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Research Notes in Economics

Alternative Approaches for Modelling Corporate Sector Credit Risk

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Abstract

This note aims to estimate credit riskiness of the corporate sector in Turkey with alternative methods for January 2007 - March 2019 period. Initially, probability of default is calculated by option pricing method for the listed companies and the relationship with non-performing loan (NPL) ratio is examined. In the one-year period following the increase (decrease) in the probability of default, a similar upward (downward) movement is observed in the corporate NPL ratio of the banking sector. Since the option pricing method focuses on relatively large scale companies listed on the stock exchange, credit riskiness is also calculated using NPL additions and commercial loan interest rates to increase the comprehensiveness of the study and include financials of the relatively small scale firms (SMEs). Although the sample size and assumptions differ, credit risk indicators estimated by alternative methods move together. Therefore, the credit riskiness indicators estimated with high frequency market data is important for monitoring the financial fragilities of corporate sector and their reflections on asset quality of the banking sector.

Özet

Bu çalışmada, Türkiye'de faaliyet gösteren reel sektör firmalarının kredi riskliliği alternatif yöntemlerle Ocak 2007- Mart 2019 dönemi için tahmin edilmektedir. Öncelikle opsiyon fiyatlama yöntemiyle borsaya kote firmalar için temerrüt olasılığı hesaplanmakta ve firma kredisi tahsili gecikmiş alacak (TGA) oranıyla arasındaki ilişki incelenmektedir. Analiz sonuçlarına göre reel sektörün temerrüt olasılığındaki artışı (azalışı) izleyen bir yıllık süreçte bankacılık sektörü TGA oranında da benzer bir yukarı (aşağı) yönlü hareket olduğu görülmektedir. Opsiyon fiyatlama yönteminde borsaya kote görece büyük ölçekli firmalara odaklanıldığı için, temsil kuvvetini arttırmak ve nispeten küçük ölçekli firmaların finansal gelişmelerini de analize dâhil etmek amacıyla kredi riskliliği, TGA ilaveleri ve ticari kredi faiz oranları kullanılarak da hesaplanmaktadır. Kapsanan örneklem ve varsayımlar farklı olsa da alternatif yöntemlerle hesaplanan kredi riski göstergelerinin beraber hareket ettiği görülmektedir. Dolayısıyla, yüksek frekanstaki piyasa verileri kullanılarak hesaplanan kredi riskliliği göstergelerinin, gecikmeli finansal tablo veri akışına sahip reel kesim firmalarının finansal kırılganlıklarının izlenmesi ve bankacılık sektörü aktif kalitesine yansıması için önemli bir gösterge olduğu değerlendirilmektedir.

Introduction

Soundness of the corporate sector financials has crucial importance for sustainable economic growth. Impairment in debt repayment capacity and financial soundness of the corporate sector might lead to an increase in bounced checks and protested bills as well as deterioration in the asset quality of the banking sector. Disrupted corporate financials can be reflected as non-performing loans (NPLs) into banks' balance sheets if the borrowers do not repay loans properly and on time as required. An important part of the banking sector's assets are composed of corporate loans, therefore it is vital to monitor corporate sector financials to assess banking sector asset quality.

Analyses on corporate sector credit risk and bankruptcy estimation mainly employ methods that focus on periodically published financial statement information. The earliest model for failure estimation was proposed by Beaver (1966). He used a univariate discriminant analysis to differentiate default firms among survived ones and concluded that cash flow to total debt ratio is the main explanatory variable to differentiate firm performance. On the other hand, since the use of single variable for firm performance and failure estimation may not be considered as comprehensive; Altman (1968) extended the literature via multivariate discriminant approach. He employed five financial ratio variables which are working capital / total assets, retained earnings / total assets, earnings before interest and taxes (EBIT) / total assets, market value of equity / book value of equity and sales / total assets to explain firm failures. The model is known as Altman z-score and widely used by practitioners to evaluate firm performance. In multivariate discriminant analysis, the aim is to find the discriminant function that maximizes between-group variance and minimizes within-group variance. One of the drawback of Altman z-score is that the score is only used to classify firms and does not give insight on the probability of failure. To handle this issue, statistical approaches as logit and probit models were proposed in the literature (Ohlson, 1980; Zmijewski, 1984). The other advantage of logit / probit models over multivariate discriminant analysis is the possibility of inclusion of non-financial factors besides financial ratios in failure estimation. Financial ratios indicate information about firm specific factors, on the other hand non-financial factors capture the link regarding macroeconomic data. Contrary to these advantages, in case of insufficient number of defaults, reliable parameter estimation may not be possible in these models. In line with the technological advances and evolved studies on artificial intelligence and machine learning, more complex models as neural networks and support vector machines have been used for prediction of bankruptcy (Odom and Sharda, 1990; Shin et al.,2005).

