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The Ability of Altman's Z"-Score Model to Detect the Economic Distress of Kazakh Banks

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Abstract

This study contributes to the literature by evaluating the ability of Altman's Z"-score model to predict the economic distress of twelve Kazakh banks over the period of 2008 to 2014. The original Z"-score model with a cut-off point implied by Altman (2005) produces a prediction accuracy ratio of 44.05%, and correctly classifies 76.19% of the observations originally assigned to the economically distressed group. The study then re-estimates the model using three approaches, namely: the "leave-one-out", Direct, and Wilk's methods, and identifies new, optimal cut-off points for the re-estimated models. The re-estimated models, together with the new, optimal cut-off points, improve the prediction accuracy ratio to 70%, and correctly classifies over 90% of the observations originally assigned to the economically distressed group. The results imply that the Kazakh banking regulators and other market participants could use the Altman's Z"-score model to detect economically distressed banks.

Keywords: Altman's Z"-score model, Kazakhstan, distress, banks, emerging market.

JEL: G21, G33, C53, C61.

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The Ability of Altman's Z"-Score Model to Detect the Economic Distress of Kazakh Banks

1. Introduction

Economic distress refers to vulnerabilities in both the financial health and the business model of a bank. It is broader than the concept of insolvency, which represents the probability that the cash buffer a firm has against variations in cash flows may be insufficient, leaving the firm unable to meet its financial obligations (Beaver, 1966). It is also broader than the concept of financial distress. Altman et al. (2019, p.8) explain the differences between financial and economic distresses; *"A firm in financial distress experiences a shortfall in cash flow needed to meet its debt obligations. Its business model does not necessarily have fundamental problems and its products are often attractive. In contrast, firms in economic distress have unsustainable business models and will not be viable without asset restructuring. In practice, many distressed firms suffer from a combination of the two."*

The Z-score model developed by Altman in 1968 is probably the first multivariate failure prediction model. This model has gained wide popularity in the literature, which is evident by a total citation of 22,041 times on Google Scholar as of June 2, 2022. It has several advantages such as simplicity, possibility to work with limited information, comparability of indicators, ability to produce a binary classification of companies into bankrupt and non-bankrupt firms with high predictive accuracy, and reliance on accounting-based measures which enables the application of the model to private companies. In this context, this study evaluates the ability of the original and re-estimated Altman's Z"-score models to predict the economic distress of twelve Kazakh banks over the period of 2008 to 2014.

This study is closely related to studies evaluating the ability of original Altman's Z-score model and its variations to predict corporate bankruptcy and financial distress and assess firms' financial health. Most prior studies use samples from developed countries (e.g., Almamy et al., 2016; Grice and Ingram, 2001; Xu and Zhang, 2009), whereas relatively fewer studies are conducted for emerging markets (e.g., Chouhan et al., 2014; Zhang et.al, 2010) and none on Kazakh banks. In this context, this study contributes to the literature by investigating the ability of Altman's models to predict the economic distress of Kazakh banks. It is also closely related

to studies that use the Altman's Z-score model and its variations in the banking industry to predict bank failure and assess banks' financial soundness (e.g., Al Zaabi, 2011; Ngwa, 2016; Vaziri et al. 2012).

Using data from twelve Kazakh banks over the period of 2008 to 2014, this study further contributes to the literature by assessing the classification performance of Altman's Z"-score model in Kazakhstan. As an emerging market and a post-soviet state, Kazakhstan provides a unique case to study the economic distress of banks. According to the National Bank of Kazakhstan (NBK), the country had a nonperforming loans to total gross loans ratio of 2.4% at the beginning of 2008, which had dramatically increased to 36% by the beginning of 2014 (NBK, 2015). The World Bank ranked Kazakhstan the first in the world in terms of the percentage of nonperforming loans to total gross loans in 2012 (Salina et al., 2021). However, to date, there seems to be a lack of studies on the Kazakhstan banking sector. In addition, following prior studies (e.g., Begley et al. 1996; Moyer, 1977; Nasledov, 2013; Wu et al., 2010), this study re-estimates the original Z"-score model using three approaches, namely: the "leave-one-out", Direct, and Wilk's methods, and calculates new, optimal cut-off points for the re-estimated models. It further examines whether the re-estimated versions of Altman's Z"-score model outperform the original Z"-score model. Using the original Altman's Z"-score model and a cut-off point, which is equivalent to the minimum Z"-score of the US firms which have "BBB" ratings, this model only correctly classifies 44.05% of the observations into the economically distressed and non-distressed groups. However, it correctly classifies 76.19% of the observations initially assigned to the economically distressed group. The re-estimated models, together with the new, optimal cut-off points, produce prediction accuracy ratios ranging from 52.38% to 70.24% and they correctly classify more than 90% of the observations initially assigned to the economically distressed group.

The results, especially those produced by the re-estimated models, indicate that the Altman's Z"-score model is effective in detecting economically distressed Kazakh banks. Therefore, it could be used by the Kazakh banking regulators¹ to monitor the risk of bank failure and detect distressed banks that may require early intervention from the regulators and government. Other financial market participants could also use the model to differentiate economically distressed

¹ Agency for Regulation and Development of the Financial Market (AFR), National Bank of Kazakhstan (NBK) and the Astana Financial Services Authority (AFSA) are the regulators of Kazakh banks.

from non-distressed Kazakh banks, which may help them decide whether to invest in these banks.

The rest of this chapter is organized as follows. Section 2 briefly reviews the history of the Kazakh banking system since Kazakhstan's independence from the USSR. Section 3 reviews related studies. Section 4 describes the dataset and research design of this study. Section 5 presents and discusses the findings. Section 6 concludes this study.

