STATISTICAL MEASURES OF SYSTEMIC RISK:

AN APPLICATION FOR THE TURKISH BANKING SYSTEM

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DECLARATION OF ORIGINALITY

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ABSTRACT

Statistical Measures of Systemic Risk:

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In this paper, we basically apply market data based statistical methods to measure systemic risk for the Turkish banking sector. In order to have a broad perspective on systemic risk with different dimensions, we employ four widely used systemic risk measures namely, MES, SRISK, CES and ΔCoVaR. First, aggregate versions of our systemic risk measures show the relative increase in systemic risk during 2000 - 2001 and 2008 crisis periods together with a pick-up in SRISK towards 2018-end. We test for predictive accuracy of SRISK as a conditional capital shortfall forecast using four cases of realized market downturns during crisis periods and results indicate that predicted SRISK levels of individual banks seem to be an acceptable estimate for realized capital shortfalls with some positive bias in particular. Tobit panel regressions of probability of defaults (PD) of individual banks on systemic risk measures indicate that, increased level of systemic risk is significantly associated with higher levels of PD up to 3-months horizon. Additionally, we compare model results in terms of their SIFI rankings which indicates that systemic risk measures have an importance in terms of ranking financial institutions based on risk characteristics beyond what can be observed by the ordinary market risk measures like VaR. As a way of comparing the relative reliability of systemic risk measures, we calculate guilt probabilities of banks associated with MES and ΔCoVaR and conclude that overall, MES and consequently MES based systemic risk metrics are relatively more reliable in terms of detecting the possible SIFIs in the Turkish banking system, albeit with a high degree of estimation risk.

ÖZET

Sistemik Riskin İstatistiksel Ölçütleri:

Türk Bankacılık Sistemi için bir Uygulama

Bu çalışmada, Türk bankacılık sektöründeki sistemik riskin ölçülmesi için piyasa verisi temelli istatistiksel yöntemler kullanılmıştır. Sistemik riskin çeşitli boyutlarını kapsamlı bir şekilde incelemek adına, yaygın olarak kullanılan dört sistemik risk ölçütü (MES, SRISK, CES ve ΔCoVaR) ele alınmıştır. Sistemik risk ölçütlerinin sektörel toplu versiyonları 2000 - 2001 ve 2008 kriz dönemlerinde (2018 sonundaki SRISK artışı ile birlikte) görece artış göstermektedir. Kriz dönemlerinde piyasada ciddi düşüşlerin yaşandığı dört vaka üzerinden SRISK ölçütünün bir koşullu sermaye açığı tahmincisi olarak tahmin doğruluğu incelenmiş ve tahmin edilen SRISK seviyelerinin gerçekleşen banka sermaye açıklarını (bir miktar pozitif yanlıklıkla ile) açıklayabildiği görülmüştür. Panel tobit regresyonu sonuçlarına göre, banka seviyesinde yüksek sistemik risk seviyeleri üç aylık vadeye kadar geçerli olmak üzere yüksek temerrüt olasılığı (TO) ile istatistiki olarak anlamlı seviyede ilişkili gözükmektedir. Bunlara ek olarak, model sonuçları sistemik önemli banka sıralamaları açısından karşılaştırıldığında, sistemik risk ölçütlerinin VaR gibi standart piyasa riski ölçütleri tarafından gözlemlenen risk karakteristiklerinin ötesinde sıralamalar sunduğu görülmüştür. Sistemik risk ölçütlerinin göreceli güvenirliğini karşılaştırmak adına, MES ve ΔCoVaR üzerinden bankaların suçluluk olasılıkları hesaplanmış; yüksek tahmin riski bulunmasına karşın, MES ve MES tabanlı sistemik risk ölçütlerinin riskli bankaları saptama adına göreceli olarak daha güvenilir olduğu sonucuna varılmıştır.

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CHAPTER 1

INTRODUCTION

The experience of 2008 global crisis put the concept of systemic risk directly into the agenda of academics and policymakers. Since then, while there has been quite an effort for the correct measurement of systemic risk on the academics side, regulators started to implement policies including extra capital buffers for systemically risky banks with the aim of addressing certain characteristics associated with systemic risk such as size, interconnectedness and complexity. In that sense, true detection of a systemically important financial institution (SIFI) and correct ranking of banks in terms of their systemic risk contribution reveals great importance for minimizing possible social costs through implementing pro-active macro-prudential regulations for the anticipated risky institutions.

While the current Basel regulations uses an ad-hoc scoring methodology for the classification of banks according to their systemic risk, there has been a growing literature on systemic risk analysis and measurement that use publicly available data especially after the 2008 financial crisis. The first strand of literature uses network topology theory methods to analyze interbank linkages and financial system interconnections. Among them, Billio et al. (2012) uses principal component analysis and network structures derived from Granger causality analysis. Diebold & Yilmaz (2014) use variance decompositions from vector autoregressions as a tool for constructing time-varying network structures. Demirer et al. (2018) apply a similar methodology of Diebold & Yilmaz (2014) to a wider set of global financial institutions extending the model with a Lasso-selection framework. In their theoretical analysis, Acemoglu, Ozdaglar & Salehi (2015) argue that a high degree of interconnection in a financial system may indeed act as a buffer against shocks as long as the magnitude of shock is sufficiently small. Otherwise, in case of major shocks, interbank linkages work as a propagation mechanism making the overall financial system more fragile.

The second strand of literature, which this paper will focus on basically, relies on statistical methods that use publicly available market data. Acharya et al. (2017) builds a theoretical framework in which individual banks generate systemic risk as a result of their individual profit-maximizing decisions and does not take into account the externalities they create. They argue that, this externality can be internalized by banks using a tax system based on each bank's contribution to the systemic risk which can be measured by their Marginal Expected Shortfall (MES) defined as the expected equity return of a bank conditional on a crisis. Based on the theoretical framework and concept of MES developed by Acharya et al. (2017), Brownlees & Engle (2017) proposes the measure of SRISK, expected capital shortfall of a financial institution in case of a serious financial downturn. The measure they propose is also practically relevant in the sense that it conceptually mimics the stress tests made by regulators. Engle, Jondeau & Rockinger (2015) is an application of SRISK measure to the major European financial institutions taking into account the interaction between individual firm, European and global financial markets. Another popular systemic risk measure introduced by Adrian & Brunnermeier (2016) is ΔCoVaR. CoVaR is the Value-at-Risk (VaR) of a financial system conditional on a particular institution is in distress (at its VaR level) and ΔCoVaR is the difference between CoVaR conditional on the firm being in distress and firm at its median state. As for MES, ΔCoVaR is also a directional measure (with reverse direction of conditioning) in the sense that conditionality runs from individual firm to the whole financial system. As an extension to this model structure with the same direction of conditionality, Hautsch, Schaumburg & Schienle (2015) proposes Systemic Risk Beta defined as the marginal effect of a firm's VaR on the system's VaR. By means of the econometric methodology (lasso-quantile regression) they use, in addition to measuring systemic importance of a particular firm, it is also possible to shed some light on the interconnectedness of the system network structure.

Other related work that analyze systemic risk with statistical methods using market based data include Distress Insurance Premium of Huang, Zhou & Zhu (2009), CES of Banulescu & Dumitrescu (2015), Co-CoVaR of Boucher et al. (2013), CATFIN of Allen, Bali & Tang (2012). For a more detailed and comprehensive summary of systemic risk literature and related measures, check Bisias et al. (2012) and Benoit et al. (2017).

There are also some findings in the related literature that makes some criticisms and warnings for the imprudent use of these systemic risk measures. Danielsson et al. (2016b) discuss the potential existence of model risk for market risk and market risk based systemic risk measures. The degree of divergence between different risk models, which they define as model risk, seems to increase during market turmoil which makes it harder for policymakers and market practitioners to make correct decisions. In addition to that, even if we do have a technically perfect systemic risk measure which gives us the correct ranking of systemically risky banks when we have an infinite amount of data, Danielsson et al. (2016a) shows that estimation risk alone may mislead us in terms of inferring the true risk ranking of institutions with the limited data sample in our hands in reality. Thus, any macroprudential regulation (like extra capital requirements) that depends on such a statistical measure, for a specific potentially risky bank, should be implemented with great caution without creating additional distortions in the banking system.

Applications of systemic risk methodologies for Turkish financial markets are rather limited. Among network topology methods, Saltoglu & Yenilmez (2010), Saltoglu & Yenilmez (2015) and Kuzubas, Omercikoglu, Saltoglu (2014) use inter-bank repo market data to investigate the network structure of Turkish banking system in 2000 crisis. One common finding of these studies is the coexistence of declining interconnectivity and increasing concentration (around Demirbank which was the focal point of 2000 crisis) before the crisis which adds an additional dimension to be considered when analyzing systemic risk and interconnectivity relationship.

In the class of statistical approaches using market data, Binici, Koksal & Orman (2013) examines the co-movement in bank stock returns (as an indicator for herding behavior) using pairwise correlations and relates them to firm characteristics and macroeconomic factors. Their approach gives a general picture of aggregate systemic risk by depicting sector-level co-movements, but falls short of showing the dependence structure in the tail and providing firm specific rankings. Employing MES measure of Acharya et al (2017), Talasli (2013) compares MES and leverage of financial institutions with other market risk measures (such as expected shortfall, market beta and stock return volatility) cross-sectionally in a time-invariant setting for 2000-2001 and 2008 crisis. Due to static nature of the analysis and limited number of banks in the financial system, it is hard to make a clear judgment on the superiority of MES over other market risk measures in terms of its explanatory power for losses in crisis periods.

In this paper, we basically apply market data based statistical methods to measure systemic risk for the Turkish banking system. In order to analyze the direction of conditionality from both sides (financial system to firm and firm to financial system) and to cover the different dimensions of systemic risk such as size, interconnectedness and comovement, we specifically employ four widely used systemic risk measures: MES of Acharya et al. (2017), SRISK of Brownlees & Engle (2017), CES of Banulescu & Dumitrescu (2015) and ΔCoVaR of Adrian & Brunnermeier (2016).

First, we display aggregate systemic risk dynamics of the Turkish banking system with the use of aggregate versions of MES, CES and ΔCoVaR and show the relative increase in systemic risk levels for 2000 – 2001 and 2008 crisis periods as well as the recent pick up in the aggregate risk after 2018 August with the sharp depreciation of Turkish lira. In addition to aggregate measures of systemic risk, we also present the total SRISK of the Turkish banking system, for which we also observe a pick-up for the period through 2018-end mainly due to worsening in market to book ratios and increase in nominal values of bank liabilities after rapid currency depreciation. Since SRISK is a conditional capital shortfall estimate denominated in Turkish liras and can be regarded as a market based version of stress tests applied by regulatory authorities, we compared realized capital shortfalls with predicted SRISK figures and conclude that predicted SRISK levels seem to be an acceptable predictor for realized capital shortfalls with some positive bias in particular.

Next, we turn into the relationship between systemic risk measures and level of financial stress for a particular institution and tested whether systemic risk measures of SRISK and COVaR relate with banks' probability of default (PD) estimated with a Merton type structural model. Due to truncated nature of PD estimates, we have employed a Tobit panel regression setting with contemporaneous and lagged specifications. Regression results indicate that high levels of %SRISK and ΔCoVaR are significantly associated with increased probability of default even after controlling for related risk metrics such as leverage, value-at-risk and size and this relationship holds for up to three months lag for %SRISK.

After having a general picture of Turkish banking system through the lens of statistical systemic risk measures, we then compare model results in terms of their SIFI rankings through time with the use of Kendall rank correlations. Although there exists some degree of heterogeneity in rankings for different systemic risk measures, there are some points to be emphasized. First, asset size of a bank seems to be a dominant factor in rankings although it is not an input for systemic risk metrics except indirectly for CES and SRISK. Second, we do not observe a particular change in the dynamics of rank correlations during crisis periods which would possibly affect the reliability of a policy recommendation based on the results of these metrics. Lastly, Kendall rank correlations of VaR based rankings with other systemic risk measures are rather low and close to zero which shows us that systemic risk measures covered in this analysis has an importance in terms of ranking financial institutions based on risk characteristics beyond what can be observed by the ordinary market risk measures like VaR.

Lastly, as a way of comparing the relative reliability of systemic risk measures and to check the extent of possible estimation errors, we calculate guilt probabilities of banks associated with MES and ΔCoVaR and conclude that overall, MES (and consequently MES related systemic risk metrics such as SRISK and CES) is relatively more reliable in terms of detecting the possible SIFIs in the Turkish banking system.

CHAPTER 2

METHODOLOGY: STATISTICAL MEASURES OF SYSTEMIC RISK

In this chapter, we will present the methodology behind the systemic risk measures that we cover in our analysis for MES, SRISK, CES and ΔCoVaR. Since all these measures depend on market risk statistics such as Value-at-Risk (VaR) and Expected Shortfall (ES), we will first briefly go over these metrics.

2.1 Market risk measures: Value-at-risk and expected shortfall

Value-at-Risk is a very commonly used risk measure answering the following question: for a given asset or portfolio and for a given time horizon, what is the worst level of return (loss) that will be surpassed with $(1 - q)\%$ of probability? Since the aim is to have an estimate on possible worst case scenarios, q is usually selected to be 1% or 5%.

There are several methods to estimate VaR including non-parametric methods such as historical simulation and parametric methods like variance-covariance modelling or models using extreme-value theory. Regardless of the estimation method, VaR became a standard measure to assess market risk that is widely used both by market participants and regulators. According to Basel accords of Bank of International Settlements, banks need to hold a certain amount of capital as a buffer against potential market risks for which VaR methods are used extensively.

