INSTITUTO
UNIVERSITÁRIO
DE LISBOA

The effects of Systemic Risk in Portugal: a CoVaR approach

Bárbara Mendes Ferreira

Master in Finance

Supervisor:
Dr. António Barbosa, Assistant Professor,
ISCTE Business School

October, 2020

The effects of Systemic Risk in Portugal: a CoVaR approach

Bárbara Mendes Ferreira

Master in Finance

Supervisor:
Dr. António Barbosa, Assistant Professor,
ISCTE Business School

October, 2020

Acknowledgement

I would like to thank my supervisor António Barbosa, for his help, comprehension and patience throughout this long and challenging journey.

I also want to thank my family and friends for their advices, help and motivation. Specially to Aléxio Vieira and Bruno Taborda who were always there to encourage me to finish one more step in my academic life.

Resumo

No contexto da globalização financeira, a Grande Recessão aumentou o interesse na medição do risco sistémico. O principal objetivo desta dissertação é o estudo do risco sistémico no sistema financeiro português entre 02/06/2003 e 30/06/2020. Especificamente, é analisado o impacto da crise dos bancos portugueses no sistema financeiro nacional e as repercussões de uma crise no sistema financeiro português nos bancos nacionais. Para esse efeito, é utilizado como medida de risco sistémico o ΔCoVaR. Adicionalmente, o teste *bootstrap* KS é aplicado para determinar a precisão estatística das estimativas de ΔCoVaR e para ordenar os bancos de acordo com a sua importância e a sua vulnerabilidade sistémica. Ao longo da dissertação são utilizadas várias metodologias para obter os retornos dos bancos e o VaR de forma a analisar a sensibilidade dos valores de ΔCoVaR e VaR estimados.

Os resultados empíricos mostram que nenhum banco português pode ser considerado sistemicamente importante ou vulnerável no período analisado. No entanto, entre os bancos considerados, todos apresentam uma maior contribuição para o risco sistémico do sistema e uma maior vulnerabilidade aos choques do sistema no contexto da Grande Recessão. Adicionalmente, o BES e o BNF são mais vulneráveis ao sistema na última fase dos seus ciclos de vida. Entre 02/06/2003 to 13/10/2010, o BCP é o banco que contribui mais para o risco do sistema e o mais vulnerável aos impactos do sistema. Por fim, as estimativas de ΔCoVaR e VaR revelaram-se sensíveis às metodologias utilizadas para calcular os retornos dos bancos e o VaR.

Abstract

The Great Recession in the context of financial globalization raised the interest in systemic risk's measurement. The main goal of this dissertation is the study of systemic risk dynamics in the Portuguese financial system between 02/06/2003 and 30/06/2020. Specifically, we analyze the impact of Portuguese banks distress on the domestic financial system as well as the repercussions of a crisis in the Portuguese financial system on domestic banks. For that purpose, we use ΔCoVaR systemic risk measure. Furthermore, the bootstrap KS test is applied to determine the statistical accuracy of the ΔCoVaR forecasts and to rank banks according to their systemic importance and systemic vulnerability. Throughout this dissertation alternative methodologies to obtain banks returns and to estimate VaR are applied to analyze the sensitivity of VaR and ΔCoVaR forecasts.

The empirical results reveal that no Portuguese bank is considered systemic important or vulnerable in the analyzed period. However, considering the studied banks, all of them present its highest contribution to the financial system's systemic risk and its highest vulnerability to the system's shocks in the context of the Great Recession. Furthermore, BES and BNF are more vulnerable to the Portuguese financial system's impact in the last phase of their life cycles. Additionally, from 02/06/2003 to 13/10/2010, BCP is the bank with the major contribution to the financial system's systemic risk and the most vulnerable to system's shocks. Finally, VaR and ΔCoVaR estimates reveal sensitivity to the banks returns computation methodology as well as to the VaR model used.

Keywords: Value-at-Risk, Conditional Value-at-risk, Systemic Risk, Quantile Regressions, Portuguese listed banks

JEL Classification: G01, G21

Index

List of Abbreviations

BCP	Millennium BCP
BES	Banco Espírito Santo
BNF	Banif
BPI	Banco Português de Investimento
CDF	Cumulative Distribution Function
CoVaR	Conditional Value-at-Risk
DIP	Distress Insurance Premium
EWMA	Exponentially Weighted Moving Average
FNB	Finibanco
GARCH	Generalized Autoregressive Conditional Heteroscedasticity
KS	Kolmogorov-Smirnov
MES	Marginal Expected Shortfall
QR	Quantile Regressions
SES	Systemic Expected Shortfall
SIFIs	Systemically Important Financial Institutions
SMA	Simple Moving Average
VaR	Value-at-Risk

Introduction

How does a financial system's crisis impact banks? Moreover, how does a crisis in one bank affect the financial system? These are questions that have been raised, acquiring great importance to investors, regulators and researchers after the recent global financial crisis.

In September 2008, the bankruptcy of Lehman Brothers triggered the strictest impacts of the 2007-2009 financial crisis (Acharya, Engle, & Richardson, 2012). The consequences were initially felt in the United States financial system but quickly spread to Europe, given the existing interconnectedness between cross-border financial institutions (Wong & Fong, 2011). Financial markets had never experienced a crisis of this dimension, which shows a disadvantage of financial globalization (Wong & Fong, 2011).

Several researchers have been studying the causes of this crisis, the chain reaction that appears to exist between the affected financial institutions and the adverse consequences to the financial system and, ultimately, to the real economy. In particular, academics found that the risk of a specific financial institution cannot properly be measured without taking into account the externalities on other entities (Hautsch, Schaumburg, & Schienle, 2015). Additionally, the traditional microprudential financial regulation view, as in Basel I and Basel II, needs to be enriched with a macroprudential approach (Huang, Zhou, & Zhu, 2012). This kind of regulation requires the identification of the Systemically Important Financial Institutions (SIFIs) (Acharya et al., 2012), that is, financial institutions that threat the stability of the financial system when experiencing deep distress (Brownlees & Engle, 2017; Cipra & Hendrych, 2017).

These types of crisis are considered systemic events, involving the entire financial system, through systemic risk (Billio, Getmansky, Lo, & Pelizzon, 2012). After the 2007-2009 financial crisis alternative systemic risk measures arose (Giglio, 2014). These alternative risk measures are based on principal components analysis and Granger-causality tests (Billio et al., 2012), default probabilities (Huang et al., 2012) and marginal expected shortfall (Acharya, Pedersen, Philippon, & Richardson, 2017; Brownlees & Engle, 2017).

In this dissertation we apply the Conditional Value-at-Risk (CoVaR) measure proposed by Adrian and Brunnermeier (2011), to understand the contribution each financial institution has to the systemic risk of the overall financial system and the contribution of the financial system to the systemic risk of each bank. According to the authors, systemic risk is measured as the difference between the Value-at-Risk (VaR) of an entity conditional on the distress of other entity and its VaR conditional on the median state of the other institution.

Owing to the widespread interest in this issue there are many empirical analysis that apply these methodologies to different economies (Anghelache & Oanea, 2014; Bernal, Gnabo, & Guilmin, 2014; Drakos & Kouretas, 2015; Girardi & Ergün, 2013; Karimalis & Nomikos, 2018). However, to the best of our knowledge, unrepresented in the literature is the study of systemic risk contagion in the Portugal, one of the most affected economies during the recent financial crisis. Therefore, the main goal of this dissertation is the analysis of contagion effect among Portuguese commercial banks and its effects on the Portuguese financial system. For that purpose, we study not only the impact of nationalization or bankruptcy of Portuguese banks on the Portuguese financial system, but also the repercussions of Portuguese financial system's crisis on domestic banks.

Furthermore, the existent literature on CoVaR methodology base the analysis on the concept of market-valued total assets proposed by Adrian and Brunnermeier (2011) and compute the VaR using quantile regressions. In this dissertation three alternative methods to obtain banks returns are used. Furthermore, VaR is estimated using not only quantile regressions, but also exponentially weighted moving average and volatility adjusted historical simulation methodologies. The analysis of CoVaR's sensitivity to different returns' computation methodologies and VaR estimation methods is another contribution of this research to the existing literature.

The empirical results show that, in the analyzed period, no Portuguese bank is considered systemic important or systemic vulnerable. Considering the full period, from 02/06/2003 to 30/06/2020, the Great Recession lead banks not only to their highest contribution to the Portuguese financial system's systemic risk but also to their highest susceptibility to system's impact. Excluding the Great Recession period, the highest vulnerability to the system's shocks and the highest VaR estimates for BES and BNF occur in the last phase of their life cycles. Additionally, in the context of coronavirus pandemic, BCP presents not only its highest susceptibility to the financial system's impacts but also its highest VaR.

From 02/06/2003 to 13/10/2010, BCP is the bank with the major contribution to the system's systemic risk and the most vulnerable to the financial system's shocks. Furthermore, FNB is the less susceptible bank to the financial system's shocks and BNF is the one with lower impact on the Portuguese financial system's systemic risk.

Results also reveal that VaR and CoVaR estimates present sensitivity to the banks returns computation methodology as well as to the VaR model applied.

The rest of the dissertation is organized as follows: Chapter 1 provides the literature review about systemic risk and its measures; Chapters 2, 3, 4 and 5 present a description of the necessary concepts to develop our analysis and the methodology applied; Chapter 6 describes the dataset and the software used; Chapter 7 analyses the obtained results; Chapter 8 concludes the dissertation by summarizing the main findings, analyzing the dissertation limitations and giving suggestions for future investigations.

CHAPTER 1

Literature Review

In an increasingly globalized world, financial markets are not an exception, being progressively integrated (Billio et al., 2012; Lehar, 2005). Our history has shown that, during crisis, losses of financial institutions spread across other financial institutions due to spillover effects (Adrian & Brunnermeier, 2011). These interdependencies between financial institutions impact the financial system, with foreseeable externalities to the rest of the economy (Acharya et al., 2017; Karimalis & Nomikos, 2018; López-Espinosa, Moreno, Rubia, & Valderrama, 2012).

In the last years, the interconnectedness within financial systems have received significant attention in the literature (Acemoglu, Ozdaglar, & Tahbaz-Salehi, 2015; Caballero, 2015; Giudici, Sarlin, & Spelta, 2017; Hautsch et al., 2015).

The spillover effects can arise directly as a consequence of distressed counterparties (Adrian & Brunnermeier, 2011) or as result of common exposures that financial institutions can have (Giudici et al., 2017; López-Espinosa et al., 2012), as well as indirectly due to fire sales (Gauthier, Lehar, & Souissi, 2012) and liquidity spirals (Adrian & Brunnermeier, 2011). This links lead to co-movements that play a central role in shaping systemic risk (Acemoglu et al., 2015), i.e. the risk that a circumstance that threatens the stability of a financial institution may affect others, with consequences to the financial system at large (Billio et al., 2012).

According to Caballero (2015) and Calluzzo and Dong (2015) a higher level of financial integration tends to be associated with a greater incidence of banking crisis, due to the effects of systemic risk.

Basel I and Basel II Accords introduced in financial regulation the VaR as the risk measure for each isolated financial institution (Drakos & Kouretas, 2015), leading to the micro-prudential regulation in the banking system. However, the several financial crisis experienced by the global markets demonstrated that this type of policy is not enough to forestall the propagation of financial distress (Mendonça & Silva, 2018).

Regulators are trying to implement a more macro-prudential vision of financial regulation (Lehar, 2005), thus recognizing the importance of containing systemic risk (Acharya et al., 2017). With this approach, it is possible to internalize the externalities within the financial system, reducing massively the default risk of each financial institution (Gauthier et al., 2012). Consequently, there is growing literature on alternative risk measures that embody the main determinants of systemic risk.

Billio et al. (2012) propose the measurement of systemic risk based on Granger causality between banks as well as among other financial institutions. The authors use Granger-causal network relations to understand the lagged spread of return spillovers. Furthermore, the authors resort to a Markov-switching model of asset returns to access the propagation of the increased volatility between financial institutions.

Huang et al. (2012) introduce a systemic risk measure based on the Distress Insurance Premium (DIP), defining it as the price that one financial institution needs to pay to be protected against systemic financial crisis. The risk factors considered in this methodology are the probability of default, estimated from credit default swap spreads, and the asset return correlations between financial institutions, based on the co-movements on equity's price. Considering the marginal contribution of each financial institution to DIP, it is possible to understand the most systemically important entities.

Brownlees et al. (2017) propose the SRISK measure, based on the computation of the expected capital shortfall of a financial institution conditional on a systemic event. This systemic risk measure is dependent on the size and leverage of the institution as well as on its long run marginal expected shortfall, i.e. the expected loss on the equity of the financial entity conditional on the market distress. Applying this methodology, the authors can rank financial institutions according to its contribution to the undercapitalization of the system during financial crisis.

Acharya et al. (2017) study the susceptibility of a financial institution to be undercapitalized provided that the financial system is undercapitalized. They develop an ex-ante systemic risk measure, the Systemic Expected Shortfall (SES), based on the conditional expected shortfall that enlarge the expected losses of a bank in times of crisis. With this methodology, it is possible to understand the institutions that are most exposed to financial crisis, based on its Marginal Expected Shortfall (MES) and on the financial institution's leverage.

In this dissertation we use the CoVaR risk measure, proposed by Adrian and Brunnermeier (2011). According to these authors, systemic risk is measured by one financial institution's VaR conditional on other entity experiencing financial distress. By applying this methodology, it is possible to understand not only the institutions that contribute the most for the systemic risk of the overall financial system, but also which institutions are more susceptible to the effects of a systemic crisis. Furthermore, since it is based on the most commonly adopted risk measure, its results are easily understandable for all financial agents.

CoVaR can be obtained through Bayesian quantile regressions methodology (Bernardi, Gayraud, & Petrella, 2013), multivariate GARCH estimation techniques (Girardi & Ergün, 2013), Markov-Switching models and Shapley value (Bernardi, Maruotti, & Petrella, 2014; Cao, 2014) or using copulas (Oh & Patton, 2017).

Throughout this dissertation we use the quantile regression methodology, proposed by Adrian and Brunnermeier (2011). It is an appealing approach due to the lack of assumptions needed to regress the model and to its overall simplicity that makes the data collection possible, even for markets with scarcity of public data, like the Portuguese market.

There exist several empirical studies that apply the CoVaR methodology to assess systemic risk in the different markets. Regarding the United States financial system, Girardi and Ergün (2013) conclude that in the pre-crisis period the banking sector was the one that contributes the most to the systemic risk of the overall financial system. Drakos and Kouretas (2015) conclusion for periods of distress are consistent with the previous ones, with the banking sector contributing more to systemic risk than insurance and other financial services industries. Furthermore, they found that foreign banks concur to the risk of the financial system, even though the main drivers of systemic risk are the national banks. They also detect that the main triggers of systemic risk are the returns, the volatility, the real estate returns, the liquidity spread and the credit spread changes.

Concerning the Eurozone financial markets, Bernal et al. (2014) found that, between 2004 and 2012, services, banking and insurance sectors contribute significantly to systemic risk, being the banking sector the one that concurs the most. Furthermore, there exist several studies that rank financial institutions of different countries according to its systemic importance. Anghelache and Oanea (2014) rank the main Romanian commercial banks during the recent financial crisis. Karimalis and Nomikos (2018) categorize 46 large banks from 15 European countries according to its systemic relevance.

CHAPTER 2

Value-at-Risk

The Value-at-Risk (VaR) is the portfolio loss that, over a given time horizon (h), will not be exceeded with a certain confidence level $(1-q)$ (Alexander, 2008). Statistically, the VaR at time t, significance level q and for a time horizon h, is minus the q-quantile of returns' distribution loss over h-days at time t $\left(X_{ht}^{i}\right)$ that is exceeded with 100q% probability:

$$P\left(X_{ht}^{i} < -VaR_{ht,q}^{i}\right) = q \quad (1)$$

In order to estimate VaR it is necessary to specify the values for parameters h and q and the estimation model to be performed.

