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Constantinos Kyriakopoulos [*], ***Alexandros Koulis*** [**], ***Gerasimos Varvounis*** [***]

[*] *Department of Mathematics, National and Kapodistrian University of Athens, Greece*

E-mail (corresponding author): k_kiriak@otenet.gr

[**] *Department of Regional Development, Ionian University, Corfu, Greece*

E-mail: akoulis@ionio.gr

[***] *Business Mathematics, Interdisciplinary Postgraduate Program, National and Kapodistrian University of Athens, Greece*

E-mail: gerasimosvarv@gmail.com

Importance of the Contingent Claims Analysis in Detecting Banking Risks: Evidence from the Greek Bank Crisis

Abstract: In this paper we apply the Contingent Claims Analysis (CCA) to the banking sector in Greece with a particular focus on the years of the Greek debt crisis. Greece was selected primarily because its banking sector was hit hard due to the country's government debt default and its large exposure to domestic loans. The results obtained on the SIB's level and on the banking sector level gave us particular insight into the benefits of CCA for micro- and macroprudential policy reasons. The Distance-to-Distress (DtD) risk metric produced is particularly useful for detecting banks' vulnerabilities and resilience before they are revealed in the market. Moreover, the reduced volatility of DtD time series makes it an ideal candidate for tool predictions purposes and ultimately for policy reasons.

Keywords: Distance-to-Distress, banking risks, Contingent Claims Analysis, Greek crisis.

JEL Classification: G1,G2,G13,G32,G33,H63.

1. Introduction

In this paper, the Continent Claims Analysis (CCA) is applied individually to four Greek Systemically Important Banks (SIBs) and to the Greek banking sector as a whole. The results show that the Distance-to-Distress (DtD) met-

ric have pointed to the vulnerabilities of the banks and the banking sector during or more importantly before the major crises (subprime crisis, Greek debt crisis, and the outbreak of COVID-19). Also, *DtD* has shown the banks' resilience and possible recovery before this is captured by the markets as manifested on the stock exchange. This strengthen the view that CCA should be used as an additional tool for micro- and macroprudential policy because it spots regime changes not easily captured by the classical Top-Down (TD) or Bottom-Up (BU) banking stress test methodologies[1] (Dees, Jerôme, and Reiner, 2017).

CCA has its roots in option pricing theory (Black and Scholes, 1973; Merton , 1973) and it has the main objective of producing risk indicators (such as Distance-to-Default (*DtD*), Probability of Default (*PD*), Expected Loss (*EL*), etc.) in order to highlight the vulnerabilities of the entity under investigation. The main feature of CCA is the production of risk-adjusted balance sheets by combining data from static accounting balance sheets with market based information on the price and the volatility of the equity and the consideration that equity is a contingent claim on the assets. This procedure, in turn, leads to the calculation of risk indicators able to capture the non-linear risks in a forward looking perspective. Moreover, these indicators can also be used in conjunction with more conventional measures of risks like Value-At-Risk. The CCA is extremely flexible and can be applied at micro and macro level, with various objectives ranging from the estimation of the default risk of a specific firm up to the computation of the interlinks across sectors within the economy and be used as a policy tool to inspect the risks' transmission. Usually CCA is applied either to specific company's balance sheet or to the whole sectors like Banking or Credit Institution Sector (BS),[2] Non-financial corporations (NFC) sector, the government (GVT) sector and the households (HH) sector. NFC sector is the most straightforward step to expand CCA analysis from firm-level to aggregate level. For example, Gapen, Gray, Lim and Xiao (2004) apply the CCA to corporate sector's aggregated balance sheets and address the risk of spillovers towards the financial and public sectors. Gapen, Gray, Lim and Xiao (2008) implement CCA to sovereigns balance sheet and show that the Merton approach overcomes the traditional purely accounting-based measures of risk for emerging countries government (GVT) sector. Similarly Brière, Ferrarini, and Ramayandi (2016) focus on Asia emerging countries` governments and Keller, Kunzel, and Souto (2007) on Turkey`s GVT

[1] Liquidity stress tests tools are not considered in this paper. For consistency between liquidity and solvency stress test methodologies (see Taruna, Harun and Nattan, 2020)

[2] In this paper the terms "banking sector", "credit institution sector" and "financial sector" are used interchangeably although understandably the financial sector is more broad since it includes financial companies that do not provide credit.

sector, assessing the role of rising market volatility and of policy adjustments in scenarios valuation. The use of CCA on sovereigns can also be found in Bodie and Brière (2013) where the authors investigate Chile`s public sector, with a particular focus on guarantees to private corporations. They find that this analysis can be extremely useful in terms of sovereign wealth management, especially with respect to sovereign wealth funds and foreign exchange reserves. In addition, from an investor`s perspective, Gray, Merton, and Bodie (2007a) explore through CCA credit risk deriving from sovereign debts. Nevertheless, as presented in Gray, Gross, Paredes and Sydow (2013), the application of CCA to the GVT sector is not straightforward when it comes to non-emerging markets, leading to models which rely on sovereign Credit Default Swaps (CDS). Recently the household sector (HH) has been modelled according to Merton's theory too. Lai 2016 underlines how credit risk measure variations correspond to economic growth in Singapore by evaluating balance sheet data and implied households market data and detects that the usual CCA conclusion of assets volatility as risk driver holds for this sector as well. Vojtěch and Szabo (2021) propose modification of CCA on the liability side in order for the risk metrics to have more forward looking ability and be used in the stress testing methodology.

