costs (Isik and Topuz, 2017).

To briefly understand the SFA, now assume that a bank has a production function $f(x_i,\beta)$. In a setting without error or inefficiency, the *i*th bank would produce $y_i = f(x_i,\beta)$. SFA recognizes that each bank potentially produces less than it might actually due to inefficiency. Specifically, $y_i = f(x_i,\beta)\xi_i$, where ξ_i is the level of efficiency for bank *i*; ξ_i must be in the interval (0,1]. In this form, ξ_i represents the portion by which y_i falls short of the goal and has a natural interpretation as proportional or percentage efficiency. If $\xi_i = 1$ *(100%)*, the bank is achieving the optimal output with the technology exemplified in the production function $f(x_i,\beta)$. When $\xi_i < 1$, the bank is not making the most of the inputs x_i given the technology represented in the production function $f(x_i,\beta)$. Because the output is assumed to be strictly positive (that is, $y_i > 0$), the degree of technical efficiency is assumed to be strictly positive (that is, $\xi i>0$). Unlike the DEA, the SFA acknowledges that output is also subject to random shocks, implying that $y_i = f(x_i,\beta)\xi_i \exp(v_i)$, where y_i is observed outcome (goal attainment); $f(x_i,\beta)\xi_i$ is the optimal frontier goal [e.g.; maximal output (TEs) or profit (PROFEs) or revenue (REVEs) or minimum cost (CEs), given a vector of inputs, x_i] pursued by the bank; β is the vector of technology parameters. $f(x_i,\beta)$ is the deterministic part of the frontier and $v_i \sim N[0, \sigma_v^2]$ is the stochastic part, which together build the "stochastic frontier." Usually, the production or cost model is based on a Cobb-Douglas, translog or other form of logarithmic model. Thus, taking the natural log of both sides generates:

$$\ln(\boldsymbol{y}_i) = \ln[\boldsymbol{f}(\boldsymbol{x}_i,\boldsymbol{\beta})] + \boldsymbol{ln}(\boldsymbol{\xi}_i) + \boldsymbol{v}_i \tag{2}$$

Assuming *n* inputs and linear in logs production function, and $u_i = -\ln(\xi_i)$ yields:

[10] Some of these studies tend to suffer severely from "data mining/hacking" issues. In a hypothesis-driven approach, analysts use data to test and ultimately, prove (or disprove) assertions. Contrarily, in an exploratory data approach, analysts "dive" into data in search of patterns (or lack thereof). With no hypothesis a priori, Canbas et al. (2005) first "dive" into 49 financial ratios (page 530) from 1997 to 2001, published on the website of BAT, and "mine" three ratios with the highest discriminating ability between failed and healthy banks and then employ them as explanatory variables in their failure prediction models to boost their accuracy ratio (page 539). Unlike these papers, in this hypothesis-driven paper, we mainly test the theoretical claim that inefficiently run firms are more likely to fail and suffer from a banking crisis after controlling for other important factors.

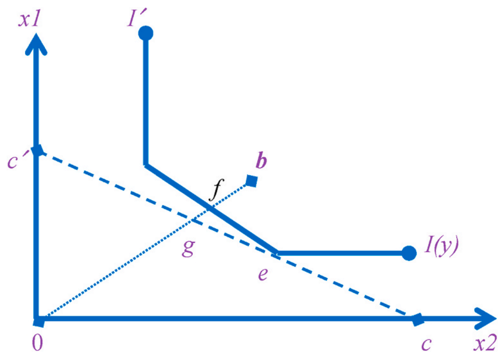

Fig. 2. DEA cost efficiency (CE).

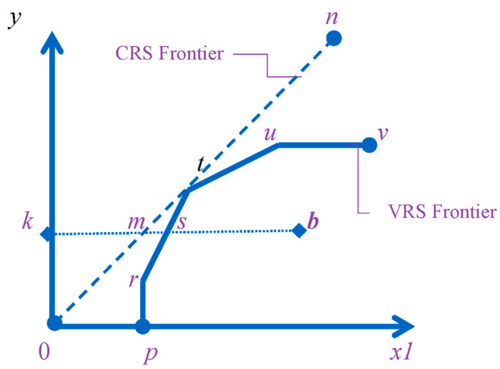

Fig. 3. DEA technical efficiency (TE).

$$\boldsymbol{ln}(\boldsymbol{y}_i) = \boldsymbol{\beta}_0 + \sum_{j=1}^{n} \boldsymbol{\beta}_j \ln(\boldsymbol{x}_{ji}) + \boldsymbol{v}_i - \boldsymbol{u}_i \tag{3}$$

Because u_i is subtracted from $ln(y_i)$, restricting $u_i \geq 0$ implies that $0 < \xi_i \leq 1$. Coelli et al. (2005) show that performing an analogous derivation in the dual cost function problem permits us to define the problem as:

$$\ln(\boldsymbol{c}_i) = \boldsymbol{\beta}_0 + \boldsymbol{\beta}_y \ln(\boldsymbol{y}_i) + \sum_{j=1}^{n} \boldsymbol{\beta}_j \ln(\boldsymbol{p}_{ji}) + \boldsymbol{v}_i - \boldsymbol{u}_i \tag{4}$$

where y_i is output, the x_{ji} are input quantities, c_i is cost, and the p_{ji} are input prices. Intuitively, the inefficiency effect is required to lower output or raise expenditure, depending on the specification. The model that we fit has the general form:

$$\boldsymbol{ln}(\boldsymbol{q}_i) = \boldsymbol{\beta}_0 + \sum_{j=1}^{n} \boldsymbol{\beta}_j z_{ji} + \boldsymbol{v}_i - \boldsymbol{d}\boldsymbol{u}_i \tag{5}$$

where $d = 1$ for production functions (TEts, TEms, PROFEs and REVEs) and $d = -1$ for cost functions (CEts, CEms). So in the context of the discussion above, $q_i = \ln(y_i)$ and $z_{ji} = \ln(x_{ji})$ for a production function; $q_i = \ln(c_i)$, the z_{ji} are the $\ln(p_{ji})$, and $\ln(y_i)$ for a cost function. We obtained the natural logarithm transformation of the data before estimation to interpret the estimation results correctly for an SFA production or cost model. Following the common tradition in practice, we assume that the random component *(v)* is normally distributed with zero mean and inefficiency component (ξ) is independently half-normally distributed. *Stochastic cost efficiency* scores, CEts & CEms, are measures of how close a bank's cost is to what a best practice bank's cost would be for producing the same (traditional or modern) output bundle under the same conditions. Whereas, *stochastic technical efficiency* scores, TEts and TEms, *stochastic profit efficiency* score, PROFEs and *stochastic revenue efficiency* score, REVEs, measure how close a bank is to producing the maximum possible (traditional or modern) outputs, profits and revenues, respectively, given the same conditions.[11]

[11] A complete description of the DEA and SFA methodologies, which are standard by now, is beyond the scope of this paper. Please see Berger and Humphrey (1997), Fethi and Pasiouras (2010) and Coelli et al. (2005) for more technical detail.

4. Data and empirical design

Our dataset (1995–2003) on Turkish banks is obtained from the Banks Association of Turkey (BAT). It contains a total of 609 gross observations from 68 banks in 1995, 69 in 1996, 72 in 1997, 75 in 1998, 81 in 1999, 79 in 2000, 61 in 2001, 54 in 2002 and 50 in 2003.[12] Since we would like to see the developments in the efficiency performance of a banking industry approaching a major crisis, we have divided our study period into three sub-periods; *pre-crisis*, *crisis* and *post-crisis* years. Unlike earlier papers, we adopt alternative "*factual crisis*" definition in which we consider a year as the "crisis year" if it witnesses at least three bank failures.[13] With this new definition, we aim to distinguish between *fragility* and *crisis* in general and *official* and *factual crisis* in particular. As Fig. 1 depicts, 1998, 1999, 2000 and 2001 years conform to this crisis definition.[14] Although imperfect, this is an objective way to define a financial crisis in an emerging market, because authoritarian and non-transparent governments common in these countries usually do not officially admit that there is a crisis in the country until it becomes impossible to hide it. This definition is also consistent with the 1994 crisis of Turkey, the second severest crisis in its modern history, when only three banks had failed. Accordingly, the years preceding the *crisis period* (1998–2001) define the *pre-crisis period* (1995–1997) and the years succeeding it characterize the *post-crisis period* (2002).[15] To refine the dataset against potential outliers, we omitted those observations whose input prices could not be attained and/or are more than three standard deviations away from the mean value. Although the assessment of bank failure occurs at a certain point in time, it may be the product of specific policy errors made over several years. Thus, performance indicators should be inspected over time to provide full information about the progress of the failed bank. Accordingly, instead of estimating a common frontier across all years, we opted for separate annual frontiers, i.e., for each bank in each year, we estimated efficiency relative to all banks in the given year. This flexibility is a critical issue for studying the effects of a changing business environment on bank performance as it allows frontiers and efficiencies to react to the environmental shocks. As well, because the subjects of comparison should be relatively homogenous in a performance analysis, possessing similar outputs and inputs, we excluded the central bank, export and import banks, clearing house bank, participation (Islamic) banks, development banks, and investment banks. This data clearing process left us with 447 net observations (51 banks in 1995, 53 in 1996, 57 in 1997, 56 in 1998, 57 in 1999, 51 in 2000, 46 in 2001, 39 in 2002 and 36 in 2003).

Since modern bank managers carry on a multitude of functions and makes a plethora of decisions, a model that adequately captures modern managers' allocation and control decisions requires the identification of several inputs and outputs.[16] DEA is a linear programming technique that converts multiple inputs and outputs into a scalar measure of efficiency. Yet, there have been almost as many uses of inputs and outputs as there have been efficiency applications due to the differences in the availability of data and purpose of these studies. Adopting the so-called *asset* and *intermediation approaches* (Berger & Humphrey, 1997), we first model Turkish banks under the *traditional banking technology* as multi-product/multi-input firms, converting 3 inputs, [1] physical capital (Fix-Cap): the book value of bank premises, fixtures and other fixed assets, [2] short-term (money market) and long-term (capital market) funds (SLT-Fund): loanable funds encompassing the sum of Turkish Lira (TL) and foreign exchange (FX) denominated deposits (demand and time) and non-deposit funds and [3] human capital (Hum-Cap): the number of full-time employees on the payroll, into 2 outputs: [1] loans and leases (LLs): the total of short-term and long-term conventional loans and leases to private and public entities & special sectors, and [2] other earning assets (OEA), all non-loan earning assets such as investment securities (public and private), equity participations and others (total *traditional* outputs, TotOutTrad [1 + 2], variable is used in estimating stochastic technical, TEt, and cost efficiency, CEt, scores). For the *traditional model* presented herein, the banks are represented in a two-stage process in which they first acquire deposits and then bundle together these funds to produce on-balance sheet loans and other earning assets with the help of physical and human capital. Hence, total banking costs (TotCost) incurred in this process include both interest expense and operating costs and are proxied by the sum of physical and human capital as well as loanable funds expenditures (banks in our sample are modeled to minimize TotCost given the inputs and their prices). All input prices are accordingly calculated as flows over the year divided by these stocks: [1] price of Fix-Cap P[1]: expenditures on premises and fixed assets plus depreciation expense divided by gross value of premises and fixed assets; [2] price of SLT-Fund P[2]: interest expenses on deposit and non-deposit funds divided by loanable funds; [3] price of Hum-Cap P[3]: expenditures on employees such as salaries, employee benefits and reserves for retirement divided

[12] Regulation of inflation adjustment in financial statements and the taxation of net income according to the principle of inflation accounting after 2002 preclude the extension of the post-crisis period in this study.

[13] This crisis definition, although unusual, is not unprecedented. In 1996, the IMF and the World Bank published comprehensive studies of bank distress in their member countries (Caprio & Klingebiel, 1996; Lindgren et al., 1996), which showed that the extent and nature of the problems varied substantially, including cases of insolvency of *one* or *two* large banks. In their cross-country study of twin crises, Kaminsky and Reinhart (1999) define the onset of a banking crisis as the coincidence of depositor runs leading to the closure or take-over of *one* or *more* banks, or as large-scale government intervention to assist, take over, merge, or close *one* or *more* financial institutions. Laeven and Valencia (2012) include *significant bank nationalizations* in their definition of banking crises without giving a specific number to update their database on systemic banking crises around the world. They define significant nationalizations as takeovers by the government of systemically important financial institutions, which include cases where the government takes a majority stake in the capital of such financial institutions.

[14] Evidently, the BAT refers to a recession in 1999 and twin crises in 2000 and 2001, while acknowledging 2001 as the zenith year of the crisis.

[15] The post-crisis period includes only 2002, because the consistent data end after 2002. In our failure prediction models, all explanatory variables are lagged except for the dummy variable for bank defaults. Thus, 2003 year is used only for our default dummy variable to account for the failures in this year.

[16] A performance model based on accounting ratios fails to indicate the resource allocation and product decisions made by these managers since the numerator and denominator are aggregate measures (DeYoung, 1998; Siems, 1992).

by the total number of employees. All variables, except for Hum-Cap, are measured in U.S. dollars in order to control for inflation as well as facilitate international comparison. Turkish banks began to report off-balance sheet items recently, which enables us to develop an alternative model, *modern banking technology.* This could better represent the nature of contemporary banking today. Under this alternative approach, we define banks as intermediaries that transform loanable funds raised from traditional (demand and time deposits) and modern (money and capital market) sources into a mix of traditional interest-earning (on-balance sheet) and modern fee-generating (off-balance sheet) products, with the help of human and physical capital. Accordingly, *modern managerial efficiency indexes* are estimated by using three inputs [1] Hum-Cap, [2] Fix-Cap, and [3] SLT-Fund and three outputs: [1] LLs, [2] OEA and [3] off-balance sheet items (Off-BS) that contain contingent assets and liabilities such as loan sales, credit lines, commitments, guarantees, and derivative instruments, etc. (the variable of total *modern* outputs, TotOutMod [1 + 2+3], is used to construct stochastic technical, TEms, and cost, CEms, efficiencies). Off-balance sheet activities yield substantial fee income for banks and help them diversify their revenue sources. Thus, they are often effective substitutes for traditional loans and demand similar information gathering, origination, monitoring, and control costs. Thus, ignoring these non-traditional activities might bias the efficiency results, especially for those banks that are heavily invested in them (Isik and Hassan, 2002a,b; Isik and Hassan, 2003a,b,c). To investigate the existence and magnitude of such bias, we estimate our efficiency scores first by ignoring off-balance sheet items (CEtd, AEtd, TEtd, PTEtd, SEtd, CEts, TEts) and then by recognizing them (CEms, AEms, TEms, PTEms, SEms, CEms, TEms, PROFEms, REVEms) in our estimations, where the suffixes *t*, *m*, *d* and *s* represent traditional, modern, DEA and SFA frontier technologies, respectively.[17]

In Table 2, the annual means and standard errors of the production variables are compared first to the base year (1995) and then to the previous year counterparts for statistical significance. The consecutive letters A, B, C and X stand for 1%, 5%, 10%, and more than 10% significance level, respectively, for the parametric *t*-tests, which test if the variables of two years are drawn from the same efficiency distributions. The first notable observation is that off-balance items (OFF-BS) are the largest bank output, even larger than the sum of loans and leases (LLs) and other earning assets (OEA) in every year. This justifies the calls to include them in modeling efficiency for unbiased estimation, as we did with the *modern banking technology* in this paper. Turning the spot light on 2001, the epicenter year of the crisis, we observe a dramatic fall in all bank outputs, except for OEA, in accordance with the sharp contraction in the economic and financial activity during the crisis. Expressively, bank loans and leases recorded their lowest level and first drop in 2001 since 1995. OFF-BS outputs also halted its annual growth for the first time in 2001 by losing nearly half of its value. These observations suggest credit and asset booms ahead of crises and bursts after crises as the *asymmetric information theory* predicts (Mishkin, 1991) and empirical studies document (Sachs et al., 1996; Demirguc-Kunt and Detragiache, 1998, 2002). Apparently, thriving times and bloated scales tend to precede eventual banking troubles (Isik and Folkinshteyn, 2017). In contrast, the volume of other earning assets (OEA) more than doubled in 2001, even reaching its highest level since 1995. OEAs are mainly banks' investment portfolios, which are dominated by government securities. Apparently, Turkish banks lost their appetite for risk and ultimately ran to safety during the chaos. Recall that similar behavior had been observed globally during the 2008 financial crisis, when the central banks, financial institutions, and investors around the world rushed to park their monies in the safe haven of U.S. treasury securities.[18] Clearly, not only the demand, but also the supply of government securities reaches its peak in times of crisis, pushing the "crowding out effect" to alarming levels. This resulted in states hoarding most of the available funds in the system to finance their expensive bail-outs, stimuli, and social programs. As for the input variables, let alone decline, there exists a slight increase in their average values during the crisis. Evidently, bank inputs are less elastic than bank outputs in times of distress. This observation also supports the prediction of agency theory: due to exacerbated adverse selection and moral hazard problems created by government safety nets, while bank outputs soar before crises and shrink after crises, bank inputs remain fairly stable. Moreover, while the *prices* of physical (Fix-Cap), P[1], and human capital (Hum-Cap), P[3], inputs practically did not change, the price of short term and long term funds (SLT-Fund), P[2], more than doubled in 2001, reflecting high risk premiums demanded by risk averse investors during crises. Eventually, such a chaotic environment seemed to have inflated banking costs (TotCost) (by about 50%) and totally eradicated bank profits (NetProf) in 2001 (the sector's first negative profit experience since 1995). The standard errors of the bank variables in 2001 as compared to those of the base year 1995 are significantly higher, obviously depicting heightened risk and uncertainty in business conditions of hard times. Overall, sinking outputs, steady inputs, surging risks, costs, and losses during the crisis (as compared to the pre- and post-crisis control years) suggest that its impact on bank efficiency, however calculated, should be negative. Hence, employing a large array of efficiency scores, this paper aims to see if they can validate this casual observation and if they do, which one does a better job?

5. The empirical analysis of the association of efficiency with crisis and default

To test if there is a fall in bank efficiency during a crisis, all years are first compared to the base year, 1995, and then to the previous

[17] The sample size in this study (53 banks on average) compares favorably with most of the other small samples in the banking crisis and failure literature [e.g., 8 Australian banks by Moradi-Motlagh and Babacan (2015), 9 Jamaican banks by Wallace (2009), 14 Chinese banks by Luo et al. (2011, pp. 805–825), 11 to 23 Korean banks by Sufian and Habibullah (2009), 18 failed large U.S. banks by Luo (2003), 24 Taiwanese banks by Kao and Liu (2004), 26 to 43 Croatian banks by Kraft et al. (2006), 22 to 40 Czech banks by Pruteanu-Podpiera and Podpiera (2008); 33 to 36 Malaysian banks by Sufian (2009 a,b); 47 failed U.S. banks by Wheelock and Wilson (1995)] and exceeds the critical sample sizes demanded by both conservative [15 = 3*(2 + 3) & 18 = 3*(3 + 3)] and non-conservative views [6=(2*3) & 9=(3*3)] for our traditional and modern banking models, respectively.