2. A Concise History of the Banking System of Kazakhstan

The Republic of Kazakhstan is a post-soviet state, which gained its independence from the Soviet Union on December 16, 1991. The latest World Economic Situation Prospects classifies Kazakhstan as an “economy in transition”, which means that the country is still in the process of transforming from a centrally planned economy to a market economy (United Nations, 2022). Upon its independence, Kazakhstan inherited a domestic banking system, which was built during the Soviet era and dominated by a few large state-owned banks.

According to the legislation governing the NBK, the country has a two-tier banking system: the NBK, which is the central bank and forms the top tier of the system, and all the other banks form the second tier (The Republic of Kazakhstan, 1995). The second-tier banks resemble the commercial banks operating in other countries; they perform financial intermediation and supply credit to the real economy. Salina (2017) documents a series of reforms initiated by the government of Kazakhstan during the period of 1991-2007, which aimed to improve the financial stability of its domestic banking system and boost market confidence. For example, a deposit insurance scheme was introduced in November 1999; minimum capital reserve requirements for second-tier banks were introduced in February 2000; initial share capital requirements for opening a new second-tier bank were introduced in June 2001 and tightened in October 2004; full compliance with the Basel I Standards started in 2000, and adoption of the International Accounting Standards (IAS) by all second-tier banks for external reporting began in 2002. These reforms and the booming domestic economy during the period 2000-2007 have stimulated fast growth in banks' assets, deposits, and earnings, which all peaked at the end of 2007 (NBK, 2015). During the same period, the Kazakh banking sector became more internationalised; large Kazakh second-tier banks expanded into overseas markets and

many foreign banks increased their presence in Kazakhstan. However, the global financial crisis of 2008-2009 triggered a banking crisis in Kazakhstan.

Like their counterparts in many developed economies, several Kazakh banks were heavily exposed to high levels of credit risk caused by their lending to the domestic real estate and construction sectors and liquidity risk caused by over-reliance on short-term borrowings from the international wholesale funding market (Glass et al., 2013). The bursting of the domestic real estate bubble, which was formed during the economic boom of 2000-2007, resulted in a sharp rise in non-performing loans and a record decline in banks' profits (NBK, 2015). The freezing of the international wholesale funding during the global financial crisis significantly reduced the availability of short-term funding for Kazakh banks and increased their funding costs. The sale of Kazakh banks' securities by foreign investors and the withdrawal of their deposits exacerbated the liquidity crisis. As a result, three large banks (BTA Bank, Alliance Bank, and Temirbank) were at the brink of collapse. To stabilise the domestic banking system, the government of Kazakhstan decided to provide financial assistance to troubled banks. For example, the National Fund of Kazakhstan (a flagship sovereign wealth fund), injected 3.24 billion USD into four troubled banks (Kazkommertsbank, Halyk Bank, BTA Bank, and Alliance Bank) and became their major shareholder. Further financial assistance was given to three of them to restructure their non-performing loans. The Chairman of the NBK, Mr Kairat Kelimbetov, claimed that it costed Kazakhstan around six percent of its GDP to assist its banking sector to deal with the negative impact of this banking crisis (Kelimbetov, 2014). Nonetheless, the non-performing loans to total gross loans ratio of the whole banking sector went up from 2.7% at the beginning of 2008 to 36% by the beginning of 2014 (NBK, 2015).

The government of Kazakhstan introduced new reforms to address the weaknesses exposed by the crisis and control the risk within the banking system. For example, Salina (2017) documents that more stringent prudential standards, including higher minimum capital reserve requirements were introduced on July 1, 2009. Also, the NKB announced the transition to BASEL III standards in 2015 and aimed for full compliance by 2022. The Kazakh banking regulators also take initiatives to establish effective mechanisms to identify the risk factors within the banking system and detect deterioration in the financial conditions of banks. In this context, Altman's Z-score model and its variations could help detect the economic distress of banks since previous studies show that these models are effective tools for assessing the

financial health of banks and predicting bank failure (e.g., Al Zaabi, 2011; Ullah et al., 2021; Vaziri et al., 2012).

3. Literature Review

In this section, we review Altman's Z-score model and its variations. We then justify the use of Altman's Z"-score model in this study and discuss the potential contributions of the study.

3.1 A review of Altman's models

Altman's models are a family of Linear Discriminant Functions (LDF) which use company-level financial ratios as their predictors. A typical LDF can be mathematically expressed as follows:

$$D = \beta_0 + \beta_1X_1 + \beta_2X_2 + \dots + \beta_nX_n \quad (\text{Eq.1})$$

where D is the discriminant score, β_0 is an estimated intercept, β_n are the estimated coefficients, and X_n are the predictors. LDFs are derived by using Multiple Discriminant Analysis (MDA), which enables a classification of observations into distinctive groups based on their discriminant scores.

