CAHIER D'ÉTUDES
WORKING PAPER

N° 118

HOW MUCH DOES BOOK VALUE DATA TELL US ABOUT SYSTEMIC RISK AND ITS INTERACTIONS WITH THE MACROECONOMY?

A LUXEMBOURG EMPIRICAL EVALUATION

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FEBRUARY 2018

BANQUE CENTRALE DU LUXEMBOURG

EUROSYSTÈME

How Much Does Book Value Data Tell Us about Systemic Risk and Its Interactions with the Macroeconomy? A Luxembourg Empirical Evaluation*

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February 2018

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.[1] The forward-looking systemic risk measures $\Delta CoES$, $Shapley - \Delta CoES$, $SRISK$ and conditional concentration risk 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 $\Delta CoES$ 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 $Shapley - \Delta CoES$ 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.

JEL Classification: C1, E5, F3, G1

Keywords: financial stability; systemic risk; macro-prudential policy; dynamic copulas; value at risk; shapley values; risk spillovers.

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I am grateful to colleagues for the comments received, in particular from A. Rouabah, J. Theal, G. Queffelec and the members of BCL's editorial committee. Correspondence can be sent to: Xisong Jin, Banque centrale du Luxembourg, 2, boulevard Royal L-2983 Luxembourg, Tel: (352) 4774-4462; E-mail: xisong.jin@bcl.lu.

[1] The banks considered in this study include domestic Luxembourg banks, subsidiaries of European banking groups, and the parent banking groups of these subsidiaries.

Non-technical summary

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. 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. Actually, several risk metrics such as the Value at Risk and the Expected Shortfall can be applied directly to individual balance-sheet items.

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[2] for the balance-sheet items for each financial institution in the system. In order to deal with the 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

[2]The systemic risk measures considered in this study include Exposure Co-expected Shortfall ($\Delta CoES$) defined by Adrian and Brunnermeier (2011)[2], $Shapley-\Delta CoES$ presented at Drehmann and Tarashev (2013)[20], Systemic Risk of Expected Capital Shortage (SRISK) described by Brownlees and Engle (2017)[15] and Conditional Concentration Risk (CCR) as in Christoffersen *et al.* (2012)[18].

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.

Résumé non technique

Depuis la crise financière, le monde académique et les régulateurs ont accru leurs efforts afin de développer la palette d'outils disponibles dans le domaine de l'analyse macroprudentielle et notamment les mesures du risque systémique. Dans ce cadre, la plupart des méthodologies développées sont basées sur des données de marché, telles que les marchés d'actions, obligataires et des produits dérivés, qui permettent de suivre au plus près l'évolution du risque systémique. Néanmoins, ces données ne sont pas toujours disponibles car un nombre important d'entités ne sont pas publiquement cotées et ne déclarent que des données bilantaires. Les mesures de risque qui s'appuient sur la règle de comptabilisation à la valeur de marché sont, par ailleurs, limitées par construction à quelques principales lignes du bilan. Ainsi, le développement de vulnérabilités dans les différentes rubriques du bilan sont susceptibles de ne pas être détectées à temps par les autorités compétentes.

Pourtant, chaque composante du bilan contribue à la situation financière agrégée de l'ensemble du système. Une mesure de risque systémique construite à partir de chaque ligne du bilan peut potentiellement identifier différents aspects du niveau général du risque systémique. Par agrégation de nombreux postes bilantaires, il est possible de mesurer la contribution globale au risque. Le niveau du risque systémique peut, ainsi, être estimé sur l'ensemble du bilan en incorporant de nombreuses sous-catégories, telles que les actifs et les passifs à court et à long terme. De la même manière qu'il est possible d'attribuer un prix de marché à un actif selon la règle de comptabilisation au prix de marché (*Mark-to-Market*), il est possible d'associer à chaque ligne bilantaire une contribution au risque agrégé (*Mark-to-Systemic-Risk*) en considérant celles-ci pour chaque institution financière simultanément. L'approche "*Mark-to-Systemic-Risk*" apporte alors une analyse de la contribution de chaque entité financière au risque global en fonction de l'importance de chaque poste bilantaire. Ainsi, plusieurs mesures, telles que la *Value at Risk* et l'*Expected Shortfall*, peuvent s'appliquer directement à toutes lignes du bilan.

Afin de montrer comment le concept de "*Mark-to-Systemic-Risk*" peut être mis en pratique, cette étude se concentre, en premier lieu, sur le capital des banques luxembourgeoises et des groupes bancaires européens, puis sur les parts émises par les fonds d'investissement, et caractérise les risques systémiques et les risques de transmission sur la période 2003-2016. Une approche dite *dynamic grouped t-copula*, pertinente pour modéliser des distributions dynamiques de grande dimension, est proposée afin d'estimer plusieurs mesures[3] construites sur la base des données individuelles propres à chaque institution financière. Afin de tenir compte de la dimension procyclique du système financier, l'approche proposée est complétée en reliant les mesures de risque systémique dans le système financier à une large base de données macro-financière.

Cette étude documente plusieurs phénomènes importants sur la période 2009-2016. Premièrement, les filiales luxembourgeoises se révèlent être plus sensibles aux évènements défavorables véhiculés par les fonds d'investissement qu'à ceux transmis par les groupes bancaires européens.

[3]Les mesures de risque systémique considérées dans cette étude incluent l'*Exposure Co-expected Shortfall* ($\Delta CoES$), définie par Adrian et Brunnermeier (2011)[2], la *Shapley* $-\ \Delta CoES$, proposée par Drehmann et Tarashev (2013)[20], la *Systemic Risk of Expected Capital Shortage* ($SRISK$), décrite par Brownlees et Engle (2017)[15], et la mesure *Conditional Concentration Risk* (CCR) de Christoffersen *et al.* (2012)[18].

Deuxièmement, les fonds d'investissement ont été plus sensibles aux évènements défavorables issus des groupes bancaires européens qu'en provenance des filiales luxembourgeoises. Troisièmement, alors que les fonds monétaires apparaissent comme ayant la contribution marginale au risque total des banques luxembourgeoises la plus élevée, les fonds de type actions ont la contribution la plus faible. Aussi, la contribution des fonds mixtes, obligataires et des fonds alternatifs s'est accrue uniquement à la fin de l'année 2016. De plus, les déterminants macroéconomiques du risque systémique agrégé des banques luxembourgeoises, des groupes bancaires européens et des fonds d'investissement, et les contributions marginales de 15 pays au risque systémique agrégé des banques luxembourgeoises et de leurs groupes bancaires respectifs sont tous différents. Au regard de ces résultats, cette approche pourrait constituer un outil pertinent pour évaluer les risques dynamiques pouvant affecter la stabilité du système financier.

1 Introduction

Since the 2007-2009 US subprime mortgage crisis, both academics and national authorities all over the world have been stepping up their efforts to improve their ability to identify and assess systemic risk for the purpose of macroprudential policy. These efforts have been successful and a large number of systemic risk measures have been developed. Bisias *et al.* (2012)[12] contains a recent survey of over thirty systemic risk indices. Some approaches often associate systemic risk with the probability of joint distress of a large proportion of firms in the financial system, while the marginal probabilities of distress are derived from market data by option pricing models, as in Lehar (2005)[35], Gray *et al.* (2007)[29], and Goodhart and Segoviano (2009)[26]. Other approaches have been developed based on the traditional risk metrics of Value at Risk (VaR) and expected shortfall (ES). These measures include CoVaR and $\Delta CoVaR$ from Adrian and Brunnermeier (2011)[2], marginal expected shortfall (MES) from Acharya *et al.* (2017)[1], MES-BE, a version of marginal expected shortfall proposed by Brownlees and Engle (2012)[16], a system wide systemic risk index called CATFIN from Allen *et al.* (2012)[7], and $SRISK$ introduced by Brownlees and Engle (2017)[15]. Still, other strands of the literature gauge systemic risk using the comovement of risk indicators through the financial market. Billion *et al.* (2012)[11] propose a measure of connectedness based on principal-component analysis and Granger-causality networks. The Composite Indicator of Systemic Stress (CISS) of the ECB proposed by Hollo *et al.* (2012)[31] actually aggregates five segment-specific stress measures into a composite indicator by way of standard portfolio theory. However, Giglio *et al.* (2016)[25] evaluate 19 measures of systemic risk in the US and Europe spanning several decades, and report that many systemic risk indicators proposed in the literature lack the predictive power necessary to identify downside macroeconomic risk.

All the methodologies mentioned above rely on data from stock, bond and derivative markets with implied interdependence among financial institutions. Since Luxembourg banks and a large proportion of investment funds are unlisted, most of these systemic risk measurements can not be applied to financial institutions in Luxembourg. Nevertheless, the financial ratios from balance sheet data have long been proven to be very useful predictors of the default of small and medium sized enterprises (see, e.g., Altman and Sabato (2006)[8]). By the mark-to-market accounting rule, the values on the balance sheet can still track the changes of market conditions in a timely manner, and some systemic risk measurements can be applied to the book-value data directly. For example, as shown by Souto *et al.* (2009)[40] and Blavy and Souto (2009)[13], book-based Merton's credit risk measures are highly correlated with market-based Merton's credit risk measures.[4] The so called fair value or mark-to-market accounting rule has the advantage of reflecting the true and relevant values of the balance sheets of financial institutions thereby allowing regulators, investors and other users of accounting information to better assess the risk profile of financial institutions.[5] Luxembourg financial institutions publish their annual and consolidated accounts according to Luxembourg Banking GAAP, IFRS, or a mix of both regimes. IFRS requires certain assets and liabilities - in particular certain financial items - to

[4] See also Gray and Jones (2006)[28], for an early application of this idea.

[5] Please see Allen and Carletti (2008a[5]&b[6]). Mark-to-market accounting is also thought to lead to excessive and artificial volatility. As a consequence, under this accounting system the value of the balance sheets of financial institutions may be driven by short-term fluctuations in the market that do not reflect the value of the fundamentals and the long-term values of assets and liabilities.

be measured using the fair value or mark-to-market accounting rules. The Luxembourg law of 16 March 2006 has transposed the fair value and modernisation directives into legislation, and enables the use of certain provisions of IFRS as adopted by the EU.

Due to the contingent nature of many risks, balance sheet data do not provide a complete picture of all the risks facing financial institutions in a country. Gray and Malone (2008)[27] show that the contingent-claims approach (CCA) provides a methodology to combine balance sheet information with widely used finance and risk management tools to construct marked-to-market balance sheets that better reflect the degree of underlying risk. However, some assumptions of CCA models may not be appropriate if CCA is applied to book-value data directly. As shown by Adrian *et al.* (2013)[3], the key state variable in applying financial frictions to asset pricing models is leverage as the ratio of total assets to book equity, rather than the ratio of total assets to book debt with the debt being held largely exogenous as defined in Merton's model.[6] Furthermore, as credit risk indicators are usually built from a few major balance-sheet items on a consolidated database, the slow build-up of vulnerabilities on the vast sub-heading items might be overlooked.

Similar to the idea of the Mark-to-Market accounting rule, the "Mark-to-Systemic-Risk" approach can be applied to the broader set of balance-sheet items including not only the major heading items such as total assets, liabilities and equity but also the vast sub-heading items such as current assets, fixed assets, current liabilities, and long-term liabilities. The balance sheet offers a snapshot of a financial institution's overall health. Using the Mark-to-Systemic-Risk approach, the extended analysis allows for a more complete description of the degree of systemic risk in each balance-sheet item by simultaneously comparing this risk across other financial institutions in the system. Each component of a financial institution's financial condition is an integral part of the aggregate financial statement of the whole system. The identified component systemic risks can therefore potentially capture all aspects of the overall systemic risk of an entire system.

To this end, applying the "Mark-to-Systemic-Risk" approach to the major balance-sheet items for both Luxembourg banks and investment funds is first examined in this paper. The parent banking groups are also included for comparison. The other major heading items and vast sub-heading items will be explored later in separate papers.

Several approaches developed from the traditional metrics of VaR and ES can be applied to the "Mark-to-Systemic-Risk". The CoVaR methodology of Adrian and Brunnermeier (2011) is one of the common approaches for measuring systemic risk in the literature. However, the sub-additivity property of risk measures may not hold for CoVaR, implying that the sum of individual CoVaR values might be greater than the total CoVaR of the system. Following Drehmann and Tarashev (2013)[20] and Cao (2014)[17], this study proposes a novel framework in which the forward-looking systemic risk measures $\Delta CoES$, $SRISK$ and Conditional Concentration

[6] For example US banks' leverage tends to fluctuate over the cycle via changes in the size of their balance sheet in tandem with changes in total debt, and with equity being the exogenous variable. This seems to be also the case for Luxembourg banks as the coefficient of a regression of annual changes in assets on annual changes in total debt is 98% and highly significant.

Risk (CCR) are estimated by using a large-scale dynamic grouped t-copula and their common components by the generalized dynamic factor model (GDFM). The Shapley value methodology is used to efficiently allocate this systemic risk to each financial institution in the system. Not only the risk spillovers in the equity returns among Luxembourg banks, their European banking groups, and investment funds are investigated but also 6 Luxembourg Other Systemically Important Institutions (O-SIIs), 4 Global Systemically Important Banks (G-SIBs), and 6 investment fund categories are ranked by their forward-looking $Shapley - \Delta CoES$. The additivity property of the Shapley value of $\Delta CoES$ ensures that the sum of each institution's Shapley value of systemic risk contribution is exactly equal to the $Multi - \Delta CoES$ of all the financial institutions in the system. This paper also focuses the analysis on the interactions between systemic risk and the macroeconomy to highlight which measures are valuable from the regulatory or policy perspective, and to identify a subset of systemic risk measures that might be relevant for future production, employment or consumption. This allows us to shed light on the links between financial distress and macroeconomic risks. The marginal contributions to the aggregate $SRISK$ from 15 counties are identified, and these macroeconomic factors underlying the aggregate $SRISK$ of three sectors are also compared. The framework could be a valuable addition to the traditional toolkit for assessing time varying risks to the stability of the financial system.

