Banking Systemic Vulnerabilities: A Tail-risk Dynamic CIMDO Approach

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Abstract

This study proposes a novel framework which combines marginal probabilities of default estimated from a structural credit risk model with the consistent information multivariate density optimization (CIMDO) methodology of Segoviano, and the generalized dynamic factor model (GDFM) supplemented by a dynamic t-copula. The framework models banks' default dependence explicitly and captures the time-varying non-linearities and feedback effects typical of financial markets. It measures the banking systemic credit risk in three forms: (1) credit risk common to all banks; (2) credit risk in the banking system conditional on distress on a specific bank or combinations of banks and; (3) the buildup of banking system vulnerabilities over time which may unravel disorderly. In addition, the estimates of the common components of the banking sector short-term and conditional forward default measures contain early warning features, and the identification of their drivers is useful for macroprudential policy. Finally, the framework produces robust out-of-sample forecasts of the banking systemic credit risk measures. This paper advances the agenda of making macroprudential policy operational.

JEL Classification: C30, E44, G1

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I. Introduction and Motivation

This paper is concerned with developing measures of banking systemic vulnerabilities that help making macroprudential policy operational. While there is no widely accepted definition of macroprudential policy, its objective or its instruments (Galati and Moessner, 2011), this paper will consider that the objective of macroprudential policy is financial stability. So, macroprudential policy will be viewed as geared toward limiting systemic risk in order to minimize the costs of financial instability on the economy (ECB, June 2010). However, this paper will circumscribe the sources of financial instability to those that may result from the banking sector.

Definitions of systemic risk can be qualitative or quantitative. An early qualitative definition of systemic risk was suggested by De Bandt and Hartmann (2000) as the risk of experiencing events when the financial institutions affected in the second round of effects or latter fail as a result of the initial shock, although they were fundamentally solvent *ex ante*. Perotti and Suarez (2009) instead view systemic risk as propagation risk whereby shock effects spread beyond their direct impact and disrupt the real economy. Alternatively, systemic risk is viewed as endogenous and reflects the mutual interaction between the financial system and the real economy producing overextension during booms, which becomes the seed of the subsequent downturn (Borio *et al*, 2001). Therefore, second-round effects and propagation are parts of this definition of systemic risk. From a quantitative viewpoint, systemic risk refers to events in the financial system that result in high losses with a small probability of occurrence and potentially harm the real economy (Drehmann and Tarashev, 2011).

This paper adopts a combined approach: it combines both the endogenous view of systemic risk of Borio *et al* (2001) together with the tail-risk view of the above-mentioned quantitative perspective of Drhemann and Tarashev (2011). As a result, systemic risk circumscribed to the banking sector will be able to take three forms: first, as a common shock that affects the whole banking system and gets transmitted to the real economy or *systematic risk*; second, as the outcome of an idiosyncratic shock to a financial institution that is propagated to the rest of the financial sector and ends up affecting the real economy and; third, as a slow build up of vulnerabilities in the banking system that may unravel in a disorderly manner and affect the real economy.

In addition, this paper's approach covers the cross-section dimension as well as the time-dimension of banking sector systemic risk. The former dimension is concerned with assessing default dependence across banks at a point in time, and the latter is concerned with the evolution of default risk over time (e.g., Borio and Lowe, 2002, Schwaab *et al*, 2011, Gorea and Radev, 2011, and Jin and Nadal De Simone, 2012). This relatively broader perspective of systemic risk is gathering acceptance (Bisias *et al*, 2012).

Besides agreeing on a definition of systemic credit risk in the banking sector, the measurement of that risk is necessary in order to make macroprudential policy operational.[1] Yet, as elegantly put in Borio *et al* (2001), p. 5, "…Experience indicates that widespread financial system stress rarely arises from contagion or domino effects associated with the failure of an individual institution owing to purely institution-specific factors. More often, financial system problems have their financial roots in financial institutions underestimating their exposure to a common factor, most notably the financial/business cycle in the economy as a whole." Therefore, measurement of such a complex and time-varying phenomenon ideally requires a framework that, despite markets' recognized misperceptions of risk, is capable of identifying as early as possible the build up of endogenous imbalances as well as of detecting in a timely manner the occurrence of exogenous shocks that after affecting banks' probabilities of default (PDs) get propagated across financial institutions and, eventually, to the real economy and back to the financial sector. At a minimum, this framework should model financial institutions' interdependence explicitly; be flexible to also reflect contagion across financial institutions located in different jurisdictions and; take into account both the observable and the latent links between financial institutions and the real economy.

This study uses Delianedis and Geske (2003) compound option-base structural credit risk model to estimate implied neutral PDs. The timeliness of this model in reflecting credit risk events was assessed in Jin and Nadal De Simone (2011a) and Jin *et al* (2011b). In addition, and given the previous observation that markets misprice risk over time, the use of Delianedis and Geske model which allows the estimation of the time-structure of PDs is at a premium. However, to understand the risk of simultaneous systematic defaults, the ensuing distribution of losses, and the effects on financial stability, it is necessary to also model dependence between default events and between credit quality changes (Lando, 2004). To that aim, this paper uses the Consistent Information Multivariate Density Optimizing Methodology (CIMDO) of Segoviano (2006). The CIMDO approach characterizes the whole dependence structure of financial institutions, i.e., the linear and non-linear dependence embedded in multivariate densities and has been used to model tail-risk (Segoviano and Goodhart, 2009). [2]

[1] This study is not concerned with the development of tools or instruments to address systemic credit risk in the banking sector.

[2] Mechanisms for obtaining default dependence are versions of, and possible mixtures of three issues: (1) PDs are influenced by common observable variables and there must be a way of linking the joint movement of a reduced set of factors and how PDs depend on them; (2) PDs depend on unobserved background

Importantly, this structure is allowed to change as PDs change over time consistent with the economic cycle. However, the general dependence measures calculated via the CIMDO approach are tightly related to the initial choice of correlation for the prior distribution (Gorea and Radev, 2011). As a result, this study uses the simple time-varying covariance targeting scalar BEKK model of Engle and Kroner (1995), which has been widely used in both academia and in the financial industry. It has the advantage to be applicable to cases with a large number of dimensions by using the composite likelihood method of Engle, Shephard and Sheppard ,2008.

A final difficulty intimately related to risk misperception is the procyclicality of the financial system. During the business cycle upswing, perceived risk tends to be small, risk premia fall, margin requirements and haircuts decline, and leverage increases while capital requirements fall as a result of lower risk weights. Such developments reinforce the upswing. Conversely, during the business cycle downswing, perceived risk rises, risk premia increase accordingly, margin requirements and haircuts rise and financial institutions deleverage reducing credit, deflating assets prices and exacerbating the downturn. These regularities have led policymakers to propose “through-the-cycle” haircuts and margin requirements, which is one additional reason to prefer Delinedis and Geske credit risk model as it allows estimating the time structure of PDs. But, this is clearly not enough. More fundamentally, if risk misperceptions affect equity prices and make them procyclical, the implied probabilities of default estimated from structural credit risk models are likely to be themselves also distorted. In order to deal with the procyclicality of the financial system and markets’ poor assessment of systemic risk over time, the framework of this paper is completed by linking the PDs and measures of systemic credit risk in the banking sector with a large macrofinancial database using the Generalized Dynamic Factor Model (GDFM) of Forni *et al* (2005). The GDFM has been used extensively to exploit the information from a large dataset and also for forecasting (e.g., Kabundi and Nadal De Simone, 2011, De Nicolò and Lucchetta (2012), and D’Agostino and Giannone, forthcoming). However, Forni *et al* (2003) forecasting method is not easily applicable to a large number of underlying assets simultaneously, and does not generate the distribution of forecasts. As a result, this paper introduces an approach similar to Jin and Nadal De Simone’s (2012) that combines the GDFM with a dynamic t-copula to improve the GDFM forecasting capacity. Specifically, the forward dependence information is first generated from the t-copula, and then marginal information is loaded up to get the forward standardized residuals. The common components and idiosyncratic components from the GDFM are projected by plugging-in marginal dynamics which enables customizing the information of means and volatility clusters. The forecasted

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variables and credit events result in an update of the latent variables which updates PDs and; (3) direct contagion from a credit event.

marginal credit risk measures are the sum of these two components. Thus, reverse engineering uncovers the tail risk or the PDs by using not only information from individual banks, but also from a large data set of macro-financial variables revealing thereby not only credit risk emanating from banks' interconnectedness, but also from the macro environment. This allows tracking the macro-financial factors driving the PDs and measures of risk as well as the increase of exposures to common factors during booms and subsequently revealed during busts.

While following the CIMDO approach empirically illustrated by Segoviano and Goodhart (2009) and estimating their proposed banking stability measures, this study departs from theirs. It improves upon theirs in several significant ways. The main results and contributions of this study are as follows. First, given the lack of CDS and bonds data for many banks in this study, and the fact that an important set of banks are not publicly quoted, the structural credit risk model is estimated using accounting information as in Souto *et al* (2009), Blavy and Souto (2009), and Jin and Nadal De Simone, (2011a). Second, this paper explicitly identifies the linkages between measures of credit risk in the banking system and macro-financial variables. Third, the proposed framework generates a structural early-warning indicator based on the forward probability of default and indentifies its drivers, i.e., economic activity, credit growth and interbank activity, as recently surveyed in Frankel and Saravelos (2010). Fourth, by identifying the drivers of vulnerabilities in the banking system, the proposed framework explicitly identifies the economic processes that policymakers should reverse if banking sector instability is to be avoided. Fifth, by incorporating the GDFM, the framework produces robust out-of-sample forecasts of banking system credit risk measures in agreement with recent work by Koopman *et al* (2010) and Schwaab *et al* (2010). Finally, this framework also contributes to the literature on the systemic importance of financial institutions by allowing to rank them according to the distress in the banking system that results from distress in a specific bank (Drehmann and Tarashev, 2011).