3.1.1 Altman's Z-score model

In 1968, Edward Altman developed the Z-score model for predicting corporate bankruptcy, which uses a set of financial ratios. These ratios measure a company's liquidity, profitability, leverage, solvency, and efficiency. A sample of US listed manufacturing firms, consisting of thirty-three firms that filed bankruptcy during the period of 1946-1965 and thirty-three firms that were still in existence in 1966, was used to estimate the LDF that can best classify these firms into bankrupt and non-bankrupt firms. The resulting LDF is described as follows:

$$Z = 0.012X_1 + 0.014X_2 + 0.033X_3 + 0.006X_4 + 0.999X_5 \quad (\text{Eq.2})$$

where X_1 is the ratio of working capital to total assets, X_2 is the ratio of retained earnings to total assets, X_3 is the ratio of earnings before interest and taxes to total assets, X_4 is the market value of equity deflated by the book value of total liabilities, X_5 is the ratio of sales to total assets, and Z is the discriminant score generated by the LDF (Z-score). When using this model, one should insert absolute percentage values (e.g., 10%) for variables X_1 to X_4 and decimals for variable X_5 (e.g., 1.1). Altman (2013) suggested a more convenient specification of Eq.2, as described by Eq.3, which has gradually become more popular:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5 \quad (\text{Eq.3})$$

Definitions for all the variables in Eq. 3 remain the same. However, when using Eq.3, one can insert decimals for all the predictors. Eq.2 and Eq.3 are commonly referred to as the Altman's Z-score model. The five predictors included in this model measure several attributes of a firm that are correlated to the risk of bankruptcy. X_1 measures a firm's liquidity scaled by its asset size; a firm which is experiencing consecutive financial losses will have shrinking current assets relative to its total assets. Firms having high liquidity risk are more likely to go bankrupt. X_2 measures a firm's cumulative profitability and considers both the age and profitability of a firm. Younger and less profitable firms are more likely to go bankrupt. X_3 measures a firm's profitability or the productivity of its assets. More profitable/productive firms are less likely to go bankrupt. X_4 measures how much a firm's assets can decline in value before the value of liabilities exceeds the value of assets. The higher the ratio, the lower the solvency risk. X_5 measures the efficiency of a firm's assets to generate sales revenue. More efficient firms are less likely to fall into financial distress. In summary, variables X_1 to X_5 are, in theory, all positively correlated to the Z-score; the higher (lower) the Z-score, the lower (higher) the chance of bankruptcy.

Altman (1968) applied the Z-score model to both the original sample used to estimate this model and new samples to assess its classification performance by using the following indicators:

- Classification accuracy ratio calculated as the number of correct classifications divided by sample size,
- Type I error rate defined as the number of bankrupt firms mistakenly classified by the model as non-bankrupt firms divided by the number of bankrupt firms in the sample, and
- Type II error rate defined as the number of non-bankrupt firms incorrectly classified by the model as bankrupt firms divided by the number of non-bankrupt firms in the sample.

The outcome of this assessment shows that the level of accuracy of the model for predicting bankruptcy depends on the length of out-of-sample prediction window. To illustrate, when prediction of bankruptcy was made one year in advance, the model correctly classified 95% of the sixty-six sample firms and produced a Type I error rate of 6% and a Type II error rate of 3%. The classification accuracy dropped to 83% when prediction is made two years in advance. In addition, the Type I error rate increased to 28%, while the Type II error rate remained at 6%.

Altman (1968) also applied the model to two holdout samples: one consisting of twenty-five bankrupt firms and the other consisting of sixty-six firms that experienced financial losses during 1958-1961 but did not file bankruptcy. The model correctly classified twenty-four out of the twenty-five firms in the first sample (a classification accuracy ratio of 96%); however, it misclassified fourteen out of the sixty-six firms in the second sample (a classification accuracy ratio of 79% and a Type II error rate of 21%).

Altman (1968) also proposed the concepts of “safe zone”, “grey zone”, and “distress zone”. Sample firms with Z-scores greater than 2.99 were all correctly classified by the Z-score model as non-bankrupt firms. This implies that any firm with a Z-score greater than 2.99 could be considered financially safe. Sample firms with Z-scores smaller than 1.81 were all correctly classified by the model as bankrupt firms. This indicates that any firm with a Z-score lower than 1.81 could be considered financially distressed or bankrupt. Sample firms that have Z-scores greater than 1.81 but smaller than 2.99 are prone to misclassifications. Therefore, it is unclear whether firms with Z-scores within this range could be considered financially safe. It is worth noting that the cut-off point used to classify sample firms can be different from the boundary values for the three zones. The cut-off point is a value that maximises the classification accuracy and minimises the sum of Type I and Type II errors. Altman (1968) used a cut-off point of 2.675; firms with Z-scores greater than this value were classified as non-bankrupt firms while firms with Z-scores smaller than this value were classified as bankrupt firms. However, Altman (2002; 2013) used a cut-off point of 1.81, which is the average Z-score of “B” rated firms included in the samples of these two studies. This implies that firms with credit ratings lower than a “B” grade were considered in the “distress zone” by these two studies.

3.1.2 Variations of the Altman's Z-score model

As mentioned above, the Z-score model was originally derived from a sample of US listed manufacturing firms. Also, the numerator of variable X_4 included in the model is the market value of equity. Therefore, this model cannot be applied to firms whose shares are not listed on a stock exchange (e.g., privately held companies). To accommodate these firms, Altman (1993) substituted the book value of equity for the market value of equity in the definition for X_4 and re-estimated the coefficients by employing the sample used to estimate the coefficients of the original Z-score model. The definitions for X_1 , X_2 , X_3 and X_5 remain the same as those used in the original Z-score model. The resulting model is the so-called Altman's Z'-score model for private firms:

$$Z' = 0.717X_1 + 0.847X_2 + 3.107X_3 + 0.420X_4 + 0.998X_5 \quad (\text{Eq.4})$$

Altman (2013) reports that when applied to the sample used to derive the original Z-score model, the Z'-score model produced slightly lower classification performance; Type I error rate increased from 6% to 9%, and the classification accuracy ratio declined from 95% to 94%, but the Type II error rate did not change. Because the Z'-score model uses a different definition for X₄ and different estimated coefficients for the five predictors, its boundary values for the “safe zone”, “grey zone”, and “distress zone” also differ from those of the Z-score model. Altman (2013) indicates that firms with Z'-scores greater than 2.90 are in the “safe zone”, those with Z'-scores between 1.23 and 2.90 are in the “grey zone”, and those with Z'-scores lower than 1.23 are in the “distress zone”.