The main contributions of this study are as follows. First, to the best of the author' knowledge, this study is the first comprehensive application of $\Delta CoES$, $Shapley - \Delta CoES$, $SRISK$ to the book-value data of the banking and investment fund sectors reported by Eurosystem central banks to the ECB. Second, this paper explicitly identifies the risk spillovers of equity returns among these three sectors - Luxembourg banks, their parent banking groups, and investment funds. Finally, this paper also explicitly identifies the linkages between the aggregate $SRISK$ of these sectors in the financial system and macro-financial variables. By identifying the main variables more closely associated with vulnerabilities in the financial system, the proposed approach explicitly pinpoints the economic and financial variables that may be of interest of authorities if financial instability is to be avoided.

The main findings are the following. First, in terms of equity returns during 2009-2016, compared with the banking groups, Luxembourg banks' Sharpe-ratios and skewness were lower and their excess kurtosis was higher on average, reflecting a diminished performance of Luxembourg banks during this period. However, investment funds with the highest average annualized returns, Sharpe-ratios and skewness performed much better than both banking groups and Luxembourg banks. The volatility profiles of all three sectors look similar though at different scales. It suggests that book-value equity by the fair value or the mark-to-market accounting rule reflects market events in a timely manner. In addition, the copula correlations or lower tail dependencies of investment funds were lower than those of banking groups, however, they were still higher than those of Luxembourg banks. Furthermore, the dependencies were higher within sectors than those across sectors, and the cross-section dependencies were low, around zero, except for those between banking groups and investment funds.

Second, measured by $\Delta CoES$ of equity returns in the period of 2009-2016, Luxembourg banks were more sensitive to adverse events from investment funds than banking groups, and investment funds were more sensitive to adverse events from banking groups than from Luxembourg banks. Ranked by $Shapley - \Delta CoES$, money market funds had the highest marginal contribution to the total risk of Luxembourg banks while equity funds exhibited the least share. The systemic risk contribution of bond funds, mixed funds and hedge funds became more important toward the end of 2016 given the prevalence of low interest rate environment.

Finally, the aggregate $SRISK$ for Luxembourg banks, banking groups and investment funds was explored. The SRISK of Luxembourg banks 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 decreased to a level lower than 2004 without being significantly impacted by the European crisis around 2012. As for investment funds, the risk measure was very volatile with a long-term uptrend over time until the middle of 2015, illustrating the potential accumulation of vulnerabilities in the investment fund sector. The underlying macroeconomic determinants of the aggregate $SRISK$ of three sectors are different. In the case of the required fraction of assets $k = 0.08$, for banking groups, the changes in the aggregate $SRISK$ measure were driven by the interest rate spread and the market price index during 2003-2016. However, for Luxembourg banks, the changes were driven by the interest rate spread, liquidity spread and the commodity S&P GSCI energy index in the same period. Additionally, 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, 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.

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 Multi-CoVaR defined by Adrian and Brunnermeier (2011) and aggregate $SRISK$ introduced by Brownlees and Engle (2017)[15] 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)[23].

The remainder of this section reviews the methodological and statistical approaches used to estimate systemic risk. The multivariate GARCH techniques are extended into the grouped t-copula to introduce the dynamic forecasting framework. The use of the GDFM to nest macro-financial variables is outlined, and the empirical measures of systemic risk are discussed.

2.1 Multi-CoES

Adrian and Brunnermeier (2011)[2] defined the conditional expected shortfall $CoES_{q,t}^{sys/i}$[7] as expected shortfall (ES) of the financial system at confidence level q conditional on some events of institution i, at time t. Thus $\Delta CoES_{q,t}^{sys/i}$ denotes the difference between the ES of the financial system conditional on financial institution i being in a tail event and the ES of the financial system conditional on financial institution i being in a normal state. However, this pairwise model between the financial system and financial institution 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)[17]:

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

$$CoES_{q,t}^{1,...,S} = -E_{t-1}(r_t^{sys} | r_t^{sys} \leq -CoVaR_{q,t}^{1,...,S}), \tag{2}$$

where r_t^i is the return of institution i at time t, and $CoVaR_{q,t}^{1,...,S}$ is the VaR of the financial system return r_t^{sys} at confidence level q conditional on some event $\{C(r_t^1), ..., C(r_t^s)\}$ of a set of institutions $\{1, ..., S\}$ 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 $\{1, ..., S\}$ to the risk in the financial system is denoted by:

$$\Delta CoES_{q,t}^{1,...,S} = CoES_{q,t}^{r^1 \leq VaR_q^1, ..., r^s \leq VaR_q^s} - CoES_{q,t}^{r^1 \leq VaR_{0.5}^1, ..., r^s \leq VaR_{0.5}^s}. \tag{3}$$

Therefore, $\Delta CoES_{q,t}^{1,...,S}$ 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 economics 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 which could be potentially useful for regulators.

[7] To save the space, this paper focuses on the ES and CoES only. The expected loss conditional on a VaR event has a number of advantages relative to VaR. In particular, the VaR is not subadditive and does not take distributional aspects within the tail into account. The distribution within the tails can also be estimated by the proposed copula approach.

2.2 The Dynamic Conditional t-Copula

Adrian and Brunnermeier (2011)[2] 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)[17] 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)[39] 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 a more general set of Dynamic Conditional Elliptical Copulas, for instance, the Dynamic t-Copula and the Dynamic Grouped t-Copula which are good candidates that are especially tractable for high dimensions. A semi-parametric form of the marginal distributions and new estimation methods are adopted for multivariate GARCH models.

2.2.1 Definition of Grouped t-Copula

Copula theory provides an easy way to deal with complex multivariate modeling problems. The advantage of the copula approach is its flexibility, because the dependence structure can be separated from the univariate marginal components, and hence the dependence structure between these marginal variables can be modeled in the second stage, after the univariate distributions have been calibrated. In many cases, the copulas are also relatively parsimoniously parameterized, which facilitates calibration and reduces the impact of parameter uncertainty, which is typically a matter of concern in risk management applications (see Bams *et al.* (2009)[10]). The dynamic conditional t-copula is defined as follows:[8]

$$C(\eta_1, \eta_2, ..., \eta_n; R_t, v_t) = T_{R_t,v_t}(t_{v_t}^{-1}(\eta_1), t_{v_t}^{-1}(\eta_2), ..., t_{v_t}^{-1}(\eta_n)), \tag{4}$$

where $\eta_i = F_i(\epsilon_i)$ for $i = 1, 2, ..., n$, and $\epsilon_t \sim iid(0, 1)$ are the standardized residuals from the marginal dynamics, for example, AR(p)-GARCH(1,1) process. 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.

Engle (2002)[21] proposes a class of models - the Dynamic Conditional Correlation (DCC) class of models - that preserves the ease of estimation of Bollerslev's (1990)[14] constant correlation model while allowing the correlations to change over time. These kinds of dynamic processes can also be extended to t-copulas. 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:

[8] See Patton (2006)[38] for the definition of a general conditional copula.

$$Q_t = (1-\alpha_{dcc}-\beta_{dcc})\bar{Q} + \alpha_{dcc}(\epsilon^*_{t-1}\epsilon^{*'}_{t-1}) + \beta_{dcc}Q_{t-1}, \tag{5}$$

where $\alpha_{dcc} > 0$, $\beta_{dcc} > 0$, $\alpha_{dcc} + \beta_{dcc} < 1$, $\epsilon^*_i = t^{-1}_{v_t}(\eta_i = F_i(\epsilon_i))$, $Q_t = |q_{ij,t}|$ is the auxiliary matrix driving the copula correlation dynamics, the nuisance parameters $\bar{Q} = E[\epsilon^*_t\epsilon^{*'}_t]$ with sample analog $\bar{Q} = T^{-1}\sum_{t=1}^{T}\epsilon^*_t\epsilon^{*'}_t$, so that R_t is a matrix of copula correlations $q_{ij,t}$ with ones on the diagonal, $\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ij,t}}\sqrt{q_{jj,t}}}$.

Misspecification of 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 $F_i(\epsilon_i)$. The marginal densities are estimated by using a Gaussian kernel for the central part of the distribution mass, and a parametric Generalized Pareto distribution (GP) for the two tails; hence, the asymmetry can be examined directly by estimating the left and right tails separately. This approach is often referred to as the distribution of exceedances or peaks-over-threshold method (see refer McNeil (1999)[36] and McNeil and Frey (2000)[37] for more details).

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 $\sqrt{v/\chi^2_v}$. Partition $\{1, ..., n\}$ into m subsets of sizes $s_1, ..., s_m$. Let $R^k_t = G_{v_k^{-1}}(U)$ for $k = 1, ..., m$. If

$$Y = (R^1_t Z_1, ..., R^1_t Z_{s_1}, R^2_t Z_{s_1+1}, ..., R^2_t Z_{s_1+s_2}, ..., R^m_t Z_n)', \tag{6}$$

then the random vector $(Y_1, ..., Y_s)$ has an s_1-dimensional t-distribution with v_1 degrees of freedom and, for $k = 1, ..., m-1$, $(Y_{s_1+...+s_{k+1}}, ..., Y_{s_1+...+s_{k+1}})'$ 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)[19].

2.2.2 Estimation of Grouped t-Copula and Simulation

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 $\rho_{GC} = Corr(\Phi^{-1}(\eta_i), \Phi^{-1}(\eta_j))$ and a t-copula correlation $\rho_{TC} = Corr(t^{-1}_v(\eta_i), t^{-1}_v(\eta_j))$ is almost equal to one, R_t can be well approximated by the $R^{Gaussian}_t$ from the dynamic Gaussian Copula[9]. In this dynamic grouped t-copula application, a two-step algorithm is adopted for convenience, which means R_t is first estimated from the dynamic Gaussian

[9]The dynamic multivariate Gaussian copula is defined similarly to the t-copula as follows:

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. This incidental parameter problem causes likelihood-based inference to have economically important biases in the estimated dynamic parameters, with α especially displaying a significant downward bias. Engle, Shephard and Sheppard (2008)[22] suggest an approach to construct a type of composite likelihood, which is then maximized to deliver the preferred estimator:

$$CL(\psi) = \sum_{t=1}^{T} \frac{1}{N} \sum_{i=1}^{N} log\ f(Y_{j,t}; \psi), \tag{7}$$

where $Y_{j,t}$ is composed of all unique pairs of data, ψ is a set of parameters, N is the number of all pairs, and $t = 1, 2, ..., T$. The composite likelihood is based on summing up the quasi-likelihood of all subsets. Each subset yields a valid quasi-likelihood, but this quasi-likelihood is only mildly informative about the parameters. By summing up many subsets, it is possible to construct an estimator which has the advantage of making the inversion of large dimensional covariance matrices unnecessary. Further, and vitally, the estimator is not affected by the incidental parameter problem. It is also a very fast algorithm without the intrinsic biases in the usual likelihood estimator when the cross-section is large. This dynamic Gaussian copula can also be estimated by maximizing the m-profile subset composite likelihood (MSCL)[10] using contiguous pairs, which is attractive from the statistical and computational viewpoints for large dimensional problems compared with the m-profile composite likelihood (MCLE) using all the pairs.

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. The one-step-ahead simulation is illustrated in Appendix I. The $CoES$ and $\Delta CoES$ can be easily obtained by these simulated returns for each asset. The multi-period ahead $CoES$ and $\Delta CoES$ 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)[20] and Cao (2014)[17]. The Shapley value of

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$$C(\eta_1, \eta_2, ..., \eta_n; R_t^{Gaussian}) = \Phi_{R_t^{Gaussian}}(\Phi^{-1}(\eta_1), \Phi^{-1}(\eta_2), ..., \Phi^{-1}(\eta_n)),$$

where $\eta_i = F_i(\epsilon_i)$ for $i = 1, 2, ..., n$, and $\epsilon_t \sim iid(0, 1)$ are again the innovations from the marginal dynamics introduced in the previous section. $R_t^{Gaussian}$ is the Gaussian copula correlation matrix. The copula correlation dynamics is similarly driven by the two parameters listed above for the t-copula. However, $\epsilon_i^* = \Phi^{-1}(\eta_i = F_i(\epsilon_i))$.

[10] A moment-based profile likelihood, or m-profile likelihood for short, in which the nuisance parameters are not maximum quasi-likelihood estimators but attractive moment estimators.

$\Delta CoES$ can be defined as:

$$Shapley_i(\Delta CoES) = \sum_{S \subseteq N\{i\}} \frac{|S|!(n-|S|-1)!}{n!} (\Delta CoES(S \cup \{i\}) - \Delta CoES(S)), \qquad (8)$$

where $\Delta CoES$ 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)[15] can also be simulated in the framework of a dynamic conditional grouped t-copula. Consider a panel of financial institutions indexed by $i = 1, ..., I$ observed at times $t = 1, ..., T$. 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:

$$CS_{it+h|t} = -kD_{it} + (1-k)W_{it}MES_{it+h|t}(VaR_q^{R_{mt+h:t}}), \qquad (9)$$

where $MES_{it+h|t}(VaR_q^{R_{mt+h:t}}) = E_t(exp(R_{it+h:t})|R_{mt+h:t} < -VaR_q^{R_{mt+h:t}})$ is the tail expectation of the firm equity returns conditional on the systemic event expressed by $VaR_q^{R_{mt+h:t}}$ at $q\% - quantile$ of the conditional probability distribution of $R_{mt+h:t}$, 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)[15] in the financial system is:

$$SRISK_t = \sum_{i=1}^{I} max(0, CS_{it}). \qquad (10)$$

$SRISK$ 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 case of a crisis. Clearly $MES_{it+h|t}(VaR_q^{R_{mt+h:t}})$ depends on modeling a dynamic distribution. Brownlees and Engle (2017)[15] 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 GDFM Analysis

Following Jin and Nadal De Simone (2012)[33], this paper uses the two-sided GDFM of Forni et al (2000)[23] 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)[23] and 2005[24]) 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[11]. 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 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.

[11]This paper follows Hallin and Liska's (2007)[30] log criterion to determine the number of dynamic factors, and Alessi, Barigozzi and Capasso (2009)[4], who modify Bai and Ng (2002)[9] criterion, to determine the number of static factors in a relatively more robust manner. These tests suggest three dynamic factor and nine static factors in this study. Jin and Nadal De Simone (2014)[34] discuss how the number of factors may change over time, which stresses the need to use the above-mentioned statistical tests especially when the objective is to do real-time updates of measures of systemic risk even when using the one-sided GDFM of Forni et al (2005)[23].

