2. BOOK VALUE FOR ASSESSING SYSTEMIC RISK: LUXEMBOURG EMPIRICAL EVALUATION

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ABSTRACT

In order to efficiently capture the contribution to the aggregated systemic risk of each financial institution arising from various important balance-sheet items, this study proposes a comprehensive approach of "Mark-to-Systemic-Risk" to integrate book value data of Luxembourg financial institutions into systemic risk measures. It first characterizes systemic risks and risk spillovers in equity returns for 33 Luxembourg banks, 30 European banking groups, and 232 investment funds. The forward-looking systemic risk measures including ΔCoES, Shapley-ΔCoES, and SRISK are estimated by using a large-scale dynamic grouped t-copula, and their common components are determined by the generalized dynamic factor model. Several important facts are documented during 2009-2016: (1) Measured by ΔCoES of equity returns, Luxembourg banks were more sensitive to the adverse events from investment funds compared to European banking groups, and investment funds were more sensitive to the adverse events from banking groups than from Luxembourg banks. (2) Ranked by Shapley-ΔCoES values, money market funds had the highest marginal contribution to the total risk of Luxembourg banks while equity funds exhibited the least share of the risk, and the systemic risk contribution of bond funds, mixed funds and hedge funds became more important toward the end of 2016. (3) The macroeconomic determinants of the aggregate systemic risk of banking groups, Luxembourg banks and investment funds, and the marginal contributions from 15 countries to the aggregate systemic risk of Luxemburg banks and their parent banking groups are all different.

1 INTRODUCTION

Since the Global Financial Crisis, both academics and regulators have been stepping up their efforts to improve the tools and models used in the field of macroprudential analysis, and especially to develop measures of systemic risk. Most of the existing methodologies are based on market data such as stocks, bonds and derivatives which allow tracking systemic risk in a very timely manner. However, market data is not always available because a significant number of credit institutions are not publicly listed and only report balance sheet data. Credit risk indicators that rely on mark-to-market accounting rules can be constrained by construction to a few main balance sheet items. Hence it is possible that the slow accumulation of vulnerabilities on different balance sheet items may not be detected by the authorities in a timely manner.

Each individual balance-sheet item contributes towards the aggregate financial statement of the broader financial system. Hence, a systemic risk measure constructed from individual balance sheet items could potentially help identify individual contributions to the overall degree of systemic risk in the financial sector. The level of systemic risk can be estimated based on the broader set of balance-sheet items by including the vast sub-heading items such as current assets, fixed assets, current liabilities, and long-term liabilities. Indeed, similar to the idea of the Mark-to-Market accounting rule, each balance-sheet item can be marked to the level of systemic risk by simultaneously considering the same balance sheet items across all financial institutions in the system. The so-called "Mark-to-Systemic-Risk" approach can provide an analysis of a financial institution's risk position in relation to each balance-sheet item. In fact, several risk metrics such as the Value at Risk and the Expected Shortfall can be applied directly to individual balance-sheet items.

70 Financial Stability Department, Banque centrale du Luxembourg. This contribution is a shortened version of BCL Working paper n°118. The conclusions may not be shared by policymakers in the BCL or the Eurosystem.

To demonstrate how the "Mark-to-Systemic-Risk" concept can be applied in practice, this paper first examines the book value equity for Luxembourg banks and investment funds. European banking groups with market data are also added for comparison. It characterizes systemic risks and risk spillovers for the period of 2003-2016. A large-scale dynamic grouped t-copula approach, which is appropriate to track a time-varying high dimensional distribution, is proposed to estimate several systemic risk measures for the balance-sheet items for each financial institution in the system. The systemic risk measures considered in this study include Exposure Co-expected Shortfall (ΔCoES) defined by Adrian and Brunnermeier (2011), Shapley-ΔCoES described in at Drehmann and Tarashev (2013), and Systemic Risk of Expected Capital Shortage (SRISK) developed by Brownlees and Engle (2017). In order to deal with procyclicality in the financial system's activities, the adopted framework is also completed by linking the measures of systemic risk in the financial sector with a large set of macrofinancial variables.

Several important facts are documented in this study for the period spanning 2009-2016. First, Luxembourg banks were determined to be more sensitive to the adverse events from investment funds compared to European banking groups. Second, investment funds were found to be more sensitive to the adverse events from banking groups than from Luxembourg banks. Third, money market funds had the highest marginal contribution to the total risk of Luxembourg banks while equity funds had the least contribution. Bond funds, mixed funds and hedge funds only became more important in their contribution to total risk toward the end of 2016. In addition, the macroeconomic determinants of the aggregate systemic risk of banking groups, Luxembourg banks and investment funds, and the marginal contributions from 15 countries to the aggregate systemic risk of Luxemburg banks and European banking groups are all different. In view of these results, the framework might provide a valuable addition to the traditional toolkit for assessing time varying risks to the stability of the financial system.

The remainder of the study is organized as follows. Section 2 briefly introduces the integrated modeling framework, and explains the methodological and statistical approaches used to estimate systemic risk. Section 3 discusses the data, describes the empirical measures of financial systemic risk, and examines the empirical results. Section 4 concludes and discusses the potential macro-prudential policy implications.

2 DYNAMIC MODELS OF SYSTEMIC RISK

This study proposes the dynamic copula approach to estimate the CoES defined by Adrian and Brunnermeier (2011) and aggregate SRISK introduced by Brownlees and Engle (2017) to measure systemic risk emanating from the balance-sheet items for each financial institution in the system. The approach also uses the Shapley value rule to assign the systemic risk contribution to each institution. In order to deal with the procyclicality of the financial system's activities and markets' poor assessment of systemic risk over time, the approach in this paper is completed by linking the measures of systemic risk in the financial sector with a large set of macrofinancial variables using the two-sided generalized dynamic factor model (GDFM) of Forni et al. (2000).

3 MULTI-CONDITIONAL EXPECTED SHORTFALL

Adrian and Brunnermeier (2011) defined the conditional expected shortfall $\boldsymbol{CoES_{q,t}^{sys/i}}$ as expected shortfall (ES) of the financial system at confidence level $\boldsymbol{q}$ conditional on some events of institution $\boldsymbol{i}$ at time $\boldsymbol{t}$. Thus $\boldsymbol{\Delta CoES_{q,t}^{sys/i}}$ denotes the difference between the ES of the financial system conditional on financial institution $\boldsymbol{i}$ being in a tail event and the ES of the financial system conditional on financial institution $\boldsymbol{i}$ being in a normal state. However, this pairwise model between the financial system and financial institution $\boldsymbol{i}$ might ignore the fact that several financial institutions could be in financial distress at the same time during a financial crisis. In order to measure the diverse scenarios resulting from the risk spillover effects among financial institutions during a financial crisis in this paper, the Multi-CoES is defined similar to Cao (2014):

$$Pr\ (r_t^{sys} \leq -CoVaR_{q,t}^{1,\dots,S}\ /\ C(r_t^1),\dots,C(r_t^S)) = q,$$

$$CoES_{q,t}^{1,\dots,S} = -E_{t-1}\ (r_t^{sys} | r_t^{sys} \leq -CoVaR_{q,t}^{1,\dots,S}),$$

where r_t^i is the return of institution i at time t, and $CoVaR_{q,t}^{1,\dots,S}$ is the VaR of the financial system return r_t^{sys} at confidence level q conditional on some event $\{\ C(r_t^1),\dots,C(r_t^S)\}$ of a set of institutions $\{1,\dots,S\}$ at time t. The negative sign is needed because VaR and ES are usually defined as a positive number. The contribution of the set of institutions $\{1,\dots,S\}$ to the risk in the financial system is denoted by:

$$\Delta CoES_{q,t}^{1,\dots,S} = CoES_{q,t}^{r^1 \leq VaR_q^1,\dots,r^S \leq VaR_q^S} - CoES_{q,t}^{r^1 \leq VaR_{0.5}^1,\dots,r^S \leq VaR_{0.5}^S}.$$

Therefore, $\Delta CoES_{q,t}^{1,\dots,S}$ denotes the difference between the CoES of the financial system conditional on a set of institutions $[s]$ being in a tail event and the CoES of the financial system conditional on the set of institutions $[s]$ being in a normal state.

The principles of multi-CoES are quite similar to those of standard CoES. However, the multi-CoES has three advantages. First, it allows for calculating the total contribution of systemic risk in the financial system which can be attributed to each financial institution via an allocation rule. Secondly, it allows for calculating the marginal contribution of financial institution i to the risk in the financial system for a given set of institutions $[s]$ already in distress. Finally, the multi-CoES can provide the systemic risk contribution of different groups of institutions which could be potentially useful for regulators.

2.2 THE DYNAMIC CONDITIONAL T-COPULA

Adrian and Brunnermeier (2011) use quantile regressions to estimate the time-varying CoVaR. This approach reduces the high dimensional model to a set of state variables and, as a result, the robustness of CoVaR also depends on the selected state variables. In order to avoid having to decide which state variables should be selected, Cao (2014) proposes a multi-t distribution with volatility modeled by TGARCH, and correlation modeled by DCC. However, the modeling of the dynamic multivariate distribution is of crucial importance, and any misspecification of the marginal distributions can lead to important biases in the dependence measure estimation. Correlation modeled by DCC is still linear correlation depending on both the marginal distributions and the copula, and is not considered to be a robust measure as a single observation can have an disproportionally strong impact.