In spite of its popularity, since it is a point estimate, VaR metric has a disadvantage of not showing the potential losses that exceed the estimated VaR level. Two assets with the same VaR level may have very different tail distributions which hinders the informativeness of the measure. One potential solution to this problem comes from Expected Shortfall (ES) measure which concerns not only with the percentage of return losses that exceed the VaR level but also the magnitude of them. Similar to the VaR, ES is defined for a certain probability level and gives us the expected return of an asset at its worst $q\%$ quantile. So, VaR is estimated as an intermediary-step for ES calculation. Following formal mathematical definitions also show the relationship between two risk measures:

$$\Pr\left(R_{t+1} \middle| R_{t+1} \leq VaR_{t+1}^{q}\right) = q\%$$

$$ES_{t+1}^{q} = -E\left[R_{t+1} | R_{t+1} < VaR_{t+1}^{q}\right]$$

2.2 MES

Acharya et al.'s (2017) Marginal Expected Shortfall (MES) is a systemic risk measure that can be regarded as the multivariate version of ES that takes into account the interdependencies between individual bank and the system. Suppose that return of the financial system can be represented by the weighted average of individual bank returns:

$$R^{m} = \sum_{i} w^{i} R^{i}$$

where R^{m} and R^{i} are market and individual bank returns and w^{i} is the market share of bank i. From the definition of expected shortfall, we can write the expected shortfall of the system as:

$$ES_{q}^{m} = -\sum_{i} w^{i} E\left[R^{i} | R^{m} < VaR_{q}^{m}\right]$$

Then, each bank's contribution to the systemic risk can be measured by its marginal contribution to the total expected shortfall of the market:

$$MES_{q}^{m} = \frac{\partial ES_{q}^{m}}{\partial w^{i}} = -E\left[R^{i} | R^{m} < VaR_{q}^{m}\right]$$

As can be seen from the definition above, MES is a simple yet intuitive approach for measuring systemic risk. It simply shows the expected return for a bank when the financial system in total is in distress (below its VaR level). As we'll see in the following sections, MES also lays the foundation for other proposed systemic risk measures such as SRISK and CES.

2.3 LRMES and SRISK

SRISK of Brownlees & Engle (2017) builds on the capital shortfall of a financial institution which is the necessary capital that an institution needs to hold by regulation less existing capital. At any time t, capital shortfall of an individual bank can be expressed by:

$$
\begin{aligned}
CS_t &= k.A_t - W_t \\
&= k(D_t + W_t) - W_t \\
&= k.D_t - (1-k)W_t
\end{aligned}
$$

where D_t is the book value of debt, W_t is the market value of equity (which makes A_t to be quasi-assets) and k is the macroprudential capital adequacy ratio.

SRISK is then defined as the expected capital shortfall of an institution conditional on a serious market crash for a given horizon h:

$$
\begin{aligned}
SRISK_t^i &= E(CS_{t+h} | R_{t+h}^m < C) \\
&= k.E(D_{t+h} | R_{t+h}^m < C) - (1-k)E(W_{t+h} | R_{t+h}^m < C) \\
&= k.D_t - (1-k)E(W_{t+h} | R_{t+h}^m < C)
\end{aligned}
$$

where R_{t+h}^m is defined to be multi-period market return between period t and $t+h$ and C is the market decline threshold. In our estimations, h is chosen to be one month (22 working days) as in Brownlees & Engle (2017). For the crisis threshold C, unlike their choice of 10% market drop for US equity markets, we chose 25% market drop which takes into account the relative volatility of Turkish equity markets and corresponds to almost once a decade event.[1] Lastly, for the last step in above equation, debt is assumed to be non-negotiable and constant in a crisis scenario which drops down the expectation operator.

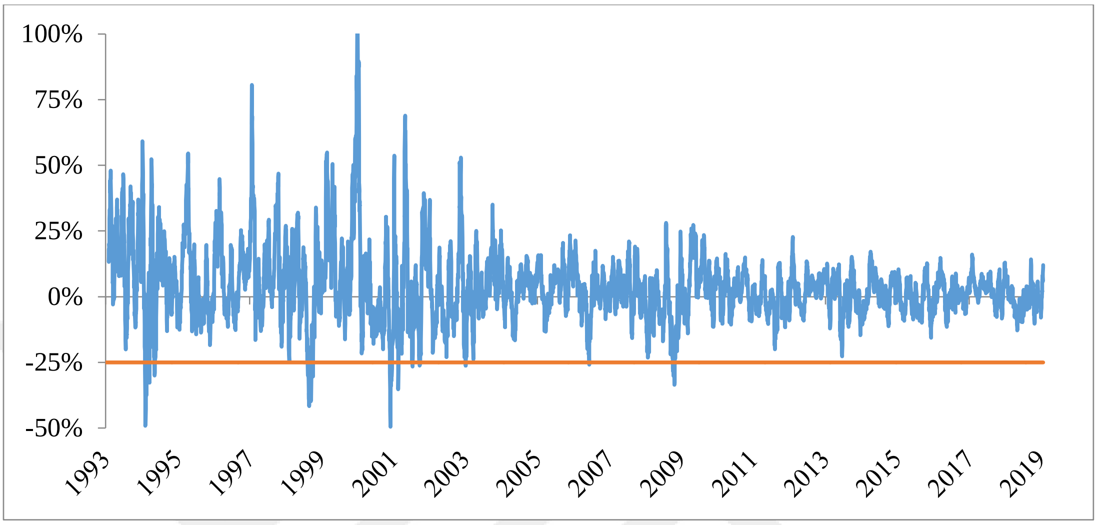


Figure 1. BIST100 index monthly return

Defining Long-Run Marginal Expected Shortfall (LRMES) as the expected firm return conditional on a market fall, $LRMES_t = -E\left(R^i_{t+h} \middle| R^m_{t+h} < C\right)$ and modifying the above equation a little bit yields

$$SRISK^i_t = k.D_t - (1-k)(1 - LRMES_t)W_t$$

Lastly, expressing quasi-leverage (quasi-assets over market value of equity) as $Lev_t = \frac{D_t + W_t}{W_t}$, we derive a more intuitive way of writing the same expression,

$$SRISK^i_t = W_t[k.Lev_t + (1-k)LRMES_t - 1]$$

which says SRISK of a firm is an increasing function of its size (market capitalization), quasi-leverage and LRMES.

Systemic risk contribution of a particular firm i is, then, defined as

[1] Volatility of daily returns for BIST100 and S&P 500 indices are 2.4% and 1.1% respectively for the 1993-2018 period which necessitates a higher crisis treshold for Turkey. Figure 1 presents the instances for which monthly BIST100 return exceeded 25% market drop threshold.

$$\%SRISK_t^i = \frac{SRISK_t^i}{SRISK_t}$$

where system's total capital shortfall is $SRISK_t = \sum_{i=1}^{N} SRISK_t^i$ and $SRISK_t^i$ being non-negative which means excess capital of a particular firm in a crisis scenario cannot be allocated to ones that are in distress.

As can be seen from the SRISK equation above, computation of SRISK requires LRMES estimation as a first step. For that, one needs to construct a model for firm and market returns that represents their tail relationship. In this paper, we have used the same DCC-GARCH model structure employed by Brownlees & Engle (2017) which is a GJR-GARCH approach (Glosten, Jagananthan & Runkle (1993), Rabemananjara & Zakoian (1993)) for modeling volatilities and Dynamic Conditional Correlation (DCC) approach (Engle (2002)) for modeling correlations. This type of econometric models have a wide application range especially in financial time-series, since they offer flexible structures to model asymmetries in volatility and dynamic correlation framework which makes sense for systemic risk analysis.

After modeling volatilities and dynamic correlations, we employed a Monte-Carlo type simulation procedure for estimating LRMES as Brownlees & Engle (2017), since there is no closed-form solution in this type of a dynamic setting. Resampling with replacement using DCC-GARCH standardized residuals, we derive S number of simulated paths for h = 22-days of market and firm log-returns which then can be used to compute arithmetic returns R_{t+h}^m and R_{t+h}^i. LRMES, then, is the simple average of simulated arithmetic firm returns conditional on market is in distress:

$$LRMES_t^i = \frac{\sum_{s=1}^{S} R_{t+h}^i \, I\{R_{t+h}^m < C\}}{\sum_{s=1}^{S} I\{R_{t+h}^m < C\}}$$

2.4 CES

Component Expected Shortfall (CES) by Banulescu & Dumitrescu (2015) is an extension to MES of Acharya et al. (2017) and is defined as the product of MES of an individual bank and its share in the banking system:

$$CES_q^i = w^i \frac{\partial ES_q^m}{\partial w^i} = -w^i E\left[R^i | R^m < VaR_q^m\right]$$

Thus, CES take into account the size of the bank as a systemic risk indicator in addition to other risk features measured by MES. As opposed to MES, CES measures the absolute (not marginal) systemic contribution of an individual bank to the total risk in the system. By its nature, sum of individual banks' CES gives the total expected shortfall of the market which makes it possible to denote CES of an institution as a percentage of market ES.

2.5 ΔCoVaR

As like LRMES measure is based on the expected shortfall (ES) used for market risk purposes, CoVaR has a close relationship with Value-at-Risk (VaR). Recall that VaR_q^i level indicates that with probability $q\%$, return of a given firm R^i (for a given time horizon) will exceed that VaR level. Similarly, $CoVaR_q^{m|i}$ is defined as the VaR level of the financial system conditional on firm i being on its VaR level:

$$\Pr\left(R^m \middle| C(R_i) \leq CoVaR_q^{m|R^i=VaR_q^i}\right) = q\%$$

For measuring the systemic contribution of a specific firm to the market distress, Adrian & Brunnermeier (2016) then offers $\Delta CoVaR_q^{m|i}$:

$$\Delta CoVaR_q^{m|i} = CoVaR_q^{m|R^i=VaR_q^i} - CoVaR_q^{m|R^i=VaR_{50\%}^i}$$

which is the difference in the VaR of the financial system conditional on firm i being in distress (at its VaR level) and firm i being in normal circumstances (median level).

There are several ways to estimate CoVaR including multivariate GARCH models and copula methods. In this analysis, as in Adrian & Brunnermeier (2016), we have used quantile regression approach developed by Koenker & Bassett (1978). Unlike OLS, quantile regressions estimate the relationship between variables on the $q\%$ quantile. So, OLS can be interpreted as a special case of quantile regression where $q = 50\%$. For the estimation of $CoVaR_q^{m|i}$, think of a $q\%$ quantile regression of system returns on the returns of firm i:

$$\hat{R}_q^m = \hat{\alpha} + \hat{\beta}R^i$$

where $\hat{\alpha}$ and $\hat{\beta}$ are estimated quantile regression parameters and $\hat{R}_q^m$ is the fitted value. $\hat{R}_q^m$ can also be interpreted as the $q\%$ VaR of the system conditional on firm i returns. So, if we specify conditioning event as $R^i = VaR_q^i$, we end up with an estimate of system VaR conditional on firm i being at its VaR level:

$$CoVaR_q^i = \hat{\alpha} + \hat{\beta}VaR_q^i$$

Similarly, $\Delta CoVaR_q^i$ can be estimated using the same quantile regression estimated above evaluated also at the median return level of firm i:

$$\begin{aligned}\Delta CoVaR_q^i &= CoVaR_q^i - CoVaR_q^{m|R^i=VaR_{50\%}^i} \\ &= \hat{\alpha} + \hat{\beta}VaR_q^i - \hat{\alpha} + \hat{\beta}VaR_{50\%}^i \\ &= \hat{\beta}(VaR_q^i - VaR_{50\%}^i)\end{aligned}$$

Depending on the method for estimating VaR and the estimation window size, we have calculated two types of ΔCoVaR: a static one, as in Adrian & Brunnermeier (2016), with full sample size and VaR estimated by historical simulation and a time-varying ΔCoVaR with 5-year rolling estimation window size and VaR estimated by a GARCH model. As we present in the following chapters, the former version is used to make comparisons with VaR estimates while the latter one is used for systemic risk ranking analysis and testing explanatory power for financial stress.

CHAPTER 3

DATA AND DESCRIPTIVE STATISTICS

In our analysis, we use an unbalanced panel data of 14 publicly traded Turkish commercial banks including 12 private and 2 public banks for the period between 1993 and 2018. Our sample of 14 banks has a high representative power for the whole banking sector in the sense that it constitutes around 80% of the capital of the total banking system (Figure 2). Check Table 1 for a full list of abbreviations used and respective periods for equity price data.

Table 1. List of Abbreviations for Data Sample

Abbreviation	Name	Start	End
AKBNK	Akbank T.A.Ş.	Jan-93	Dec-18
ALBRK	Albaraka Türk Katılım Bankası A.Ş.	Jul-07	Dec-18
ALNTF	Alternatifbank A.Ş.	Jul-95	Jun-15
ASYAB	Asya Katılım Bankası A.Ş.	May-06	Jun-16
DENIZ	Denizbank A.Ş.	Oct-04	Dec-18
QNBFB	QNB Finansbank A.Ş.	Jan-95	Dec-18
GARAN	Türkiye Garanti Bankası A.Ş.	Jan-93	Dec-18
HALKB	Türkiye Halk Bankası A.Ş.	May-07	Dec-18
ISBNK	Türkiye İş Bankası A.Ş.	Jan-93	Dec-18
SEKER	Şekerbank T.A.Ş.	Apr-97	Dec-18
TEBNK	Türk Ekonomi Bankası A.Ş.	Mar-00	Mar-15
TSKB	Türkiye Sınai Kalkınma Bankası A.Ş.	Jan-93	Dec-18
VAKIF	Türkiye Vakıflar Bankası T.A.O.	Nov-05	Dec-18
YKBNK	Yapı ve Kredi Bankası A.Ş.	Jan-93	Dec-18
BIST100	BIST 100 Index	Jan-93	Dec-18

For estimation of all systemic risk measures, we have used daily log return series compiled from Bloomberg and Borsa Istanbul. We have used adjusted closing prices for calculating returns which are adjusted for corporate actions such as dividend payments and stock splits. For financial system returns, BIST100 index is used which is highly representative for all publicly listed companies (with a high share of financial institutions in the index). Table 2 presents descriptive statistics of daily log returns which validates some stylized facts about equity returns such as presence of fat-tails and dominance of standard deviation over mean.