With respect to the Banking Sector, CCA is commonly applied to reveal the mechanisms of risk transmission within the sector and the implications for financial stability. The development of a "Systemic CCA" (Gray and Jobst, 2010, 2011) is meant to pursue the objective of taking a closer look to spillovers between the financial and government sectors. Romero, Gonza´lez, Quintero and Mosquera (2013), focusing on the Colombian financial system, consider the joint distribution of expected losses and the cost of an implicit bailout for the government. According to Nagel and Purnanandam (2019), the usual CCA must be applied with care. Indeed, considering the typical asset portfolio of the banks, it is mostly composed of debt claims (such as mortgages or bonds), which is not fully consistent with the Merton's (1973) assumption of log-normally distributed assets because this part of the banking sector assets is not uncapped but it is limited to the full repayment of the borrowers. One effective remedy for this is the general method proposed by Salleo, Grassi, and Kyriakopoulos (2020) that models with CCA the bank's obligors (in essence the assets of the banks: bonds, mortgages, etc) and then find the usual DtD and other risk metrics. But in any form the CCA[3] is applied either on a bank or on a systemic level it can reveal nonlinear vulnerabilities that can be very useful for micro or macro prudential reasons. In this direction Antunes and Silva 2010, studying Portuguese banks, also stressed

[3] CCA methodology can easily be complemented with the usual satellite modelling for macro variables (Rakotonirainy, Razafindravonona, and Rasolomanana, 2020).

the importance of *DtD* in assessing risk, even though they notice the role played by lack of economic fundamentals in the common CCA approach for the banks.

The paper is organized as follows: in section 2 the structure of the Greek banking sector is presented. In section 3 the CCA is explained and section 4 presents the data used for the analysis. Results for the SIBs and the banking sector exist in section 5. Conclusions and future directions are in Section 6.

2. The Greek banking Sector

The structure of the Greek banking sector includes 13 banks and 21 branches of foreign banks most of them incorporated in EU. Four banks, National Bank of Greece(NBG), Bank of Piraeus (TPEIR), EFG Eurobank (EUROB), and Alpha Bank (ALPHA), characterized as systemically important banks (SIBs). Since 2008 (where the first indication of the debt crisis appeared in Greece following the 2007 subprime crisis in the USA) the Greek Banking Sector has been highly concentrated. The percentage of assets held by the three major banks in Greece increased from around 60% in 2008 to 75% in 2017.[4] Following the international trend of bank acquisitions (Antoniadis, Alexandridis and Sariannidis, 2014) and the impact of the debt crisis on the economy, the number of banks in Greece (excluding foreign branches) has been dramatically decreased, resulting in 13 banks in 2020. The asset share of the largest five banks is around 97%.[5]

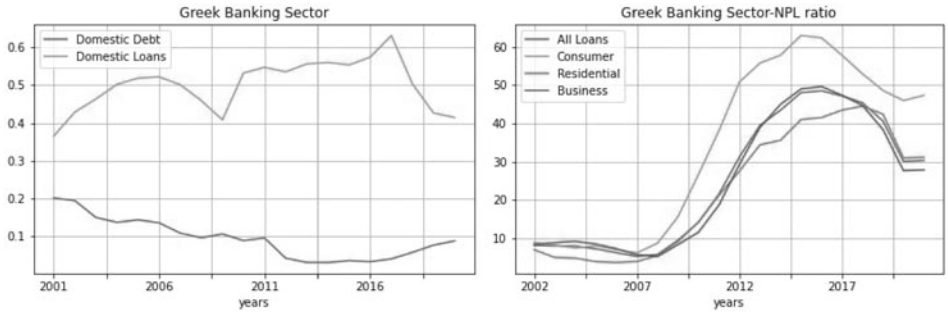
Although the roots of the Greek debt crisis does not lie in the banking sector (Andruszklewicz, Mathis, Vassiliadis, Peppas and Gatopoulos 2020) local banks were heavily affected. The Greek economy contracted from 2008 until 2015 more than 30% and the banks were heavily hit partly because of their high exposure to Greek debt and loans. In particular, the shooting up of the Non Performance Loans (NPLs) across all the sectors of the economy (Figure 1) made Greek banks severely undercapitalized. A combination of relief measures were used for the stabilization of the Greek banking system: facility lines (25 billion euros committed under the European Stability Mechanism (ESM), accounting engineering (a system of Deferred Tax Credits for boosting bank's capital and bringing the necessary solvency indices, such as the Capital Adequacy Ratio, in line with Basel Accords and the requirements of the European Institutions and the International Monetary Fund), and rounds of capital injections through equity increases.

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[4] https:/www.theglobaleconomy.com/Greece

[5] In 2020, the four SIBs had total assets of EUR 261.9 billion. The fifth largest bank is Attica Bank.

Figure 1: Exposure of the Greek Banking Sector in major assets classes



(a) Domestic Debt and loans as percentage of assets for the entire Greek Banking Sector

(b) NPLs for the Greek Banking Sector

Source: Bloomberg L.P.

As it is shown in Figure 1(a), the Greek Debt in the hands of Greek banks was around 10% in 2011, something that the P.S.I (the Private Sector Involvement Program took place in March 2012 with nominal haircut around 53.5% (Cheng 2020) made them suffer huge losses. Moreover, the exposure of banks to domestic loans was more than 50% and this fact made them extremely vulnerable as the economy collapsed and the NPLs were multiplied as the economy was plunging. Figure 1(b) shows the evolution of the NPL ratio for the various sectors of the economy. There was a steep NPL ratio increase in all sectors of the economy with consumer loans shooting up in 2015 more than 60% and business loans more than 49%. Even in 2020 (after three financial assistances with a combined assistance of 288.7 billion euros, a series of structural changes in the economy, various commitments and plans for debt maturity extension and reports from the EU financial institutions and the IMF that the Greek Debt is sustainable), the level of NPLs in Greek economy, although has started to deescalate[6] remains at rather elevated levels (the general level of NPLs more than 30%, business loans more than 27%, consumer loans more than 45%, and residential loans more than 30%).

With the help of the CCA and its built-in forward looking mechanism for capturing non-linear risks, the regulators will be able to spot banking vulnerabilities in the system and on an individual level well before they materialize. Also, the fact that CCA analysis and the corresponding DtD metric are a function of small number of parameters (like the equity volatility) makes the design of baseline

[6] Unfortunately, the COVID-19 pandemic reduced the speed of this progress.

and adverse scenarios for the TD and BU stress test much easier. Later in this paper we see that the application of CCA in the Greek banking sector revealed in time or even before the direction of vulnerabilities and the regulator could have taken prevention measures sooner.