[18] The amount of money invested in U.S. Treasury securities from this "flight to quality" was so large that the yield on the three-month T-bills went below zero for the first time ever. Global investors were essentially paying the U.S. treasury to borrow money.

Table 2
Sample statistics of bank outputs, inputs and input prices for the DEA and SFA frontiers [1995–2002].

	1995		1996		1997		1998		1999		2000		2001		2002	
	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE	Mean	SE
OUTPUTS																
[1] LLs	501	1046	610^{X,X}	1167^{X,X}	699^{X,X}	1369^{B,X}	739^{X,X}	1211^{X,X}	679^{X,X}	1171^{X,X}	913^{X,X}	1555^{A,B}	585^{X,X}	948^{X,A}	798^{X,X}	1297^{X,C}
[2] OEA	161	261	274^{X,X}	485^{A,A}	250^{X,X}	385^{A,C}	349^{B,X}	511^{A,B}	548^{A,X}	798^{A,A}	597^{A,X}	923^{A,X}	1302^{A,C}	2422^{A,A}	1577^{A,X}	3017^{A,X}
[3] Off-BS	874	1070	967^{X,X}	1316^{X,X}	1382^{B,X}	1713^{X,C}	1673^{A,X}	1940^{A,X}	2234^{A,X}	2503^{A,C}	2912^{A,X}	3879^{A,A}	1461^{C,B}	1922^{A,A}	3343^{A,C}	5746^{A,A}
TotOutTrad [1 + 2]	1218	2146	1473^{X,X}	2569^{X,X}	1572^{X,X}	2687^{C,X}	2000^{X,X}	3373^{A,C}	2344^{C,X}	4095^{A,X}	2863^{B,X}	4948^{A,X}	2903^{B,X}	4754^{A,X}	3196^{B,X}	5478^{A,X}
TotOutMod [1 + 2+3]	1536	2203	1851^{X,X}	2035^{X,X}	2332^{X,X}	3127^{A,A}	2761^{B,X}	3384^{A,X}	3461^{A,X}	4096^{A,X}	4422^{A,X}	5865^{A,A}	3348^{A,X}	4679^{A,X}	5718^{A,X}	9165^{A,A}
TotRev	303	594	380^{X,X}	802^{B,B}	406^{X,X}	819^{B,X}	592^{C,X}	1126^{A,A}	743^{C,X}	1569^{A,A}	647^{C,X}	1258^{A,X}	903^{B,X}	2016^{A,A}	786^{B,X}	1532^{A,C}
NetProf	30	65	41^{X,X}	76^{X,X}	45^{X,X}	95^{A,C}	45^{X,X}	161^{A,A}	74^{B,X}	124^{A,C}	12^{X,X}	241^{A,A}	−167^{A,B}	475^{A,A}	59^{X,A}	144^{A,A}
INPUTS																
[1] Fix-Cap	75	248	79^{X,X}	264^{X,X}	68^{X,X}	213^{X,X}	83^{X,X}	220^{X,X}	75^{X,X}	157^{A,A}	95^{X,X}	169^{A,X}	136^{X,X}	275^{X,A}	284^{B,X}	638^{A,A}
[2] SLT-Fund	975	1756	1232^{X,X}	2222^{C,C}	1293^{X,X}	2203^{C,X}	1639^{X,X}	2820^{A,C}	1918^{C,X}	3460^{A,X}	2395^{B,X}	4216^{A,X}	2501^{A,X}	4032^{A,X}	2658^{A,X}	4577^{A,X}
[3] Hum-Cap	2711	5945	2684^{X,X}	5629^{X,X}	2589^{X,X}	5435^{X,X}	2838^{X,X}	5785^{X,X}	2990^{X,X}	6204^{X,X}	3081^{X,X}	6307^{X,X}	3403^{X,X}	6399^{X,X}	3038^{X,X}	4968^{X,X}
INPUT PRICES																
P[1]	0.29	0.32	0.27^{X,X}	0.27^{X,X}	0.29^{X,X}	0.28^{X,X}	0.32^{X,X}	0.28^{X,X}	0.31^{X,X}	0.26^{X,X}	0.31^{X,X}	0.24^{B,X}	0.28^{X,X}	0.21^{A,X}	0.28^{X,X}	0.19^{A,X}
P[2]	0.16	0.10	0.17^{X,X}	0.10^{X,X}	0.17^{X,X}	0.11^{X,X}	0.22^{A,C}	0.15^{A,B}	0.22^{A,X}	0.13^{C,X}	0.17^{X,B}	0.09^{X,A}	0.35^{A,A}	0.36^{A,A}	0.18^{X,A}	0.14^{A,A}
P[3]	0.02	0.01	0.02^{X,X}	0.01^{X,X}	0.02^{X,X}	0.01^{X,X}	0.02^{A,A}	0.01^{B,B}	0.03^{A,C}	0.02^{A,A}	0.03^{A,C}	0.02^{A,X}	0.03^{A,X}	0.03^{A,B}	0.03^{A,X}	0.03^{A,X}
TotCost	258	549	324^{X,X}	769^{A,A}	342^{X,X}	771^{A,X}	504^{X,X}	1063^{A,A}	616^{C,X}	1468^{A,B}	582^{C,X}	1168^{A,X}	880^{B,X}	1776^{A,A}	696^{B,X}	1369^{A,X}

Note: The letters A, B, C and X stand for 1%, 5%, 10%, and more than 10% significance level, respectively. The first mean difference test is with respect to the base year 1995 and the latter is with respect to the previous year. Outputs: [1] LLs: the total of short-term and long-term conventional loans and leases to private and public entities & special sectors, [2] OEA: all non-loan earning assets such as investment securities (public and private), equity participations and others; [3] Off-BS: contingent assets and liabilities such as loan sales, credit lines, commitments, guarantees, and derivative instruments, and others. Inputs: [1] Fix-Cap: the book value of bank premises, fixtures and other fixed assets, [2] SLT-Fund: loanable funds encompassing the sum of Turkish Lira (TL) and foreign exchange (FX) denominated deposits (demand and time) and non-deposit funds and [3] Hum-Cap: the number of full-time employees on the payroll. Input prices: [1] price of Fix-Cap P[1]: expenditures on premises and fixed assets plus depreciation expense divided by gross value of premises and fixed assets; [2] price of SLT-Fund P[2]: interest expenses on deposit and non-deposit funds divided by loanable funds; [3] price of Hum-Cap P[3]: expenditures on employees such as salaries, employee benefits and reserves for retirement pay divided by the total number of employees. All variables, except for Hum-Cap, are measured in U.S. dollars to control for inflation and facilitate international comparison.

year statistically in Table 3. The relatively "tranquil" years (1995, 1996, 1997 and 2002) and periods (pre-crisis, 1995–97, and post-crisis, 2002) serve as controls. Again, we focus our attention on the crisis period [column 11], especially the year 2001 [column 8]. The grand average of all the 16 efficiency scores in 2001 (0.69, col. 8) at the bottom row of the table is significantly lower than those of both the previous year 2000 (0.75, col. 7) and the base year 1995 (0.77, col. 2) at the 1% level. The overall efficiency performance in 2001, the severest point of the crisis, is also the lowest among the eight years between 1995 and 2002. The grand average (0.73, col. 11) of the efficiency scores for the crisis period (1998–2001) is also significantly lower than that (0.78, col. 10) of the pre-crisis period (1995–1997). The results also show that overall efficiency performance followed a U-shape pattern, beginning to decline during the pre-crisis period, pitching headlong during the crisis period and rebounding during the post-crisis period, as the post-crisis aggregate average (0.83, col. 12) significantly outperforms the averages of the crisis (0.73, col. 11) and pre-crisis (0.78, col. 10) periods. Moreover, the grand efficiency averages of the individual crisis years (1998–2001, col. 5–8) are invariably lower than those of the pre- (1995–1997, col. 2–4) and post-crisis (2002, col. 12) years. The overall results suggest that the impact of a crisis on bank efficiency is negative and efficiency scores could *jointly* foretell or mimic an approaching crisis. However, when we look at the individual scores, we see that DEA scores drive the main results. The grand averages of all DEA scores (col. 11), without exception, are lower during the crisis period than those of both the pre- [col. 10] and post-crisis periods [col.12]. Among the ten DEA scores, CEtd and CEmd, the nexuses of the DEA scores, have recorded the largest drop during the crisis period (col.11), 14% and 13% respectively. The impact of the crisis on traditional and modern PTE scores was minimal (−4%). On the other hand, the overall SFA scores fail to show the expected negative performance jointly. Only, the TEms and REVEms scores individually follow the observed overall U-shaped pattern, with the former demonstrating the biggest fall during the crisis period (−17%, col. 11 vs col. 10).

The above analysis is based on *averages* of the efficiency scores, which may be highly sensitive to extreme observations. For an illustration, assume that a banking sector consists of just four banks, E, B, R, and U, whose efficiencies before the crisis were all the same, 0.50; hence, the industry average was 0.50. Now assume that, while the efficiency scores of E, B, and R banks all dropped to 0.40, the efficiency of Bank U remarkably rose to 1 during the crisis, hence the industry average becomes 0.55. These scores indicate that while banks E, B and R suffered an efficiency fall, bank U recorded an extreme efficiency jump. The results based on averages would falsely suggest that banking industry experienced 5% higher efficiency during the crisis. The results based on *percentages* (numbers), conversely, would correctly suggest that 75% of banks in the industry registered an efficiency *decrease*, while 25% experienced an efficiency *increase* during the crisis. Hence, as a robustness check, we present the developments in the efficiency of Turkish banks based on percentages in Table 4. The overall results displayed in the bottom row show that 51% of banks [col. 17] experienced a fall, 39% a rise [col. 16] and 10% no change [col. 18] in their overall efficiencies in 2001. The overall percentage of banks that suffered from efficiency decrease is higher during the crisis period (47%, col. 23) than those in both the pre-crisis (40%, col. 20) and post-crisis (19%, col. 26) periods. Again, when we delve to the individual performance of efficiency scores, we observe that DEA scores produce results more compatible with the theory and most of the previous empirical findings. DEA traditional (modern) scores together show that percentage of banks that suffered from an efficiency decrease was 69% (49%) in 2001 (col. 17) and 52% (51%) during the crisis period (col. 23). The performance of CEtd score is especially noteworthy as it demonstrates that 92% (col. 17) of banks incurred an efficiency loss in 2001 and 63% during the entire crisis period (col. 23). We are also able to observe the U-shape pattern in efficiency scores with the percentage analysis: the share of banks that enjoyed an efficiency boost rose substantially in the post-crisis period (col. 25) with respect to the crisis period (col. 22) (from 41% to 70%). While both DEA and SFA scores attest to a recovery in efficiency after the crisis, DEA scores are the ones that reflect most of the deterioration in efficiency during the crisis. Among the SFA scores, TEms and REVEms are the only ones that confirm the negative association between crisis and efficiency, showing that 56% and 64% of banks faced an efficiency loss during the crisis period, respectively. What about the entire *distributions* of efficiency scores? Like averages and percentages, do they also reveal the negative association between bank efficiency and crisis? For another robustness check, we exhibit the Kernel distributions of the 16 DEA and SFA efficiency scores of Turkish banks in Fig. 4. A kernel distribution is a nonparametric representation of the probability density function of a random variable. Fig. 4 contains both kernel distributions and histograms for comparison in the order of *pre-crisis*, *crisis* and *post-crisis* sub-periods for each score. Kernel density estimates are closely related to histograms but can perform better in terms of smoothness or continuity.[19] In general, we observe a lower mode and strong leftward shift in the kernel density curve for the *crisis period* (the middle distributions), meaning that banks tend to be more inefficient during the crisis years. In addition, there appears a clear rightward shift in the density curves for the *post-crisis period* with respect to the same for the crisis period. These results confirm our earlier findings that the efficiency performance of Turkish banking sector recovered rapidly during the *post-crisis period*. Among the 16 efficiency scores, those distributions that belong to DEA scores invariably confirm the U-shaped pattern in efficiency scores, perhaps with the exception of PTE scores. Amidst the SFA scores, only REVEs distribution seems to produce the same result.

The average, percentage and distribution analyses above were based on *point estimates* of efficiency scores. Although useful, they did not control for other factors that could affect the efficiency of the banking industry. Thus, to see if the observed negative association between efficiency and crisis hitherto would withstand a multivariate test, we run a parsimonious model where each efficiency score becomes a dependent factor and pre-crisis, crisis and post-crisis period dummies become independent factors of special interest (pre-crisis dummy is omitted as the base case to prevent perfect collinearity). Environmental factors such as budget deficits to GDP

[19] The smoothness of the kernel density estimate is indeed evident in our figures compared to the discreteness of the histogram, as kernel density estimates converge faster to the true underlying density for continuous random variables. The TEts, CEms, and TEms SFA scores are highly concentrated in the upper range of possible efficiency scores, while others are more spread around the range, hence the spikes for these SFA scores in Fig. 4.

Table 3
DEA and SFA efficiencies of the Turkish banking industry during the pre-crisis, crisis and post-crisis periods.

[1]	[2[	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]
Efficiency	Pre-Crisis Years			Crisis Years [# Failure ≥ 3]				Post-Crisis Years	Pre-Crisis	Crisis	Post-Crisis	All
	1995	1996	1997	1998	1999	2000	2001	2002	95–97	98–01	2002	95–02
DEAt												
CEtd	0.62	0.59^{X,X}	0.66^{X,B}	0.45^{A,A}	0.55 ^{B,A}	0.53 ^{B,X}	0.37^{A,A}	0.78^{A,A}	0.62	0.48^{A}	0.78^{A}	0.57
AEtd	0.80	0.79^{X,X}	0.81^{X,X}	0.71^{A,A}	0.78^{X,B}	0.72 ^{B,C}	0.59^{A,A}	0.88^{A,A}	0.80	0.71^{A}	0.88^{A}	0.76
TEtd	0.79	0.76^{X,X}	0.81^{X,C}	0.67^{A,A}	0.71B^{,X}	0.73^{X,X}	0.63^{A,B}	0.88^{A,A}	0.79	0.69^{A}	0.88^{A}	0.75
PTEtd	0.90	0.91^{X,X}	0.91^{X,X}	0.87^{X,C}	0.87^{X,X}	0.87^{X,X}	0.88^{X,X}	0.96^{B,A}	0.91	0.87^{A}	0.96^{A}	0.89
SEtd	0.88	0.84^{X,X}	0.89^{X,B}	0.77^{A,X}	0.82 ^{C,X}	0.84^{X,X}	0.72^{A,A}	0.92^{C,A}	0.87	0.79^{A}	0.92^{A}	0.84
Average	*0.80*	*0.78 ^{X,X}*	*0.82$^{X, B}$*	*0.69 ^{A,A}*	*0.74^{A,A}*	*0.74^{B,X}*	*0.64^{A,A}*	*0.89 ^{A,A}*	*0.80*	*0.71^{A}*	*0.89 ^{A}*	*0.76*
DEAm												
CEmd	0.59	0.61^{X,X}	0.66 ^{C,X}	0.51 ^{C,A}	0.52^{X,X}	0.47^{A,X}	0.47^{B,X}	0.74^{A,A}	0.62	0.49^{A}	0.74^{A}	0.57
AEmd	0.80	0.80^{X,X}	0.84^{X,X}	0.70 ^{B,A}	0.78^{X,B}	0.72^{A,X}	0.72^{A,X}	0.86^{C,A}	0.82	0.73^{A}	0.86^{A}	0.78
TEmd	0.73	0.76^{X,X}	0.78^{X,X}	0.71^{X,X}	0.66^{X,X}	0.65^{X,X}	0.65^{X,X}	0.85^{A,A}	0.76	0.67^{A}	0.85^{A}	0.72
PTEmd	0.85	0.87^{X,X}	0.86^{X,X}	0.82^{X,X}	0.80^{X,X}	0.79^{X,X}	0.89^{X,B}	0.93^{B,X}	0.86	0.82^{C}	0.93^{A}	0.85
SEmd	0.86	0.88^{X,X}	0.90^{X,X}	0.87^{X,X}	0.83^{X,X}	0.82^{X,X}	0.73^{A,B}	0.91^{X,A}	0.88	0.82^{A}	0.91^{A}	0.85
Average	*0.77*	*0.78 ^{X,X}*	*0.81^{X,X}*	*0.72 ^{X,A}*	*0.72^{X,X}*	*0.69 ^{A,X}*	*0.69 ^{B,X}*	*0.86^{A,A}*	*0.79*	*0.71^{A}*	*0.86^{A}*	*0.75*
SFAt												
CEts	0.76	0.73^{X,X}	0.71^{X,X}	0.76^{X,B}	0.78^{X,X}	0.76^{X,X}	0.76^{X,X}	0.76^{X,X}	0.73	0.76^{A}	0.76^{X}	0.75
TEts	0.82	0.998^{A,A}	0.99812^{A,A}	0.99903^{A,A}	0.99874^{A,A}	0.99843^{A,A}	0.99842^{A,A}	1.00^{A,A}	0.94	1.00^{A}	1.00^{A}	0.98
Average	*0.79*	*0.86^{A,A}*	*0.85 ^{A,A}*	*0.88^{A,B}*	*0.89 ^{A,A}*	*0.88^{A,X}*	*0.88 ^{A,X}*	*0.88^{A,X}*	*0.84*	*0.88^{A}*	*0.88^{X}*	*0.86*
SFAm												
CEms	0.9953	0.99867^{A,A}	0.58^{A,A}	0.99919^{A,A}	0.99830^{A,A}	0.99938^{A,A}	0.99482^{A,A}	0.63^{A,A}	0.85	1.00^{A}	0.63^{A}	0.90
TEms	0.51	0.98502^{A,A}	0.59^{A,A}	0.55^{X,X}	0.49^{X,C}	0.64^{A,A}	0.29^{A,A}	0.99^{A,A}	0.70	0.51^{A}	0.99^{A}	0.63
PROFEs	0.72	0.43^{A,A}	0.52^{A,B}	0.74^{X,A}	0.44^{A,A}	0.84^{A,A}	0.90^{A,C}	0.55^{A,A}	0.55	0.71^{A}	0.55^{A}	0.63
REVEs	0.69	0.74 ^{B,B}	0.74^{B,X}	0.67^{X,A}	0.66^{X,X}	0.65^{C,X}	0.48^{A,A}	0.65^{X,A}	0.72	0.62^{A}	0.65^{X}	0.67
Average	*0.73*	*0.79 ^{A,A}*	*0.61 ^{A,A}*	*0.74^{X,A}*	*0.65^{A,A}*	*0.78^{A,A}*	*0.66^{A,A}*	*0.71 ^{X,C}*	*0.70*	*0.71^{X}*	*0.71^{X}*	*0.71*
OVERALL	*0.77*	*0.79 ^{C,C}*	*0.77 ^{X,X}*	*0.74 ^{B,B}*	*0.73 ^{B,X}*	*0.75 ^{B,C}*	*0.69 ^{A,A}*	*0.83 ^{A,A}*	*0.78*	*0.73^{A}*	*0.83^{A}*	*0.76*

Note: Table 3 presents average efficiencies of the Turkish banks between 1995 and 2002, where crisis is defined as "factual crisis", a year in which at least 3 banks fail; hence, Pre-crisis = 1995–1997, Crisis = 1998–2001 and Post-Crisis = 2002. The letters A, B, C and X stand for 1%, 5%, 10%, and more than 10% significance level, respectively, for the parametric *t*-test that tests the null hypothesis to see if efficiency indexes that belong to different years and periods are drawn from the same distributions. Cost (CEtd, CEmd, CEts, CEms), Allocative (AEtd, AEmd), Technical (TEtd, TEmd, TEts, TEms), Pure technical (PTEtd, PTEmd), Scale (SEtd, SEmd), Profit (PROFEms) and Revenue (REVEms) efficiency scores are computed based on Data Envelopment Analysis (d) and Stochastic Frontier Analysis (s) using traditional (t) banking technology, which does not account for off-balance sheet outputs and modern banking technology (m), which does, respectively.