The copulas provide a robust method of consistent estimation for dependence and are also very flexible (see e.g., Patton (2012) for a review). In light of the recent advancements in multivariate GARCH techniques for a large number of underlying securities, in this study, the DCC framework is extended to the Dynamic t-Copula and the Dynamic Grouped t-Copula which are good candidates that are especially tractable for high dimensions. The dynamic conditional t-copula is defined as follows:

$$C(\eta_1, \eta_{2,\dots,}\eta_n; R_t, v_t) = T_{R_t,v_t}\left(t_{v_t}^{-1}(\eta_1), t_{v_t}^{-1}(\eta_2), \dots, t_{v_t}^{-1}(\eta_n)\right),$$

where $\eta_i = F_i(\varepsilon_i)$ for $i = 1,2,\dots,n$ and $\varepsilon_t \sim iid(0,1)$ are the standardized residuals from the marginal dynamics, for example, AR(p)-GARCH(1,1) process. Misspecification of the marginal distributions can lead to significant biases in the estimation of dependence. In order to allow for flexible marginal distributions, this study does not specify marginal distributions, rather it adopts a semi-parametric form for the marginal distributions $F_i(\varepsilon_i)$ (see McNeil (1999) and McNeil and Frey (2000) for more details). R_t is the copula correlation matrix, and v_t is the degree of freedom. $t_{v_t}^{-1}(\eta_i)$ denotes the inverse of the t cumulative distribution function. R_t and v_t can be assumed to be constant, or a dynamic process through time. The simplest copula correlation dynamics considered in this study is the symmetric scalar model where the entire copula correlation matrix is driven by two parameters as in Engle (2002):

$$Q_t = (1 - \alpha_{dcc} - \beta_{dcc})\overline{Q} + \alpha_{dcc}(\varepsilon_{t-1}^{*}\varepsilon_{t-1}^{*'}) + \beta_{dcc}Q_{t-1},$$

Where $\alpha_{dcc} > 0, \alpha_{dcc} - \beta_{dcc} < 1$, $\varepsilon_i^{*} = t_{v_t}^{-1}(\eta_i = F_i(\varepsilon_i))$, $Q_t = |q_{ij,t}|$ is the auxiliary matrix driving the copula correlation dynamics, the nuisance parameters $\overline{Q} = T^{-1}(\varepsilon_t^{*}\varepsilon_t^{*'})$ with sample analog $\overline{Q} = T^{-1}\sum_{t=1}^{T}\varepsilon_t^{*}\varepsilon_t^{*'}$, so that R_t is a matrix of copula correlations $\rho_{ij,t}$ with ones on the diagonal, and $\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ij,t}}\sqrt{q_{ij,t}}}$.

In risk management, the tail dependence is very important. For the standard t-copula, the assumption of one global degree of freedom parameter may be over-simplistic and too restrictive for a large portfolio. Empirically, with more assets, the estimated degrees of freedom could easily become very large. As in a block correlation dynamic model, different degrees of freedom for different groups can be assumed, for example, corresponding to industries or ratings.

Consider now the following model. Let $Z_t \sim N_n(0, R_t)$, where R_t is an arbitrary linear correlation matrix, be independent of U, a random variable uniformly distributed on (0, 1). Furthermore, let G_v denote the distribution function of $\sqrt{v/\mathcal{X}_v^2}$. Partition $\{1, \dots, n\}$ into m subsets of sizes $s_1, \dots, s_m$. Let $R_t^k = G_{v_k}^{-1}(U)$ for $k = 1, \dots, m$. If

$$Y = (R_t^1 Z_1, \dots, R_t^1 Z_{s_1}, R_t^2 Z_{s_1+1}, \dots, R_t^2 Z_{s_1+s_2}, \dots, R_t^m Z_n)' ,$$

then the random vector $(Y_1, \dots, Y_s)$ has an s_1-dimensional t-distribution with $v_1$degrees of freedom and, for $k = 1, \dots, m-1$, $(Y_{s_1+\dots+s_{k+1}}, \dots, Y_{s_1+,\dots+s_{k+1}})'$ has an s_{k+1}-dimensional t-distribution with v_{k+1} degrees of freedom. The grouped t-copula is described in more detail in Daul et al. (2003).

For the calibration of, and simulation from, the grouped t-copula, there is no need for an explicit copula expression. The calibration of this model is identical to that of the t-distribution except that the ML-estimation of the m degrees of freedom parameters has to be performed separately on each of the m risk factor subgroups. Given that the correlation between the Gaussian copula correlation $Corr(\Phi^{-1}(\eta_i), \Phi^{-1}(\eta_j))$ and a t-copula correlation $Corr(t_v^{-1}(\eta_i), t_v^{-1}(\eta_j)$ is almost equal to one, R_t can be well approximated by the R_t^{Gaussian} from the dynamic Gaussian Copula. The dynamic multivariate Gaussian copula is defined similarly to the t-copula as follows: $C(\eta_1, \eta_{2,\dots,}\eta_n; R_t^{\text{Gaussian}}) = \Phi_{R_t^{\text{Gaussian}}}(\Phi^{-1}(\eta_1), \Phi^{-1}(\eta_2), \dots, \Phi^{-1}(\eta_n))$. The copula correlation dynamics are also driven by the two parameters listed above for the t-copula. However, $\varepsilon_i^{*} = \Phi^{-1}(\eta_i = F_i(\varepsilon_i))$. In the dynamic grouped t-copula application, a two-step algorithm is adopted for convenience, which means R_t is first estimated from the dynamic Gaussian copula, and then degrees of freedom v_k are recovered for each group from the grouped t-copula with R_t^k fixed from the first step. While the quasi-likelihood function for dynamic Gaussian copula could be computed, in high dimensions convergence is not guaranteed and sometimes it fails or is sensitive to the starting values. To avoid the intrinsic biases in the usual likelihood estimator when the cross-section is large, in this study, the dynamic Gaussian copula is estimated by maximizing the composite likelihood proposed by Engle, Shephard and Sheppard (2008).

Using conditional dynamic copulas, it is relatively easy to construct and simulate multivariate distributions built on marginal distributions and a dependence structure. The GARCH-like dynamics in both variance and copula correlation offers multi-step-ahead predictions of a portfolio's returns simultaneously. In this study, the one-step-ahead simulation is explored. The CoES and ΔCoES can be easily obtained by these simulated returns for each asset. The multi-period ahead CoES and ΔCoES can also be obtained by simulating multi-periods ahead in a similar way.

2.3 SHAPLEY VALUE METHODOLOGY

In this paper, the Shapley value methodology is employed as an allocation rule to assign a systemic risk contribution to each institution in the financial system. Since systemic risk can be distributed among financial institutions fairly, the additivity or efficiency property of Shapley values has a big advantage for macro-prudential policy. An introduction to Shapley values is presented in Drehmann and Tarashev (2013) and Cao (2014). The Shapley value of ΔCoES can be defined as:

$$Shapley_i(\Delta CoES) = \sum_{S \subseteq N\{i\}} \frac{|S|!\,(n-|S|-1)!}{n!} \big(\Delta CoES(S \cup \{i\}) - \Delta CoES(S)\big),$$

where ΔCoES is the "characteristic function" considered, and n is the total number of financial institutions and the sum extends over all subsets S of N not containing financial institution i. This formula can be interpreted as the expected marginal contribution of financial institution i over the set of all permutations of the set of financial institutions.

2.4 THE EXPECTED CAPITAL SHORTAGE

The expected capital shortage introduced by Brownlees and Engle (2017) can also be simulated in the framework of dynamic conditional grouped t-copula. Consider a panel of financial institutions indexed by $i = 1, \dots, I$ observed at times $t = 1, \dots, T$. For each financial institution, D_i and W_i denote respectively the book value of its debt and the market or book value of its equity. Assuming that prudential management would restrict each institution to maintain equity as a fraction k of its total assets, the expected capital shortage can be defined as:

$$CS_{it+h|t} = -kD_{it} + (1-k)W_{it}MES_{it+h|t}(VaR_q^{R_{m\,t+h:t}})$$

where $MES_{it+h|t}\big(VaR_q^{R_{m\,t+h:t}}\big) = E_t(exp(R_{it+h:t})|R_{m\,t+h:t} < -VaR_q^{R_{m\,t+h:t}})$ is the tail expectation of the firm equity returns conditional on the systemic event expressed by $VaR_q^{R_{m\,t+h:t}}$ at $q\% - quantile$ of the conditional probability distribution of $R_{m\,t+h:t}$, and the return of total equity is denoted as the log return. The aggregated systemic risk of expected capital shortage – SRISK described by Brownlees and Engle (2017) in the financial system is

$$SRISK_t = \sum_{i=1}^{I} \max{(0, CS_{it})},$$

SRISK is a function of a firm's size, leverage, and its expected equity loss given a market downturn. It can be thought of as the total amount of capital that the government would have to provide to bailout the financial system in the event of a crisis. Clearly $MES_{it+h|t}\big(VaR_q^{R_{m\,t+h:t}}\big)$ depends on modeling a dynamic distribution. Brownlees and Engle (2017) propose several models only for a bivariate distribution. In this paper, the dynamic high-dimensional multivariate distribution modeled by the time varying grouped t-copula provides a more flexible way to assess the aggregated systemic risk of expected capital shortage under multiple adverse scenarios.

2.5 THE GENERALIZED DYNAMIC FACTOR MODEL ANALYSIS

Following Jin and Nadal De Simone (2012), this paper uses the two-sided GDFM of Forni et al. (2000) to examine total asset and equity emanating from the macro environment and from banks' and investment funds' interconnectedness. The GDFM of Forni et al. (2000 & 2005) enables the efficient estimation of the common and idiosyncratic components of very large data sets. The GDFM assumes that each time series in a large data set is composed of two sets of unobserved components. First, the common components are driven by a small number of shocks that are common to the entire panel - each time series, has its own loading associated with the shocks. Second, the idiosyncratic components are specific to a particular variable and linearly orthogonal with the past, present, and future values of the common shocks. The common component of assets or equity values is best interpreted as the result of the underlying unobserved systemic risk process, and it is thus expected that it will be relatively persistent. The idiosyncratic component instead reflects local aspects of total assets or equity that are transient especially in the short term. However, it is far from negligible. This part of the integrated framework, therefore, links the dynamic behaviour of total assets or equity and the derived systemic risk measures to the evolution of the market as described by the macro-financial information matrix.

3 ECONOMIC APPLICATION

In this section, the different data sets of European banking groups, Luxembourg banks and investment funds are described, and the univariate model is briefly discussed. The proposed conditional dynamic grouped t-copula is applied to total equity returns and their corresponding common components estimated from the GDFM. Subsequently, several empirical measures of systemic risk are estimated, and the risk spillovers between banking groups, Luxembourg banks and investment funds are fully explored. Finally, the potential macroeconomic drivers of aggregate SRISK are investigated.