3. Methodology

The CCA methodology uses balance sheet and market data and by exploiting option pricing theory provides risk-adjusted balance sheets that can reveal firm's risks. The non-linear nature of this approach, makes the key risk metrics indicators, *DtD* and *PD*, forward looking, in contrast with the historical metrics produced by adopting only balance sheet data with the usual accounting lags (Gapen et al., 2004). The CCA employs the concept of distress barrier (*B*): it is defined as a certain amount of debt assumed to be the lower bound for the assets, such that if they fall below it, the firm (or sector) is in distress (or even default - depending on the severity of the threshold because the promised amount (*B*) cannot be re payed). Admittedly, banks actual default depends also on the regulatory environment which seems to be more protective in recent years due to their systemic role of banks for the economy. According to the mainstream empirical methodology in this field, specifically carried on by Moody's with the KMV model (Crosbie and Bohn, 2019; Gray and Malone, 2008), the general rule is to employ the sum of the short-term debt (D_S) and a fraction of the long term debt (D_L) as distress barrier (*B*):

$$B = D_S + \alpha D_L, \qquad \alpha \in [0,1] \tag{1}$$

The distress barrier will be calibrated according to each specific sector and, therefore, α used to determine the barrier will conform to the particular features of the sector. In this paper we chose not to calibrate α due to the lack of adequate data points but to take the literature standard instead which is $\alpha = 0.5$. The CCA methodology focuses on the nature of risky debt and on its default likelihood. A given risky debt is composed of a default-free portion minus an expected loss, which is modelled here as an implicit put option on the assets of the balance sheet with the distress barrier as strike price. This is so because debt holders can be considered as writers to the equity holders of a put option and they have to pay the difference between the assets and the default-free debt whenever the assets are lower than the distress barrier. This can be written as:

$$D_t = Be^{-(T-t)} - P_t \tag{2}$$

where D_t is the value of risky debt at time t, B is the distress barrier, T is the maturity, r is the risk-free rate and P_t is the implicit put option at time t. The risky debt is equal to the default-free debt minus a guarantee against default, which in the previous equation (2) is exactly a put option with exercise price equal to B.

The assets are usually assumed to follow a stochastic process as:

$$\frac{dA}{A} = \mu_A dt + \sigma_A dZ(t) \tag{3}$$

where μ_A and σ_A are the instantaneous drift and the volatility of the assets respectively, $Z(t)$ represents the random component of the process modelled as a standard Brownian motion. In discrete time setting the random part has a normal distribution (with zero mean and variance equal to the square root of the time step dt) and in a continuous context the equation above is referred to as a geometric Brownian motion, where $Z(t)$ is a Wiener-process with $dZ(t) \sim N(0,dt)$ (Karatzas and Shreve, 1991). The value of the assets at time t is:

$$A_t = A_0 e^{\left(\mu_A - \frac{\sigma_A^2}{2}\right)t + \sigma_A Z(t)} \tag{4}$$

Given the value of the distress barrier at time t, B_t, a firm is in distress if the assets are below this threshold. The probability of this event is:

$$P(A_t \leq B_t) = N\left(-\frac{\ln\left(\frac{A_0}{B_t}\right) + \left(\mu_A - \frac{\sigma_A^2}{2}\right)t}{\sigma_A\sqrt{t}} = -d_{2,\mu}\right) = N(-d_2) \tag{5}$$

where $N(\cdot)$ is the standard cumulative normal distribution function. The quantity $d_{2,\mu}$ is called Distance to Default (*DtD*) and it depends on the drift and the volatility of the assets. The Probability of Default (*PD*) calculated with this procedure is the so-called "actual" probability of default, which is outside of the common CCA/Merton Model (Gray, Merton, and Bodie 2007b). The "risk-neutral" *PD* is obtained by replacing in the above formulas the growth rate of the asset μ_A with the risk-free rate r. Normally the risk-free rate is lower than the asset drift rate μ_A, resulting in lower actual than risk-free default probabilities. Throughout the analysis, consistent to "risk-neutral" measures (Gray et al.) need of the estimation of asset drift μ_A is spared. This is sufficient for our needs since the primary focus is on the comparison of *DtDs* either among the different sectors or through time.

The equity value can be described as a junior claim on the assets, and hence as a call option on them. The assets is the sum of equity and debt, and the value of the risky debt is:

$$D_t = A_t - E_t \tag{6}$$

where E_t is the market value of equity at time t and A_t is the market value of the assets. For the sake of simplicity, we assume $t = 0$ (the case where $t > 0$ is handled with a simple time shift). Being E a call option on the assets, we can write (Black and Scholes, 1973):

$$E = AN(d_1) - Be^{-rT} N(d_2) \tag{7}$$

and

$$D = A - AN(d_1) + Be^{-rT} N(d_2) \tag{8}$$

Where

$$d_1 = \frac{\ln\left(\frac{A}{B}\right) + \left(r + \frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}}, \quad d_2 = d_1 - \sigma_A\sqrt{T} \tag{9}$$

In order to find the market value of the debt, we rely on the market value of the assets and on their volatility. Although we cannot directly observe these two values, we can retrieve from the market equity and σ_E and A and σ_A are calculated by applying Itˆo's lemma on E:

$$dE = \left(\frac{\partial E}{\partial A}\mu A + \frac{\partial E}{\partial t} + \frac{1}{2}\frac{\partial^2 E}{\partial A^2}\sigma^2 A^2\right)dt + \frac{\partial E}{\partial A}\sigma A dZ \tag{10}$$

We get:

$$E\sigma_E = A\sigma_A \frac{\partial E}{\partial A} = A\sigma_A N(d_1) \tag{11}$$

This last equation, together with equation (7), defines a system of two equations and two unknowns (A and σ_A) which allows to obtain the implicit market value of the assets and their volatility. From a practical perspective, the above two by two non-linear system is highly sensitive to the initial condition of E and σ_E[7]. A and

[7] Simulations have shown that when the put is at the money then the system is unstable and even small differences in the initial conditions produce large output deviations.