Table 4

Percentage of banks with an increase or decrease in their DEA and SFA efficiencies during the pre-crisis, crisis and post-crisis periods.

Columns	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]	[16]	[17]	[18]	[19]	[20]	[21]	[22]	[23]	[24]	[25]	[26]	[27]
	1995–1996 %[#Bnks = 49]			1996–1997 % [#Bnks = 52]			1997–1998 % [#Bnks = 54]			1998–1999 % [#Bnks = 51]			1999–2000 % [#Bnks = 47]			2000–2001 % [#Bnks = 36]			Pre-Crisis %[#Bnks = 51]			Crisis %[#Bnks = 47]			Post-Crisis % [#Banks = 35]		
%Change →	+	-	*No*	+	-	*No*	+	-	*No*	+	-	*No*	+	-	*No*	+	-	*No*	+	-	*No*	+	-	*No*	+	-	*No*
DEAt																											
CEtd	39	57	4	73	23	4	9	87	4	82	10	8	30	62	9	5	92	3	56	40	4	32	63	6	91	6	3
AEtd	59	37	4	50	42	8	33	63	4	59	37	4	30	64	6	17	83	0	55	40	6	35	62	4	83	14	3
TEtd	33	55	12	62	25	13	9	81	9	61	25	14	49	30	21	14	75	11	48	40	13	33	53	14	83	6	11
PTEtd	27	37	37	33	31	37	13	50	37	33	27	39	34	19	47	25	25	50	30	34	37	26	30	43	37	11	51
SEtd	31	61	8	58	21	21	7	80	13	69	18	14	40	40	19	14	69	17	45	41	15	33	52	16	83	6	11
Average	*38*	*49*	*13*	*55*	*28*	*17*	*14*	*72*	*13*	*61*	*24*	*16*	*37*	*43*	*20*	*15*	*69*	*16*	47	39	15	32	52	16	*75*	*9*	*16*
DEAm																											
CEmd	49	45	6	63	31	6	15	80	6	37	53	10	36	55	9	39	61	0	56	38	6	32	62	6	80	17	3
AEmd	49	47	4	60	27	13	17	74	9	55	39	6	28	60	13	39	56	6	55	37	9	35	57	9	77	20	3
TEmd	41	45	14	46	37	17	24	59	17	31	57	12	32	45	23	42	50	8	44	41	16	32	53	15	63	26	11
PTEmd	33	33	35	25	38	37	24	43	33	24	31	45	21	36	43	42	11	47	29	36	36	28	30	42	23	23	54
SEmd	29	53	18	52	29	19	31	48	20	33	51	16	40	36	23	25	67	8	41	41	19	32	51	17	74	14	11
Average	*40*	*44*	*16*	*49*	*32*	*18*	*22*	*61*	*17*	*36*	*46*	*18*	*31*	*46*	*22*	*37*	*49*	*14*	45	38	17	32	51	18	*63*	*20*	*17*
SFAt																											
CEts	43	55	2	37	52	12	78	19	4	35	25	39	47	47	6	42	53	6	40	54	7	51	36	14	54	43	3
TEts	100	0	0	2	98	0	2	98	0	100	0	0	100	0	0	100	0	0	51	49	0	76	25	0	100	0	0
Average	*71*	*28*	*1*	*19*	*75*	*6*	*40*	*58*	*2*	*68*	*13*	*20*	*73*	*23*	*3*	*71*	*26*	*3*	45	52	4	63	30	7	*77*	*21*	*1*
SFAm																											
CEms	100	0	0	100	0	0	98	2	0	4	96	0	100	0	0	100	0	0	100	0	0	76	25	0	100	0	0
TEms	100	0	0	2	98	0	28	69	4	14	76	10	98	2	0	22	78	0	51	49	0	41	56	4	89	11	0
PROFEs	4	96	0	62	37	2	89	7	4	8	90	2	89	4	6	64	31	6	33	67	1	63	33	5	11	86	3
REVEs	63	31	6	54	37	10	9	89	2	47	41	12	36	53	11	28	72	0	59	34	8	30	64	6	71	23	6
Average	*67*	*32*	*2*	*54*	*43*	*3*	*56*	*42*	*2*	*18*	*76*	*6*	*81*	*15*	*4*	*53*	*45*	*1*	61	38	3	52	45	3	*68*	*30*	*2*
OVERALL	*50*	*41*	*9*	*49*	*39*	*12*	*30*	*59*	*10*	*43*	*42*	*14*	*51*	*35*	*15*	*39*	*51*	*10*	50	40	11	41	47	12	*70*	*19*	*11*

Note: Table 7 presents percentage changes in the efficiencies of the Turkish banks between 1995 & 2002, where crisis is defined as "factual crisis", a year in which at least 3 banks fail; hence, Pre-crisis = 1995–1997, Crisis = 1998–2001 and Post-Crisis = 2002. Efficiency indexes, cost (CEtd/CEmd), allocative (AEtd/AEmd), technical (TEtd/TEmd), pure technical (PTEtd/PTEmd) and scale (SEtd/SEmd) efficiency, are based on DEA efficiency frontiers using traditional (t) banking technology, which does not account for off-balance sheet outputs and modern banking technology (m), which does, respectively. Assume that each efficiency score is EFF. Efficiency increase (+): EFFt > EFFt-1; Efficiency decrease (−): EFFt < EFFt-1; No efficiency change (No): EFFt = EFFt-1.

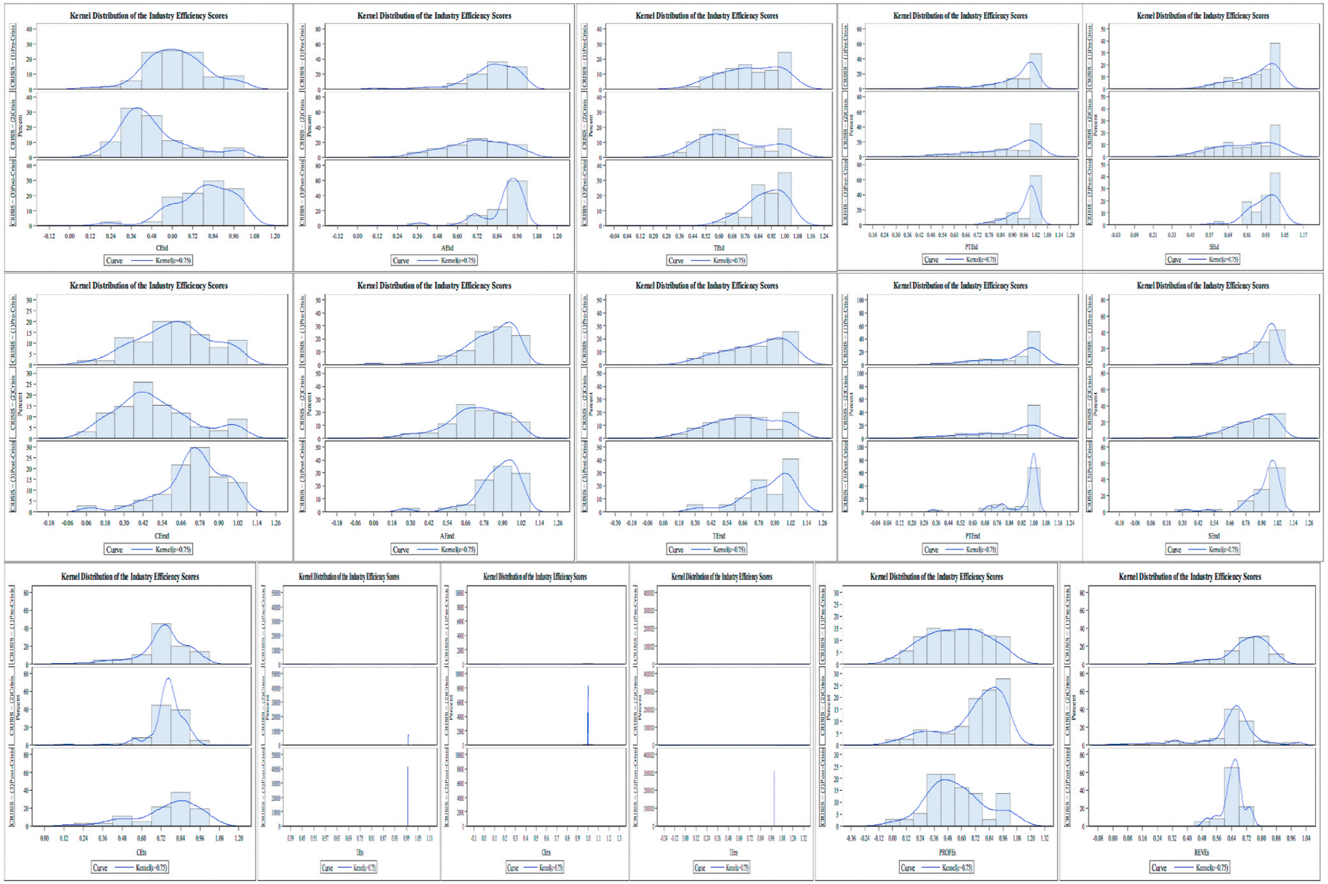

Fig. 4. Kernel distributions of the DEA and SFA efficiency estimates during the pre-crisis, crisis and post-crisis periods.

(BudDefGDP), average interest rates (AvIntRat) and provisions for loans losses to assets in the industry (PPL_TA) serve as control variables. Because efficiency measures are limited (truncated) dependent variables, we use the methodology of non-linear Tobit regressions, essentially logistical functional forms, which ensure that the predicted efficiency values remain inclusively between 0 and 1. Additionally, to get adequate coverage of the confidence intervals for the standard errors, we did 2,000 bootstrap iterations (k = 2,000) in our models. The regression results presented in Table 5 yield negative coefficients for the crisis dummy and positive coefficients for the post-crisis dummy in all traditional and modern DEA models. These associations between DEA scores and crisis dummies are also statistically significant at the comfortable levels (mostly at 1%), indicating that DEA scores followed the expected U-shape pattern during the period. Confirming our earlier observations, among the SFA scores, only TEms and REVEms show the expected negative association between crisis and efficiency. Among the DEA scores, CEtd model has the highest adjusted R-square (26%), while PTEmd has the lowest (4.6%). Among the SFA scores, as TEms model has the highest explanatory power (38%), CEtd has the lowest (3.8%).[20] As for the control variables, budget deficits (BudDefGDP) prove to be positively associated with efficiency. This makes sense because budget deficits increase the borrowing requirement of governments, hence the supply of treasury securities to finance these deficits. Banks, as the dominant financial institutions, are the main investors in government securities, which require little management and resources, boosting bank outputs as compared to inputs; hence leading to higher efficiencies for banks investing in them. The results also show that average interest rates (AvIntRat) tend to be negatively associated with bank efficiency. Given that the cost of funding is the largest and most expensive financial input in banking operations (see SLT-Fund and P[2] in Table 2), the observation that soaring interest rates result in lower efficiencies is also hardly surprising. Also, individuals and firms with the riskiest investment projects are those who are willing to pay the highest interest rates. When interest rates soar during crises, good credit risks are less likely to want to borrow as opposed to bad credit risks, which are still willing to borrow. Because of the resulting increase in *adverse selection*, banks tend to reduce their loan and service production during crises, which consequently dampen their efficiency. The regressions also suggest that the higher the loan provisions (PLL_TA), the lower the bank efficiency. Evidently, the banks that set aside more provisions for possible loan losses seem to be less efficient. This finding is in line with the so-called "*bad luck hypothesis*" of Berger and DeYoung (1997): external shocks precipitate an increase in problem loans for the bank, which demands substantial resources to resolve. Evidently, banks must set aside additional inputs necessary to administer the exploding troubled assets and have to eventually charge off more bank outputs during crisis, naturally lowering their efficiencies. This suggests that prudential regulation and supervision could reduce the risk of crisis by limiting bank's exposures to such shocks (e.g., diversification) or by better insulating banks from external shocks (e.g., higher capital requirements). The model statistics (*Wald* Chi^2s) reject the null hypothesis that all coefficients of crisis and control variables are equal to zero in the population.

The robustness tests so far indicated that financial crises and efficiency tend to be negatively associated. The DEA approach endows us with an opportunity to trace the sources of the efficiency losses observed during the crisis, recalling that CE = AE*TE and TE = PTE*SE. Table 6 indicates that overall DEA results (DEAt + DEAm) for the crisis period clearly picture the destructive power of the crisis on bank performance. In terms of cost efficiency (CE), most of the banks (63%) faced a decline, 32% achieved an increase and 6% stagnated. As regards to technical efficiency (TE), the majority (53%) recorded a decline, 33% a rise and 15% no change. The results attribute the fall in CE mainly to a reduction in AE (55%) rather than TE (45%). Most of the TE problems are driven by decreases in SE (61%) instead of PTE (39%).[21] The overall crisis period results signify the bigger role of allocation mistakes in cost mismanagement. Most of the Turkish banks, 63%, suffered from cost inefficiency because of exacerbated allocative inefficiency during the crisis, while only 37% suffered due to increased technical inefficiency. The literature suggests that while allocative inefficiencies are mainly driven by external factors such as market conditions and regulatory policies, technical inefficiency is primarily driven by internal factors such as poor management, organizational and governance structures, etc. (Isik and Folkinshteyn, 2017). Our results tend to blame external factors (AE) rather than internal factors (TE) for banks' operational problems during crises. In a chaotic environment, where input prices radically rise and widely vary, bank managers are likely to make inefficient allocation decisions. The results also reveal that technical inefficiencies arose mainly due to scale inefficiency during the crisis. In a stable environment, banks generally operate at or near the correct scale (bottom portion of long run average cost curve); otherwise, they cannot survive in a competitive market. However, in an unstable crisis environment, bank managers apparently miss the scale target due to the market-forced contractions in

[20] In Table 5, we report adj-R^2 stats from GLS model instead of pseudo-R^2 stats from Tobit model because the latter may take values above 1 and less than zero. This occurs because for continuous distributions, the log likelihood is the log of a density. Since density functions can be greater than 1, the log likelihood can be positive or negative. Similarly, mixed continuous/discrete likelihoods like Tobit can also have a positive log likelihood. Hence, pseudo-R^2 can give answers >1 or <0 for continuous or mixed continuous/discrete likelihoods like tobit. For instance, McFadden's pseudo-R^2 measures changes in likelihood functions, which have no obvious interpretation. Unless the pseudo-R^2 is either 0 or 1, the statistic is uninterpretable in relation to data.

[21] The traditional DEA (DEAt) results are much sharper in portraying the impact of the crisis on banks: in 2001, only 5% of banks achieved an increase in cost efficiency (CEtd) while the great majority, 92%, suffered a loss. Of these banks with a cost efficiency decrease in 2001, 52% experienced it mainly due to allocative inefficiency, whereas 48% faced it mostly due to technical inefficiency.

Table 5
Multivariate bootstrapped Tobit regressions - with DEA and SFA frontier efficiencies.