3.1 DATA

This study is applied to 30 major European banking groups, their respective 31 subsidiaries active in Luxembourg, two domestic Luxembourg banks, as well as 232 investment funds. All seven types of investment funds reported by national central banks of the Eurosystem to the ECB (Equity Funds, Bond Funds, Mixed Funds, Real Estate Funds, Hedge Funds, Other Funds and Money Market Funds) are also included in the analysis. The database contains quarterly balance sheet information from March 2003 to December 2016 for Luxembourg banks. However, for investment funds, the data is only available for the period from December 2008 to December 2016. All the Luxembourg banks and investment funds considered are unlisted, so quarterly book value data from the Banque centrale du Luxembourg's database are used. The 31 subsidiaries registered in Luxembourg represent about 55% of the total assets of the Luxembourg banking sector. When the two domestic Luxembourg banks are added to the list, the database represents nearly 62% of the total assets of the Luxembourg banking sector. Out of almost 4000 investment funds, the 232 investment funds selected by the rank-size distribution represent about 74% of the total assets of the Luxembourg investment fund sector.

For banks and investment funds, the book value equity is the difference between total assets and total liabilities. For European banking groups, stock prices, short-term borrowing including securities sold under repo agreement, long-term debt, and current number of shares outstanding are downloaded from Bloomberg; and the bank's asset values are estimated by the Merton model. The macroeconomic database used for the GDFM consists of government bond yields, stock price indices, industrial production, employment, GDP, consumer prices, housing prices, exchange rates, liquidity spreads, loans to households, loans to non-financial corporations, etc. from Bloomberg, DataStream, the BIS, Eurostat, and the ECB. The database comprises 234 series including three measures of the credit-to-GDP gap for the euro area, the UK and the US.

Figure 1 provides visual insights into the boom and bust of the financial sector. The figure shows the cumulative quarterly returns at median and interquartile range for each sector in the period of 2003-2016 and 2009-2016 respectively. The right panels in Figure 1 present the results of their corresponding common components. Between July 2005 and June 2007 the banking groups had steep growth, and starting from July 2007 their cumulative returns fell dramatically, hit the bottom at the beginning of 2009 and started a slow recovery that was interrupted by the European crisis in 2012 and Chinese stock market turbulence in 2015-16. However the interquartile range of cumulative returns of Luxembourg banks climbed up slowly until the end of 2009, and remained flatter and more dispersed later. In the short period from 2009, the performance of Luxembourg banks was muted with only marginal growth at the end of 2014. In contrast, Luxembourg investment funds had recorded a steady growth of total equities in the interquartile range over the whole sample period.

3.2 IN-SAMPLE ANALYSIS

To model the dynamic systemic risk, and to match to the monthly data of European banking groups and macroeconomic variables, the quarterly book-value data are converted to monthly frequency by cubic spline interpolation. An autoregressive model of order six, AR(6) is used to capture the return dependence over two quarters, a simple GARCH(1,1) model is employed to capture the second moment dependence for each financial institution, and a dynamic conditional grouped t-copula is used to model the dependence of these marginal distributions of all standardized residuals. The advantage of the composite likelihood approach is that the longest time span for each institution-pair can be used when estimating the model parameters, thus making the best possible use of a cross-section of data time series of unequal length.

Figure 2 shows the volatilities of equity returns at median and interquartile range for each sector in the two periods. The quarterly volatilities are aggregated by summing up the monthly volatilities in each quarter. The profiles of volatilities all look similar though at different scales. It suggests that the book-value equity obtained via the fair value or mark-to-market accounting rule reflects underlying market events. The volatilities of Luxembourg banks were more dispersed, mainly driven by their idiosyncratic components, while the common components for investment funds were more volatile, and the volatilities of investment funds have declined slowly since 2010.

Figure 3 shows the copula correlation of equity returns at median and interquartile range between these three sectors in the two periods. The copula correlations within a given sector ranked about 0.4 for banking groups, 0.2 for investment funds with a wider dispersion, and 0.1 for Luxembourg banks. However, the copula correlations across sectors were around zero except for those around 0.1 between banking groups and investment funds which is consistent with the unconditional correlations.

3.3 FORWARD-LOOKING ES AND ΔCOES

In order to fully examine the forward-looking measures of systemic risk through time, the parameters of the AR(6)-Garch(1,1), grouped t-copula and marginal semi-parametric form are all fixed as those estimated from the full sample, then all equity returns are simulated one-step-ahead. The measures of systemic risk constructed in this semi-forward-looking way still predict future, rather than contemporaneous events.

Figure 4 depicts the quarterly ES at $q = 0.05$ of equity returns at the median and interquartile range for these three sectors in the two periods. ES values for banking groups were higher around 25% on average and followed market events closely; however for Luxembourg banks, ES values were more volatile around 4% with the 25% quantile above zero, and reflected their important idiosyncratic components. In contrast, the ES values for investment funds were a little lower around 2% and matched well with the European sovereign debt crisis and Chinese market turmoil.

In order to better understand the risk spillovers of equity returns across these three sectors, Table 1 outlines the key descriptive statistics of forward-looking ΔCoES of the value-weighted portfolios of three sectors conditional on events of each institution from these sectors for the period from December 2009 to December 2016. The ranking of risk transmission is based on the range of Quantile 75% - Max which is the most important range for systemic risk monitoring. For instance, ranking by the median of Max of ΔCoES from top to bottom gives the following: banking groups (11.34%), investment funds (9.98%), Luxembourg banks (7.03%) for the portfolio of banking groups; Luxembourg banks (2.39%), investment funds (1.76%), banking groups (0.86%) for the portfolio of Luxembourg banks; investment funds (4.97%), banking groups (3.09%), Luxembourg banks (2.51%) for the portfolio of investment funds. The results are the same if based on other descriptive statistics and those of common components. It suggests that in equity returns, the expected loss of Luxembourg banks was more sensitive to the adverse events from investment funds than from banking groups, and the expected loss of investment funds (banking groups) was more sensitive to the adverse events from banking groups (investment funds) than from Luxembourg banks.

3.4 FORWARD-LOOKING SHAPLEY-ΔCOES

Table 2 provides the summary statistics of the estimated forward-looking Shapley-ΔCoES series and standard-ΔCoES series for Luxembourg's banking sector conditional on simultaneous distress in several panels of six Luxembourg's O-SIIs, four parent European G-SIBs, and 6 investment fund categories respectively during 2009-2016. The total risk, obtained by summing the marginal contribution of each constituent, gives the overall systemic risk contribution to the system when all constituents in the considered panel are in distress. The Shapley-ΔCoES of each constituent presents its own expected marginal contribution to the total risk which equals the sum of the Shapley values of each component of the system. Thus the total systemic risk can be attributed among constituents precisely. This additive property is desirable since it may help to facilitate the calibration of macro-prudential tools at the component level. The G-SIBs and O-SIIs can be ranked by their Shapley-ΔCoES values. For example, on average over this period, among the four G-SIBs (the six O-SIIs), the highest marginal systemic risk contribution was from BG A (Lux E), whereas, based on their common components of Shapley-Δ CoES, it was from BG C (Lux D). The standard-ΔCoES measure is calculated on the adverse events of the considered institution independently from others. Thus the sum of the standard-ΔCoES measure is different from the total systemic risk in case of the simultaneous distress of all constituents in the considered panel. Actually it was larger than the total risk in the panel of O-SIIs, and was smaller than the total risk in the panel of G-SIBs. This is because the correlations between O-SIIs were much smaller than those between G-SIBs in this period. If the authorities access the systemic risk based solely on standard ΔCoES, they might penalize the economy without gauging the potential contagion that an individual institution contributes to the financial system.

In the previous section, the analysis of ΔCoES of Luxembourg banks is only conditional on individual investment funds. Here the estimation of Shapley-ΔCoES values of these six investment fund categories can further help to rank their marginal contributions to the total risk of the Luxembourg banking sector by the fair and efficient allocation rule of Shapley values in mean or median. From highest to lowest, they are ranked as follows: MM Funds, RE Funds, Bond Funds, Mixed Funds, Hedge Funds, and Equity Funds. In contrast, according to their common components, the ranking from top to bottom is: MM Funds, RE Funds, Mixed Funds, Bond Funds, Equity funds and Hedge Funds. It suggests that the idiosyncratic portion of the marginal contributions to total risk for some categories played an important role during this period. Furthermore, the marginal contribution to the total risk from bond funds, mixed funds and hedge funds became more important in 2016 given the persistent low interest rate environment in the euro area[71].

3.5 FORWARD-LOOKING SRISK AND ITS ECONOMIC DETERMINANTS

In this section, the aggregate SRISK for all three sectors is explored at several difference levels, k (prudential ratios), and then the marginal effects from the market indices of 15 countries are examined. Finally, the macroeconomic determinants of the aggregate SRISK are fully assessed.

3.5.1 FORWARD-LOOKING SRISK

Figure 5 depicts the aggregate SRISK for 32 Luxembourg banks and 30 banking groups and 232 investment funds in the two periods. The SRISK series is computed using k = 8%, 12%, 22% and 33% respectively for both Luxembourg banks and banking groups. The profile of SRISK values for banking groups were mainly driven by the global financial crisis of 2007-2009 and the European crisis around 2012. As for the SRISK of Luxembourg banks, the series increased starting in 2004, and has maintained a higher level since the middle of 2005 and peaked around 2007-2008. It declined quickly from the middle of 2008, a half year before the decline of the banking groups. It became more sustained since the middle of 2010, and got down to a level lower than 2004, even without the dramatic impacts from the European sovereign debt crisis around 2012. In addition, considering the marginal contributions from 15 counties to the aggregate SRISK of Luxembourg banks and their parent banking groups in the period of 2009-2016[72], France and Italy mattered most for banking groups. However, Luxembourg banks were more vulnerable to the systemic risk events from Luxembourg, the Netherlands, the United States, Denmark, and the United Kingdom. This result suggests that the aggregate SRISK of Luxembourg banks was affected differently by country compared with those of banking groups.