Estimation of monthly SRISK and probability of default of Merton model requires both balance sheet and market data. We collected monthly market capitalization data and quarterly balance sheet data of total assets, total debt and total equity (in book values) from Bloomberg. Quarterly balance sheet data of total debt is converted to monthly frequency assuming the level of debt being constant and non-negotiable in a crisis situation as we mentioned in the previous chapter. Total book value of capital of the banking sector is compiled from monthly database of Banking Regulation and Supervision Agency and quarterly financial reports from the Banks Association of Turkey database.

As for static version of CoVaR, we have used weekly equity returns for quantile regression estimations as in Adrian & Brunnermeier (2016). With the same set of 14 banks, we computed weekly equity log returns by summing daily log returns. For market returns, we have again used BIST100 index returns in order to preserve comparability with LRMES and SRISK estimates.[2]

[2] As a robustness check, Borsa Istanbul Banks Index (XBANK) is also used as an alternative for financial system returns which did not change the results significantly.

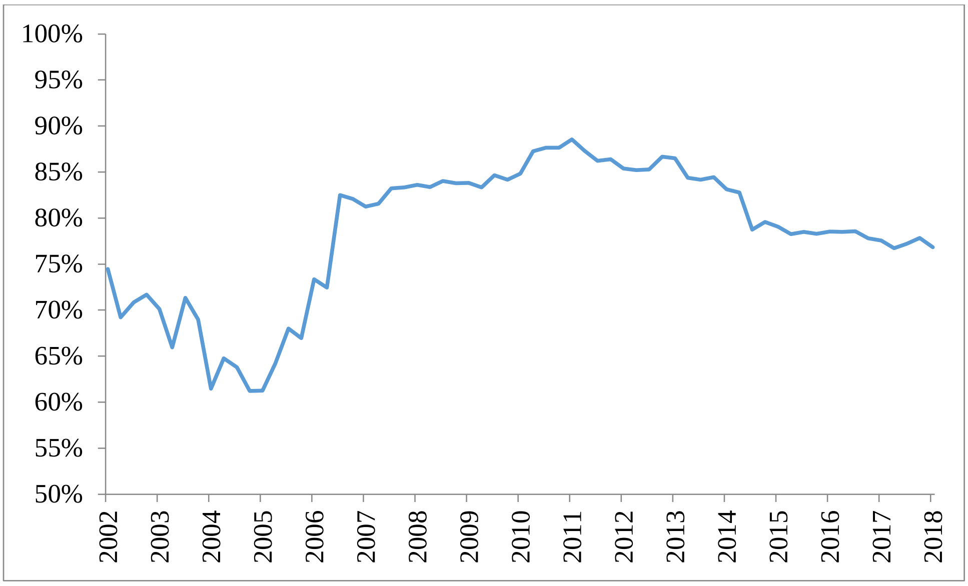


Figure 2. Capital share of 14 banks in total banking system

Table 2. Descriptive Statistics for Stock Returns

Bank	Mean	SD	Min	Max	Obs	Skewness	Kurtosis
AKBNK	0.002	0.034	-0.20	0.33	6497	0.65	5.21
ALBRK	0.000	0.020	-0.14	0.21	2913	0.82	10.80
ALNTF	0.002	0.040	-0.24	0.34	4980	0.84	6.62
ASYAB	0.000	0.032	-0.20	0.23	2537	0.42	7.70
DENIZ	0.001	0.034	-0.20	0.23	3603	0.90	12.82
QNBFB	0.002	0.036	-0.22	0.27	6483	0.85	6.52
GARAN	0.002	0.036	-0.22	0.21	6494	0.40	3.90
HALKB	0.000	0.027	-0.14	0.20	2942	0.17	4.03
ISCTR	0.002	0.036	-0.19	0.23	6488	0.55	4.02
SEKER	0.001	0.035	-0.20	0.27	5410	0.81	6.98
TEBNK	0.001	0.032	-0.19	0.22	3788	0.69	5.92
TSKB	0.002	0.034	-0.15	0.24	6472	0.68	4.34
VAKIF	0.001	0.026	-0.12	0.18	3319	0.07	2.38
YPKRD	0.002	0.038	-0.21	0.22	6487	0.31	3.87
BIST100	0.001	0.024	-0.18	0.19	6497	0.26	5.79

CHAPTER 4

ESTIMATION OF SYSTEMIC RISK MEASURES FOR THE TURKISH BANKING SECTOR

In this section, we will apply statistical measures of systemic risk for the Turkish financial sector with the methodologies explained in Chapter 2. We will first go over the estimation results of individual systemic risk metrics. Then, aggregate systemic risk of the Turkish banking system will be examined with a special emphasis on SRISK. Relationship between systemic risk measures and individual bank probability of default levels will be investigated. Lastly, we will look into SIFI rankings implied by different systemic risk measures from a comparative perspective and check the relative reliability of systemic risk measures in terms of rankings.

4.1 MES estimation

As in Acharya et al. (2017), MES is estimated as the simple average of bank returns on the worst 5% days of market losses. We have used a rolling estimation window of one year (252 days) and estimated MES for each month-end for the period 1999-2018. Descriptive statistics for estimated MES and other systemic risk metrics are presented in Table 3. As can be seen from Table 3, on average, MES is estimated to be above 4% daily loss for most of the banks in our sample. In Figure 3, we have also presented time-series of selected systemic risk measures used in this analysis for two particular banks (AKBNK and GARAN) as a comparative example. As Figure 3 shows, estimated MES of these two banks appear to increase during both crisis periods with more notable increases in GARAN relative to AKBNK.

4.2 LRMES and SRISK estimation

For the estimation of LRMES, we have chosen conditioning event C as 25% market drop in one month which corresponds to around 1-2% quantile of system returns. Using daily market and bank log-returns, for each month-end, we have estimated LRMES using the simulation procedure used by Brownlees & Engle (2017). For 14 banks and for each month between 1999 and 2018, first we estimate DCC-GARCH volatility and correlation models using only the available data up to that month. Then, using DCC-GARCH standardized innovations from the estimated models, we sample with replacement $S = 100.000$ of 22-day innovations. Feeding these innovations back into DCC-GARCH filters gives us S number of simulated 22-day market and firm log-returns which can be converted to monthly arithmetic returns. Finally, simple average of monthly firm returns corresponding to simulations in which market returns was below $C = -25\%$ gives us the LRMES estimate.

Summary statistics for estimated LRMES measures are presented in Table 4. As can be seen, most of the banks have an average LRMES higher than 25% which is an indication of market beta higher than one for that particular bank. From the time-series perspective, LRMES exhibits quite high heterogeneity among banks. Although there is no data available for public banks for the pre-crisis period before 2008, on average, public banks exhibit higher estimated expected losses than private banks for the recent period after 2014 which is also evident from higher average LRMES figures for VAKIF and HALKB relative to private banks in Table 3.[3]

As explained in Chapter 2, for the calculation of SRISK (which is the expected capital shortfall of a financial institution conditional on a crisis), we need to combine LRMES estimates with banks' balance sheet information. For the macro-

[3] VAKIF and HALKB are listed in the Borsa Istanbul as of 2005 and 2007 respectively.

prudential capital ratio, in accordance with Basel regulations, the current practice of Banking Regulation & Supervision Agency (BRSA) requires banks to hold capital of minimum 8% of their risk-weighted assets although in practice, a minimum capital adequacy ratio of 12% is implemented as an extra macro-prudential buffer. For this reason, we chose macro-prudential ratio to be $k = 12\%$, while different selections would basically have a level effect on SRISK but would not change time-series or cross-sectional properties that much. Together with the LRMES estimate, market capitalization and balance sheet data and a capital adequacy ratio of 12%, we are able to calculate monthly SRISK for each bank using the SRISK equation defined in Chapter 2.

4.3 CES estimation

As described in Chapter 2, computation of CES requires an estimate of MES as an input. For this analysis, we decided to use Long-Run MES (LRMES) rather than daily MES, since the former is a more forward-looking and elaborate measure than the latter. Thus, for the same sample of 14 banks, CES is estimated by multiplying each banks' LRMES estimate (which has been estimated by the simulation procedure described above) with its respective market share calculated by the market cap.

Table 3 presents summary statistics for CES estimates for the entire estimation period and Figure 3 presents time series of CES estimates for AKBNK and GARAN. As can be seen from the average CES estimates from Table 3, size (as measured by market share) of the banks manifests itself as the dominant factor of this systemic risk metric which makes CES estimates more stable in the time series dimension.

4.4 ΔCoVaR estimation

With the quantile regression methodology explained in Section II, we have estimated static version of CoVaR for the same set of 14 banks using weekly log-returns using the full estimation window. For comparison, in Figure 3, we have presented the scatter-plot of static CoVaR and ΔCoVaR estimates with VaR estimates of banks for $q = 1\%$. Figure 4 validates the empirical observation of Adrian & Brunnermeier (2016) also for the Turkish banking system that, while there is a positive relationship between CoVaR and VaR in the cross-section; ΔCoVaR seems to be uncorrelated with VaR. This implies that, it is possible to infer extra information from ΔCoVaR in terms of systemic risk contribution on top of market risk that is measured by VaR. For instance, although GARAN and SEKER have more or less the same level of VaR, GARAN has a higher level of ΔCoVaR than SEKER suggesting that the former has a larger contribution to systemic risk than the latter.

As the next step, we estimated time-varying versions of ΔCoVaR with the methodology explained in Chapter 2. For each month end, using 5-year rolling estimation windows, we have estimated 1% quantile regressions of daily system returns on bank returns. We have used $q = 1\%$ for time-varying CoVaR estimations since 5% significance level does not pose an extreme enough event for a VaR based method such as CoVaR as argued in Danielsson (2016b). Then with the same sample window, VaR measures for $q = 1\%$ and $q = 50\%$ are calculated with a basic GARCH(1,1) model which is more elaborate than historical simulation for reflecting time-series properties of volatility. Finally, with the estimated parameters from quantile regressions and VaR estimates, time-varying ΔCoVaR are computed using the formula presented in Chapter 2.

As can be seen from Figure 3, unlike the case for cross-section, time series pattern of ΔCoVaR is closely linked to VaR as can be expected from the definition of the measure itself. Nevertheless, heterogeneity among average ΔCoVaR estimates from Table 3 indicates that, it may be more appropriate to use this metric for cross-sectional ranking purposes rather than analyzing time-series evolution of systemic risk.