σ_A are then used to calculate two risk-measures: the distance to default/distress (*DtD*) and the probability of default/distress (*PD*). The *DtD* is defined as:

$$DtD = \frac{\ln\left(\frac{A}{B}\right) + \left(r - \frac{\sigma_A^2}{2}\right)T}{\sigma_A\sqrt{T}} = d_2 \tag{12}$$

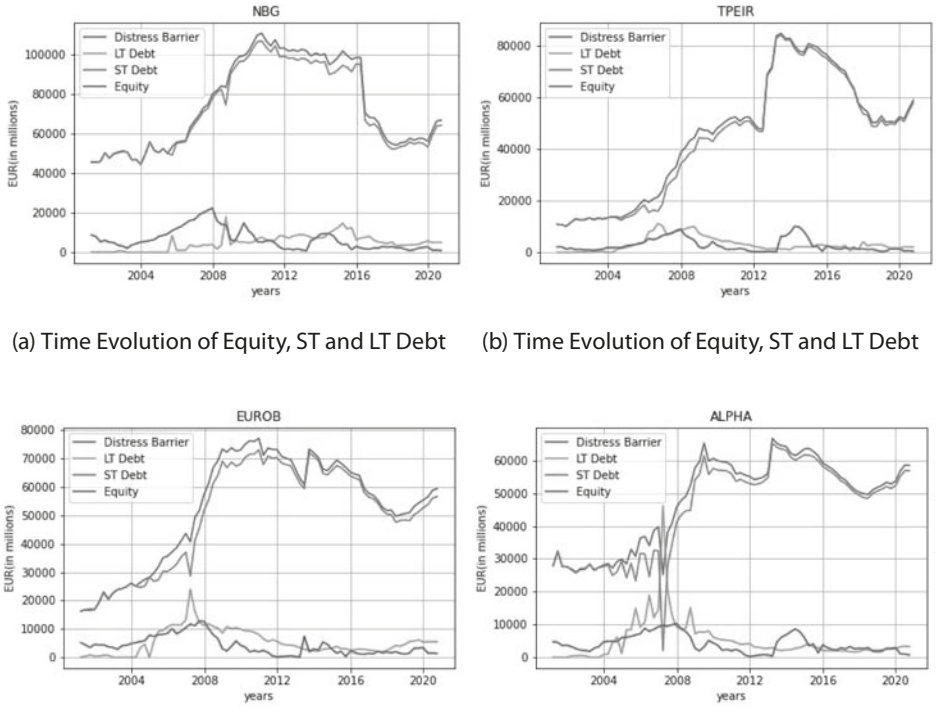
or more naively as $DtD = \frac{A-B}{A\sigma_A}$. It is a measure that expresses the number of standard deviations the expected value of the assets is away from the threshold given by the distress barrier. The associated probability is $PD = N(-DtD)$. *DtD* and *PD*) are usually computed in the risk-neutral setting: $PD = N(-d_2) = N(-DtD)$. Although *DtD* and *PD* behave the same way (since the normal cumulative distribution function N() is an increasing function) the use of PDs is not always satisfactory. It has been shown (see for instance Bharath and Shumway, 2008) that this mapping produces distorted default probabilities due to the thin tails of the normal distribution usually assumed. That is why the Moody's KMV model, in order to find the expected default frequencies (EDF^{TM}), uses empirical data (for instance, historical defaults) to create a reliable map to the real *PDs* (Crosbie and Bohn 2003) in its effort to get fatter tails. Also, $N(\cdot)$ is a strictly monotonic increasing function, it preserves the ranking provided by the distance to default and therefore does not return any new information to the comparative analysis (Jessen and Lando, 2015). For the above reasons, in this paper we use the risk metric *DtD* in order to show the extent of the vulnerability of a particular bank or of the whole banking sector.

4. Data

The analysis developed in this paper covers the period from 2001 until 2020 with quarterly frequency for the four SIBs in Greece: National Bank of Greece(NBG), Bank of Piraeus (TPEIR), EFG Eurobank S.A (EFG) and Alpha Bank (ALPHA). The value of equity, Long Term debt (LT-maturity greater than a year), Short Term (ST)debt and distress barrier exist in Figure 2.[8]

[8] All data used in this paper are taken from Bloomberg L.P.

Figure 2: Time Evolution of Equity, ST and LT Debt



(a) Time Evolution of Equity, ST and LT Debt

(b) Time Evolution of Equity, ST and LT Debt

(c) Time Evolution of Equity, ST and LT Debt

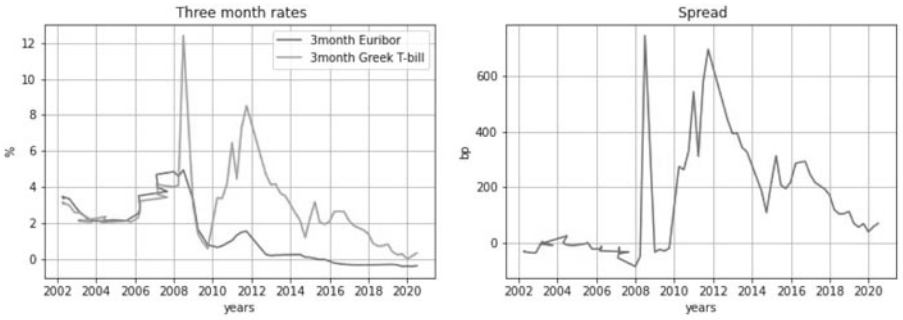
(d) Time Evolution of Equity, ST and LT Debt

* Equity expressed in market values at the daily closing price. Short and Long term debts are in nominal values.

One common characteristics among the four banks is the chronically high level of short term borrowing compared to the long term borrowing and equity value. This fact elevates the distress barrier as well. This is partly due to the inability of Greek banks to borrow long term especially at the beginning of the millennium due to low ratings, the nature of banking operations especially under the normal positive slope yield curve where borrowing took place in short term, lending or investment in long term and, of course, the Greek crisis that started at the end of 2008. This phenomenon has been exacerbated in 2012 during the Greek debt restructuring program P.S.I., and started to normalize only after 2016 when the Greek economy has started to show the first signs of recovery. Also, it is noted that the market value of equity was considerably smaller compared to the long and short term borrowing reflecting the leverage business model Greek banks were using following the international trend.