For banks and investment funds, the short-term debt includes deposits of up to one-year maturity, short term funding, and repos, while the long-term debt includes time deposits of over one-year maturity and other long-term funding. The book value equity is the difference between total assets and total liabilities. For European banking groups, stock prices, short-term borrowing (F0636), long-term debt (BS051), and current number of shares outstanding (DS124) are downloaded from Bloomberg; and the bank's asset values are estimated by the Merton model.[12]

The macroeconomic database used for the GDFM includes data from 15 countries: Belgium, Canada, Denmark, France, Germany, Greece, Japan, Luxembourg, the Netherlands, Italy, Spain, Sweden, Switzerland, the United Kingdom, and the United States. The market data consist 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 (see Appendix II for a detailed list of data sources for market indices and macroeconomic time series). The database comprises 234 series including three measures of the credit-to-GDP gap for the euro area, the UK and the US.

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. The panel [1a] in Table [1] contains the descriptive statistics of monthly log returns of total equity values for 32 (33) Luxembourg banks, their 30 parent banking groups and 232 investment funds in the period of 2003-2016 (2009-2016). It is noted that the first-order autocorrelations are fairly high for both Luxembourg banks and investment funds. The Ljung-Box (LB) test that the first 20 monthly autocorrelations are zero is rejected. It is partly because the data have been interpolated by cubic spline functions.

In the period of 2003-2016, the median of annualized equity returns for banking groups was 6.23% with interquartile range 1.34%-8.06%, versus 5.53% with interquartile range 0.61%-8.32% for Luxembourg banks. The equity returns reflected the median of annual standard deviation at 35.2% with interquartile range 30.48%-44.67% for banking groups, versus only 14.65% with interquartile range 10.04%-22.96% for Luxembourg banks. Thus the Sharpe-ratios of Luxembourg banks were overall much higher than those of banking groups.[13] The excess kurtosis of Luxembourg banks was also higher, suggesting possibly more tail risk than banking groups. However, their median of skewness was slightly higher than that of banking groups, suggesting that Luxembourg banks were not more risky from this perspective.

[12]See Jin and Nadal De Simone (2011)[32], for a detailed discussion of estimation of credit risk models, and the data filtering rules on short-term borrowing and long-term debt in annual, semi-annual, and quarterly frequencies.

[13]Because the data for Luxembourg banks and investment funds have been interpolated by cubic splines, their Sharpe-ratios could be a little exaggerated when compared with those of banking groups.

Table 1: Descriptive Statistics on Equity Returns

(a) Sample Moments

		Annual Mean (%)	Annual Standard Deviation	Sharpe Ratios	Skewness	Excess Kurtosis	1st Order Auto-Correlation	LB(20) P-Value on Returns	LB(20) P-Value on Absolute Returns
					2003M4-2016M12				
Banking Groups	Median	6,23	35,20	0,16	-0,06	3,63	0,11	0,33	0,00
	$Q_{25\%}$	1,34	30,48	0,04	-0,41	1,21	0,03	0,01	0,00
	$Q_{75\%}$	8,06	44,67	0,25	0,55	6,88	0,18	0,74	0,04
Luxembourg Banks	Median	5,53	14,65	0,29	0,16	5,66	0,69	0,00	0,00
	$Q_{25\%}$	0,61	10,04	0,06	-0,52	3,15	0,66	0,00	0,00
	$Q_{75\%}$	8,32	22,96	0,64	1,81	12,43	0,75	0,00	0,00
					2009M1-2016M12				
Banking Groups	Median	7,47	39,43	0,19	0,11	1,94	0,05	0,62	0,48
	$Q_{25\%}$	3,40	31,36	0,09	-0,33	0,58	-0,01	0,28	0,07
	$Q_{75\%}$	14,55	44,77	0,37	0,69	4,36	0,14	0,90	0,78
Luxembourg Banks	Median	0,88	11,45	0,10	0,07	2,60	0,71	0,00	0,00
	$Q_{25\%}$	-3,94	8,98	-0,30	-0,82	1,35	0,66	0,00	0,00
	$Q_{75\%}$	7,44	21,04	0,46	0,50	4,68	0,73	0,00	0,00
Investment Funds	Median	16,25	12,26	1,24	0,36	2,00	0,80	0,00	0,00
	$Q_{25\%}$	5,69	9,04	0,39	-0,29	0,91	0,75	0,00	0,00
	$Q_{75\%}$	27,64	18,14	1,98	1,31	6,56	0,85	0,00	0,00

(b) Corrrelations

	Banking Groups - Banking Groups	Luxembourg Banks - Luxembourg Banks	Investment Funds - Investment Funds	Banking Groups - Luxembourg Banks	Banking Groups - Investment Funds	Luxembourg Banks - Investment Funds
			2003M4-2016M12			
Median	0,43	0,06		-0,05		
$Q_{25\%}$	0,30	-0,03		-0,12		
$Q_{75\%}$	0,55	0,18		0,03		
			2009M1-2016M12			
Median	0,49	0,13	0,17	-0,03	0,14	0,00
$Q_{25\%}$	0,32	-0,01	0,01	-0,11	0,03	-0,12
$Q_{75\%}$	0,58	0,27	0,37	0,06	0,24	0,12

Note: This table reports sample moments and average sample correlations on monthly equity returns for 32 (33) Luxembourg banks, 30 banking groups, and 232 investment funds in the long (short) sample period.

When investment funds are added in the period of 2009-2016, compared with banking groups, the Sharpe-ratios and skewness (excess kurtosis) of Luxembourg banks were generally lower (higher), reflecting a diminished performance of Luxembourg banks during this period. However, investment funds with the highest average annualized returns, Sharpe-ratios and skewness performed much better than both banking groups and Luxembourg banks.

The unconditional correlations of monthly equity returns of these three sectors are shown in panel [1b] of Table [1]. In both periods, the correlations within banking groups were much higher than those within Luxembourg banks or investment funds. The Luxembourg banks were more correlated in the period 2009-2016 than in the period 2003-2016. Interestingly, the correlations between banking groups and investment funds were higher at median of 0.14% with interquartile range 3%-24%, whereas the other cross-section correlations were close to zero.

Figure [1] gives visual insights on 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. The quarterly returns have not been interpolated with cubic splines. 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 kept flatter and more dispersed later. In the short period from 2009, the performance of Luxembourg banks look even worse only with a tiny growth at the end of 2014. In contrast, Luxembourg investment funds had recorded a steady growth of total equities in the interquartile range for the whole sample period.

3.2 In-Sample Analysis

Since the data of both Luxembourg banks and investment funds has been interpolated by cubic spline functions, and the Ljung-Box (LB) test that the first 20 monthly autocorrelations are zero is rejected, an autoregressive model of order six, AR(6) is used to capture this return dependence over two quarters, and a simple GARCH(1,1) model is employed to capture this second moment dependence for each financial institution. Tables [2a] and [2b] summarize the results from the estimation of the AR(6)-GARCH(1,1) model on all available data for each institution in the period from June 2003 to December 2016. The median of the volatility updating parameter, Arch (autoregressive variance parameter, Garch), is 0.12 (0.54) for investment funds, 0.18 (0.73) for banking group, and 0.15 (0.68) for Luxembourg banks. The model-implied variance persistences are all high above 0.96 in median. The Ljung-Box (LB) test on the model residuals shows that the AR(6) models are able to pick up the evidence of return predictability found in Table [1].

Table 2: Summary of AR-GARCH Estimation

(a) Equity Returns

	Banking Groups			**Luxembourg Banks**			**Investment Funds**		
	Median	$Q_{25\%}$	$Q_{75\%}$	Median	$Q_{25\%}$	$Q_{75\%}$	Median	$Q_{25\%}$	$Q_{75\%}$
Constant	0,001	0,000	0,002	0,000	0,000	0,000	0,000	0,000	0,000
Arch	0,181	0,127	0,345	0,149	0,039	0,653	0,123	0,000	0,740
Garch	0,734	0,529	0,799	0,682	0,159	0,899	0,537	0,071	0,858
Variance Persistence	0,955	0,909	1,000	0,997	0,902	1,000	0,985	0,692	1,000
AR (1)	0,087	-0,007	0,162	1,558	1,413	1,745	1,700	1,582	1,768
AR (2)	-0,047	-0,076	0,011	-1,500	-1,694	-1,284	-1,500	-1,634	-1,314
AR (3)	0,040	-0,024	0,100	0,793	0,537	1,060	0,863	0,619	1,053
AR (4)	0,005	-0,069	0,082	-0,290	-0,561	-0,061	-0,327	-0,580	-0,052
AR (5)	0,011	-0,023	0,075	0,075	-0,105	0,308	0,042	-0,147	0,225
AR (6)	-0,042	-0,086	-0,020	-0,053	-0,136	0,054	0,023	-0,066	0,100
Residual Mean	-0,044	-0,084	-0,018	-0,001	-0,025	0,009	0,003	-0,008	0,052
Residual Standard Deviation	1,004	0,999	1,011	1,003	0,992	1,060	1,009	1,002	1,057
Residual Skewness	-0,197	-0,490	0,020	1,395	0,492	3,272	0,629	0,096	1,259
Residual Excess Kurtosis	1,103	0,559	2,614	10,272	4,374	19,942	4,001	2,304	7,578
Residual 1st Order Auto-Correlation	0,010	-0,006	0,032	0,031	-0,007	0,057	0,034	0,000	0,097
LB(20) P-Value on Residuals	0,834	0,467	0,980	0,050	0,003	0,510	0,685	0,310	0,919
LB(20) P-Value on Absolute Residuals	0,471	0,356	0,640	0,008	0,000	0,219	0,247	0,040	0,559

Notably, the GARCH models are also able to pick up the strong persistence in absolute returns found in Table [1]. However, the skewness and kurtosis of residuals are not damped down for all

(b) Common Components

	Banking Groups			Luxembourg Banks			Investment Funds		
	Median	$Q_{25\%}$	$Q_{75\%}$	Median	$Q_{25\%}$	$Q_{75\%}$	Median	$Q_{25\%}$	$Q_{75\%}$
Constant	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
Arch	0,322	0,268	0,396	0,296	0,253	0,709	0,386	0,140	0,714
Garch	0,678	0,604	0,732	0,691	0,274	0,747	0,383	0,002	0,610
Variance Persistence	1,000	1,000	1,000	1,000	1,000	1,000	0,917	0,740	1,000
AR (1)	-0,090	-0,201	-0,021	1,255	1,072	1,498	1,754	1,592	1,854
AR (2)	-0,128	-0,201	-0,028	-1,012	-1,278	-0,716	-1,548	-1,801	-1,337
AR (3)	0,052	-0,033	0,133	0,504	0,300	0,710	0,824	0,587	1,134
AR (4)	0,080	-0,004	0,176	-0,210	-0,382	-0,005	-0,226	-0,538	0,034
AR (5)	0,150	0,033	0,192	0,071	-0,037	0,226	-0,066	-0,299	0,194
AR (6)	0,076	0,016	0,129	-0,030	-0,084	0,080	0,081	-0,012	0,199
Residual Mean	-0,105	-0,124	-0,086	-0,006	-0,046	0,026	0,003	-0,027	0,040
Residual Standard Deviation	1,026	1,014	1,042	1,039	1,002	1,050	1,006	1,004	1,022
Residual Skewness	-0,539	-0,905	-0,373	0,213	-0,300	1,098	0,261	-0,026	0,519
Residual Excess Kurtosis	0,987	0,684	1,746	3,246	1,305	6,215	1,017	0,474	1,763
Residual 1st Order Auto-Correlation	0,021	0,005	0,060	0,056	-0,003	0,087	0,042	0,001	0,092
LB(20) P-Value on Residuals	0,711	0,402	0,905	0,183	0,022	0,272	0,712	0,455	0,889
LB(20) P-Value on Absolute Residuals	0,464	0,226	0,735	0,300	0,110	0,586	0,643	0,310	0,853

Note: This table reports sample moments and average sample correlations on monthly equity returns for 32 (33) Luxembourg banks, 30 banking groups, and 232 investment funds in the long (short) sample period.

three sectors, suggesting the need for the semi-parametric form for the marginal distributions in the second step. The results for the common components of equity returns are similar. Tables [1] and [2] suggest that AR(6)-GARCH(1,1) models are appropriate for modeling the white-noise residuals that are required in order to obtain unbiased estimates of the dynamic copula correlations.

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 the 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 dropped slowly since 2010.

Table [3] reports the parameter estimates for the dynamic conditional grouped t-copula model. The Luxembourg banks and investment funds are divided into small, medium and large sized institutions. The market indices of 15 countries and Euro area are also added. Including their common components, this sample consists of 648 data series spanning the period from June 2003 to December 2016. 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.

Table 3: Dynamic Conditional Grouped T-Copula Estimation

α	0,06		
β	0,58		
Correlation Persistence	0,63		

	Numbers of Data Series	DoF	DoF Common Components
Banking Groups	30	87	58
Small Lux Banks	16	11	76
Medium Luxembourg Banks	11	7	405
Large Luxembourg Banks	6	4	58
Investment Fund Index	7	39	46
Market Index	16	48	27
Small Investment Funds	111	21	22
Medium Investment Funds	79	768	108
Large Investment Funds	42	224	213

Note: This table reports the estimation results for the Dynamic Conditional Grouped T-Copula model. The sample consists of 636 data series in the period from June, 2003 to December, 2016.

There are a lot of discrepancies in the degree of freedoms (DF) among these groups. For example, the DFs of Luxembourg banks are comparably lower at 4 for the large Luxembourg banks, 7 for the medium Luxembourg banks, and 11 for the small Luxembourg banks. The DFs for their corresponding common components are on average much higher. Therefore assuming only one global DF parameter could be over-simplistic and too restrictive for a large portfolio. The dependence updating parameter, α, is 0.06, and the autoregressive parameter, β, is 0.58 with persistence of 0.63. Thus the copula correlation is highly dynamic.

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, 0.20 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 found in Table [1].