In addition to the approaches above, contingent claim analyses which interprets financial statement data and market data together with the aim of reflecting risk more accurately is also used in the literature to model failure prediction. Merton (1974) shows that the value of equity of the firms can be modelled as a contingent claim on the residual value of its assets. Using option-pricing theory (based on Black and Scholes (1973) model), he models the value of equity as the call option written on the asset value of the firms, where debt level of the firm constitute the strike price of the option.

There are quite a number of studies in the literature that use Merton (1974) model to estimate default probability and further enhance the analysis. To name a few, Vassalou and Xing (2004) tried to explain the effect of default risk estimated with Merton (1974) model on equity returns. Chan-Lau et al (2004) estimated the default probability for 38 banks in 14 emerging countries and indicated that default probability can predict the deterioration in credit quality of a bank nine months in advance. Blavy and Souto (2009) examined the relation between expected default frequency (*EDF*) of banks and resiliency indicators of Mexican banking system. They estimate *EDF* via book value data since most large banks are not listed on the exchange market. They show that there is a high correlation between EDF and NPL, so EDF can be used as an early warning indicator.

The literature on the estimation of bankruptcy prediction for Turkish companies via Merton model is limited. Most of the studies for Turkish companies' credit risk analysis use only financial statement data (Okay, 2015; Aktan, 2011; Boyacioglu et al., 2009; Canbas et al., 2005; Erdogan, 2013; Ugurlu and Aksoy, 2006). However, Yayla et al (2008) and Yıldırım Güngör (2012) make use of Merton model in their studies for Turkish companies. Yayla et al. (2008) calculated the default probability of Turkish banks via Merton model for the period 2000-2006 to compare the performance of various periods while Yıldırım Güngör (2012) discussed Turkish non-financial corporate default probabilities for 1999-2011 period and its connection with NPL along with fundamental macroeconomic indicators.

Chan-Lau (2006) documents some alternative measures to estimate probability of default using market prices such as credit default swap premiums, bond and equity prices. Saunders and Cornett (2011) list some latest credit risk models that use financial theory and mostly use market price data such as term structure of credit risk model, RAROC model and mortality rate approach.

In this paper, Turkish non-financial corporates' (NFCs) market and balance sheet data are used together to estimate the probability of default of these companies via Merton (1974) model. Then the relation between asset quality of the banking sector and probability of default is investigated. Along with the Merton model, alternative default estimation methods were also examined to validate these probabilities. Since credit risk accumulation and cyclicality for small and medium size enterprises (SME) and large-scale companies may differ, default probabilities for these companies is also examined separately.

Data and Methodology

In this study, we calculate default probability of Turkish corporates via three different approaches. The first approach is the application of Merton option pricing method for Turkey. Since this approach uses equity (market) prices, probability of default can grasp the deterioration in firm financials well in advance. However, the applicability of the approach is limited only to firms listed on the stock exchange. The second approach calculates probability of default with NPL add-ons, while the third approach makes use of corporate interest rates. These approaches are more comprehensive in terms of firm coverage but they also have certain drawbacks as they rely on some assumptions. The details of these methods are covered in the rest of this section.

i. Corporate Default Probability with Option Pricing Methodology (Merton,1974 Model)

The asset size of the corporate sector in Turkey is double the GDP, and about half of it belongs to large-scale firms. Financial data of total NFC population is publicly disclosed on a yearly basis but with a time lag via the Entrepreneur Information System platform run by the Ministry of Industry and Technology. On the other hand, it is possible to access more frequent and quarterly market data by using financial statements of mainly large-scale firms listed on the stock exchange, Borsa Istanbul (BIST). For estimation of the probability of default via the option pricing model (Merton model), market price and financial statement information of 322 corporate sector firms quoted on the BIST are used.

In Merton's option pricing model, there are two main assumptions. The first assumption is that the market price of a firm's assets (A_T) is the total of the market value of shares and the firm's liabilities which are considered as a bond (without coupon payment and with a face value of D at maturity $T=t$). The other assumption is that the firm's asset value follows the geometric Brownian movement as shown in equation 1.

$$dA_t = A_t \mu d_t + A_t \sigma_A dW \qquad (1)$$

Change in the asset value is a function of the deterministic drift term (μ) and stochastic term ($\sigma_A dW$) where W denotes Wiener process and σ_A denotes volatility of the asset.[1] Drift coefficient equals to risk-free rate and assumed not to change during the one-year period where probability of default is estimated.