For performing the CCA we use as a proxy of equity volatility metric the 30-days daily volatility and as a proxy for the risk free rate the 3 month T-bill for Greece was chosen. We preferred not to choose as a proxy for the risk free rate a Euro index (one candidate could have been the 3-month Euribor) because this choice would not capture the particular circumstances that Greece found itself in during the Greek debt crisis. As it is shown in Figure 3(a) in the beginning the debt crisis the 3-month Greek yield rose to more than 12% (also the 3 month Euribor shot up more than 4%). Figure 3b shows the unstable pattern of the spread between the 3-month Greek yield and 3-month Euribor where twice in the two peaks during the crisis - at the beginning and at the time of P.S.I. when it increased to more than 600 basis points. Despite that, the "risk-free" feature of the 3-month T-bills was saved since T-Bills were excluded from the debt restructuring program.

Figure 3: Evolution of 3-month Greek yield, 3-month Euribor and their spread

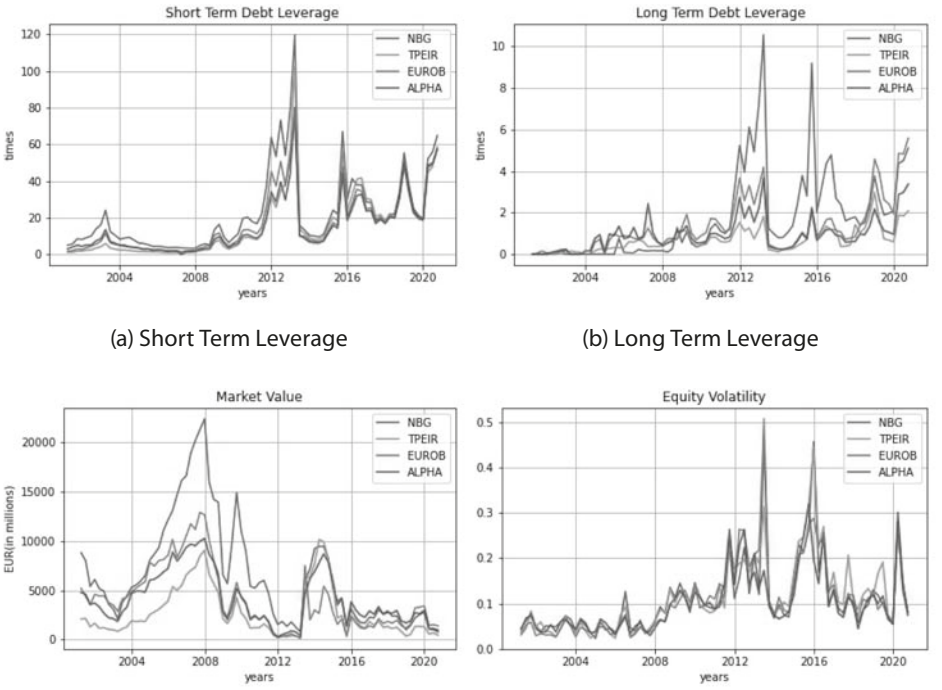


(a) 3 month rates

(b) 3 month Greek rate-3 month Euribor

The comparison of short term debt, long term debt, market value and equity volatility for the four SIBs is shown in Figure 4.

Figure 4: SIBs' leverage and volatility



(a) Short Term Leverage

(b) Long Term Leverage

(c) Market Value

(d) 30-days daily volatility

Source: Bloomberg, LP

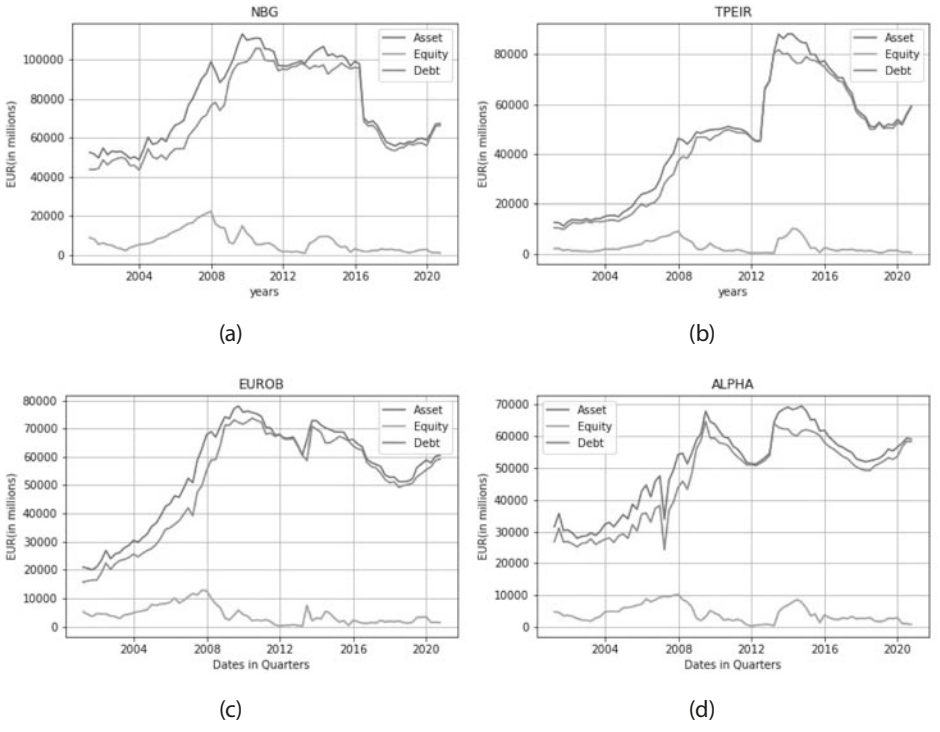
As it shown in Figures 4(a) and (b), SIBs' leverage before the crisis was similar and moderate. The leverage skyrocketed after the debt crisis emergence as a result not of additional debt but rather of the collapse of the banks' equity market value (Figure 4(c)). Moreover, as it was expected in this period, the short term equity volatility started to increase and it topped many times when the road to normality seemed to have been blocked?. In any case, the National Bank of Greece, as the bank with the largest market capitalization, was hit the most and it was something that seemed natural because it had the biggest exposure to the government debt and loans.