The t-copula generalizes the normal copula by allowing for non-zero dependence in the extreme tails.[14] The coefficient of tail dependence seems to provide a useful measure of the extreme dependence between two random variables. In this multivariate case, a pairwise approximation called lower quantile dependence by simulation from the grouped t-copula is obtained by using the quantile 0.05 for the lower tail dependence which is defined analogously. In order to reveal the full range of lower tail dependence especially when the DFs in these groups are high on average, other extreme quantiles such as 0.001 are not selected. Figure [4] shows the lower quantile

[14]This type of dependence is measured by τ^U upper tail dependence, and τ^L lower tail dependence:

$$\tau^L = \lim_{\xi \to 0} Pr[\eta_1 \leq \xi | \eta_2 \leq \xi] = \lim_{\xi \to 0} Pr[\eta_2 \leq \xi | \eta_1 \leq \xi] = \lim_{\xi \to 0} (\frac{C(\xi, \xi)}{\xi}),$$

$$\tau^U = \lim_{\xi \to 1} Pr[\eta_1 > \delta | \eta_2 > \delta] = \lim_{\xi \to 1} Pr[\eta_2 > \delta | \eta_1 > \delta] = \lim_{\xi \to 1} \frac{1 - 2\delta + C(\delta, \delta)}{1 - \delta}.$$

Two random variables exhibit lower tail dependence, for instance, if $\tau^L > 0$. The normal copula imposes that this probability is zero. The two parameters of the t-copula, ρ_t and v_t, jointly determine the amount of dependence between the variables in the extremes. Since it is a symmetric copula, the dependence between the variables during extreme appreciations is restricted to be the same as during extreme depreciations, and is given by:

$$\tau_t^U = \tau_t^L = 2 - 2T_{v_{t+1}} (\sqrt{v_{t+1}} \sqrt{\frac{1 - \rho_t}{1 + \rho_t}}).$$

dependence of equity returns at median and interquartile range among these three sectors of financial institutions in the two periods. The dynamics are similar to the copula correlation however at a lower level. The lower quantile dependence of investments funds was much higher than that of Luxembourg banks, and their interquartile range kept shrinking until the Chinese market turmoil of 2015-16.

3.3 Forward-Looking Conditional Concentration Risk

In order to fully reveal the forward-looking measures of systemic risks 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 following the steps illustrated in Appendix I. The measures of systemic risk constructed in this semi-forward-looking way still predict future, rather than contemporaneous events.

To aggregate the tail risk for these institutions, a conditional concentration risk measure is constructed on an equal-weighted portfolio of selected financial institutions. Derived from the diversification benefits as in Christoffersen *et al.* (2012)[18], the CCR is defined as

$$CCR_t(p) = 1 - \frac{\overline{ES_t(p)} - ES_t(p)}{\overline{ES_t(p)} - \underline{ES_t(p)}}, \tag{11}$$

where $ES_t(p)$ denotes the expected shortfall with probability threshold p of the portfolio at hand, $\overline{ES_t(p)}$ denotes the average of the ES across institutions, which is an upper bound on the portfolio ES, and $\underline{ES_t(p)}$ is the portfolio VaR, which is a lower bound on the portfolio ES. The $CCR_t(p)$ measure takes values on the [0 1] interval, and is increasing in the level of conditional concentration risk. Expected shortfall is additive in the conditional mean and it therefore cancels out in the numerator and denominator. By construction, CCR does not depend on the level of expected returns, and takes into account the concentration risk arising from all higher-order moments rather than just the variance.

Figure [5] depicts the CCR at q=0.05 of an equal-weighted portfolio of equity returns between three sectors in the two periods. Not surprisingly, CCRs were overall lower than their common components which were driven by common macro-factors. CCRs were higher around 20% for banking groups, and around 10% for both Luxembourg banks and investment funds with a mild increase observed during 2014-2015. For the portfolio of banking groups and Luxembourg banks together, the CCRs were driven mainly by banking groups, however at a lower level compared with the CCRs of banking groups. Since there are 232 investment funds, the CCRs of investment funds combined with banks were dominated by investment funds. Interestingly, the common components of CCRs for the portfolio of investment funds and Luxembourg banks was lower than those of investment funds combined with banking groups.

3.4 Forward-Looking ES and $\Delta CoES$

Figure [6] 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 the 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.

Figure [7] shows the quarterly forward-looking $\Delta CoES$ at median and interquartile range for the value-weighted portfolio of Luxembourg banks contributed by each institution from these three sectors respectively in the two periods. Luxembourg banks' forward-looking $\Delta CoES$ conditional on Luxembourg banks were more dispersed and overall positive around 1%, tracking market events closely over time. However, conditional on banking groups, the $\Delta CoES$ were lower than zero especially after the big downside jump in the first quarter of 2008, which is consistent with their common components. The $\Delta CoES$ values conditional on investment funds were volatile even though they were around zero. It suggests that the marginal expected loss of the Luxembourg banking sector was more sensitive to the adverse events from Luxembourg banks than from investment funds or banking groups.

For banking groups as shown in Figure [8], the $\Delta CoES$ conditional on banking groups were all positive around 15% tracking market events timely. However, conditional on Luxembourg banks, the $\Delta CoES$ were lower than zero especially during the global financial crisis, and their common components were even more volatile and dispersed. The $\Delta CoES$ conditional on investment funds decreased over time. However they were still above zero on average. In addition, their common components were more volatile and also above zero at the end of the period. It seems that the marginal expected loss of the banking groups was more sensitive to the adverse events from banking groups and investment funds than from Luxembourg banks.

As for the value-weighted portfolio of investment funds as shown in Figure [9], the $\Delta CoES$ values conditional on investment funds were all positive around 3% tracking market events closely. However, conditional on Luxembourg banks, the $\Delta CoES$ were around zero. The $\Delta CoES$ conditional on banking groups were volatile but still above zero on average. It suggests that the marginal expected loss of the investment fund sector was more sensitive to the adverse events from investment funds and banking groups than from Luxembourg banks.

In order to better understand the risk spillovers of equity returns across these three sectors, Table [4] outlines the key descriptive statistics of forward-looking $\Delta CoES$ of the value-weighted portfolios of three sectors conditional on events of each institution from these sectors respectively 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 portion for systemic risk monitoring. For instance, ranking by the median of Max of $\Delta CoES$ from top to bottom gives the following: banking groups (11.34%), investment fund (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.

Table 4: Matrix of Forward-Looking $\Delta CoES$ in Percentage

		Min	Mean	$Q_{25\%}$	Median	$Q_{75\%}$	Max	Min	Mean	$Q_{25\%}$	Median	$Q_{75\%}$	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
	$Q_{25\%}$	-0,65	7,30	6,60	7,99	8,90	9,38	2,84	11,15	10,39	11,87	12,17	12,19
	$Q_{75\%}$	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
	$Q_{25\%}$	-10,24	-0,68	-3,64	-0,52	1,70	5,76	-27,82	-5,36	-10,68	-5,17	0,94	5,58
	$Q_{75\%}$	-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
	$Q_{25\%}$	-15,32	1,88	-0,04	2,37	4,16	8,97	-25,27	1,76	-0,35	2,21	3,91	8,59
	$Q_{75\%}$	-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
	$Q_{25\%}$	-1,57	-0,41	-0,75	-0,40	-0,11	0,56	-2,06	-1,09	-1,51	-1,13	-0,80	0,06
	$Q_{75\%}$	-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
	$Q_{25\%}$	-0,83	0,88	0,41	0,80	1,38	2,10	-0,83	0,70	0,26	0,73	1,17	1,51
	$Q_{75\%}$	-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
	$Q_{25\%}$	-2,21	-0,28	-0,81	-0,35	0,25	1,50	-2,20	-0,25	-0,78	-0,27	0,19	1,30
	$Q_{75\%}$	-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
	$Q_{25\%}$	-0,93	0,69	-0,16	0,48	1,32	2,54	-0,59	0,36	0,09	0,37	0,62	1,06
	$Q_{75\%}$	-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
	$Q_{25\%}$	-1,54	-0,23	-0,87	-0,49	0,14	1,90	-2,34	-0,16	-0,69	-0,24	0,23	1,13
	$Q_{75\%}$	-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
	$Q_{25\%}$	-1,80	2,00	0,57	2,09	3,10	3,64	-2,27	0,93	0,50	1,19	1,51	1,57
	$Q_{75\%}$	-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 $\Delta CoES$ 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.

3.5 Forward-Looking $Shapley - \Delta CoES$

Table [5] provides the summary statistics of the estimated forward-looking $Shapley - \Delta CoES$ series and standard-$\Delta CoES$ series for Luxembourg's banking sector conditional on the simultaneous distress in several panels of six Luxembourg's O-SIIs, four parent G-SIBs, and 6 investment fund categories respectively during 2009-2016. The total risk 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 $Shapley - \Delta CoES$ of each constituent presents its own expected marginal contribution to the total risk which equals to 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 $Shapley - \Delta CoES$ 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 $Shapley - \Delta CoES$, it was from BG C (Lux D). The standard-$\Delta CoES$ measure is calculated on the adverse events of the considered institution independently from others. Thus the sum of the standard-$\Delta CoES$ 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 on standard $\Delta CoES$, they might penalize the economy inefficiently without gauging the potential contagion that an individual institution contributes to the financial system.

In the previous section, the analysis of $\Delta CoES$ of Luxembourg banks is only conditional on individual investment funds. Here the estimating of $Shapley - \Delta CoES$ 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 the highest to the lowest, they are ranked as follows: MM Funds, RE Funds, Bond Funds, Mixed Funds, Hedge Funds, and Equity Funds. Overall in this period, money market funds provided the most marginal contribution to the total risk while equity funds provided the least. In contrast, according to their common components, the ranking from the top to the bottom is: MM Funds, RE Funds, Mixed Funds, Bond Funds, Equity funds and Hedge Funds. It suggests that idiosyncratic portion of the marginal contributions to total risk for some categories played an important role during this period. Figure [10] shows the quarterly $Shapley - \Delta CoES$ values of these six investment fund categories with respect to Luxembourg's banking sector for the period of 2009-2016. It seems that the marginal contribution to the total risk from bond funds, mixed funds and hedge funds became more important in 2016 given the prolonged low interest rate environment in the euro area.

Table 5: $Shapley - \Delta CoES$ and Standard $\Delta CoES$ in Percentage

	Shapley Value							**Standard Value**						
	Mean	Std	Min	$Q_{25\%}$	Median	$Q_{75\%}$	Max	Mean	Std	Min	$Q_{25\%}$	Median	$Q_{75\%}$	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 $Shapley - \Delta CoES$ and Standard $\Delta CoES$ 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.

3.6 Forward-Looking $SRISK$ and its Economic Determinants

In this section, the aggregate $SRISK$ for all three sectors are 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.

3.6.1 Forward-Looking SRISK

Figure [11] 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 dramatic impacts from the European sovereign debt crisis around 2012.

Out of all monthly data points from the 232 investment funds[15], at least 98.3% (90%) have a fraction of equity over its 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.

Table [6] reports the key descriptive statistics for the differences between the aggregate $SRISK$ computed using each country market index and the benchmark euro area market index for both 32 (33) Luxembourg banks and 30 banking groups for the long (short) sample period. The $SRISK$ series is computed using k = 8% or 12% respectively. For the aggregate $SRISK$ of Luxembourg banks, the countries with a positive interquartile range were Japan and the United States for the period of 2004-2016. In the shorter period of 2009-2016, the countries with a positive interquartile range were Denmark, Japan, Luxembourg, the Netherlands, the United Kingdom and the United States in the case of k = 8%, and only Luxembourg and United States in the case of k = 12%. The only country with a negative interquartile range was Sweden (France) in the case of k = 8% (k = 12%). As regards the banking groups, the countries with a positive interquartile range in the case of k = 8% were France in the longer period, and France and Italy in the shorter period, while in the case of k = 12%, it was only Italy. Clearly, by definition of $SRISK$, the systemic risk events are represented by the low quantile 5% of market index in each country; in the period of 2009-2019, France and Italy mattered most for banking groups, however they mattered less than other countries as mentioned above for Luxembourg banks. This result suggests that the aggregate $SRISK$ of Luxembourg banks was affected differently by country compared with those of banking groups.

[15]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.

Table 6: Marginal SRISK Sensitivity for Each Country (Euro Millions)