[1] Wiener process has a normal distribution with mean 0 and variance t.

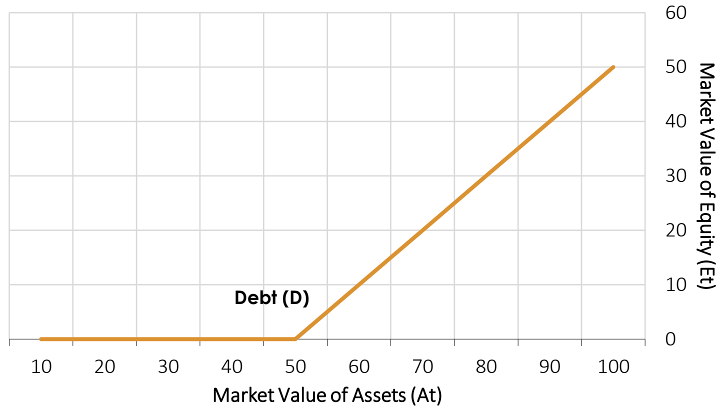
The amount that the lenders or shareholders will receive at maturity varies depending on the value of the firm's assets at that time. At maturity (*t=T*), if the firm's asset value is greater than the value of the debt, then the lenders can receive the whole amount they lent, while the potential gain by shareholders is limited to the remaining amount as lenders have precedence over shareholders. On the other hand, if the firm's asset value is smaller than the value of the debt at maturity, the shareholders will not be able to receive equity invested while lenders will receive the total asset value.

Table 1: Receivables by Counterparties

Case	Receivables by the lender	Receivables by the shareholder
$A_t > D$	D	$A_t - D$
$A_t < D$	A_t	0

Under these assumptions, the market value of the firm is priced primarily as a call option over the firm's assets (Chart 1). The strike price of this call option is the value of firm's debt (*D*). As the value of assets of the company exceeds the debt level, the shareholders start to earn value. In this context, the distance to default and the default probability of the firm are calculated by estimation of the capability of the market value of the firm's assets to cover its debt.

Chart 1: Relationship Between the Value of Call Option and the Market Value of the Assets of the Firm



Market value of the firm's assets (*A*) and its volatility (σ_A) cannot be observed in the market, however these variables can be estimated by solving equations 2 and 3 together using the firm's market value of equity (*E*) and the volatility of its equity return (σ_E).

$$E_0 = Call\ option\ price = A_0 N(d_1) - De^{-rT} N(d_2) \tag{2}$$

$$d_1 = \frac{\ln\left(\frac{A_0}{D}\right) + \left(r_f + \frac{\sigma_A^2}{2}\right)T}{\sigma_A \sqrt{T}} \quad ; \quad d_2 = d_1 - \sigma_A \sqrt{T}$$

$$\sigma_E = \frac{A_0}{E_0} N(d_1) \sigma_A \tag{3}$$

Equation 2 indicates the price of the call option and Equation 3 indicates the relationship between equity return volatility and asset return volatility. Debt data used in these equations is obtained from publicly announced financial statements of corporates via Finnet which has a quarterly frequency. To be able to calculate probability of defaults in a more frequent pattern, quarterly financial statement data is linearly interpolated[2] and converted to a monthly frequency. The volatility of equity returns (σ_E) is

[2] We prefer to use linear interpolation since interpolated data is the outstanding stock debt level. Change in stock debt levels may indicate various transactions such as additional debt usage and debt repayment; however outstanding debt level within a quarter may not record huge variation from the financial reporting period except periods with high volatility in financial conditions within a limited time period. Moreover, in the literature linear interpolation is used to fill the balance sheet series (see e.g. Simona, 2014).

calculated by using equity prices of NFCs listed on BIST. First, logarithmic equity returns are calculated and then volatility of these returns is calculated via taking 34-day moving standard deviation of equity returns. Standard deviations calculated using daily equity price changes is annualized via multiplying with$\sqrt{252}$. As the risk-free rate, we use the generic Treasury bond rate for one year maturity. As the equation 1 implies, this rate is used in a continuous compounding fashion.