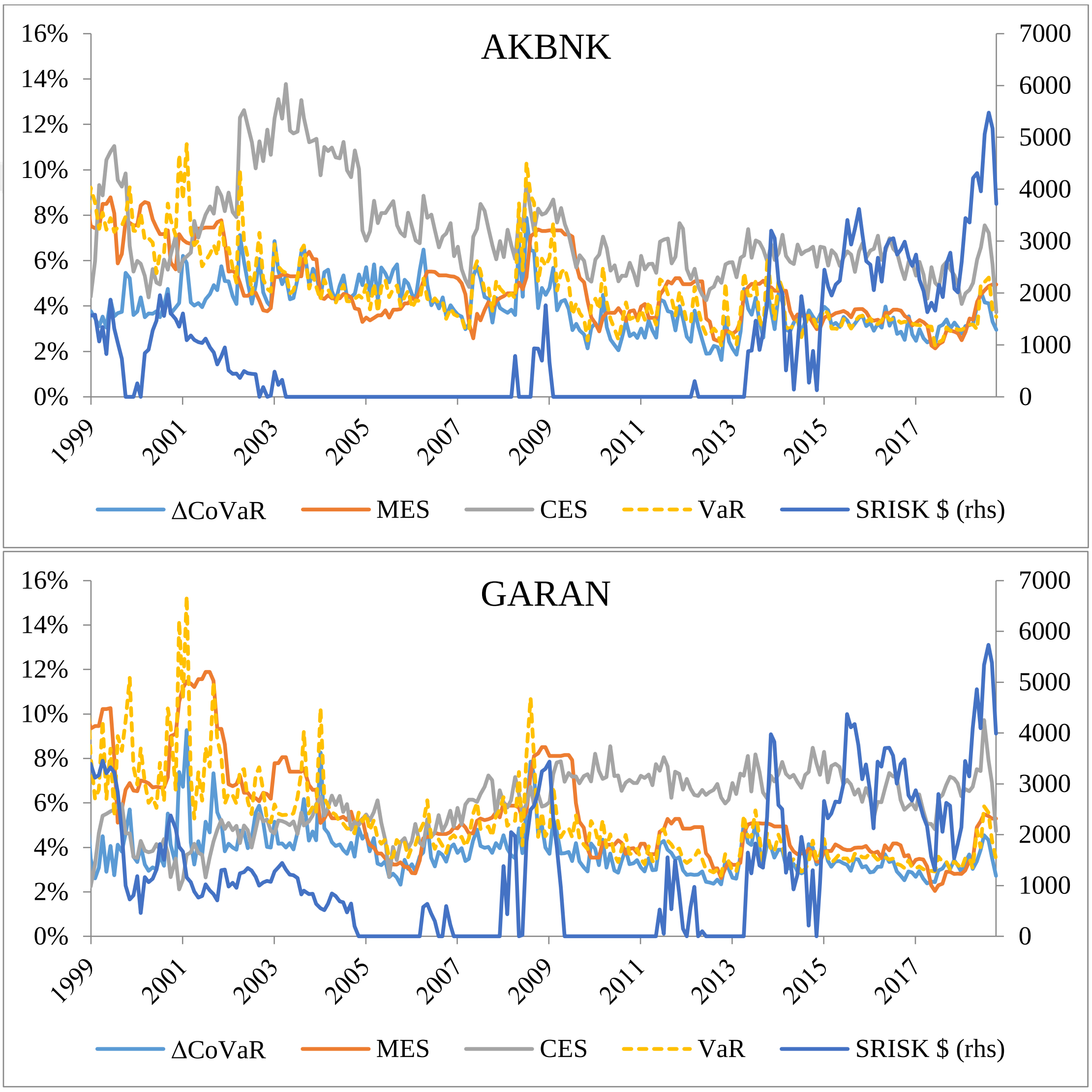


Figure 3. Time-series of selected systemic risk metrics

Table 3. Descriptive Statistics for Systemic Risk Metrics

	MES			LRMES			ΔCoVaR			CES		
	Mean	SD	# of months	Mean	SD	# of months	Mean	SD	# of months	Mean	SD	# of months
AKBNK	4.8%	1.6%	240	28.0%	3.7%	240	3.9%	1.1%	240	7.3%	2.1%	240
ALBRK	2.9%	0.8%	138	21.3%	3.4%	103	1.8%	0.7%	103	0.2%	0.0%	103
ALNTF	4.2%	2.9%	209	22.0%	7.6%	198	2.2%	1.0%	198	0.1%	0.1%	198
ASYAB	3.3%	2.2%	134	24.6%	10.8%	80	2.1%	1.0%	86	0.4%	0.2%	80
DENIZ	2.8%	1.4%	168	19.7%	7.4%	133	1.1%	0.7%	136	1.2%	0.9%	133
QNBFB	3.8%	2.6%	240	19.3%	8.4%	240	2.2%	1.6%	240	1.1%	0.7%	240
GARAN	5.5%	2.2%	240	30.6%	4.4%	240	3.8%	1.0%	240	5.9%	1.3%	240
HALKB	4.6%	1.4%	138	32.6%	2.8%	105	2.9%	0.5%	105	3.4%	0.9%	105
ISCTR	5.1%	1.7%	240	29.9%	3.7%	240	4.1%	1.2%	240	7.9%	4.1%	240
SEKER	4.0%	2.0%	240	25.4%	7.2%	225	2.2%	0.9%	240	0.2%	0.1%	225
TEBNK	4.2%	2.1%	192	24.1%	5.1%	146	2.5%	0.9%	146	0.5%	0.1%	146
TSKB	4.3%	1.9%	240	21.9%	5.6%	240	2.7%	0.8%	240	0.3%	0.1%	240
VAKIF	4.5%	1.1%	157	31.2%	2.3%	123	3.3%	0.6%	122	2.3%	0.3%	123
YPKRD	5.5%	2.4%	240	28.8%	3.5%	240	3.5%	1.5%	240	4.0%	1.7%	240

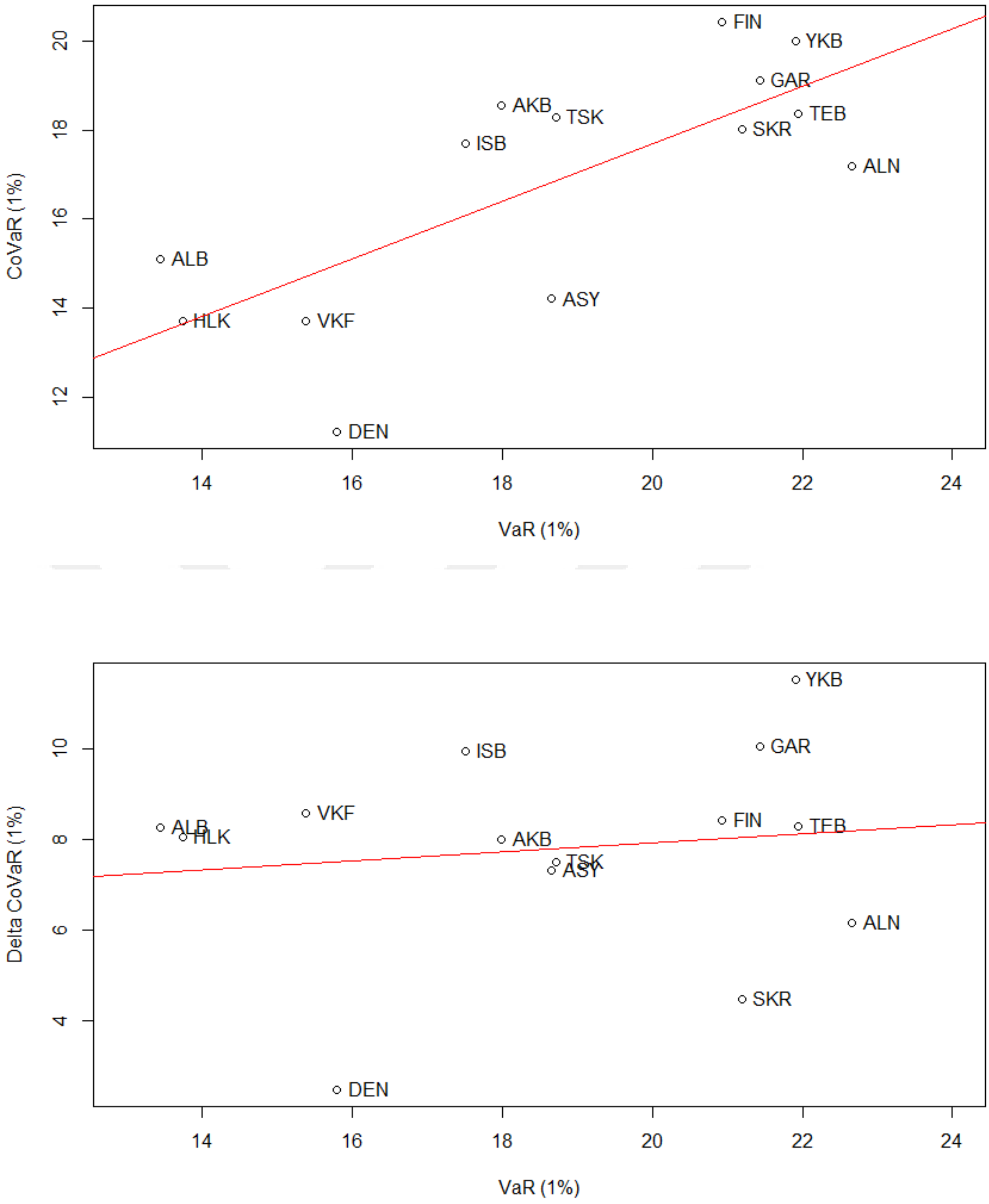


Figure 4. ΔCoVaR and VaR in cross section

4.5 Aggregate systemic risk of the Turkish banking system

From the set of systemic risk metrics that we estimated, we can derive four separate measures as a proxy for aggregate systemic risk of the system: market cap weighted versions of total MES, LRMES & ΔCoVaR and aggregate SRISK of the system. Note that, by definition, market cap weighted LRMES is equivalent to sum of individual CES measures (aggregate CES):

$$\sum_i CES_q^i = \sum_i w^i LRMES_q^i$$

Figure 5 presents aggregate systemic risk measures of MES, LRMES and ΔCoVaR which are computed as the sum of individual bank systemic risk metrics weighted by their market capitalization. Firstly, although the direction of conditionality and estimation methods differs between the risk measures, there seems to be a comovement between three risk metrics for most of the time period. Second, all three aggregate systemic risk measures rise rapidly during 2000 - 2001 and 2008 crisis especially with LRMES estimates reaching similar risk levels a couple of times more afterwards. We also observe a pickup in aggregate systemic risk measures of MES and LRMES for the recent financial stress period after the sharp currency depreciation of 2018. Lastly, due to different estimation methodologies employed for MES and LRMES estimates, while aggregate MES displays a step-wise pattern (with 1-year rolling estimation window) and aggregate LRMES responds more rapidly to changes in volatility and correlation dynamics.

In addition to these market based statistics of aggregate level of systemic risk, Figure 6 presents total SRISK of the Turkish banking system. Recall that SRISK is an estimate of the expected capital shortfall of a bank (or aggregate banking system) in case of a crisis which is defined to be 25% market drop in a month for our analysis. So unlike the other alternatives we discussed above, SRISK is a nominal measure denominated in Turkish Liras. As the top chart of Figure 6 shows, SRISK of the Turkish banking sector is around 25 trillion liras during 2008 crisis, whereas this number reaches to a level of ten times higher in the course of sharp currency depreciation after August 2018. There are mainly two reasons behind this result. First, since SRISK is a conditional capital shortfall measure based on the market value of equity and book value of debt, it is responsive to rapid changes in book to market ratios observed during crisis periods. Put differently, changes in the regulatory capital in book values take place more slowly relative to rapid changes in the price of an equity in the market which makes quasi-leverage values used in SRISK calculation more responsive to financial stress periods. Secondly, since the ratio of foreign currency denominated items in the asset side are higher than that of equities in the Turkish banking system, sharp depreciation of Turkish Lira results in a lower level of capital adequacy ratio, or to put it differently, a higher level of leverage. In order to look at this relationship and also controlling for the effects of currency depreciation and inflation, in the second panel of Figure 6, we presented quasi-leverage of the total system with the total SRISK of the banking system denominated in US dollars. It is clear from the figure that SRISK responds rapidly to changes in quasi-leverage which is also implied by the SRISK equation defined in Chapter 3.

According to current regulatory framework of BIS, banks need to hold a minimum level of capital as a ratio of their risk weighted assets which in turn is composed of three parts: credit risk, operational risk and market risk. Top chart of Figure 6 also shows that as of December 2018, total capital of the Turkish banking system is around 380 trillion TL and only 8 trillion TL should be allocated for market risk purposes whereas total SRISK is around 193 trillion liras. We can also observe from Figure 6 that even though the differences in level are quite high, time-series of SRISK and minimum capital required for market risk are actually positively related indicating the common characteristics of risk affecting these two elements.

Although we should note that the level of SRISK depends on the assumption of prudential ratio (k) and crisis threshold (C), through the whole analysis period, estimated SRISK constitutes a sizable portion of total capital in the banking system. In the bottom panel of Figure 6, we presented total SRISK of the banking system as a percentage of total capital of the banking sector. The graph clearly indicates that Turkish banking system was relatively well capitalized during 2008 crisis relative to 2000-2001 crisis with the notable pick-up also in the recent period. We should also note that the level of SRISK is strongly affected from book to market ratio of equity due to definitional distinctions between regulatory capital and market value of equity.