	k = 0.08						k = 0.12					
	Mean	Min	$Q_{25\%}$	Median	$Q_{75\%}$	Max	Mean	Min	$Q_{25\%}$	Median	$Q_{75\%}$	Max
Panel A: Luxembourg Banks												
2004Q1-2016Q4												
Belgium	-12,6	-184,5	-20,6	-4,9	2,2	118,6	-70,0	-1087,2	*-80,1*	*-24,5*	*-2,7*	192,6
Canada	7,7	-72,5	-10,8	2,2	30,3	91,6	17,7	-213,6	-19,1	14,5	51,1	384,1
Denmark	-4,6	-79,4	-20,2	-4,9	6,7	71,2	-9,6	-245,6	-30,4	5,1	25,9	184,3
France	6,5	-21,9	-4,2	2,6	17,1	47,9	12,8	-36,1	-14,4	3,4	27,3	133,2
Germany	11,7	-26,9	-3,0	6,5	19,6	195,6	27,9	-173,1	-5,7	12,2	47,8	364,1
Greece	3,8	-106,0	-20,0	2,2	18,9	125,6	-21,7	-401,2	-63,6	-2,4	48,4	296,3
Italy	1,9	-70,6	-6,7	2,4	13,7	77,0	-2,8	-196,5	-23,4	-1,6	17,4	181,3
Japan	34,3	-32,0	**7,2**	**20,5**	**49,3**	200,9	83,4	-52,9	**16,7**	**55,6**	**98,5**	524,2
Luxembourg	12,8	-164,1	-5,2	10,4	42,1	252,4	-45,4	-1345,7	-38,8	17,7	73,6	786,8
Netherlands	-3,4	-87,4	-17,0	2,4	11,8	87,1	-27,6	-290,0	-68,5	-7,5	25,7	189,6
Spain	5,4	-108,6	-4,2	1,7	14,1	94,4	4,1	-185,0	-17,7	-2,2	29,2	170,1
Sweden	-3,8	-102,4	-15,6	-4,7	5,1	79,2	-2,1	-278,6	-23,5	2,0	17,4	164,5
Switzerland	1,8	-77,7	-13,0	1,2	21,0	120,7	-10,8	-295,8	-68,7	9,7	48,0	229,2
United Kingdom	-3,6	-52,6	-13,5	-3,7	6,8	63,6	-17,0	-201,3	-40,1	-7,2	18,1	213,2
United States	22,7	-44,2	**8,2**	**19,3**	**32,2**	98,1	49,9	-136,4	**8,8**	**42,0**	**78,5**	314,3
2009Q4-2016Q4												
Belgium	3,8	*-37,1*	*-5,4*	*2,6*	*7,7*	33,9	-3,2	-128,9	-51,1	-1,3	31,1	237,6
Canada	-9,3	-77,7	-16,0	0,6	5,3	17,9	-30,8	*-394,9*	*-74,3*	*-10,0*	*34,6*	252,0
Denmark	9,2	-10,0	**0,8**	**7,6**	**18,5**	46,1	14,0	-117,7	-1,5	14,2	32,9	106,8
France	-4,4	*-19,3*	*-10,7*	*-5,0*	*1,8*	18,9	-9,5	-211,4	*-23,6*	*-17,0*	*-3,7*	214,0
Germany	-1,2	*-39,4*	*-8,9*	*-1,2*	*11,2*	27,6	-16,2	-170,7	-43,9	-17,9	1,9	165,1
Greece	-3,2	-52,5	-15,4	3,7	9,8	25,2	-9,0	-172,3	-27,3	5,4	26,7	149,9
Italy	2,2	*-13,6*	*-4,7*	*1,4*	*6,3*	21,2	12,2	-238,4	-10,2	4,2	13,0	370,8
Japan	6,8	-45,2	**3,1**	**6,9**	**14,6**	32,0	-17,3	-208,4	-47,8	-0,8	23,0	157,2
Luxembourg	36,3	-3,2	**26,6**	**33,0**	**47,2**	65,4	70,4	-63,9	**23,1**	**49,6**	**90,5**	358,4
Netherlands	21,4	-10,5	**10,8**	**20,9**	**28,6**	59,1	14,3	-128,7	-19,8	16,5	61,6	106,4
Spain	0,0	-31,6	-5,8	0,8	6,3	35,6	-6,0	-228,3	-19,7	-0,4	18,8	100,9
Sweden	-8,2	-36,0	*-14,3*	*-7,3*	*-1,8*	20,8	-4,8	-139,6	-17,3	-0,5	18,6	167,7
Switzerland	2,4	-26,6	-7,7	0,4	11,0	27,7	-41,9	-260,3	-68,5	-24,3	6,6	46,3
United Kingdom	4,8	-48,7	**0,4**	**7,1**	**14,5**	39,1	29,9	-137,6	-5,0	28,7	44,1	302,5
United States	15,2	-9,5	**5,4**	**11,5**	**24,1**	53,5	34,4	-75,0	**3,7**	**22,3**	**60,8**	293,1
Panel B: Banking Groups												
2004Q1-2016Q4												
Belgium	-3950,8	-13223,2	*-5493,7*	*-3734,0*	*-2078,6*	540,2	-6543,7	-19203,8	*-8278,1*	*-5874,1*	*-3566,2*	-87,7
Canada	-12417,4	-27084,8	*-19357,9*	*-10936,2*	*-5901,7*	-3265,7	-19383,4	-35834,9	*-26296,0*	*-20427,4*	*-13204,6*	-4606,0
Denmark	-9925,5	-23513,7	*-14206,9*	*-8466,4*	*-5004,1*	-2117,4	-15365,8	-30547,8	*-18985,3*	*-13771,7*	*-11044,1*	-7274,7
France	473,1	-1885,7	**109,6**	**389,6**	**918,3**	2226,4	500,5	-1683,4	-14,8	469,9	1023,4	3126,2
Germany	-1156,9	-6223,8	*-1783,6*	*-897,6*	*-234,7*	1566,2	-1486,1	-7070,5	*-2434,5*	*-1621,4*	*-42,3*	1980,2
Greece	-2782,3	-8972,5	*-5026,9*	*-2025,1*	*-905,1*	3445,7	-4452,4	-16203,4	*-7163,2*	*-3507,2*	*-1815,8*	4489,9
Italy	-550,0	-3920,8	**-1657,8**	**-782,7**	**459,0**	3176,3	-1262,3	-12133,7	-3115,3	-1355,6	1386,8	4167,0
Japan	-14681,6	-29104,8	*-21284,5*	*-11363,6*	*-8303,3*	-4479,1	-23002,0	-40350,4	*-29232,3*	*-22905,0*	*-15364,6*	-5786,7
Luxembourg	-14767,7	-33861,7	*-21612,6*	*-11553,7*	*-7078,8*	-1932,7	-22883,6	-43722,2	*-29820,1*	*-22795,0*	*-16198,5*	-6103,0
Netherlands	-4433,2	-10186,6	*-6211,6*	*-4166,9*	*-2168,9*	-709,1	-6710,2	-15037,4	*-9510,2*	*-6542,2*	*-3539,3*	-46,3
Spain	-2602,9	-8647,0	*-4325,1*	*-1667,8*	*-801,6*	1922,2	-3748,9	-12492,2	*-6015,2*	*-2646,9*	*-1118,6*	3349,1
Sweden	-4447,2	-11683,9	*-7050,6*	*-3667,8*	*-1926,8*	491,1	-6134,2	-14329,6	*-8995,1*	*-5814,3*	*-1870,3*	576,9
Switzerland	-4971,9	-15959,3	*-7056,5*	*-3779,4*	*-2437,7*	1593,1	-7673,4	-21344,8	*-11787,4*	*-6231,2*	*-3694,8*	1340,6
United Kingdom	-4634,6	-9762,0	*-7032,9*	*-3938,8*	*-2774,2*	-287,0	-7747,5	-18607,1	*-10114,3*	*-7804,3*	*-5745,4*	104,7
United States	-8251,4	-18102,3	*-11568,2*	*-7370,8*	*-5084,7*	-1796,2	-13068,8	-23934,3	*-16716,5*	*-12146,1*	*-9698,1*	-4813,9
2009Q4-2016Q4												
Belgium	-4592,8	-14012,5	*-5833,4*	*-4350,0*	*-2335,5*	-582,9	-7513,6	-17747,6	*-8689,3*	*-6561,7*	*-5016,6*	-1234,9
Canada	-13729,1	-28249,9	*-18668,7*	*-14372,7*	*-7858,1*	-4704,7	-22344,8	-36413,8	*-28559,1*	*-22458,5*	*-16623,4*	-9306,5
Denmark	-8585,6	-16175,3	*-12866,7*	*-8480,4*	*-4238,8*	-2344,3	-13273,1	-21533,4	*-17836,4*	*-13689,8*	*-8759,2*	-5374,3
France	392,0	-1744,8	**29,0**	**554,1**	**759,3**	1995,2	707,1	-1154,3	-94,5	730,3	1490,0	3519,1
Germany	-3309,5	-9663,9	*-5245,3*	*-2435,8*	*-1000,8*	298,2	-4906,2	-11228,6	*-7274,8*	*-3991,2*	*-2208,5*	-588,0
Greece	-1732,4	-7951,1	*-2865,7*	*-1124,8*	*-48,5*	2687,5	-3116,5	-10522,3	*-5062,6*	*-2919,9*	*-688,1*	3826,2
Italy	954,3	-792,7	**142,4**	**913,3**	**1564,4**	4055,4	1576,1	-893,4	**791,8**	**1390,0**	**2279,2**	5609,1
Japan	-15735,4	-29770,0	*-22304,2*	*-15368,1*	*-8954,9*	-4754,5	-25922,7	-42524,4	*-30587,6*	*-26234,8*	*-19721,9*	-13460,3
Luxembourg	-14442,1	-33960,4	*-19485,6*	*-13393,4*	*-8283,1*	-4689,5	-22483,3	-43473,3	*-24791,5*	*-21102,1*	*-16935,6*	-13632,5
Netherlands	-5014,8	-8871,2	*-6633,4*	*-5196,5*	*-2891,9*	-1789,6	-7922,4	-14099,8	*-10153,6*	*-7511,2*	*-5103,2*	-3757,6
Spain	-1772,5	-7048,3	*-2456,4*	*-1154,5*	*-431,8*	2176,7	-2284,6	-8347,7	*-3155,2*	*-1685,0*	*-456,6*	3997,3
Sweden	-5502,8	-12158,0	*-8360,8*	*-4987,9*	*-2855,9*	-1520,2	-7762,3	-14664,2	*-9924,2*	*-7833,3*	*-5667,1*	-1511,7
Switzerland	-6930,6	-16786,2	*-10724,5*	*-5156,6*	*-3070,4*	-1734,6	-10965,8	-22054,8	*-14190,8*	*-10224,3*	*-7500,8*	-3437,6
United Kingdom	-5514,3	-10222,1	*-7545,6*	*-4799,5*	*-3619,7*	-2080,7	-9213,9	-13265,5	*-11396,8*	*-8300,0*	*-7128,7*	-6398,2
United States	-10140,9	-22864,7	-14203,1	-9195,0	-6103,7	-3332,5	-16208,2	-28744,0	*-20165,4*	*-15617,7*	*-12334,0*	-7812,4

Note: This table reports the key descriptive statistics of the differences between the aggregate SRISK computed by country market index and that by EU market index for both 32 (33) Luxembourg banks and 30 banking groups for the long (short) sample period. The SRISK series is computed using k = 8% or 12% respectively. A bold value indicates positive interquartile range, whereas an italic value indicates negative interquartile range.

3.6.2 Forward-Looking SRISK's Economic Determinants

In an effort to better understand the forward-looking $SRISK$ discussed in this paper, linear regressions of $SRISK$ measures on various macroeconomic determinants were investigated for banking 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 (see Appendix II for a detailed list of data sources for market indexes and macroeconomic time series):

- The log of GDP in current prices
- The log of HICP all-items
- The log of unemployment rates
- Consumer confidence indicator
- Short-term interest rates: 3M
- Interest rate spread: 10YR interest rates - 3M interest rates
- Liquidity spread: 3M Euribor rates - 3M Germany T-bill rates [16]
- 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
- The log of US dollar

[16] 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%.

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.[17] 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 [7] 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 $k = 0.08$, the most relevant determinants of $SRISK$ in the short-term deviations were market price index, bank price index, Japanese yen, liquidity spread, and marginally loans to VSTOXX volatility index. In the case of $k = 0.12$, 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 loans to 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 $k = 0.08$, and liquidity spread, commodity S&P GSCI energy index and Japanese yen in the case of $k = 0.12$. Table [6] also shows that the aggregate $SRISK$ of Luxembourg banks was sensitive to the systemic market events in Japan. Since Luxembourg banks are more or less liquidity providers, the determinants underlying the $SRISK$ of Luxembourg banks might be very different from those of banking groups.

Table [7] also reports the regression results of aggregate $SRISK$ for the investment fund sector in the case of k = 90% and 70% respectively in the period of 2009-2016. The results of the regression in 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 $k = 90\%$, 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 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 $k = 0.90$, and interest rate spread, US dollar, and marginally GDP and property price in the case of $k = 0.70$.

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

Table 7: 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.

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 $\Delta CoES$, $Shapley - \Delta CoES$, $SRISK$ 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 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)[23].

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 $\Delta CoES$ 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 $Shapley - \Delta CoES$ 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 is 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.

In future research, the comprehensive "Mark-to-Systemic-Risk" approach will be explored in the context of broader balance-sheet items to integrate book value data of Luxembourg financial institutions into systemic risk measures. This new approach could help to efficiently capture the systemic performance of each financial institution within various balance-sheet items. Dimension reduction estimators will be proposed for constructing systemic risk indices from these cross-sectional measures, and their ability to predict of the lower tail of macroeconomic shocks will be evaluated.