Out of all monthly data points from the 232 investment funds[73], at least 98.3% (90%) have a fraction of equity over total assets more than 0.6 (0.9). In contrast, for these 33 Luxembourg banks, 97.4% of all data points have a fraction of equity over their total assets less than 0.33. The aggregate SRISKs for investment funds at k = 60%, 70%, 80%, and 90% are also explored. The values were very volatile with a long-term uptrend roughly until the middle of 2015, illustrating the important potential build-up of vulnerabilities in the investment fund sector.

3.5.2 FORWARD-LOOKING SRISK'S ECONOMIC DETERMINANTS

In an effort to better understand the forward-looking SRISK measure discussed in this paper, linear regressions of SRISK measures on various macroeconomic determinants were investigated for banking

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72 This table is not shown here to save space.

73 In Luxembourg, UCITS and non-UCITS are regulated by a set of national laws that have implemented the European Commission's UCITS IV Directive, the Sicar Law (Luxembourg, 2004), the Specialized Investment Funds Law (Luxembourg, 2007, 2010), and the 2013 Law that implemented the European Commission's Alternative Investment Fund Managers Directive (AIFMD). This regulatory framework is a comprehensive set of rules regarding the type of investors who can access different types of investment funds, the eligible investments, investment restrictions, the asset valuation approach and its frequency, funds' permitted leverage and exposure. In accordance with article 11 (2), article 28 (1) b) of the Law of 20 December 2002 relating to Undertakings for Collective Investment (as amended) - ("the Law"), a UCITS may borrow up to 10% of its NAV on a temporary basis (i.e. on a non-revolving basis) to meet redemptions. For non-UCITS funds which are to be sold to retail investors, total borrowing for investment purposes must not exceed 25 per cent of net assets.

groups, Luxembourg banks in the longer period, and all three sectors in the shorter period. The selected macroeconomic variables include the obvious measures of risk in the equity and CDS markets, government term structures and a number of macro variables which are reasonable additional metrics of the state of the economy, as well as a measure of liquidity risk. More precisely the set of euro area explanatory variables considered consists of the following variables: the log of GDP in current prices, the log of HICP all-items, the log of unemployment rates, consumer confidence indicator, three-month short-term interest rates, interest rate spread (10YR interest rates - 3M interest rates), liquidity spread (3M Euribor rates - 3M Germany T-bill rates)[74], the log of property prices, the log of loans to households, the log of loans to non-financial corporations, the log of market price index, the log of bank price index, the log of bank sector CDS index, the log of VSTOXX volatility index, the log of commodity S&P GSCI energy index, the log of Japanese yen, and the log of US dollar.

In order to avoid spurious regression results, the analyses were performed using short-term deviations and first differences. The short-term deviation is defined as the difference between a variable and its long-run trend extracted by Baxter-King filter.[75] The first difference of a variable also includes the change in its long-run trend. Running the regressions in short-term deviations enables us to track the short-term effects along their long-run trends, while running the regressions in the differences allows us to address the impact of persistence on our variables.

Table 3 reports the regression results of aggregate SRISK for both 32 Luxembourg banks and 30 banking groups in the period of 2003-2016. The SRISK series is computed using k = 8% or 12% respectively. Regressions are run in short-term deviations and first differences with Newey-West robust standard errors using a Bartlett kernel. A bold coefficient value indicates significance at the 95% level, whereas an italic value indicates significance at the 90% level. For banking groups, the results convey that the most relevant determinants of SRISK in the short-term deviations for both cases were the interest rate spread, bank price index, commodity S&P GSCI energy index, and consumer confidence indicator with signs in line with economic intuition. As for the results of the first differences, the most relevant determinants of SRISK were interest rate spread and market price index.

As regards Luxembourg banks, in the case of $\boldsymbol{k} = 0.08$, the most relevant determinants of SRISK in the short-term deviations were market price index, bank price index, Japanese yen, liquidity spread, and marginally VSTOXX volatility index. In the case of $\boldsymbol{k} = 0.12$, the most relevant determinants of SRISK were consumer confidence indicator, unemployment rate, loans to non-financial corporations, liquidity spread, commodity S&P GSCI energy index, Japanese yen, and marginally bank price index. It is interesting to note that without considering the long run trends, when loans to non-financial corporations were high, the expected capital shortage was actually low. As for the results of the first differences, the most relevant determinants of SRISK were interest rate spread, liquidity spread and commodity S&P GSCI energy index in the case of $\boldsymbol{k} = 0.08$, and liquidity spread, commodity S&P GSCI energy index and Japanese yen in the case of $\boldsymbol{k} = 0.12$. Since Luxembourg banks are liquidity suppliers to the parent institutions, the determinants underlying the SRISK of Luxembourg banks might be very different from those of banking groups.

Table 3 also reports the regression results of aggregate SRISK for the investment fund sector in the case of $\boldsymbol{k}$ = 90% and 70% respectively in the period of 2009-2016. The results of the regression in

74 This spread represents the European equivalent of the TED spread, which is the difference between the interest rates on interbank loans and on short-term government debt ("T-bills"). Market participants look at this difference as a proxy for short-term liquidity risk. Clearly, it cannot be excluded that the proxy also captures some credit risk, and one could even argue an implicit government guarantee. However, the correlation between this measure and other proxies for liquidity also used in the literature, such as Euribor-OIS 3M spread, is almost 94%.

75 The bandpass filter overcomes to some extent the well known drawbacks of the Hodrick-Prescott filter.

short-term deviations show that GDP, 3M interest rate, bank price index, commodity S&P GSCI energy index, and marginally VSTOXX volatility index and Japanese yen were the significant determinants in the case of $\boldsymbol{k}$ = 90%, whereas GDP, 3M interest rate, VSTOXX volatility index, commodity S&P GSCI energy index, US dollar and marginally bank price index and property price in the case of $\boldsymbol{k}$ = 70%. As for the results of the first difference, it is interesting to note that the most relevant determinants of SRISK were interest rate spread in the case of $\boldsymbol{k}$ = 0.90, and interest rate spread, US dollar, and marginally GDP and property prices in the case of $\boldsymbol{k}$ = 0.70.

4 CONCLUSIONS AND POSSIBLE MACRO-PRUDENTIAL POLICY IMPLICATIONS

In this paper, the idea of "Mark-to-Systemic-Risk" is first applied to the major balance sheet items for both Luxembourg banks and investment funds. Their parent banking groups with market data are also added for comparison. This study characterizes systemic risks and risk spillovers in equity returns for 33 Luxembourg banks, their 30 parent banking groups and 232 investment funds in the periods of 2003-2016 and 2009-2016 respectively. A dynamic grouped t-copula approach is proposed to estimate the forward-looking systemic risk measures ΔCoES, Shapley-ΔCoES, SRISK and CCR emanating from the balance-sheet items for each financial institution in the system, and the Shapley value rule is used to rank the systemic risk contributions from 6 Luxembourg O-SIIs, 4 parent European G-SIBs, and 6 investment fund categories. In order to deal with the procyclicality of the financial system activities and markets' generally poor assessment of systemic risk over time, the approach of this paper is also completed by linking the measures of systemic risk in the financial sector with a large set of macrofinancial variables using the two-sided GDFM of Forni et al. (2000).

Among other findings, six important stylized facts are documented in this study. First, in terms of equity returns, investment funds performed much better than both banking groups and Luxembourg banks, while Luxembourg banks revealed a diminished performance in the period of 2009-2016. Second, the similar profiles of volatilities for banking groups, Luxembourg banks and investment funds prove that the book-value equities by the fair value or mark-to-market accounting rule do reflect market events in a timely manner. Third, the dependencies of investment funds were lower than those of banking groups, however, they were still higher than those of Luxembourg banks. The dependencies were higher within their own sectors than those between sectors, and the cross-sectional dependencies were around zero except for those between banking groups and investment funds. Fourth, measured by ΔCoES of equity returns, Luxembourg banks were more sensitive to the adverse events from investment funds than banking groups, and investment funds were more sensitive to the adverse events from banking groups than from Luxembourg banks. Fifth, ranked by Shapley-ΔCoES values, money market funds had the highest marginal contribution to the total risk of Luxembourg banks while equity funds shared the least, and bond funds, mixed funds and hedge funds became more important toward the end of 2016 given the prolonged low interest rate environment. Finally, the aggregate SRISK for Luxembourg banks, banking groups, and investment funds was fully explored. The underlying macroeconomic determinants of SRISK of the three sectors are different. For instance, the changes in aggregate SRISK of banking groups were mainly driven by the interest rate spread and market price index, however, for Luxembourg banks they were driven by the interest rate spread, liquidity spread and commodity S&P GSCI energy index. Additionally, as regards the marginal contributions to the aggregate SRISK in the period of 2009-2016, France and Italy mattered most for banking groups, however, Luxembourg banks were more vulnerable to systemic risk events from Luxembourg, the Netherlands, the United States, Denmark, and the United Kingdom.

The approach could provide a valuable addition to the traditional toolkit for assessing time varying risks to the stability of the financial system. It also represents a tool that can track changes in forward-looking systemic risks and risk spillovers in the financial system in the context of a build-up of vulnerabilities. Given that this paper's approach explicitly links systemic risk measures with the state of the macroeconomy in order to determine their underlying macro factors, it helps to facilitate a more informed discussion of the potential measures to address the observed vulnerabilities. In particular, the approach may be useful for assisting the calibration of the instruments of the macro-prudential toolkit.