It is assumed that the firm will default when the market value of the firm's assets falls short of meeting firm's liabilities/default point. In the literature, different definitions for default point is used. While some studies use total outstanding debt of the company as the default point, the widely used KMV model considers default point as the sum of short-term debt and half of long-term debt. The reasoning behind this definition is that companies in financial distress may manage cash flows by modified business strategy especially for debt repayments due more than one year. We follow the same default point definition as used in KMV model. Following this definitions, the distance to default and the probability of default are estimated by equations 4 and 5.

$$Distance\ to\ default = DD = \frac{A_T - default\ point}{\sigma_A A_T} \tag{4}$$

$$Probability\ of\ default = PD = N(-DD) \tag{5}$$

ii. Default Probability Implied by NPL Add-ons

Due to the need of stock market data for option pricing approach, probability of default can only be calculated for firms listed on the stock exchange market with that approach. However, change in the default probability of corporates also affect banking sector loan quality, so NPL realizations can also be used to estimate default probability of the corporate sector. The estimated default probability with NPL realizations is an indicator for the performance of firms that have used bank loans and has a wider coverage compared to the option pricing approach.

Change in outstanding non-performing loan amount can be explained by total of NPL additions, and net of collections, write-offs and transition to performing loans. Data for the items in equation 6 that explains the change in corporate NPLs is available at a monthly frequency since 2013.

$$NPL_{t+1} = NPL_t + NPL\ Addon_{t+1} - NPL\ Collections_{t+1} - Writeoff_{t+1} - \ Trans.to\ Performing\ Loan_{t+1} \tag{6}$$

While NPL add-on shows the deterioration of borrower performance, NPL collections and transition to performing loans shows the improvement in borrower performance. On the other hand, write-off of non-performing loans is in the discretion of banks and not necessarily dependent on macroeconomic conditions or borrower performance in the related period. Therefore, we model net NPL add-on as defined in equation 7 as a function of exposure at default (*EAD*) and default probability (PD).

$$Net\ NPL\ Addon_t = NPL\ Addon_t - NPL\ Collections_t - \ Transition\ to\ Performing\ \ Loan_t \tag{7}$$

Taking *EAD* as outstanding performing corporate loan amount, probability of corporate default can be derived from NPL add-on realizations with equation 8. Estimation of default probability from NPL realizations is also used in bank stress testing models (Fungáčová and Jakubík, 2013; Onder et al., 2016).

$$Net\ NPL\ Addon_t = PD_t * EAD_t \tag{8}$$

iii. Default Probability Implied by Corporate Interest Rates

The use of interest rates in default probability estimation is known as term structure derivation of credit risk approach (Saunders and Cornett, 2011). According to this approach, expected return of a risk-free instrument, r_f and risky instrument, *r* with a default probability should be same for an investor. While, the default probability of a risk-free instrument is zero, risky instrument can default with some probability. If the risky instrument does not default, the investor gets the full return, however if the risky instrument defaults then investor can get only the recovered amount.

$$(1 + r_f) = (1 + r) * PD * RR + (1 + r) * (1 - PD) \tag{9}$$

Equation 9 shows this relation where *RR* stands for recovery rate and based on this equation, default probability of an instrument can be calculated via equation 10.

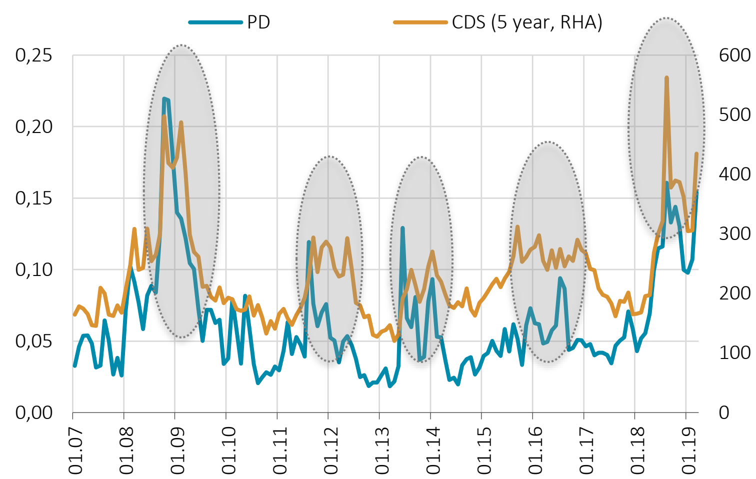
$$PD = \frac{r - r_f}{1 + r - RR - RR * r} \tag{10}$$

These equations are valid under the assumption that there is not any maturity risk premium difference between risk-free and risky instruments, so the maturities of risky and risk-free instrument should be same for the equations to hold. For example, if the maturity of the risk-free instrument is higher than the maturity of the risky instrument, then on the left side of the equation 9, there should be maturity (term) premium difference of the instruments. In the calculations, as the risk-free instrument, r_f, we use benchmark rate. Since benchmark rate has a maturity of 2 years and average TL corporate loans have also maturity close to 2 years, we ignore the effect of maturity risk premium.