To further accommodate non-manufacturing companies, Altman (1993) proposed another variation of the Z-score model, the Z''-score model, which is described as follows:

$$Z'' = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4 \quad (\text{Eq.5})$$

X₅, the ratio of sales to total assets, was removed because it is industry-sensitive and might introduce specific industry effect into the Z''-score model. The definitions for X₁, X₂, X₃ and X₄ remain the same as those used in the Z'-score model. Because the Z''-score model is developed from the Z'-score model, in theory, it is more versatile than the Z'-score model and can be applied to both unlisted and non-manufacturing firms. Altman and Hotchkiss (2006) claim that when tested on US samples comprising both manufacturing and nonmanufacturing companies, the Z''-score model produced classification performance comparable to that produced by the Z-score and Z'-score models. Because the Z''-score model has different coefficients for the predictors, its boundary values for the “safe zone”, “grey zone”, and “distress zone” also differ from those of the Z-score and Z'-score models. Altman (2002) indicates that firms with Z''-scores smaller than 1.10 are considered in the “distress zone”, those with Z''-scores between 1.10 and 2.6 are considered in the “grey zone”, and those with Z''-scores greater than 2.6 are considered in the “safe zone”.

In addition, another specification of the Z''-score model was used by Altman et al. (1998) and Altman (2005) to estimate bond rating equivalent for both US and Mexico companies. Because Mexico is an emerging market, this new specification is often referred to as the emerging market scoring model or the EMS model:

$$Z'' = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4 + 3.25 \quad (\text{Eq.6})$$

The only difference between Eq.5 and Eq.6 is an intercept of 3.25. Altman et al. (1998) introduced this intercept to standardise their analysis so that a Z'' score equal to or lower than zero is equivalent to a default bond rating (i.e., a “D” rating). Altman et al. (1998) and Altman (2005) did not specify clear boundary values for the “safe zone”, “grey zone”, and “distress zone” for Eq.6.; however, these can be derived by adding 3.25 to the boundary values of the original Z'' -score model (i.e., Eq.5). For example, the lower bound for the “safe zone” should be 5.85 (2.6+3.25), and the upper bound for the “distress zone” should be 4.35 (1.10+3.25).

Altman et al. (2017) used a large international sample to assess the classification performance of the Z'' -score model and its derivatives, which includes firms from 35 developed and emerging countries. Eq.6 was referred to as the Z'' -score model in their study and used as the baseline model.

3.1.3 Model selection and research contributions

Following Altman et al. (2017), this study employs Altman’s Z'' -score model, as specified by Eq.6, to predict the economic distress of Kazakh banks. The Z'' -score is chosen because it can be applied to non-manufacturing firms from emerging markets (Altman et al., 1998; Altman, 2005; Altman and Hotchkiss, 2006). In addition, this model has been used in prior studies to assess the financial strength of banks from emerging countries and predict bank failure (e.g., Al Zaabi, 2011). This study makes several contributions to the existing literature.

Firstly, this is the first study to assess the classification performance of Altman’s Z'' -score model in Kazakhstan. Most prior studies assessing the classification performance of Altman’s models used samples from developed countries (e.g., Almamy et al., 2016; Grice and Ingram, 2001; Wu et al., 2010; Xu and Zhang, 2009). Altman and Narayanan (1997) suggest that corporate failure prediction studies conducted for developed markets benefit from several institutional factors, which might be absent in emerging markets, such as data availability, clear bankruptcy code, well-developed banking infrastructures, strong regulations for protecting investors, and low likelihood of government intervention if corporate failure occurs. Hence, the performance of Altman’s models might be uneven between developed and emerging markets. Indeed, using samples from thirty-five developed and emerging countries, Altman et al. (2017) find that the performance of the Z'' -score model varies across countries. However,

contrary to the conventional wisdom, they find that this model performs well in several emerging economies that have weak institutional environment such as China and Russia, while it delivers relatively poor performance for several developed countries that have strong institutional environment such as Norway, Ireland, Iceland, and Germany. This highlights the importance of advancing our understanding of country-specific classification performance of Altman's models. Although there is growing number of studies using Altman's models to assess firms' financial health and predict financial distress in emerging markets (e.g., Zhang et al., 2010; Al Zaabi, 2011; Chouhan et al., 2014; Altman et al. 2021; Wu et al., 2022), there are only limited number of studies examining these models' classification performance in emerging markets (e.g., Zhang et al., 2010). For example, Hájek et al. (2017; 2021) calculate the Z- and Z'-scores for two small samples of confectionary companies operating in Kazakhstan and then compare the scores to the boundary values for the "safe", "grey", and "distress" zones to assess the financial strength of these companies. However, these Kazakh studies are conducted for non-financial firms and do not assess the classification performance of Altman's models. In contrast, our study evaluates the classification performance of the Z"-score model, which is more suitable for predicting the economic distress of banks from emerging markets.

Secondly, this study further contributes to the literature by using three approaches to re-estimate Altman's Z"-score model for a sample of Kazakh banks, namely the "leave-one-out", Direct, and Wilk's methods as well as identifying new, optimal cut-off points for the re-estimated models. It also assesses whether the re-estimated versions of Altman's Z"-score model outperform the original Z"-score model. This is because Altman (2013), Grice and Ingram (2001), and Altman et al. (2017) find that the classification performance of Altman's models changes over time and varies across industries and countries. The re-estimation often results in different coefficients for the predictors included in the original versions of Altman's models. To the best of our knowledge, this is the first study to re-estimate the Z"-score model by using a Kazakh sample and compare the classification performance of the re-estimated Z"-score model with that of the original Z"-score model.