Dep. Vars.	Independent Variables						Model Statistics			
	Crisis	Post-crisis	BudDefGDP	AvIntRat	PLL_TA	Constant	*N*	Bootsrap	Wald-Chi^2	Adj-R^2
DEAt										
CEtd	−0.132^{A}	0.106^{A}	0.754^{A}	−0.029^{A}	−0.711^{A}	0.609^{A}	447	2,000	115.01^{A}	0.260
AEtd	−0.086^{A}	0.015	0.831^{A}	−0.030^{A}	−0.331	0.780^{A}	447	2,000	62.99^{A}	0.144
TEtd	−0.098^{A}	0.101 ^{B}	0.331	−0.015 ^{C}	−0.816^{A}	0.810	447	2,000	53.54^{A}	0.143
PTEtd	−0.040 ^{C}	0.162^{A}	−0.360	0.012	−0.970 ^{C}	1.004^{A}	447	2,000	25.61^{A}	0.070
SEtd	−0.081^{A}	0.024	0.492^{A}	−0.020^{A}	−0.128	0.884^{A}	447	2,000	38.98^{A}	0.110
DEAm										
CEmd	−0.117^{A}	0.130^{A}	0.047	−0.004	−0.850^{A}	0.634^{A}	447	2,000	46.03^{A}	0.113
AEmd	−0.083^{A}	0.048	0.142	−0.005	−0.558^{A}	0.823^{A}	447	2,000	31.71^{A}	0.073
TEmd	−0.086^{A}	0.135 ^{B}	−0.057	−0.001	−0.890^{A}	0.804^{A}	447	2,000	28.47^{A}	0.066
PTEmd	−0.032	0.285^{A}	−1.197^{A}	−0.041^{A}	−0.936 ^{B}	1.020^{A}	447	2,000	21.07^{A}	0.046
SEmd	−0.065^{A}	0.002	0.546^{A}	−0.022^{A}	−0.163	0.898^{A}	447	2,000	25.21^{A}	0.058
SFAt										
CEtd	0.040^{A}	0.044	−0.057	0.003	−0.687^{A}	0.733^{A}	447	2,000	20.14^{A}	0.038
TEtd	0.057^{A}	0.031^{A}	0.219^{A}	−0.009^{A}	0.006	0.938^{A}	447	2,000	84.94^{A}	0.187
SFAm										
CEms	0.147^{A}	−0.190^{A}	−0.256 ^{C}	0.010 ^{C}	−0.029	0.856^{A}	447	2,000	181.71^{A}	0.367
TEms	−0.184^{A}	0.132^{A}	1.726^{A}	−0.065^{A}	−0.180	0.649^{A}	447	2,000	191.53^{A}	0.382
PROFEms	0.177^{A}	0.213^{A}	−1.941^{A}	0.070^{A}	−1.656^{A}	0.613^{A}	447	2,000	112.44^{A}	0.242
REVEms	−0.094^{A}	−0.169^{A}	0.991^{A}	−0.036^{A}	−0.167	0.694^{A}	447	2,000	95.16^{A}	0.208

Note: A, B, C stand for 1%, 5%, 10% significance level, respectively. Multivariate tobit models try to estimate the impact of crisis dummy (where Crisis = 1, if a year belongs to the crisis years 1998–2001, in which at least three banks failed; otherwise 0) and post-crisis period (where Postcrisis = 1, if a year belongs to the recovery year 2002; otherwise 0) on efficiency scores: Cost (CEtd, CEmd, CEts, CEms), Allocative (AEtd, AEmd), Technical (TEtd, TEmd, TEts, TEms), Pure technical (PTEtd, PTEmd), Scale (SEtd, SEmd), Profit (PROFEms) and Revenue (REVEms) efficiency scores computed based on Data Envelopment Analysis (d) and Stochastic Frontier Analysis (s) using traditional (t) banking technology, which does not account for off-balance sheet outputs and modern banking technology (m), which does, respectively. Environmental variables such as budget deficits to GDP (BudDefGDP), average interest rates (AvIntRat) and provisions for loans losses to assets in the industry (PPL_TA) serve as control variables. Pre-crisis dummy (Precrisis = 1, if the year belongs to 1995–1997; otherwise 0) is excluded as the base case to prevent perfect collinearity. For an adequate coverage of the confidence intervals for the standard errors, the models were run with 2,000 bootstrap iterations (k = 2,000).

their operations. Evidently, average scale efficiencies between 1995 and 2000 are all higher than that in 2001. Given that deposit insurance, aggregate demand, general prices, and stability of markets are macroeconomic factors that are managed by governments (politicians, bureaucrats, and regulators), most of the increased inefficiencies observed in banking during crises can be seen as "negative externalities" created by policy and regulatory errors.[22]

As Fig. 1 displays, although about half of the Turkish banks defaulted around the 2001 crisis, the other half survived. Why did one bank survive while another failed when facing identical circumstances? By examining the characteristics of survivors and failures, can we identify a bank's potential for default? If the quality of management is vital for the viability of banks, as the literature advocates (e.g., Barr et al., 1994; Siems, 1992), then the lack or weakening of that quality should have a direct impact on survival of banks. The quality of management, as proxied by efficiency measures, should be also closely related to navigational skills. It may be that weak and inefficient management, unable to meet the rigorous requirements of the chaotic times, contributes heavily to failure; hence, turbulent times serve as a *litmus test* to judge the true quality of management (Isik and Folkinshteyn, 2017). Thus, survivor banks serve as control group for failed banks. Navigational skills have utter importance especially in emerging markets given their risky business environment. To broaden the literature, we also test the hypothesis that inefficient banks tend to have a higher potential to fail even in an emerging market setting. The prevalent definition for bank failures in the literature is "*official insolvency*", i.e., if banks are closed, seized by regulators involuntarily, or declare bankruptcy voluntarily (e.g., Barr et al., 1994; Isik and Folkinshteyn, 2017; Luo, 2003; Wheelock and Wilson, 1995). In contrast, under "*factual insolvency*", we define any bank as "failed" if its net worth drops below 2%,

[22] In the face of system-wide instability during the 1994 crisis, a temporary full insurance coverage was adopted for both TL and FX deposits to calm the panic. Although the 100% insurance policy stabilized the system, it stayed in effect for a longer time than envisioned (until July 2005); thereby its risk taking effect must outweighed its stability effect, i.e., because deposit insurance offers subsidy for risk-taking, full insurance might have given banks free ride to take excessive risks boosting bank outputs; the safe gamble of "heads bank wins, tails insurance fund loses." Accordingly, most of the banks, especially failures (78%) versus survivors (59%), seem to have suffered from diseconomies of scale ahead of crisis (not shown). The presence of strong moral hazard due to blanket guarantees in the pretty much "laisses fare" environment of the 1990s seems to have led to swollen scales in banking in the advent of the crisis and drastic shrinkage in the aftermath of the crisis.

Table 6
Dominant source of cost and technical efficiency increase or decrease during the pre-crisis, crisis, and post-crisis periods.

		Cost Efficiency (CE) Increase (+) or Decrease (−)							Technical Efficiency (TE) Increase (+) or Decrease (−)						
					CE + due to %		CE - due to %					TE + due to %		TE - due to %	
Δ→	*#*	*+%*	*-%*	*No %*	*AE+*	*TE +*	*AE-*	*TE -*	*+%*	*-%*	*No%*	*PTE+*	*SE+*	*PTE-*	*SE-*
DEAt															
1996	49	39	57	4	58	42	39	61	33	55	12	56	44	30	70
1997	52	73	23	4	45	55	67	33	62	25	13	22	78	38	62
1998	54	9	87	4	80	20	45	55	9	81	9	40	60	27	73
1999	51	82	10	8	52	48	80	20	61	25	14	23	77	54	46
2000	47	30	62	9	57	43	76	24	49	30	21	39	61	36	64
2001	36	5	92	5	100	0	52	48	14	75	11	60	40	22	78
2002	35	91	6	3	53	47	50	50	83	6	11	24	76	50	50
Pre-Crisis	*51*	*56*	*40*	*4*	*52*	*49*	*53*	*47*	*48*	*40*	*13*	*39*	*61*	*34*	*66*
Crisis	*47*	*32*	*63*	*6*	*72*	*28*	*63*	*37*	*33*	*53*	*14*	*41*	*60*	*35*	*65*
Post-Crisis	*35*	*91*	*6*	*3*	*53*	*47*	*50*	*50*	*83*	*6*	*11*	*24*	*76*	*50*	*50*
DEAm															
1996	49	49	45	6	46	54	45	55	41	45	14	60	40	41	59
1997	52	63	31	6	52	48	38	63	46	37	17	29	71	63	37
1998	54	15	80	6	50	50	65	35	24	59	17	54	46	56	44
1999	51	37	53	10	63	37	30	70	31	57	12	56	44	48	52
2000	47	36	55	9	53	47	58	42	32	45	23	47	53	57	43
2001	36	39	61	0	43	57	36	64	42	50	8	53	47	11	89
2002	35	80	17	3	39	61	50	50	63	26	11	18	82	44	56
Pre-Crisis	*51*	*56*	*38*	*6*	*49*	*51*	*42*	*59*	*44*	*41*	*16*	*45*	*56*	*52*	*48*
Crisis	*47*	*32*	*62*	*6*	*52*	*48*	*47*	*53*	*32*	*53*	*15*	*53*	*48*	*43*	*57*
Post-Crisis	*35*	*80*	*17*	*3*	*39*	*61*	*50*	*50*	*63*	*26*	*11*	*18*	*82*	*44*	*56*
DEAt + DEAm															
Pre-Crisis	*51*	*56*	*39*	*5*	*51*	*50*	*48*	*53*	*46*	*41*	*15*	*42*	*59*	*43*	*57*
Crisis	*47*	*32*	*63*	*6*	*62*	*38*	*55*	*45*	*33*	*53*	*15*	*47*	*54*	*39*	*61*
Post-Crisis	*35*	*86*	*12*	*3*	*46*	*54*	*50*	*50*	*73*	*16*	*11*	*21*	*79*	*47*	*53*
OVERALL	*48*	*40*	*55*	*6*	*58*	*42*	*53*	*48*	*37*	*49*	*14*	*45*	*55*	*40*	*60*

Note: Table 6 presents the major sources of the developments in the cost (CE) and technical efficiency (TE) of the Turkish banks between 1995 and 2002, where crisis is defined as "factual crisis", a year in which at least 3 banks fail; hence Pre-crisis = 1995–1997, Crisis = 1998–2001 and Post-Crisis = 2002. Efficiency indexes, cost (CEtd/CEmd), allocative (AEtd/AEmd), technical (TEtd/TEmd), pure technical (PTEtd/PTEmd) and scale (SEtd/SEmd) efficiency, are based on DEA efficiency frontiers using traditional (t) banking technology, which does not account for off-balance sheet outputs and modern banking technology (m), which does, respectively. Definition of the sources is as follows: Cost efficiency increase (+%) because of AE increase: CEt > CEt-1, and AEt > AEt-1 and (AEt-AEt-1)> (TEt-TEt-1); Cost efficiency increase because of TE increase: CEt > CEt-1, and TEt > TEt-1 and (TEt-TEt-1)> (AEt-AEt-1); Cost efficiency decrease (-%) because of AE decrease: CEt < CEt-1, and AEt < AEt-1 and (AEt-AEt-1)< (TEt-TEt-1); Cost efficiency decrease because of TE increase: CEt < CEt-1, and TEt < TEt-1 and (TEt-TEt-1)< (AEt-AEt-1); Technical efficiency increase (+%) because of PTE increase: TEt > TEt-1, and PTEt > PTEt-1 and (PTEt-PTEt-1)> (SEt–SEt-1); Technical efficiency increase because of SE increase: TEt > TEt-1, and SEt > SEt-1 and (SEt–SEt-1)> (PTEt-PTEt-1); Technical efficiency decrease (-%) because of PTE decrease: TEt < TEt-1, and PTEt < PTEt-1 and (PTEt-PTEt-1)< (SEt–SEt-1); Technical efficiency decrease because of SE increase: TEt < TEt-1, and SEt < SEt-1 and (SEt–SEt-1)< (PTEt-PTEt-1). No change (No%) in cost efficiency = CEt = CEt-1; no change in technical efficiency = TEt = TEt-1.

even though regulators might not have acknowledged the default.[23] Given that the Turkish regulators did not close any of the insolvent banks until the intervention of International Monetary Fund (IMF) in the late 1990s shows that the official closure process may be heavily politicized in Turkey.[24] If bank failures are determined largely by politics, rather than simply by insolvency, then models that fail to incorporate the political dimension may be incorrectly specified. As seen in Fig. 1 and Table 11, the existence of political interference in closures is clear in our dataset; "*factual insolvency*" definition identifies 35 default episodes between 1995 and 2003, while "*official insolvency*" definition detects 28 defaults; therefore, implying the presence of 7 insolvent but living so-called zombie

[23] Our "factual insolvency" definition is inspired by the U.S. experience. The U.S. regulators demonstrated a stance of *regulatory forbearance* during the thrift crisis in the early 1980s, when they refrained from exercising their regulatory right to put the insolvent thrifts out of business despite the fact that 750 thrifts (over half of the industry) had a negative net worth by some estimates. The total cost of the delayed bailout of the thrift industry in the 1980s was so huge, about $500 billion, that the U.S. lawmakers adopted a new regulation in 1991, the FDIC Improvement Act, which contains "prompt corrective action" provisions that require regulators to intervene earlier and close banks if their equity capital falls below 2%.

[24] For instance, the seizure of the politically connected Etibank, contrary to the examiners' reports, was delayed from December 1999 until October 2000, which increased bank's net loss from TL 97 trillion to TL 313 trillion and its open position from $45 million to $641 million (Isik and Folkinshteyn, 2017).

banks in the system.[25]

In Table 7, we compare survivors to failures in terms of efficiency under both failure definitions. We also perform mean difference *t*-tests when comparing the performance across periods between these groups, i.e., testing the hypothesis that the true survivor and failure means are equal. Individual or grand group averages of DEAt, DEAm, SFAt and SFAm scores indicate that however we measure the efficiency and however we define the bank default, survivors have been more efficient than failed banks during the entire study period at the 1% significance level. This suggests that poor management of failed banks was not accidental, or casual but somewhat permanent. The mean significance tests also reveal that the performance distinction between failures and survivors has become more visible when failures were defined *factually* rather than *officially*. We also check for the first time in the literature if the overall efficiency of failed banks plays any significant role in the resolution policies of bank regulators after failure. Turkish regulators basically adopted four kinds of resolution forms when dealing with failed banks: 1) mergers with healthy banks, 2) sale to new owners, 3) liquidation of assets, and 4) nationalization of the private bank. We statistically compare the efficiency performance of these failed bank groups by treating "merged failures" as the base group. The most noteworthy observation is that the least efficient group of failed banks is "nationalized banks", regardless of the way we measure efficiency. Apparently, these banks were not attractive for private bidders, mergers, and acquisition, thus, the state had to take them over and nationalize. This finding confirms Wheelock and Wilson (2000), who showed that even inefficient banks with no default history are less likely to be acquired. Managerial inefficiency could mean excessive use of or payment for bank inputs; hence, the cost of turning around an inefficient bank could be prohibitively high.[26]

In Table 8, we trace the *efficiency mobility*, survival and death experience of the 50 banks that were present in 1995 until the end of the crisis in 2001. To the best of our knowledge, this will be the first such analysis in the literature. We sorted these 50 banks by quintiles [from the least efficient (efficiency <0.2) to the most efficient (efficiency $0.8 < 1$)] and created five efficiency classes. Creating an efficiency distribution of all banks in the sample, we traced their efficiency growth in the pre-crisis period (1995–1997) versus crisis period (1998–2001) to check if there was a shift in the mobility and survival performance of efficient and inefficient banks during the crisis period. Tables 8a, 8b, and 8c provide vital statistics for DEA traditional, DEA modern, and SFA frontier efficiency scores, respectively. We observe that of the 50 banks alive in 1995, 49 survived to 1997 and only 1 did not survive. Of the 49 banks that made it to 1997, 38 survived to 2001 while 11 did not. 11 (92%) of the 12 total failures among the 1995 banks happened during the crisis period, suggesting that banks are more likely to default in turbulent times, confirming the findings of Kaminsky and Reinhart (1999) and Demirguc-Kunt and Detragiache (2005). This result is perhaps expected and not newsworthy; nonetheless, what is interesting is the sheer existence of many survivors at the same time. Evidently, rough environment only serves to highlight the difference between the good and poor managers, which thriving times so often hide. Indeed, our overall results reveal that the least efficient had the lowest survival rate and the most efficient the highest survival rate. According to the traditional DEA (Table 8a.), survival rate among the most efficient banks during the crisis range from 75% with AEtd to 100% with CEtd. Modern DEA results in Table 8b give a range of 75% with SEmd and 94% with CEmd, for the survival rate. SFA results in Table 8c confirm the survival rate supremacy of most efficient banks with a range of 80% with CEts and 100% with CEms, TEms and PROFEms. The *learning curve theory* claims that firms learn to do tasks faster and more economically as they do the same thing over and over. Hence, uninterrupted, firms are expected to be more efficient as they age and mature (Isik, 2008; Isik and Topuz, 2017). The 50 banks that were alive in 1995 are supposed to drive the learning curve and demonstrate upward efficiency mobility over time in normal circumstances. Therefore, the first question is whether this conjecture is valid, and the second question is if it is valid, is there a *shift* in the efficiency mobility of banks during chaotic times? According to the CEtd/CEmd scores, respectively, during the pre-crisis period, of the 49 survivors, 18/16 (38%/33%) remained in the same efficiency class. Of the remaining survivors, the majority (20/27, 41%/55%) moved up one or more efficiency classes. Demotions were rarer during this relatively healthy pre-crisis period, only 11/6 banks (23%/12%). The matrixes in Table 8a and 8b show that banks in the lowest efficiency categories achieved higher growth rates, suggesting that growth opportunities are higher for less efficient banks as they have more room to improve; however, the picture totally changes during the crisis period. CEtd results indicate that let alone promotion, no bank was able to maintain its pre-crisis efficiency level, i.e., all banks have experienced demotion during the crisis period. According to CEmd score, the rate of efficiency promotion was also zero during the crisis. The subcomponent efficiency indexes of the DEA scores CEtd and CEmd portray a similar outcome, so do CEts, TEts and REVEms scores amid the SFA results. Overall, it is safe to conclude that upward efficiency mobility of Turkish banks has come to a full stop during the crisis.

To uncover why some banks default while others survive independently, we run a comprehensive model relating the risk of default to several factors, with special emphasis on management quality. In modeling the probability distribution, we employ the probit

[25] Wheelock and Wilson (2000), the only exception in the efficiency-failure literature aside from us, detected 51 zombie banks after abandoning the official closure definition. Martin (1977), the first author to use a probability model to assess bank failures (without efficiency predictors), also defines institutional failure as banks whose net worth "… declines drastically over a year or less."

[26] The liquidated bank's slightly higher efficiency is somewhat puzzling though. The only speculation we can make at this point is that given that our comparison includes all the years before failure, these banks were extreme in hiding their toxic assets or inflating their true value and earnings to deter or delay regulatory scrutiny and closure. We can also claim the same for the zombie banks whose efficiencies are generally high.

Table 7
DEA and SFA efficiencies of the Turkish failed banks (official versus factual insolvency).