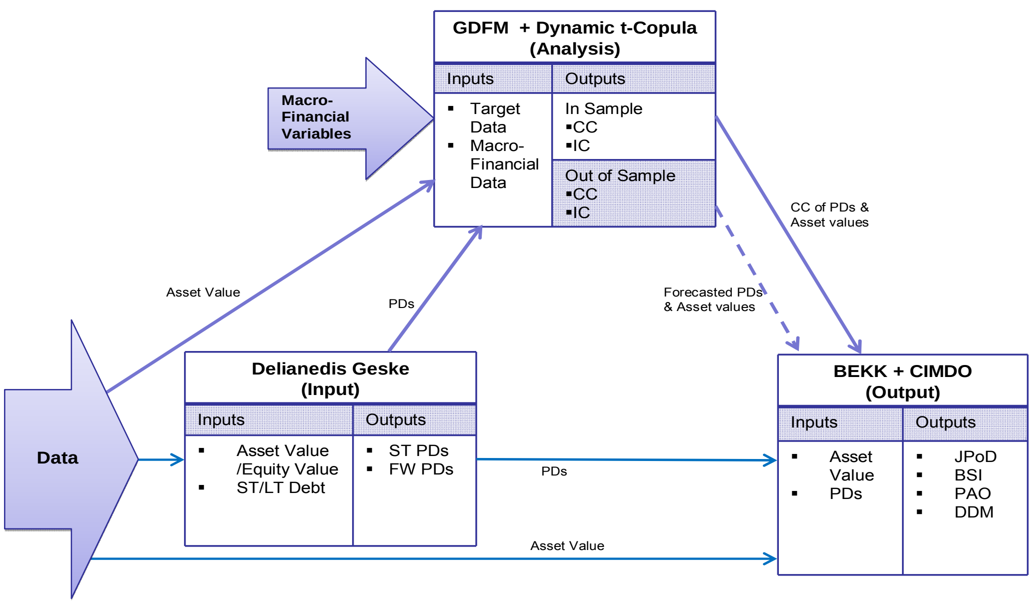
The remainder of the study is organized as follows. Next section introduces the novel integrated modeling framework, explains how to combine Delianedis and Geske (2003) model and the GDFM with the CIMDO into a dynamic forecasting framework of default probabilities, and Section III describes systemic credit risk measures applied to the banking system. Section IV discusses the data. Section V examines the empirical results. Section VI concludes. Appendix I describes data filtering rules; Appendix II discusses the data sources and; Appendix III presents Delianedis and Geske model (2003).

II. Banking Systemic Risk: An Integrated Modeling Framework

In statistics, operations research and engineering, complex information is often broken down into several smaller, less complex and more manageable sub-tasks that are solvable by using existing tools, and then, their solutions are combined in order to solve the original problem. For example, decomposition of time series is considered to be a practical way to improve forecasting (Fisher, 1995). Ideally, the selected models are expected to be integrated into the same theoretical framework. However, this is not always possible. Sometimes, the models put together have been developed to solve specific questions in different strands of literature. This is the case with the framework proposed in this paper. The structural credit risk model of Delianedis and Geske (2003) assesses credit risk using option pricing. The GDFM is instead an econometric tool to perform factor analysis on large datasets and do forecasting. Copulas are a fundamental tool for modeling multivariate distributions and are used extensively in risk management; however, the lack of data makes it impossible to adequately calibrate the assumed parametric distributions. Therefore, the CIMDO approach, which is based on cross-entropy, serves as an alternative to generate probability multivariate densities from partial information and without having to make parametric assumptions. A few examples integrating these models already exist. De Nicolò and Lucchetta (2012) use a dynamic factor model with many predictors combined with quantile regression techniques. Alessi, Barigozzi and Capasso (2007a&b) propose two new methods for volatility forecasting, which combine the GDFM and the GARCH model, and have been proved to outperform the standard univariate GARCH in most cases by exploiting cross-sectional information. Segoviano and Goodhart (2009) define a set of banking stability measures using the CIMDO approach.

This study develops an integrated framework to measure systemic credit risk emanating from banks' interconnectedness and from the macro environment. It consists of three highly integrated multi-functional parts (or data processors) which are illustrated by the following information flow chart.

First, let us look at the output part, the combined BEKK and CIMDO model. In this part of the framework, the prior dependence structure information incorporated into CIMDO is exogenously estimated by BEKK using asset returns. The outputs are several important systemic credit risk measures: the Joint Probability of Default (JPoD) and the Banking Stability Index (BSI) which measure common distress in the banking system; the Distress Dependence Matrix (DDM) which measures distress between specific banks; and the Probability that at Least One Bank Becomes Distressed (PAO) which measures the distress in the system by contagion as a result of distress associated with a specific bank. The CIMDO approach has several important advantages. It allows the recovery of multivariate distributions from the limited available information (e.g., the marginal PDs) in a relatively efficient manner. It circumvents the need to explicitly choose and calibrate parametric density functions with the well-known estimation difficulties under restricted-data environments. While this is possible without explicitly including information about the dependence structure between the assets comprising the portfolio, if such dependence structure information is available, it can be easily incorporated into the modelling framework. This is done in this paper by the BEKK. In addition, the CIMDO approach describes the linear and non-linear dependencies among the variables, dependencies which have the desirable feature of being invariant under increasing and continuous transformations of the marginal distributions. Finally, and fundamentally, while the dependence structure is characterized over the entire domain of the multivariate density, the CIMDO approach appears to be more robust in the tail of the density, where the main interest of this paper lies.[3]



[3] Segoviano and Goodhart (2009) show by Monte Carlo simulation that the CIMDO outperforms several widely used parametric distributions, especially in the region of default which is of interest here. Those distributions are the standard and conditional Normal distributions, the t-distribution, and the mixture of normal distributions.

Second, the input part is Delianedis and Geske (2003) compound option-based structural credit risk model which is used to track the term structure of default risk over time: it allows the estimation of the short-term PDs and the forward PDs, conditional on not defaulting on the short-term debt. These PDs, together with asset returns, are direct inputs to the combined BEKK and CIMDO model. However, as discussed above, risk mispricing over time suggest that fully reliance on market prices may hide the buildup of vulnerabilities over time and fail to deliver a systemic risk tracking framework well adapted to making macroprudential policy operational.

Therefore, a final component of the proposed framework is the combined Generalized Dynamic Factor Model with a dynamic t-copula or the analysis part. This part of the framework not only decomposes the target information into two sets of unobserved components, the common component and the idiosyncratic component, but also provides a dynamic forecasting framework by applying a dynamic t-copula to these components. The common component is best viewed as the result of the underlying unobserved systematic factors, and it is thus expected to be relatively persistent. The idiosyncratic component instead reflects information that while far from negligible, especially in the short term, is transient. The conditional dynamic t-copula is relatively easy to construct and simulate from multivariate distributions built on marginals and dependence structure. A GARCH-like dynamics in the t-copula variance and rank correlation offers multi-step-ahead predictions of the estimated GDFM common and idiosyncratic components simultaneously. In addition, the framework also provides robust out-of-sample forecasts of systemic credit risks.

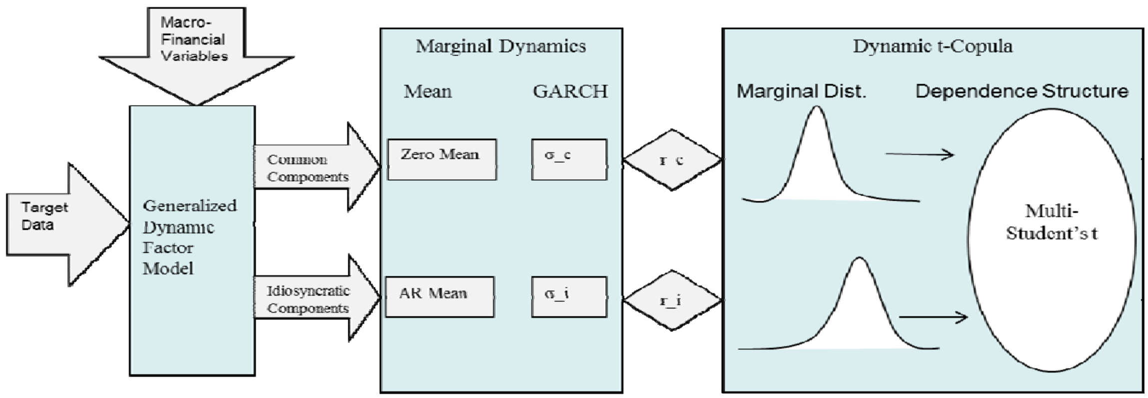
The remainder of this section reviews the methodological and statistical approaches used to estimate systemic banking credit risk. First, the GDFM model is outlined, and then the multivariate GARCH techniques are extended into the t-copula to introduce the dynamic forecasting framework.[4] Finally, the CIMDO approach together with BEKK correlation model are explained, and empirical measures of banking systemic credit risk are introduced.