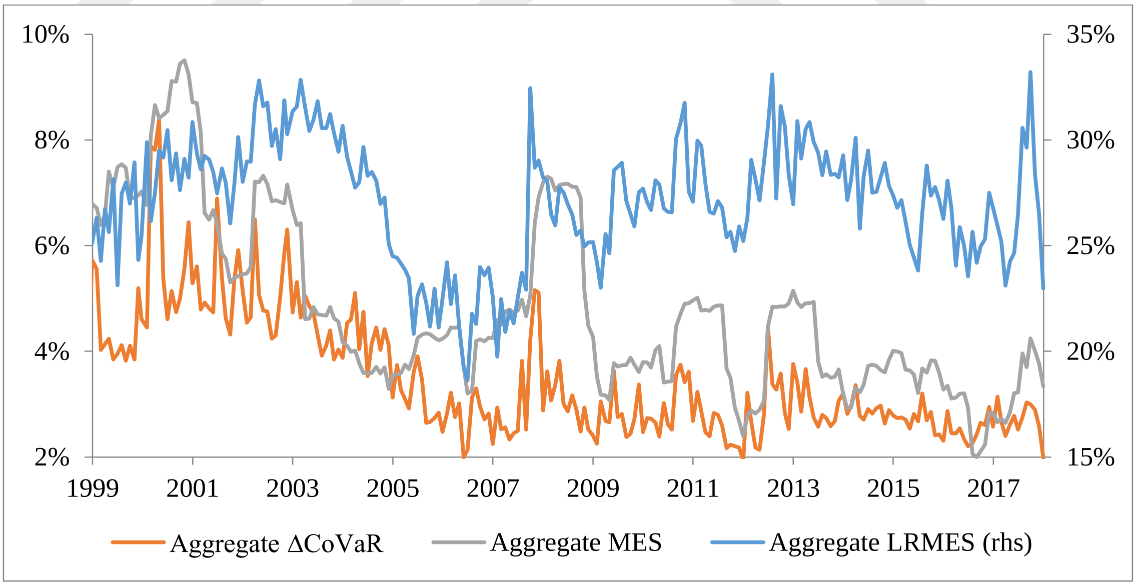


Figure 5. Aggregate MES, LRMES & ΔCoVaR weighted by market capitalization

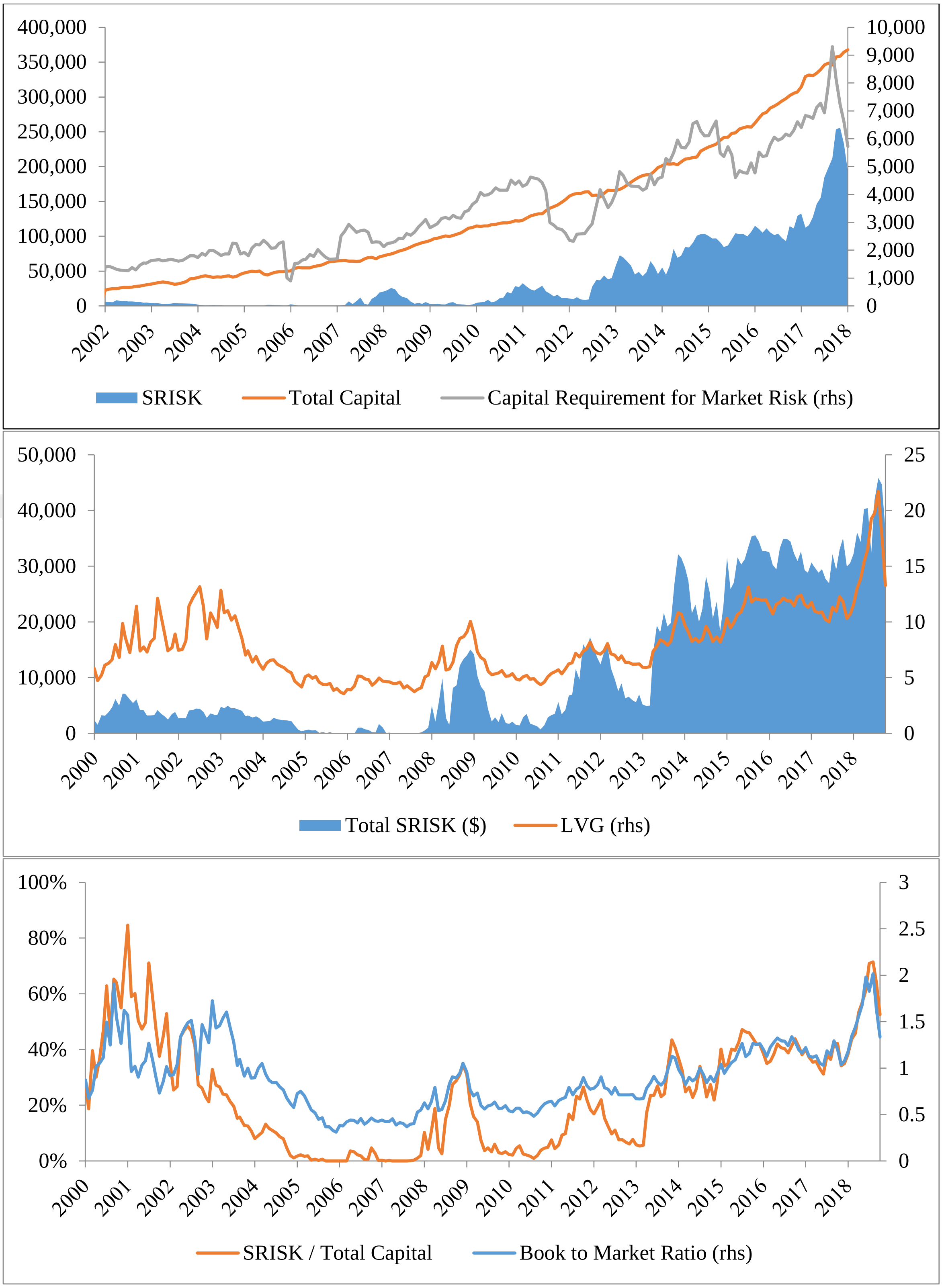


Figure 6. Aggregate SRISK of the Turkish banking sector

Since SRISK is a nominal estimate of a possible capital shortfall that a bank can experience, we can make an additional exercise to associate estimated SRISK with real market events. Recall that SRISK is a conditional estimate of expected capital shortfall with conditioning event being more than 25% market drop in one month in our case. For our sample period, considering end of month arithmetic returns, there are four cases for which monthly market return was below or equal to -25% threshold (two for 2000-2001 crisis and two for 2008 crisis). For these time periods, we have calculated actual capital shortfalls realized as of the end of month using the capital shortfall formula described in Chapter 2. In Table 4, we compare these figures with predicted SRISK levels which are estimated using the only available data as of the end of previous month. Negative values are also reported in the table showing the levels of capital surplus. First of all, in terms of estimates for individual banks, predicted SRISK levels seem to be an acceptable predictor for realized capital shortfalls (CS) with some positive bias in particular which can also be observed from the scatterplot presented in Figure 7. In addition to nominal levels, SRISK and capital shortfalls are also reported as a ratio of total assets and total market capitalizations for the sample of banks that we have estimates. Total CS and SRISK values show that the banking system was well-capitalized at the 2008 crisis compared to 2000-2001 period with the evident capital surplus levels for the former case as a consequence of reforms and regulations implemented especially after the first crisis. Lastly, SRISK was relatively better at predicting capital shortfalls for 2000-2001 crisis as deviations in terms of total assets and market capitalization was higher with some positive bias during 2008 crisis (around 5% deviation for former and above 10% for the latter case).

Table 4. Realized Capital Shortfall and Predicted SRISK (million TL)

Market Drop	Nov-00 -35.4%		Sep-01 -29.9%		Jan-08 -25.5%		Oct-08 -24.7%	
Bank	CS	SRISK	CS	SRISK	CS	SRISK	CS	SRISK
AKBNK	947	1,063	1,175	1,648	-10,444	-8,785	-4,541	-1,591
ALNTF	-32	-34	-26	-24	-31	-63	147	144
ASYAB							-311	-530
DENIZ					-1,024	-1,542	-620	-971
QNBFB	644	628	586	599	-3,850	-3,329	-3,331	-1,851
GARAN	1,201	1,027	1,395	1,199	-5,392	-3,933	294	2,375
HALKB							584	1,178
ISCTR	-2,006	-2,322	-675	-479	-4,727	-2,136	638	2,461
SEKER	193	158	236	241	-612	-610	447	373
TEBNK					82	139	1,019	996
TSKB	84	74	121	119	27	62	202	204
VAKIF							2,290	2,645
YPKRD	628	449	1,272	1,386	-3,176	-2,910	-150	-178
Total	1,658	1,042	4,084	4,690	-29,147	-23,107	-3,332	5,254
% Capital	9%	6%	35%	40%	-69%	-55%	-6%	9%
% Market Cap	17%	11%	44%	50%	-38%	-30%	-5%	8%

* Negative values indicate capital surplus

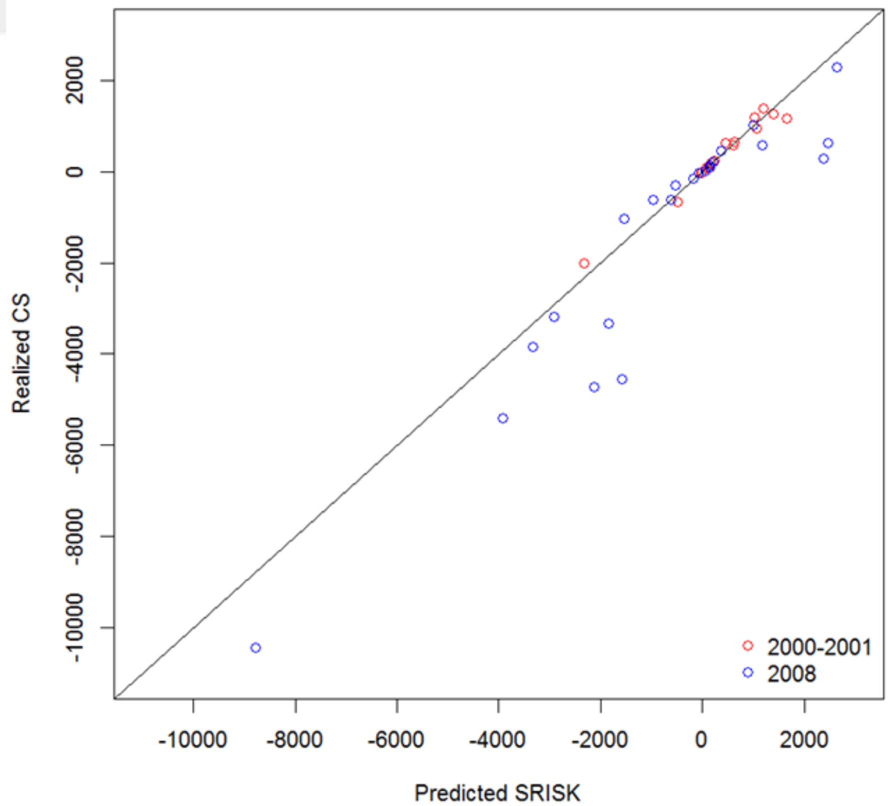


Figure 7. Realized capital shortfall and predicted SRISK (million TL)

4.6 Systemic risk measures and probability of default

Having an aggregate overview for the systemic risk in the Turkish banking system, in this section we turn into the relationship between systemic risk measures and level of financial stress for a particular institution. For this purpose, as a financial stress indicator, we have estimated probability of default (PD) in 3 months for each bank using a structural Merton model. The estimated PDs make use of balance sheet structure and equity volatility for a certain bank and they can be considered as a proxy for realized stress level during financial turmoil (The methodology and further details regarding the model estimation are explained in the Appendix).

In order to see the relationship between financial stress of a bank and systemic risk measures, we have run panel regressions of ΔCoVaR and %SRISK on probability of default levels[4]. As can be seen from Figure 11 in Appendix, probability of default levels are very close or equal to zero except for crisis periods. Thus, since PDs are non-negative by definition, our dependent variable is truncated at zero which leads us to use Tobit regression analysis instead of a standard panel regression setting for the modeling the relationship between systemic risk measures and financial stress. In addition to analyzing the contemporaneous relationship, we also tested the predictive power of systemic risk measures using lagged values up to 3 months.

Estimated Tobit panel regressions are presented in Table 5. Bank fixed effects are included in all specifications to account for firm specific structural factors that might have a level effect on PD levels, but they are not reported in the table for the brevity of illustration. For the models with no lags, systemic risk measures are positively associated with probability of default with significant coefficients and this

[4] Since it is a nominal measure denominated in Turkish liras, we have used percent version of SRISK in order to preserve its comparability for different time periods.

is also confirmed by the model when we include crisis fixed effects. After controlling for other relevant variables such as leverage, value-at-risk and size, systemic risk metrics are still significantly associated with probability of default both for %SRISK and ΔCoVaR.

In order to test the predictive power of systemic risk measures for a possible financial stress scenario, the same set of models has also been estimated with one and three month lags of %SRISK, ΔCoVaR and additional set of explanatory variables. For both one and three month horizons, systemic risk measures remain statistically significant predictors of probability of default even after controlling for crisis fixed effects and including additional regressors of leverage, value-at-risk and size. The only exception is ΔCoVaR which becomes insignificant for 3 month horizon case with the full model specification.

Lastly, as a comparison of the predictive performance of systemic risk measures, for almost all model specifications, models with %SRISK result in lower values of Bayesian Information Criteria (BIC) relative to models with ΔCoVaR. This indicates that %SRISK is a relatively better measure than ΔCoVaR in terms of its performance for predicting future levels of probability of default.

Table 5. Tobit Panel Regression with Bank Fixed Effects

No lag	Dependent variable: Probability of Default					
	(1)	(2)	(3)	(4)	(5)	(6)
%SRISK	0.967***	0.875***	0.452***			
	(0.144)	(0.133)	(0.14)			
ΔCoVaR				24.464***	21.167***	10.779***
				(1.202)	(1.145)	(1.418)
LVG			0.006***			0.004**
			(0.002)			(0.002)
VAR			13.452***			10.027***
			(0.772)			(0.845)
SIZE			-0.275			-0.931***
			(0.335)			(0.307)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Crisis FE		Yes	Yes		Yes	Yes
Observations	2525	2525	2501	2787	2787	2634
BIC	5365	5045	4702	5338	5086	4857

1-month lag	Dependent variable: Probability of Default					
	(1)	(2)	(3)	(4)	(5)	(6)
%SRISK	0.839***	0.738***	0.540***			
	(0.144)	(0.134)	(0.146)			
ΔCoVaR				15.193***	12.566***	2.962**
				(1.251)	(1.177)	(1.5)
LVG			0.008***			0.009***
			(0.002)			(0.002)
VAR			7.763***			6.972***
			(0.796)			(0.892)
SIZE			0.627*			0.104
			(0.352)			(0.326)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Crisis FE		Yes	Yes		Yes	Yes
Observations	2516	2516	2489	2780	2780	2622
BIC	5361	5046	4887	5583	5297	5106

3-months lag	Dependent variable: Probability of Default					
	(1)	(2)	(3)	(4)	(5)	(6)
%SRISK	0.703***	0.585***	0.460***			
	(0.144)	(0.134)	(0.147)			
ΔCoVaR				9.515***	8.327***	-0.635
				(1.262)	(1.175)	(1.535)
LVG			0.012***			0.013***
			(0.002)			(0.002)
VAR			4.223***			4.763***
			(0.805)			(0.919)
SIZE			0.982***			0.615*
			(0.357)			(0.331)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Crisis FE		Yes	Yes		Yes	Yes
Observations	2492	2492	2461	2766	2766	2594
BIC	5305	5003	4886	5634	5318	5102

***, **, and * represent 1%, 5%, and 10% significance, respectively.

4.7 Systemic risk rankings and detection of SIFI for the Turkish banking system

Considering the role of certain financial institutions such as Lehman Brothers for 2008 global crisis, true detection of a systemically important financial institution is of great importance for avoiding great social costs on the economy through macro prudential policy regulations. In this section, first, we will go over the current regulatory framework for the detection of SIFIs. Next, we will present systemic risk rankings of the Turkish banking system with the set of systemic risk metrics presented in the previous sections. Then, we will check to what extent different risk metrics comply with each other and lastly, we will show and discuss the reliability of these systemic risk rankings.