Columns	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]	[16]	[17]
	Official insolvency (bank failures by government closure)										*Factual insolvency* (bank failures if net worth <2%)						
	Government resolution forms for failed banks																
	Merged [12, 43%]	Liquidated [6, 21%]	Sold [7, 25%]	Nationalized [3, 11%]	All Failed [28, 44%]			All Survived [35, 66%]			All Failed [35, 66%]			All Survived [28, 44%]			Zombies [7, 11%]
Years →	95–02	95–02	95–02	95–02	95–97	98–01	95–02	95–97	98–01	95–02	95–97	98–01	95–02	95–97	98–01	95–02	95–02
DEAt																	
CEtd	0.52	0.64^{B}	0.51^{X}	0.44 ^{B}	0.58	0.45	0.53	0.66^{A}	0.50^{X}	0.59^{A}	0.60	0.44	0.53	0.64^{A}	0.50^{A}	0.59^{A}	0.64
AEtd	0.72	0.73^{X}	0.76^{X}	0.77^{X}	0.77	0.70	0.74	0.82 ^{B}	0.71^{X}	0.78 ^{C}	0.79	0.70	0.75	0.81^{X}	0.71 ^{C}	0.77 ^{C}	0.83
TEtd	0.73	0.88 ^{B}	0.67 ^{C}	0.62 ^{B}	0.76	0.66	0.72	0.81^{X}	0.70^{X}	0.76 ^{B}	0.77	0.64	0.71	0.80^{A}	0.71^{A}	0.76^{A}	0.76
PTEtd	0.88	0.96 ^{C}	0.81 ^{B}	0.82 ^{C}	0.88	0.83	0.86	0.93 ^{B}	0.89^{A}	0.91^{A}	0.89	0.82	0.86	0.92^{A}	0.89^{A}	0.91^{A}	0.88
SEtd	0.83	0.91 ^{C}	0.85^{X}	0.76 ^{C}	0.87	0.80	0.84	0.87^{X}	0.79^{X}	0.84^{X}	0.86	0.78	0.83	0.87^{X}	0.80 ^{C}	0.84^{A}	0.86
Average	*0.74*	*0.83* ^{C}	*0.72* ^{X}	*0.68* ^{C}	*0.77*	*0.69*	*0.74*	*0.82* ^{A}	*0.72* ^{X}	*0.78*^{A}	*0.78*	*0.68*	*0.74*	*0.81* ^{A}	*0.72* ^{A}	*0.77* ^{A}	*0.79*
DEAm																	
CEmd	0.57	0.55^{A}	0.43^{A}	0.42^{A}	0.56	0.43	0.51	0.67^{A}	0.52^{A}	0.60^{A}	0.62	0.48	0.56	0.62 ^{B}	0.50 ^{B}	0.57^{A}	0.74
AEmd	0.76	0.68^{X}	0.74^{X}	0.76^{X}	0.78	0.69	0.74	0.84 ^{B}	0.75 ^{C}	0.80^{A}	0.81	0.72	0.77	0.82^{X}	0.73^{X}	0.78^{X}	0.87
TEmd	0.74	0.79^{A}	0.58^{A}	0.59^{A}	0.72	0.63	0.68	0.79 ^{B}	0.69^{X}	0.75^{A}	0.76	0.66	0.72	0.76^{A}	0.68 ^{B}	0.73^{A}	0.84
PTEmd	0.82	0.91 ^{C}	0.73 ^{B}	0.74 ^{C}	0.82	0.76	0.80	0.89 ^{B}	0.85^{A}	0.87^{X}	0.85	0.77	0.81	0.87^{A}	0.84^{X}	0.86^{A}	0.92
SEmd	0.90	0.86^{A}	0.82 ^{B}	0.79^{A}	0.87	0.84	0.86	0.88^{X}	0.81^{X}	0.85^{X}	0.89	0.86	0.88	0.87^{X}	0.80 ^{C}	0.84^{A}	0.91
Average	*0.76*	*0.76* ^{A}	*0.66* ^{A}	*0.66* ^{A}	*0.75*	*0.67*	*0.72*	*0.81* ^{A}	*0.72* ^{B}	*0.77*^{A}	*0.78*	*0.70*	*0.75*	*0.79* ^{A}	*0.71* ^{B}	*0.76* ^{A}	*0.85*
SFAt																	
CEts	0.91	0.92^{X}	0.90^{X}	0.93^{X}	0.86	1.00	0.91	0.85^{X}	1.00 ^{B}	0.90 ^{B}	0.87	1.00	0.92	0.84^{A}	1.00^{A}	0.89^{A}	0.92
TEts	0.96	0.97^{X}	0.96^{X}	0.96^{X}	0.93	1.00	0.97	0.95^{X}	1.00^{A}	0.98 ^{B}	0.93	1.00	0.96	0.95^{A}	1.00^{X}	0.98^{A}	0.96
Average	*0.84*	*0.88* ^{X}	*0.84* ^{X}	*0.84* ^{X}	*0.83*	*0.87*	*0.85*	*0.84* ^{X}	*0.89* ^{B}	*0.87* ^{A}	*0.83*	*0.87*	*0.85*	*0.84* ^{A}	*0.89* ^{A}	*0.87* ^{A}	*0.88*
SFAm																	
CEms	0.66	0.53^{X}	0.58^{X}	0.54^{X}	0.66	0.50	0.60	0.72^{X}	0.51^{A}	0.65^{X}	0.69	0.54	0.63	0.70^{X}	0.49^{X}	0.63^{X}	0.67
TEms	0.73	0.78 ^{B}	0.72^{X}	0.72 ^{B}	0.72	0.75	0.73	0.74^{X}	0.77^{X}	0.76 ^{C}	0.73	0.75	0.74	0.73^{A}	0.77 ^{B}	0.76^{A}	0.80
PROFEs	0.47	0.68^{X}	0.62^{A}	0.40^{X}	0.46	0.61	0.53	0.63^{A}	0.76^{A}	0.69^{A}	0.45	0.57	0.51	0.63^{X}	0.77^{A}	0.69^{A}	0.64
REVEs	0.68	0.70^{X}	0.65^{X}	0.65^{X}	0.71	0.63	0.67	0.73^{X}	0.62^{X}	0.66^{X}	0.70	0.64	0.67	0.74^{A}	0.62 ^{B}	0.67^{A}	0.61
Average	*0.68*	*0.71* ^{C}	*0.69* ^{X}	*0.63* ^{C}	*0.67*	*0.69*	*0.68*	*0.73* ^{A}	*0.72* ^{B}	*0.72* ^{A}	*0.68*	*0.69*	*0.68*	*0.73* ^{A}	*0.72* ^{A}	*0.72* ^{A}	*0.71*
OVERALL	*0.74*	*0.78* ^{B}	*0.71* ^{C}	*0.68* ^{B}	*0.75*	*0.71*	*0.73*	*0.80* ^{B}	*0.74* ^{B}	*0.77* ^{A}	*0.76*	*0.71*	*0.74*	*0.79* ^{A}	*0.74* ^{A}	*0.77* ^{A}	*0.80*

Note: A, B, C stand for 1%, 5%, 10% significance level for mean difference significance tests, respectively (for columns 1 to 4, the base group is merged failures and survivors and failures are compared in pre-crisis (97-97), crisis (98-02) and entire (95-02) periods under both official insolvency [failure = 1 if closed by regulators; 0 otherwise] and factual insolvency [failure = 1, if capitalization ratio (TE/TA)< %2; 0 otherwise]); Cost (CEtd, CEmd, CEts, CEms), Allocative (AEtd, AEmd), Technical (TEtd, TEmd, TEts, TEms), Pure technical (PTEtd, PTEmd), Scale (SEtd, SEmd), Profit (PROFEms) and Revenue (REVEms) are efficiency scores computed based on Data Envelopment Analysis (d) and Stochastic Frontier Analysis (s) using traditional (t) banking technology, which does not account for off-balance sheet outputs and modern banking technology (m), which does, respectively.

Table 8a

Efficiency mobility, survival and death of banks during the pre-crisis and crisis periods – DEA traditional frontier [failure if TE/TA <2%].

	PRE-CRISIS PERIOD: 1995–1997									CRISIS PERIOD: 1998–2001								
	1995 Alive	All survivors	# of survivors by 1997 efficiency class					All defaults		1997 Alive	All survivors	# of survivors by 2001 efficiency class					All defaults	
	#	#	<.2	.2 < .4	.4 < .6	.6 < .8	.8 < 1	#	%	#	#	<.2	.2 < .4	.4 < .6	.6 < .8	.8 < 1	%	#
CEtd																		
<.2	0	0	**0**	0	0	0	0	0	n/a	1	0	0	0	0	0	0	1	100
.2 < .4	4	3	0	**1**	1	0	1	1	25	1	0	0	0	0	0	0	1	100
.4 < .6	23	23	1	0	**8**	13	1	0	0	14	12	9	3	0	0	0	2	14
.6 < .8	15	15	0	0	4	**7**	4	0	0	25	18	5	12	1	0	0	7	28
.8 < 1	8	8	0	0	1	5	**2**	0	0	8	8	1	4	1	2	0	0	0
All	*50*	*49*	*1*	*1*	*14*	*25*	*8*	*1*	*2*	*49*	*38*	*15*	*19*	*2*	*2*	*0*	*11*	*22*
AEtd																		
<.2	0	0	0	0	0	0	0	0	.	1	0	0	0	0	0	0	1	100
.2 < .4	1	0	0	0	0	0	0	1	100	0	0	0	0	0	0	0	0	.
.4 < .6	6	6	0	0	1	2	3	0	0	1	1	0	1	0	0	0	0	0
.6 < .8	13	13	0	0	0	6	7	0	0	15	13	4	2	2	4	1	2	13
.8 < 1	30	30	1	0	0	7	22	0	0	32	24	5	2	9	6	2	8	25
All	*50*	*49*	*1*	*0*	*1*	*15*	*32*	*1*	*2*	*49*	*38*	*9*	*5*	*11*	*10*	*3*	*11*	*22*
TEtd																		
<.2	0	0	0	0	0	0	0	0	.	1	0	0	0	0	0	0	1	100
.2 < .4	2	2	0	0	1	0	1	0	0	0	0	0	0	0	0	0	0	.
.4 < .6	8	8	1	0	3	4	0	0	0	4	3	2	0	1	0	0	1	25
.6 < .8	15	15	0	0	0	8	7	0	0	23	17	4	2	7	4	0	6	26
.8 < 1	25	24	0	0	0	11	13	1	4	21	18	3	2	6	3	4	3	14
All	*50*	*49*	*1*	*0*	*4*	*23*	*21*	*1*	*2*	*49*	*38*	*9*	*4*	*14*	*7*	*4*	*11*	*22*
PTEtd																		
<.2	0	0	0	0	0	0	0	0	.	1	0	0	0	0	0	0	1	100
.2 < .4	0	0	0	0	0	0	0	0	.	0	0	0	0	0	0	0	0	.
.4 < .6	5	5	0	0	2	1	2	0	0	2	2	1	0	0	1	0	0	0
.6 < .8	6	6	1	0	0	1	4	0	0	5	4	2	0	2	0	0	1	20
.8 < 1	39	38	0	0	0	3	35	1	3	41	32	6	1	0	4	21	9	22
All	*50*	*49*	*1*	*0*	*2*	*5*	*41*	*1*	*2*	*49*	*38*	*9*	*1*	*2*	*5*	*21*	*11*	*22*
SEtd																		
<.2	0	0	0	0	0	0	0	0	.	1	0	0	0	0	0	0	1	100
.2 < .4	0	0	0	0	0	0	0	0	.	0	0	0	0	0	0	0	0	.
.4 < .6	3	3	0	0	0	3	0	0	0	1	0	0	0	0	0	0	1	100
.6 < .8	11	11	1	0	1	3	6	0	0	8	6	1	1	3	1	0	2	25
.8 < 1	36	35	0	0	0	2	33	1	3	39	32	8	1	4	10	9	7	18
All	*50*	*49*	*1*	*0*	*1*	*8*	*39*	*1*	*2*	*49*	*38*	*9*	*2*	*7*	*11*	*9*	*11*	*22*
Overall	*250*	*245*	*5*	*1*	*22*	*76*	*141*	*5*	*2*	*245*	*190*	*51*	*31*	*36*	*35*	*37*	*55*	*22*

Note: All percentage figures were calculated as percentage of the number of firms alive in 1995 for the pre-crisis period (1995–1997) and 1997 for the crisis-period (1998–2001). Cost (CEtd), allocative (AEtd), technical (TEtd), pure technical (PTEtd) and scale (SEtd) efficiency scores are based on Data Envelopment Analysis (d) using traditional (t) banking technology, which does not account for off-balance sheet outputs. Defaults are based on "factual insolvency" definition, where a bank defaults if its equity ratio falls below 2%. All defaults percentage (%): percentage of failed banks as percentage of the number of banks alive in 1995 in the respective size class for the pre-crisis period and in 1997 for the crisis period.

Table 8b
Efficiency mobility, survival and death of banks during the pre-crisis and crisis periods – DEA modern frontier [failure if TE/TA <2].

	PRE-CRISIS PERIOD: 1995–1997									CRISIS PERIOD: 1998–2001								
	1995 Alive	All survivors	# of survivors by 1997 efficiency class					All defaults		1997 Alive	All survivors	# of survivors by 2001 efficiency class					All defaults	
	#	#	<.2	.2 < .4	.4 < .6	.6 < .8	.8 < 1	#	%	#	#	<.2	.2 < .4	.4 < .6	.6 < .8	.8 < 1	#	%
CEmd																		
<.2	*2*	*1*	*0*	*0*	*0*	*0*	*1*	*1*	*50*	*1*	*0*	*0*	*0*	*0*	*0*	*0*	*1*	*100*
.2 < .4	11	11	1	4	4	1	1	0	0	5	4	2	2	0	0	0	1	20
.4 < .6	17	17	0	1	3	12	1	0	0	10	8	4	3	0	0	1	2	20
.6 < .8	11	11	0	0	2	2	7	0	0	16	10	3	5	2	0	0	6	38
.8 < 1	9	9	0	0	1	1	7	0	0	17	16	4	3	6	2	1	1	6
All	50	49	1	5	10	16	17	1	2	49	38	13	13	8	2	2	11	22
AEmd																		
<.2	0	0	0	0	0	0	0	0	.	1	0	0	0	0	0	0	1	100
.2 < .4	1	0	0	0	0	0	0	1	100	0	0	0	0	0	0	0	0	.
.4 < .6	7	7	0	0	0	4	3	0	0	3	2	0	0	0	1	1	1	33
.6 < .8	13	13	1	0	1	3	8	0	0	9	7	2	0	2	2	1	2	22
.8 < 1	29	29	0	0	2	2	25	0	0	36	29	7	0	6	11	5	7	19
All	50	49	1	0	3	9	36	1	2	49	38	9	0	8	14	7	11	22
TEmd																		
<.2	1	1	0	0	0	0	1	0	0	1	0	0	0	0	0	0	1	100
.2 < .4	5	5	0	0	3	1	1	0	0	3	3	0	2	1	0	0	0	0
.4 < .6	12	11	1	2	4	2	2	1	8	7	5	3	0	1	0	1	2	29
.6 < .8	7	7	0	1	0	3	3	0	0	13	8	1	1	5	1	0	5	38
.8 < 1	25	25	0	0	0	7	18	0	0	25	22	6	2	2	5	7	3	12
All	50	49	1	3	7	13	25	1	2	49	38	10	5	9	6	8	11	22
PTEmd																		
<.2	0	0	0	0	0	0	0	0	.	1	0	0	0	0	0	0	1	100
.2 < .4	1	1	0	0	1	0	0	0	0	2	2	0	1	0	1	0	0	0
.4 < .6	6	6	0	2	2	1	1	0	0	4	2	0	0	1	0	1	2	50
.6 < .8	9	9	1	0	1	2	5	0	0	9	5	2	1	0	1	1	4	44
.8 < 1	34	33	0	0	0	6	27	1	3	33	29	7	1	0	1	20	4	12
All	50	49	1	2	4	9	33	1	2	49	38	9	3	1	3	22	11	22
SEmd																		
<.2	1	1	0	0	0	0	1	0	0	1	0	0	0	0	0	0	1	100
.2 < .4	0	0	0	0	0	0	0	0	.	1	1	0	1	0	0	0	0	0
.4 < .6	4	3	0	0	0	2	1	1	25	0	0	0	0	0	0	0	0	.
.6 < .8	9	9	1	1	0	3	4	0	0	7	7	1	1	2	1	2	0	0
.8 < 1	36	36	0	0	0	2	34	0	0	40	30	8	1	5	7	9	10	25
All	50	49	1	1	0	7	40	1	2	49	38	9	3	7	8	11	11	22
Overall	*250*	*245*	*5*	*11*	*24*	*54*	*151*	*5*	*2*	*245*	*190*	*50*	*24*	*33*	*33*	*50*	*55*	*22*

Note: All percentage figures were calculated as percentage of the number of firms alive in 1995 for the pre-crisis period (1995–1997) and 1997 for the crisis-period (1998–2001). Cost (CEmd), allocative (AEmd), technical (TEmd), pure technical (PTEmd) and scale (SEmd) efficiency scores are based on Data Envelopment Analysis (d) using modern (b) banking technology, which accounts for off-balance sheet outputs. Defaults are based on "factual insolvency" definition, where a bank defaults if its equity ratio falls below 2%. All defaults percentage (%): percentage of failed banks as percentage of the number of banks alive in 1995 in the respective size class for the pre-crisis period and in 1997 for the crisis period.

Table 8c

Efficiency mobility, survival and death of banks during the pre-crisis and crisis periods – SFA frontier [failure if TE/TA <2%].