Empirical Results

By using option pricing approach, we calculate probability of default for 322 firms that have operated between January 2007 and March 2019, in a monthly frequency. In order to be able to calculate a single probability of default for the whole corporate sector listed on the stock exchange market, the estimated probability of defaults for individual firms have been weighted by the market values of these firms. Initially, the weighted average default probabilities of the firms included in the sample are compared with the credit default swap (CDS) spreads of Turkey in Chart 2. The high correlation (83 percent) between the two data indicates that the probability of default estimation captures periods with macroeconomic/financial fragilities. As a matter of fact, it can be seen that the default probabilities of the firms in this study increase similar to the increase in credit default swap spreads due to the global crisis in 2008, the European debt crisis in 2011, the onset of US tapering in 2013, and the domestic and geopolitical developments in 2016. During August 2018, due to geopolitical and international political developments financial vulnerabilities increased. With the depreciated TL and increased interest rates, funding conditions deteriorated which was followed by weakening corporate sector financials and increased credit risk accumulation. Enhanced vulnerability was observed in corporate sector financials as a rise in probability of default. Since Merton model integrates market data and market volatility fluctuations with financial statement data, probability of default estimated with that approach is able to grasp the volatilities in the economy.

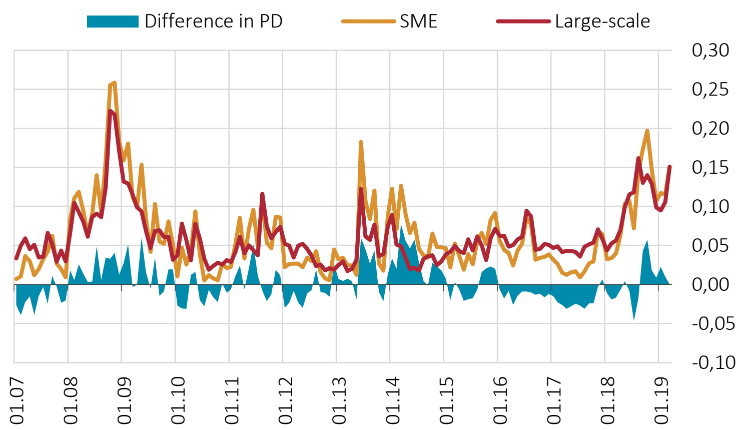
Chart 2: Probability of Default (PD) **of the Corporate Sector and Credit Default Swap** (CDS)



Source: Bloomberg, Finnet, Staff Calculations Last Observation: 03.2019

Since credit risk accumulation and cyclicality for SMEs and large-scale companies may differ, default probability for these companies is also examined separately. Turkish firms are classified as SME or large-scale firms according to the criteria defined by Ministry of Industry and Technology. For a firm to be defined as SME, number of employees should be less than 250 and yearly net sales revenue or total assets should be less than 125 million TL. This size criteria was 25 million TL before November 4th 2012 and 40 million TL between November 4th 2012 and June 24th 2018. Using quarterly data, firms that cannot satisfy sales revenue, total assets and number of employee criteria in the related period are assumed to be SME. Firms are grouped as an SME or a large-scale company on a quarterly basis and these assignments are interpolated to be used with monthly market prices and financial statements. For example, we assumed that an SME assignment for month March is valid for months March, April and May and assignment made using June financial statement is used for months June, July and August. Probability of default for SMEs and large-scale firms weighted by the market capitalization of these firms are given in Chart 3. It is seen that PDs of these companies move coherently together. As expected, in general terms PD of SMEs is higher than large-scale firms. The difference becomes 8 percent at its peak and might also become negative. For example, in 2017 SMEs were supported by Credit Guarantee Fund (CGF) loans which was effective in improving their cash-flows management and decreasing their PDs. During recessions or periods with increased uncertainty, difference of spreads between junk-bonds and other corporate bonds or treasury bonds increase. Supporting this evidence, especially in the global-financial crisis period, the difference in PD across SMEs and large-scale companies became larger for a longer time period.