Under the current regulation of BRSA (also in compliance with Basel accords), an indicator based approach is used for the detection and classification of domestic systemically important banks (D-SIB). For that, regulatory authority collects data from institutions covering four main categories which are size, interconnectedness, complexity and substitutability. Then based on these criteria (including several sub-indicators), each year, banks are categorized into different buckets which then constitutes the basis for an additional (buffer) capital requirement. Although BRSA does not publicly disclose the list of D-SIBS, we can infer the respective risk group (bucket) of a particular bank from the capital requirement buffer in the quarterly financial reports. As of 2019, the list of D-SIB is consisting of AKBNK, GARAN (Group 3), ISCTR, YPKRD (Group 2), VAKIF, HALKB (Group 1) (Ziraat Bank, which is not listed in the stock exchange, is also classified as Group 3).

Table 6 shows the systemic risk rankings of the Turkish banking system as of September 2008 and December 2018 for the risk metrics MES, LRMES, %SRISK, CES and CoVaR. We also present the average rankings of institutions with equal weights among systemic risk metrics and VaR based rankings in the last two columns for comparison purposes. One of the first points to be emphasized is that for both time periods of 2008 and 2018, top six banks (ISCTR, HALKB, GARAN, YPKRD and AKBNK) according to average systemic risk rankings are also the largest six banks according to asset size. It means that, even though size of the bank is not an input for systemic risk metrics except for CES and SRISK (indirectly through market capitalization and quasi-leverage), these banks' contribution to systemic risk is also estimated to be higher via other channels such as interconnectedness and correlation with the market.

Average ranks presented in Table 6 also constitute a good benchmark for comparison for D-SIB's selected with the indicator based approach explained above. First of all, six banks classified as D-SIBs are also the same top six banks according to average systemic risk rankings as of 2018 end. Having said that, we observe some differences in terms of rankings. While two public banks are listed in top three in average rankings, they are classified in the Group 1 (least risky group) of D-SIB buckets. While YPKRD is in Group 2 of D-SIB, its average ranking is marginally higher than that of TSKB or SEKER.

Table 6 gives us a snapshot of discrepancies and similarities among rankings implied by different systemic risk measures. In order to have a better understanding on the degree of homogeneity between these measures through time, we applied a historical rank analysis. First, for each time-t, all the banks (with available data) are sorted based on four systemic risk measures, namely LRMES, %SRISK, ΔCoVaR and CES. Then Kendall rank correlations are calculated for each systemic risk metric pair for each month. Kendall rank correlation shows the ratio of matching concordant pairs between two rankings. A coefficient of one indicates that two ranking methods imply exactly the same ordering, while minus one means that the methods show completely reverse orderings. Figure 8 shows time-varying Kendall rank correlation coefficients for each systemic risk metric pair. For the sake of analysis, we plotted only non-negative coefficients, which show the ratio of matching concordant pairs. The first thing indicated from the figure is that, different systemic risk metrics have different risk orderings through time implied by a Kendall Coefficient ranging between 0.2 and 0.8 for nearly all of the systemic risk measure pairs. As can be seen from average Kendall Coefficients presented in Table 7, the most contradicting rankings are between %SRISK and the other three systemic risk measures. As an illustration of time series dynamics of rank relationships, Figure 9 presents the average Kendall correlation between the systemic risk metrics. We do not observe any particular change in the dynamics of rank correlations during crisis periods which would possibly affect the reliability of a policy recommendation based on the results of these metrics.

A possible question is whether we can have additional information regarding systemic risk level of banks on top of what we already know through widely used market risk measures like VaR. In order to investigate this, we have also calculated risk rankings based on VaR metrics which are estimated with Normal GARCH(1,1) model with $q = 5\%$ and has a rolling estimation window of three years. As we can see from Table 6, as of 2018 December, risk rankings based on systemic risk metrics and VaR show an obvious discrepancy such that while DENIZ and QNBFB are the top 2 banks according to VaR level, they are among the least systemically risky banks according to almost all systemic risk measures. This disparity is more evident when we check the Kendall rank correlations. As can be observed from in Figure 8 and Table 7, Kendall rank correlations of VaR based rankings with other systemic risk measures are rather low and close to zero which shows us that systemic risk measures covered in this analysis has an importance in terms of ranking financial institutions based on risk characteristics beyond what can be observed by the ordinary market risk measures like VaR.

Table 6. Systemic Risk Rankings of the Turkish Banking System

Systemic Risk Rankings as of September 2008

Ranking	MES		LRMES		%SRISK		CES		ΔCoVaR		Average Rank		VaR	
1	HALKB	6.23%	VAKIF	38%	VAKIF	25%	AKBNK	9.4%	AKBNK	7.9%	VAKIF	2.8	AKBNK	10.3%
2	VAKIF	5.88%	AKBNK	37%	ISCTR	24%	ISCTR	6.5%	ISCTR	5.9%	GARAN	3.2	ALNTF	8.6%
3	GARAN	5.61%	HALKB	36%	GARAN	23%	GARAN	6.0%	GARAN	5.7%	AKBNK	3.6	HALKB	8.3%
4	TEBNK	5.35%	GARAN	36%	HALKB	11%	YPKRD	4.3%	VAKIF	4.2%	ISCTR	3.8	GARAN	8.2%
5	AKBNK	5.27%	ISCTR	34%	TEBNK	10%	HALKB	3.5%	YPKRD	3.3%	HALKB	4.0	TEBNK	8.1%
6	SEKER	5.12%	ALNTF	31%	SEKER	4%	VAKIF	2.6%	TEBNK	3.3%	TEBNK	6.4	VAKIF	7.7%
7	TSKB	5.05%	YPKRD	29%	TSKB	2%	QNBFB	2.1%	HALKB	2.8%	YPKRD	7.6	QNBFB	7.3%
8	ISCTR	5.04%	TEBNK	27%	ALNTF	1%	DENIZ	1.6%	ALNTF	2.8%	SEKER	8.8	ISCTR	6.3%
9	YPKRD	4.96%	DENIZ	25%	AKBNK	0%	TEBNK	0.5%	TSKB	2.3%	TSKB	9.0	DENIZ	6.2%
10	ASYAB	4.84%	TSKB	25%	ASYAB	0%	ASYAB	0.5%	SEKER	1.8%	ALNTF	9.2	YPKRD	5.6%
11	ALNTF	4.49%	SEKER	24%	DENIZ	0%	SEKER	0.2%	QNBFB	1.4%	DENIZ	10.4	TSKB	5.4%
12	DENIZ	4.10%	QNBFB	23%	QNBFB	0%	TSKB	0.2%	DENIZ	1.1%	QNBFB	11.0	SEKER	5.1%
13	QNBFB	2.79%	ASYAB	19%	YPKRD	0%	ALNTF	0.1%	ASYAB	0.9%	ASYAB	11.2	ASYAB	4.2%

* ALBRK is excluded from the list since there is not enough data available as of September 2008 for the estimation of risk metrics

Systemic Risk Rankings as of December 2018

Ranking	MES		LRMES		%SRISK		CES		ΔCoVaR		Average Rank		VaR	
1	GARAN	5.30%	HALKB	31%	ISCTR	21%	DENIZ	6.9%	AKBNK	3.0%	GARAN	3.0	DENIZ	10.3%
2	VAKIF	5.03%	VAKIF	29%	HALKB	20%	GARAN	4.7%	ISCTR	2.8%	AKBNK	3.6	QNBFB	5.4%
3	AKBNK	4.95%	SEKER	29%	VAKIF	18%	AKBNK	3.7%	GARAN	2.7%	VAKIF	3.6	TSKB	3.7%
4	HALKB	4.19%	GARAN	28%	YPKRD	16%	ISCTR	2.5%	TSKB	2.6%	HALKB	4.2	AKBNK	3.5%
5	TSKB	4.12%	AKBNK	27%	GARAN	11%	QNBFB	2.0%	VAKIF	2.0%	ISCTR	4.4	GARAN	3.5%
6	YPKRD	4.09%	ALBRK	26%	AKBNK	10%	VAKIF	1.4%	YPKRD	2.0%	YPKRD	6.8	SEKER	3.2%
7	ISCTR	3.82%	TSKB	25%	ALBRK	2%	HALKB	1.4%	HALKB	1.9%	TSKB	6.8	HALKB	3.1%
8	SEKER	2.91%	ISCTR	25%	SEKER	2%	YPKRD	1.2%	DENIZ	1.6%	DENIZ	7.4	VAKIF	3.0%
9	DENIZ	2.60%	DENIZ	22%	TSKB	1%	TSKB	0.3%	SEKER	0.9%	SEKER	7.6	ISCTR	2.9%
10	ALBRK	2.18%	YPKRD	17%	DENIZ	0%	SEKER	0.2%	ALBRK	0.8%	ALBRK	8.8	ALBRK	2.6%
11	QNBFB	-0.20%	QNBFB	13%	QNBFB	0%	ALBRK	0.1%	QNBFB	0.7%	QNBFB	9.8	YPKRD	2.5%

* ALNTF, ASYAB and TEBNK are excluded from the list since they are not listed in the BIST as of December 2018

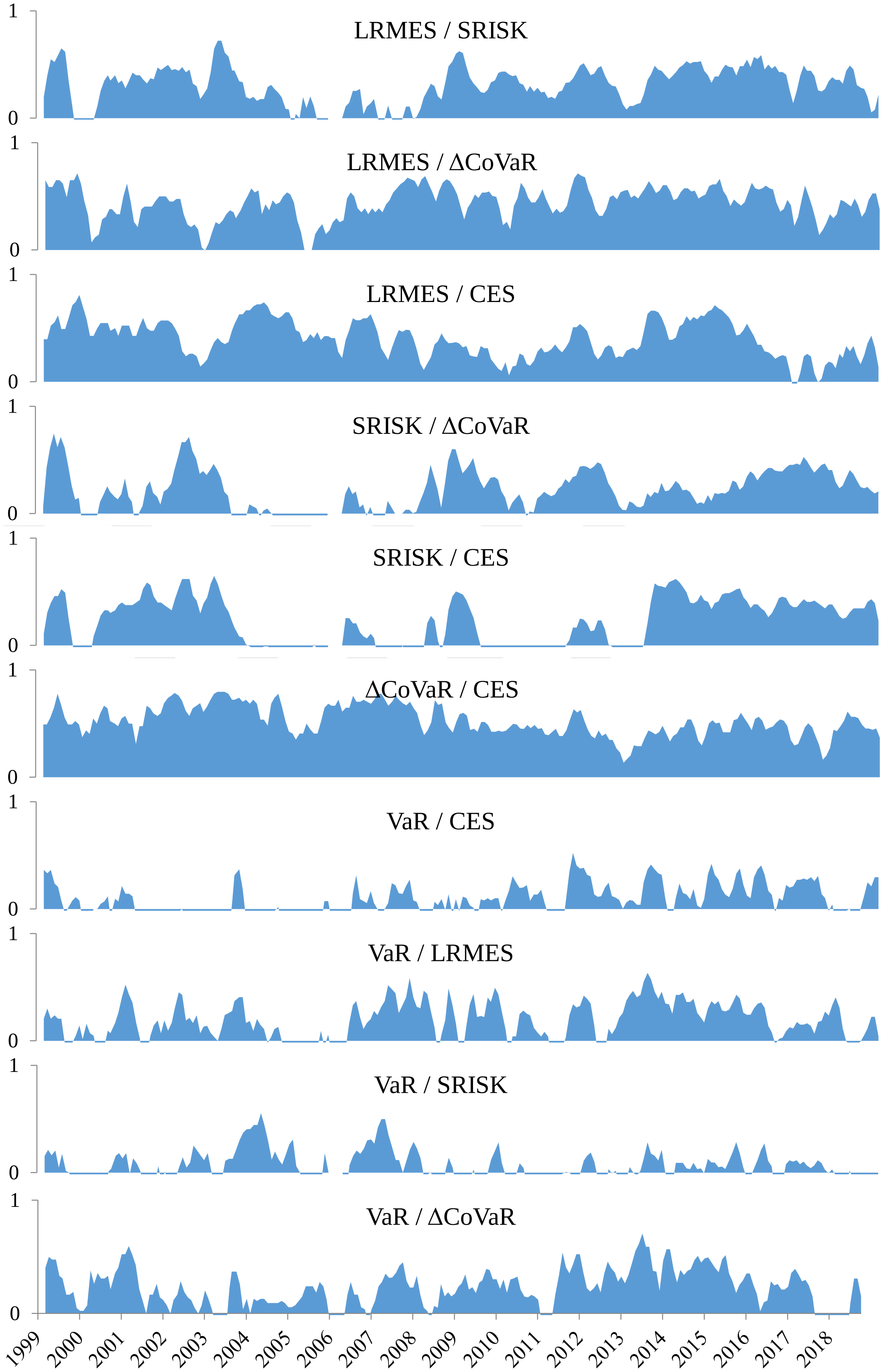


Figure 8. Kendall rank correlations for estimated systemic risk metrics (3m MA)