	1995 Alive	PRE-CRISIS PERIOD: 1995–1997									1997 Alive	CRISIS PERIOD: 1998–2001								
		All survivors	# of survivors by 1997 efficiency class					All defaults				All survivors	# of survivors by 2001 efficiency class					All defaults		
	#	#	<.2	.2 < .4	.4 < .6	.6 < .8	.8 < 1	#	%		#	#	<.2	.2 < .4	.4 < .6	.6 < .8	.8 < 1	#	%	
CEts																				
<.2	0	0	0	0	0	0	0	0	.		1	0	0	0	0	0	0	1	100	
.2 < .4	3	3	0	0	1	1	1	0	0		0	0	0	0	0	0	0	0	.	
.4 < .6	7	6	0	0	2	3	1	1	14		7	6	4	0	1	1	0	1	14	
.6 < .8	13	13	0	0	2	8	3	0	0		31	24	5	0	1	18	0	7	23	
.8 < 1	27	27	1	0	2	19	5	0	0		10	8	0	0	0	5	3	2	20	
All	*50*	*49*	1	0	7	31	10	1	2		49	*38*	*9*	*0*	*2*	*24*	*3*	*11*	*22*	
TEts																				
<.2	0	0	0	0	0	0	0	0	.		1	0	0	0	0	0	0	1	100	
.2 < .4	0	0	0	0	0	0	0	0	.		0	0	0	0	0	0	0	0	.	
.4 < .6	2	2	0	0	0	0	2	0	0		0	0	0	0	0	0	0	0	.	
.6 < .8	13	13	0	0	0	0	13	0	0		0	0	0	0	0	0	0	0	.	
.8 < 1	35	34	1	0	0	0	33	1	3		48	38	9	0	0	0	29	10	21	
All	*50*	*49*	1	0	0	0	48	1	2		49	*38*	*9*	*0*	*0*	*0*	*29*	*11*	*22*	
CEms																				
<.2	0	0	0	0	0	0	0	0	.		1	0	0	0	0	0	0	1	100	
.2 < .4	0	0	0	0	0	0	0	0	.		4	4	0	0	0	0	4	0	0	
.4 < .6	0	0	0	0	0	0	0	0	.		17	12	2	0	0	0	10	5	29	
.6 < .8	0	0	0	0	0	0	0	0	.		25	20	7	0	0	0	13	5	20	
.8 < 1	50	49	1	4	17	25	2	1	2		2	2	0	0	0	0	2	0	0	
All	*50*	*49*	1	4	17	25	2	1	2		49	*38*	*9*	*0*	*0*	*0*	*29*	*11*	*22*	
TEms																				
<.2	5	5	0	2	2	1	0	0	0		1	0	0	0	0	0	0	1	100	
.2 < .4	6	5	0	3	1	1	0	1	17		9	7	6	0	0	0	1	2	22	
.4 < .6	22	22	1	3	6	12	0	0	0		11	8	5	1	1	0	1	3	27	
.6 < .8	16	16	0	1	2	7	6	0	0		21	16	13	1	0	0	2	5	24	
.8 < 1	1	1	0	0	0	0	1	0	0		7	7	3	1	1	0	2	0	0	
All	*50*	*49*	1	9	11	21	7	1	2		49	*38*	*27*	*3*	*2*	*0*	*6*	*11*	*22*	
PROFms																				
<.2	1	1	1	0	0	0	0	0	0		6	4	1	0	0	1	2	2	33	
.2 < .4	1	1	1	0	0	0	0	0	0		16	10	5	0	0	0	5	6	38	
.4 < .6	10	10	4	5	1	0	0	0	0		12	10	3	0	0	0	7	2	17	
.6 < .8	21	21	0	11	9	1	0	0	0		10	9	1	0	0	2	6	1	10	
.8 < 1	17	16	0	0	2	9	5	1	6		5	5	0	0	0	0	5	0	0	
All	*50*	*49*	6	16	12	10	5	1	2		49	*38*	*10*	*0*	*0*	*3*	*25*	*11*	*22*	
REVEms																				
<.2	0	0	0	0	0	0	0	0	.		1	0	0	0	0	0	0	1	100	
.2 < .4	2	2	0	0	1	1	0	0	0		0	0	0	0	0	0	0	0	.	
.4 < .6	10	10	0	0	1	9	0	0	0		2	2	1	1	0	0	0	0	0	
.6 < .8	28	28	0	0	0	23	5	0	0		37	28	10	9	3	5	1	9	24	
.8 < 1	10	9	1	0	0	4	4	1	10		9	8	2	2	0	2	2	1	11	
All	*50*	*49*	1	0	2	37	9	1	2		49	*38*	*13*	*12*	*3*	*7*	*3*	*11*	*22*	
Overall	*300*	*294*	11	29	49	124	81	6	2		294	*228*	*77*	*15*	*7*	*34*	*95*	*66*	*22*	

Note: All percentage figures were calculated as percentage of the number of firms alive in 1995 for the pre-crisis period (1995–1997) and 1997 for the crisis-period (1998–2001). Cost (CEts, CEms) or Technical (TEts, TEms) or Profit (PROFEms) or Revenue (REVEms) efficiency score computed based on either Stochastic traditional (ts) or modern (ms) banking frontier; defaults are based on "factual insolvency" definition, where a bank defaults if its equity ratio falls below 2%. All defaults percentage (%): percentage of failed banks as percentage of the number of banks alive in 1995 in the respective size class for the pre-crisis period and in 1997 for the crisis period.

functional form.[27] The probability that a default will occur at a particular time is hypothesized to be a function of a vector of lagged explanatory variables. The explanatory factors we used fall into two main categories: 1) *managerial quality factors*, which are proxied by ten DEA and six SFA efficiency scores, 2) *other control factors*, which are bank specific and macroeconomic factors that are plausibly associated with the probability of bank failure. Many banks in our sample did not experience default during the crisis and hence serve as controls. Because economic conditions play an important role in the failure of banks, variables to proxy a bank's economic environment are also critical to consider. All explanatory factors are lagged one year to predict future defaults. In these models, the dependent variable ($y = Failure$) is a dummy that took on the value of 0 for survivors and 1 for defaults according to two different failure definitions, *official insolvency* in Panel A and *factual insolvency* in Panel B. Hence, a negative (positive) coefficient means that the variable is inversely (directly) related to default and directly (inversely) related to survival.[28] We insert each efficiency score separately into the models while keeping the same set of controls to detect the net predictive power of each efficiency score.[29] Furthermore, different years could have different average efficiency across the population of banks, such that a given absolute value of the efficiency metric can be relatively good or relatively bad, depending on the year.[30] Hence, unlike other *failure-efficiency* studies, efficiency scores used in our probit regressions are adjusted by the average for the year, i.e., we normalized our efficiency variables by aggregating them into deciles within each year, with 'one' being the lowest and 'ten' being the highest decile within each efficiency measure for each year. The models with *quantile* efficiency measures are reported in Table 9, while the models with *absolute* efficiency scores are provided in Appendix C for comparison. As a final refining, we also incorporated the differences in certain variables as explanatory variables in probit models to see if the momentum of variation in these variables have any failure prediction power.

As hypothesized, the results suggest that the probability of bank failures is *negatively* associated with efficiency. The lower the efficiency, regardless which sort and what failure definition, the lower the probability of survival. Less efficient banks are apparently also poor in economizing resources (TE and PTE), allocating bank inputs (AE), making scale choices (SE), generating enough revenues (REVE), controlling costs (CE), and eventually making profits (PROFE). Most and the strongest statistical associations between efficiency and risk of default are seen under the "*factual insolvency*" definition, suggesting that politics might be involved in the official closure decisions of regulators. Since one major mission of this study is to assess the importance of the managerial efficiency in the prediction of bank failures, we also present the classification results with and without efficiency measures. We assess the quality of the prediction models based on three criteria: 1) overall indicator of model fit, 2) Akaike Information Criterion (AIC), and 3) classification accuracy. For measuring model fit, we resort to McFaden's Pseudo-R^2, which is based on the ratio of the likelihoods that suggests the level of improvement over the intercept model offered by the full model. Thus, when comparing two models on the same data, the higher McFadden's R^2 would be better for the model. The AIC is calculated as minus the log-likelihood of the model plus the number of parameters being estimated, and it is hence smaller for better models. To judge the prediction accuracy of the various models, we use the percentage of defaults that are correctly classified by the model. When *no efficiency* measure was used, the model correctly classified 73.91% of the failures under "*official insolvency*" and 75.25% under "*factual insolvency*" definitions. Using efficiency measures, irrespective of the kind, considerably increased the accuracy of failure prediction, underlining the importance of management in the success or failure of a bank. Specifically, model statistics reveal that PTEmd and TEmd scores (technical efficiency scores computed with DEA under modern banking technology with VRS and CRS assumptions respectively) under the "*factual insolvency*" definition achieves the highest default prediction = 90.63% with the highest psedudo-R^2 = 38% and the lowest AIC = 150.18. The same scores also provide the highest failure prediction power stats (86.96%) under the "*official insolvency*" definition but with lower values.[31] Our 16% improvement in failure prediction by means of certain efficiency scores significantly outperforms the 3% improvement achieved

[27] The probit model is commonly used in studying banking failures. See, for example, Barr et al. (1994) and Isik and Folkinshteyn (2017). A probit model with random effects is compatible with utilizing the whole dataset. With this approach, the probability that a default occurs is assumed to be a function of a vector of explanatory variables. A probit econometric model is fitted to the data and an estimate of the default probability is obtained by maximizing the likelihood function. Hence, the model generates a summary measure of fragility (the estimated probability of default) which makes the best possible use of the information in the explanatory variables.

[28] The estimated coefficients in Table 9 do not indicate the increase in the probability of a failure given a one-unit increase in the corresponding independent variables as in standard linear regression models. Rather, the coefficients capture the effect of a change in an independent variable. Hence, while the sign of the coefficient *does* indicate the direction of the change, the magnitude depends on the slope of the cumulative distribution function. The precise marginal effect of an independent variable could be attained by: $\frac{\delta P(y=1|\, x)}{\delta x_c} = \varphi(\mathbf{x\beta})\boldsymbol{\beta}_c$, where φ denotes the standard normal probability density function.

[29] Because our emphasis is on managerial efficiency, we provide the averages of the coefficients for the control variables in probit regressions with each efficiency score. The significance of the coefficients of these control variables reflects the most frequently observed (mode) significance.

[30] Individual or average efficiency scores, say 0.57 in year X, when times were good could be poor, while the same performance could be a good performance when times were bad; a 0.57 efficiency score could be in the 50th percentile in some years and the 90th percentile in others.

[31] These scores are also among the top performers in predicting the risk of failures under the models with absolute efficiency levels summarized in Appendix C. These results confirm the choices of some earlier researchers of *technical efficiency* as a proxy for management quality while studying failures. Perhaps, there is substantial noise in input and output prices that go into non-technical efficiency measures, such as AE, CE, PROFE and REVE or we simply fail to correctly estimate them.

by Barr et al. (1994) and 5% by Isik and Folkinshteyn (2017).[32] When we compare the models that use the *deciles of efficiency* (Table 8) with the models that use *absolute levels* of efficiency (Appendix C), we see that the highest accuracy achieved is 90.63% in the former while it is 84.38% in the latter. Evidently, both are accomplished when default is defined as "*factual insolvency.*" Also, the wedge between failure definitions is preserved for individual scores save PROFEms. The fact that we achieved the largest accuracy improvement in the relevant literature by efficiency scores, especially those computed based on modern banking technology, deciles of efficiency, and factual insolvency, underlines the significance of accurate formulation of the efficiency and failure models.

As for other factors, some have strong and independent associations with failure on top of managerial quality. We find that well-capitalized banks (CapRat) are less likely to default, as expected. Such banks have a larger safety cushion to absorb shocks and losses. Also, higher capital accumulated over the years may signal lower moral hazard problem and *ex-post* profitability, franchise value, and reputation. We also see that most of the defaulted banks suffered from inadequate liquidity with respect to their assets. The coefficients of LA_TA and ΔLA_TA are negative and significant at the 1% and 5% levels, respectively, under "*factual insolvency.*" In critical times, those banks that lack liquid assets or have exhausted their borrowing capacity are evidently susceptible to bank runs and even sudden death. Also, we found that the larger the FXA_FXL and ΔFXA_FXL ratios, the lower the probability of default, with significant negative coefficients in all models (1% = A to 5% = B), implying that banks with low open FOREX positions, i.e., large amount of 'FX Assets' to cover their "FX Liabilities" (FXA_FXL) are more likely to survive. The heavy foreign exchange borrowings of Turkish banks in a more liberal environment seem to have created large open positions in bank portfolios (unhedged FX positions rose to 120% of their capital in the 1990s), which naturally made them vulnerable to capital flights and sharp devaluations. Moreover, the "Cong_Aff" dummy variable, which attains the value of 1 if the bank is controlled by a business conglomerate, 0 otherwise, has a significant positive coefficient in all models. This suggests that banks associated with such groups are more likely to fail. The charters of these affiliated banks were mostly granted right before major elections, evidences of insider lending were rampant in these banks, and most of them failed soon in the first major test; all of which implies that they were probably pure adverse selection episodes. Finally, substantial hikes in average interest rates (ΔAvIntRat) seem to be negatively related to default. Banks are notorious in adjusting the interest rates on loans faster than the rates on deposits. Given the higher elasticity of loan rates, banks seem to benefit in times of serious interest rate jumps. However, we should caution that this negative association is statistically significant only in models with "*official insolvency.*"[33]

Incorporating an endogenous factor into a multivariate model can bias the coefficients even on the exogenous variables, and perhaps all variables we use are partly endogenous and partly exogenous. Hence, in addition to the multivariate probit regressions, to further assess the usefulness of efficiency measures, we calculated univariate correlation coefficients between failure dummy and efficiency scores. The results that are presented under the column labeled CORR in Table 9 confirm that all efficiency scores are negatively correlated with failure and even more strongly so under "*factual insolvency*" definition. In general, DEA scores seem to have higher correlation with failure than SFA scores do. The TEmd and PTEmd scores, which had the highest failure prediction accuracies under the multivariate probit models, are also among the variables that demonstrate the closest association with failure. In the spirit of Bauer et al. (1998), we also tested the connection of our DEA as well as SFA efficiency scores with popular financial ratios.[34] Table 10 presents the correlations between 16 efficiency scores and four traditional performance ratios: OUT_INP (total outputs divided by total inputs; a proxy for technical efficiency); COST_TA (total operational costs to total assets; a proxy for cost inefficiency); TA_EMP (total bank assets per employee; a proxy for labor productivity); and ROA (return on assets; a proxy for overall managerial efficiency). The null hypothesis is that the correlation between two factors is zero. The results suggest that our DEA and SFA efficiency measures are strongly positively associated with input (OUT/INP), labor (TA/EMP) and asset (ROA) productivities and significantly negatively correlated with higher costs (COST/TA), suggesting that our efficiency estimates are rather robust. PROFEs score among the SFA measures and the CE score among the DEA measures have the highest association with raw measures of performance. As far as the frontiers, efficiency estimates based on DEA rather than SFA, modern as opposed to traditional banking technology tend to be more consistent with the proxy-measures of performance in Table 10 (as well as with the crisis dummy in Table 6 and failure dummy in Table 9). Also, we observe that, although based on much smaller sample size, Turkish banking efficiency scores are more closely associated with traditional ratios than their U.S. counterparts, as reported by Bauer et al. (1998) [e.g.; DEA: CE-ROA = 0.11; CE-COST/TA = −0.10; SFA: CE-ROA = 0.24; CE-COST/TA = −0.22] and Berger and Mester (1997) [SFA: CE-ROA = 0.25; CE-COST/TA = −0.21]. It may be that since the U.S. banking market is much larger, it contains more heterogeneous banks with very different business orientations, local market, and regulatory conditions.

Hitherto, in the efficiency/crisis analysis (e.g., Table 3), we compared industry efficiency across years, and in the efficiency/default analysis (e.g., Table 7), we contrasted the efficiency of failed and survived banks with scores coming from different annual frontiers. Because the reference frontier may not be the same across years due to innovation/shock and entries/exits in the industry, "static"

[32] Our about 91% failure accuracy is higher than 89.5% of Barr et al. (1994) whose model outperformed the accuracy of earlier models with no efficiency measure in the US. The bankruptcy literature indicates that the predictive value of financial variables is diminished when the sample firms fail because of fraud and defalcation. Thus, improvement record of our models should be fairly judged given the fact that the owners of many failed banks were prosecuted by Turkish regulators for fraud and embezzlement as well as the existence of noise inherent in emerging market data (Isik and Folkinshteyn, 2017).

[33] Change in asset quality (ΔNPL_TL), profitability (ROE) and economic growth (GDPGrwth), do not seem to exert any significant effect on risk of default as they either lose their explanatory power once other factors are taken into account or our measures are simply poor proxies.

[34] To be consistent with reality and be believable, regardless of the frontier they are borne from, efficiency scores should be closely related to traditional (non-frontier) measures of performance. However, the associations need not be perfect (1.00), as the financial ratios represent not only the efficiencies, but also the differences in input prices and other external factors over which managers have limited control.

Table 9
Multivariate failure models - with DEA and SFA frontier efficiencies by deciles.

Variables	Panel A: Official insolvency					Panel B: Factual insolvency				
	β	AIC	Pseu- R^2	FailPre%	CORR	β	AIC	Pseu-R^2	FailPre%	CORR
No efficiency	–	125.93	0.36	73.91	–	–	159.82	0.33	81.25	–
Efficiency Variables										
DEAt										
CEtd	−0.15	125.61	0.38	78.26	−0.15^{A}	−0.22^{B}	155.52	0.36	78.13	−0.23^{A}
AEtd	−0.05	127.54	0.36	78.26	−0.09^{C}	−0.09	160.15	0.33	84.38	−0.08^{C}
TEtd	−0.10^{C}	124.94	0.38	82.61	−0.10^{C}	−0.15^{A}	153.50	0.37	87.50	−0.25^{A}
PTEtd	−0.06	126.53	0.37	82.61	−0.17^{A}	−0.10^{B}	157.00	0.35	87.50	−0.26^{A}
SEtd	−0.09	125.79	0.38	78.26	−0.00	−0.09^{C}	158.54	0.34	87.50	−0.13^{A}
DEA-m										
CEmd	−0.14^{C}	124.73	0.38	82.61	−0.18^{A}	−0.20^{A}	154.17	0.36	84.38	−0.17^{A}
AEmd	−0.04	127.69	0.36	78.26	−0.14^{A}	−0.07	160.57	0.33	87.50	−0.05
TEmd	−0.16^{B}	122.46	0.40	86.96	−0.13^{A}	−0.21^{A}	150.18	0.38	90.63	−0.19^{A}
PTEmd	−0.11^{C}	124.23	0.38	86.96	−0.17^{A}	−0.17^{A}	150.46	0.38	90.63	−0.15^{A}
SEmd	−0.08	127.06	0.37	78.26	−0.02	−0.04	161.56	0.33	81.25	−0.13^{A}
SFAt										
CEts	−0.32^{A}	118.25	0.42	78.26	−0.10^{C}	−0.20^{B}	157.02	0.35	87.50	−0.21^{A}
TEts	−0.27^{B}	122.02	0.40	78.26	−0.11^{B}	−0.17^{C}	158.42	0.34	87.50	−0.15^{A}
SFAm										
CEms	−0.07	127.44	0.37	78.26	−0.04	−0.01	161.79	0.33	81.25	0.07
TEms	−0.00	127.93	0.36	78.26	−0.08^{C}	−0.03	161.55	0.33	81.25	−0.19^{A}
PROFEms	−0.03	127.78	0.36	78.26	−0.27^{A}	−0.02	161.64	0.33	78.13	−0.15^{A}
REVEms	−0.09	127.05	0.37	78.26	−0.02	−0.01	161.81	0.33	78.13	−0.20^{A}