5. Results

5.1. CCA for SIBs

We apply the CCA first for the four SIBs[9]. The results are most revealing since the *DtD* time is proved to reveal vulnerabilities before its realizations, as expressed by the fall in market value. The CCA analysis was performed quarterly and the output was the "market" value of assets, the asset volatility, and the *DtD*. The term market is under quotation because the value of assets does not come directly from observing market prices but is rather implied as the solution for the non-linear system of equations 7 & 11 where the market value of equity and the equity volatility were used as inputs. The "market" value of debt is simply the difference between the assets and the equity. This way the risk adjusted balance sheets are created through the CCA. The results for the assets and debt for the four SIBs are shown in Figure 5.

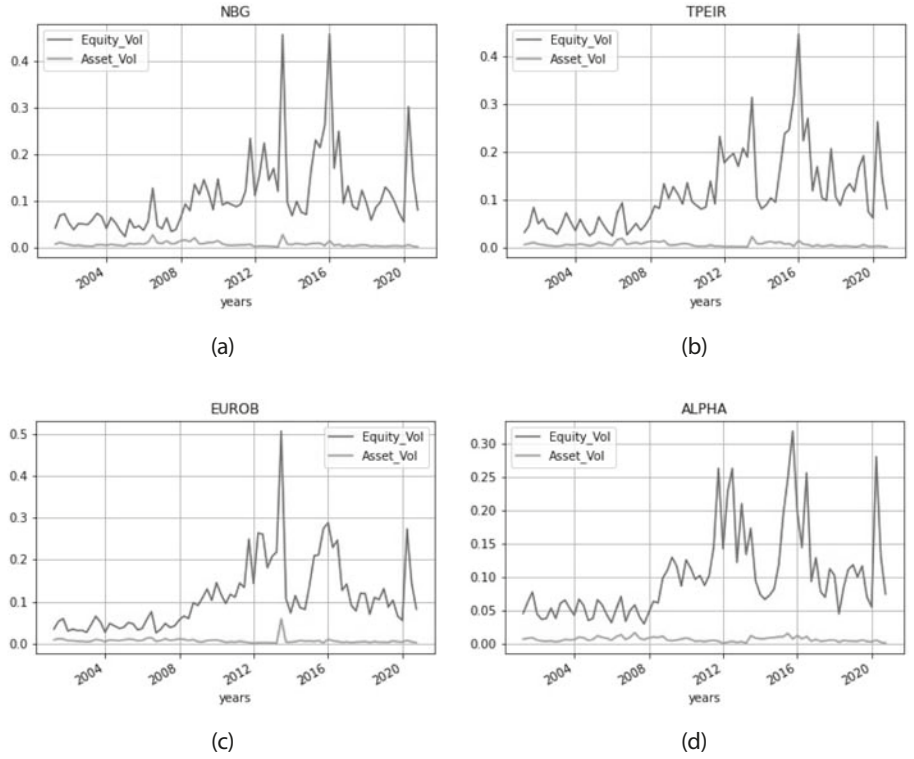
Figure 5: CCA - "Market" Value of Assets and Debt



[9] The code developed for this paper is in Python and is available to the reader upon request.

Given the high level of debt and the low level of equity it comes as no surprise that the assets follow closely the pattern of the distress barrier. Also assets are higher than the distress barrier. An interesting outcome resulting from the CCA analysis on the four SIBs is the comparison of equity and asset volatility. This comparison exists in Figure 6 and shows that assets volatility is much smoother and lower than equity volatility, something that could be used in prediction models.

Figure 6: CCA - Asset and Equity Volatility



Finally, Figure 7 shows the *DtD* for the four SIBs and its behaviour in comparison to the equity value. It is clear that *DtD* captures non-linear risks that the other classical balance sheet methods for detecting bank vulnerabilities miss to identify.