Following the Basel Committee on Banking Supervision guidelines, throughout this dissertation the distress state is defined at the 1% quantile $(q = 1\%)$. Furthermore, we use 1-day VaR estimates $(h = 1)$.

Besides the choice of the VaR model itself, the explanatory variables considered in each model influence its performance and, consequently, the predicted VaR.

VaR models may be specified using any independent variable that is believed to explain VaR dynamics. The vast majority of VaR models consider return's standard deviation a key element. According to Morgan and Reuters (1996), the main reason behind this is the predictability of financial returns' volatility. Being predictable, its forecasts are a good way to estimate return distribution's future values.

It follows that the volatility forecasting methodology is directly related with the performance of the VaR model. The traditional volatility forecasting method, Simple Moving Average (SMA), gives the same weight to every observation in the sample, regardless of how recent or hold it is. This methodology is often disregarded since it is to slow to reflect changes in market conditions and it is sensitive to the sample size. Exponentially Weighted Moving Average (EWMA) and Generalized Autoregressive Conditional Heteroscedasticity (GARCH) are the most common used alternative methodologies. These two methods attribute the highest weight to the latest market conditions in the volatility estimate, in comparison to oldest observations.

Following Morgan and Reuters (1996), the chosen method for volatility estimation throughout this study is EWMA.

According to Alexander (2008), the EWMA variance $(\hat{\sigma}_t^2)$ recursive equation is the following:

$$\hat{\sigma}_t^2 = (1-\lambda)X_{t-1}^2 + \lambda\hat{\sigma}_{t-1}^2 \tag{2}$$

where λ represents de smoothing factor, that is, the parameter that determines the relative weights of each observation in the future variance. According to Morgan and Reuters (1996), the optimal smoothing factor for daily data is 0.94 $(\lambda = 0.94)$.

Apart from all these specifications, the most important decision relies on the estimation method used to compute VaR, since it strongly affects the VaR forecasts (Beder, 1995).

There are several ways to estimate VaR that can be split into three main categories based on the way returns distribution are modeled: parametric, semi-parametric and non-parametric. Within the parametric models framework, the distributional and model form are fully specified. On the order hand, semi-parametric models make some assumptions regarding the distribution of errors or the model dynamics. Non-parametric models make either minimal or no assumptions (Gerlach, Chen, & Chan, 2011).

Three different VaR models are used to test CoVaR's sensitivity to the different VaR estimation methods: exponentially weighted moving average, volatility adjusted historical simulation and quantile regressions.

2.1. RiskMetrics

Parametric VaR methodologies model returns based on the assumption that they follow a specific distribution function. The well-known RiskMetrics methodology, described in the technical document developed by Morgan and Reuters in 1996, base VaR estimations on the assumption that financial returns (X^i) follow a Normal distribution with a certain mean (μ_t) and standard deviation (σ_t):

$$X_{t+1}^i = \mu_t^i + \sigma_t^i \varepsilon_t^i \tag{3}$$

where ε_t^i is the error term, assumed to be i.i.d. (independent and identically distributed) normal with zero mean and unit variance, that is, a standard normal distribution.

The 100q% h-day RiskMetrics VaR for institution i at time t $(VaR_{ht,q}^i)$ is formulated as:

$$VaR_{ht,q}^i = \Phi^{-1}(1-q)\sigma_h^i - \mu_h^i \tag{4}$$

where Φ^{-1} represents the inverse standard normal cumulative distribution function (CDF).

Since this dissertation is focused on 1-day VaR estimates, it is reasonable to assume that the mean return is equal to zero $\left(\mu_h^i = 0\right)$ (Morgan, & Reuters, 1996). Moreover, Alexander (2008) proved that neglecting drift adjustment does not create any bias in the results when the time horizon (h) is less than one month. Therefore, the VaR formulation is simplified, depending only on the returns' volatility:

$$VaR_{ht,q}^i = \Phi^{-1}(1-q)\sigma_h^i \tag{5}$$

Since this model estimates the VaR based on EWMA volatility, for simplicity reasons, henceforth this VaR model will be designated EWMA VaR.

Despite the strong assumptions made to estimate VaR, the RiskMetrics methodology acquired great importance among financial institutions due to its simplicity and ease of computation.

2.2. Volatility Adjusted Historical Simulation

Historical Simulation is one of the most commonly used VaR models, as it does not require any distributional assumptions neither about returns' distribution nor regarding volatility dynamics (Pérignon & Smith, 2010). Nevertheless, this non-parametric methodology is very sensitive to sample size and assumes that the empirical return distribution does not change, not reflecting the current market conditions in the best possible way.

Seeking to overcome these shortcomings, Hull and White (1998) developed the semi-parametric methodology based on the volatility adjustment of returns to better reflect current market conditions, using the volatility changes over time. In this dissertation this method is designated Volatility Adjusted Historical Simulation.

EWMA volatility estimates obtained from equation 2 are used to adjust the series of returns:

$$\hat{X}_t^i = \frac{\hat{\sigma}_T^i}{\hat{\sigma}_t^i} * X_t^i \tag{6}$$

where $\hat{\sigma}_T^i$ is the current volatility estimate for institution i's returns and $\hat{\sigma}_t^i$ is the past volatility estimate for institution i's returns, computed at time t.

Historical VaR is estimated by extracting minus the q-quantile of the adjusted series of returns.

2.3. Quantile Regressions

Adrian and Brunnermeier (2011) proposed a different way to estimate VaR, using quantile regressions. VaR forecasts are based on the financial returns of institution i at time t $\left(X_t^i\right)$, that have the following linear factor structure:

$$X_t^i = \alpha^i + \gamma^i M_{t-1} + \varepsilon_t^i \tag{7}$$

where α^i is the constant, M_{t-1} is a vector of lagged state variables and ε_t^i is the error term, assumed to be i.i.d. with zero mean and unit variance.

The coefficients estimates $\hat{\alpha}_q^i$ and $\hat{\gamma}_q^i$ are determined within the quantile regression framework, through the minimization of the errors' sum for the q-quantile (Adrian & Brunnermeier, 2011):

$$\min_{\alpha_q^i, \gamma_q^i} \sum_t \begin{cases} q\left|X_t^i - \alpha_q^i - \gamma_q^i M_{t-1}\right| & if\ \left(X_t^i - \alpha_q^i - \gamma_q^i M_{t-1}\right) \geq 0 \\ (1-q)\left|X_t^i - \alpha_q^i - \gamma_q^i M_{t-1}\right| & if\ \left(X_t^i - \alpha_q^i - \gamma_q^i M_{t-1}\right) < 0 \end{cases} \tag{8}$$

The predicted VaR for institution i at time t $\left(VaR_t^i\right)$ for the q-quantile is computed as:

$$\mathrm{VaR}_t^i(q) = -\left(\hat{\alpha}_q^i + \hat{\gamma}_q^i M_{t-1}\right) \tag{9}$$

The state variables used by Adrian and Brunnermeier (2011), adapted to the Portuguese context and specified in chapter 6, are not statistically significant in institution i's returns regression. Therefore, only EWMA volatility estimates are used, as in the other two models, which makes models easier to compare.

CHAPTER 3

Conditional Value-at-Risk

VaR is the most used risk measure as it is a unique simple variable that aggregates all the risk information of an individual institution, being easily understandable by investors and regulators. However, this risk measure has several shortcomings (Drakos & Kouretas, 2015). Particularly, VaR underestimates systemic risk, since it is a risk measure for institutions seen in isolation and, consequently, does not fully reflect its relation to the aggregate systemic risk (Adrian & Brunnermeier, 2011).

Building on the VaR methodology, Adrian and Brunnermeier (2011) developed the first risk measure based on balance sheet features (Hautsch et al., 2015) combined with market returns data, the Conditional Value-at-Risk (CoVaR).

According to Adrian and Brunnermeier (2011), $CoVaR_q^{j|\mathbb{C}(X^i)}$ is the VaR of one entity j conditional on some event $\mathbb{C}(X^i)$ of other institution i, being defined as the q-quantile of the conditional probability distribution:

$$Pr\left(X^j | \ \mathbb{C}\left(X^i\right) \leq CoVaR_q^{j|\mathbb{C}(X^i)}\right) = q \tag{10}$$

In this dissertation the conditioning event is institution i being in distress, that is $\mathbb{C}(X^i)$: $X^i = VaR_q^i$. In this context, CoVaR is defined as:

$$CoVaR_q^{j|X^i=VaR_q^i} = VaR_q^j \ | \ VaR_q^i \tag{11}$$

Therefore, the CoVaR of institution j conditional on institution i $\left(CoVaR^{j|i}\right)$ is defined as the VaR of institution j conditional on the distress of institution i (Adrian & Brunnermeier, 2011).

This is a statistical measure based on tail-dependency, thus it can underestimate the impacts of spillover effects. To overcome this possible shortcoming of the model, Adrian and Brunnermeier (2011) emphasize that causal relations can only be observed within a specific model. Since, CoVaR is also sensitive to aggregate macroeconomic risk factors that are exogenous to financial institutions, the authors include a vector of state variables in the regressions. That vector must contain variables that reflect the most important changes in the macroeconomy in which financial institutions are inserted. The effect of these macroeconomic variables in the systemic risk of financial entities generally is delayed, thus these variables must be lagged in the regression. In this way, the conditional distribution function of institution j's returns depends not only on institution i's returns but also on a vector of lagged state variables.

The contribution of institution i to the systemic risk of institution j $\left(\Delta CoVaR_q^{j|i}\right)$ is given by the difference between the CoVaR of institution j conditional on institution i being in distress and the CoVaR of institution j conditional on the median state of institution i:

$$\Delta CoVaR_q^{j|i} = CoVaR_q^{j|X^i=VaR_q^i} - CoVaR_q^{j|X^i=VaR_{50}^i} \tag{12}$$

where $CoVaR_q^{j|X^i=VaR_q^i}$ is the VaR of j's asset returns when institution i's returns reflect its financial distress and $CoVaR_q^{j|X^i=VaR_{50}^i}$ represents the VaR of j when institution i's returns are in their normal state.

It follows that, institution j's returns $\left(X_t^j\right)$ are modelled as:

$$X_t^j = \alpha^{j|i} + \beta^{j|i}X_t^i + \gamma^{j|i}M_{t-1} + \varepsilon_t^{j|i} \tag{13}$$

where $\alpha^{j|i}$ is the constant, M_{t-1} is a vector of lagged state variables and $\varepsilon_t^{j|i}$ is the error term, assumed to be i.i.d. with zero mean and unit variance. Furthermore, $\beta^{j|i}$ represents the contribution of institution i's return to the system's return.

Over this dissertation, the distress of institution i is considered at the 1% quantile. Therefore, coefficients $\alpha^{j|i}$, $\beta^{j|i}$ and $\gamma^{j|i}$ are estimated, for the 1% quantile, using quantile regression estimation techniques, specifically equation 8.

The CoVaR of institution j conditional on institution i at time t $\left(CoVaR_t^{j|i}\right)$ for the 1% quantile is given by:

$$CoVaR_t^{j|i}(1\%) = \alpha^{j|i} + \beta^{j|i}\, VaR_t^i(1\%) + \gamma^{j|i}M_{t-1} \tag{14}$$

Finally, to estimate the institution i's contribution to the institution j's systemic risk we compute $\Delta CoVaR_t^{j|i}$, as the difference between the CoVaR in times of distress of institution i (1% quantile) and the CoVaR in a median state of institution i (50% quantile):

$$\Delta CoVaR_t^{j|i}(1\%) = CoVaR_t^{j|i}(1\%) - CoVaR_t^{j|i}(50\%) \tag{15}$$

Therefore, institution i's marginal contribution to the systemic risk of institution j is simply:

$$\Delta CoVaR_t^{j|i}(1\%) = \beta^{j|i}\left(VaR_t^i(1\%) - VaR_t^i(50\%)\right) \tag{16}$$

This analysis is carried out on a weekly basis. The daily values for CoVaR are estimated in-sample, using the coefficients estimates obtained in the weekly regressions. Furthermore, is used a rolling sample than contains the last 500 observations, that is approximately the last 2 years of data.

CHAPTER 4

Bank Returns

Systemic risk is a threat for the economic welfare since financial crisis can lead to an inefficient decline in the credit supply, with meaningful consequences for the real economy. Banks total assets information is the publicly available data that is most closely related to each bank credit supply. To reflect the systemic risk real impacts, VaR and CoVaR analysis should be based on growth rates of market-valued financial assets (Adrian & Brunnermeier, 2011).

Adrian and Brunnermeier (2011) recognize that there are several ways to compute the market-valued total assets. Therefore, two alternative methods, proposed by the authors, are selected to analyze the impact of the market-valued total assets' computation methodology on VaR and CoVaR outcomes.

Firstly, the market-valued total assets $\left(MVA1_t^i\right)$ are obtained from the book-valued total assets $\left(BVA_t^i\right)$ multiplied by the market-to-book equity ratio:

$$MVA1_t^i = BVA_t^i * \frac{MVE_t^i}{BVE_t^i} = BVA_t^i * \frac{P_t^i * N_t^i}{BVE_t^i} \tag{17}$$

where BVE_t^i is the book value of institution i's total assets at time t and MVE_t^i is the market value of equity of institution i at time t, computed as institution i's closing price per share at time t $\left(\mathrm{P}_t^i\right)$ multiplied by institution i's total number of shares at time t $\left(\mathrm{N}_t^i\right)$.

The growth rate of market-valued total assets of institution i at time t $\left(X_t^i\right)$ is defined as:

$$X_t^i = \frac{MVA1_t^i - MVA1_{t-1}^i}{MVA1_{t-1}^i} \tag{18}$$

Alternatively, the market value of assets $\left(MVA2_t^i\right)$ can be computed as the sum of the market value of equity $\left(MVE_t^i\right)$ with the book value of debt $\left(BVD_t^i\right)$:

$$MVA2_t^i = MVE_t^i + BVD_t^i = P_t^i * N_t^i + BVD_t^i \tag{19}$$

In this case, the growth rate of the market value of assets of institution i at time t $\left(X_t^i\right)$ is defined as:

$$X_t^i = \frac{MVA2_t^i - MVA2_{t-1}^i}{MVA2_{t-1}^i} \tag{20}$$

For simplicity reasons, henceforth the growth rates of market-valued total assets are designated MVA1 returns and the growth rates of the market value of assets are designated MVA2 returns.

Finally, the returns on the market value of equity $\left(MVE_t^i\right)$ are used to understand if the market capitalization of the banks can also reflect systemic risk real impacts:

$$X_t^i = \frac{MVE_t^i - MVE_{t-1}^i}{MVE_{t-1}^i} = \frac{P_t^i * N_t^i - P_{t-1}^i * N_{t-1}^i}{P_{t-1}^i * N_{t-1}^i} \tag{21}$$

CHAPTER 5

Significance and Dominance Tests

Within the CoVaR framework we estimate each institution's systemic risk contribution. However, we develop some additional tests to understand the real meaning of the ΔCoVaR values obtained.

As described in chapter 3, ΔCoVaR is the difference between two conditional quantile functions. Hence, it can be seen as a quantile treatment effect $\left(\varrho(q)\right)$ of two samples in the distribution loss's upper tail, where $CoVaR_t^{j|i}(q\%)$ is the treatment group and $CoVaR_t^{j|i}(50\%)$ represents the control group (Castro & Ferrari, 2014).