2.1. The Combined GDFM and Dynamic t-Copula: A Dynamic Forecasting Framework

Following Jin and Nadal De Simone (forthcoming) this paper presents an integrated framework that combines the GDFM and a dynamic t-copula in order to examine credit risk emanating from the macro environment and from banks' interconnectedness. First,

[4] To conserve on space and also because it is well known, a brief description of Delianides and Geske model (2003) is presented in Appendix III.

the GDFM part generates an early warning framework that in the tradition of Borio and Lowe (2002), associates the buildup of banking sector vulnerabilities with the real economy cycle and credit growth. The text chart illustrates the information flow of the first part of this paper's framework:

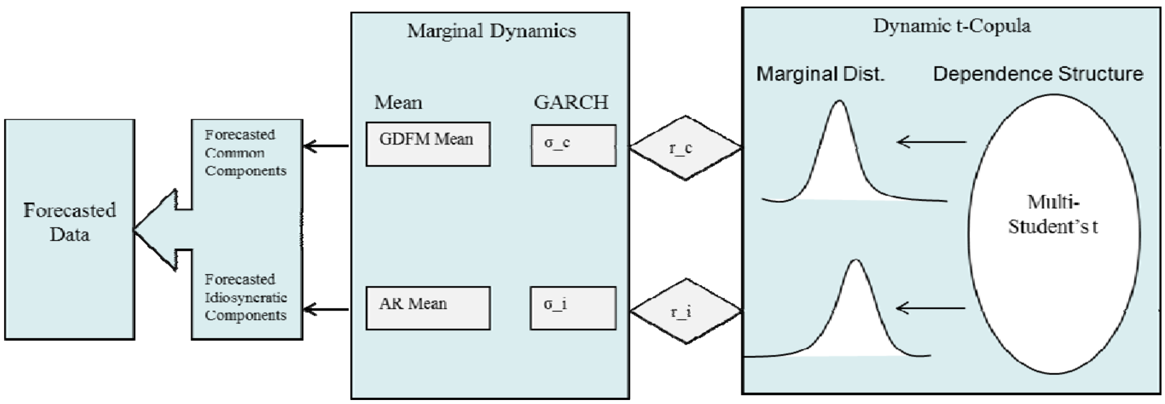


1. The target data, PDs or asset values, together with a large database of macro-financial variables are decomposed into common components and idiosyncratic components by the GDFM;
2. Those components are then broken down into their means and volatilities by the marginal dynamics of AR-GARCH models. For the in-sample estimation, a zero mean is assumed for the common components in order to keep their multi-step-ahead predictions emanating from the GDFM;
3. The standardized residuals from the marginal dynamics, which are $iid(0,1)$ usually with skewness and fat tails, are glued together by a dynamic t-copula with a multivariate GARCH structure;[5]
4. By the copula approach, the standardized residuals can be further decomposed into two subsets of information: (i) information on each random variable; i.e., the marginal distribution of each variable; and (ii), information about the dependence structure (nonlinear) among the random variables.

Second, the dynamic t-copula part is a dynamic forecasting framework for each bank by simulation from multivariate distributions built on marginal distributions and dependence structure. As shown by the following text chart, the simulation is actually an information loading process through the dynamic structures built in the first step. The forward

[5] The converse of Sklar's theorem implies that it is possible to couple together any marginal distribution, of any family, with any copula function, and a valid joint density will be defined. The corollary of Sklar's theorem is that it is possible to extract the implied copula and marginal distributions from any joint distribution (Nelsen, 1999). This framework alleviates the statistical inefficiency associated with the fact that PDs are generated regressors.

dependence information is first generated from a multi-student's t-copula, and then marginal information is loaded up to get the forward standardized residuals. The forecasted common components and idiosyncratic components of PDs or asset values are projected by plugging-in their marginal dynamics which enables customizing the information of means and volatility clusters. Last, the forecasted marginal target measures are the sum of these two components. Thus, reverse engineering uncovers the tail risk or asset value by using not only information from individual banks, but also from a large data set of macro-financial variables.



The following sections describe the statistical methods used to estimate bank's credit risk. First the GDFM used to nest macro-financial variables is outlined, and then, the multivariate GARCH techniques are extended to the t-copula to introduce the dynamic forecasting framework.

2.1.1. The Generalized Dynamic Factor Model

In recent years, large-dimensional dynamic factor models have become popular in empirical macroeconomics. The GDFM enables the efficient estimation of the common and idiosyncratic components of very large data sets. The GDFM assumes that each time series in a large data set is composed of two sets of unobserved components. First, the common components, which 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, which are specific to a particular variable and linearly orthogonal with the past, present, and future values of the common shocks. The common component of PDs or asset values is best viewed 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 credit risk or asset value that while far from negligible, especially in the short term, are transient.

Assume a vector of n series expressed as $x_t^i = \alpha^i(L)u_t + v_t^i$ where $x_t = \left(x_t^1, x_t^2, ..., x_t^n\right)'$ is a n-dimensional vector of stochastic stationary process with zero mean and variance 1; $u_t = \left(u_t^1, u_t^2, ..., u_t^q\right)'$ is a q-dimensional vector of mutually orthogonal common shocks with zero mean and unit variance, and with $q < n$; $v_t = \left(v_t^1, v_t^2, ,..., v_t^n,\right)'$ is a n-dimensional vector of idiosyncratic shocks; and $\alpha^i(L)'$ is a $(n \times q)$ matrix of rational functions with the lag operator L. The model allows for correlation between v_t^i variables, but the variances of v_t^i are bounded as $i \to \infty$. When n is large, the idiosyncratic components, which are poorly correlated, will vanish, and only the common components will be left, and will be identified (see Forni and others, 2000, for a technical proof).

The GDFM model is estimated using the one-sided estimator proposed by Forni *et al* (2005). The procedure comprises two steps: first, estimating the spectral density matrix of the vector stochastic process x_t^i and, second, using the calculated q largest (real) eigenvalues—and their corresponding eigenvectors—of the spectral density matrix to estimate the generalized common components. In this study, the x_t^i $(t \times n)$ vector stochastic stationary process has *t* = 93 monthly observations and *n* includes 283 market indexes and macroeconomic variables for Euro area, Belgium, Canada, Denmark, France, Germany, Greece, Japan, Netherland, Italy, Spain, Sweden, Switzerland, United Kingdom, United States, and Luxembourg. Adding the macroeconomic variables to the Delianedis and Geske's PDs (asset values), there are 496 (354) series. The number of dynamic factors is *q* = 3 underlying PDs (asset values). Accordingly, there are 496 (354) idiosyncratic shocks. In the $\alpha^i(L)'$ $(n \times q)$ matrix of rational functions with the lag operator *L*, the number of lags is 2, and total the number of static factors is 9.[6]

Since the common factors are derived on the standardized first difference of PDs or log values of assets, the common component of the log difference of asset values can be input for BEKK directly, whereas the accumulated common component of PDs has to be constructed from the initial PDs, the standard deviation (STD) and the mean (M) of the first difference of PDs; for example, $PDs_t^{AccumulatedCC} = M + \alpha_i(L)u_t STD + PDs_{t-1}^{AccumulatedCC}$, and $PDs_0^{AccumulatedCC} = PDs_1$. Therefore, the accumulated common component shows the

[6] See Hallin and Liska (2007) for the *log criterion* to determine the number of dynamic factors, and Alessi, Barigozzi and Capasso (2009), who modify Bai and Ng (2002) criterion for determining the number of static factors in a more robust manner.

hypothetical path of credit risk if it were purely driven by the common factors. The accumulated idiosyncratic component is simply the residual risk between PDs and its accumulated common component. The correlation between the accumulated common component and the accumulated idiosyncratic component can be statistically significant even if the idiosyncratic component is linearly orthogonal to the common factors (i.e., Pearson correlation coefficients are not statistically different from zero).[7]

2.1.2. A Dynamic Forecasting Framework

Forni *et al* (2005) provide a good framework for multi-step-ahead predictions of the common component. Nevertheless, the idiosyncratic (credit risk) component also plays an important role for financial instability and cannot be neglected (see Schwaab *et al*, 2010). The idiosyncratic component is in general autocorrelated, and therefore, can be predicted. Forni *et al* (2003) construct a linear forecasting model with the contemporaneous common component and the lagged idiosyncratic component. However, their forecasting method is not easily applied to a large number of underlying assets simultaneously, and also does not generate the distribution of these forecasts. The input to the GDFM is a vector of stochastic covariance-stationary processes with zero means and finite second-order moments. Given that currently there is no structural credit risk model directly combined with the GDFM, the standardized first difference of PDs or the log value of assets (difference stationary processes) can be regarded as exogenous inputs to the GDFM. Similar to the algorithms for combining the GDFM and the GARCH model in Alessi, Barigozzi and Capasso (2007a&b), this study introduces a novel approach to combine the GDFM with a dynamic t-copula. First, the AR (or zero mean)-GARCH model can be applied to both the common components and the idiosyncratic components for all variables. Then, a dynamic t-copula is used to glue together the standardized residuals or innovations from those marginal components. Formally, the dynamic forecasting model becomes:

$$
\begin{aligned}
&X_{t+1}^{F} = X_{t+1}^{CC\_F} + X_{t+1}^{IC\_F} \\
&X_{t+1}^{CC\_F} = X_{t+1}^{GDF\_F} + \sigma_{t+1}^{CC}\varepsilon_{t+1}^{CC} \\
&X_{t+1}^{IC\_F} = \sum_{i=1}^{p} X_{t+1-i}^{IC} + \sigma_{t+1}^{IC}\varepsilon_{t+1}^{IC} \\
&\sigma_{t+1}^{2} = \alpha_0 + \alpha(\sigma_t\varepsilon_t)^2 + \beta\sigma_t^2 \\
&\varepsilon_{t+1} \sim iid(0,1) \\
&F(\varepsilon_{t+1}^{1}, \varepsilon_{t+1}^{2}, \ldots, \varepsilon_{t+1}^{2n}) = C_T(F_1(\varepsilon_{t+1}^{1}), F_2(\varepsilon_{t+1}^{2}), \ldots, F_3(\varepsilon_{t+1}^{2n}); R_t, v_t),
\end{aligned}
$$

[7] Results are available from the authors' upon request.

where the forecast X_{t+1}^{F} of the marginal credit risk is the sum of its forecasted common component $X_{t+1}^{CC\_F}$ and idiosyncratic component $X_{t+1}^{IC\_F}$; $X_{t}^{CC} = \alpha_i(L)u_t$ is the common component, and $X_{t}^{IC} = v_t^i$ is the idiosyncratic component from the GDFM. Both common and idiosyncratic components are simply assumed to follow a GARCH (1,1) process. The mean of $X_{t+1}^{CC\_F}$ is the prediction of the common component $X_{t+1}^{GDF\_F}$ by the GDFM as in Forni *et al* (2005), whereas the mean of $X_{t+1}^{IC\_F}$ is an autoregressive process of order *p*, AR (p). The multivariate distribution $F(\varepsilon_{t+1}^{1}, \varepsilon_{t+1}^{2}, ..., \varepsilon_{t+1}^{2n})$ for *i*=1,2,...,2n, which includes standardized residuals from both the common and the idiosyncratic components and has a time-varying t-copula form.