Table 7. Mean Kendall Rank Correlations for Estimated Systemic Risk Metrics

	LRMES	%SRISK	ΔCOVAR	CES	VaR
LRMES	1.000				
%SRISK	0.316	1.000			
ΔCOVAR	0.441	0.214	1.000		
CES	0.400	0.202	0.523	1.000	
VaR	0.183	0.031	0.222	0.055	1.000

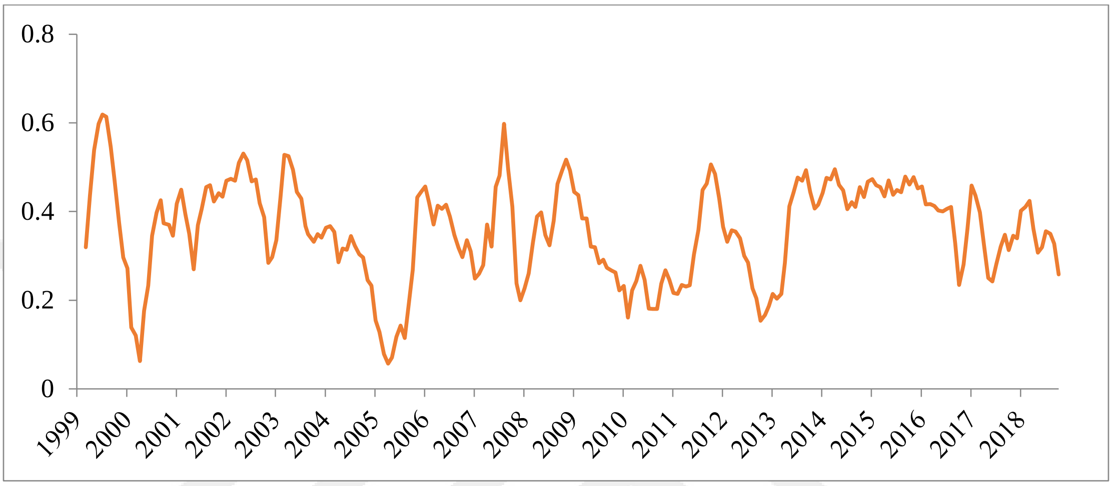


Figure 9. Average Kendall correlation between systemic risk metrics (3m MA)

4.8 Reliability of systemic risk measures

As we have seen in the previous section, individual systemic risk metrics differs to some extent in terms of ranking the financial institutions and consequently detecting the potential SIFIs. In order to test for the relative reliability of these metrics and also checking for possible estimation errors associated with them, we have estimated guilt probabilities of the banks with the methodology proposed by Danielsson (2016a). This analysis basically tries to answer the following question: Assuming p% of banks are systemically risky for the banking system, to what extent are we sure that a certain risk measure can correctly identify the SIFI?

Over the period of 2005-2018, the number of banks listed in the stock exchange varies between 9 to 14. Throughout this analysis, we have assumed there exists 1 or 2 systemically risky banks in the system (which corresponds to around $p = 10\%$ and $p = 20\%$ of the total banks respectively). For this analysis, we have compared MES and ΔCoVaR systemic risk metrics since the other measures we covered are either directly dependent on MES for estimation (such as CES) or are more elaborate versions of MES with the same direction of conditionality (for LRMES and SRISK). For comparison purposes, MES is estimated as the daily expected bank return conditional on the system exceeding its 5% VaR and ΔCoVaR is estimated using 1% quantile regressions of weekly financial system returns on bank returns as we did for previous exercises. Guilt probabilities are estimated with 5-year rolling estimation windows for each systemic risk metric and for each year-end. Only banks with the available return data for each 5-year interval is used (so number of available banks each year differs depending on the data availability). So, for the estimation of guilt probabilities, for each year-end, from the 5-year estimation sample, we draw block bootstraps with blocks of 40-days (block of 6 weeks for ΔCoVaR) with 10.000 trials. As indicated by Danielsson (2016a), use of block-bootstraps accounts for both time-series and cross section properties of the data. Then, for each bank and for each of 10.000 bootstrap sample, we estimate systemic risk metrics of MES and ΔCoVaR. This enables us to rank the set of banks according to estimated systemic risk metric for each bootstrap sample. Lastly, share of incidences for which a particular bank is ranked in the first $p\%$ (top 1 or top 2) of banks among 10.000 trials gives us the estimated guilt probability of that bank for that risk metric.

The results of estimated guilt probabilities for MES and ΔCoVaR and for the assumption of one or two systemically risky banks in the system are presented in Table 8 and Table 9. The cases for which the guilt probability of certain bank is found to be over 90% are presented in bold which are defined to be "guilty beyond a reasonable doubt" by Danielsson (2016a). For our sample of banks, there exists no bank who has a guilt probability over 90% with one risky bank case for both MES and ΔCoVaR. When we check the two risky banks in the system case, we observe five incidences of guilt probabilities over 90% for MES while this number is only two for ΔCoVaR. We should also note that four out of five incidences for the former case of MES are for public banks for the recent 2016-2017 period.

In Figure 10, we have also plotted the time series of guilt probabilities for the banks with the highest and second highest median systemic risk scores among bootstrap trials. Both for MES and ΔCoVaR, under the assumption of one systemically risky bank in the system, it is hard to identify the correct SIFI (Figure 10 (c)) since the guilt probabilities fall short of giving a robust evidence (both below 90%). However on average MES performs marginally better than ΔCoVaR with 43% vs 51% average guilt probabilities. With the assumption of 2 SIFI's in the system, especially for the recent period, MES has a better performance than ΔCoVaR in terms of detecting the 2 risky banks (Figure 10 (a) & (b)). Throughout the analysis period, MES gives higher guilt probabilities on average close to the 90% threshold (which is also consistent with Danielsson (2016a)). From that, we conclude that MES (and consequently MES related systemic risk metrics such as SRISK and CES) is relatively more reliable in terms of detecting the possible SIFIs in the Turkish banking system.

Table 8. Estimated Guilt Probabilities of Being a Systemically Risky Bank (Based on MES)

Guilt Probabilities of Being the Top 1 Systemically Risky Bank (MES Rankings)

Year	AKBNK	ALBRK	ALNTF	ASYAB	DENIZ	QNBFB	GARAN	HALKB	ISCTR	SEKER	TEBNK	TSKB	VAKIF	YPKRD
2005	0.00	-	9.13	-	-	1.80	6.79	-	7.31	3.27	0.00	0.00	-	71.70
2006	0.06	-	45.54	-	-	0.38	8.43	-	9.50	3.80	0.08	0.05	-	32.16
2007	0.80	-	5.32	-	-	0.00	15.96	-	75.58	0.00	0.46	1.19	-	0.69
2008	3.73	-	8.31	-	-	0.00	53.97	-	19.16	0.55	10.90	0.50	-	2.88
2009	14.37	-	5.35	-	0.00	0.00	34.49	-	20.98	3.51	18.45	1.41	-	1.44
2010	6.25	-	0.00	-	0.02	0.00	57.44	-	4.69	1.62	2.15	0.00	12.12	15.71
2011	6.32	-	0.00	0.30	0.03	0.00	56.29	-	4.95	1.54	1.78	0.00	12.76	16.03
2012	14.48	0.00	0.00	1.30	0.02	0.00	23.44	28.99	2.36	3.42	4.95	0.00	9.97	11.07
2013	4.93	0.00	0.00	0.23	0.00	0.00	2.14	43.04	0.80	0.18	0.01	0.01	7.62	41.04
2014	0.07	0.00	0.00	0.47	0.00	0.00	1.65	31.42	0.44	0.01	0.00	0.00	30.84	35.10
2015	0.11	0.00	-	0.01	0.00	0.01	1.10	36.53	0.32	0.00	-	0.00	24.94	36.98
2016	0.04	0.00	-	-	0.00	0.00	0.42	66.01	0.23	0.00	-	0.00	31.74	1.56
2017	0.02	0.00	-	-	0.00	0.00	0.12	71.87	0.11	0.00	-	0.00	26.76	1.12
2018	0.13	0.00	-	-	0.00	0.00	27.21	28.47	0.03	0.00	-	0.00	44.14	0.03

Guilt Probabilities of Being in the Top 2 Systemically Risky Banks (MES Rankings)

Year	AKBNK	ALBRK	ALNTF	ASYAB	DENIZ	QNBFB	GARAN	HALKB	ISCTR	SEKER	TEBNK	TSKB	VAKIF	YPKRD
2005	0.00	-	23.07	-	-	7.58	49.58	-	25.53	8.68	0.00	0.00	-	85.56
2006	0.45	-	68.82	-	-	1.80	32.17	-	30.01	9.48	0.24	0.99	-	56.04
2007	17.46	-	11.78	-	-	0.00	66.66	-	**94.08**	0.20	1.29	4.15	-	4.38
2008	12.49	-	18.61	-	-	0.00	79.19	-	44.99	2.07	21.87	1.90	-	18.88
2009	30.15	-	12.26	-	0.00	0.00	63.86	-	38.75	12.24	32.39	3.95	-	6.40
2010	13.77	-	0.00	-	0.03	0.00	87.59	-	16.33	5.99	5.47	0.00	31.56	39.26
2011	13.89	-	0.00	0.90	0.03	0.00	86.50	-	15.90	5.78	4.98	0.00	32.51	39.51
2012	27.45	0.00	0.00	3.10	0.06	0.00	50.30	49.34	8.19	6.68	9.29	0.00	20.71	24.88
2013	18.76	0.00	0.00	1.80	0.00	0.00	13.19	61.03	6.91	0.39	0.13	0.02	27.92	69.85
2014	1.39	0.00	0.00	1.64	0.00	0.01	12.25	53.05	5.30	0.02	0.04	0.00	63.42	62.88
2015	1.40	0.00	-	0.08	0.01	0.02	8.73	61.33	3.88	0.00	-	0.00	61.40	63.15
2016	0.41	0.00	-	-	0.00	0.00	4.80	**92.55**	2.24	0.00	-	0.00	**93.74**	6.26
2017	0.18	0.00	-	-	0.00	0.00	3.10	**95.35**	0.92	0.00	-	0.00	**94.86**	5.59
2018	1.85	0.00	-	-	0.00	0.00	62.19	49.84	0.74	0.00	-	0.00	85.16	0.22

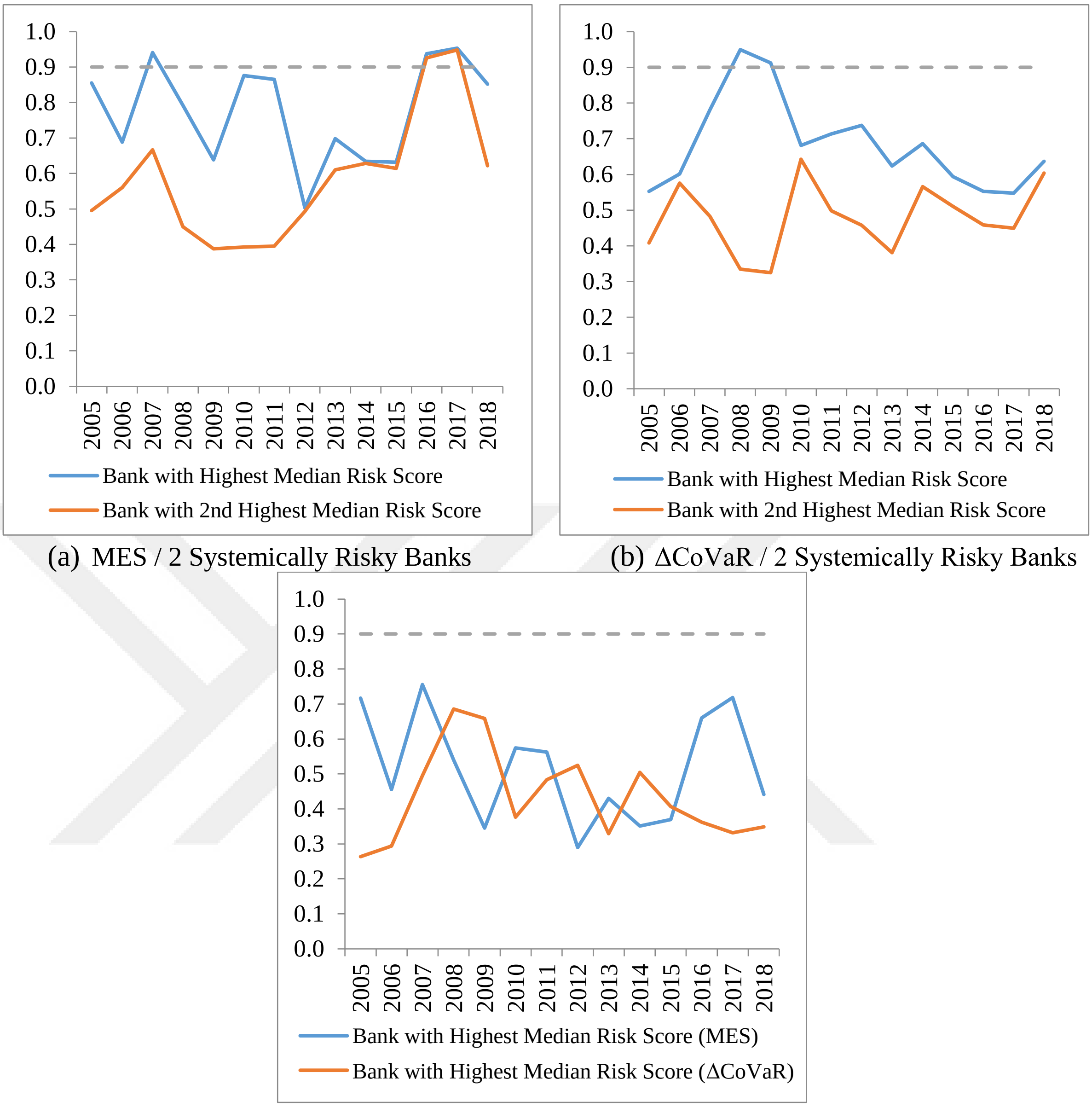
Table 9. Estimated Guilt Probabilities of Being a Systemically Risky Bank (Based on ΔCoVaR)