Thirdly, this study advances knowledge on the ability of Altman's models to predict the economic distress of banks from emerging markets. Prior studies not only used the Z-scores derived from Altman's models to measure the default risk of non-financial firms, but also the default risk of banks (Hogan, 2015). In addition, Altman's Z-score model and its variations have been used to assess banks' financial health and predict bank failure for developed markets

(e.g., Ngwa, 2016; Vaziri et al. 2012). However, there are relatively less attempts to use Altman's models to assess the financial strength of banks or predict bank failure in the context of emerging markets. For example, Al Zaabi (2011) used the Z'' -score model to assess the financial health of a sample of Islamic banks from the UAE. To the best of our knowledge, this is the first study to use Altman's Z'' -score model to predict the economic distress of Kazakh banks.

4. Data Collection and Research Design

4.1 Data collection

This study uses data from twelve Kazakh banks (see Table 1), which are divided into two groups. The first group consists of six banks that received financial assistance from the Kazakh government, failed to meet their obligations or/and were forced to merge with other banks to avoid failure after the banking crisis of 2008-2009. These six banks are hence classified as economically distressed banks in this study. The second group consists of six banks, which are comparable to the six economically distressed banks in terms of bank size, business lines, and number of branches. These six banks are not considered in economic distress because they did not fail to meet their obligations and were not forced to merge with other banks during the sample period. Financial data of these banks at the start of each year are obtained from the central bank of Kazakhstan and covers the period of January 1, 2008, to January 1, 2014. The final sample includes seven annual observations for each bank and eighty-four observations in total. Table 1 shows that the sample banks control 81.3% of the total assets held by the entire Kazakh banking sector on January 1, 2014, and form a representative sample.

[Insert Table 1 here]

4.2 Research Design

This study evaluates the ability of the original and re-estimated Altman's Z'' -score models to predict the economic distress of twelve Kazakh banks over the period 2008 to 2014. The data analysis is divided into two parts.

In the first part of the analysis, we use the original Z'' -score model (Eq. 6) and the financial ratios of the sample banks to calculate the Z'' -scores of these banks. Then we compare the obtained Z'' -scores to the lower bound of the "safe zone", which equals 5.85. We classify any

observation with a Z -score that is lower than 5.85 as economically distressed. This is because it is unclear whether firms, whose Z -scores are in the “grey zone”, can be correctly classified either as bankrupt or non-bankrupt firms (Altman, 1968). Furthermore, Altman (2005) showed that the minimum Z -score of sample firms that have “BBB” ratings is 5.85, which is the same as the lower bound of the “safe zone” for the Z -score model (Eq.6). Firms with credit ratings lower than the “BBB” grade are considered vulnerable to default risk and their bonds are “speculative”. For example, Fitch Ratings considers firms with its “BB” ratings, one grade below the “BBB” rating, to have “*an elevated vulnerability to default risk, particularly in the event of adverse changes in business or economic conditions over time*” (Fitch Ratings, 2022). Therefore, our approach of using 5.85 as the cut-off point is also motivated by credit rating agencies’ definition of corporate vulnerability.

In the second part of the analysis, we use three re-estimation methods that are suitable for studies with small samples. Studies applying Altman’s models for predicting bankruptcy and financial distress usually use a “training” sample for re-estimation, and a “holdout” sample for assessing classification performance (e.g., Altman, 1968; Grice and Ingram, 2000). However, this approach might not be possible for studies with relatively small samples. Obtaining a large sample of banks from an emerging market can be challenging because the domestic banking market is likely to be dominated by a few large banks. In addition, even though this study only employs a sample of twelve banks, they control more than 80% of the total assets held by the whole Kazakh banking sector. Also, it is not uncommon for prior studies not to have “held-out” samples. For example, Bellovary et al. (2007) reviewed bankruptcy prediction studies published between 1930 and 2007 and found that less than half of these studies used “hold-out” samples for prediction.

The first re-estimation method applied in this study is the “leave-one-out” approach proposed by Nasledov (2013). Under this approach, the learning algorithm leaves one selected observation out and uses all the remaining observations as the training set for re-estimation. The re-estimated model is then used to make a prediction for the selected observation (i.e., one unique re-estimated model for each selected observation). We also apply two re-estimation approaches proposed by Moyer (1977), namely: the Wilks and Direct approaches. The Wilks’ approach adds variables into a discriminant function in a stepwise manner up to the point where the Wilk’s Lambda is minimised. The Direct approach, by default, includes all the predictors of the Z -score model into the discriminant function. Essentially, each of these two methods

generates one unique, re-estimated model and then this model is used to make predictions for the whole sample (i.e., one re-estimated model for all observations). When using the three re-estimation methods, we also employ a technique used in Begley et al. (1996) and Wu et al. (2010) to generate new, optimal cut-off points, which are then used to classify the sample banks.

5. Findings and Discussion

5.1 Results from the original Altman's Z"-score model

The application of the original Altman's Z"-score model involves two steps. Firstly, the means and standard deviations of the four predictors included in the model are calculated for each of the two groups of banks. Then a T-test and a F-test are used to identify whether the means and standard deviations for the first group are statistically different from those of the second group. Secondly, financial data of the sample banks are inserted into Altman's Z"-score model (Eq.6) to work out the Z-scores. Any observation with a Z"-score lower than 5.85 is classified as economically distressed.