Chart 3: Probability of Default (PD) for SME and Large-Scale Companies

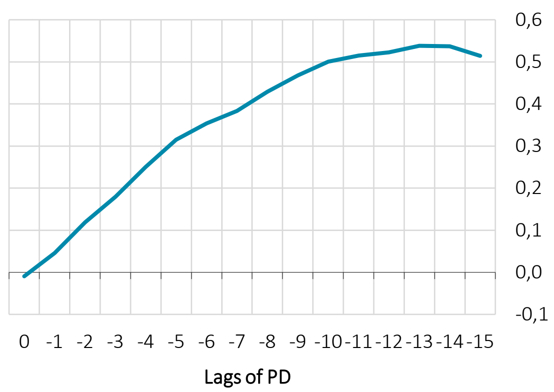


Source: Bloomberg, Finnet, Staff Calculations Last Observation: 03.2019
Difference in PD is calculated as subtracting the PD of SME from PD of large-scale.

Similar to the analysis in Blavy and Souto (2009), the relationship between the default probabilities of firms estimated by option pricing approach and the NPL indicators of banks is investigated for Turkey. Since the firms listed on the BIST are relatively large-scale firms, NPL indicators for large-scale firms are used rather than those for SMEs. The correlation between the weighted average default probability and large-scale firm NPL ratios has been examined with respect to different lag periods since the effect of an increase in the probability of default on NPL ratios of banks will appear with a lag due to regulations. A bank can classify its loan as a non-performing loan if its payment is overdue more than 90 days or set aside provisions for life-time expected credit risk considering internal credit models. Eventually, it is seen that the highest value of correlation for these two series is between the probability of default at period *t* and the NPL ratio at period *t + 12* during the years from 2007 to 2019 (Chart 4).

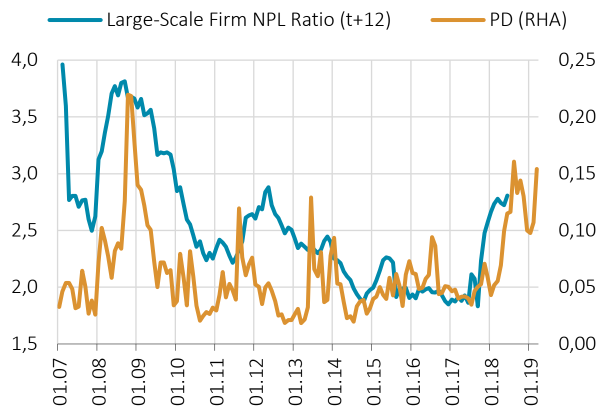
The analysis shows that the probability of default calculated using option pricing methodology is successful in predicting the one-year-ahead increase in the NPL of large scale firms, particularly in the global financial crisis period in 2008 and the European debt crisis period in 2011 (Chart 5). On the other hand, it should be noted that we should leave a margin of safety in this inference because of the inclusion of the entire firm universe in the calculation of the large-scale firms' NPL ratio although the probability of default in the study is calculated only for a limited number of large-scale firms, more clearly only for firms listed on the stock exchange.

Chart 4: Correlation between PD and Large-Scale Firm NPL Ratios for Different Lags of PD



Source: CBRT, Author Calculations

Chart 5: PD and Large-Scale Firm NPL Ratio

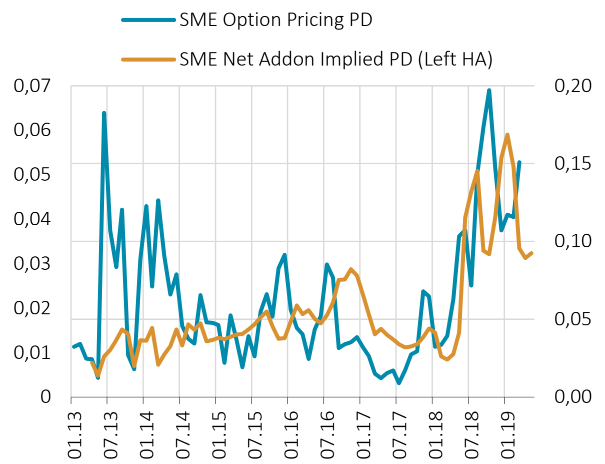


Source: CBRT, Author Calculations Last Observation: 03.2019

To estimate the probability of default from net NPL add-ons at time *t*, we divide the sum of net NPL add-ons in months *(t)*, *(t-1)* and *(t-2)* to the performing loan level at time *(t-3)* and then annualize this probability of default by multiplying by four. We sum net NPL add-ons for three months since data is volatile and divide to the previous month's performing loan level since due to regulatory reasons, banks classify a loan as NPL mainly that is overdue after 90 days.