The literature on quantile treatment effects rely frequently on the following hypothesis tests (Koenker, 2005):

- No effect hypothesis: $H_0: \varrho(q) = 0$
- Constant effect hypothesis: $H_0: \varrho(q) = \varrho$
- Dominance hypothesis: $\begin{cases} H_0: \varrho(q) \geq 0 \\ H_a: \varrho(q) < 0 \end{cases}$

The no effect hypothesis test and the dominance hypothesis test acquire great importance within the CoVaR framework.

To determine if the ΔCoVaR values can classify institutions as being systemically important we develop a statistical significance test, based on the no effect hypothesis.

The systemically important financial institutions can be identified as those institutions for which $CoVaR_t^{j|i}(q\%)$ is significantly different from $CoVaR_t^{j|i}(50\%)$, that is, institutions for which $\Delta\mathrm{CoVaR}_\mathrm{t}^{\mathrm{j|i}}(\mathrm{q})$ is statistically different from zero (Mendonça & Silva, 2018). Therefore, to determine the systemically significant institutions we develop a hypothesis test under the following null hypothesis:

$$H_0: \Delta CoVaR_t^{j|i}(q) = 0 \tag{22}$$

Furthermore, based on the dominance hypothesis, we perform a statistical significance test to rank institutions according to their systemic importance.

To determine, if institution i is statistically more systemically important than institution z, that is, institution i's contribution to the systemic risk of institution j $\left(\Delta\mathrm{CoVaR}_\mathrm{t}^{\mathrm{j|i}}(\mathrm{q})\right)$ is greater that institution z's contribution $\left(\Delta\mathrm{CoVaR}_t^{j|z}(q)\right)$, we develop a hypothesis test under the following null hypothesis:

$$H_0\colon \Delta CoVaR_t^{j|i}(q) > \Delta CoVaR_t^{j|z}(q) \tag{23}$$

5.1. Bootstrap Kolmogorov–Smirnov test

The Kolmogorov-Smirnov (KS) test is quite appealing in a quantile regression framework, since it is a way to measure the discrepancy between distributions while being asymptotically free. That is, one can define the test statistic's distribution under the null hypothesis without specifying the underlying distribution of the data (Castro & Ferrari, 2014).

Nevertheless, the test statistic's asymptotic distribution under the null hypothesis is often unknown (Abadie, 2002).

Within the CoVaR framework, we are estimating values for ΔCoVaR. Therefore, the cumulative distribution functions (CDF) of ΔCoVaR are "estimated" as well. That is, the estimation process may introduce some nuisance in the test statistic's asymptotic distribution under the null hypothesis. Therefore, the KS test's distribution-free character can be compromised by the estimation process (Bernal et al., 2014).

Abadie (2002) proposed a bootstrap strategy to surpass this issue, since resampling with replacement throughout all the sample is a simple but efficient technique to estimate a null distribution (Romano, 1988). Throughout this dissertation, we use this bootstrap KS test to execute all the aforementioned hypothesis tests, since this and other versions of the KS test are often used for inference based on quantile processes (Castro & Ferrari, 2014).

The significance test aims to clarify if the CoVaR's CDF for the 1% quantile equals the CoVaR's CDF for the 50% quantile, meaning that financial institution i is not systemically important. The two-sample bootstrap KS statistic, proposed by Abadie (2002), is defined as:

$$T = \left(\frac{mn}{m+n}\right)^{1/2} sup_x |F_m(x) - G_n(x)| \tag{24}$$

where m and n are the size of the two compared samples and $F_m(x)$ and $G_n(x)$ represent the two CDF to be analyzed.

The dominance test is performed to understand if the CDF of $\Delta CoVaR_t^{j|i}$ is greater than the CDF of $\Delta CoVaR_t^{j|z}$, meaning that financial institution i is systemically more important than financial institution z.

The two-sample bootstrap KS statistic for the dominance test is defined as:

$$T = \left(\frac{mn}{m+n}\right)^{1/2} sup_x\big(A_m(x) - B_n(x)\big) \tag{25}$$

here m and n are the size of the two compared samples and $A_m(x)$ and $B_n(x)$ represent the ΔCoVaR's CDF for institution i and z, respectively.

The bootstrap strategy can be described in the following steps (Abadie, 2002):

- Compute the KS statistic for CoVaR or ΔCoVaR values, depending on the type of test to perform, significance or dominance respectively;
- Resample all the observations (n) with replacement and compute the KS statistic for the resampled values;
- Repeat the previous step, B times;
- Compute the p-values of the test as:

$$p - value = \frac{\sum_{b=1}^{B} 1\{\hat{T}_{n,b} > T_n\}}{B} \tag{26}$$

where $\hat{T}_{n,b}$ represents the KS statistic for the resampled values and T_n is the KS statistic for the original values. In this dissertation the bootstrap is performed 10000 times, that is $B = 10000$.

The null hypothesis of the test is rejected, with 95% confidence, if the p-value is smaller then $\alpha = 0.05$.

CHAPTER 6

Data

This dissertation is focused on Portuguese banks that were listed at the beginning of the century, namely Millennium BCP (BCP), Banco Português de Investimento (BPI), Banco Espírito Santo (BES), Banif (BNF) and Finibanco (FNB). For each institution we considered daily closing prices and quarterly balance sheet data, namely book value assets, book value of equity and total number of shares.

For this analysis, the financial system could be represented by a capitalization weighted index of all Portuguese publicly traded commercial banks. However, the Portuguese banking system changed significantly over the last years, and the number of listed banks that would be part of the index declined sharply, from December 13th, 2010 onwards, reaching just one bank at the end of the period. Therefore, and following Bernal et al. (2014), Castro and Ferrari (2014) and Girardi and Ergün (2013) methodology, the financial system is represented by the Portuguese stock market index, PSI 20.

Following Adrian and Brunnermeier (2011), a set of state variables that usually capture the time-varying dynamics of asset returns are used. To capture the Portuguese economy features in the European context, the following variables are considered:

- Change in the three-month German treasury bill rate;
- Difference between the ten-year German bond rate and the ten-year Portuguese bond rate;
- Liquidity spread measured as the difference between the three-month EURIBOR rate and the three-month German treasury bill rate;
- STOXX Europe 600 index market return;
- Real estate sector market return;
- PSI20 volatility estimated based on the EWMA model.

The study was performed from June 2nd, 2003 until June 30th, 2020. However, it was necessary to collect data prior to the analyzed period to properly apply the EWMA model. Therefore, the total sample comprises daily data for the above-mentioned variables, pulled from the Bloomberg database, for the period ranging from January 2nd, 2000 to June 30th, 2020.

The meaningful changes in the Portuguese financial system during this period determined the development of the study in different periods for each bank. Every analysis starts at June

2nd, 2003 but the studied periods' end was determined by each institution's last trading day. The below table depicts the analyzed period per institution:

Table 6. 1. Analyzed period for each bank.

Institution	**Analyzed period**
BCP	June 2nd, 2003 – June 30th, 2020
BPI	June 2nd, 2003 – December 14th, 2018
BES	June 2nd, 2003 – August 1st, 2014
BNF	June 2nd, 2003 – December 17th, 2012
FNB	June 2nd, 2003 – December 13th, 2010

CHAPTER 7

Results

In this investigation we analyze each bank's contribution to the financial system's systemic risk and the contribution of the financial system to each bank's systemic risk, using the CoVaR methodology proposed by Adrian and Brunnermeier (2011).

This dissertation has its entire practical application carried out using Matlab, which includes VaR and CoVaR estimation through quantile regressions as well as the bootstrap Kolmogorov-Smirnov test application.

The comparative analysis between banks can only ben made for the period that comprises all the studied banks, from 02/06/2003 to 13/12/2010, henceforward designated as first period. However, each's banks evolutive analysis is carried out for the full period studied.

7.1. Bank Returns

The alternative methodologies to compute banks returns presented in chapter 4 generate different outcomes, which descriptive statistics are presented in table 7.1.1.

Table 7.1. 1. Bank returns descriptive statistics.

Bank	Return	Mean	Median	Max.	Min.	St. dev.	Skew.	Kurt.
BCP	MVA1	0.007%	-0.034%	0.268	-0.151	0.028	0.569	6.971
	MVA2	0.005%	0.002%	0.012	-0.011	0.001	0.490	7.273
	MVE	0.014%	0.000%	0.281	-0.152	0.028	0.596	7.416
BPI	MVA1	0.013%	-0.047%	0.268	-0.130	0.023	1.375	15.347
	MVA2	0.003%	-0.002%	0.029	-0.008	0.001	3.295	69.922
	MVE	0.029%	0.000%	0.270	-0.131	0.023	1.336	15.532
BES	MVA1	-0.017%	0.001%	0.197	-0.421	0.027	-2.122	44.300
	MVA2	0.021%	0.027%	0.007	-0.011	0.001	-0.278	5.449
	MVE	-0.022%	0.000%	0.197	-0.421	0.027	-2.139	43.942
BNF	MVA1	0.012%	0.000%	0.288	-0.141	0.026	1.208	14.152
	MVA2	0.040%	0.031%	0.017	-0.015	0.002	0.582	18.477
	MVE	0.001%	0.000%	0.288	-0.143	0.026	1.142	14.039
FNB	MVA1	0.084%	0.005%	0.143	-0.094	0.018	1.520	10.220
	MVA2	0.040%	0.032%	0.012	-0.010	0.002	0.815	7.883
	MVE	0.089%	0.000%	0.142	-0.095	0.018	1.493	10.080

The differences between the banks returns computation methodologies are quite visible. On average, BCP, BPI and FNB present higher returns when is used MVE computation method.

For BES and BNF, on average, the highest returns' estimates are obtained using MVA2 computation methodology. Furthermore, the standard deviation of banks returns based on MVA1 or MVE computation methods are equal, while MVA2 returns present a significant lowest standard deviation.

7.2. Value-at-Risk

Based on the obtained returns, the $VaR_{q,t}$ for each bank is estimated according to the 3 chosen models, described in chapter 2. The forecasted VaR's detailed descriptive statistics are presented in appendix A.

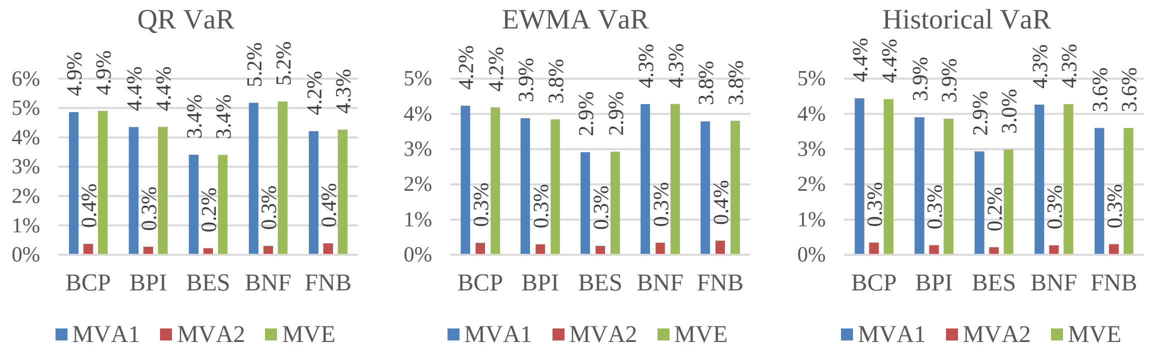

Figure 7.2. 1. Average VaR (1%) estimates for the period from 02/06/2003 to 13/12/2010.

For the first period, the VaR based on MVA2 returns is smaller and presents a smaller standard deviation than the VaR based on MVA1 returns or MVE returns, regardless of the methodology used to compute VaR. On the other hand, the VaR obtained through quantile regressions is generally higher than the VaR computed using EWMA or volatility adjusted historical simulation methodologies.

The average VaR for BNF is the highest, when based on MVA1 returns or MVE returns and for QR or EWMA VaR. When the VaR is based on volatility adjusted historical simulation, the highest VaR is obtained for BCP. The average VaR for BES is the lowest, when based on MVA2 returns or MVE returns, regardless the VaR methodology in place.

Following Adrian and Brunnermeier (2011), we use the QR VaR to analyze each bank's VaR evolution in the full studied period.

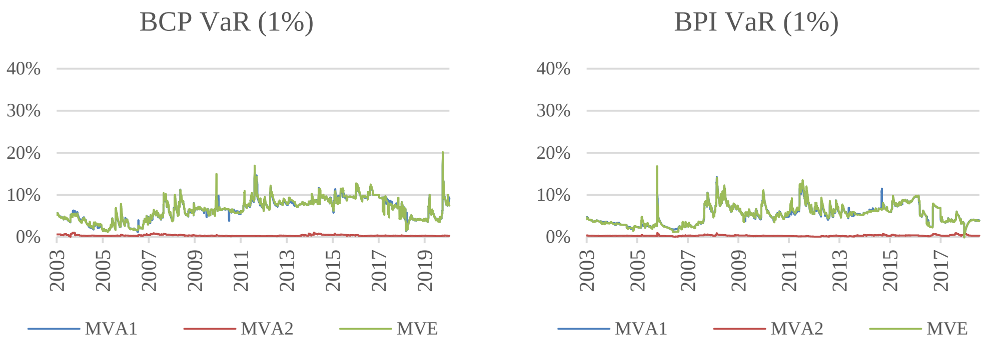

Figure 7.2. 2. BCP and BPI QR VaR (1%) estimates.

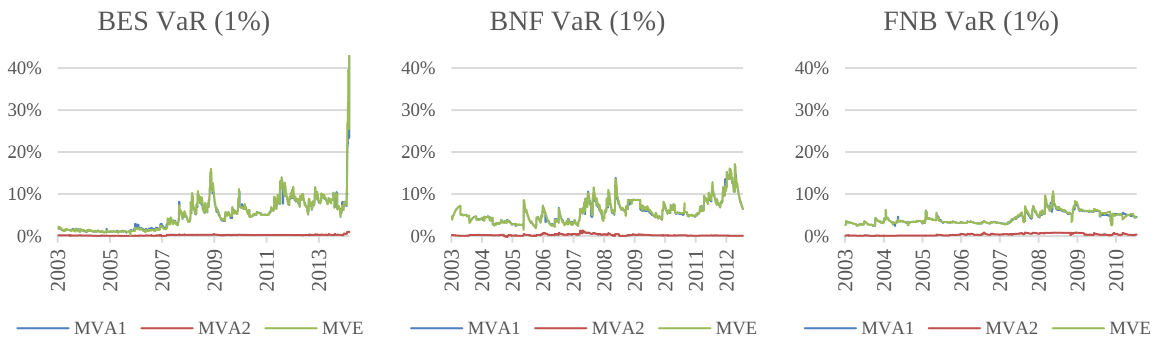

Figure 7.2. 3. BES, BNF and FNB QR VaR (1%) estimates.

The higher VaR estimates for BES and BNF are seen before each bank get out of the market. Furthermore, coronavirus pandemic led BCP, the only Portuguese listed bank at that time, to register its highest VaR estimate.

7.3. Conditional Value-at-Risk

The VaR estimates are firstly used to obtain each bank's contribution to the systemic risk of the financial system. Based on equation 16, ΔCoVaR is defined as:

$$\Delta CoVaR_t^{system|i}(1\%) = \beta^{system|i}\left(VaR_t^i(1\%) - VaR_t^i(50\%)\right) \tag{27}$$

Detailed descriptive statistics for $\Delta CoVaR^{system|i}$ are presented in appendix B.