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5 Annex

Figure 1: Cumulative Equity Returns

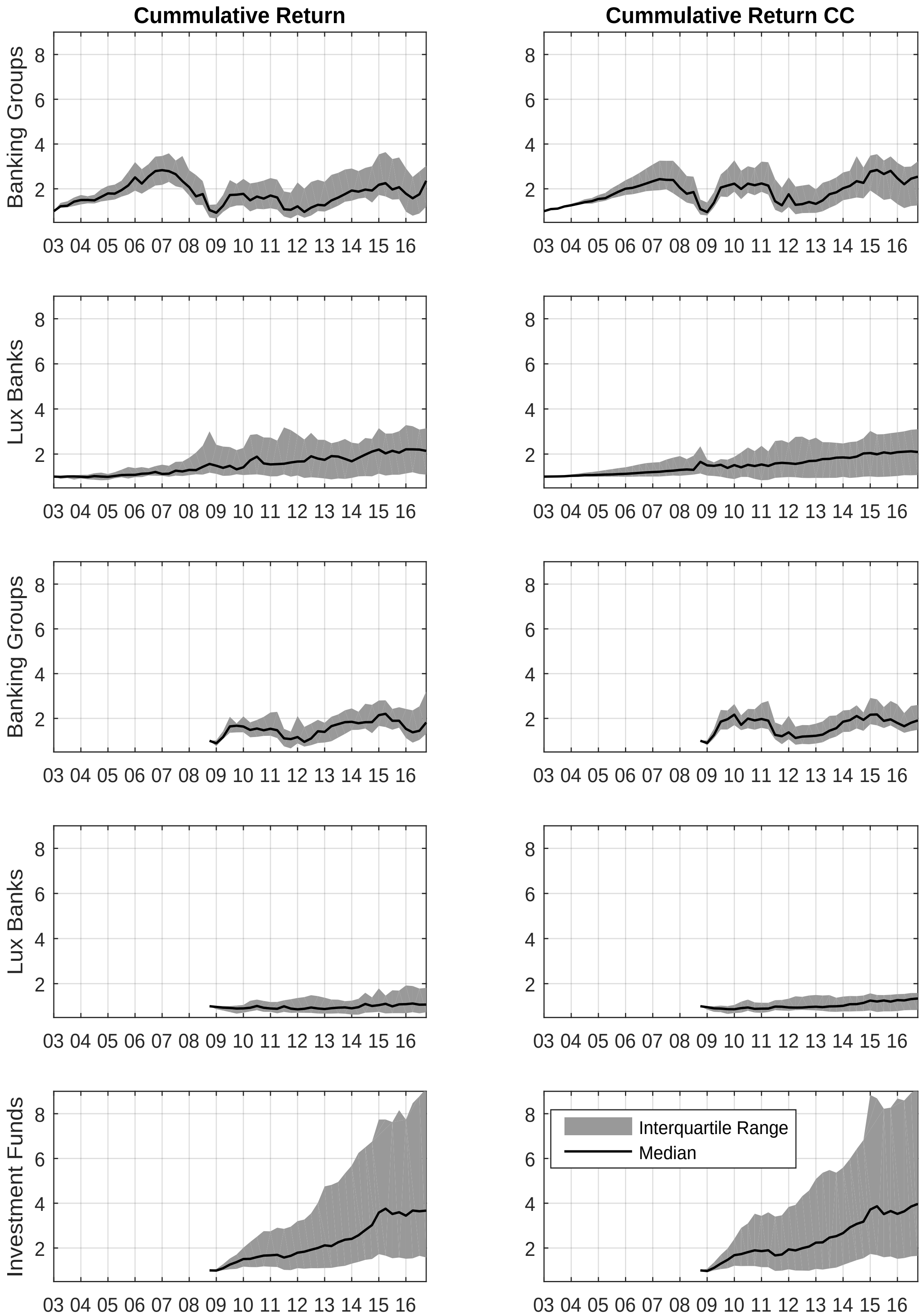


Figure 2: Volatility of Equity Returns

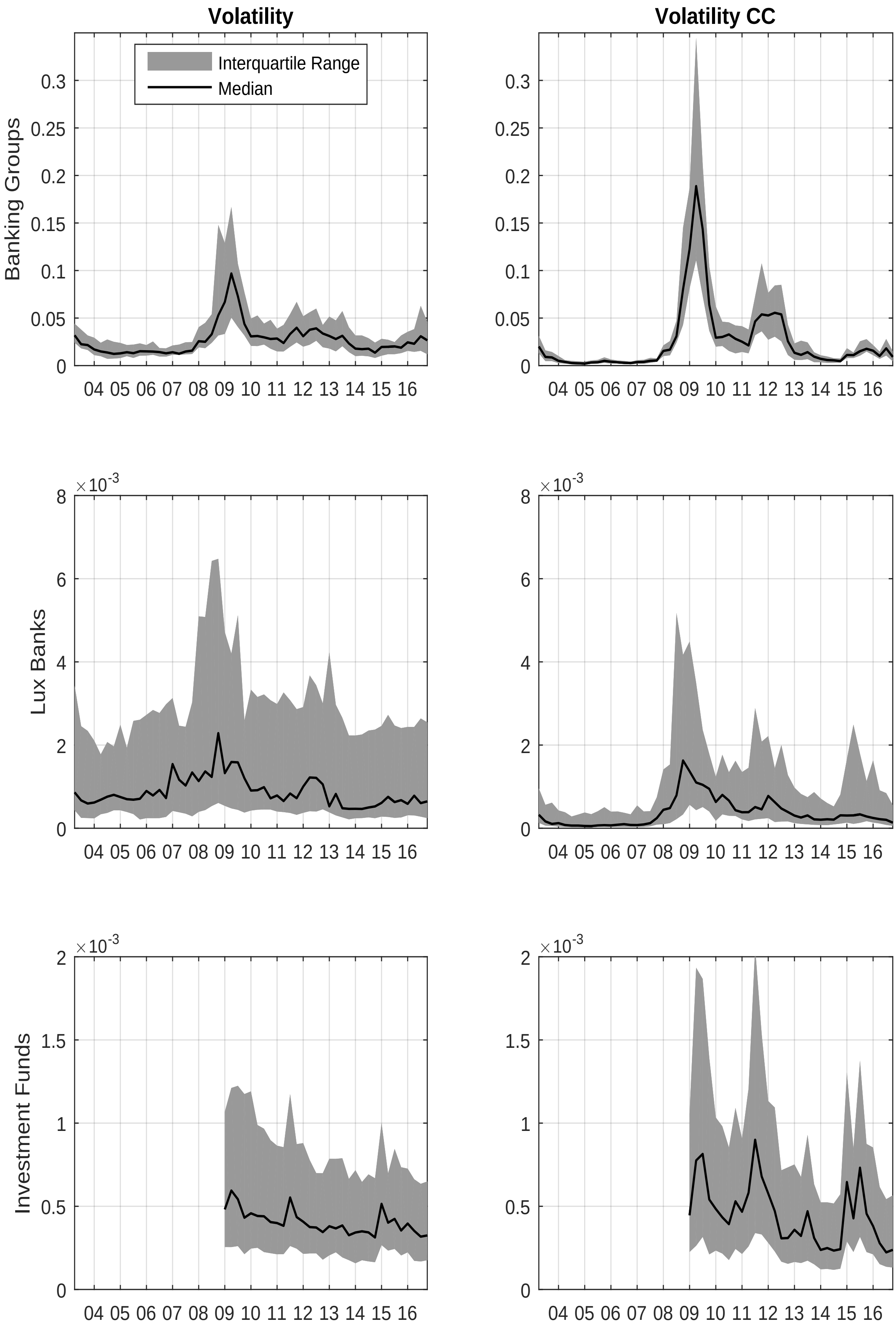


Figure 3: Copula Correlations of Equity Returns

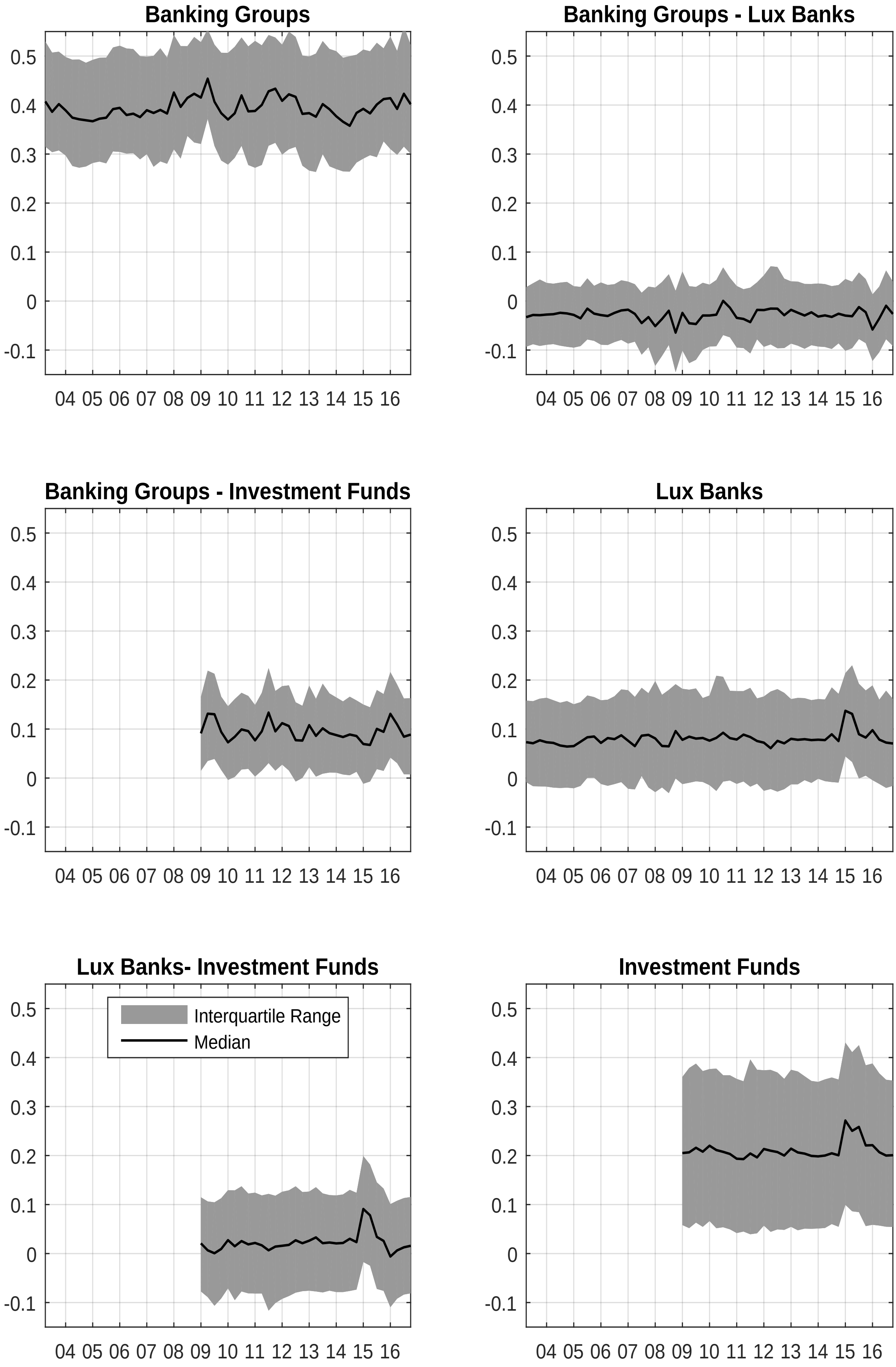


Figure 4: Lower Quantile Dependence of Equity Returns

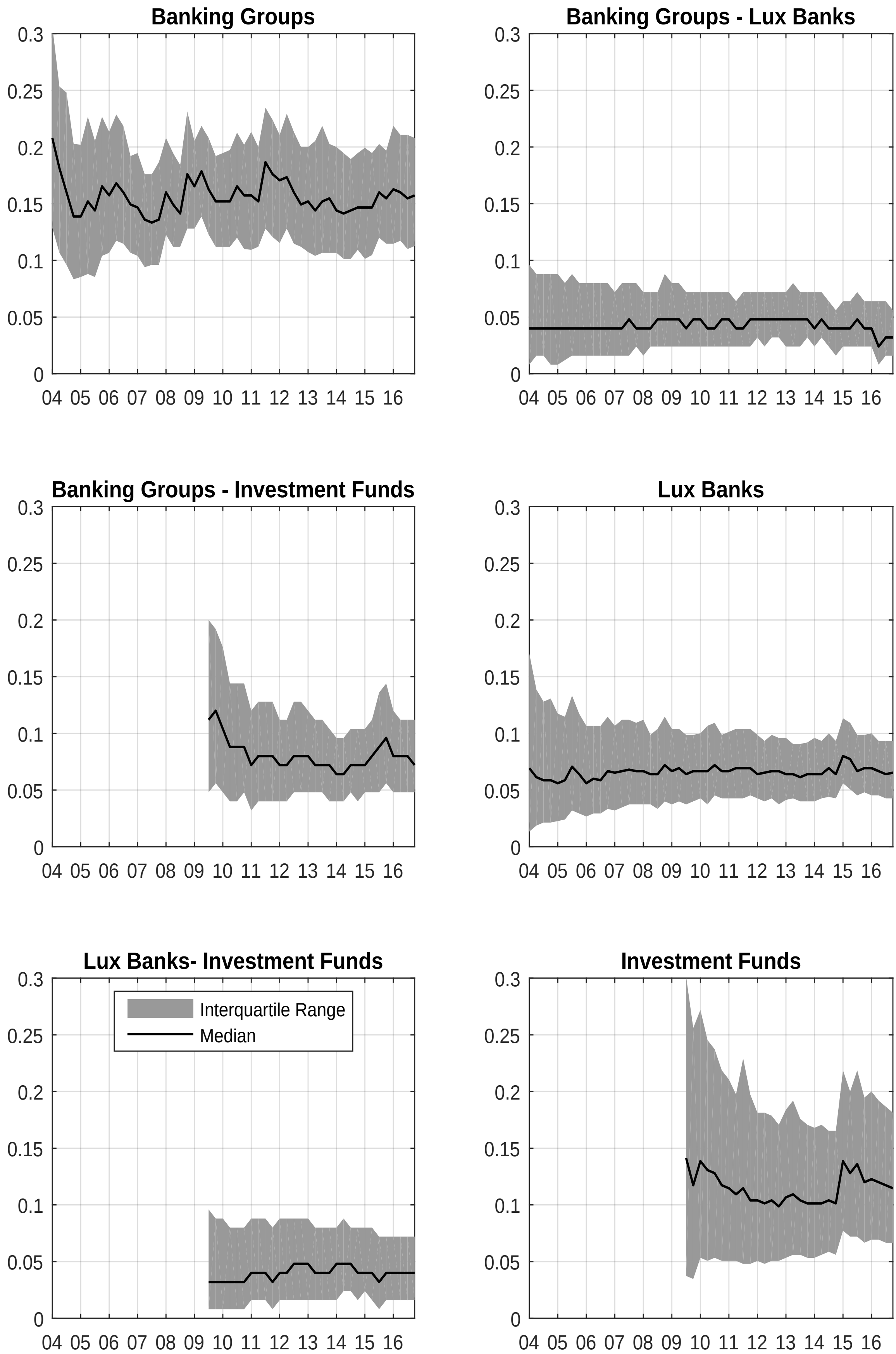


Figure 5: Forward-Looking Conditional Concentration Risk (Equal-Weighted)