Guilt Probabilities of Being the Top 1 Systemically Risky Bank (ΔCoVaR Rankings)

Year	AKBNK	ALBRK	ALNTF	ASYAB	DENIZ	QNBFB	GARAN	HALKB	ISCTR	SEKER	TEBNK	TSKB	VAKIF	YPKRD
2005	12.24	-	0.54	-	-	9.24	19.96	-	26.38	0.12	9.28	0.00	-	22.24
2006	6.56	-	0.26	-	-	10.32	29.40	-	28.24	0.66	7.44	0.00	-	17.12
2007	23.42	-	0.14	-	-	5.94	15.58	-	49.48	2.10	0.80	0.02	-	2.52
2008	3.18	-	0.02	-	-	0.28	2.70	-	68.58	0.06	3.62	0.00	-	21.56
2009	3.88	-	0.10	-	0.02	0.02	6.40	-	65.84	0.06	9.78	0.12	-	13.78
2010	4.18	-	0.02	-	0.00	0.06	3.14	-	30.86	0.04	21.76	0.62	1.72	37.60
2011	6.38	-	0.00	8.32	0.00	0.00	2.24	-	17.86	0.60	11.22	0.68	4.40	48.30
2012	2.98	2.32	0.00	7.30	0.00	0.00	1.68	1.26	15.14	0.86	13.04	0.50	2.42	52.50
2013	11.02	0.64	0.08	5.46	0.00	0.00	32.96	1.22	20.44	0.04	0.18	0.56	13.58	13.82
2014	26.73	1.72	0.00	0.56	0.00	0.01	5.45	4.76	3.43	0.00	0.01	0.18	50.42	6.73
2015	26.12	1.92	-	0.00	0.32	0.00	15.12	12.16	2.50	0.00	-	0.16	40.68	1.02
2016	36.22	1.54	-	-	5.52	0.00	17.98	23.84	9.08	0.00	-	1.74	0.84	3.24
2017	33.20	1.56	-	-	8.70	0.00	18.20	15.64	13.76	0.00	-	1.54	3.90	3.50
2018	34.86	0.20	-	-	0.78	0.00	33.64	7.26	15.22	0.00	-	0.16	3.04	4.84

Guilt Probabilities of Being in the Top 2 Systemically Risky Banks (ΔCoVaR Rankings)

Year	AKBNK	ALBRK	ALNTF	ASYAB	DENIZ	QNBFB	GARAN	HALKB	ISCTR	SEKER	TEBNK	TSKB	VAKIF	YPKRD
2005	23.50	-	4.56	-	-	25.68	33.58	-	55.30	0.50	15.92	0.14	-	40.82
2006	13.92	-	0.72	-	-	22.84	60.16	-	57.60	1.24	10.92	0.04	-	32.56
2007	48.28	-	1.14	-	-	13.80	44.08	-	78.12	5.00	3.22	0.08	-	6.28
2008	16.40	-	0.56	-	-	1.14	32.08	-	**94.96**	0.40	20.98	0.02	-	33.46
2009	19.12	-	0.44	-	0.02	0.04	32.50	-	**91.20**	0.38	30.44	0.48	-	25.38
2010	8.80	-	0.10	-	0.00	0.10	11.84	-	68.12	0.10	33.60	2.28	10.82	64.24
2011	12.58	-	0.08	14.48	0.00	0.02	9.30	-	49.82	2.58	20.78	2.72	16.26	71.38
2012	8.14	6.88	0.00	15.36	0.00	0.00	7.14	5.36	45.80	4.18	20.24	1.50	11.66	73.74
2013	25.04	1.64	0.12	9.62	0.00	0.00	62.36	3.30	34.34	0.16	0.60	1.14	23.54	38.14
2014	56.55	4.20	0.00	1.63	0.00	0.02	18.07	12.70	9.17	0.01	0.03	0.90	68.61	28.11
2015	51.04	4.78	-	0.04	0.48	0.00	40.24	28.42	9.24	0.00	-	0.88	59.40	5.48
2016	55.28	5.96	-	-	6.70	0.00	43.22	45.86	27.84	0.00	-	3.78	3.42	7.94
2017	54.74	4.68	-	-	10.34	0.00	44.94	29.62	33.04	0.00	-	3.08	11.22	8.34
2018	63.70	0.50	-	-	1.10	0.00	60.34	18.06	27.32	0.00	-	0.72	11.22	17.04



(a) MES / 2 Systemically Risky Banks

(b) ΔCoVaR / 2 Systemically Risky Banks

(c) MES & ΔCoVaR / 1 Systemically Risky Bank

Figure 10. Estimated guilt probabilities of being a SIFI

CHAPTER 5

CONCLUSION

Correct measurement of the systemic risk and true detection of a systemically important financial institution has a great importance for today's highly integrated and rather complex financial environment. In this study, we have applied some of the widely used market data based statistical measures of systemic risk for the Turkish banking system. Particularly, we have used systemic risk metrics of MES, SRISK, CES and ΔCoVaR for our panel of 14 banks which are listed in the Borsa Istanbul.

First, we have used aggregate versions of our systemic risk measures in order to observe the behavior of system wide systemic risk. Particularly all aggregate measures indicate the relative increase in systemic risk during 2000 – 2001 and 2008 crisis periods with some apparent stabilization in total risk before the 2008 global crisis. In addition to these aggregate measures, we also estimated total SRISK of the Turkish banking system which is a nominal measure denominated in TL and can be regarded as a market-based version of stress tests applied by regulatory authorities. Similar to other aggregate measures, total SRISK of the banking system as a share of total capital in the system appears to increase during crisis periods with more notable increase during 2001 crisis relative to 2008 global crisis.

We also tested for predictive accuracy of SRISK as a conditional capital shortfall forecast using four cases of realized market downturns during crisis periods and conclude that predicted SRISK levels of individual banks seem to be an acceptable estimate for realized capital shortfalls with some positive bias in particular. We should also note that, capital shortfall definition used in this setting is not a direct counterpart for shortfall definitions that depend on capital adequacy calculations which are based on regulatory capital and risk-weighted assets but should be regarded as a market-based version. In that respect, when combined with rapid depreciations in currency, large deviations in market to book values of equity has a significant effect on estimated SRISK levels which manifests itself during periods like we observed after 2018 August.

Next, we checked the relationship between systemic risk measures and financial stress experienced by a particular bank and tested predictive power of %SRISK and ΔCoVaR on probability of defaults of individual banks estimated by a Merton type structural model. Tobit panel regressions with bank and crisis fixed effects indicate that, even after controlling for leverage, size and value-at-risk, systemic risk measures of %SRISK and ΔCoVaR are significantly associated with probability of default and this conclusion is also valid for %SRISK up to three months horizon.

In order to look at the issue in terms of SIFI detection standpoint, we put forward the systemic risk rankings implied by the measures we evaluate for the periods 2008 September and 2018 December. For both time periods of 2008 and 2018, top five banks (ISCTR, HALKB, GARAN and AKBNK) according to average systemic risk rankings are also the largest five banks according to asset size. Thus, even though asset size is not a direct input for each of the systemic risk metrics (except for CES and SRISK indirectly), other aspects of systemic risk (such as co-movement with market and interdependence) of these banks manifested themselves in these metrics and made them the SIFI. In addition to that, top six banks as of 2018 also constitute six D-SIBS (excluding Ziraat Bank) as of 2018 end, classified by the current indicator based regulatory framework of Basel accords, implemented locally by BRSA. There are certain differences regarding the risk orderings though with D-

SIBS, with higher rankings of public banks implied by average systemic risk rankings for example.

As a comparison of rankings implied by different systemic risk metrics, we estimated time series of Kendall rank correlations which is a measure of the degree of similarity between two rankings. Our results show that while the overall rank correlations are positive for all systemic risk metric pairs there seems to be some level of heterogeneity among different systemic risk measures. We should also note that, there is no particular change in the dynamics of rank correlations during crisis periods.

A possible question is whether we can have additional information regarding systemic risk level of banks on top of what we already know through widely used market risk measures like VaR. Kendall rank correlations of VaR based rankings with other systemic risk measures are rather low and close to zero which shows us that systemic risk measures covered in this analysis has an importance in terms of ranking financial institutions based on risk characteristics beyond what can be observed by the ordinary market risk measures like VaR.

Lastly, as a check for the reliability and test of estimation errors of systemic risk metrics of MES and ΔCoVaR, we have estimated guilt probabilities proposed by Danielsson (2016a). Estimation results from block bootstraps show that, depending on the assumed number of risky banks in the system, it is not easy to blame a bank for creating systemic risk as we observe guilt probabilities below 90% for both systemic risk metrics with certain exceptions for a couple of years especially for MES. When we plot the time series of the guilt probabilities with the first and second highest median systemic risk scores, we observe, on average, reliability of MES is higher than ΔCoVaR which would possibly apply to other MES based metrics.

APPENDIX

MERTON MODEL AND PROBABILITY OF DEFAULT

In his seminal paper, Merton (1974) offered a structural model of credit risk and equity valuation which is still used by market practitioners and academics. The model is basically an earlier implementation of Black-Scholes option pricing formula to credit risk estimation with some simplifying assumptions.

Let V be the total assets of a company with the debt level of D. From the point of view of shareholders, the value of equity is the difference between assets and total debt as long as the company can fulfill all its debt obligations. If not, the company defaults and shareholders receive nothing. Thus, the payoff of shareholders is like a call option on company assets V, with strike price D:

$$E_T = \max(V_T - D, 0)$$

So, assuming the firm's assets following a Brownian motion, formula of Black-Scholes option pricing can be used to link asset and equity structure of the firm:

$$E_0 = V_0 \Phi(d_1) - De^{-rT}\Phi(d_2)$$

$$d_1 = \frac{\ln\left(\frac{V_0}{D}\right) + \left(r + \frac{\sigma_V^2}{2}\right)T}{\sigma_V\sqrt{T}}$$

$$d_2 = d_1 - \sigma_V\sqrt{T}$$

where σ_V^2 is the asset volatility, r is risk-free interest rate, T is the time horizon and Φ is cumulative standard normal distribution. Thus, according to formula, value of equity of a company today is increasing with assets and decreasing with debt and volatility. In this setting, the probability of the assets V being less than debts D at the end of period T, which is simply probability of default, can be calculated by PD $=$

$\Phi(-d_2)$. The market value of assets V and asset volatility σ_V^2 are unobservable. But we can derive them from observable market value of equity and equity volatility σ_E^2 using the following relationship between asset and equity volatility:

$$\sigma_E E_0 \ = \Phi(d_1)\sigma_V V_0$$

Solving above equations together yields estimates of V, σ_V and accordingly PD $= \Phi(-d_2)$ with given values of market capitalization, equity volatility, debt level and debt maturity for risk free-interest rate r.

For our sample set of banks, we have used market capitalization and book value of debt data from Bloomberg, 22-day rolling annualized volatility of bank equity for equity volatility. For risk free rate, 1-year Government bond yield is used. Lastly, T is chosen to be 0.25 (3-months) as average maturity of Turkish banks' liabilities are rather short. Probability of default for each bank is then estimated at monthly frequency assuming a constant level of debt within a quarter (Figure 11).

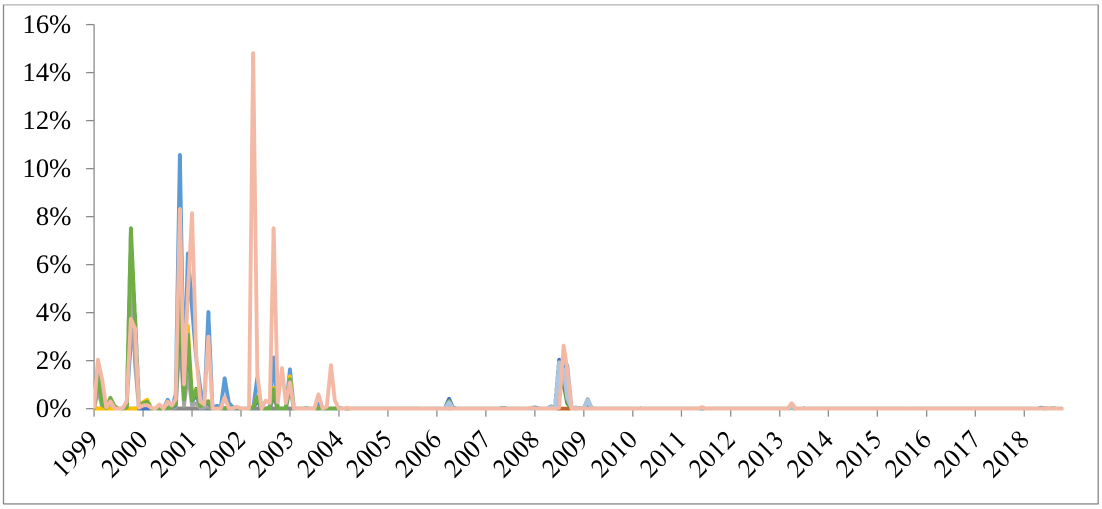


Figure 11. Probability of default (Merton model) of Turkish banks

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