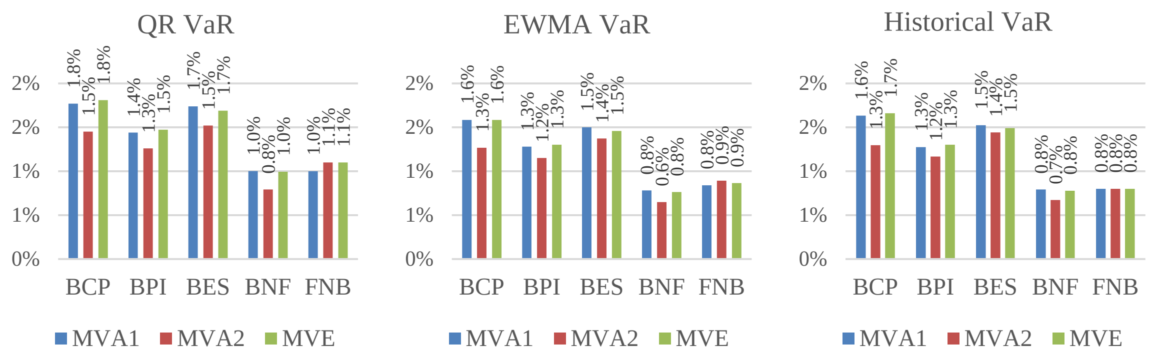

Figure 7.3. 1. Average $\Delta CoVaR^{system|i}$ estimates for the period from 02/06/2003 to 13/12/2010.

The differences between ΔCoVaR computed using alternative methodologies to obtain banks returns and different VaR models are negligible. However, it can be noticed a slightly smaller ΔCoVaR, for all banks except FNB, when computations are based on MVA2 returns.

Regardless of the methodology used to obtain banks returns and the model used to estimate the VaR, on average, ΔCoVaR for BCP is the highest (except for MVA2 returns) and ΔCoVaR for BNF is the lowest. Therefore, BCP is the bank that contributes most to the Portuguese financial system's systemic risk, while BNF is the bank with lowest impact in the system.

Following Adrian and Brunnermeier (2011), we analyze each bank's $\Delta CoVaR^{system|i}$ evolution, based on QR VaR, in the full studied period.

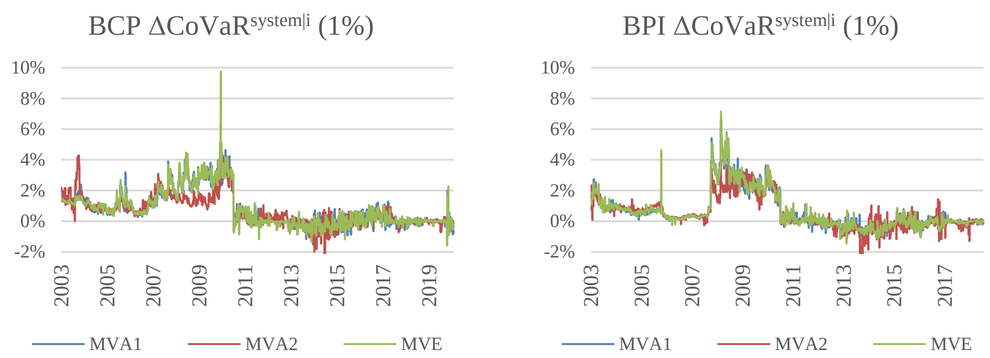

Figure 7.3. 2. BCP and BPI $\Delta CoVaR^{system|i}$ (1%) estimates, based on QR VaR.

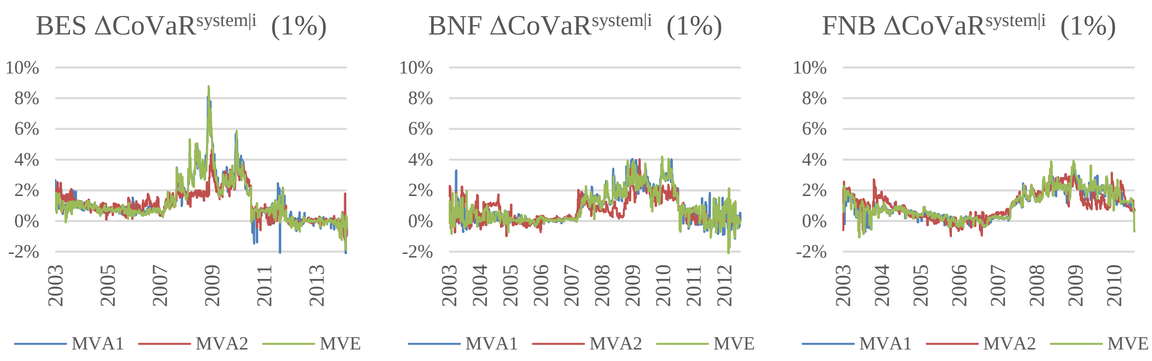

Figure 7.3. 3. BES, BNF and FNB ΔCoVaR$^{system|i}$ (1%) estimates, based on QR VaR.

For BPI, BES and FNB, the ΔCoVaR$^{system|i}$ forecasts reach the highest values between 2008 and 2009, while BCP's and BNF's highest ΔCoVaR$^{system|I}$ highest estimates are presented between 2009 and 2010. Therefore, the highest contribution of the Portuguese banks to the national financial system's systemic risk is observed in the context of the Great Recession.

Finally, the contribution of the financial system to each bank's systemic risk, based on equation 16, is computed as:

$$\Delta CoVaR_t^{i|system}(1\%) = \beta^{i|system}\left(VaR_t^{system}(1\%) - VaR_t^{system}(50\%)\right) \qquad (28)$$

Detailed descriptive statistics for ΔCoVaR$^{i|system}$ are presented in appendix B.

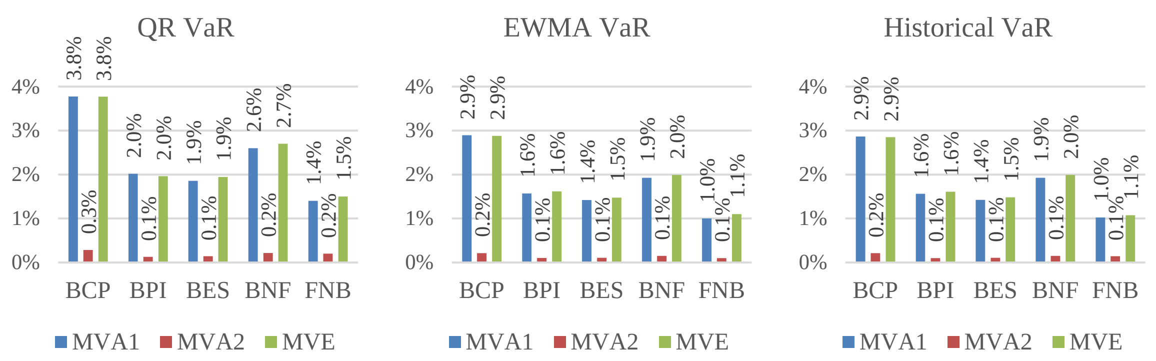

Figure 7.3. 4. Average ΔCoVaR$^{i|system}$ estimates for the period from 02/06/2003 to 13/12/2010.

In this case, the ΔCoVaR based on MVA2 returns is smaller and presents a smaller standard deviation than the ΔCoVaR based on MVA1 returns or MVE returns, regardless the methodology used to compute VaR.

Regardless of the methodology used to obtain banks returns and the model used to estimate the VaR, the average ΔCoVaR for BCP is the highest and the average ΔCoVaR for FNB is the lowest (except for MVA2 returns). Hence, BCP is the most susceptible bank to Portuguese financial system's shocks, while FNB is the bank less impacted by the system.

Following Adrian and Brunnermeier (2011), we analyze each bank's $\Delta CoVaR^{i|system}$ evolution, based on QR VaR, in the full studied period.

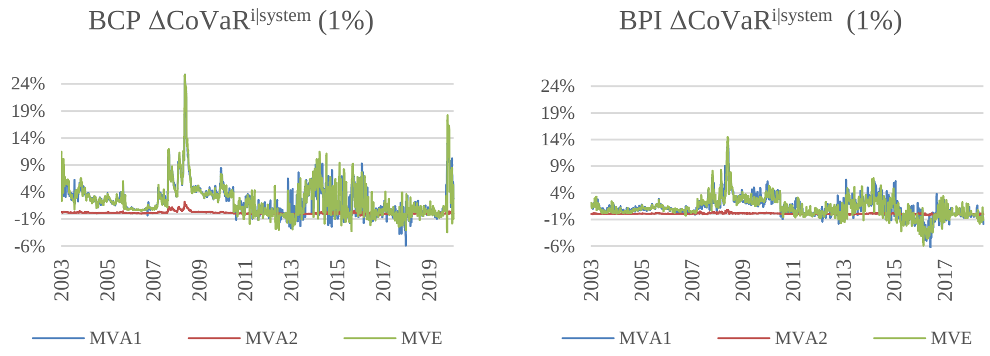

Figure 7.3. 5. BCP and BPI $\Delta CoVaR^{i|system}$ (1%) estimates, based on QR VaR.

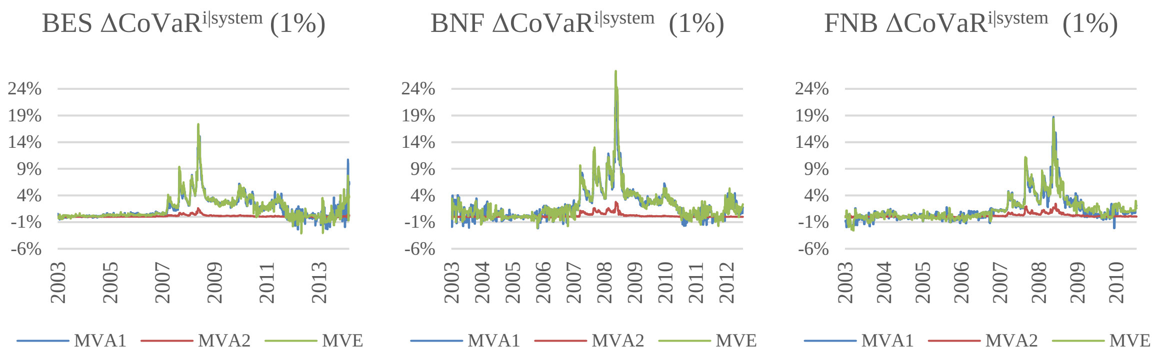

Figure 7.3. 6. BES, BNF and FNB $\Delta CoVaR^{i|system}$ (1%) estimates, based on QR VaR.

Similarly to what is seen for the $\Delta CoVaR^{system|i}$ forecasts, the highest $\Delta CoVaR^{i|system}$ estimates are observed between 2008 and 2010. That is, in the context of the Great Recession Portuguese banks were more susceptible to financial system's shocks.

Apart from this period, the higher $\Delta CoVaR^{i|system}$ estimates for BES and BNF are seen before each bank get out of the market. Therefore, these banks are more susceptible to system's shocks in the last phase of their life cycle. Furthermore, BCP presents its highest $\Delta CoVaR^{i|system}$, that is the highest fragility to the Portuguese financial system's impacts, in the begging of 2020 with the coronavirus pandemic.

7.4. Significance and Dominance Tests

The ΔCoVaR values obtained can be better understood through statistical tests. Therefore, to determine the statistical significance of ΔCoVaR values some hypothesis tests are developed. Specifically, no effect hypothesis and dominance hypothesis type of tests identify the systemically important financial institutions and the systemic vulnerable financial institutions and rank them according to their systemic importance and vulnerability.

Within the ΔCoVaR framework, the no effect hypothesis tests if $\Delta \mathrm{CoVaR}_t^{j|i}(q)$ is statistically different from zero. The p-values for this test are presented in appendix C. Since all the p-values are greater than 0.05, with 95% confidence, the CoVaR's CDF for the 1% quantile equals the CoVaR's CDF for the 50% quantile and the hypothesis of ΔCoVaR = 0 cannot be rejected. That is, regardless the methodology used to compute banks returns and the model used to estimate VaR, no Portuguese bank is considered systemically important or systemic vulnerable.

Using the dominance hypothesis test Portuguese banks are ranked according to their systemic importance. This type of test is done on a pairwise base, and determines if $\Delta \mathrm{CoVaR}_t^{\mathrm{system}|i}(q)$ is statistically greater than $\Delta \mathrm{CoVaR}_t^{\mathrm{system}|j}(q)$, meaning that bank i is systemically more relevant than bank j. The p-values for this test are presented in appendix D. Since the alternative models applied lead to different results, banks are ranked according to the most frequent test decision for each year:

Table 7.4. 1. Ranking of Portuguese banks according to their systemic importance from 2003 to 2010.

Year		**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**
Systemic Importance	↑	BCP	BNF	BNF	BNF	BPI	BCP	BCP	BCP
		BES	BPI	FNB	FNB	BNF	BPI	BPI	BPI
		BNF	FNB	BPI	BCP	FNB	BNF	BNF	BES
		FNB	BCP	BCP	BPI	BCP	FNB	FNB	BNF
		BPI	BES	BES	BES	BES	BES	BES	FNB

Table 7.4. 2. Ranking of Portuguese banks according to their systemic importance from 2011 to 2018.

Year		**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Systemic Importance	↑	BCP	BCP	BCP	BCP	BCP	BCP	BCP	BCP
		BPI	BPI	BPI	BPI	BPI	BPI	BPI	BPI
		BES	BES	BES	BES				
		BNF	BNF						

After the great depression, BCP is the most systemic important bank and BES populates the last spots of the ranking most of the years.

Furthermore, applying the dominance hypothesis test banks are ranked according to their vulnerability to shocks in the financial system. This type of test if done on a pairwise base, and determines if $\Delta \mathrm{CoVaR}_t^{i|system}(q)$ is statistically greater than $\Delta \mathrm{CoVaR}_t^{j|system}(q)$, meaning that bank i is systemically more susceptible to financial system's shocks than bank j. The p-values for this test are presented in appendix D. Considering that the alternative models applied lead to different results, banks are ranked according to the most frequent test decision for each year:

Table 7.4. 3. Ranking of Portuguese banks according to their systemic vulnerability from 2003 to 2010.

Year		**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**
Systemic Vulnerability	↑	BES	BES	BES	BES	BCP	BPI	BPI	BNF
		FNB	BPI	FNB	FNB	BPI	BCP	BES	BPI
		BPI	FNB	BNF	BCP	BES	BES	BNF	BES
		BNF	BNF	BPI	BPI	BNF	FNB	FNB	BCP
		BCP	BCP	BCP	BNF	FNB	BNF	BCP	FNB

Table 7.4. 4. Ranking of Portuguese banks according to their systemic vulnerability from 2011 to 2018.

Year		**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**
Systemic Vulnerability	↑	BCP	BCP	BCP	BCP	BCP	BPI	BCP	BCP
		BPI	BPI	BPI	BPI	BPI	BCP	BPI	BPI
		BNF	BES	BES	BES				
		BES	BNF						

Before the great depression, despite being one of the less systemic important banks, BES is the most vulnerable bank to shocks in the Portuguese financial system. After 2011, BCP is not only the most systemic important bank, but also one of the most impacted banks by the financial system.

CHAPTER 8

Conclusion

The Great Recession and its consequences on the real economy raised investigators' and regulators' attention to systemic risk. Investigations have been questioning VaR's capability to capture financial institutions' systemic risk contributions (Girardi & Ergün, 2013) and alternative risk measures have been developed (Giglio, 2014).