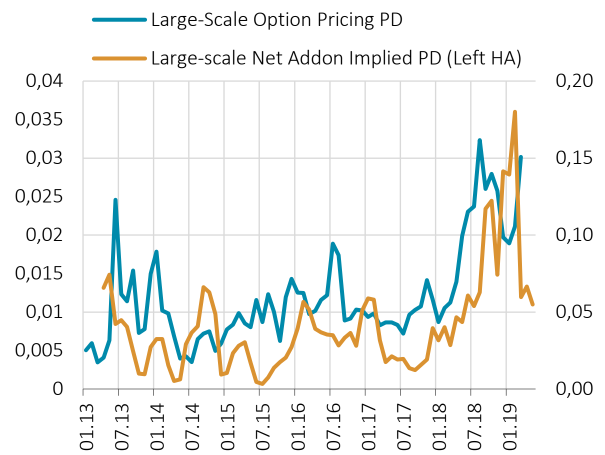
Probability of default from net NPL add-ons is calculated both for SMEs and large-scale companies by using their respective net NPL add-ons and performing loan levels. In this study, we also aim to compare PDs calculated using option pricing approach and NPL add-on. Comparison of these PDs are given in Chart 6 and 7. We find that the correlation between PD calculated using option pricing approach and net NPL add-on is about 55 percent with 3 months lag for SMEs and 67 percent with 6 month lag for large-scale companies. Following an increase in the probability of default of SME implied by option pricing, net SME NPL add-on increases in the next quarter. On the other hand, the correlation becomes highest for two quarters for large-scale companies. The correlation between PD calculated using option pricing approach and net NPL add-on may be higher for large-scale companies due to the fact that large-scale companies listed in stock markets may be dominating the large-scale firms in the loan book of the banks and SMEs that are listed on the stock exchange may constitute only a small portion of SMEs that are in the loan book of the banks.

Chart 6: Relation Between PD calculated by Option Pricing and PD implied by NPL Net Add-on for SMEs



Source: CBRT, Author Calculations

Chart 7: Relation Between PD calculated by Option Pricing and PD implied by NPL Net Add-on for Large-scale Companies



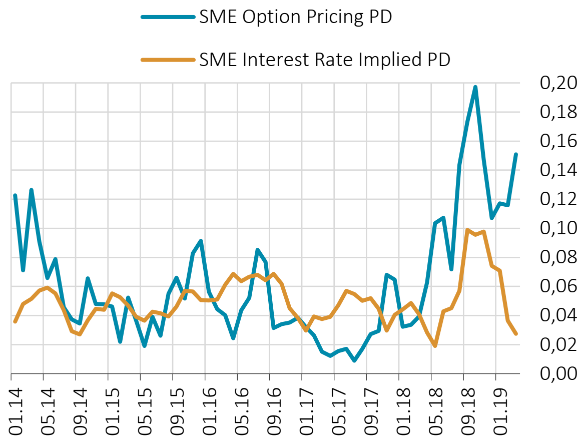
Source: CBRT, Author Calculations Last Observation: 03.2019

Even though option pricing model based default probability and net NPL add-on implied default probability implies varying levels, the movements of two series are highly correlated. On the other hand, the probability of default based on NPL add-on approach should be interpreted with caution due to the fact that restructuring of close-monitoring loans (performing loans) mitigates increases in net NPL add-on, so PDs implied by net NPL add-on are estimated lower in high restructuring periods. Moreover, firm samples covered in these two approaches are different. While, firms listed on exchange market are covered in the option pricing approach, the firms that use loans from Turkish banks are included in the NPL add-on approach.

While estimating default probability from interest rates, we use flow corporate loan rates that is available since 2002 in a weekly frequency. However, loan rates for overdraft accounts and corporate credit cards are also included in that series, which may cause misinterpretation of the interest rates. These rates can be excluded from the corporate loan rates starting from January 2014 in the breakdown of SME and large-scale companies, so this analysis is conducted for the period between January 2014 and March 2019. Focusing on TL denominated interest rates, we first calculate average of weekly flow corporate loan rates and average of daily benchmark rates for each month in the analysis period. For the recovery rate, *RR*, parameter in equation 9, we use World Bank data[3].