Table 2 presents the means and standard deviations of the four ratios included in Altman's Z"-score model and the T- and F-statistics for testing the between-group differences. The results indicate that observations originally assigned to the economically distressed group have significantly higher liquidity ratio (X_1) and lower solvency ratio (X_4) than those originally assigned to the non-distressed group. The result on X_4 is expected, but the result on X_1 may look counter intuitive at first glance because normally one expects that higher liquidity leads to lower chance of distress. However, this might be true for non-financial companies, but not for banks. Compared to their counterparts, economically distressed banks might have limited access to the money market, which limits their ability to borrow short-term funds. Using fewer short-term liabilities may result in higher working capital (the numerator of X_1). Thus, the result for X_1 may reflect the unique business model of banks; they use short-term liabilities such as deposits and commercial papers to finance long-term assets such as mortgage and corporate loans (Howells and Bain, 2007). The results on the other two predictors (i.e., X_2 and X_3) are inconclusive.

[Insert Table 2 here]

Table 3 shows the classification result based on a cut-off value of 5.85 (the minimum Z"-score to stay in the "safe zone").

[Insert Table 3 here]

The results in Table 3 show that 32 out of 42 observations originally assigned to the economically distressed group are correctly classified; the remaining 10 observations are misclassified. In other words, 76.19% of predictions made for the observations originally assigned to the economically distressed group are correct and the remaining 23.81% are incorrect (Type I errors). However, only 5 out of the 42 observations originally assigned to the non-distressed group are correctly classified; the remaining 37 observations in this group are misclassified as economically distressed. In other words, only 11.91% of predictions made for the observations originally assigned to non-distressed group are correct and the remaining 88.09% are incorrect (Type II errors). On aggregate, only 37 out of 84 observations in the sample are correctly classified, a prediction accuracy of only 44.05%.

Although the overall prediction accuracy delivered by the original Altman's Z'' -model and a cut-off point of 5.85 is below 50%, this approach correctly classifies about 80% of the observations originally assigned to the economically distressed group. From a banking regulator's point of view, the costs of not identifying economically distressed banks in advance are much higher than mistakenly identifying non-distressed banks as distressed ones. Therefore, this approach is still useful to the banking regulators even though it produces a high Type II error rate and a low prediction accuracy ratio.

The low overall prediction accuracy ratio and high Type II error rate indicate that the cut-off point of 5.85 might be too high for our sample. As we have explained in Section 1 of this paper, Altman (2005) found that the minimum Z'' -score of his US sample firms which have "BBB" ratings is 5.85. This indicates that having a "BBB" grade or equivalent rating is potentially a legitimate criterion to assess the economic distress of Kazakh banks. However, the sovereign rating for Kazakhstan never exceeded the "BBB" grade and often carried negative outlooks during the sample period (Tradingeconomics.com, 2022). The "sovereign rating ceiling" rule indicates that the ratings for Kazakh banks were likely to be lower than the "BBB" grade during the sample period.

5.2 Results from the re-estimated models

As explained in Section 4 of this paper, the "leave-one-out" approach will result in one unique re-estimated model for each observation (i.e., eighty-four models in total); for brevity, we do

not present all these models. Using the Direct and Wilks' methods to re-estimate the original Z''-score model results in two unique re-estimated models for our sample, which are expressed as follows:

$$Z''_D = 3.769 - 1.960 X_1 + 2.430 X_2 - 1.534 X_3 + 0.670 X_4 \quad (\text{Eq.7})$$

$$Z''_W = 3.932 + 2.058X_1 - 0.728X_4 \quad (\text{Eq.8})$$

The definitions for variables X_1 - X_4 are the same as those described in Section 1 of this paper. Z''_D and Z''_W are the Z''-scores generated by the two re-estimated models using the Direct and Wilks' methods, respectively. In addition, we employ a technique used by Begley et al. (1996) and Wu et al. (2010) to identify new, optimal cut-off points. The new cut-off points are then compared to the Z''-scores predicted by the re-estimated models to classify observations into economically distressed and non-distressed groups. This technique assumes that an optimal cut-off point exists between the 25th percentile and 95th percentile of the predicted Z''-scores. At this optimal cut-off point, the sum of Type I and Type II errors is minimised, and the overall prediction accuracy ratio is maximised. Table 4 shows how the optimal cut-off point is determined for the Z''-scores predicted using the "leave-one-out" approach. It shows that the classification accuracy ratio is maximised, and the sum of Type I and II error rate is minimised at the 93rd percentile of the predicted Z'' scores. Therefore, 7.899 is used as the optimal cut-off point to classify the sample into the economically distressed and non-distressed groups. The same approach is used to identify the optimal cut-off points for the re-estimated Z''-scores predicted by Equations 7 and 8.

[Insert Table 4 here]

Table 5 presents the classification results produced by using the three re-estimation methods, which are compared to those produced by the original Altman's Z''-score model with a cut-off point of 5.85. It shows that the re-estimation of the original Altman's Z''-score model combined with new, optimal cut-off points significantly improves the classification performance. The re-estimated models correctly classify over 90% of the observations originally assigned to the economically distressed group. This suggests that the re-estimated models combined with new, optimal cut-off points could be used by Kazakh banking regulators to identify economically distressed banks. In addition, re-estimated models using the Wilks' and Direct methods produce an overall classification accuracy that is well above 50% for the whole sample. This indicates that using these two methods, combined with the use of optimal-cut-off points, does not result in random predictions of the economic distress of sample banks.