In this dissertation we apply the CoVaR, an alternative risk measured proposed by Adrian and Brunnermeier (2011). This methodology is generally based on the concept of market-valued total assets proposed by the same authors and uses VaR obtained through quantile regressions. However, in this investigation alternative methods to compute banks returns and estimate the VaR are used to study ΔCoVaR's sensitivity to different returns' and VaR's approaches. Firstly, all the VaR models applied present big differences between VaR estimates based on MVA2 returns and VaR estimates based on MVA1 or MVE returns. Despite being more discreet, ΔCoVaR estimates present sensitivity to the returns' computation methodology, specifically for MVA2 returns when compared to MVA1 or MVE returns. Furthermore, QR VaR and ΔCoVaR are slightly higher than the obtained values using EWMA or Volatility Adjusted Historical Simulation.

This methodology is used to understand how the Portuguese banks impact the Portuguese financial system and how they are affected by the financial system shocks. Considering the full period, from 02/06/2003 to 30/06/2020, ΔCoVaR results show that all banks present theirs highest contribution to the Portuguese financial system's systemic risk and theirs highest vulnerability to the financial system's impact in the context of the Great Recession. Excluding the Great Recession period, BES and BNF present the highest susceptibility to the financial system's impact in the last phase of their life cycles. Furthermore, BCP reaches its highest vulnerability to system's shocks in the context of coronavirus pandemic.

From 02/06/2003 to 13/10/2010, BCP is not only the bank than contributes most to the Portuguese financial system's systemic risk but also the most vulnerable bank to system's impacts. Additionally, BNF is the bank with lowest impact on the system's systemic risk and FNB is the one less susceptible to system's shocks.

Unlike what is found in the literature on systemic risk concerning the Eurozone financial markets, based on the bootstrap Kolmogorov-Smirnov test, none of the analyzed banks can be considered statistically systemically important or vulnerable. However, this test is also used to rank banks according to their systemic importance and their systemic vulnerability. Before 2007, despite being one of the less systemic important banks, BES is the most impacted bank by the financial system. After 2011, BCP is the most systemic important bank as well as one of the most susceptible banks to the financial system's impacts.

This study adds to the literature not only by analyzing VaR and ΔCovaR sensitivity to different returns' computations and VaR's models, but also by ranking the Portuguese listed banks according to their systemic importance and vulnerability. However, it fails to deliver a complete study of the Portuguese banking system since CoVaR model can only be applied to listed banks and not all Portuguese banks are listed (e.g. Caixa Geral de Depósitos).

In the future it would be interesting to extend this kind of approach to other European banks, to understand if the Portuguese financial system is affected by foreign banks, despite not being impacted by national banks.

Bibliography

Abadie, A. (2002). Bootstrap Tests for Distributional Treatment Effects in Instrumental Variable Models. *Journal of the American Statistical Association*, *97*, 284–292.

Acemoglu, D., Ozdaglar, A. E., & Tahbaz-Salehi, A. (2015). Systemic Risk and Stability in Financial Networks. *American Economic Review*, *105*(2), 564–608.

Acharya, V., Engle, R., & Richardson, M. (2012). Capital shortfall: A new approach to ranking and regulating systemic risks. *American Economic Review*, *102*(3), 59–64.

Acharya, V. V., Pedersen, L. H., Philippon, T., & Richardson, M. (2017). Measuring Systemic Risk. *The Review of Financial Studies*, *30*(1), 2–47.

Adrian, T., & Brunnermeier, M. K. (2011). *Covar* (No. 17454). Retrieved from http://www.nber.org/papers/w17454

Alexander, C. (2008). *Market Risk Analysis IV: Value-at-Risk Models*. John Wiley & Sons.

Anghelache, G., & Oanea, D. (2014). Main Romanian Commercial Banks Systemic Risk during Financial Crisis: a CoVar Approach. *The Review of Finance and Banking*, *6*(2), 69–80.

Beder, T. S. (1995). VAR: Seductive but Dangerous. *Financial Analysts Journal*, *51*(5), 12–24.

Bernal, O., Gnabo, J.-Y., & Guilmin, G. (2014). Assessing the contribution of banks, insurance and other financial services to systemic risk. *Journal of Banking & Finance*, *47*, 270–287.

Bernardi, M., Gayraud, G., & Petrella, L. (2013). *Bayesian inference for CoVaR*. Retrieved from http://arxiv.org/abs/1306.2834

Bernardi, M., Maruotti, A., & Petrella, L. (2014). *Multivariate Markov-Switching models and tail risk interdependence*. Retrieved from http://arxiv.org/abs/1312.6407

Billio, M., Getmansky, M., Lo, A. W., & Pelizzon, L. (2012). Econometric measures of connectedness and systemic risk in the finance and insurance sectors. *Journal of Financial Economics*, *104*(3), 535–559.

Brownlees, C., & Engle, R. F. (2017). SRISK: A Conditional Capital Shortfall Measure of Systemic Risk. *The Review of Financial Studies*, *30*(1), 48–79.

Caballero, J. (2015). Banking crises and financial integration: Insights from networks science. *Journal of International Financial Markets, Institutions and Money*, *34*, 127–146.

Calluzzo, P., & Dong, G. N. (2015). Has the financial system become safer after the crisis? The changing nature of financial institution risk. *Journal of Banking & Finance*, *53*, 233–248.

Cao, Z. (2014). *Multi-CoVaR and Shapley value : A Systemic Risk Measure*.

Castro, C., & Ferrari, S. (2014). Measuring and testing for the systemically important financial institutions. *Journal of Empirical Finance*, *25*, 1–14.

Cipra, T., & Hendrych, R. (2017). Systemic risk in financial risk regulation. *Finance a Uver - Czech Journal of Economics and Finance*, *67*(1), 15–38.

Drakos, A. A., & Kouretas, G. P. (2015). Bank ownership, financial segments and the measurement of systemic risk: An application of CoVaR. *International Review of Economics & Finance*, *40*, 127–140.

Gauthier, C., Lehar, A., & Souissi, M. (2012). Macroprudential capital requirements and systemic risk. *Journal of Financial Intermediation*, *21*(4), 594–618.

Gerlach, R. H., Chen, C. W. S., & Chan, N. Y. C. (2011). Bayesian Time-Varying Quantile Forecasting for Value-at-Risk in Financial Markets. *Journal of Business & Economic Statistics*, *29*(4), 481–492.

Giglio, S. (2014). *Credit Default Swap Spreads and Systemic Financial Risk*. Retrieved from https://www.esrb.europa.eu/pub/pdf/other/cds_spreads_2014.pdf

Girardi, G., & Ergün, A. T. (2013). Systemic risk measurement: Multivariate GARCH estimation of CoVaR. *Journal of Banking & Finance*, *37*(8), 3169–3180.

Giudici, P., Sarlin, P., & Spelta, A. (2017). The interconnected nature of financial systems: Direct and common exposures. *Journal of Banking & Finance*, 105149.

Hautsch, N., Schaumburg, J., & Schienle, M. (2015). Financial Network Systemic Risk Contributions. *Review of Finance*, *19*(2), 685–738.

Huang, X., Zhou, H., & Zhu, H. (2012). Systemic Risk Contributions. *Journal of Financial Services Research*, *42*, 55–83.

Hull, J., & White, A. (1998). Incorporating volatility updating into the historical simulation method for Value-at-Risk. *Journal of Risk*, *1*, 5–19.

Karimalis, E. N., & Nomikos, N. K. (2018). Measuring systemic risk in the European banking sector: a copula CoVaR approach. *The European Journal of Finance*, *24*(11), 944–975.

Koenker, R. (2005). *Quantile Regression*. Cambridge University Press.

Lehar, A. (2005). Measuring systemic risk: A risk management approach. *Journal of Banking & Finance*, *29*(10), 2577–2603.

López-Espinosa, G., Moreno, A., Rubia, A., & Valderrama, L. (2012). Short-term wholesale funding and systemic risk: A global CoVaR approach. *Journal of Banking & Finance*, *36*(12), 3150–3162.

Mendonça, H. F., & Silva, R. B. (2018). Effect of banking and macroeconomic variables on systemic risk: An application of ΔCOVAR for an emerging economy. *The North American Journal of Economics and Finance*, *43*, 141–157.

Morgan Guaranty Trust Company, & Reuters Ltd. (1996). *RiskMetrics—Technical Document* (4th ed.). New York.

Oh, D. H., & Patton, A. J. (2017). Time-Varying Systemic Risk: Evidence From a Dynamic Copula Model of CDS Spreads. *Journal of Business and Economic Statistics*, *36*(2), 181–195.

Pérignon, C., & Smith, D. R. (2010). The level and quality of Value-at-Risk disclosure by commercial banks. *Journal of Banking & Finance*, *34*(2), 362–377.

Romano, J. P. (1988). A Bootstrap Revival of Some Nonparametric Distance Tests. *Journal of the American Statistical Association*, *83*(403), 698–708.

Wong, A. Y. T., & Fong, T. P. W. (2011). Analysing interconnectivity among economies. *Emerging Markets Review*, *12*(4), 432–442.

Appendices

Appendix A – Value-at-Risk Estimates

Table A. 1. QR VaR descriptive statistics for the period from 02/06/2003 to 13/12/2010.

Bank	Return	Mean	Median	Max.	Min.	St. dev.	Skew.	Kurt.
BCP	MVA1	0.049	0.049	0.112	0.011	0.020	0.146	-0.559
	MVA2	0.004	0.003	0.010	0.000	0.002	1.084	0.661
	MVE	0.049	0.050	0.150	0.011	0.021	0.295	-0.043
BPI	MVA1	0.044	0.036	0.143	0.017	0.022	1.249	1.245
	MVA2	0.003	0.003	0.009	0.001	0.001	1.880	7.754
	MVE	0.044	0.036	0.168	0.011	0.023	1.256	1.679
BES	MVA1	0.034	0.023	0.150	0.004	0.026	1.262	1.252
	MVA2	0.002	0.002	0.005	0.001	0.001	0.316	-1.097
	MVE	0.034	0.019	0.160	0.002	0.027	1.333	1.624
BNF	MVA1	0.052	0.048	0.139	0.019	0.019	0.868	0.797
	MVA2	0.003	0.002	0.014	-0.003	0.002	1.727	4.645
	MVE	0.052	0.049	0.136	0.016	0.020	0.805	0.462
FNB	MVA1	0.042	0.036	0.094	0.018	0.014	0.771	-0.007
	MVA2	0.004	0.003	0.009	0.000	0.002	0.609	-0.923
	MVE	0.043	0.036	0.107	0.019	0.015	0.939	0.532

Table A. 2. EWMA VaR descriptive statistics for the period from 02/06/2003 to 13/12/2010.

Bank	Return	Mean	Median	Max.	Min.	St. dev.	Skew.	Kurt.
BCP	MVA1	0.042	0.041	0.119	0.013	0.019	0.592	-0.032
	MVA2	0.003	0.003	0.011	0.001	0.002	1.314	1.077
	MVE	0.042	0.040	0.119	0.013	0.019	0.650	0.027
BPI	MVA1	0.039	0.033	0.152	0.006	0.022	1.391	2.278
	MVA2	0.003	0.003	0.017	0.001	0.002	3.852	24.275
	MVE	0.038	0.033	0.152	0.007	0.022	1.365	2.143
BES	MVA1	0.029	0.020	0.138	0.005	0.024	1.509	2.209
	MVA2	0.003	0.002	0.007	0.001	0.001	0.779	0.252
	MVE	0.029	0.020	0.141	0.004	0.024	1.550	2.443
BNF	MVA1	0.043	0.041	0.118	0.005	0.019	0.625	0.436
	MVA2	0.003	0.003	0.011	0.001	0.002	1.252	1.549
	MVE	0.043	0.041	0.117	0.005	0.019	0.613	0.387
FNB	MVA1	0.038	0.036	0.139	0.012	0.016	1.476	4.442
	MVA2	0.004	0.004	0.011	0.001	0.002	0.733	0.106
	MVE	0.038	0.036	0.138	0.012	0.016	1.438	4.134

Table A. 3. Historical VaR descriptive statistics for the period from 02/06/2003 to 13/12/2010.

Bank	Return	Mean	Median	Max.	Min.	St. dev.	Skew.	Kurt.
BCP	MVA1	0.044	0.043	0.124	0.013	0.020	0.602	0.002
	MVA2	0.003	0.003	0.011	0.001	0.002	1.234	0.759
	MVE	0.044	0.042	0.125	0.013	0.020	0.660	0.071
BPI	MVA1	0.039	0.033	0.155	0.007	0.022	1.413	2.403
	MVA2	0.003	0.002	0.016	0.001	0.001	3.876	24.623
	MVE	0.039	0.033	0.154	0.006	0.022	1.389	2.310
BES	MVA1	0.029	0.019	0.140	0.005	0.024	1.505	2.170
	MVA2	0.002	0.002	0.006	0.001	0.001	0.739	0.090
	MVE	0.030	0.020	0.145	0.004	0.025	1.549	2.424
BNF	MVA1	0.043	0.040	0.112	0.005	0.019	0.606	0.306
	MVA2	0.003	0.002	0.009	0.001	0.001	1.300	1.921
	MVE	0.043	0.040	0.111	0.005	0.019	0.583	0.190
FNB	MVA1	0.036	0.033	0.141	0.010	0.016	1.578	5.022
	MVA2	0.003	0.003	0.010	0.001	0.002	0.767	0.385
	MVE	0.036	0.033	0.139	0.010	0.016	1.524	4.624

Appendix B – Conditional Value-at-Risk Estimates

Table B. 1. $\Delta CoVaR^{system|i}$ *descriptive statistics based on QR VaR for the period from 02/06/2003 to 13/12/2010.*

Bank	Return	Mean	Median	Max.	Min.	St. dev.	Skew.	Kurt.
BCP	MVA1	0.018	0.015	0.046	-0.006	0.010	0.479	-0.826
	MVA2	0.015	0.013	0.043	0.000	0.008	1.260	1.520
	MVE	0.018	0.015	0.098	-0.007	0.011	1.001	2.561
BPI	MVA1	0.014	0.008	0.066	-0.002	0.013	1.124	0.733
	MVA2	0.013	0.009	0.040	-0.003	0.009	0.600	-0.814
	MVE	0.015	0.009	0.072	-0.003	0.013	1.120	0.829
BES	MVA1	0.017	0.011	0.083	0.003	0.014	1.542	2.542
	MVA2	0.015	0.013	0.046	0.001	0.008	0.965	0.512
	MVE	0.017	0.010	0.088	-0.001	0.014	1.611	2.957
BNF	MVA1	0.010	0.005	0.040	-0.007	0.011	0.795	-0.559
	MVA2	0.008	0.007	0.040	-0.010	0.009	0.648	-0.205
	MVE	0.010	0.006	0.042	-0.009	0.011	0.796	-0.398
FNB	MVA1	0.010	0.009	0.035	-0.007	0.009	0.391	-0.738
	MVA2	0.011	0.010	0.031	-0.010	0.009	0.187	-0.774
	MVE	0.011	0.009	0.039	-0.011	0.009	0.501	-0.391

Table B. 2. $\Delta CoVaR^{system|i}$ descriptive statistics based on EWMA VaR for the period from 02/06/2003 to 13/12/2010.

Bank	Return	Mean	Median	Max.	Min.	St. dev.	Skew.	Kurt.
BCP	MVA1	0.016	0.014	0.061	-0.005	0.010	0.946	0.925
	MVA2	0.013	0.011	0.038	0.002	0.007	1.190	0.931
	MVE	0.016	0.012	0.078	-0.006	0.010	1.299	2.892
BPI	MVA1	0.013	0.007	0.060	-0.002	0.012	1.180	0.684
	MVA2	0.012	0.010	0.045	-0.003	0.008	0.696	-0.316
	MVE	0.013	0.008	0.059	-0.002	0.012	1.224	0.800
BES	MVA1	0.015	0.009	0.080	0.002	0.013	1.787	3.712
	MVA2	0.014	0.012	0.049	0.001	0.007	1.151	1.535
	MVE	0.015	0.009	0.077	-0.001	0.012	1.804	3.620
BNF	MVA1	0.008	0.003	0.039	-0.006	0.009	0.994	0.180
	MVA2	0.006	0.005	0.035	-0.011	0.007	0.713	0.351
	MVE	0.008	0.004	0.041	-0.007	0.009	1.072	0.506
FNB	MVA1	0.008	0.007	0.038	-0.009	0.008	0.721	0.651
	MVA2	0.009	0.009	0.037	-0.016	0.008	0.197	0.419
	MVE	0.009	0.007	0.038	-0.010	0.008	0.733	0.783

Table B. 3. $\Delta CoVaR^{system|i}$ descriptive statistics based on Historical VaR for the period from 02/06/2003 to 13/12/2010.