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Table 1:

Matrix of Forward-Looking ΔCoES in Percentage

		MIN	MEAN	Q25%	MEDIAN	Q75%	MAX	MIN	MEAN	Q25%	MEDIAN	Q75%	MAX
		PORTFOLIO OF BANKING GROUPS						COMMON COMPONENTS					
BANKING GROUPS	MEDIAN	0.83	8.95	7.78	9.74	10.67	11.34	5.30	13.28	12.91	14.71	15.08	15.09
	Q25%	-0.65	7.30	6.60	7.99	8.90	9.38	2.84	11.15	10.39	11.87	12.17	12.19
	Q75%	1.54	9.92	8.87	10.89	12.13	12.58	8.81	17.88	18.01	19.69	20.35	20.36
LUXEMBOURG BANKS	MEDIAN	-8.16	-0.25	-3.16	-0.10	2.16	7.03	-21.78	-4.29	-8.76	-3.77	1.84	8.91
	Q25%	-10.24	-0.68	-3.64	-0.52	1.70	5.76	-27.82	-5.36	-10.68	-5.17	0.94	5.58
	Q75%	-6.38	0.10	-2.12	0.29	3.55	9.79	-14.47	-2.79	-6.85	-1.86	2.84	11.56
INVESTMENT FUNDS	MEDIAN	-11.91	2.38	0.26	3.31	5.65	9.98	-16.56	2.50	0.24	3.23	5.93	12.50
	Q25%	-15.32	1.88	-0.04	2.37	4.16	8.97	-25.27	1.76	-0.35	2.21	3.91	8.59
	Q75%	-8.82	4.64	2.13	5.57	8.08	12.00	-11.48	3.47	0.86	5.80	9.10	16.75
		PORTFOLIO OF LUXEMBOURG BANKS						COMMON COMPONENTS					
BANKING GROUPS	MEDIAN	-1.27	-0.32	-0.63	-0.34	-0.03	0.87	-1.84	-0.94	-1.25	-1.00	-0.66	0.19
	Q25%	-1.57	-0.41	-0.75	-0.40	-0.11	0.56	-2.06	-1.09	-1.51	-1.13	-0.80	0.06
	Q75%	-1.16	-0.25	-0.54	-0.26	0.10	1.05	-1.46	-0.76	-1.04	-0.76	-0.45	0.41
LUXEMBOURG BANKS	MEDIAN	-0.53	1.00	0.51	1.01	1.49	2.39	-0.67	0.81	0.31	0.86	1.42	1.77
	Q25%	-0.83	0.88	0.41	0.80	1.38	2.10	-0.83	0.70	0.26	0.73	1.17	1.51
	Q75%	-0.37	1.19	0.65	1.23	1.89	2.80	-0.46	1.05	0.46	1.09	1.75	2.11
INVESTMENT FUNDS	MEDIAN	-1.86	-0.07	-0.50	-0.04	0.33	1.76	-1.93	-0.07	-0.48	-0.07	0.30	1.50
	Q25%	-2.21	-0.28	-0.81	-0.35	0.25	1.50	-2.20	-0.25	-0.78	-0.27	0.19	1.30
	Q75%	-1.64	0.07	-0.36	0.07	0.49	2.00	-1.39	0.08	-0.35	0.10	0.54	1.87
		PORTFOLIO OF INVESTMENT FUNDS						COMMON COMPONENTS					
BANKING GROUPS	MEDIAN	-0.73	0.97	0.15	0.75	1.64	3.09	-0.34	0.51	0.17	0.54	0.86	1.23
	Q25%	-0.93	0.69	-0.16	0.48	1.32	2.54	-0.59	0.36	0.09	0.37	0.62	1.06
	Q75%	-0.60	1.10	0.34	0.98	1.85	3.96	-0.18	0.71	0.32	0.81	1.16	1.65
LUXEMBOURG BANKS	MEDIAN	-1.40	-0.04	-0.77	-0.40	0.33	2.51	-1.54	-0.09	-0.49	-0.10	0.30	1.34
	Q25%	-1.54	-0.23	-0.87	-0.49	0.14	1.90	-2.34	-0.16	-0.69	-0.24	0.23	1.13
	Q75%	-1.23	0.23	-0.69	-0.16	0.77	3.16	-1.30	0.02	-0.36	-0.02	0.39	1.92
INVESTMENT FUNDS	MEDIAN	-1.55	2.42	0.95	2.50	4.19	4.97	-1.86	1.17	0.63	1.51	1.89	1.95
	Q25%	-1.80	2.00	0.57	2.09	3.10	3.64	-2.27	0.93	0.50	1.19	1.51	1.57
	Q75%	-1.27	3.27	1.25	3.33	5.64	6.18	-1.63	1.46	0.87	1.88	2.36	2.43

Note: This table reports the key descriptive statistics of Forward-looking ΔCoES of the value-weighted financial systems which consists of 30 banking groups, 33 Luxembourg banks, and 232 investment funds respectively conditional on events of each financial institution in these three sectors in the sample period from December, 2009 to December, 2016.

Source: BCL

Table 2:

Shapley - ΔCoES and Standard ΔCoES in Percentage

	SHAPLEY VALUE							STANDARD VALUE						
	MEAN	STD	MIN	Q25%	MEDIAN	Q75%	MAX	MEAN	STD	MIN	Q25%	MEDIAN	Q75%	MAX
BG A	0.26	0.39	-0.60	-0.01	0.36	0.58	0.83	0.22	0.60	-1.44	-0.10	0.37	0.57	1.17
BG B	0.11	0.31	-0.61	-0.11	0.10	0.35	0.61	-0.24	0.35	-0.83	-0.44	-0.32	-0.07	0.52
BG C	-0.59	0.35	-1.44	-0.80	-0.62	-0.32	0.10	-0.51	0.45	-1.37	-0.77	-0.56	-0.23	0.52
BG D	0.05	0.37	-0.84	-0.10	0.21	0.33	0.68	-0.05	0.59	-1.26	-0.34	-0.01	0.17	1.53
Total Risk (Sum)	-0.17	0.57	-1.58	-0.47	0.02	0.20	0.78	-0.58	1.70	-3.98	-1.15	-0.52	0.24	3.61
Lux A	0.25	0.18	-0.14	0.14	0.29	0.37	0.62	2.04	0.61	0.45	1.64	2.12	2.47	3.13
Lux B	0.06	0.23	-0.50	-0.06	0.12	0.18	0.59	1.60	0.67	0.37	1.14	1.44	1.95	3.09
Lux C	-0.25	0.39	-0.96	-0.50	-0.26	0.05	0.49	0.84	1.09	-1.16	-0.06	0.88	1.49	3.23
Lux D	-0.36	0.34	-1.16	-0.46	-0.33	-0.17	0.20	1.40	0.32	0.79	1.14	1.41	1.63	2.04
Lux E	0.26	0.13	-0.01	0.18	0.26	0.35	0.53	2.21	0.51	1.17	1.95	2.28	2.50	3.40
Lux F	0.00	0.36	-1.06	-0.15	0.11	0.27	0.44	1.84	0.70	0.45	1.23	1.95	2.22	3.18
Total Risk (Sum)	-0.03	0.08	-0.35	-0.00	0.00	0.00	0.00	9.93	2.72	4.96	8.66	9.78	11.52	15.95
Equity Funds	-0.13	0.14	-0.32	-0.24	-0.15	-0.04	0.27	-0.48	0.61	-1.61	-0.80	-0.47	-0.24	1.08
Bond Funds	-0.01	0.18	-0.36	-0.10	0.01	0.11	0.31	-0.14	0.82	-1.77	-0.81	-0.12	0.24	1.66
Mixed Funds	-0.04	0.13	-0.27	-0.13	-0.03	0.07	0.26	-0.09	0.65	-1.46	-0.57	-0.15	0.21	1.40
Real Estate Funds	0.03	0.22	-0.45	-0.13	0.03	0.19	0.47	-0.11	0.60	-1.77	-0.46	-0.19	0.17	1.23
Hedge Funds	-0.04	0.18	-0.37	-0.18	-0.06	0.06	0.41	-0.10	0.72	-1.15	-0.68	-0.22	0.26	1.69
Money Market Funds	0.21	0.22	-0.20	0.05	0.18	0.33	0.76	0.38	0.51	-0.94	0.07	0.37	0.70	1.43
Total Risk (Sum)	0.02	0.03	-0.01	-0.00	0.00	0.04	0.12	-0.54	2.37	-4.85	-2.03	-1.05	1.96	4.12
	COMMON COMPONENTS													
BG A	-0.26	0.23	-0.55	-0.46	-0.27	-0.11	0.41	-1.15	0.54	-2.11	-1.56	-1.26	-0.72	0.03
BG B	-0.72	0.36	-1.77	-0.96	-0.73	-0.61	0.15	-1.64	0.54	-2.83	-2.04	-1.51	-1.22	-0.75
BG C	-0.22	0.22	-0.68	-0.37	-0.22	-0.07	0.24	-0.85	0.36	-1.61	-1.16	-0.84	-0.58	-0.11
BG D	-0.44	0.33	-1.52	-0.71	-0.37	-0.20	0.18	-1.33	0.58	-2.43	-1.93	-1.25	-0.98	-0.33
Total Risk (Sum)	-1.63	0.76	-3.28	-2.21	-1.64	-1.11	-0.26	-4.98	1.67	-8.52	-6.08	-4.87	-3.68	-2.08
Lux A	-0.01	0.13	-0.36	-0.08	0.02	0.07	0.23	1.29	0.47	0.56	0.95	1.20	1.54	2.27
Lux B	0.08	0.15	-0.23	-0.04	0.10	0.18	0.37	1.41	0.56	0.62	0.94	1.36	1.78	2.56
Lux C	-0.36	0.25	-0.84	-0.56	-0.32	-0.14	-0.02	0.51	0.47	-0.40	0.13	0.55	0.86	1.47
Lux D	0.27	0.07	0.13	0.23	0.26	0.31	0.43	1.82	0.41	1.16	1.50	1.76	2.11	2.73
Lux E	-0.08	0.20	-0.49	-0.22	-0.11	0.10	0.26	1.11	0.52	0.23	0.74	1.07	1.36	2.20
Lux F	0.04	0.17	-0.42	-0.02	0.06	0.17	0.25	1.63	0.47	0.86	1.29	1.59	1.89	2.72
Total Risk (Sum)	-0.05	0.07	-0.24	-0.11	-0.00	-0.00	0.00	7.77	2.00	4.84	6.28	7.64	8.74	12.16
Equity Funds	-0.11	0.16	-0.37	-0.22	-0.15	-0.03	0.25	-0.45	0.45	-1.57	-0.77	-0.44	-0.16	0.45
Bond Funds	-0.07	0.14	-0.43	-0.12	-0.06	0.04	0.11	-0.48	0.40	-1.46	-0.73	-0.46	-0.25	0.43
Mixed Funds	0.01	0.12	-0.27	-0.09	0.02	0.09	0.25	-0.09	0.53	-1.49	-0.42	-0.23	0.29	0.84
Real Estate Funds	0.19	0.17	-0.08	0.07	0.19	0.28	0.80	0.28	0.67	-0.88	-0.16	0.07	0.86	1.65
Hedge Funds	-0.23	0.30	-0.99	-0.49	-0.23	-0.02	0.24	-0.69	1.17	-3.24	-1.51	-0.56	-0.05	1.67
Money Market Funds	0.22	0.20	-0.08	0.08	0.16	0.40	0.72	0.06	0.68	-1.27	-0.44	0.18	0.53	1.45
Total Risk (Sum)	0.01	0.03	-0.00	-0.00	0.00	0.00	0.13	-1.36	2.68	-5.49	-3.23	-2.01	-0.17	4.30

Note: This table reports the key descriptive statistics of Shapley-ΔCoES and Standard ΔCoES for 6 Luxembourg's Other Systemically Important Institutions (OSIIs), 4 Global Systemically Important Banks (G-SIBs), and 6 investment fund categories in the sample period from December, 2009 to December, 2016.