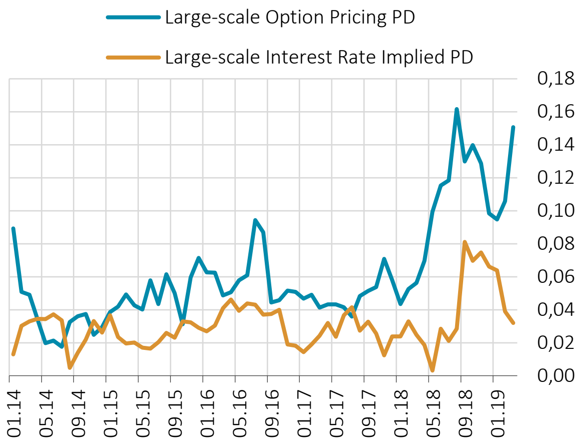
[3] https://www.doingbusiness.org/en/data/exploretopics/resolving-insolvency

Chart 8: Relation Between PD calculated by Option Pricing and PD Implied by Corporate Interest Rates for SMEs



Source: CBRT, Author Calculations

Chart 9: Relation Between PD calculated by Option Pricing and PD Implied by Corporate Interest Rates for Large-scale Companies



Source: CBRT, Author Calculations Last Observation: 03.2019

Default probabilities estimated from corporate interest rates are shown by comparing with the default probabilities calculated via option pricing approach for SMEs and large-scale companies in Chart 8 and 9. We find that the correlation between default probability calculated via option pricing and corporate interest rates is quite high with one month lag for SMEs and three months lag for large-scale companies. The increase (decrease) in option pricing based default probability is followed with an increase (decrease) in interest rate implied default probability. The correlations between these series is high because interest rates is also used as a parameter in option pricing approach. In the analysis, we use a low level of recovery rate, however Onder et al. (2016) model recovery rate to be between 40 percent and 55 percent for Turkish banking sector. If a higher recovery rate is used the default probability estimated from interest rates increase and two series become closer.

The correlations between option pricing approach based default probability and default probability estimated via other approaches are summarized in Table 2. The estimated correlations are quite high especially for large-scale companies because the firms classified as large-scale in the loan book are generally listed firms in the stock exchange.

Table 2: Correlations Between PDs Calculated by Different Approaches

	Total Corporates	Large-scale	SME
Option Pricing and Net NPL Add-on	70	67	55
Option Pricing and Interest Rates	68	72	53

Note: Maximum correlations according to different lags are shown in the table.

It is worth mentioning that differences in lag periods for PDs by option pricing methodology, by corporate loan interest rates and by NPL add-ons are mainly due to differences in NPL classification standards and usage of market data. As mentioned above, option pricing methodology makes use of equity prices (market data), so captures movements in market prices, while NPL add-ons are determined as a result of actual debt repayment capacity. Moreover, loans are classified as NPL in bank loan books after ninety days overdue payment. Since PDs derived from interest rates and option pricing use recent market data and for NPL classification there should pass ninety days over overdue payment, the relation between PD implied by option pricing and interest rates indicate a shorter lag period compared to the relation between PD implied by option pricing and NPL add-on.

Conclusion

Monitoring corporate sector vulnerabilities has crucial importance to mitigate systemic risk and potential repercussions on banking sector asset quality due to deterioration in NFC debt repayment capacity especially for regulatory authorities with financial stability mandate.

NFC asset size is double the size of GDP thus continuous corporate sector activity with a robust financial structure is vital for maintaining sustainable economic growth while NFC debt repayment performance is a significant determinant of the banking sector credit risk accumulation.

This study focuses on probability of default estimations derived by three different methodologies for Turkish corporate sector including option pricing method along with those implied by NPL movements and corporate interest rate risk premium. We find that estimated corporate default probabilities and banking sector corporate NPL ratios indicate a significant relation. We show that option pricing method based default probability acts as a 12 months' ahead leading indicator for the realizations of corporate NPL ratio.

In an environment where financial statement information of the corporate sector is available with two to nine months lag, corporate sector credit risk developments can be estimated in a timelier manner using market data of the listed companies, interest rates and NPL movements of the corporate universe at high frequency. Thus, corporate sector vulnerabilities and risks stemming from their financial structure can be analyzed with high frequency data for financial stability purposes. Additionally, these estimation methods can be utilized to increase effectiveness of prudential measures and their timing to mitigate systemic risk.

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