The copula is a fundamental tool for modeling multivariate distributions. It provides a robust method for a consistent estimation of dependence structures, and is very flexible. Correlation, which usually refers to Pearson's linear correlation, depends on both the marginal distributions and the copula, and it is not a robust measure given that a single observation can have an arbitrarily high influence on it. Instead, the use of the conditional dynamic copula makes it relatively easy to construct and simulate from multivariate distributions built on marginal distributions and dependence structure. The following sections explain in detail the modelling of marginal dynamics, dynamic t-copulas, and forward simulation procedures.

2.1.3. Modelling Marginal Dynamics

This study does not specify marginal distributions, but adopts a semi-parametric form for the marginal distributions. Misspecification of marginal distributions can lead to dangerous biases in dependence measure estimation. This is why the semi-parametric approach is quickly becoming the standard in joint multivariate modelling. Time series data, like the common and idiosyncratic components of financial data, usually reveal time-varying variance and heavy-tailedness. While keeping the multi-step-ahead prediction of the common components from Forni *et al*, 2005, a GARCH (1,1) process is fitted to the common components and an AR(p) - GARCH (1,1) process is fitted to the idiosyncratic components. The proposed marginal dynamics are formally defined as:

$$X_t^{CC} = \sigma_t^{CC} \varepsilon_t^{CC}$$
$$X_t^{IC} = \sum_{i=1}^{p} X_{t-i}^{IC} + \sigma_t^{IC} \varepsilon_t^{IC}$$
$$\sigma_t^2 = \alpha_0 + \alpha(\sigma_{t-1}\varepsilon_{t-1})^2 + \beta\sigma_{t-1}^2$$
$$\varepsilon_t \sim iid(0,1),$$

where X_t^{CC} is the common component, and X_t^{IC} is the idiosyncratic component from Forni *et al* (2005). The model is estimated directly by Quasi-Maximum Likelihood. The best AR (p) - GARCH (1,1) can be selected by an automatic model selection criteria, such as the Akaike Information Criterion Corrected Version (AICC). Since in the database, book-value data are actually quarterly, an AR (3) process is used to track dynamic changes, which is especially important for macroprudential policy.

Given the standardized i.i.d. residuals ε_t from the estimation of the marginal dynamics, the empirical cumulative distribution function (cdf) of these standardized residuals is estimated with a Gaussian kernel. This smoothes the cdf estimates, eliminating the rugged shape of the sample cdf. However, although non-parametric kernel cdf estimates are well-suited for the interior of the distribution where most of the data are found, they tend to perform poorly when applied to the upper and lower tails. Therefore, to improve the efficiency of the tails of the distribution's estimates, the upper and lower, e.g. 10% thresholds of the residuals, are reserved for each tail. Then, the amount by which those extreme residuals in each tail fall beyond the associated threshold is fitted to a parametric Generalized Pareto distribution (GP) by maximum likelihood. Since in our study there are only 93 monthly observations, 20% thresholds are used to ensure that there are sufficient data points at the tails to conform well to a GP. Extreme Value Theory (EVT) in general, and in particular the GP distribution, provide an asymptotic theory of tail behavior. Under the assumption of a strict white noise process, i.e. an independent, identically distributed process, the theory shifts the focus from modelling the whole distribution to modelling tail behaviour; hence, even asymmetry may be examined directly by estimating the left and right tails separately. In addition, EVT has the advantage of requiring just a few degrees of freedom. This approach is often referred to as the distribution of exceedances or peaks-over-threshold method (see, for instance, McNeil (1999), McNeil and Frey (2000) or Nystrom and Skoglund (2002a&b)).

2.1.4. The Dynamic Conditional t-Copula

As stated above, copula theory provides an easy way to deal with (otherwise) complex multivariate modeling. Its main advantage is its flexibility: it allows the definition of the joint distribution through the marginal distributions and the dependence between the variables. In addition, copulas are often relatively parsimoniously parameterized, which facilitates calibration. Recently, copula theory has been extended to the conditional case, allowing the use of copulas to model dynamic structures (e.g., Dias and Embrechts 2004, Patton, 2004, 2006a&b, and Jondeau and Rockinger, 2003, 2006). The conditional copula has been shown to be a very powerful tool for active risk management (Fantazzini 2009, and Jin and Lehnert, 2011).

The t-copula, the copula of the multivariate standardized *t* distribution, is a good candidate for the high-dimensional problem dealt with in this paper as it allows for non-zero dependence in the tails. The conditional dynamic t-copula is defined as follows[8]:

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

where $\eta_n = F_n(\varepsilon_n)$ for *i*=1,2,...,n, and $\varepsilon_t \sim iid(0,1),$ are the innovations from the marginal dynamics introduced in the previous section. R_t is the rank correlation matrix, and v_t is the degrees of freedom. $t_{v_t}^{-1}(\eta_n)$ 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) proposed a class of models - the Dynamic Conditional Correlation (DCC) class of models - that preserves the ease of estimation of Bollerslev (1990)'s constant correlation model while allowing correlation to change over time. These kinds of dynamic processes can also be extended into t-copulas. The simplest rank correlation dynamics considered empirically is the symmetric scalar model where the entire rank correlation matrix is driven by two parameters:

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

where $\alpha_{dcc}\geq 0,\beta_{dcc}\geq 0,\alpha_{dcc}+\beta_{dcc}\leq 1$, $\varepsilon_t^{*}=t_{v_t}^{-1}(\eta_n=F_n(\varepsilon_n))$, $Q_t =| q_{ij,t} |$ is the auxiliary matrix driving the rank correlation dynamics and the nuisance parameters $\bar{Q}=E[\varepsilon_t^{*}\varepsilon_t^{*'}]$

---

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

have a sample analog $\bar{Q} = T^{-1}\sum_{t=1}^{T}\varepsilon_t^* \varepsilon_t^{*'}$, so that R_t is a matrix of rank correlations $q_{ij,t}$ with ones on the diagonal, $\rho_{ij,t} = \dfrac{q_{ij,t}}{\sqrt{q_{ii,t}}\sqrt{q_{jj,t}}}$.

Given that the correlation between the Gaussian rank correlation $\rho_{GR} = Corr(\Phi^{-1}(u)\Phi^{-1}(v)$ and a t-copula rank correlation $\rho_{TR} = Corr(t_v^{-1}(u)t_v^{-1}(v)$ is almost equal to one, R_t can be well approximated by the $R_t^{Gaussian}$ from the dynamic Gaussian Copula (Bouye *et al*, 2000). For convenience, this study adopts a two-step algorithm for estimation which means that R_t is estimated from the dynamic Gaussian copula first, and then, with R_t fixed, the degrees of freedom are recovered from the t-copula.

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

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

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

While the quasi-likelihood function for the dynamic Gaussian copula could be computed, convergence is not guaranteed in high dimensions, and sometimes it fails, or it 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 specially α displaying a significant downward bias. As a result, Engle, Shephard and Sheppard (2008) suggest an approach to construct a type of composite likelihood, which is then maximized to deliver the preferred estimator:

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

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 not making necessary the inversion of large dimensional covariance matrices. Further, and vitally, the estimator is not affected by the incidental parameter problem discussed above. It can also be very fast, and does not have the biases intrinsic in the usual likelihood estimator when the cross-section of the database is large. This dynamic Gaussian copula can also be estimated by maximizing m-profile subset composite likelihood (MSCL)[9] using contiguous pairs rather than using all the pairs, which is attractive from statistical and computational viewpoints for large dimensional problems, at least compared with the m-profile composite likelihood (MCLE) which uses all the pairs. In this paper, to avoid the known estimation difficulties of high-dimensional t-copulas, m-profile subset composite likelihood (MSCL) are maximized using contiguous pairs. The degrees of freedom for the t-copula is simply the 50th quantile of all degrees of freedom derived from pairwise t-copulas.

2.1.5. Forward Simulation

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 rank correlation offers multi-step-ahead predictions of the common and the idiosyncratic components of the variables of interest.

The following steps describe the one-step-ahead simulation:

1. Draw independently $\varepsilon_{t+1}^{*i1},...,\varepsilon_{t+1}^{*im}$ for each component from the n-dimensional *t* distribution with zero mean, forecast correlation matrix R_{t+1}, and degrees of freedom v_{t+1} to obtain $\mu_{t+1}^{i1},...,\mu_{t+1}^{im}$ by setting $\mu_{t+1}^{ik} = t_{v_{t+1}}(\varepsilon_{t+1}^{*ik})$, where *k=1,...,m*, is the total paths of the simulation, and *i=1,...,n*, is the number of components;
2. Obtain $\varepsilon_{t+1}^{i1},...,\varepsilon_{t+1}^{im}$ by setting $\varepsilon_{t+1}^{ik} = F_i^{-1}(\mu_{t+1}^{ik})$, where F_i is the empirical marginal dynamics distribution for component *i*;
3. Obtain $z_{t+1}^{i1},...,z_{t+1}^{im}$ by setting $z_{t+1}^{ik} = \varepsilon_{t+1}^{ik}\sigma_{t+1}^{i}$, where σ_{t+1}^{i} is the forecast standard deviation using a GARCH (1,1) model for component *i*;

[9] 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 due to the relative easiness of their estimation.