Source: BCL

Table 3:

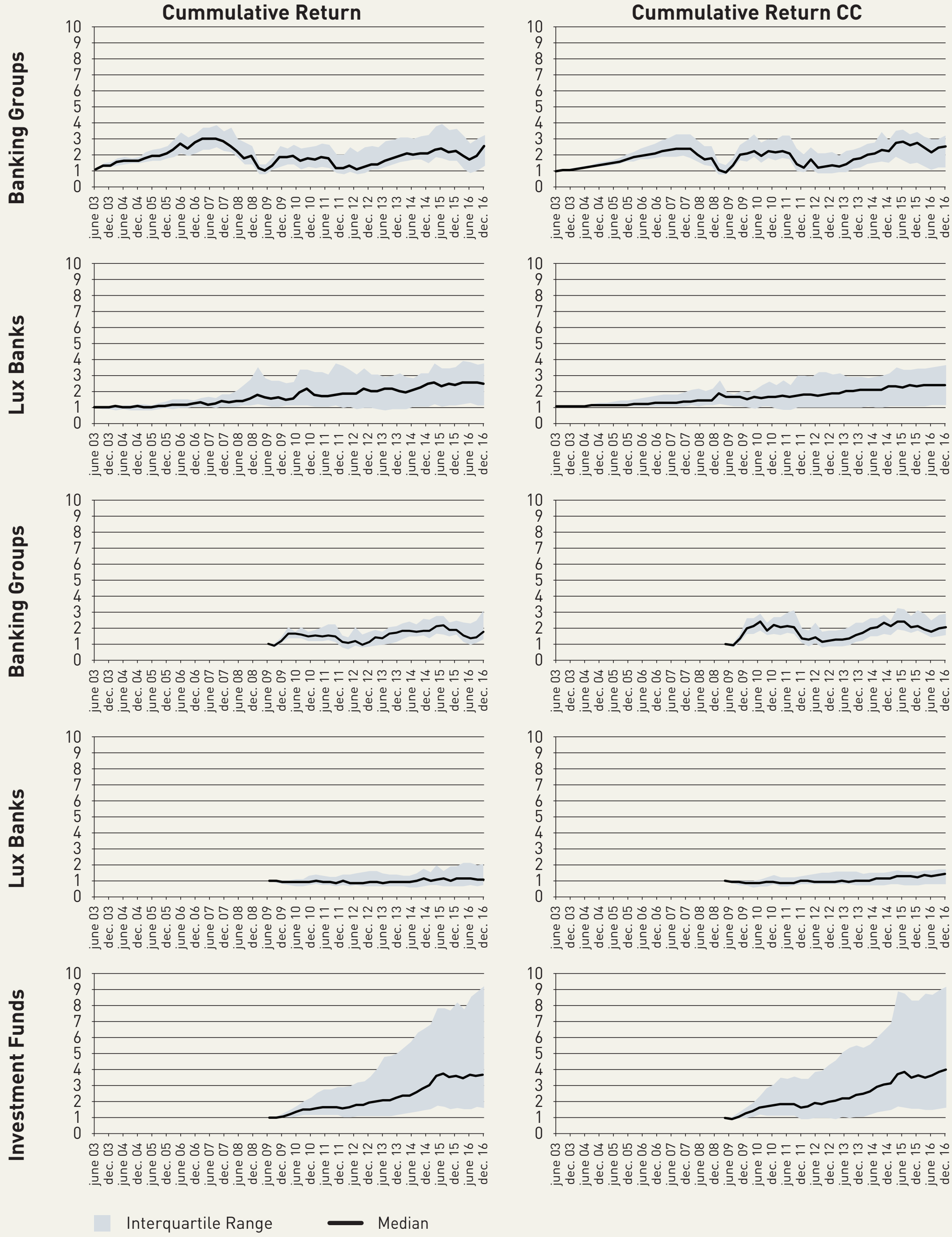
Macroeconomic Determinants of Aggregate SRISK