Bank	Return	Mean	Median	Max.	Min.	St. dev.	Skew.	Kurt.
BCP	MVA1	0.016	0.014	0.063	-0.005	0.010	0.961	1.054
	MVA2	0.013	0.011	0.038	0.002	0.007	1.194	0.895
	MVE	0.017	0.013	0.082	-0.006	0.011	1.334	3.153
BPI	MVA1	0.013	0.008	0.060	-0.002	0.012	1.220	0.838
	MVA2	0.012	0.010	0.047	-0.003	0.008	0.714	-0.246
	MVE	0.013	0.008	0.060	-0.002	0.012	1.254	0.939
BES	MVA1	0.015	0.009	0.081	0.002	0.013	1.777	3.648
	MVA2	0.014	0.012	0.053	0.001	0.008	1.176	1.586
	MVE	0.015	0.009	0.079	-0.001	0.013	1.798	3.582
BNF	MVA1	0.008	0.003	0.040	-0.006	0.009	1.035	0.284
	MVA2	0.007	0.006	0.036	-0.011	0.008	0.692	0.330
	MVE	0.008	0.004	0.043	-0.007	0.009	1.100	0.592
FNB	MVA1	0.008	0.006	0.039	-0.008	0.008	0.849	0.790
	MVA2	0.008	0.008	0.038	-0.014	0.007	0.252	0.317
	MVE	0.008	0.007	0.039	-0.009	0.008	0.838	0.870

Table B. 4. $\Delta CoVaR^{i|system}$ descriptive statistics based on QR VaR for the period from 02/06/2003 to 13/12/2010.

Bank	Return	Mean	Median	Max.	Min.	St. dev.	Skew.	Kurt.
BCP	MVA1	0.038	0.033	0.257	-0.003	0.031	3.173	15.355
	MVA2	0.003	0.002	0.022	0.000	0.003	2.730	8.738
	MVE	0.038	0.032	0.257	0.003	0.032	3.136	14.482
BPI	MVA1	0.020	0.014	0.132	-0.005	0.018	2.577	10.006
	MVA2	0.001	0.001	0.008	0.000	0.001	2.384	8.821
	MVE	0.020	0.015	0.145	-0.003	0.018	2.724	12.305
BES	MVA1	0.019	0.006	0.170	-0.005	0.024	2.404	8.498
	MVA2	0.001	0.001	0.016	-0.001	0.002	2.830	10.779
	MVE	0.019	0.005	0.174	-0.004	0.025	2.306	7.757
BNF	MVA1	0.026	0.019	0.268	-0.022	0.035	2.569	10.740
	MVA2	0.002	0.001	0.028	-0.002	0.004	2.745	8.863
	MVE	0.027	0.017	0.274	-0.021	0.037	2.845	11.780
FNB	MVA1	0.014	0.006	0.188	-0.021	0.027	2.641	9.341
	MVA2	0.002	0.001	0.025	-0.002	0.004	2.644	8.380
	MVE	0.015	0.008	0.184	-0.026	0.025	2.541	9.094

Table B. 5. $\Delta CoVaR^{i|system}$ descriptive statistics based on EWMA VaR for the period from 02/06/2003 to 13/12/2010.

Bank	Return	Mean	Median	Max.	Min.	St. dev.	Skew.	Kurt.
BCP	MVA1	0.029	0.025	0.137	-0.003	0.020	2.039	6.332
	MVA2	0.002	0.002	0.012	0.000	0.002	2.130	5.002
	MVE	0.029	0.025	0.138	0.002	0.021	2.055	6.306
BPI	MVA1	0.016	0.011	0.075	-0.004	0.013	1.840	4.049
	MVA2	0.001	0.001	0.005	0.000	0.001	1.483	3.411
	MVE	0.016	0.011	0.081	-0.002	0.012	1.669	3.702
BES	MVA1	0.014	0.006	0.091	-0.003	0.017	1.619	2.791
	MVA2	0.001	0.001	0.009	0.000	0.001	2.049	5.260
	MVE	0.015	0.005	0.093	-0.003	0.017	1.569	2.550
BNF	MVA1	0.019	0.015	0.143	-0.019	0.023	1.614	4.133
	MVA2	0.001	0.000	0.015	-0.001	0.003	2.190	5.028
	MVE	0.020	0.013	0.146	-0.019	0.024	1.885	5.204
FNB	MVA1	0.010	0.005	0.100	-0.027	0.017	1.929	4.619
	MVA2	0.001	0.001	0.014	-0.002	0.002	2.062	4.619
	MVE	0.011	0.006	0.098	-0.012	0.016	1.793	4.138

Table B. 6. $\Delta CoVaR^{i|system}$ descriptive statistics based on Historical VaR for the period from 02/06/2003 to 13/12/2010.

Bank	Return	Mean	Median	Max.	Min.	St. dev.	Skew.	Kurt.
BCP	MVA1	0.029	0.024	0.139	-0.003	0.021	2.099	6.549
	MVA2	0.002	0.002	0.012	0.000	0.002	2.156	5.123
	MVE	0.029	0.025	0.139	0.002	0.021	2.121	6.580
BPI	MVA1	0.016	0.011	0.076	-0.004	0.013	1.854	4.097
	MVA2	0.001	0.001	0.005	0.000	0.001	1.522	3.508
	MVE	0.016	0.011	0.082	-0.002	0.013	1.686	3.753
BES	MVA1	0.014	0.006	0.092	-0.003	0.017	1.639	2.876
	MVA2	0.001	0.001	0.009	0.000	0.001	2.075	5.406
	MVE	0.015	0.005	0.094	-0.003	0.018	1.587	2.622
BNF	MVA1	0.019	0.015	0.145	-0.019	0.023	1.658	4.307
	MVA2	0.001	0.000	0.015	-0.001	0.003	2.215	5.184
	MVE	0.020	0.013	0.148	-0.019	0.025	1.922	5.369
FNB	MVA1	0.010	0.005	0.102	-0.027	0.017	1.968	4.798
	MVA2	0.001	0.001	0.014	-0.002	0.002	2.087	4.737
	MVE	0.011	0.006	0.100	-0.012	0.016	1.827	4.293

Appendix C – Significance Tests

Table C. 1. P-values of the significance test of $\Delta CoVaR^{system|i} = 0$, from 2003 to 2010.

Bank	VaR	Return	2003	2004	2005	2006	2007	2008	2009	2010
BCP	QR	MVA1	0.37	0.74	0.56	0.64	0.49	0.57	0.53	0.50
		MVA2	0.56	0.48	0.50	0.63	0.49	0.60	0.58	0.64
		MVE	0.60	0.69	0.57	0.59	0.64	0.58	0.54	0.52
	EWMA	MVA1	0.79	0.61	0.67	0.60	0.48	0.54	0.57	0.51
		MVA2	0.71	0.57	0.63	0.60	0.58	0.65	0.53	0.54
		MVE	0.60	0.59	0.55	0.68	0.49	0.67	0.54	0.61
	Historical	MVA1	0.59	0.63	0.64	0.54	0.47	0.52	0.64	0.51
		MVA2	0.66	0.55	0.47	0.65	0.53	0.66	0.55	0.59
		MVE	0.67	0.54	0.53	0.58	0.56	0.63	0.54	0.53
BPI	QR	MVA1	0.55	0.53	0.54	0.63	0.63	0.52	0.60	0.63
		MVA2	0.61	0.58	0.54	0.60	0.52	0.64	0.57	0.68
		MVE	0.54	0.56	0.58	0.68	0.59	0.61	0.56	0.51
	EWMA	MVA1	0.52	0.63	0.62	0.53	0.61	0.50	0.56	0.64
		MVA2	0.56	0.60	0.60	0.59	0.62	0.69	0.65	0.54
		MVE	0.62	0.56	0.60	0.69	0.62	0.52	0.59	0.50
	Historical	MVA1	0.57	0.59	0.61	0.55	0.60	0.56	0.56	0.61
		MVA2	0.60	0.59	0.53	0.65	0.60	0.57	0.58	0.52
		MVE	0.55	0.60	0.62	0.65	0.61	0.50	0.53	0.51

Bank	VaR	Return	2003	2004	2005	2006	2007	2008	2009	2010
BES	QR	MVA1	0.54	0.55	0.65	0.70	0.59	0.55	0.54	0.63
		MVA2	0.58	0.52	0.60	0.58	0.61	0.67	0.56	0.50
		MVE	0.74	0.60	0.60	0.54	0.52	0.66	0.55	0.53
	EWMA	MVA1	0.63	0.63	0.67	0.58	0.50	0.56	0.48	0.74
		MVA2	0.60	0.61	0.56	0.60	0.54	0.60	0.58	0.55
		MVE	0.77	0.55	0.65	0.53	0.60	0.57	0.55	0.67
	Historical	MVA1	0.65	0.61	0.63	0.57	0.49	0.54	0.49	0.78
		MVA2	0.60	0.54	0.65	0.58	0.58	0.61	0.50	0.54
		MVE	0.79	0.60	0.74	0.54	0.60	0.55	0.55	0.67
BNF	QR	MVA1	0.67	0.68	0.65	0.68	0.65	0.55	0.51	0.54
		MVA2	0.56	0.70	0.70	0.64	0.65	0.53	0.57	0.55
		MVE	0.70	0.64	0.69	0.69	0.63	0.61	0.52	0.60
	EWMA	MVA1	0.93	0.64	0.69	0.65	0.65	0.68	0.58	0.57
		MVA2	0.66	0.64	0.82	0.72	0.63	0.52	0.56	0.59
		MVE	0.89	0.76	0.66	0.54	0.61	0.65	0.53	0.66
	Historical	MVA1	0.95	0.65	0.62	0.74	0.63	0.66	0.62	0.56
		MVA2	0.51	0.66	0.88	0.74	0.57	0.54	0.53	0.58
		MVE	0.89	0.74	0.70	0.70	0.63	0.63	0.57	0.65
FNB	QR	MVA1	0.60	0.50	0.69	0.61	0.55	0.61	0.58	0.68
		MVA2	0.58	0.73	0.74	0.54	0.67	0.57	0.53	0.60
		MVE	0.57	0.55	0.71	0.80	0.77	0.53	0.56	0.60
	EWMA	MVA1	0.58	0.61	0.64	0.68	0.74	0.58	0.56	0.63
		MVA2	0.56	0.57	0.53	0.57	0.74	0.55	0.60	0.67
		MVE	0.57	0.63	0.69	0.77	0.78	0.59	0.62	0.85
	Historical	MVA1	0.68	0.64	0.61	0.60	0.81	0.64	0.56	0.61
		MVA2	0.56	0.52	0.65	0.60	0.83	0.61	0.59	0.69
		MVE	0.53	0.57	0.59	0.71	0.82	0.64	0.67	0.86

Table C. 2. P-values of the significance test of $\Delta CoVaR^{system|i} = 0$, from 2011 to 2020.

Bank	VaR	Return	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
BCP	QR	MVA1	0.77	0.92	0.66	0.53	0.75	0.94	0.91	0.92	0.98	0.87
		MVA2	0.63	0.73	0.71	0.64	0.84	0.93	0.84	0.66	0.96	0.55
		MVE	0.72	0.63	0.58	0.80	0.71	0.94	0.91	0.97	0.85	0.99
	EWMA	MVA1	0.83	0.85	0.76	0.68	0.85	0.93	0.89	0.84	0.97	0.96
		MVA2	0.64	0.76	0.54	0.62	0.82	0.97	0.92	0.65	0.94	0.58
		MVE	0.72	0.60	0.62	0.77	0.65	0.76	0.83	0.80	0.84	0.99
	Historical	MVA1	0.86	0.83	0.72	0.67	0.79	0.93	0.84	0.82	0.92	0.97
		MVA2	0.66	0.77	0.54	0.58	0.76	0.98	0.85	0.70	0.97	0.58
		MVE	0.64	0.61	0.58	0.78	0.67	0.79	0.89	0.82	0.84	0.99

Bank	VaR	Return	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
BPI	QR	MVA1	0.57	0.92	0.90	0.59	0.55	0.86	0.97	0.78		
		MVA2	0.57	0.79	0.58	0.70	0.92	0.81	0.80	0.92		
		MVE	0.64	0.79	0.52	0.61	0.91	0.74	0.60	0.86		
	EWMA	MVA1	0.77	0.71	0.85	0.63	0.52	0.89	0.95	0.70		
		MVA2	0.69	0.89	0.55	0.66	0.92	0.61	0.69	0.90		
		MVE	0.70	0.59	0.59	0.59	0.76	0.89	0.77	0.79		
	Historical	MVA1	0.84	0.79	0.85	0.62	0.56	0.91	0.89	0.68		
		MVA2	0.69	0.71	0.59	0.80	0.91	0.80	0.75	0.95		
		MVE	0.75	0.66	0.61	0.60	0.82	0.87	0.78	0.79		
BES	QR	MVA1	0.89	0.53	0.99	0.89						
		MVA2	0.88	0.69	0.90	0.81						
		MVE	0.81	0.83	0.99	0.79						
	EWMA	MVA1	0.86	0.62	0.99	0.75						
		MVA2	0.95	0.70	0.89	0.85						
		MVE	0.73	0.76	1.00	0.74						
	Historical	MVA1	0.83	0.64	0.99	0.75						
		MVA2	0.93	0.61	0.89	0.82						
		MVE	0.70	0.78	1.00	0.74						
BNF	QR	MVA1	0.73	0.75								
		MVA2	0.77	0.77								
		MVE	0.74	0.74								
	EWMA	MVA1	0.68	0.83								
		MVA2	0.74	0.93								
		MVE	0.82	0.68								
	Historical	MVA1	0.66	0.75								
		MVA2	0.62	0.84								
		MVE	0.79	0.71								

Table C. 3. P-values of the significance test of $\Delta CoVaR^{i|system} = 0$, from 2003 to 2010.