4. Obtain $X_{t+1}^{i1},..., X_{t+1}^{im}$ by setting $X_{t+1}^{ik} = \lambda_{t+1}^{i} + z_{t+1}^{ik}$, where λ_{t+1}^{i} is the forecast mean using an AR (p) model for the idiosyncratic component *i*, and the prediction of the common component using Forni *et al* (2005);
5. Finally, sum the predicted idiosyncratic and common components at *t+1*.

In a similar way, several period predictions can be obtained. In case of PDs, both the idiosyncratic and common components are derived on the standardized first difference of the PDs. The simulated cumulative PDs have to be truncated by $Max(DPs^{Simulated},0)$. This forward simulation approach therefore integrates the one-sided forecasting features of the GDFM into the dynamic t-copula framework.

2.2. The Combined BEKK and CIMDO Approach

The CIMDO-approach developed by Segoviano (2006) is centered on the concept of cross-entropy introduced by Kullback (1959). The CIMDO methodology implies minimizing the cross-entropy objective function that links the prior and posterior distributions under a set of constraints on the posterior. For example, in case of two banks, say X and Y, with their logarithmic returns represented by random variables x and y, the following function can be minimized:

$$
\begin{aligned}
L(p,q) = & \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} p(x,y)\ln[\frac{p(x,y)}{q(x,y)}]dxdy \\
& + \lambda_1[\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} p(x,y)dxdy - 1] \\
& + \lambda_2[\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} p(x,y)I_{[x_d^x,\infty)}dxdy - PD_t^x] \\
& + \lambda_3[\int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} p(x,y)I_{[x_d^y,\infty)}dxdy - PD_t^y]
\end{aligned}
$$

where $p(x;y), q(x;y) \in \Re^2$ are the posterior and the prior distributions accordingly, with λ_1, λ_2, and λ_3 being the Lagrange multipliers of the probability additivity constraint and the two consistency constraints, i.e., the constraint that probabilities are non-negative. The region of default PD_t for each obligor is described in the upper part of a distribution over its default-threshold x_d^x or x_d^y respectively. The optimal solution for the posterior density is of the form:

$$p^{*}(p,q)=q(x,y)\exp\{-[1+\lambda_1+(\lambda_2 I_{[x_d^x,\infty)})+(\lambda_3 I_{[x_d^y,\infty)})]\}$$

This solution stresses the importance of the distress thresholds and PDs. The posterior joint density will diverge from its prior whenever one or both random variables will have values above the specified cutoff values, e.g. in times of distress, more mass will be shifted toward the realizations in the tails of the distribution. This technique allows the adjustment of the prior guess about the joint distribution function. As proven in Segoviano (2006), the CIMDO-recovered distribution outperforms the most commonly used parametric multivariate densities under the Probability Integral Transformation Criterion. In this paper, the prior distribution is assumed to be a multivariate normal distribution based on the parametric assumption behind the basic version of the structural approach (Merton, 1974). The default threshold is one of the central parameters of the CIMDO methodology. Following the intuition of Goodhart and Segoviano (2009), a through-time-average default-threshold is assumed for each bank, which is the standard normal inverse of its through-time-average DPs.

Note that the CIMDO methodology is the inverse of the standard copula approach. The CIMDO density contains the dependence structure among the PDs. Once the CIMDO density is inferred, then it is possible to extract the copula function that describes such dependence structure. By construction, the CIMDO copula puts a greater emphasis on the distress region of the joint distribution. Therefore, the copula approach provides a robust and consistent method to estimate banks' default dependence. Correlation analysis instead, which usually refers to linear correlation, depends on both the marginal distributions and the copula, and is not a robust measure given that a single observation can have an arbitrarily high influence.

However, the general dependence measures calculated via the CIMDO approach are tightly related to the initial choice of correlation for the prior distribution (Gorea and Radev, 2011). Assuming a joint normal density function with zero correlation as our prior could lead to a significant understatement of the dependence, which is evident in several recent studies applying the CIMDO approach. As a result, this study uses the simple time-varying covariance scalar BEKK model of Engle and Kroner (1995), which has been widely used in both academia and industry. To capture the dynamic dependence across all asset values, the dynamic conditional correlation model of Engle (2002) and Tse and Tsui (2002) allows for more flexibility. However, the model requires many more data points than are available for Luxembourg banks. Therefore, this study uses the dynamic asset correlation implied by the BEKK model as the prior correlation input to the CIMDO. In this model, the return on asset i at time t is assumed to follow the following dynamics:

$$R_{i,t} = \mu_{i,t} + \varepsilon_{i,t} = \mu_{i,t} + \sigma_{i,t} z_{i,t}$$
$$\Sigma_t = (1 - \alpha_{BEKK} - \beta_{BEKK})\Sigma + \alpha_{BEKK}\varepsilon_{t-1}\varepsilon_{t-1}^{'} + \beta_{BEKK}\Sigma_{t-1}$$

where Σ_t denotes the covariance matrix, and the conditional mean dynamics, $\mu_{i,t}$, can be specified using a simple univariate autoregressive model. The sample variance-covariance matrix, $\hat{\Sigma} = \frac{1}{T}\sum_{t=1}^{T}\varepsilon_{t-1}\varepsilon_{t-1}^{'}$ is used as an estimate of the unconditional variance-covariance matrix, Σ. It is evident that the conditional covariance in the BEKK model is a weighted average of the long-run covariance, yesterday's innovation cross-product, and yesterday's conditional covariance. This model can be applied to hundreds of dimensions by the composite likelihood (Engle, Shephard and Sheppard, 2008) as discussed at the previous section.

III. Empirical Measures of Banking Systemic Credit Risk

The multivariate density that results from the framework proposed in this study contains all the necessary information to estimate measures of banking systemic credit risk that are consistent with the ECB (2009) definition of systemic risk referred to above, albeit circumscribed to the banking sector. Segoviano and Goodhart (2009) describe and calculate two measures to address common distress in the banking system, the Joint Probability of Distress (JPoD) and the Banking Stability Index (BSI); they propose one measure to address distress between specific banks, the Distress Dependence Matrix; and they estimate a measure of distress in the system by contagion as a result of distress associated with a specific bank, the Probability that at Least One Bank Becomes Distressed (PAO). However, those measures do not cover another, more insidious manner in which banking systemic risk can manifest itself, i.e., the slow build up of vulnerabilities over time that may unravel disorderly. Measuring it requires a structural approach and a link between a banking sector measure of vulnerability and the macroeconomy. One way this can be obtained is suggested in this study. It consists of estimating Delianedis and Geske (2003) forward probability of default (FW PD), conditional on not having defaulted during the first year, and relating it to a broad set of macrofinancial variables that drive it by using the GDFM. In fact, combining structural credit risk models with CIMDO and the GDFM makes it possible to observe a couple of years ahead the buildup of vulnerabilities not only via the FW PD of Delianedis and Geske, but also by estimating the common components of Segoviano and Goodhart (2006) measures of banking stability. What follows briefly reviews the measures proposed by the latter adopting their terminology to avoid confusion.

3.1. Common Distress

The first form that banking systemic credit risk can take is as the result of a common shock that affects the whole banking system and gets transmitted to the real economy. Two measures can be calculated. First, the joint Probability of Distress (JPoD) is the probability that all banks in the system become distressed, i.e., the banking system tail risk. This reflects credit risk not only at the individual bank level, but also the linear and nonlinear interconnections among banks in the system which makes the JPoD larger than the mere multiplication of individual banks' PDs. Assuming for simplicity a banking system made of three banks whose asset value processes are characterized by the random variables x, y, and z, this measure is calculated as follows:

$$JPoD = \int_{x_d^x}^{+\infty}\int_{x_d^y}^{+\infty}\int_{x_d^z}^{+\infty} p(x,y,z)dxdydz\ .$$

JPoD describes the upper part of a distribution over its default-threshold x_d^x , x_d^y or x_d^z , respectively.

Second, the Banking Stability Index (BSI) measures the expected number of banks that will become distressed conditional on one bank having become distressed. When BSI=1, the linkages across banks are minimal. As BSI increases, dependence among banks increases. The measure can be written as follows:

$$BSI = \frac{P\left(X \geq \chi_d^x\right) + P\left(Y \geq \chi_d^y\right) + P\left(Z \geq \chi_d^z\right)}{1 - P\left(X < \chi_d^x, Y < \chi_d^y, Z < \chi_d^z\right)}.$$

3.2. Distress Between Specific Banks or Groups of Banks

Pair-wise conditional PDs provide significant information about contagion and interlinkages between banks or groups of banks. For example, for macroprudential policymakers is important to assess numerically the PD of a banking group defaulting conditional on its subsidiary defaulting, or the probability of a systemic bank defaulting if other systemic bank defaults. This information can be displayed in the Distress Dependence Matrix. For example, the probability of distress of bank X conditional on bank Z becoming distressed is:

$$P\left(X \geq \chi_d^x / Z \geq \chi_d^z\right) = \frac{P\left(X \geq \chi_d^x, Z \geq \chi_d^z\right)}{P\left(Z \geq \chi_d^z\right)}.$$