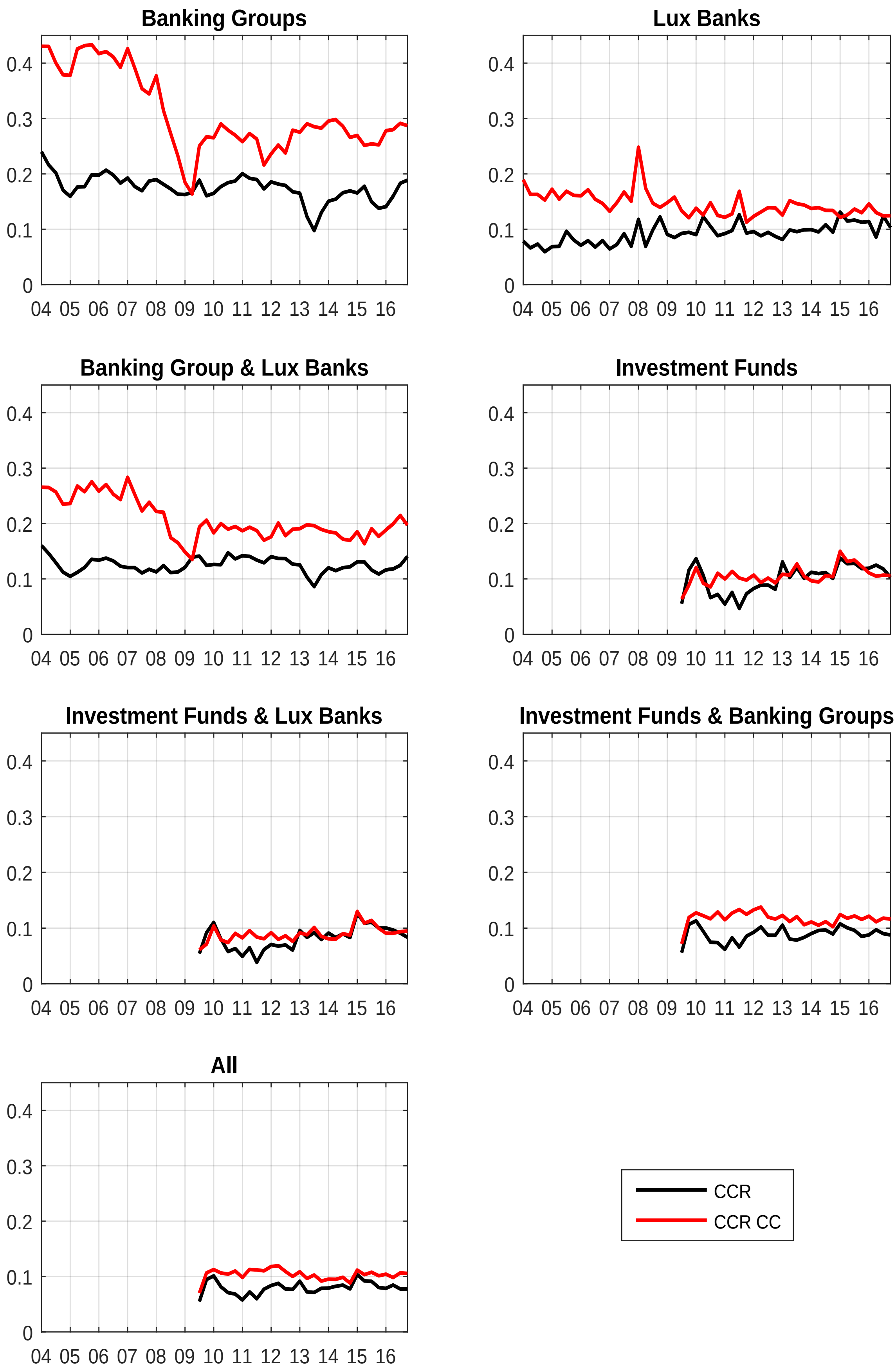


Figure 6: Forward-Looking ES of Equity Returns

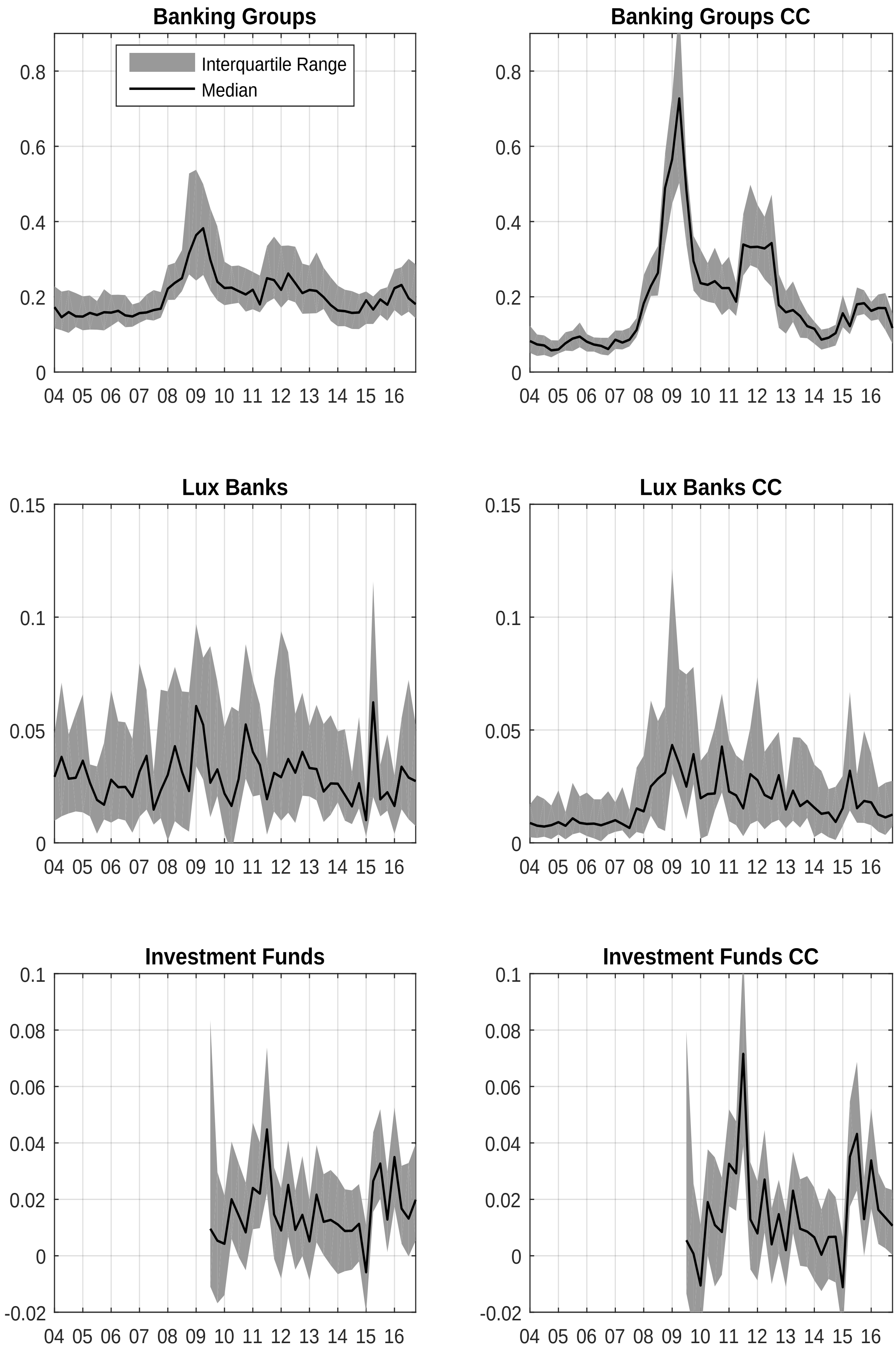


Figure 7: Forward-Looking ΔCoE of Luxembourg Banks (Value-Weighted)

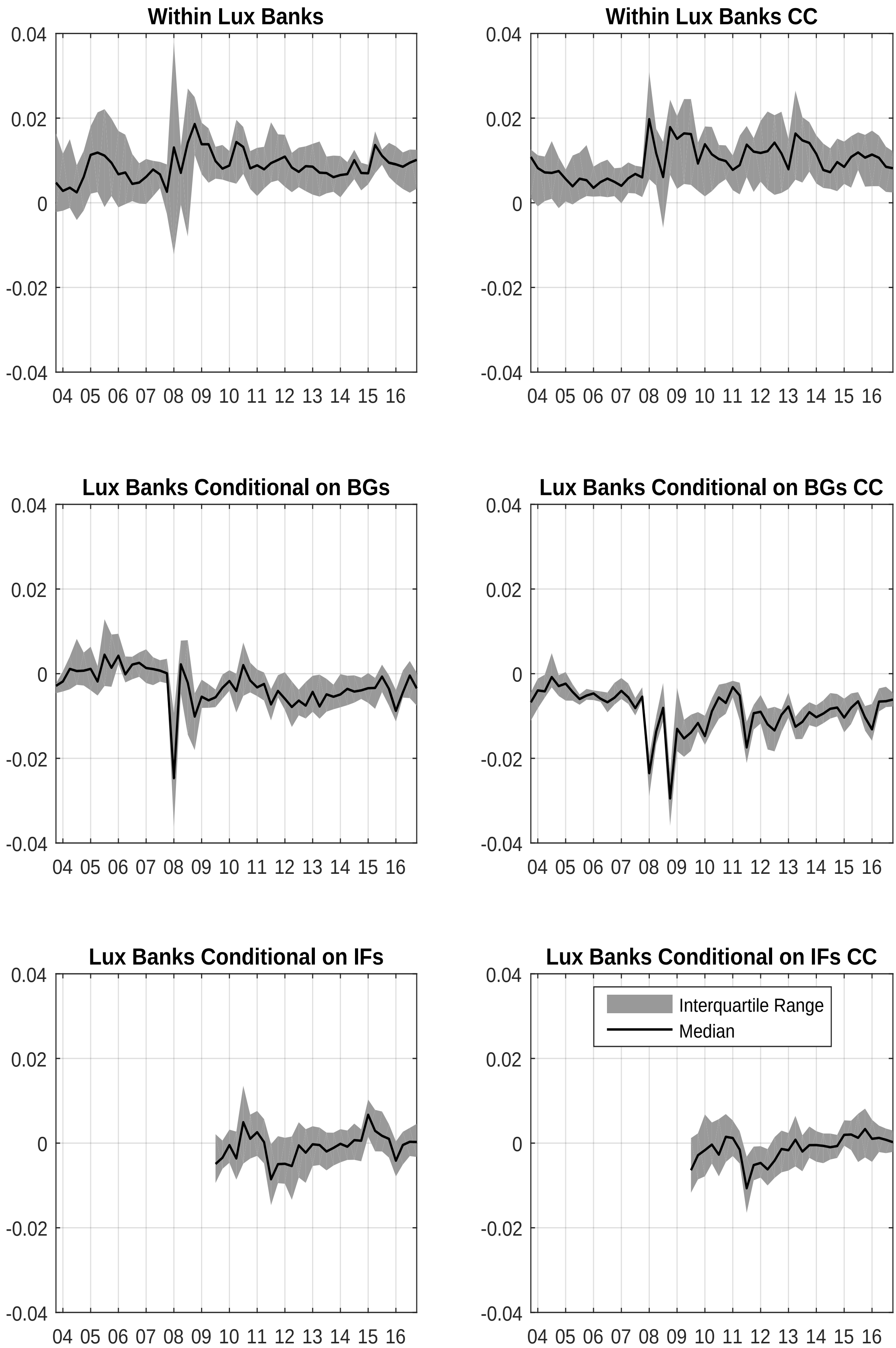


Figure 8: Forward-Looking ΔCoE of Banking Groups (Value-Weighted)

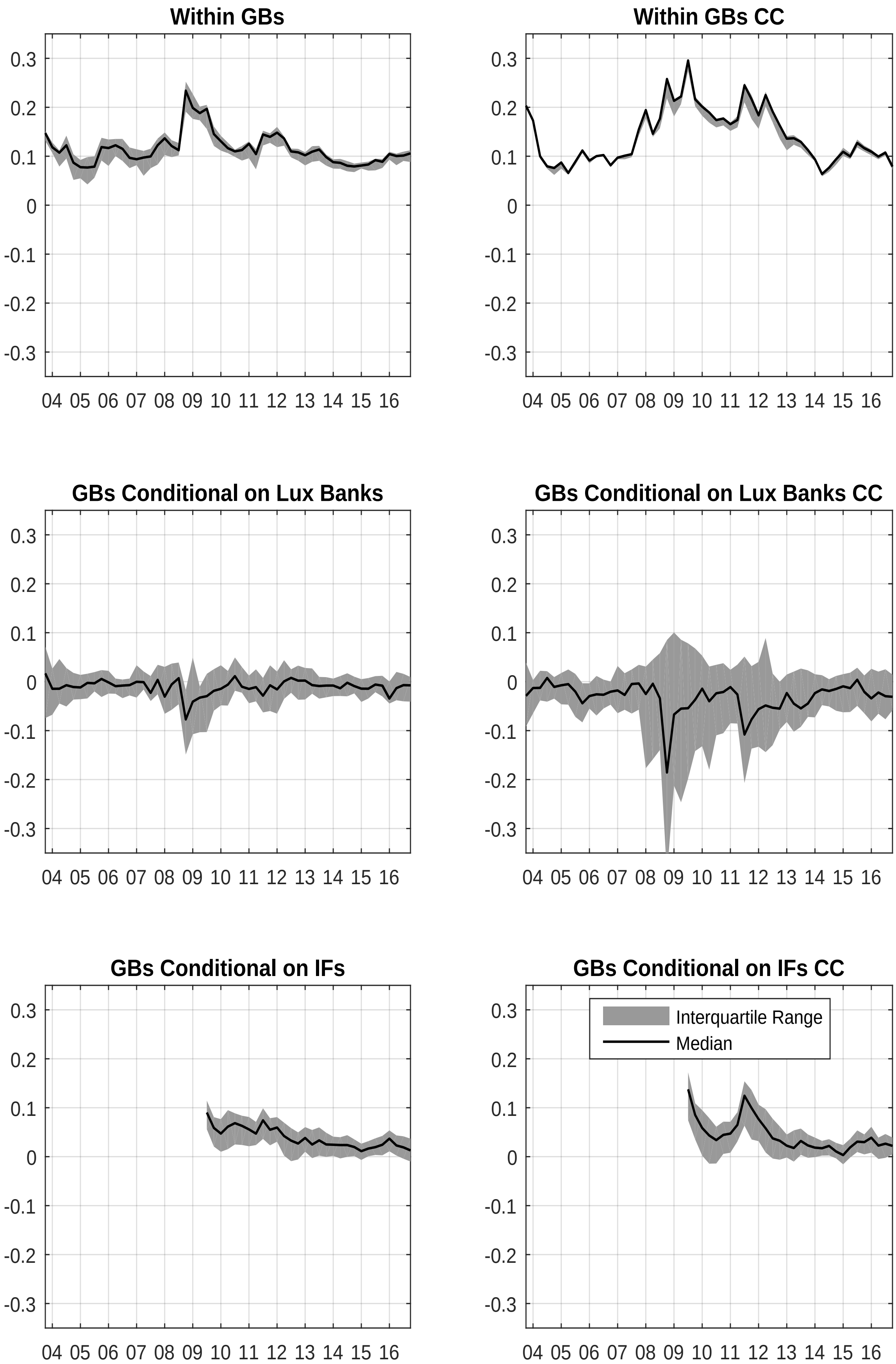


Figure 9: Forward-Looking ΔCoE of Investment Funds (Value-Weighted)