Bank	VaR	Return	2003	2004	2005	2006	2007	2008	2009	2010
BCP	QR	MVA1	0.61	0.57	0.60	0.55	0.53	0.42	0.63	0.61
		MVA2	0.62	0.53	0.58	0.62	0.70	0.47	0.64	0.48
		MVE	0.54	0.51	0.53	0.59	0.59	0.52	0.59	0.53
	EWMA	MVA1	0.68	0.58	0.59	0.61	0.71	0.54	0.57	0.63
		MVA2	0.68	0.58	0.51	0.66	0.61	0.51	0.58	0.54
		MVE	0.62	0.67	0.61	0.57	0.56	0.49	0.56	0.68
	Historical	MVA1	0.56	0.57	0.63	0.57	0.68	0.53	0.58	0.68
		MVA2	0.62	0.63	0.56	0.64	0.61	0.57	0.58	0.56
		MVE	0.65	0.69	0.67	0.53	0.60	0.52	0.36	0.67

Bank	VaR	Return	2003	2004	2005	2006	2007	2008	2009	2010
BPI	QR	MVA1	0.66	0.55	0.57	0.56	0.48	0.66	0.55	0.65
		MVA2	0.62	0.58	0.77	0.67	0.61	0.63	0.57	0.54
		MVE	0.54	0.49	0.67	0.62	0.82	0.58	0.58	0.50
	EWMA	MVA1	0.58	0.54	0.59	0.80	0.50	0.55	0.66	0.62
		MVA2	0.64	0.61	0.66	0.54	0.64	0.73	0.66	0.53
		MVE	0.58	0.57	0.57	0.64	0.78	0.56	0.62	0.63
	Historical	MVA1	0.64	0.57	0.60	0.80	0.58	0.57	0.70	0.60
		MVA2	0.65	0.57	0.75	0.53	0.73	0.70	0.66	0.53
		MVE	0.52	0.54	0.63	0.66	0.77	0.55	0.61	0.67
BES	QR	MVA1	0.82	0.95	0.59	0.69	0.58	0.48	0.55	0.61
		MVA2	0.52	0.74	0.97	0.68	0.58	0.48	0.63	0.56
		MVE	0.65	0.77	0.50	0.62	0.64	0.36	0.67	0.75
	EWMA	MVA1	0.60	0.96	0.58	0.85	0.70	0.56	0.61	0.67
		MVA2	0.57	0.75	0.98	0.65	0.69	0.50	0.63	0.56
		MVE	0.81	0.92	0.57	0.58	0.59	0.63	0.60	0.62
	Historical	MVA1	0.71	0.96	0.60	0.81	0.73	0.55	0.60	0.64
		MVA2	0.68	0.68	0.97	0.70	0.74	0.59	0.64	0.61
		MVE	0.79	0.94	0.58	0.54	0.58	0.62	0.58	0.55
BNF	QR	MVA1	0.59	0.58	0.58	0.79	0.67	0.55	0.56	0.56
		MVA2	0.95	0.67	0.79	0.70	0.55	0.55	0.55	0.47
		MVE	0.59	0.75	0.81	0.81	0.63	0.59	0.58	0.55
	EWMA	MVA1	0.63	0.54	0.59	0.78	0.70	0.64	0.56	0.60
		MVA2	1.00	0.72	0.61	0.84	0.69	0.57	0.56	0.54
		MVE	0.78	0.85	0.79	0.69	0.62	0.63	0.52	0.69
	Historical	MVA1	0.59	0.61	0.67	0.78	0.70	0.68	0.62	0.56
		MVA2	0.93	0.80	0.66	0.83	0.70	0.49	0.55	0.51
		MVE	0.79	0.85	0.69	0.68	0.62	0.68	0.54	0.65
FNB	QR	MVA1	0.62	0.62	0.55	0.65	0.60	0.62	0.64	0.59
		MVA2	0.57	0.59	0.83	0.68	0.57	0.56	0.55	0.78
		MVE	0.62	0.82	0.74	0.58	0.64	0.67	0.64	0.56
	EWMA	MVA1	0.52	0.60	0.59	0.86	0.56	0.62	0.67	0.76
		MVA2	0.77	0.61	0.84	0.60	0.56	0.63	0.69	0.85
		MVE	0.60	0.86	0.74	0.73	0.64	0.55	0.60	0.53
	Historical	MVA1	0.59	0.66	0.58	0.82	0.55	0.63	0.62	0.72
		MVA2	0.55	0.61	0.84	0.61	0.60	0.63	0.70	0.88
		MVE	0.66	0.82	0.82	0.66	0.60	0.59	0.61	0.53

Table C. 4. P-values of the significance test of $\Delta CoVaR^{i|system} = 0$, from 2010 to 2020.

Bank	VaR	Return	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
BCP	QR	MVA1	0.61	0.83	0.57	0.59	0.69	0.72	0.77	0.70	0.58	0.61
		MVA2	0.55	0.63	0.57	0.61	0.70	0.63	0.72	0.58	0.67	0.69
		MVE	0.84	0.83	0.62	0.73	0.68	0.64	0.87	0.73	0.71	0.49
	EWMA	MVA1	0.69	0.72	0.54	0.60	0.65	0.59	0.85	0.74	0.52	0.59
		MVA2	0.61	0.61	0.53	0.81	0.68	0.69	0.71	0.57	0.66	0.60
		MVE	0.77	0.96	0.76	0.66	0.65	0.65	0.89	0.66	0.87	0.52
	Historical	MVA1	0.66	0.67	0.54	0.55	0.69	0.65	0.79	0.71	0.54	0.56
		MVA2	0.62	0.61	0.55	0.79	0.73	0.66	0.67	0.55	0.65	0.62
		MVE	0.76	0.95	0.70	0.66	0.68	0.62	0.85	0.67	0.92	0.52
BPI	QR	MVA1	0.61	0.54	0.56	0.55	0.81	0.73	0.77	0.50		
		MVA2	0.82	0.79	0.54	0.54	0.74	0.92	0.86	0.78		
		MVE	0.62	0.91	0.64	0.62	0.70	0.64	0.65	0.71		
	EWMA	MVA1	0.60	0.60	0.65	0.64	0.65	0.55	0.74	0.51		
		MVA2	0.68	0.76	0.57	0.59	0.76	0.79	0.71	0.67		
		MVE	0.53	0.83	0.80	0.62	0.68	0.63	0.79	0.61		
	Historical	MVA1	0.59	0.62	0.66	0.62	0.70	0.64	0.69	0.49		
		MVA2	0.68	0.68	0.59	0.56	0.78	0.75	0.82	0.68		
		MVE	0.50	0.76	0.81	0.64	0.65	0.64	0.76	0.63		
BES	QR	MVA1	0.61	0.81	0.67	0.77						
		MVA2	0.60	1.00	0.77	0.61						
		MVE	0.69	0.64	0.78	0.67						
	EWMA	MVA1	0.55	0.90	0.72	0.68						
		MVA2	0.65	0.96	0.64	0.60						
		MVE	0.73	0.61	0.94	0.70						
	Historical	MVA1	0.54	0.90	0.75	0.69						
		MVA2	0.72	0.91	0.67	0.64						
		MVE	0.72	0.52	0.94	0.72						
BNF	QR	MVA1	0.93	0.70								
		MVA2	0.81	0.85								
		MVE	0.90	0.72								
	EWMA	MVA1	0.87	0.76								
		MVA2	0.92	0.89								
		MVE	0.93	0.78								
	Historical	MVA1	0.82	0.76								
		MVA2	0.92	0.90								
		MVE	0.89	0.78								

Appendix D – Dominance Tests

Table D. 1. P-values of the dominance test of $\Delta CoVaR^{system|i} > \Delta CoVaR^{system|j}$, from 2003 to 2010.

Bank	VaR	Return	2003	2004	2005	2006	2007	2008	2009	2010
BCP > BPI	QR	MVA1	0.65	0.49	0.00	0.00	0.00	0.54	0.54	0.55
		MVA2	0.64	0.43	0.65	0.02	0.00	0.50	0.54	0.23
		MVE	0.51	0.00	0.34	0.33	0.00	0.59	0.03	0.42
	EWMA	MVA1	0.58	0.00	0.00	0.36	0.00	0.58	0.64	0.56
		MVA2	0.67	0.00	0.61	0.36	0.00	0.53	0.55	0.52
		MVE	0.57	0.00	0.00	0.35	0.00	0.67	0.56	0.44
	Historical	MVA1	0.62	0.00	0.00	0.35	0.00	0.59	0.58	0.52
		MVA2	0.66	0.00	0.66	0.36	0.00	0.50	0.56	0.51
		MVE	0.55	0.00	0.00	0.36	0.00	0.65	0.53	0.44
BCP > BES	QR	MVA1	0.45	0.60	0.51	0.43	0.20	0.51	0.53	0.75
		MVA2	0.54	0.60	0.67	0.70	0.00	0.56	0.58	0.80
		MVE	0.44	0.58	0.59	0.00	0.10	0.66	0.60	0.54
	EWMA	MVA1	0.58	0.65	0.01	0.42	0.16	0.62	0.57	0.49
		MVA2	0.65	0.78	0.55	0.59	0.43	0.56	0.58	0.59
		MVE	0.46	0.49	0.17	0.53	0.13	0.71	0.53	0.60
	Historical	MVA1	0.44	0.58	0.00	0.47	0.05	0.63	0.53	0.47
		MVA2	0.57	0.25	0.59	0.51	0.43	0.57	0.49	0.56
		MVE	0.56	0.01	0.10	0.55	0.00	0.64	0.58	0.60
BCP > BNF	QR	MVA1	0.42	0.00	0.00	0.00	0.00	0.24	0.51	0.45
		MVA2	0.44	0.00	0.58	0.00	0.00	0.05	0.58	0.45
		MVE	0.50	0.00	0.00	0.00	0.01	0.32	0.47	0.42
	EWMA	MVA1	0.47	0.00	0.00	0.00	0.00	0.00	0.00	0.45
		MVA2	0.44	0.00	0.42	0.00	0.00	0.17	0.58	0.47
		MVE	0.39	0.00	0.00	0.00	0.00	0.00	0.00	0.43
	Historical	MVA1	0.53	0.00	0.00	0.00	0.00	0.00	0.01	0.45
		MVA2	0.46	0.00	0.44	0.00	0.00	0.06	0.55	0.54
		MVE	0.45	0.00	0.00	0.00	0.00	0.00	0.00	0.42
BCP > FNB	QR	MVA1	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.41
		MVA2	0.86	0.50	0.00	0.00	0.00	0.54	0.49	0.42
		MVE	0.48	0.00	0.00	0.00	0.00	0.05	0.58	0.49
	EWMA	MVA1	0.53	0.00	0.00	0.00	0.00	0.00	0.00	0.41
		MVA2	0.67	0.54	0.00	0.00	0.00	0.70	0.62	0.50
		MVE	0.54	0.00	0.00	0.00	0.00	0.05	0.07	0.49
	Historical	MVA1	0.47	0.00	0.00	0.00	0.00	0.00	0.00	0.41
		MVA2	0.53	0.53	0.00	0.00	0.00	0.66	0.60	0.72
		MVE	0.56	0.00	0.00	0.00	0.00	0.00	0.00	0.49

Bank	VaR	Return	2003	2004	2005	2006	2007	2008	2009	2010
BPI > BES	QR	MVA1	0.32	0.68	0.52	0.55	0.41	0.46	0.64	0.50
		MVA2	0.57	0.56	0.62	0.48	0.46	0.49	0.53	0.56
		MVE	0.01	0.53	0.55	0.50	0.52	0.46	0.50	0.57
	EWMA	MVA1	0.00	0.58	0.67	0.57	0.64	0.46	0.58	0.75
		MVA2	0.66	0.62	0.54	0.60	0.60	0.46	0.45	0.54
		MVE	0.00	0.57	0.67	0.58	0.46	0.52	0.53	0.75
	Historical	MVA1	0.00	0.57	0.65	0.58	0.67	0.46	0.60	0.61
		MVA2	0.57	0.65	0.61	0.60	0.60	0.49	0.53	0.62
		MVE	0.00	0.57	0.68	0.58	0.48	0.48	0.54	0.79
BPI > BNF	QR	MVA1	0.39	0.00	0.00	0.00	0.47	0.55	0.54	0.62
		MVA2	0.70	0.52	0.51	0.00	0.47	0.38	0.52	0.47
		MVE	0.00	0.00	0.00	0.28	0.48	0.52	0.52	0.53
	EWMA	MVA1	0.00	0.31	0.00	0.00	0.51	0.55	0.43	0.71
		MVA2	0.50	0.56	0.54	0.00	0.47	0.40	0.47	0.44
		MVE	0.00	0.00	0.00	0.00	0.47	0.52	0.00	0.58
	Historical	MVA1	0.00	0.03	0.00	0.00	0.49	0.56	0.44	0.58
		MVA2	0.49	0.55	0.52	0.00	0.47	0.40	0.55	0.45
		MVE	0.00	0.00	0.00	0.00	0.48	0.54	0.05	0.59
BPI > FNB	QR	MVA1	0.00	0.65	0.41	0.00	0.47	0.47	0.06	0.42
		MVA2	0.48	0.57	0.00	0.00	0.63	0.66	0.25	0.41
		MVE	0.00	0.10	0.00	0.00	0.47	0.52	0.53	0.48
	EWMA	MVA1	0.01	0.64	0.31	0.00	0.53	0.46	0.00	0.43
		MVA2	0.66	0.66	0.00	0.00	0.55	0.46	0.00	0.43
		MVE	0.39	0.55	0.33	0.00	0.50	0.47	0.58	0.48
	Historical	MVA1	0.00	0.74	0.08	0.00	0.55	0.46	0.00	0.45
		MVA2	0.61	0.54	0.00	0.00	0.60	0.46	0.00	0.51
		MVE	0.02	0.56	0.00	0.00	0.53	0.49	0.59	0.48
BES > BNF	QR	MVA1	0.39	0.00	0.00	0.00	0.59	0.00	0.62	0.49
		MVA2	0.50	0.45	0.41	0.00	0.55	0.00	0.55	0.47
		MVE	0.52	0.00	0.00	0.00	0.72	0.00	0.49	0.56
	EWMA	MVA1	0.00	0.00	0.00	0.00	0.48	0.00	0.00	0.46
		MVA2	0.57	0.00	0.53	0.00	0.00	0.00	0.07	0.48
		MVE	0.39	0.00	0.00	0.00	0.04	0.00	0.00	0.46
	Historical	MVA1	0.00	0.00	0.00	0.00	0.04	0.00	0.00	0.50
		MVA2	0.46	0.07	0.54	0.00	0.00	0.00	0.01	0.71
		MVE	0.43	0.00	0.00	0.00	0.01	0.00	0.00	0.51

Bank	VaR	Return	2003	2004	2005	2006	2007	2008	2009	2010
BES > FNB	QR	MVA1	0.68	0.00	0.31	0.00	0.47	0.03	0.00	0.41
		MVA2	0.83	0.54	0.00	0.00	0.35	0.62	0.58	0.45
		MVE	0.50	0.00	0.00	0.00	0.61	0.37	0.47	0.41
	EWMA	MVA1	0.67	0.60	0.00	0.00	0.00	0.03	0.00	0.41
		MVA2	0.54	0.03	0.00	0.00	0.00	0.02	0.01	0.02
		MVE	0.59	0.73	0.00	0.00	0.00	0.00	0.00	0.40
	Historical	MVA1	0.48	0.04	0.00	0.00	0.00	0.01	0.00	0.40
		MVA2	0.67	0.02	0.00	0.00	0.00	0.56	0.00	0.01
		MVE	0.53	0.47	0.00	0.00	0.00	0.47	0.00	0.40
BNF > FNB	QR	MVA1	0.49	0.50	0.58	0.51	0.51	0.54	0.43	0.00
		MVA2	0.59	0.49	0.54	0.71	0.53	0.64	0.63	0.54
		MVE	0.49	0.55	0.59	0.60	0.52	0.65	0.51	0.49
	EWMA	MVA1	0.48	0.54	0.51	0.64	0.57	0.55	0.58	0.55
		MVA2	0.58	0.49	0.58	0.76	0.56	0.55	0.46	0.57
		MVE	0.49	0.53	0.56	0.61	0.59	0.66	0.45	0.44
	Historical	MVA1	0.47	0.53	0.50	0.65	0.52	0.60	0.41	0.33
		MVA2	0.57	0.57	0.57	0.63	0.55	0.53	0.47	0.57
		MVE	0.49	0.56	0.58	0.61	0.57	0.59	0.44	0.34

Table D. 2. P-values of the dominance test of $\Delta CoVaR^{system|i} > \Delta CoVaR^{system|j}$, from 2011 to 2018.