[Insert Table 5 here]

However, our classification results, especially those produced by the re-estimated models, are weaker than those reported by earlier studies, which use the Altman's Z-score model and its variations to predict bankruptcy and financial distress for non-financial companies. For example, Altman (1968; 2013) reported that the overall prediction accuracy ratio produced by the original Z-score and Z'-score models is higher than 90%, and over 90% of the bankrupt firms are correctly classified if a pre-2000 US samples is used. Grice and Ingram (2001) use a sample over the period of 1985-1987 to re-estimate the Z-score model and a hold-out sample over the period of 1988-1991 to test the power of the re-estimated model for predicting financial distress. The results show that the re-estimated model has an overall prediction accuracy ratio of 88.1%, and 94.9% of the non-distressed firms are correctly classified; however, only around 55% of the distressed firms are correctly classified. However, our results are largely comparable, if not superior, to results obtained by relatively recent studies using non-financial samples. This is probably consistent with Grice and Ingram's (2001) finding that Altman's models' predictive power may decline over time. For example, Almamy et al. (2016) use a UK sample covering the period of 2000 to 2013 to re-estimate the Z-score model and assess its ability to predict corporate failure. They report an overall prediction accuracy ratio of 54.4%, and 60.6% of failed sample firms are correctly classified by the re-estimated Z-score model. Altman et al. (2017) use a sample of firms from 35 countries which covers the period of 2007 to 2010. They find that the Z''-score model estimated by using data from all 35 countries produces an average overall prediction accuracy ratio of 49%, and the Z''-score model estimated by using country-specific data produces an average overall prediction accuracy ratio of 46.6%.

Our classification results, especially those from re-estimated models, are also largely in line with the findings from a few studies that use Altman's models to predict banks' financial distress. For example, Vaziri et al. (2012) use a sample of 100 banks from the US and Europe over the period of 2001 to 2010 to assess Altman's Z''-score model's ability to predict financial distress. They find that the overall prediction accuracy ratio and the prediction accuracy ratio for distressed sample banks vary across years; the former ranges from 59% to 95% while the later ranges from 65% to 80%. Ngwa (2016) uses a sample of 6 UK high-street banks, which covers the period of 2004 to 2013, to assess Altman's Z-score model's ability to predict financial distress. They find that the overall prediction accuracy ratio and prediction accuracy

ratio for the distressed sample banks vary across three sample periods: before the financial crisis of 2007-2009, during the crisis, and after the crisis. The overall prediction accuracy ratio ranges between 66.7% and 81%, and the prediction accuracy ratio for the distressed sample banks ranges from 72.2% to 83.3%.

6. Conclusion

This study contributes to the literature by assessing the ability of the original and re-estimated Altman's Z'' -score models to predict the economic distress of twelve Kazakh banks over the period from 2008 to 2014. It first uses the coefficients of the original Z'' -score model and a cut-off point equivalent to the minimum Z'' -score of US firms that have "BBB" ratings to classify the sample into economically distressed and non-distressed groups. This approach produces a relatively low overall prediction accuracy ratio of 44.05%, but correctly classifies 76.19% of the observations originally assigned to the economically distressed group. Then, we re-estimate the original Z'' -score model by using three methods, namely: the "leave-one-out", Direct, and Wilks methods. In addition, new, optimal cut-off points are identified for the re-estimated models by following an approach used by previous studies (e.g., Begley et al. 1996; Wu et al., 2010). Compared to the results produced by the original Z'' -score model, the combination of re-estimated models and new, optimal cut-off points delivers improved prediction accuracy. The prediction accuracy ratios produced by the three re-estimated models are all higher than 50% and the ratios produced by the Direct and Wilks methods are close to 70%, which indicates that these re-estimated models do not produce random predictions for the sample banks' economic distress. In addition, all re-estimated models correctly classify over 90% of the observations originally assigned to the economically distressed group. The results from the re-estimated models are largely consistent with those from relatively recent studies that assess the ability of Altman's models to predict bankruptcy and financial distress.

The results of this study might be useful to the banking regulators in Kazakhstan and other financial market participants. The high prediction accuracy for the economically distressed observations indicates that a combination of re-estimated Z'' -score models and optimal cut-off points could be an effective tool for the Kazakh banking regulators to detect economically distressed banks. Not being able to detect economically distressed banks before further deterioration of their financial conditions could be costly to a society because these banks may fail or collapse in the future, which often requires large government bailouts and affects financial stability. Therefore, the efficacy of the re-estimated Altman's Z'' -score models in

detecting economically distressed Kazakh banks suggests that they could be used by the Kazakh banking regulators to monitor the risk of Kazakh banks and detect those that may require early or pre-emptive interventions. Other participants in Kazakh financial markets may also use the re-estimated Z '-score models to monitor Kazakh banks' risk and differentiate economically distressed from non-distressed banks. This may help them make informed investment decisions relating to Kazakh banks, such as whether to buy, hold, or sell the securities issued by a Kazakh bank.

The study, however, is not free from limitations; therefore, our findings should be interpreted with caution. Firstly, because we use a relatively small sample, we are not able to test the predictive power of the re-estimated Z '-score model on a "hold-out" sample. Testing the model on the sample used to estimate it may inflate the prediction accuracy, a typical problem for "in-sample" forecasting. Future studies could, for instance, obtain data on more Kazakh banks or cover longer sample period to create a "hold-out" sample to further test the predictive power of Altman's Z '-score model. Secondly, the construction of the sample and initial assignment of the observations into economically distressed and non-distressed groups are subjective, which may affect the reliability of the classification results. Future studies may collect credit ratings on Kazakh banks, where available, and use ratings to pre-assign banks into economically distressed and non-distressed groups. Finally, it is debatable whether the Altman's models estimated with discriminant analysis are superior to other types of corporate failure prediction models, such as probit/logit models and market-based contingent claim models, for predicting corporate distress and failure (e.g., Hillegeist et al., 2004; Jackson and Wood, 2013). Future studies could, for example, use probit/logit models incorporating more than the five variables included in the Z '-score model and compare the predictive power of these probit/logit models with those of Altman's models.