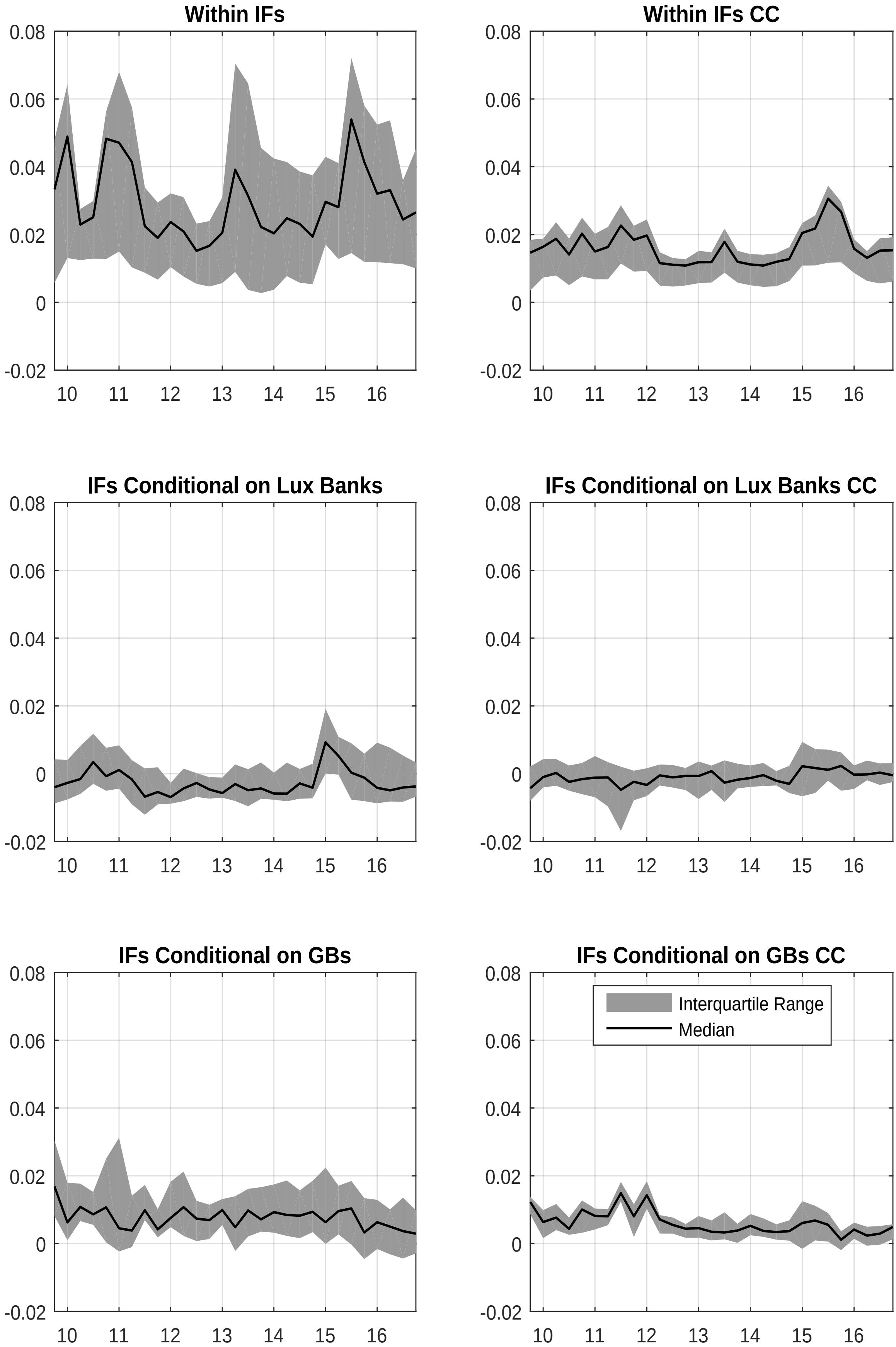


Figure 10: Forward-Looking $Shapley - \Delta CoE$ of Investment Funds on Luxembourg's Banking Sector (in Percentage)

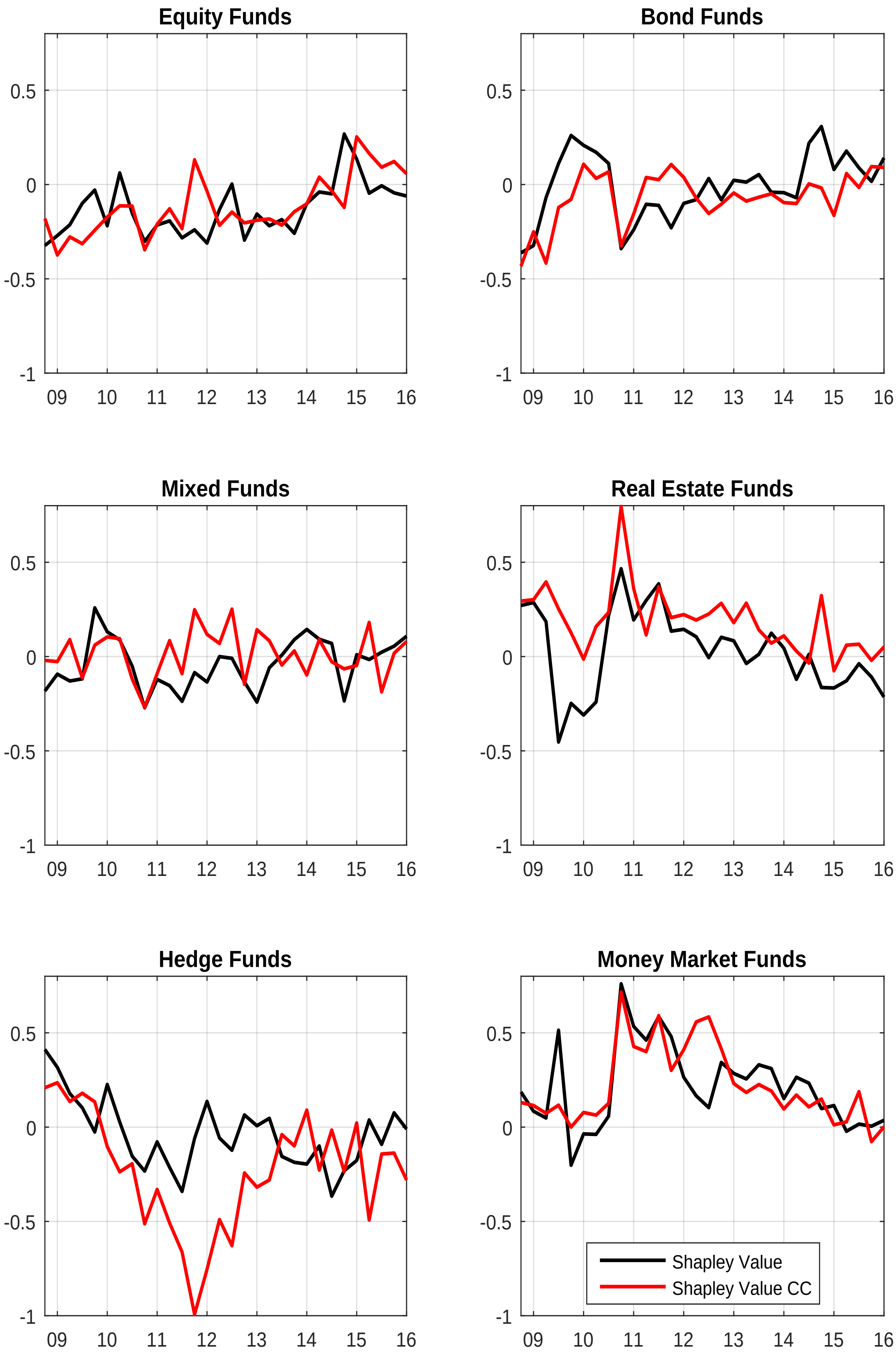
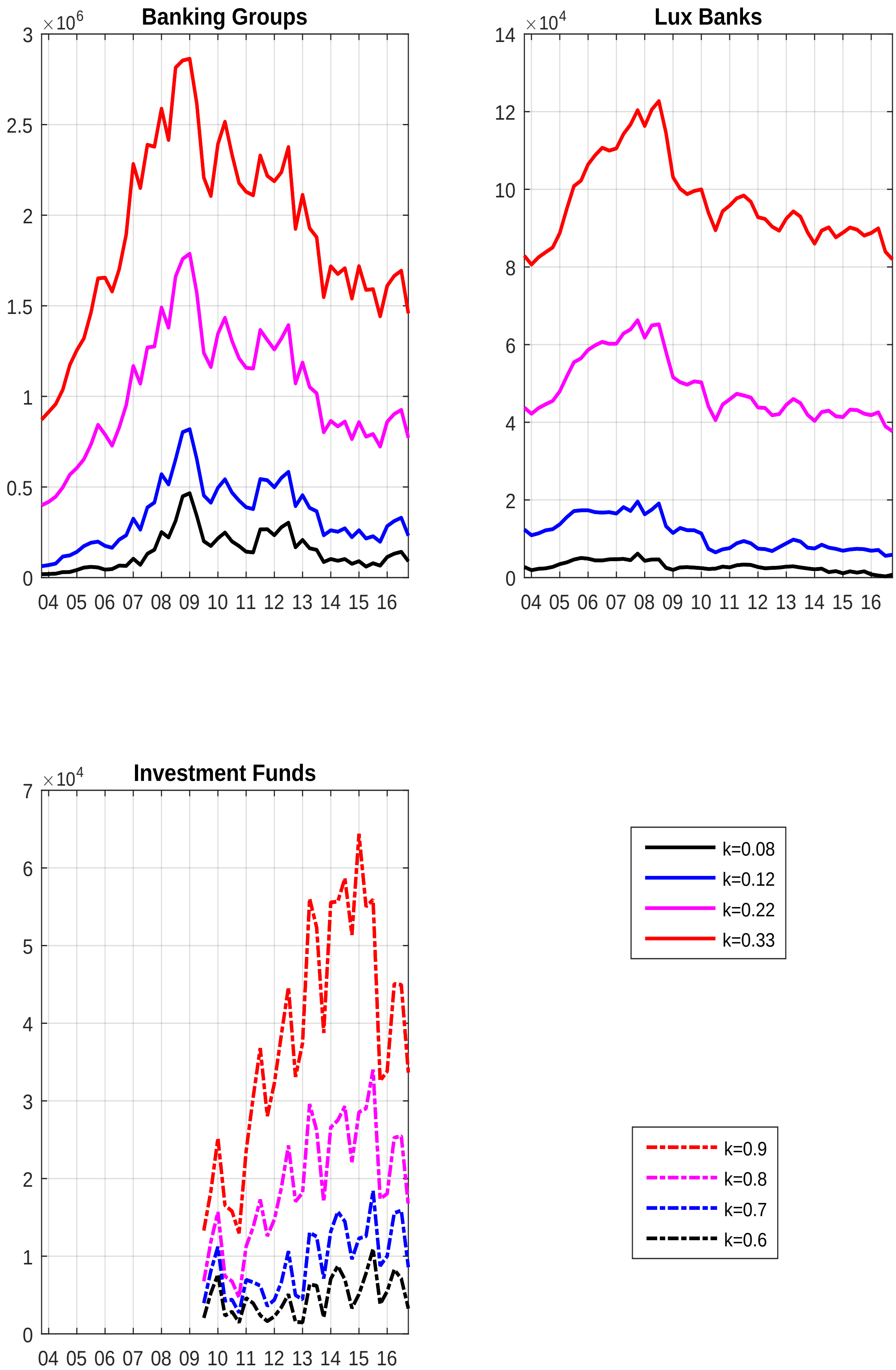


Figure 11: Forward-Looking SRISK Sensitivity in Millions



Appendix I: The Forward Simulation from the Dynamic Conditional t-Copula

Conditional dynamic copulas make it relatively easy to simulate from multivariate distributions built on marginal distributions and dependence structure. The GARCH-like dynamics in both variance and copula correlation offers multi-step-ahead predictions of the variables of interest. The following steps describe the one-step-ahead simulation based on the Dynamic Conditional t-Copula:

- Draw independently $\epsilon^{*i1}_{t+1}, ..., \epsilon^{*im}_{t+1}$ for each asset from the n-dimensional t-distribution with zero mean, forecast copula correlation matrix R_{t+1} and degrees of freedom v_{t+1} and obtain $u^{i1}_{t+1}, ..., u^{im}_{t+1}$ by setting $u^{ik}_{t+1} = t_{v_{t+1}}(\epsilon^{*ik}_{t+1})$, where $k = 1, ..., m$, the total paths of simulation, $i = 1, ..., n$, the number of assets;

- obtain $\epsilon^{i1}_{t+1}, ..., \epsilon^{im}_{t+1}$ by setting $\epsilon^{ik}_{t+1} = F_i^{-1}(u^{ik}_{t+1})$, where F_i is the empirical marginal dynamics distribution for asset i;

- obtain $z^{i1}_{t+1}, ..., z^{im}_{t+1}$ by setting $z^{ik}_{t+1} = \epsilon^{ik}_{t+1}\sigma^{i}_{t+1}$, where σ^{i}_{t+1} is the forecast standard deviation using a GARCH(1,1) model for asset i;

- obtain $X^{i1}_{t+1}, ..., X^{im}_{t+1}$ by setting $X^{i1}_{t+1} = \lambda^{i}_{t+1} + z^{ik}_{t+1}$, where λ^{i}_{t+1} is the forecast mean using an AR(p) model for asset i;

- Finally obtain the portfolio return $r^{1}_{t+1}, ..., r^{m}_{t+1}$ by setting $r^{k} = [X^{k}_{t+1}][W_{t+1}]$, where W_{t+1} is the portfolio weights at $t + 1$.

Several-period predictions can be obtained in the same way.

Appendix II: Data Sources for market indexes and macroeconomic variables

Bloomberg:

- Interest Rates Index (3M, 6M, 1Y, 10Y)
- Eurostat Industrial Production Eurozone Industry Ex Construction YoY WDA
- Eurostat Industrial Production Eurozone Industry Ex Construction MoM SA
- European Commission Economic SentiMent Indicator Eurozone
- European Commission Manufacturing Confidence Eurozone Industrial Confidence
- Sentix Economic Indices Euro Aggregate Overall Index on Euro area
- European Commission Consumer Confidence Indicator Eurozone
- European Commission Euro Area Business Climate Indicator

DataStream:

- DS Market - PRICE INDEX
- DS Banks - PRICE INDEX
- EURO STOXX - PRICE INDEX
- EURO STOXX 50 - PRICE INDEX
- VSTOXX VOLATILITY INDEX - PRICE INDEX
- EU BANKS SECTOR CDS INDEX 5Y

The Bank for International Settlements (BIS):

- Property Price Statistics

Eurostat:

- GDP
- HICP
- Unemployment Rates

European Central Bank (ECB):

- Exchange Rates
- Loan to Households
- Loan to Non-Financial Corporations

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