Control Variables	β DEAt	β DEAm	β SFAt	β SFAm	CORR	β DEAt	β DEAm	β SFAt	β SFAm
Constant	0.05	0.41	1.24	−0.08	–	2.07^{A}	2.40^{A}	2.46^{A}	1.51^{C}
CapRat	−6.39^{A}	−6.12^{A}	−5.75^{A}	−6.60^{A}	–	−5.79^{A}	−5.57^{A}	−5.11^{B}	−6.02^{A}
ΔNPL_TL	0.31	0.23	0.38	0.29	–	−0.05	−0.12	0.03	0.07
ROE	−0.03	−0.03	−0.03	−0.03	–	−0.03	−0.03	−0.02	−0.02
LA_TA	−1.16	−1.34	−1.26	−1.14	–	−3.05^{A}	−3.25^{A}	−2.77^{A}	−2.78^{A}
ΔLA_TA	0.84	0.90	1.07	0.78	–	2.56^{B}	2.62^{B}	2.43^{A}	2.43^{B}
Cong_Aff	1.08^{B}	1.13^{B}	1.26^{A}	1.02^{B}	–	0.87^{B}	0.94^{A}	0.85^{A}	0.78^{B}
FXA_FXL	−1.44^{B}	−1.55^{B}	−1.68^{B}	−1.41^{B}	–	−2.14^{A}	−2.26^{A}	−2.14^{A}	−2.05^{A}
ΔFXA_FXL	−1.19^{C}	−1.15^{C}	−1.24^{C}	−1.28^{A}	–	0.36	0.38	0.29	0.28
GDPGrwth	−0.72	−1.13	1.63	−1.47	–	−0.10	−0.88	1.00	−0.93
ΔAvIntRat	−0.14^{B}	−0.14^{B}	−0.16^{B}	−0.13^{B}	–	−0.05	−0.05	−0.05	−0.04

Note: A, B, C stand for 1%, 5%, 10% significance level, respectively. These tests are based on the deciles rather than raw values of efficiency scores [deciles within each year, with '1' being the lowest and '10' being the highest decile within each efficiency measure for each year]. Multivariate probit models try to estimate the chance of being closed by regulators (failure = 1 if closed by regulators; 0 otherwise) under "official insolvency" definition in Panel A, while they predict the risk of capitalization ratio falling below 2% under "factual insolvency" definition in Panel B (failure = 1, if capitalization ratio (TE/TA)< %2; 0 otherwise) based on a list of management quality proxy variables (16 efficiency scores) and bank specific and macro control variables: Cost (CEtd, CEmd, CEts, CEms), Allocative (AEtd, AEmd), Technical (TEtd, TEmd, TEts, TEms), Pure technical (PTEtd, PTEmd), Scale (SEtd, SEmd), Profit (PROFEms) and Revenue (REVEms) efficiency scores computed based on Data Envelopment Analysis (d) and Stochastic Frontier Analysis (s) using traditional (t) banking technology, which does not account for off-balance sheet outputs and modern banking technology (m), which does, respectively; CapRat = TE/TA = total equity divided by average total assets (TA); ΔNPL_TL = the change in the ratio of non-performing loans to total loans; ROE = return on equity measured as net income divided by TE; LA_TA = liquid current assets divided by TA (liquidity ratio); ΔLA_TA is annual change in the liquidity ratio, Cong_Aff = a dummy variable, which attains the value of 1 if the bank is controlled by a business conglomerate; 0 otherwise; FXA_FXL = foreign exchange denominated assets divided by foreign exchange denominated liabilities (forex ratio); ΔFXA_FXL is annual change in forex ratio, GDPGrwth = annual change in GDP per head = gross domestic product per capita in US dollars; ΔAvIntRat = annual change in the average interest rates. The coefficients of the control variables represent averages of the coefficients obtained by running probit regressions with each efficiency score. The coefficient significance of each control variable reflects the most frequently observed (mode) significance in the probit models run for each efficiency score.

efficiency scores (calculated only with respect to each year's annual frontier) might bias inter-temporal comparison of performance. To address this legitimate question, following Isik and Hassan (2003c) and Topuz and Isik (2009), we finally appeal to a DEA-type Malmquist *total factor productivity change* (tfpch) index (Table 11), which requires fixed frontier across years in calculating tfpch index and its sub-components, *efficiency change* (effch), movement towards the frontier and *technological change* (techch), shift in the frontier. It also decomposes effch into *pure efficiency change* (pech) and *scale efficiency change* (sech) to see if the movements under the frontier (catching up or falling behind) are mainly due to management maneuvers or size adjustments, respectively (tfpch = techch * effch and effch = pech * sech, thus, tfpch = tecch * pech * sech). In Panel A, the annual results are based on the 1995 fixed frontier; hence, a value greater (less) than one refers to an improvement (deterioration) in the relevant index in subsequent years under traditional (Panel 1) and modern (Panel 2) banking technologies. The overall Malmquist index (tfpch) falls by 14.1%–16.4% during the crisis period and rebounds by 8.6%–12.3% during the post-crisis period under traditional and modern banking technologies,

Table 10
Correlation coefficients between efficiency scores and standard measures of performance.

	OUT_INP	COST_TA	TA_EMP	ROA
DEA & SFA indices				
DEAt				
CEtd	0.54 A	−0.35 A	0.37 A	0.37 A
AEtd	0.27 A	−0.22 A	0.13	0.18 A
TEtd	0.49 A	−0.25 A	0.39 A	0.36 A
PTEtd	0.40 A	−0.20 A	0.28 A	0.38 A
SEtd	0.30 A	−0.15 A	0.27 A	0.14 A
DEAm				
CEmd	0.50 A	−0.51 A	0.36 A	0.32 A
AEmd	0.33 A	−0.40 A	0.19 A	0.19 A
TEmd	0.44 A	−0.42 A	0.34 A	0.31 A
PTEmd	0.36 A	−0.33 A	0.27 A	0.26 A
SEmd	0.24 B	−0.25 A	0.21 A	0.15 B
SFAt				
CEts	0.49 A	−0.20 B	0.33 A	0.29 A
TEts	0.22 A	−0.02	0.15 A	0.05
SFAm				
CEms	0.07	−0.17 C	0.10	0.03
TEms	0.18 A	−0.37 A	0.18 A	0.25 A
PROFEms	0.37 A	−0.22 A	0.27 A	0.26 A
REVEms	0.18 A	0.04	0.10	0.33 A
Conventional ratios				
OUT_INP	1.00	−0.32 A	0.88 A	0.22 A
COST_TA	−0.32 A	1.00	−0.24 A	−0.62 A
TA_EMP	0.88 A	−0.24 A	1.00	0.12 B
ROA	0.22 A	−0.62 A	0.12 B	1.00

Note: This table summarizes the Pearson correlation coefficients among the efficiency scores and proxy-measures of performance. A, B, C stand for 1%, 5% and 10% significance levels for the test of the null hypothesis is that the correlation coefficient between two variables is zero. DEA frontier efficiencies (d): Cost (CEtd, CEmd), Allocative (AEtd, AEmd), Technical (TEtd, TEmd) or Pure technical (PTEtd, PTEmd) and Scale (SEtd, SEmd) efficiency scores computed based on either DEA traditional (t) and DEA modern (m) banking frontiers, respectively; Stochastic frontier efficiencies (s): Cost (CEts, CEtm), Technical (TEts, TEms), Profit (PROFEms), and Revenue (REVEms) efficiency scores computed based on either stochastic traditional (ts) or modern (ms) banking frontier; where traditional (t) banking technology does not account for off-balance sheet outputs and modern banking technology (m) does; Proxy-measures of performance: OUT_INP = the sum of all bank outputs divided by the sum of all bank inputs; proxies gross productivity/efficiency; COST_TA = the sum of total interest and non-interest expenses divided by total assets, which is average cost and proxies cost efficiency; TA_EMP, total assets divided by total number of employees, proxies productivity level per employee; ROA, return on assets is net income divided by average total assets and proxies productivity of asset base.

respectively. Technological regress or shock (tecch), i.e., 13.3% & 14.6% shrinkage in the traditional & modern frontiers, respectively, and incorrect scale adjustments (sech) under both frontiers (2.9%–4.5%) seem to be the main culprits for the sharp decline in the productivity (tfpch) of banks during crisis. Overall, the Malmquist fixed frontier results (Panels A/1/2) confirm our earlier static analysis by signifying a similar U-shaped behavior in productivity around the crisis. Nevertheless, because this balanced panel dataset approach asks all banks to be present throughout the study period (we have 26 such banks), it is afflicted with *survivorship bias*; i.e., in solving the potential inter-temporal comparison bias, this method throws out the baby with the bathwater, so to speak. Alas, part of our study interest (efficiency/default) is in the performance of these non-survivors. To reconcile this conflict, we re-measured tfpch index and its sub-components based on successive (pairwise) frontiers in Panel B, i.e., we fixed the frontier in the previous year rather than the initial year (1995) for every year during the study period; hence, becoming able to cover both failed and survivor banks and maintain a common benchmark. The results from this methodological twist in Panels B/1/2 further dramatize the impact of a crisis on bank performance; all Malmquist indexes during the crisis are much lower than those in both pre- and post-crisis periods (all even below unity in Panels B/2). Furthermore, all *failed banks* have not only become less efficient (effch, pech and sech) but also less productive (tfpch) during the study period, confirming again the results from our static efficiency-default analysis.[35] Finally, the inferior performance of non-survivors tends to be more strongly underlined by the *factual insolvency* definition.

6. Summary and concluding remarks

The growing intensity, frequency and cost of banking crises and defaults, especially since the growth of liberalization and integration of financial markets in the 1980s, remind us that we have still a lot to learn about the causes and consequences of these shocks. In this paper, we turn the spotlight on the episodes and institutions of emerging markets, given the fact that they more prone to such

[35] Although "efficiency" and "productivity" terms are often used interchangeably, they refer to different aspects of production performance. A fully efficient firm may not be fully productive, as a firm may be technically efficient but may still be able to improve its productivity by exploiting economies of scale (Topuz and Isik, 2009).

Table 11
Decomposition of total factor productivity change (tfpch) during the pre-crisis, crisis, and post-crisis periods.

	Panel A: Based on fixed frontier						Panel B: Based on successive frontiers					
Panel 1	*Traditional banking technology (without OFF-BSs)*											
Year	#	tfpch	techch	effch	pech	sech	#	tfpch	techch	effch	pech	sech
1995	26	1.000	1.000	1.000	1.000	1.000	49	1.000	1.000	1.000	1.000	1.000
1996	26	1.224	1.129	1.084	0.996	1.088	49	1.263	1.197	1.055	1.051	1.004
1997	26	1.013	1.074	0.944	0.976	0.967	51	1.002	0.998	1.004	0.976	1.029
1998	26	0.984	1.044	0.943	0.995	0.947	53	0.901	1.041	0.866	0.947	0.914
1999	26	0.969	1.075	0.901	0.938	0.961	47	0.995	1.123	0.886	0.924	0.959
2000	26	0.995	0.911	1.092	1.076	1.014	45	1.069	1.043	1.025	0.983	1.043
2001	*26*	*0.964*	*0.847*	*1.137*	*1.061*	*1.072*	*35*	*0.849*	*0.959*	*0.886*	*1.045*	*0.847*
2002	26	1.064	0.951	1.119	1.013	1.104	35	0.980	0.709	1.383	1.121	1.233
Pre-crisis		1.119	1.102	1.014	0.986	1.028		1.133	1.098	1.030	1.014	1.017
Crisis		*0.978*	*0.969*	*1.018*	*1.018*	*0.999*		*0.954*	*1.042*	*0.916*	*0.975*	*0.941*
Post-crisis		1.064	0.951	1.119	1.013	1.104		0.980	0.709	1.383	1.121	1.233
Official failures		-	-	-	-	-	*27*	*1.125*	*1.078*	*1.059*	*1.032*	*1.024*
Official survivors		–	–	–	–	–	36	1.213	1.024	1.183	1.048	1.130
Factual failures		-	-	-	-	-	*35*	*1.095*	*1.068*	*1.029*	*0.998*	*1.025*
Factual survivors		–	–	–	–	–	28	1.229	1.028	1.200	1.066	1.131
Panel 2	*Modern banking technology (with OFF-BSs)*											
1995	26	1.000	1.000	1.000	1.000	1.000	49	1.000	1.000	1.000	1.000	1.000
1996	26	1.236	1.117	1.106	0.998	1.108	49	1.264	1.187	1.065	1.075	0.991
1997	26	0.991	1.057	0.937	0.969	0.967	51	1.004	0.978	1.027	0.969	1.059
1998	26	0.97	1.004	0.966	1.009	0.957	53	0.916	1.042	0.879	0.954	0.916
1999	26	1.001	1.073	0.933	0.968	0.964	47	0.977	1.067	0.916	0.947	0.967
2000	26	1.011	0.919	1.1	1.081	1.017	45	1.069	1.053	1.015	0.968	1.049
2001	*26*	*0.818*	*0.766*	*1.068*	*1.034*	*1.033*	*35*	*0.714*	*0.711*	*1.004*	*1.095*	*0.917*
2002	26	1.073	0.955	1.123	0.992	1.131	35	0.995	0.729	1.365	1.091	1.252
Pre-crisis		1.114	1.087	1.022	0.984	1.038		1.134	1.083	1.046	1.022	1.025
Crisis		*0.950*	*0.941*	*1.017*	*1.023*	*0.993*		*0.919*	*0.968*	*0.954*	*0.991*	*0.962*
Post-crisis		1.073	0.955	1.123	0.992	1.131		0.995	0.729	1.365	1.091	1.252
Official failures		-	-	-	-	-	*27*	*1.119*	*1.063*	*1.061*	*1.034*	*1.025*
Official survivors		–	–	–	–	–	36	1.184	0.983	1.209	1.049	1.154
Factual failures		-	-	-	-	-	*35*	*1.081*	*1.048*	*1.037*	*1.003*	*1.030*
Factual survivors		–	–	–	–	–	28	1.204	0.989	1.223	1.065	1.153

Note: tfpch = total factor productivity change; tecch = technological change; effch = efficiency change; pech = pure efficiency change; sech = scale efficiency change; where tfpch = tecch*effch and effch = pefch*sech. Panel A (B) indices are based on DEA Malmquist model without (with) modern banking services (OFF-BSs). Fixed (successive) frontier model uses 1995 (previous year) as the reference frontier for annual tfpch indexes. Crisis period (1998–2001) is in which there are at least 3 bank failures; pre-crisis (1995–97) and post-crisis (2002) are the years where no or less than 3 banks failed. Official failure happens when a bank is closed by regulators; factual failure occurs whenever a bank becomes insolvent (TE/TA <2%).

crisis and have limited resources to fight them. By treating Turkey as our "research laboratory", we test the usefulness of ten DEA and six SFA based efficiency measures in understanding bank defaults and crises in an emerging market. Our results indicate that bank outputs are more elastic than bank inputs during crises, i.e., the shrinkage on the output side is much greater than the downsizing on the input side. In accordance with this casual observation, one should expect a significant efficiency loss during the crisis and an efficiency rebound after the crisis. The grand average of the sixteen efficiency scores indeed shows the hypothesized U-shape evolution of the efficiency scores. These main results hold true when we conduct the analyses with percentages of banks with efficiency loss or rise rather than absolute efficiency values, when we compare the kernel distributions of efficiency scores between sub-periods, and when we analyze the linkage of efficiency measures with the crisis in a multivariate framework or with Malmquist indexes. Among the DEA scores, overall modern and traditional cost efficiency (CE) scores reflect the highest efficiency loss experienced during the crisis period. Since CE = AE*TE and TE = PTE*SE, subcomponent scores naturally tend to reflect partial changes and understate the overall changes. Our results uncover that during the crisis, increased cost inefficiencies are mostly driven by rises in allocative inefficiencies rather than technical inefficiencies, while technical efficiency problems mainly result from rises in scale inefficiencies rather than pure technical inefficiencies. Evidently, due to high and volatile inflation, prices of bank inputs swing wildly during crises, which hampers the ability of bank managers to allocate their limited resources to their best uses. Additionally, given the wild shifts in the demand for banking services during the crisis, bank managers apparently mishit the right output scale in terms of cost minimization.

Moreover, however measured, all efficiency scores individually or collectively underline the strong supremacy of survivors to failed banks in terms of efficiency and productivity during the entire study period, with a strong implication that poor management of failing banks may not be accidental. The results also demonstrate that the least efficient banks are nationalized, indicating that the lower the efficiency of failed banks, the lower the chance to be acquired by private bidders. In addition, the efficiency mobility analysis indicates that 92% of failures occurred during the crisis period. The highest efficient banks had the highest survival rate, ranging from 75% to 100%. More strikingly, while demotions to a lower efficiency class were rarer in the pre-crisis period, all banks have faced demotion during the crisis by some estimates. Finally, multivariate probit regressions suggest that the lower the efficiency, irrespective of the kind, the higher the probability of default. Thus, regulators had better deploy their limited examination resources on inefficient banks to alert and turn them around before it becomes too late. Or as in preventive medicine, regulators can contain the future bailout costs significantly by promoting efficient operations among banks. They could even consider charging inefficient banks higher deposit insurance premiums since they are more likely to fail. The DEA technical efficiency scores, which are obtained with modern banking technology, achieved the highest default prediction among the 16 alternative scores and the largest improvement (16%) reported in the efficiency literature. This notable research gain is attained with: the adoption of "*factual insolvency*" rather than "*official insolvency*" as failure definition, the inclusion of modern banking services such as off balance sheet activities in modeling efficiency, the usage of the deciles of efficiency instead of absolute values to account for distributional differences across "bad" and "good" years, the incorporation of the changes in some key variables, and the choice of more homogenous sample of banks, among other refinements. DEA scores are not only generally more consistent with traditional measures of performance than SFA scores but also perform better in analyzing crises and defaults, at least in our case. Unlike SFA, DEA is not limited to a single output, and is directed to identify the best practice units on the frontier, not central location of the data, thereby DEA might be better reflecting the growing complexity of banking and uncovering relationships that remain hidden for SFA. Among the DEA scores, we found that *cost efficiencies* are better describing the crises while *technical efficiencies* are better linking efficiency to the risk of failures. This outcome makes sense because technical efficiencies are computed with the *quantities* of output and inputs, which are mostly under the control of bank management; whereas, cost efficiencies require the *prices* of these production factors, which are either market or regulatory driven, hence, decided by external forces beyond management. Apparently, lower technical inefficiencies seem to reflect poor management to a greater extent, which is critical for the viability of banks (micro failures), while lower cost inefficiencies seem to reflect mainly poor regulatory or political management, which is critical for the health of financial systems (macro failures). At the macro level, higher *cost inefficiencies* resulting from exacerbating allocative and scale inefficiencies as well as higher costs dealing with rising problem loans during crisis blame regulators for crises. At the micro level, higher *technical inefficiencies* more commonly observed in failed banks facing the same external conditions accuse management for defaults, perhaps justifying the unifying theme of macro and micro analyses in this paper.