Bank	VaR	Return	2011	2012	2013	2014	2015	2016	2017	2018
BCP > BPI	QR	MVA1	0.56	0.41	0.49	0.57	0.67	0.14	0.50	0.51
		MVA2	0.54	0.42	0.00	0.63	0.65	0.57	0.41	0.61
		MVE	0.53	0.55	0.57	0.49	0.63	0.00	0.06	0.51
	EWMA	MVA1	0.58	0.51	0.57	0.73	0.49	0.50	0.63	0.54
		MVA2	0.55	0.31	0.00	0.59	0.71	0.46	0.44	0.74
		MVE	0.54	0.61	0.42	0.42	0.50	0.53	0.07	0.56
	Historical	MVA1	0.59	0.45	0.59	0.60	0.51	0.49	0.64	0.54
		MVA2	0.55	0.32	0.00	0.61	0.72	0.49	0.44	0.76
		MVE	0.52	0.55	0.42	0.57	0.52	0.51	0.07	0.61
BCP > BES	QR	MVA1	0.58	0.65	0.52	0.74				
		MVA2	0.53	0.49	0.57	0.49				
		MVE	0.51	0.58	0.62	0.65				
	EWMA	MVA1	0.71	0.61	0.57	0.63				
		MVA2	0.51	0.47	0.52	0.51				
		MVE	0.66	0.53	0.67	0.56				
	Historical	MVA1	0.66	0.68	0.55	0.67				
		MVA2	0.54	0.49	0.53	0.47				
		MVE	0.70	0.54	0.67	0.55				

Bank	VaR	Return	2011	2012	2013	2014	2015	2016	2017	2018
BCP > BNF	QR	MVA1	0.49	0.57						
		MVA2	0.79	0.54						
		MVE	0.57	0.59						
	EWMA	MVA1	0.58	0.52						
		MVA2	0.57	0.59						
		MVE	0.67	0.56						
	Historical	MVA1	0.58	0.50						
		MVA2	0.54	0.60						
		MVE	0.70	0.58						
BPI > BES	QR	MVA1	0.56	0.66	0.60	0.48				
		MVA2	0.47	0.63	0.49	0.49				
		MVE	0.70	0.78	0.54	0.52				
	EWMA	MVA1	0.58	0.62	0.66	0.50				
		MVA2	0.49	0.75	0.54	0.58				
		MVE	0.52	0.56	0.49	0.62				
	Historical	MVA1	0.65	0.66	0.63	0.54				
		MVA2	0.48	0.84	0.48	0.52				
		MVE	0.61	0.66	0.48	0.62				
BPI > BNF	QR	MVA1	0.62	0.48						
		MVA2	0.59	0.56						
		MVE	0.54	0.56						
	EWMA	MVA1	0.52	0.50						
		MVA2	0.51	0.48						
		MVE	0.56	0.62						
	Historical	MVA1	0.56	0.51						
		MVA2	0.48	0.50						
		MVE	0.57	0.54						
BES > BNF	QR	MVA1	0.43	0.49						
		MVA2	0.47	0.57						
		MVE	0.48	0.61						
	EWMA	MVA1	0.42	0.52						
		MVA2	0.51	0.51						
		MVE	0.02	0.54						
	Historical	MVA1	0.42	0.48						
		MVA2	0.58	0.51						
		MVE	0.03	0.54						

Table D. 3. P-values of the dominance test of $\Delta CoVaR^{i|system} > \Delta CoVaR^{j|system}$, from 2003 to 2010.

Bank	**VaR**	**Return**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**
BCP > BPI	QR	MVA1	0.00	0.00	0.00	0.71	0.38	0.00	0.00	0.45
		MVA2	0.00	0.00	0.00	0.63	0.55	0.00	0.00	0.23
		MVE	0.00	0.00	0.00	0.61	0.52	0.12	0.00	0.43
	EWMA	MVA1	0.00	0.00	0.00	0.60	0.39	0.00	0.00	0.48
		MVA2	0.00	0.00	0.00	0.57	0.59	0.00	0.00	0.24
		MVE	0.00	0.00	0.00	0.61	0.02	0.20	0.00	0.50
	Historical	MVA1	0.00	0.00	0.00	0.65	0.38	0.00	0.00	0.48
		MVA2	0.00	0.00	0.00	0.58	0.58	0.00	0.00	0.24
		MVE	0.00	0.00	0.00	0.63	0.02	0.19	0.00	0.51
BCP > BES	QR	MVA1	0.00	0.00	0.00	0.00	0.38	0.00	0.00	0.45
		MVA2	0.00	0.00	0.00	0.00	0.73	0.41	0.00	0.44
		MVE	0.00	0.00	0.00	0.00	0.63	0.42	0.00	0.71
	EWMA	MVA1	0.00	0.00	0.00	0.00	0.38	0.00	0.00	0.45
		MVA2	0.00	0.00	0.00	0.00	0.76	0.39	0.00	0.54
		MVE	0.00	0.00	0.00	0.00	0.69	0.42	0.00	0.56
	Historical	MVA1	0.00	0.00	0.00	0.00	0.38	0.00	0.00	0.45
		MVA2	0.00	0.00	0.00	0.00	0.77	0.39	0.00	0.54
		MVE	0.00	0.00	0.00	0.00	0.76	0.43	0.00	0.58
BCP > BNF	QR	MVA1	0.00	0.00	0.00	0.53	0.50	0.88	0.00	0.45
		MVA2	0.00	0.00	0.00	0.00	0.49	0.75	0.00	0.00
		MVE	0.00	0.00	0.00	0.50	0.70	0.61	0.95	0.01
	EWMA	MVA1	0.00	0.00	0.00	0.02	0.60	0.72	0.17	0.51
		MVA2	0.00	0.00	0.00	0.00	0.47	0.73	0.00	0.00
		MVE	0.00	0.00	0.00	0.61	0.54	0.75	0.65	0.06
	Historical	MVA1	0.00	0.00	0.00	0.06	0.58	0.66	0.04	0.58
		MVA2	0.00	0.00	0.00	0.00	0.47	0.78	0.00	0.00
		MVE	0.00	0.00	0.00	0.62	0.52	0.66	0.68	0.06
BCP > FNB	QR	MVA1	0.00	0.00	0.00	0.00	0.52	0.35	0.00	0.00
		MVA2	0.00	0.00	0.00	0.19	0.56	0.68	0.55	0.17
		MVE	0.00	0.00	0.00	0.00	0.55	0.43	0.08	0.00
	EWMA	MVA1	0.00	0.00	0.00	0.00	0.65	0.34	0.00	0.00
		MVA2	0.00	0.00	0.00	0.00	0.64	0.71	0.80	0.00
		MVE	0.00	0.00	0.00	0.00	0.70	0.42	0.00	0.00
	Historical	MVA1	0.00	0.00	0.00	0.00	0.61	0.35	0.00	0.00
		MVA2	0.00	0.00	0.00	0.00	0.65	0.69	0.69	0.01
		MVE	0.00	0.00	0.00	0.00	0.63	0.42	0.00	0.00

Bank	VaR	Return	2003	2004	2005	2006	2007	2008	2009	2010
BPI > BES	QR	MVA1	0.00	0.00	0.00	0.00	0.54	0.58	0.55	0.72
		MVA2	0.02	0.00	0.00	0.47	0.73	0.61	0.70	0.77
		MVE	0.00	0.00	0.00	0.00	0.67	0.54	0.68	0.61
	EWMA	MVA1	0.00	0.00	0.00	0.00	0.65	0.62	0.85	0.65
		MVA2	0.01	0.00	0.00	0.47	0.56	0.50	0.61	0.55
		MVE	0.00	0.00	0.00	0.00	0.64	0.56	0.64	0.87
	Historical	MVA1	0.00	0.00	0.00	0.00	0.64	0.62	0.88	0.66
		MVA2	0.07	0.00	0.00	0.47	0.57	0.53	0.56	0.52
		MVE	0.00	0.00	0.00	0.00	0.64	0.52	0.64	0.88
BPI > BNF	QR	MVA1	0.55	0.48	0.00	0.73	0.55	0.59	0.67	0.76
		MVA2	0.24	0.00	0.00	0.00	0.49	0.58	0.58	0.00
		MVE	0.70	0.53	0.00	0.65	0.78	0.52	0.50	0.71
	EWMA	MVA1	0.50	0.49	0.02	0.51	0.54	0.55	0.54	0.57
		MVA2	0.00	0.00	0.00	0.00	0.49	0.62	0.73	0.00
		MVE	0.70	0.51	0.00	0.52	0.54	0.66	0.58	0.59
	Historical	MVA1	0.60	0.55	0.01	0.50	0.62	0.54	0.55	0.57
		MVA2	0.00	0.00	0.00	0.00	0.48	0.65	0.69	0.00
		MVE	0.74	0.53	0.00	0.52	0.57	0.68	0.55	0.59
BPI > FNB	QR	MVA1	0.00	0.00	0.00	0.00	0.60	0.60	0.44	0.01
		MVA2	0.39	0.56	0.00	0.01	0.53	0.70	0.48	0.44
		MVE	0.00	0.47	0.00	0.00	0.51	0.54	0.52	0.00
	EWMA	MVA1	0.00	0.00	0.00	0.00	0.50	0.61	0.61	0.01
		MVA2	0.39	0.66	0.00	0.00	0.55	0.53	0.62	0.46
		MVE	0.00	0.17	0.00	0.00	0.51	0.62	0.58	0.00
	Historical	MVA1	0.00	0.00	0.00	0.00	0.52	0.60	0.56	0.01
		MVA2	0.38	0.57	0.00	0.00	0.58	0.52	0.63	0.46
		MVE	0.00	0.17	0.00	0.00	0.50	0.63	0.54	0.00
BES > BNF	QR	MVA1	0.51	0.48	0.41	0.51	0.56	0.54	0.53	0.58
		MVA2	0.53	0.51	0.61	0.50	0.48	0.56	0.61	0.00
		MVE	0.47	0.51	0.46	0.48	0.51	0.63	0.54	0.00
	EWMA	MVA1	0.53	0.49	0.42	0.52	0.60	0.56	0.52	0.89
		MVA2	0.61	0.58	0.56	0.48	0.48	0.65	0.66	0.00
		MVE	0.47	0.52	0.47	0.48	0.66	0.53	0.67	0.48
	Historical	MVA1	0.55	0.48	0.42	0.52	0.65	0.57	0.54	0.88
		MVA2	0.59	0.58	0.60	0.48	0.48	0.63	0.63	0.00
		MVE	0.47	0.52	0.45	0.47	0.58	0.54	0.67	0.48

Bank	VaR	Return	2003	2004	2005	2006	2007	2008	2009	2010
BES > FNB	QR	MVA1	0.51	0.49	0.51	0.49	0.51	0.75	0.48	0.00
		MVA2	0.61	0.48	0.65	0.54	0.69	0.76	0.75	0.39
		MVE	0.49	0.49	0.48	0.53	0.54	0.86	0.67	0.00
	EWMA	MVA1	0.62	0.49	0.59	0.53	0.57	0.55	0.55	0.00
		MVA2	0.54	0.48	0.60	0.56	0.66	0.56	0.52	0.56
		MVE	0.48	0.51	0.47	0.66	0.51	0.62	0.51	0.00
	Historical	MVA1	0.60	0.51	0.55	0.56	0.60	0.55	0.56	0.00
		MVA2	0.56	0.47	0.59	0.54	0.70	0.55	0.52	0.56
		MVE	0.47	0.49	0.46	0.65	0.47	0.70	0.52	0.00
BNF > FNB	QR	MVA1	0.58	0.67	0.53	0.44	0.47	0.03	0.42	0.00
		MVA2	0.52	0.52	0.56	0.53	0.47	0.57	0.51	0.80
		MVE	0.00	0.53	0.57	0.63	0.61	0.00	0.45	0.32
	EWMA	MVA1	0.58	0.78	0.63	0.40	0.55	0.00	0.05	0.00
		MVA2	0.54	0.55	0.57	0.60	0.54	0.81	0.53	0.47
		MVE	0.00	0.63	0.55	0.61	0.58	0.00	0.01	0.02
	Historical	MVA1	0.46	0.72	0.63	0.40	0.54	0.00	0.08	0.00
		MVA2	0.54	0.53	0.56	0.54	0.53	0.84	0.48	0.48
		MVE	0.00	0.63	0.56	0.61	0.57	0.00	0.01	0.02

Table D. 4. P-values of the dominance test of $\Delta CoVaR^{i|system} > \Delta CoVaR^{j|system}$, from 2011 to 2018.

Bank	VaR	Return	2011	2012	2013	2014	2015	2016	2017	2018
BCP > BPI	QR	MVA1	0.45	0.72	0.58	0.45	0.52	0.00	0.52	0.52
		MVA2	0.47	0.01	0.54	0.48	0.54	0.60	0.50	0.60
		MVE	0.71	0.57	0.49	0.59	0.25	0.00	0.58	0.54
	EWMA	MVA1	0.50	0.72	0.67	0.46	0.44	0.00	0.62	0.58
		MVA2	0.48	0.01	0.60	0.52	0.59	0.56	0.61	0.52
		MVE	0.65	0.56	0.54	0.49	0.01	0.00	0.70	0.52
	Historical	MVA1	0.51	0.72	0.65	0.45	0.52	0.00	0.55	0.56
		MVA2	0.47	0.01	0.62	0.51	0.57	0.55	0.56	0.49
		MVE	0.66	0.57	0.54	0.50	0.01	0.00	0.70	0.51
BCP > BES	QR	MVA1	0.58	0.61	0.48	0.38				
		MVA2	0.55	0.63	0.59	0.53				
		MVE	0.53	0.68	0.59	0.09				
	EWMA	MVA1	0.55	0.65	0.64	0.39				
		MVA2	0.51	0.65	0.54	0.53				
		MVE	0.59	0.66	0.60	0.26				
	Historical	MVA1	0.55	0.65	0.64	0.39				
		MVA2	0.52	0.65	0.54	0.52				
		MVE	0.59	0.64	0.61	0.21				

Bank	VaR	Return	2011	2012	2013	2014	2015	2016	2017	2018
BCP > BNF	QR	MVA1	0.05	0.54						
		MVA2	0.00	0.40						
		MVE	0.62	0.51						
	EWMA	MVA1	0.06	0.54						
		MVA2	0.00	0.39						
		MVE	0.59	0.51						
	Historical	MVA1	0.00	0.55						
		MVA2	0.00	0.40						
		MVE	0.58	0.50						
BPI > BES	QR	MVA1	0.47	0.57	0.09	0.54				
		MVA2	0.61	0.48	0.56	0.43				
		MVE	0.60	0.62	0.59	0.62				
	EWMA	MVA1	0.48	0.57	0.17	0.54				
		MVA2	0.60	0.47	0.52	0.53				
		MVE	0.52	0.61	0.54	0.54				
	Historical	MVA1	0.48	0.59	0.15	0.62				
		MVA2	0.58	0.47	0.52	0.52				
		MVE	0.52	0.57	0.54	0.60				
BPI > BNF	QR	MVA1	0.60	0.53						
		MVA2	0.51	0.67						
		MVE	0.52	0.50						
	EWMA	MVA1	0.58	0.58						
		MVA2	0.55	0.67						
		MVE	0.64	0.58						
	Historical	MVA1	0.61	0.57						
		MVA2	0.55	0.66						
		MVE	0.63	0.59						
BES > BNF	QR	MVA1	0.00	0.52						
		MVA2	0.00	0.46						
		MVE	0.00	0.52						
	EWMA	MVA1	0.00	0.55						
		MVA2	0.00	0.47						
		MVE	0.00	0.52						
	Historical	MVA1	0.00	0.53						
		MVA2	0.00	0.48						
		MVE	0.00	0.52						