3.3. Distress in the Banking System as a Result of Distress with a Specific Bank (or Groups of Banks)

The probability that at least one bank becomes distressed given that a specific bank (or group of banks) has become distressed (PAO) is another important measure of banking systemic risk. It is associated with the second form that systemic credit risk can take, i.e., as the outcome of an idiosyncratic shock to a financial institution that is propagated to the rest of the financial sector and ends up affecting the real economy. It is exemplified by cases such as Lehmann Brothers and is therefore an important measure for macroprudential policy in deciding, for instance, the alternative costs of inaction. While conditional probabilities do not imply causation, they provide important information as to the interlinkages in the banking system. Assuming a banking system of four banks for illustrative purposes (i.e., X, Y, R, and Z), and that bank Z becomes distressed, the measure is calculated as follows:

$$\begin{aligned} PAO = {} & P(X/Z) + P(R/Z) + P(Y/Z) \\ & - [P(X \cap R/Z) + P(X \cap Y/Z) + P(R \cap Y/Z)] \\ & + P(X \cap R \cap Y/Z) \end{aligned}$$

Note that, in addition, this measure could also be used to determine the relative systemic importance of banks. It shows the specific bank's contribution to systemic credit risk through its exposure to exogenous shocks, through its role in propagating shocks via its interdependence, and also by being itself subject to shocks.[10]

3.4. Early Warning Measures

As stated above, systemic credit risk can also manifest itself in a third, more subtle way via the buildup of vulnerabilities, often latent, over time. This form of systemic risk is more difficult to measure. Two proxies are offered in this paper framework. First, the common component of Delianedis and Geske (2003) forward conditional probability held today of defaulting at date T_2, i.e., $1-\frac{N_2(k_1,k_2;\rho)}{N(k_1)}$, has been shown to contain important early warning features (Jin and Nadal De Simone, 2012, forthcoming).

[10] This measure belongs to the set of measures of banks' systemic importance associated with the "contribution approach" suggested by Tarashev *et al* (2010).

Combining the GDFM (applied to a large macrofinancial database) with structural credit risk models not only produces an early warning indicator, but also can help identying the economic forces driving the increase in vulnerabilities. These tend to be economic activity, credit and interbank markets activity.

Second, the common components of the measures of banking systemic credit risk, i.e., the JPoD, the BSI and the PAO, also contain important leading information on the build up of vulnerabilities in the banking system. Those common components can also be easily estimated reinforcing the attraction of this study's framework for macroprudential policy.

IV. Data

This study is applied to 32 major European banking groups, to their respective 37 subsidiaries active in Luxembourg, and to two 100%-Luxembourg banks; surveillance of banking stability cannot stop at national borders. Market data used for the major European banking groups include government bond yields, stock prices and stock indices, production, employment and GDP data, consumer prices, housing prices, exchange rates, credit data, as well as the number of outstanding shares, and book value data from Bloomberg, DataStream, BIS, Eurostat, and ECB (see Appendix II for a detailed list of country and euro area series and sources). The market data start in May 2000 and finish in September 2011.

One difficulty is that short-term borrowing (BS047) and long-term debt (BS051) from Bloomberg have annual, semi-annual, and quarterly frequencies. To make the data consistent, four filtering rules as described in Appendix 2 are used. To get the "actual" PDs from neutral PDs, the expected returns are estimated using a capital-asset pricing model. The implied equity risk premiums data (Damodaran 2011) are downloaded from Damodaran Online at http://pages.stern.nyu.edu/~adamodar/. For consistency with that source, stock market returns are represented by the returns on the S&P 500 index.

All the Luxembourg banks are unlisted, so quarterly book value data from the BCL database going back to 2003Q1 are used.[11] The 37 subsidiaries registered in Luxembourg represent about 63 percent of the total assets of the Luxembourg banking industry. When the two 100% Luxembourg banks are added to the list, the database represents nearly 70 percent of the total assets of the industry. For all the selected Luxembourg banks, short term debt includes demand and time deposits of up to one-

[11] See Jin and Nadal De Simone, 2011a, for a detailed discussion of the estimation of credit risk models using balance sheet data when banks are not publicly listed.

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.

V. Empirical Results

Timeliness in reflecting credit risk events is necessary for effective macroprudential supervision. Timelines is a function of at least two factors: first, the credit risk model used, and second, the database available. As shown in Jin and Nadal De Simone (2011a) and Jin *et al* (2011b), the combined Merton/GARCH-MIDAS (Engle *et al*, 2008) model performs best among a set of traditional structural credit risk models in terms of reflecting important market events earlier than the other models.[12] However, when data are not publicly available, or available data are not sufficiently long, it is not possible to obtain a robust modeling of the short- and long-run components of credit risk using that model. In addition, as discussed above, while individuals can safely assume that the evolution of the economy is exogenous, this is not true for the system as a whole and misperceptions of risk over time are pervasive. Jin and Nadal De Simone (2012, forthcoming) propose to estimate neutral marginal PDs from Delianedis and Geske (2003) credit risk model combined with the GDFM model (Forni et al, 2005) and a t-copula. The database used includes not only individual balance sheet information, but a large number of macroeconomic and financial variables. The approach accomplishes two objectives in an integrated, internally consistent manner: first, it generates an indicator of systemic risk (a simple value/equal weighted PD index) that recognizes exogenous shocks timely and identifies the build up of endogenous imbalances over time in the tradition of early warning indicators and second; it improves on the GDFM forecasting capacity generating an out-of-sample forecast distribution of systemic risk. This paper extends these results to the systemic credit risk measures of Section III, both in sample and out of sample.

The rest of this section first discusses the results of extending the early-warning features of the FW PD of Delianides and Geske model (2003) shown in Jin and Nadal De Simone (2012, forthcoming) to Segoviano and Goodhart's measures of systemic banking risk. Then, it discusses the role of banks' size in the estimation of measures of distress. It follows a discussion of the conditional PDs between European banking groups and Luxembourg banks. Finally, the out-of-sample forecasting capabilities of the proposed framework are presented.

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[12] Jin *et al* (2011b) compare the timeliness performance of Merton (1974), Delianedis and Geske (2003), Heston and Nandi (2003) and GARCH-MIDAS (Engle *et* al, 2008) models.

5.1. In-sample Early-warning Features

Macroprudential policy is interested not only in the timeliness feature of measures of credit risk, both at the bank level and at the systemic level, but ideally would like to have on real time, and as early as possible, some indications of the buildup of vulnerabilities in the financial system as a result, among other reasons, of risk mispricing and which may unravel in a disorderly manner in the future. Timeliness is particularly important in the case of banks that are not public given the lags in the availability of balance sheet data. The in-sample early-warning feature is crucial for taking preventive actions to preserve financial stability and reduce the likelihood of systemic crises. Segoviano and Goodhart's (2009) performed an event and graphic analysis of their banking stability measures to find out the occasion and determinants of changes in the riskiness of the banking system. In contrast, this paper's approach explicitly links the state of the macroeconomy with the observed persistent increased in the FW PD and Segoviano and Goodhart's systemic risk measures in the banking system in order to extract the factors driving their steady growth in the run up to the crisis. Given that this framework permits to identify those macro-financial linkages explicitly, it lends itself to a more informed discussion of the possible policy measures to address the observed vulnerabilities.

Jin and Nadal De Simone (2012, forthcoming) analyze and illustrate the in-sample early warning features of the common component of Delianedis and Geske's FW PD. In that paper, systemic risk was explicitly modeled by using the GDFM and a t-copula. In this paper, the same early-warning features are discussed albeit not only of the common component of the FW PD of Segoviano and Goodhart's banking system stability measures, but also of their short-run components. It seems that the explicit modeling of tail-risk by the CIMDO-copula allows the detection of the growth in vulnerabilities in the banking sector even earlier, at least as measured by the common component of the JPoD, the BSI index and the PAO measures discussed above. This framework operationalizes the insight in Borio *et al* (2001), i.e., that asset returns or PDs have a systematic component which is a function of a series of stochastic risk factors common to all and an idiosyncratic component specific to the individual asset, as well as the sensitivities to each common risk factor (the factor loadings) which determine the correlation between any two assets.

As in risk management, the analysis is performed on the tail of the multivariate density distribution of the banking system, both within the sample of European banking groups and within the sample of Luxembourg banks. Multivariate densities embed the structure of linear and nonlinear default dependence among the banks included in the set used to represent the banking system. Such dependence is characterized by the CIMDO-copula function, which is time-varying as a result of changes not only in banks' PDs, as in Segoviano and Goodhart (2009), but importantly, also as a result of changes in the macrofinancial dataset directly. These sources of variation in banks' default dependence allow the modeling framework to explicitly relate systemic credit-risk and vulnerabilities with their driving forces. For the dynamic analysis, the worst five banks ranked by their weighted PD importance, either in the European banking groups' set or in the Luxembourg banks' set, are selected, and the three measures of banking stability are calculated.[13] Thus, the selected worst five banks are not always the same through time, reflecting the worst corner of the selected bank portfolio which is more sensitive to the growth in vulnerabilities in the banking sector.

Correlations are estimated using the BEKK model. For the European banking groups' risk measures, correlations are equity correlations given that there are market data available, while in the case of Luxembourg banks, correlations are asset correlations as accounting data are the source because banks are not publicly quoted. As discussed in Huang et.al (2009), the logic for using equity return correlation as a proxy for asset return correlation is supported by the fact that the equity of a firm can be viewed as a call option on the underlying firm's assets. Hence, the comovements in equity prices tend to reflect the comovements among underlying asset values more timely especially when the firm leverage is relatively constant in a short time horizon. Figure 1 shows the average asset, or its proxy correlation within or between banking groups and Luxembourg banks. The common component of correlation is derived by applying BEKK on the common components of asset returns (or equity returns for banking groups) from the GDFM. Clearly, the average correlations within banking groups are much higher than those within Luxembourg banks, but all increase in 2008-2009. Interestingly, the common components show a decrease in the same period suggesting that the recent financial crisis is more banking related. The correlations between banking groups and Luxembourg banks evolve in a similar manner, including the timing of their common components; this can be expected as most Luxembourg banks are subsidiaries which are strongly interlinked with their banking groups.