Given that today's managers run much larger and more diverse global or domestic businesses with multitude of tasks, business lines, and locations, it would be unfair to expect a single efficiency measure to reflect all the performance aspects of the modern management. Hence, given modern computing power and resources, future researchers could expand their toolkit with alternative applications and measures of performance to explain complex phenomena such as defaults and crises since many of the methods used in isolation are often incapable of accurately predicting crises and defaults. In this respect, future research may incorporate efficiency scores into artificial intelligence techniques, such as neural networks and learning machines, which is an avenue with strong potential, yet has been neglected for some time. Furthermore, future research could also integrate efficiency scores into early warning models to predict banking, financial and economic crises. Efficiency scores have been utilized in the prediction of bank defaults but not crises to the best of our knowledge. To conduct such analysis, one needs several crisis episodes, which could be achieved with sufficiently long time series datasets and "*factual insolvency*" failure definition at the country level and with several crisis episodes at the cross-country level. However, such attempts will be stronger with a sound theory that relates efficiency to financial and institutional stability. Future research could also replicate our study partially or fully with a focus on stochastic and non-stochastic productivity growth models. On the methodology side, the current discriminant models predict the likelihood of banks (economies) falling into two groups: survival (boom) and failure (bust). Future research can also seek for ways to discriminate among more groups in intermediate categories as in credit rating classifications. Finally, so far, most research is based on annual data; however, a year could be too far to foretell an approaching crisis or failure. The time it takes for adverse economic shocks to be transmitted to the banking system might be quite short. Hence, whenever and wherever more frequent data is available, the accuracy and usefulness of the models could be enhanced with up-to-date inputs, which is worth further investigation.

Authorship contributions

Conception and design of study: I. Isik; acquisition of data: I. Isik; analysis and/or interpretation of data: I. Isik, O. Uygur; drafting the manuscript: I. Isik ; revising the manuscript critically for important intellectual content: I. Isik, O. Uygur; approval of the version of the manuscript to be published (the names of all authors must be listed): I. Isik, O. Uygur.

Acknowledgement

We would like to thank the Economic Research Forum (ERF) for their research support and Daniel McFarland, Daniel Folkinshteyn, M. Kabir Hassan, Iftekhar Hasan, Ali F. Darrat, Tarun Mukherjee, Oscar Varela as well as the participants at the following conferences for their comments and insights to the different versions of the paper: Financial Management Association, Chicago, USA; Eastern Finance Association, Norfolk, USA; American Accounting Association Conference, Cherry Hill, USA; International Academy of Business and Public Administration Disciplines Conference, Athens, Greece; Management and Business Academy Conference, London, UK; Academic Research and Solutions Conference, Barcelona, Spain; the Interdisciplinary Business and Economics Research Conference, Osaka, Japan; the International Interdisciplinary Business-Economics Advancement Conference, Las Vegas, USA; Eurasia Economics and Business Society, Istanbul, Turkey; Economic Research Forum (ERF), Cairo, Egypt; and International Conference on Business, Management and Economics, Izmir, Turkey. We also thank our assistants Daniel Kline, Jessica Pratt, Jessica Beck, and Hannah Sap for their excellent research and editorial help. This research was partially conducted while the first author was on sabbatical at the Central Bank of the Republic of Turkey (CBRT). However, the views expressed in the article are those of the authors and do not necessarily

reflect the opinion of the CBRT.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.iref.2021.07.016.

Appendix A. Crises and bank efficiency/productivity: selected studies

Author (year)	Country	Sample period	Methodology	Major finding(s)
Isik & Hassan (2003a)	Turkey	1992–1996	DEA/TFP	1994 crisis resulted in productivity loss of 17% which was attributable to 10% technical regress rather than 7% efficiency decrease with greater impact on small banks.
Drake et al. (2006)	Hong Kong	1995–2001	DEA	High efficiency scores (39%–48%) impacted by macroeconomic cycle including domestic GDP and housing expenditure. Larger institutions outperformed smaller.
Ozkan-Gunay & Tektas (2006)	Turkey	1990–2001	DEA	Number of efficient banks and mean efficiency of varying output models declined throughout period immediately prior to financial crises in 1991 and 1994.
Park & Weber (2006)	Korea	1992–2002	TFP	Technical progress offset efficiency declines to produce productivity growth.
Kyj & Isik (2008)	Ukraine	1998–2003	DEA	Ukrainian banking suffered immensely in 1998 from the Russian debt crisis, since all the following years have significantly higher average efficiency scores. Evidently, while shocking in its occurrence, the overwhelming effects of the 1998 crisis appear to have been short lived.
Nitoi (2009)	Romania	2006–2008	DEA	Romanian banks average productivity decreased during the time period of financial crisis. Despite improvement in overall efficiency of 16 commercial banks post 2006, cost efficiency was low and average productivity decreased.
Sufian & Habibullah (2009)	Korea	1992–2003	DEA	Intermediation approach suggests Korean banks characterized by low levels of technical efficiency in both crisis and post crisis periods. Impact of credit risk, financial capitalization, and context profitability very by approach.
Sufian (2009a)	Malaysia	1995–1999	DEA	Efficiency is negatively related to expense preference behavior and economic conditions. Bank efficiency is positively related to loan diversity.
Sufian (2009b)	Malaysia	1995–1999	DEA/TFP	Malaysian Banks particularly experienced productivity regress due to technological regress.
Sufian (2010)	Malaysia & Thailand	1992–2003	DEA	High degree of inefficiency post-1997 crisis. Malaysian Banks show higher technological efficiency using intermediation and value-added approaches, but lower using operating approach. Thai banks showed lower TE for all approaches.
Sufian & Habibullah (2010)	Thailand	1999–2008	DEA	The crisis created a negative impact of Thai banks efficiency. Ineffectiveness resulted from scale rather than technical factors. Global financial crisis, greater credit risk, lower capitalization, and lower loan intensity negatively impact efficiency.
Luo et al. (2011)	China	1998–2008	DEA & SFA	Stock listing improved bank efficiency during IPO year. Efficiency scores of the entire sample banks had improved significantly, and this particularly explained why Chinese banks were less influenced by the global financial crisis than their Western counterparts.
Vu and Turnell (2011)	Australia	1997–2009	SFA	Australian banks experienced an adverse effect on profit efficiency, yet experienced no significant impact on cost efficiency. Banks were cost and profit efficient before crisis. Crisis negatively impacted profit efficiency with less impact on major banks.
Alzubaidi and Bougheas (2012)	E.U.	2005–2010	DEA	Fall in efficiency with differentiated impact across countries and bank specializations. Belgium, Denmark, Ireland, and Greece were the worst effected by crisis. The different impacts, created by the crisis, were across the EU countries. Belgium and Denmark banks were found to be the worst affected by the Crisis. Ireland and Greece banks were found to follow behind them.
Kumar & Charles (2012)	India	1995–2010	DEA	Both public and private sector banks were performing, during the financial crisis, better in terms of technical efficiency. Overall efficiency scores robust despite outliers. Public sector banks outperform private in scale efficiency from 2001 and technical efficiency from 2004. TFP favored public banks, although reduced during global financial crisis.
Ozkan-Gunay (2012)	Turkey	2002–2009	DEA	Efficiency of banks improved during restructuring. Efficiency scores are much lower when non-performing loans are included in analysis. Global crisis had little to no impact on managerial efficiency.
Said (2012)	Islamic banks	2006–2009	DEA	It was shown that Islamic banks had an increase in efficiency during 2006–2008 and then a decline in 2009.
Stavarek and Řepkova (2014)	Czechia	2001–2010	DEA	Czech banks average efficiency during the crisis time period experienced a deterioration. Larger banks are less efficient than small or mid-sized unless variable returns to scale are included. Average efficiency showed limited change across period except during crisis.
	Jordan	2005–2010	DEA	

(continued on next page)

(*continued*)

Author (year)	Country	Sample period	Methodology	Major finding(s)
Zeitun & Benjelloun (2012)				A significant negative impact on bank efficiency was found to be created in Jordan during the financial crisis. Few banks showed technical efficiency in managing financial resources and generating profit. Financial crisis negatively impacted efficiency.
Akhtar (2013)	Saudi Arabia	2000–2009	DEA	Cost efficiency of Saudi Arabian banks has not deteriorated during the crisis period, showing that they did not appear to be affected during the time of crisis. Although not impacted by crisis, levels do not meet frontier. High levels of inefficiency (82%) indicate input waste.
Akin et al. (2013)	Turkey	2007–2010	DEA	Foreign bank efficiencies proved higher than domestic with or without consideration of managerial inefficiencies. Foreign banks were highly or fully efficient during crisis without consideration of managerial inefficiencies.
Maredza & Ikhide (2013)	South Africa	2000–2010	DEA	Efficiency and productivity scores of South African banks experienced a mild deterioration during the crisis. Financial crisis resulted in mildly decreased total productivity and efficiency. Non-performing loans, bank size, cost-to-income ratio, profitability, and non-interest income impacted TFP.
Johnes et al. (2014)	Islamic banks	2004–2009	DEA	Although suffering a fall in gross efficiency during the crisis period, the Islamic banks experienced a partial recovery in 2009. Islamic banks show comparable gross efficiency, with higher net and lower type efficiency. May be due to lack of product standardization and better management.
Mahathanaseth & Tauer (2014)	Thailand	1998–2010	SFA	Efficient banks have fewer non-performing loans, are well-capitalized and have adequate liquidity. Commercial banks show increasing returns to scale.
Park & Baek (2014)	U.S.A	2007–2011	DEA/TFP	US banks efficiency was negatively affected by the credit crunch of 2007–2008, along with the financial crisis of 2007–2010.
Rosman et al. (2014)	Islamic banks	2007–2010	DEA	There was no effect of overall technical efficiency of Islamic banks through the crisis of 2008.
Wolters et al. (2014)	Brazil	2002–2011	DEA	During the crisis period, a considerable decrease was shown in the overall relative efficiency of the Brazilian banking sector. Larger, Brazilian-owned banks experienced lower drop in efficiency than, foreign-owned firms following economic crisis.
Moradi-Motlagh and Babacan (2015)	Australia	2006–2012	DEA	The pure technical efficiency of the Australian banks had been adversely affected during the financial crisis. Efficiency level of all banks impacted by crisis. Crisis negatively impacted scale efficiency and increased expenses for large bank. Low scale efficiency of small banks left them financially vulnerable.
Tzeremes (2015)	India	2004–2012	DEA	Industry's efficiency levels started to decline amid the beginning of the global financial crisis. In addition, it was noticed that banks experienced a higher efficiency variability during the crisis years. Ownership structure impacts technical efficiency. Foreign banks out-performed national and domestic private banks.
Andrieș and Ursu (2016)	E.U.	2004–2010	SFA	Post-crisis cost and efficiency were significantly higher. Publicly traded, large, and old member banks experienced the greatest impact on cost efficiency, but lesser on profit efficiency.
Gulati & Kumar (2016)	India	2003–2013	DEA	Profit efficiency declined during crisis, then rebounded with no lasting effect. Technology gap ratio suggested that foreign banks employed best-practice technology.
Isik et al. (2016)	Ukraine	1998–2003	DEA	The Russian bank crisis of 1998 appears to have had a short-lived negative effect especially on the large Ukrainian banks. Efficiency scores for all size groups increased after 1999.
Ramakrishna et al. (2016)	India	2002–2013	DEA	Indian banks showed declining efficiency during crisis. Technical efficiency of private commercial banks and scale efficiency of public sector banks improved after crisis.
Chesti and Khan (2018)	India	2003–2015	DEA	No significant decline in efficiency of banks in spite of crisis. Resilience attributed to public bank structure and post-crisis policy initiatives.
Mehdian et al. (2019)	U.S.A	2005–2016	DEA	The efficiency of large commercial banks in the US fell sharply during the 2008 crisis. Despite some recovery since then, it still has not reached to its pre-crisis efficiency level

Notes: DEA: Data Envelopment Analysis; SFA: Stochastic Frontier Analysis; TFP: Total Factor Productivity Change Index; E.U: European Union; U.S.A.: United States of America.

Appendix B. Defaults and bank efficiency: selected studies

Author (year)	Country	Sample period	Methodology	Major finding(s)
Barr et al. (1994)	U.S.A	1986–1989	DEA	DEA model is effective proxy for management quality while CAMEL variables are informed by local economic conditions.
Miller (1995)		1991–1992	DEA	

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Author (year)	Country	Sample period	Methodology	Major finding(s)
	U.S.A (Conn)			Probability of bank failure is negatively correlated with capital adequacy and earning performance; exposure to construction and land development loans increases probability of bank failure.
Wheelock & Wilson (1995)	U.S.A (Kansas)	1910–1928	DEA	The more efficiently banks transformed inputs into loans and demand deposits, the more likely it could survive economic downturns.
Wheelock & Wilson (2000)	U.S.A	1984–1993	DEA	Probability of failure increases with poor capitalization and poor cost or technical efficiency.
Luo (2003)	U.S.A	2000	DEA	They find that only overall technical profitability efficiency of large banks can predict the chance of banking failure. However, marketability efficiency measure and location group variables were not significant in predicting bank failures.
Cielen et al. (2004)	Belgium	1994–1996	DEA	For a small dataset with only quantitative information, a DEA model performed better in terms of accuracy, cost, deployment and comprehensibility then decision trees (C5.0).
Stryn (2004)	Russia	1998 (Q1-Q4)	DEA	Post x-inefficiency does not help to predict bank failure. Captive banks showed greater impact from primary factors such as FX risk.
Kao & Liu (2004)	Taiwan	2000	DEA	There are challenges in generating general financial conclusions from popular ratios. The solution method better predicts bank performance based on financial forecasts.
Kraft et al. (2006)	Croatia	1994–2000	SFA	Privatization does not immediately improve bank efficiency. Better cost efficiency, risk management, and cost management reduces change of failure. Foreign banks were more efficient than domestic.
Podpiera & Podpiera (2008)	Czechia	1994–2002	DFA	Hazard of bank failure correlated with management performance. Cost management can counterbalance risk issues.
Wallace (2009)	Jamaica	1989–1998 2002–2008	DEA	DEA's multiple input-output model can quantify management quality of banks. Banks with lower efficiency scores are more likely to fail.
Alvarez-Franco and Restrepo-Tobón (2016)	U.S.A	2001–2010	SFA	Profit inefficiency adequately predicts bank failures and serves as proxy for managerial inefficiency. Loan quality was better predictor of bank failure than capitalization.
Isik & Folkinshteyn (2017)	Turkey	1970–2003	DEA & SFA	Both regulatory and managerial mistakes are found to be responsible for the bank failures in Turkey; however, the shares of bank managers seem to stand out: technical inefficiencies surpass allocative inefficiencies in failed banks.

Notes: DEA: Data Envelopment Analysis; SFA: Stochastic Frontier Analysis; U.S.A.: United States of America.

Appendix C. Multivariate failure models - with DEA and SFA frontier efficiencies by raw scores/no deciles

Variables	Panel A: Official insolvency				Panel B: Factual insolvency			
	β	AIC	Pseu- R^2	FailPre %	β	AIC	Pseu-R^2	FailPre %
Efficiency Variables								
DEAt								
CEtd	−0.21	133.77	0.37	73.91	−0.93	170.19	0.34	75.00
AEtd	1.11	132.63	0.38	78.26	0.82	170.45	0.34	78.13
TEtd	-1.46^{C}	133.22	0.38	73.91	-1.57^{B}	166.59	0.35	75.00
PTEtd	−1.32	132.02	0.38	78.26	-1.45^{C}	168.48	0.35	71.88
SEtd	−1.06	132.41	0.38	78.26	−1.04	169.73	0.34	75.00
DEAm								
CEmd	−0.86	131.83	0.37	73.91	-1.18^{C}	168.68	0.34	78.13
AEmd	0.66	132.29	0.38	78.26	0.78	170.46	0.34	78.13
TEmd	-1.84^{B}	130.78	0.39	78.26	-1.99^{A}	163.26	0.37	78.13
PTEmd	-1.63^{B}	128.54	0.41	78.26	-1.80^{A}	163.77	0.37	78.13
SEmd	−0.45	128.85	0.40	78.26	−0.66	170.94	0.33	75.00
SFAt								
TEts	11.34	129.64	0.40	78.26	27.53	158.46	0.39	75.00
CEts	-2.48^{B}	130.77	0.39	78.26	-1.97^{C}	169.01	0.34	75.00
SFAm								
TEms	0.51	133.36	0.38	73.91	−0.357	171.22	0.33	75.00
CEms	−0.25	133.78	0.37	73.91	−0.722	170.85	0.33	75.00
PROFEms	-2.23^{B}	125.83	0.42	82.61	-1.88^{B}	163.25	0.37	84.38
REVEms	1.12	133.21	0.38	78.26	0.688	171.24	0.33	71.88

Note: A, B, C stand for 1%, 5%, 10% significance level, respectively. These tests are based on raw values of efficiency scores rather than the deciles of efficiency score for robustness check. Multivariate probit models try to estimate the chance of being closed by regulators (failure = 1 if closed by regulators; 0 otherwise) under "official insolvency" definition in Panel A, while they predic the risk of the capitalization ratio falling below 2% under the "factual insolvency" definition in Panel B (failure = 1, if capitalization ratio (TE/TA)< %2; 0 otherwise) based on a list of management quality proxy variables (16 efficiency scores) and bank specific and macro control variables (control variables are muted here to concentrate on management quality proxies): Cost (CEtd, CEmd, CEts, CEms) or Allocative (AEtd, AEmd) or Technical (TEtd, TEmd, TEts, TEms) or Pure technical (PTEtd, PTEmd) or Scale (SEtd, SEmd), Profit (PROFEms) and Revenue (REVEms) efficiency score computed based on Data Envelopment Analysis (d) and Stochastic

Frontier Analysis (s) using traditional (t) banking technology, which does not account for off-balance sheet outputs and modern banking technology (m), which does, respectively; CapRat = TE/TA = total equity divided by average total assets (TA); ΔNPL_TL = the change in the ratio of non-performing loans to total loans; ROE = return on equity measured as net income divided by TE; LA_TA = liquid current assets divided by TA (liquidity ratio); ΔLA_TA is annual change in the liquidity ratio, Cong_Aff = a dummy variable, which attains the value of 1 if the bank is controlled by a business conglomerate; 0 otherwise; FXA_FXL = foreign exchange denominated assets divided by foreign exchange denominated liabilities (forex ratio); ΔFXA_FXL is annual change in forex ratio, GDPGrwth = the change GDP per head = gross domestic product per capita in US dollars; ΔAvIntRat = annual change in the average short term and long term interest rates. The coefficients of the control variables are not displayed for brevity as the emphasis of this investigation is on the impact of efficiency scores on the risk of default. However, they are available from the authors upon request.

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