Figure 7: CCA - DtD and Equity

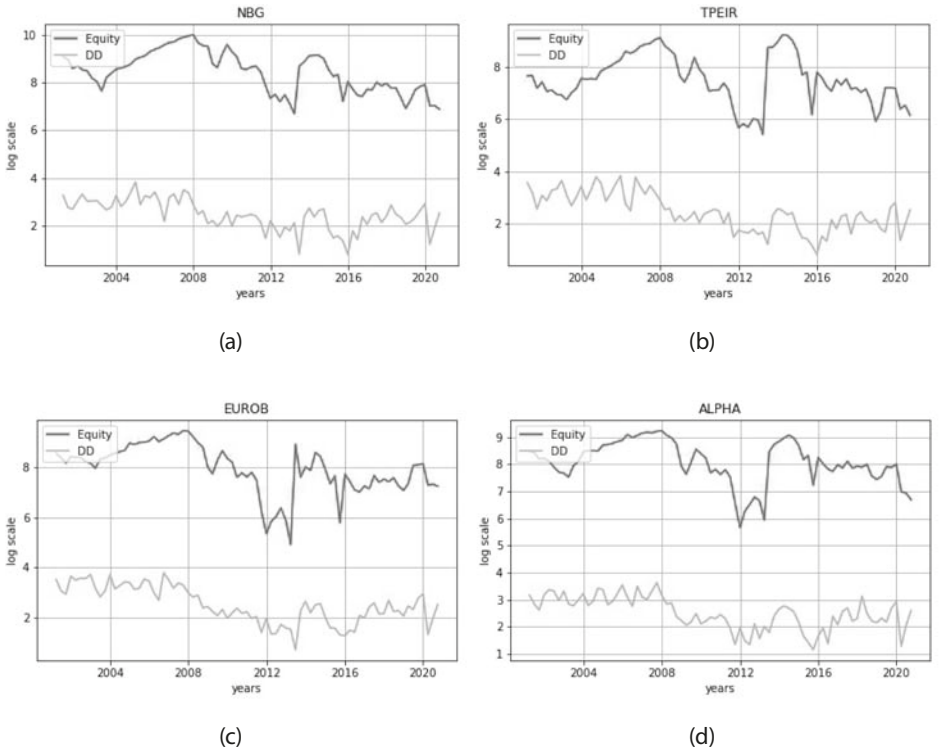
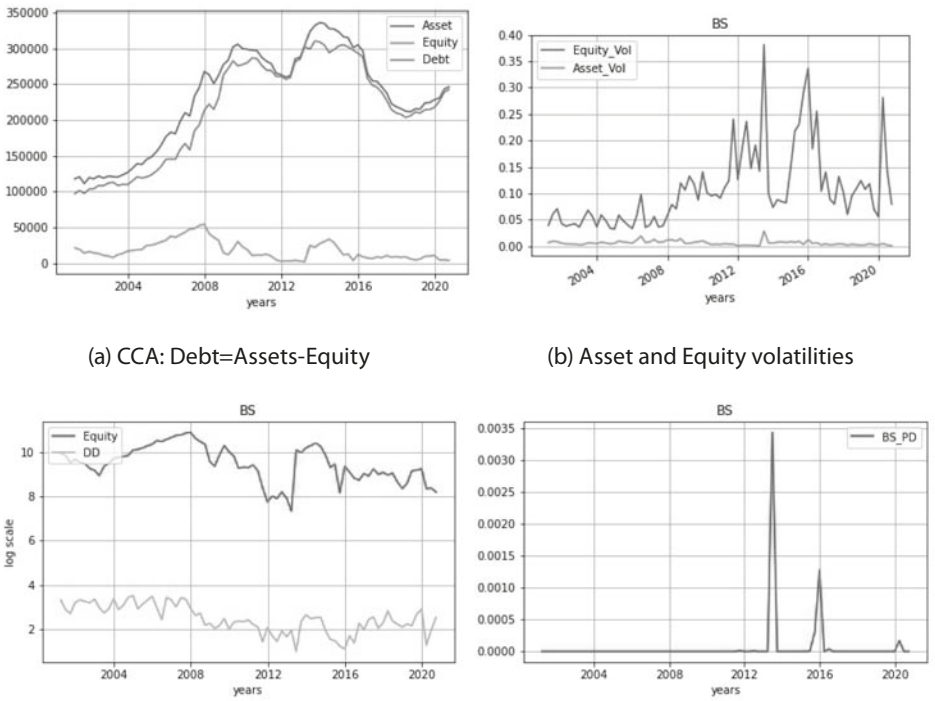


Figure 7 shows that the *DtD* time series for the four SIBs is more stable than the equity price time series and captures more timely the banks' vulnerabilities. For instance, between 2007 and 2008 when the equity was increasing, the *DtD* was pointing downwards predicting the difficulties for the banks to come. During the various stages of the Greek debt crisis (notably in years 2012 and 2016), the *DtD* showed more predicting power. Its stabilization after 2016 implied that the banks have started to improve despite the fact that this was not captured yet by the equity series. Moreover, the more stationary characteristics of the *DtD* shows that it is more suitable for microprudential policy reasons and for predicting more realistically potential bank vulnerabilities. After 2018, despite the weakness in the equity series, the *DtD* series showed strength pointing to the improvement of the SIBs' situation.

5.2. CCA for the Greek Banking Sector

Here the four SIBs' combined balance sheet? serves as a proxy for the balance sheet of the entire Banking Sector to which the CCA is applied. The equity volatility used is the market weighted average volatilities of the four SIBs, although the volatility of FTSEM index[10] could have been used. The CCA results along with the DtD and PDs are given in Figure 8.

Figure 8: CCA - Banking Sector



(a) CCA: Debt=Assets-Equity

(b) Asset and Equity volatilities

(c) DtD and Equity on a log scale

(d) Sector PDs

The results are similar to the results presented in Subsection 5.1. As it was expected, the high level of ST and LT loans resulted, through the CCA analysis, in a high level of assets that follow closely the "market" level of debt (Figure 8(a)). Moreover the asset volatility series produced through the CCA analysis is more stable than the equity volatility (Figure 8(b)) of the sector, making it a better candidate for prediction, simulation and macroprudential policy purposes.

[10] FTSEM is the Greek banking sector index. source: https://www.athexgroup.gr

Similar to the individual cases, *DtD* seems to be more capable of spotting sector vulnerabilities or resiliencies than the market determined equity (Figure 8(c)). This is remarkable since all the data (except the equity series) are coming from the quarterly reports submitted by the banks. It is this non-linear feature of the CCA that makes the risk metrics produced suitable for capturing non-linear risks missed otherwise. Figure 8(d) shows default probabilities produced under the CCA analysis. Although we still believe that the *DtD* being free from the normality assumption gives more information for bank's vulnerabilities for the whole BS, the PD are still informative at least for macroprudential purposes. For instance, we observe that the difficult situation for the Greek Banking Sector in June 2013 and December 2016 (and also, even in much less scale, in the first months of 2020 due to the initial panic induced by COVID-19) has been captured as "alarm blips" in the graph. In summary, we conclude that the application of CCA on the sector level is very informative and produces signals for the regulators that, if combined with the more classical macroprudential tools (like the TD stress test), could result in more timely supervisory actions. Moreover, this use of the CCA is ideal for simulation purposes and the design of adverse scenarios since there are much fewer parameters to stress (usually the equity and asset volatility are the most important ones).

6. Conclusions & future directions

In this short paper we applied the CCA to the four SIBs in Greece and the whole banking sector. The popularity of CCA in recent years has been on the rise as an additional forward-looking tool of micro- and macroprudential policy. Also, it is easy to apply once banks' reports are in place and market value of equity can be observed (usually through listing in the exchanges). The choice for Greece was ideal since it was the country that exhibited the most severe European debt crisis (the contraction of GDP was more than 30%) with multiple consequences for the government debt and for loans. The results produced are very encouraging because they showed that the risk metric *DtD* can capture non-linear risks in the forward-looking manner. Moreover, the asset volatility produced is more stable than the equity volatility, something that makes it suitable for prediction and simulation purposes. Future directions can include the comparison of the banks' asset values (and debt) produced by the CCA to the market value of banks' assets (for the asset classes for which this is possible) and banks' debt. In addition, since the analysis is dependent on few parameters (basically the equity volatility and the CCA-produced asset volatility), it could be interesting to compare the results of CCA for banks to the results obtained using the classical TD and BU stress tests approaches.