To illustrate the importance of modeling correlation and to relate it to the macrofinancial data to assess the time-profile of credit risk properly, Figure 2 compares the levels and the common components of the JPoD (the dynamic worst five banks ranked by their asset value weighted PDs) both taking and not taking into account correlations across banks. The JPoD level and its common components using BEKK equity correlation are several times higher, rise earlier, and are more persistent than the level and the common

[13] Recall that data on each bank share in interbank lending and borrowing is only available for Luxembourg banks. Thus, these weighing schemes do not apply to banking groups.

components of the JPoD when the correlation is assumed to be zero. The same results obtain using assets correlation (not shown).

In general, the most conspicuous result of the dynamic CIMDO framework proposed in this paper is that not only FW measures of systemic credit risk display "early-warning" features (as in Jin and Nadal De Simone, 2012, forthcoming), but also short-term measures of credit risk do so. This is an outcome of great significance for a policymaker interested in preserving financial stability. In addition, the framework allows an explicit identification of the drivers of systemic credit risk permitting the selection of the best policy instruments to preserve financial stability. These two features are a novelty of the framework.

5.1.1. Banking Systemic Credit Risk Measures

Figures 3a and 3b display the results for the three banking systemic credit risk measures from the worst five banks dynamically selected by their total asset-value weighted PDs and applied to the European banking groups and to Luxembourg banks, respectively. On the left, the charts display the measures and their common components based on the short-term (ST) Delianedis and Geske PDs, and on the right, the charts display the measures and their common components based on the Delianedis and Geske FW PDs. Figures 3c and 3d contain the same information, but applied only to Luxembourg banks weighted by each bank's share in interbank lending and interbank borrowing, respectively.

Several specific salient features are noteworthy and will be discussed in what follows. First, while its timing varies across different systemic credit risk measures, the information contained in the large macrofinancial database extracted using the GDFM detects early persistent increases in systemic credit risk. The common components of the short-term JPoD, the BSI and the PAO measures increased well before the onset of the crisis (Figure 3a, left-hand side). Note the persistent trend increase in the BSI and PAO measures of European banking groups starting around mid-2004, albeit with a one-year period of improvement in the common components from the second half of 2006 to the end of the first half of 2007. The improvement is likely associated with the start of the decline in house prices and the reduction in credit to non-financial firms in the EU. This occurred before the Fed and other central banks started relaxing their monetary policy stances as a result of the aggravation of the subprime market problems in the US, which was apparently still perceived as a circumscribed risk at the moment. This interpretation seems validated by the flatness of the common distress measure, i.e., the JPoD, and the decline in the measures of system distress associated with specific banks, i.e., BSI and the PAO.[14] Judging from the BSI viewpoint, the overall positive improvement in the common component was not offset by idiosyncratic negative events. In contrast, idiosyncratic negative events did offset the improvement in the common component of the PAO; macro-type measures did not seem to address what was perceived as a localized, asset-type, bank business-line issue. This interpretation is also consistent with the identified drivers of the common components discussed below.

Second, regarding the FW PDs, the three measures of systemic credit risk display a persistent increase starting in 2005 in the case of European banking groups (Figures 3a, right-hand side), which suggests a buildup of credit risk long-term vulnerabilities—a feature also found by Koopman *et al* (2010) and consistent with the early-warning features of the Delianedis and Geske FW PD discussed in Jin and Nadal De Simone (20012, forthcoming). The fall in the measures' common components after the first half of 2007 is consistent with the policy measures discussed above. As it was the case with the ST PDs, the risk measures suggest a picture of localized stress that macro measures have difficulty in addressing.

Third, in the case of Luxembourg banks, data availability makes it possible to construct systemic credit risk measures not just by total assets weighted PDs, but also by interbank lending and interbank borrowing weighted PDs. Overall, this weighing matters most to track the evolution of the common components of the measures than for tracking the evolution of the levels of the measures at the ST part (Figures 3b to 3d).[15] Starting in 2006, weighing by interbank borrowing, there is a clear shift in the JPoD and in the BSI measures (Figure 3d). Weighing by total assets this is obvious from 2006 only for the JPoD measure, and from 2007 for the BSI (Figures 3b). Weighing schemes do not seem to matter for the ST part of the PAO measure, perhaps because it is more associated with distress at a specific bank and its expected ST conditional impact on other banks' PDs. In general, interbank borrowing appears as a useful weighing scheme given that it tends to track better increases in systemic risk over time. At least for the current crisis, measures of credit risk stressing funding needs contain relatively useful information, a feature confirmed by the analysis of the macrofinancial drivers of the common components discussed below.[16] This buttresses again the operational value of the framework offered by this paper's framework.

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[14] The Fed cut the discount rate to 5.75% to ease a perceived credit crunch on 17 August 2007, and six days after it lent $2 billion to banks to ease credit woes. The ECB injected 250 billion euro into markets on 6 September 2007.

[15] This is consistent with results in Jin and Nadal De Simone, 2012, forthcoming.

[16] A bottom-up approach to determine the systemic importance of a specific bank consists of the expected shortfall of the whole banking system conditional on the specific bank defaulting. This can be proxied by the share of a bank in total borrowing (Drehmann and Tarashev, 2011), and it seems consistent with the apparent advantage of using interbank borrowing as a weighing scheme for the PAO measure.

Fourth, the FW component of systemic risk measures for Luxembourg banks conveys a similar message, albeit circumscribed to the BSI and to the PAO measures. Note the early-warning features of the BSI common distress measure, especially when weighed by interbank borrowing. For the PAO instead, it seems that the common components of systemic risk viewed as distress associated with a bank or sector grew monotonically since the beginning of the sample, and despite a break during part of 2007, it remained high until the end of the sample period. This is the case independently of the weighing scheme used and in contrast to the ST common component of the measure. Again, this feature stresses the usefulness of Delianedis and Geske FW PDs.

Finally, to determine the drivers of the early-warning measures, all macrofinancial variables were categorized into four classes: real variables (GDP in volume and nominal GDP, industrial production, the unemployment rate, the HICP, and agricultural and industrial property prices); funding costs (short- and long-term interest rates, foreign exchange rates, stock market prices, stock price volatility, house prices); funding quantities (total credit, loans to households, mortgages, loans to non-financial firms, and interbank lending and borrowing) and; confidence measures (various indices of consumer and business sentiment). Consistent with early work by Borio and Lowe (2002), and more recent work by Koopman *et al* (2010), regression analysis[17] shows that real economic activity, credit growth and interbank activity, funding costs and confidence, in that order of importance, significantly explain the buildup of vulnerabilities of large European banking groups in the run up to the crisis as measured by the FW JPoD. For Luxembourg banks, only funding quantities and confidence are significant drivers of the FW JPoD. Regarding the ST, confidence indicators are significant drivers of European banking groups' JPoD while funding costs, confidence and funding quantities drive the JPoD of Luxembourg banks. These results are consistent with the business models of Luxembourg banks which are net liquidity providers of their parent companies and the evidence in Jin and Nadal De Simone (2012, forthcoming) and Giordana and Schumacher (2012).

5.2. Size Matters

In discussions of financial stability, the size of banks is often very important, either because a given bank is "too large" to be saved or because being large, its default may compromise the stability of the economy. Recently, joint work by the FSB, the International Monetary Fund and the Bank for International Settlements, has resulted in the Basel Committee on Banking Supervision (BCBS) methodology for the identification

[17] To save space, this table is not shown in the paper although it is available upon request.

of global systemically important banks (G-SIBs), and the determination of their additional loss absorbency requirement (Basel Committee on Banking Supervision, 2011). This has been justified by the financial and economic costs of public interventions aimed at restoring financial stability, as conspicuously shown by the current crisis, as well as by the associated expected increase in moral hazard in a regulatory environment that does not address the cross-border negative externalities generated by those large banks.

The methodology proposed by the BCBS is indicator-based. The chosen indicators reflect the different aspects of the negative externalities G-SIBs generate: size, interconnectedness, substitutability, global activity and complexity. G-SIBs are grouped in buckets of systemic importance based on the score produced; buckets are of equal size in terms of those scores. Banks in different buckets have different magnitudes of additional loss absorbency requirements which should be met with Common Equity Tier 1 (Basel III). So, it is possible that a large-size bank may not enter the category of G-SIBs due to its local activity and reduced interconnectedness. Conversely, a relatively small bank may have a systemic impact due to its interconnectedness and cross-border activities.

To look into this matter within the framework of this paper, first, Luxembourg banks were classified into “small” (S), “medium” (M), and “large” (L) according to the observed distribution of the total value of their assets period by period. As a result of this classification, 19 banks were deemed to be in the S category, 15 in the M category and 5 in the L category, albeit not always the same banks were classified as S, M, and L. Importantly, the 5 L-size banks included the 5 Luxembourg systemic important banks only 50% of the time. Then, banks within each size category were treated as one bank and their balance sheets were aggregated as shown at Figure 4. Overall the PDs and their common components of S-size and M-size banks are much higher than those of L-size banks. Interestingly, similar to the ST part of L-size banks, there is a clearly trend up for S-size banks, which is even more striking by looking at FW PDs. Subsequently, the JPoD, the BIS and the PAO measures were estimated. As discussed above when using the five worst banks, a jump in the JPoD and the BIS measures occurs during 2008, notably in their common components, although the early-warning features also discussed earlier are not obvious anymore (not shown). The most interesting and new results, however, refer to the PAO measure and to its common components, both for the ST and for the FW parts. Figure 5 displays the ST PAO measure and its common component on the left-hand side and the FW PAO measure and its common component on the right-hand side. The ST PAOs and their common components for S- and M-size banks coincide. The PAO and its common component for L-size banks instead are about 1/3 relatively higher highlighting their systemic nature; the early-warning features of the common components become obvious again. For the FW PAO, results are similar to those of the ST PAO, except for the disappearance of the early-warning feature. As discussed in the context of the tail risk analysis above, the PAO common component declined since 2006, while its overall level rose, suggesting thereby a deterioration of the idiosyncratic component of large banks in an otherwise generally favorable and booming macroeconomic environment.