	BANKING GROUPS (2003Q4-2016Q4)											
	REGRESSION IN SHORT-TERM DEVIATIONS						REGRESSION IN DIFFERENCES					
	K = 0.08			K = 0.12			K = 0.08			K = 0.12		
	ESTIMATE	TSTAT	PVALUE	ESTIMATE	TSTAT	PVALUE	ESTIMATE	TSTAT	PVALUE	ESTIMATE	TSTAT	PVALUE
Constant	0.00	0.05	0.96	-0.00	-0.02	0.99	-0.01	-0.36	0.72	-0.00	-0.12	0.90
GDP	10.75	1.16	0.25	4.94	0.79	0.43	4.79	0.66	0.51	2.80	0.51	0.61
HICP	-2.13	-0.26	0.79	-2.04	-0.36	0.72	1.88	0.20	0.84	-2.57	-0.42	0.68
Unemployment Rate	-1.99	-0.89	0.37	0.08	0.06	0.95	-0.48	-0.27	0.78	0.20	0.18	0.85
Consumer Confidence Indicator	**-0.03**	**-2.32**	**0.02**	**-0.02**	**-2.17**	**0.03**	-0.02	-1.08	0.28	-0.01	-1.19	0.23
Interest Rate 3M	-0.10	-0.80	0.43	-0.01	-0.15	0.88	-0.05	-0.40	0.69	-0.01	-0.14	0.89
Interest Rate Spread	**-0.36**	**-4.04**	**0.00**	**-0.24**	**-3.89**	**0.00**	**-0.18**	**-2.37**	**0.02**	**-0.14**	**-2.66**	**0.01**
Liquidity Spread	0.08	1.27	0.20	0.07	1.57	0.12	0.07	0.79	0.43	0.06	0.97	0.33
Property Price	*-15.45*	*-1.70*	*0.09*	-7.47	-1.19	0.24	-4.55	-0.67	0.51	-3.05	-0.62	0.53
Loans to Households	-6.55	-0.99	0.32	-0.01	-0.00	1.00	2.65	0.50	0.62	3.39	0.82	0.41
Loans to Non-Financial Corps	-3.93	-0.62	0.54	-6.17	-1.32	0.19	1.86	0.66	0.51	1.41	0.68	0.50
Market Price Index	-0.71	-0.81	0.42	-0.17	-0.27	0.78	**-1.60**	**-2.00**	**0.05**	**-1.16**	**-1.99**	**0.05**
Bank Price Index	**-0.80**	**-2.22**	**0.03**	**-0.64**	**-2.46**	**0.01**	-0.01	-0.03	0.98	-0.04	-0.17	0.86
Bank Sector CDS Index	0.07	0.69	0.49	0.00	0.02	0.98	0.04	0.41	0.68	-0.01	-0.09	0.93
VSTOXX Volatility Index	0.04	0.29	0.77	0.03	0.31	0.75	0.04	0.33	0.74	-0.01	-0.18	0.86
Commodity S&P GSCI Energy Index	**0.45**	**2.83**	**0.00**	**0.34**	**2.92**	**0.00**	0.15	0.76	0.45	*0.24*	*1.88*	*0.06*
Japanese yen	-0.80	-1.08	0.28	-0.67	-1.35	0.18	-0.59	-0.89	0.37	-0.32	-0.72	0.47
US dollar	0.63	0.91	0.36	0.04	0.09	0.93	0.68	0.86	0.39	0.55	1.05	0.29
R-squared		0.58			0.55			0.27			0.26	
	LUXEMBOURG BANKS (2003Q4-2016Q4)											
Constant	-0.00	-0.33	0.74	-0.00	-0.12	0.90	-0.01	-0.34	0.74	-0.00	-0.08	0.93
GDP	2.02	0.31	0.76	-3.58	-1.32	0.19	-2.62	-0.50	0.62	-3.39	-1.58	0.11
HICP	3.23	0.26	0.80	**-10.24**	**-1.92**	**0.05**	5.53	0.69	0.49	-1.78	-0.66	0.51
Unemployment Rate	-2.82	-1.19	0.23	**-2.73**	**-2.68**	**0.01**	0.67	0.54	0.59	0.05	0.10	0.92
Consumer Confidence Indicator	0.01	1.23	0.22	-0.00	-0.41	0.68	0.00	0.42	0.67	0.00	1.16	0.25
Interest Rate 3M	-0.05	-0.31	0.75	-0.01	-0.25	0.80	0.12	1.15	0.25	0.03	0.66	0.51
Interest Rate Spread	0.09	1.08	0.28	-0.01	-0.40	0.69	**0.13**	**2.14**	**0.03**	-0.00	-0.06	0.95
Liquidity Spread	*0.12*	*1.92*	*0.06*	**0.05**	**1.93**	**0.05**	**0.14**	**2.38**	**0.02**	**0.06**	**2.48**	**0.01**
Property Price	-8.40	-1.07	0.29	-0.87	-0.20	0.84	2.47	0.44	0.66	2.45	1.24	0.22
Loans to Households	-3.85	-0.76	0.45	2.70	0.91	0.36	0.03	0.01	0.99	0.06	0.03	0.97
Loans to Non-Financial Corps	2.55	0.43	0.67	**-6.33**	**-2.14**	**0.03**	-0.40	-0.24	0.81	0.77	0.83	0.41
Market Price Index	**-2.74**	**-2.36**	**0.02**	0.46	1.44	0.15	-0.79	-0.91	0.36	-0.23	-0.77	0.44
Bank Price Index	**1.33**	**2.45**	**0.01**	*-0.38*	*-1.67*	*0.10*	0.64	1.40	0.16	0.05	0.35	0.73
Bank Sector CDS Index	0.02	0.22	0.82	-0.02	-0.38	0.70	0.06	0.70	0.48	-0.01	-0.31	0.76
VSTOXX Volatility Index	*-0.25*	*-1.67*	*0.10*	0.02	0.29	0.77	-0.07	-0.81	0.42	-0.04	-0.94	0.35
Commodity S&P GSCI Energy Index	0.15	0.78	0.44	**0.33**	**3.77**	**0.00**	**0.43**	**1.96**	**0.05**	**0.23**	**4.23**	**0.00**
Japanese yen	**2.56**	**2.53**	**0.01**	**1.18**	**3.80**	**0.00**	*1.08*	*1.71*	*0.09*	**0.66**	**2.82**	**0.00**
US dollar	-1.35	-1.62	0.11	0.36	1.07	0.28	-0.59	-0.82	0.41	0.03	0.16	0.87
R-squared		0.44			0.54			0.24			0.23	
	INVESTMENT FUNDS (2009Q3-2016Q4)											
	K = 0.9			K = 0.7			K = 0.9			K = 0.7		
Constant	0.00	0.13	0.90	0.00	0.12	0.90	-0.00	-0.12	0.91	-0.02	-0.26	0.79
GDP	**56.04**	**3.03**	**0.00**	**125.41**	**2.95**	**0.00**	12.93	1.54	0.12	*35.47*	*1.86*	*0.06*
HICP	-7.05	-0.37	0.71	-3.64	-0.10	0.92	4.32	0.40	0.69	8.26	0.35	0.73
Unemployment Rate	-1.40	-0.34	0.73	-4.39	-0.64	0.52	-0.79	-0.39	0.70	-1.93	-0.50	0.62
Consumer Confidence Indicator	-0.00	-0.08	0.94	0.04	1.15	0.25	0.00	0.20	0.84	0.02	0.62	0.53
Interest Rate 3M	**0.99**	**2.58**	**0.01**	**1.76**	**2.21**	**0.03**	0.11	0.47	0.64	0.04	0.08	0.93
Interest Rate Spread	-0.29	-1.39	0.16	-0.45	-1.17	0.24	**-0.29**	**-2.33**	**0.02**	**-0.48**	**-2.04**	**0.04**
Liquidity Spread	0.20	1.45	0.15	0.32	1.04	0.30	-0.10	-1.08	0.28	-0.16	-0.80	0.42
Property Price	-24.90	-1.33	0.18	*-70.75*	*-1.86*	*0.06*	-8.47	-1.14	0.26	*-22.75*	*-1.73*	*0.08*
Loans to Households	-16.05	-0.96	0.34	-47.06	-1.59	0.11	-5.93	-0.63	0.53	-16.20	-1.21	0.23
Loans to Non-Financial Corps	2.45	0.25	0.80	13.55	0.76	0.45	2.21	0.38	0.70	7.12	0.62	0.53
Market Price Index	-0.63	-0.47	0.64	-3.47	-1.30	0.19	-0.83	-0.67	0.50	-2.41	-0.90	0.37
Bank Price Index	**-1.67**	**-2.30**	**0.02**	*-2.34*	*-1.67*	*0.09*	0.12	0.20	0.84	0.82	0.68	0.50
Bank Sector CDS Index	-0.06	-0.16	0.87	0.28	0.42	0.68	0.10	0.54	0.59	0.24	0.61	0.54
VSTOXX Volatility Index	*-0.38*	*-1.78*	*0.08*	**-1.06**	**-2.53**	**0.01**	-0.16	-1.46	0.15	-0.33	-1.30	0.19
Commodity S&P GSCI Energy Index	**1.68**	**3.48**	**0.00**	**2.89**	**3.71**	**0.00**	0.52	1.57	0.12	0.63	1.12	0.26
Japanese yen	*1.41*	*1.70*	*0.09*	0.68	0.37	0.71	-0.48	-0.56	0.58	-1.17	-0.63	0.53
US dollar	1.59	0.90	0.37	**6.21**	**2.10**	**0.04**	2.13	1.50	0.13	**5.98**	**2.15**	**0.03**
R-squared		0.44			0.46			0.20			0.21	

Note: This table reports the regression results of the aggregate SRISK for both 32 Luxembourg banks and 30 banking groups in the period from December, 2003 to December, 2016, and 232 investment funds in the period from September, 2009 to December, 2016. The SRISK series is computed using k = 8%, 12% for banks, and 90%, 70% for investment funds. Regressions are run in short-term deviations and first differences with Newey-West robust standard errors using a Bartlett kernel. A bold coefficient value indicates significance at the 95% level, whereas an italic value indicates significance at the 90% level.