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Table 1: Banks included in the sample

Distressed banks		Share of the total assets held by the banking sector (%)	Non-distressed banks		Share of the total assets held by the banking sector (%)
1	Kazkommertsbank	16.2	1	Halyk Bank of Kazakhstan	15.8
2	BTA Bank	9.8	2	Bank Centercredit	6.9
3	ATF Bank	5.8	3	SB Sberbank	6.7
4	Alliance Bank	3.6	4	Tsesnabank	6.0
5	Temirbank	2.0	5	Kaspi Bank	5.5
6	Nurbank	1.6	6	Bank RBK	1.4
Total		39	Total		42.3
Total share of the two groups					81.3

This table shows the sample banks control 81.3% of the total assets held by the entire Kazakh banking sector on January 1, 2014, and forms a representative sample.

Table 2: A comparison between the means and standard deviations of the four predictors included in the original Altman Z''-score model

	Non-distressed		Distressed		F-test		T-test	
	Mean	St. Dev	Mean	St. Dev	F value	p-value	t-value	p-value
X ₁	-0.309	0.576	-0.061	0.342	2.834	0.001***	-2.398	0.010***
X ₂	0.011	0.014	-0.047	0.313	0.002	0.000***	1.192	0.120
X ₃	0.068	0.032	0.033	0.293	0.012	0.000***	0.771	0.223
X ₄	0.692	1.767	0.135	0.164	116.73	0.000***	2.031	0.021**

This table shows descriptive statistics of the four predictors included in the original Altman Z''-score model. X₁: working capital/total assets; X₂: retained earnings/total assets; X₃: EBIT/ total assets; and X₄: book value of equity/book value of total liabilities. The sample includes eighty-four observations from twelve Kazakh banks and covers the period of 1st January 2008 to 1st January 2014. *, **, ***: sig. at 10%, 5%, and 1% level, respectively.

Table 3: Application of the Z''-score model with original coefficients to predict the economic distress of Kazakh banks

Type of error	Classification performance				Obs.
	No of correct predictions	% of correct predictions	No of incorrect predictions	% of incorrect predictions	
Type I	32	76.19%	10	23.81%	42
Type II	5	11.91%	37	88.09%	42
Total	37	44.05%	47	55.95%	84

This table shows the predictive accuracy of Z''-score model. The sample includes eighty-four observations from 12 Kazakh banks and covers the period of 1st January 2008 to 1st January 2014. $Z'' = 3.25 + 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4$. Cut-off point = 5.85.

Table 4: Finding the optimal cut-off point for the Altman Z''-score model re-estimated by using the “leave-one-out” approach

Ranking of Z''-scores (percentile)	Z'' scores	Classification Performance			Sum of Type I and II error rates
		Prediction accuracy	Type I error rate	Type II error rate	
25 th	0.010	36.90%	88.10%	38.10%	126.20%
30 th	0.573	36.90%	83.33%	42.86%	126.19%
35 th	1.228	42.86%	71.43%	42.86%	114.29%
40 th	1.707	42.86%	66.67%	47.62%	114.29%
45 th	2.716	42.86%	61.90%	52.38%	114.28%
50 th	2.929	45.24%	54.76%	54.76%	109.52%
55 th	3.250	47.62%	47.62%	57.14%	104.76%
60 th	3.457	42.86%	47.62%	66.67%	114.29%
65 th	3.943	40.48%	45.24%	73.81%	119.05%
70 th	4.335	39.29%	40.48%	80.95%	121.43%
75 th	4.942	41.67%	33.33%	83.33%	116.66%
80 th	5.641	44.05%	26.19%	85.71%	111.90%
85 th	5.963	46.43%	19.05%	88.10%	107.15%
89 th	6.574	47.62%	14.29%	90.48%	104.77%
90 th	6.597	48.81%	11.90%	90.48%	102.38%
91 st	6.640	50.00%	9.52%	90.48%	100.00%
92 nd	7.106	51.19%	7.14%	90.48%	97.62%
93rd	7.899	52.38%	4.76%	90.48%	95.24%
94 th	8.077	51.19%	4.76%	92.86%	97.62%
95 th	9.938	51.19%	4.76%	92.86%	97.62%

This table shows how the optimal cut-off point is identified. The sum of Type I and II error rate is minimised at the 93rd percentile of the predicted Z'' scores, which indicates that the classification accuracy ratio is maximised. Therefore, 7.899 is used as the optimal cut-off point to classify the sample into the economically distressed and non-distressed groups.

Table 5: A comparison of the classification performance produced by the different approaches

Models	Classification accuracy			Type I error	Type II error
	Full sample	distressed	non-distressed		
Z'' model (original) ^a	44.05%	76.19%	11.91%	23.81%	88.09%
Z'' model (“leave-one-out”) ^b	52.38%	95.24%	9.52%	4.76%	90.48%
Z'' _w model ^c	69.05%	90.48%	47.62%	9.52%	52.38%
Z'' _D model ^d	70.24%	95.24%	45.24%	4.76%	54.76%

This table compares the classification performance of 4 models: a) The original Z''-score model (Eq. 6) with a cut-off point of 5.85; b) The Z''-score model re-estimated by using the “leave-one-out” approach with a cut-off point of 7.899; c) The Z''_w model re-estimated by using the Wilks method (Eq. 8) with a cut-off point of 2.644; d) The Z''_D model re-estimated by using the Direct method (Eq. 7) with cut-off point of 3.905.