References

1. Andruszklewicz O., Mathis, J.,Vassiliadis, M.,Peppas, K. and Gatopoulos, G. (2020) "Study on the Financial Sector in Greece during the economic adjustment programmes: 2010-2018". *European Commission, Final Report*.
2. Antoniadis, I., Alexandridis, A. and Sariannidis, N. (2014). "Mergers and acquisitions in the Greek banking sector: An event study of a proposal". *Procedia Economics and Finance* 14, pp. 13–22.
3. Antunes, A. and Silva, N. (2010). "An Application of Contingent Claim Analysis to the Portuguese Banking System". In: *Financial Stability Report*. May 2010 141, pp. 603–626.
4. Bharath, S. T. and Shumway T. (2008). "Forecasting default with the Merton distance to default model", *The Review of Financial Studies* 21.3, pp. 1339–1369.
5. Black, F. and Scholes M. (1973). "The pricing of options and corporate liabilities", *Journal of political economy* 81.3, pp. 637–654.
6. Bodie, Z. and Briere, M. (2013). "Sovereign wealth and risk management: a framework for optimal asset allocation of sovereign wealth", Boston U. *School of Management Research Paper* 2011-8.
7. Brière, Marie, Benno Ferrarini, and Arief Ramayandi (2016). "Contingent Claims Analysis of Sovereign Debt Sustainability in Asian Emerging Markets", *Asian Development Bank Economics Working Paper Series* 486.
8. Cheng, G. (2020). "The 2012 private sector involvement in Greece", Publication Office of the European Union, Discussion paper, No 11.Crosbie, Peter and Jeff Bohn (2003). "Modeling default risk". Moody's KMV
9. Crosbie, Peter and Jeffrey Bohn (2019). *Modeling default risk*. World Scientific, pp. 471–506.
10. Dees, S., Henry, J. and Martin, R. (2017). Stress-Test Analytics for stress Policies in the euro era. European Central Bank.
11. Gapen, M. T., Gray D., Lim C. and Xiao Y. (2004). "The Contingent Claims Approach to Corporate Vulnerability Analysis: Estimating Default Risk and Economy-wide Risk Transfer", Corporate Restructuring: Lessons from Experience. *The World Bank Group: Washington*, DC, pp. 261–300.
12. Gapen, M.T., Gray D., Lim C. and Xiao Y. (2008). "Measuring and analyzing sovereign risk with contingent claims". *IMF Staff Papers* 55.1, pp. 109–148.
13. Gray, D. and Jobst, A. A. (2010). "Systemic CCA-a model approach to systemic risk", Deutsche Bundesbank/Technische Universität Dresden Conference: Beyond the Financial Crisis: Systemic Risk, Spillovers and Regulation, Dresden. Citeseer.

14. Gray, D. and Malone, S. (2008). *Macrofinancial risk analysis*. Vol. 433. John Wiley & Sons.
15. Gray, D., Gross, M., Paredes, J. and Sydow M. (2013). Modeling banking, sovereign, and macro risk in a CCA global VAR. 13-218. International Monetary Fund.
16. Gray, D. F. and Jobst, A. A. (2011). "Modelling systemic financial sector and sovereign risk", *sveriges riksbank economic review* 2.68, p. 106.
17. Gray, D. F., Merton, R. C. and Bodie, Z. (2007). Contingent claims approach to measuring and managing sovereign credit risk. *Journal of Investment Management*, 5(4), 5.
18. Gray, D, Merton, R. C. and Bodie, Z. (2007b). "New framework for measuring and managing macrofinancial risk and financial stability". "National Bureau of Economic Research", *Research Working Paper* 13607.
19. Jessen, C. and Lando, D. (2015). "Robustness of distance-to-default", *Journal of Banking & Finance* 50, pp. 493–505.
20. Karatzas, I. and Shreve, S. (1991). *Brownian Motion and Stochastic Calculus*. Vol. 113. Springer.
21. Keller, C., Kunzel, P. and Souto, M. (2007). *Measuring sovereign risk in Turkey: an application of the contingent claims approach*. 7-233. International Monetary Fund.
22. Lai, W-N. (2016). "Evaluating the sovereign and credit risk in Singapore: A Continent Claims Approach". *Research in International Business and Finance* 37, pp. 435–447.
23. Merton, R. C. (1973). "Theory of rational option pricing". In: *Theory of Valuation*, pp. 229–288. Nagel, Nagel, S. and Purnanandam, A. (2019). Bank risk dynamics and distance to default. Tech. rep. National Bureau of Economic Research.
24. Romero, L. C., Gonza´lez, E. G., Quintero, M. L. and Mosquera, M. A. M. (2013). "Measuring systemic risk in the Colombian financial system: a systemic contingent claims approach". *Journal of Risk Management in Financial Institutions* 6.3, pp. 253–279.
25. Taruna, A. A., Harun, C. A. and Nattan, R. R. (2020). "Macroprudential Liquidity Stress Test: An Application to Indonesian Banks. *Journal of Central Banking Theory and Practice* (9).special issue(2020): 165-187.
26. Rakotonirainy, M., Razafindravonona, J. and Rasolomanana, C. (2020) "Macro stress testing credit risk: Case of Madagascar banking sector." *Journal of Central Banking Theory and Practice* 9.2: 199-218.
27. Salleo, C., Grassi, A. and Kyriakopoulos, C. (2020). "A Comprehensive approach for Calculating Banking Sector Risks". *International Journal of Financial Studies* 8.4, pp. 1–21.

28. Siuda, V. and Szabo, M. (2021). Measuring Sovereign Credit Risk of the EU countries 1. *Journal of Central Banking Theory and Practice*, 10(3), 169-192.