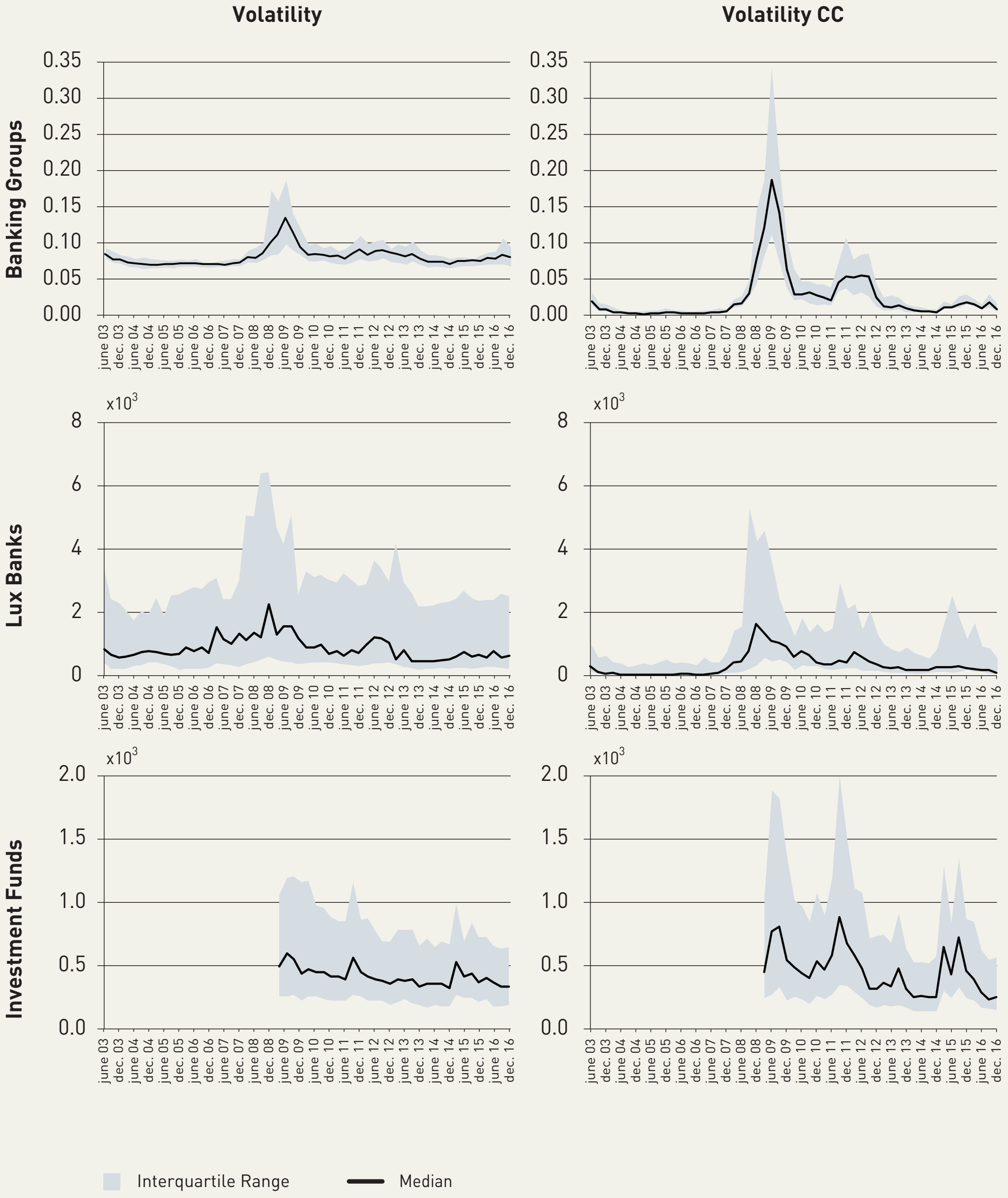
Source: BCL

Figure 1
Cumulative Equity Returns



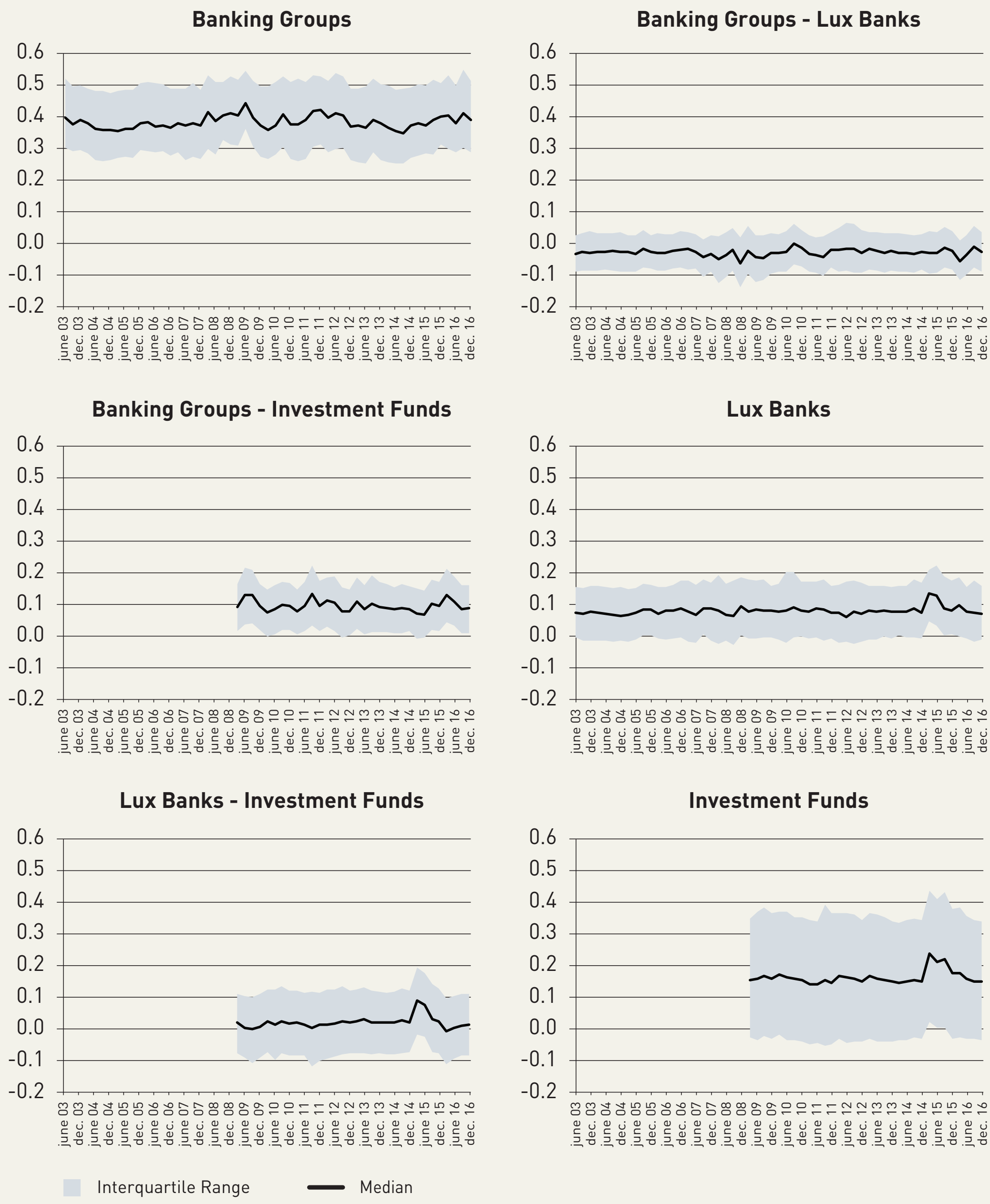
Source: BCL

Figure 2
Volatility of Equity returns



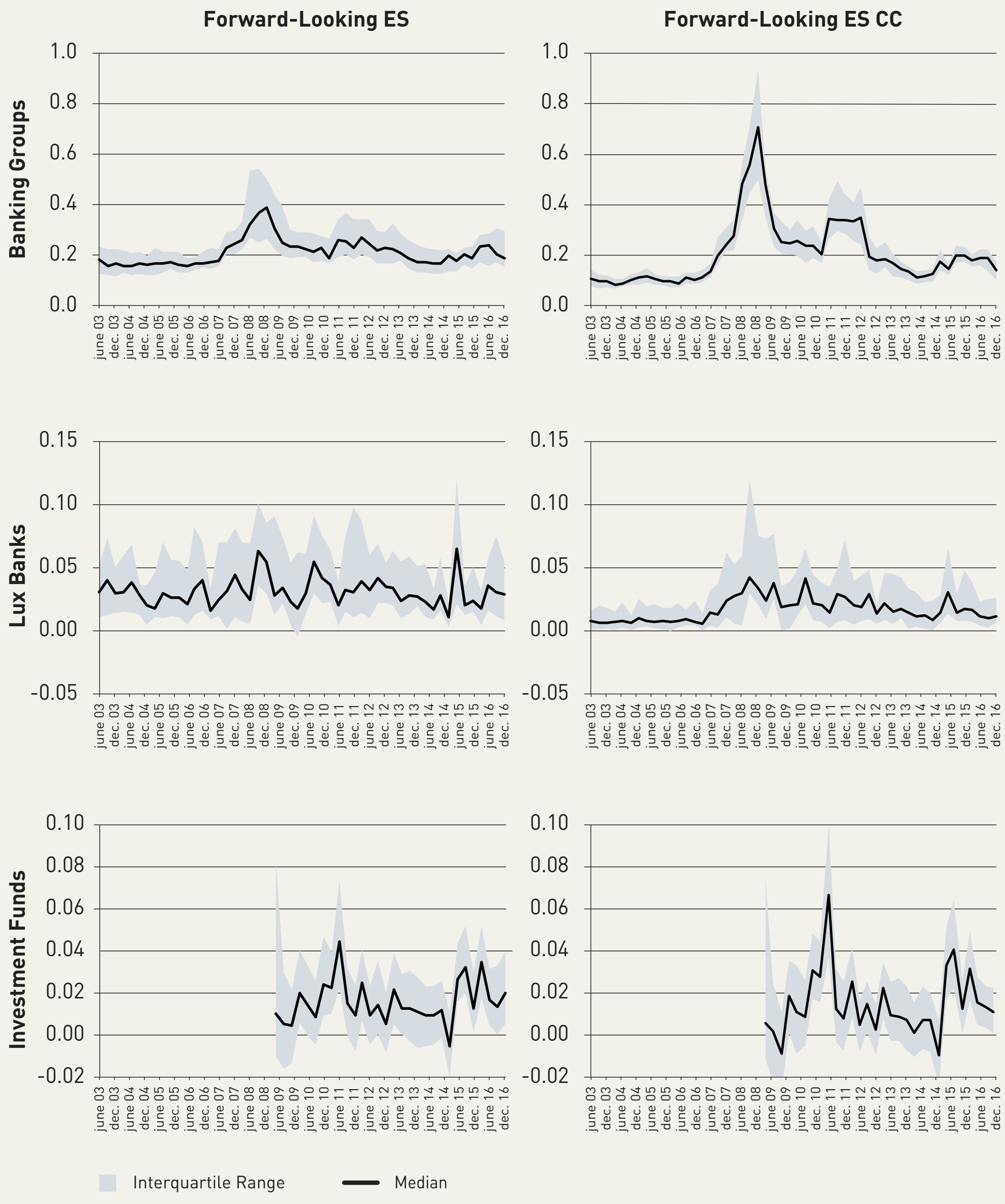
Source: BCL

Figure 3
Copula Correlations of Equity Returns



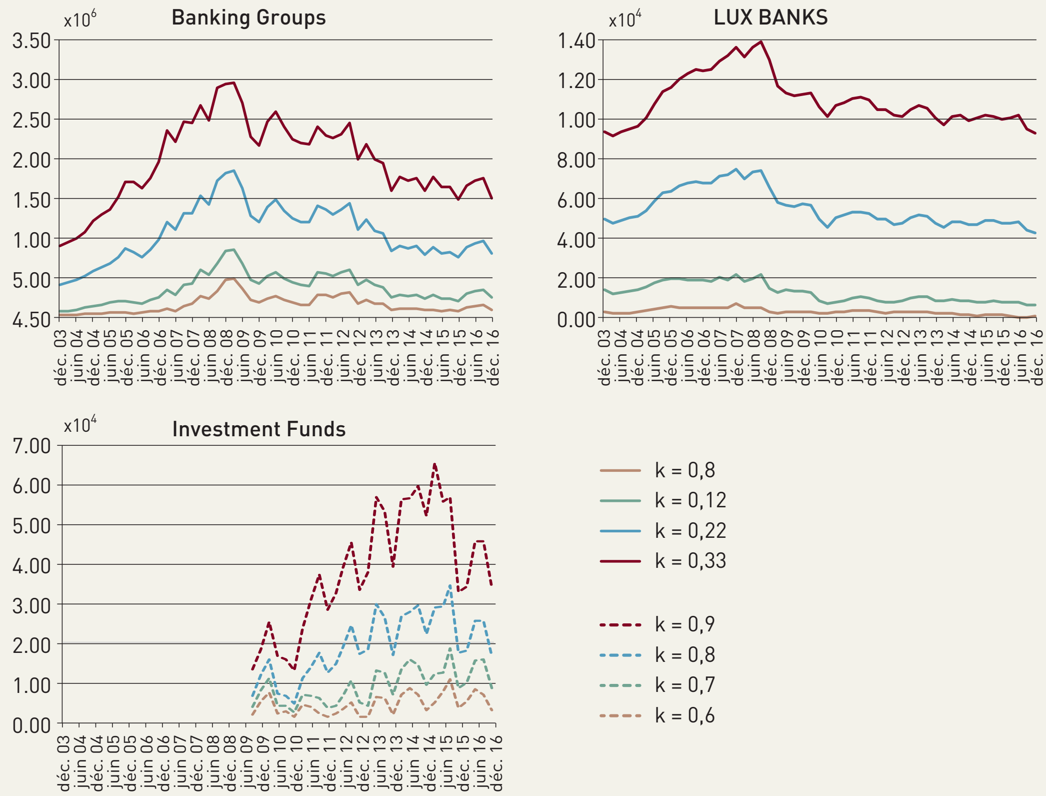
Source: BCL

Figure 4
Forward-Looking ES of Equity Returns



Source: BCL

Figure 5
Forward-Looking SRISK Sensitivity in Millions



Source: BCL