Important for recent discussions on G-SIBS, the fact that the 5 L-size banks' set included officially designated SIBs only 50% of the time, raises several policy concerns. First, while the BCBS additional loss absorbency requirements imposed on officially designated G-SIBs will contribute to enhance financial stability, it will be important to monitor other financial institutions efficiently as well. Second, a high-frequency, regular update of the official list of G-SIBs may become necessary as business lines and banks' activity evolves, a point recognized in the BCBS proposed framework for dealing with domestically systemically important banks (BCBS, 2012). Third, efficient supervision of M- and S-size financial institutions is also crucial for financial stability. Fourth, as the BCBS method cannot estimate the contribution of a given individual bank to systemic risk, a model-based approach may be also necessary. As an illustration, the framework proposed in this paper was used to that purpose. Table 1 displays the PAO estimated for the 5 Luxembourg SIBs. As of end-September 2011, according to one possible metric to assess individual banks' contribution to systemic risk, i.e., the PAO measure or the largest probability of at least one other bank becoming distressed if a specific bank became distressed, was associated with Bank C becoming distressed. This seems a useful indication of Bank C's contribution to systemic risk: if Bank C failed, the conditional probability that at least one other bank in the group of five banks became distressed was 87% at end-September 2011, the highest of all conditional PDs in the Table.

5.3. Conditional Cross-border Systemic Credit Risk

Regulation and supervision cannot stop at the national borders. This is most certainly true in the case of Luxembourg where subsidiaries and branches of foreign-headquartered banks constitute the overwhelming majority of registered banks, although with the advent of global banking this is a more general feature of the modern world. The framework of this paper is used to measure the impact of distress between specific banks by estimating a Distress Dependence Matrix (DiDe) as well as the distress in the system associated with distress in a specific bank by calculating the PAO measure.

The DiDes are presented at Table 2 for three different dates: 2007Q4, the pre-crisis period, 2008Q4, the crisis period, and 2012Q1, the post-crisis period. These matrices present the probability of distress of the bank in the row, conditional on the bank in the column being actually distressed. Several interesting points can be made. First, the links among European banking groups increased as it is shown in the conditional PD. It increased from 28% at end-2007 to 76% at end-2008. It has fallen somewhat to 61% at 2012Q1, but it is still much higher than during the pre-crisis period. Second, averages hide diverging evolutions, however. While interconnectedness as measured by the conditional PD between banking group B and group C was high before the crisis (12%), and it increased further during the crisis (70%), banking group A became more affected by a default of group B (83%) than group C (70%). During the post-crisis, however, group B default would have a larger effect on group A (76%) and C (63%). Third, banking group C has become more interconnected with the fate of group D in the post-crisis period as its conditional PD rose from 81% in 2008Q4 to 85% in 2012Q1.

Regarding the links between parent banking groups and their subsidiaries in Luxembourg, the increased in links was important as the conditional PD rose from 25% in 2007Q4 to 33% in 2008Q4, and declined to almost pre-crisis level in 2012Q1 (27%). However, it is noteworthy that while most links increased in recent times and remain close or somewhat above the pre-crisis period, Luxemburg Bank c has become less dependent on the default of all banking groups.

Finally, a look at the default dependence of European banking groups on the default of Luxembourg banks, the following is noteworthy. First, the links between the parent companies and the fate of their subsidiaries increased dramatically rising from 1% in 2007Q1 to 53% in 2008Q4, and it was still 44% in 2012Q1, well above the pre-crisis level except for banking group D. Second, banking group A remains the one of the four G-SBIs that is most dependent on the fate of its subsidiary with a conditional PD of 75%. Third, the banking group A has also become more dependent on the other Luxembourg banks default: 72%, 78% and 68% for Luxembourg banks b, c, and d, respectively.

In order to obtain a more general picture of the conditional probability of default of European banking groups and Luxembourg banks, Figure 6 presents the PAO measure of the ST and the FW PAOs, as well as their respective common components. It distinguishes between S-, M- and L-size Luxembourg banks by their total asset values, and it aggregates European banking groups into one single portfolio. The following features stand out. First, the PAO levels and their respective common components are higher for L-size Luxembourg banks than for M- and S-size Luxembourg banks. Second, the Luxembourg L-banks ST PAO although lower than the European banking groups before the crisis, it increased above the later after Lehman Brothers' default until 2009Q3. Third, the common component of the ST PAO of Luxembourg L-banks has been traditionally above the common component of the ST PAO of European banking groups. Since the ST PD common component of Banking groups are relative higher than those of the Luxembourg L-banks only during the financial crisis (shown at Figure 4), this could be largely the result of Luxembourg banks' business models, which are highly leveraged to provide liquidity to their mother companies. The result is also consistent with the observation that the main drivers of the common components are funding costs, credit and interbank market activity, and confidence indicators. Fourth, the FW PAO of Luxembourg L-banks has been traditionally above the FW PAO of European banking groups. This time it is because the FW PD common component of L-banks is less than 2% over time whereas that of European banking groups can up to 16%. As noted above, the decline in the common component of the FW PAO of Luxembourg L-banks after 2006 and until mid-2007 was associated with the improvement in the cost of financing and its availability due to policy measures. However, the idiosyncratic component more than compensated that fall so that the overall level of the FW PAO indeed increased. These developments point to a rise in the vulnerability of the banking sector since 2006, which the policy measures did not succeed in alleviating completely. Importantly, it supports the use of macroprudential policy tools in conjunction with traditional macroeconomic policies.

5.4. Out-of-sample Forecasting

In-sample results say nothing about the out-of-sample framework performance. Therefore, this section addresses the out-of-sample forecasting capabilities of the proposed framework. However, the short number of data points available constrains a full-fledged, standard evaluation of the out-of-sample forecasting capabilities of the framework. Tables 3a-3c report the coverage ratios, root-mean squared errors, as well as the bias, the variance and the covariance decomposition of Theil's inequality coefficient from 2010 to 2011 across all estimated measures of systemic credit risk, the JPoD, the BIS and the PAO, respectively, for banking groups and for Luxembourg banks.[18] The coverage ratio is the share of banks whose empirical simulated cdf for each of the estimated measures is within the range of the respective quantiles. Under the null hypothesis that this forecasting framework correctly estimates the dynamics of the banking systemic credit risk measures, the coverage ratio should approximate the range of quantiles, if the number of underlying banks were large enough.

[18] The model is re-estimated recursively adding one period at a time and forecasting always 6 months forward.

For example, during the first month of out-of-sample forecasts using the common and the idiosyncratic components, about 91% of banks' PDs are within the 5%-95% quantiles of the forecasted cdf for all three measures. The percentage just falls to 83%, 88% and 84% at month six of the out-of-sample forecasts for the JPoD, the BSI and the PAO measures, respectively. Using only the common components for the out-of-sample forecasts performs badly, especially in the case of the BSI, highlighting important idiosyncratic factors at work during the period.

Decomposing Theil's inequality coefficient into bias, variance, and covariance, it seems that the improvement in forecasting ability by adding the idiosyncratic component results from an improvement in the model's capacity to reduce the systematic bias for all three measures and to replicate the degree of variance in PDs (column "Variance Proportion") for the JPoD and the BSI, but not for the PAO. This may be due to the way the PAO measure is constructed, i.e., it is based on one specific bank defaulting as opposed to any bank in the sample defaulting. In this paper, it is assumed that the bank that defaults is the worst performer, and which bank is the worst each period is allowed to change.

Summarizing, the framework proposed in this paper does a reasonable job at forecasting the movements of the measures of systemic banking credit risk. This framework can also be used as an early-warning, out-of-sample, mechanism. It is an operational improvement over the work of Segoviano and Goodhart (2009).

VI. Conclusions and macroprudential policy implications

The framework developed in this study provides a structural early-warning measure of vulnerabilities' build up in the banking sector, estimates measures of systemic credit risk for the banking sector, and generates robust out-of-sample forecasts of them. Given that financial stability cannot stop at national borders, it uses a set of European banking groups and their affiliates in Luxembourg.

The framework can be decomposed as follows. First, marginal PDs are estimated using Delianedis and Geske (2003) compound option model, a structural credit risk model that distinguishes between the probability of default at the end of year one and the forward probability of default, conditional on not defaulting the first year. It offers a structural alternative to simple "through-the-cycle" approaches to haircuts, margins and simple averaging of PDs proposed to deal with the procyclicality of the financial system. Second, it uses book-value data to cope with the lack of market data for non-publicly quoted banks. Third, the CIMDO approach of Segoviano (2006) is used to model the time-varying linear and non-linear dependence among banks. Fourth, the framework offered by the generalized dynamic factor model applied to a large macrofinancial dataset extracts the common component of banks' marginal PDs, both at the banking group and at the subsidiary levels, illustrating how a set of common systematic factors affect both of them simultaneously, albeit with different weights. It brings out the links between measures of distress and their underlying macrofinancial drivers, and in doing so, it alleviates the well-known difficulties markets experience when it comes to pricing risk over time. Beyond real economic activity, different credit aggregates as well as the amount of interbank lending and borrowing and confidence indicators are important systemic drivers of European banking groups' risk, as suggested by Borio and Lowe (2002), and by Drehmann and Tarashev (2011), respectively. For Luxembourg, credit aggregates and interbank activity as well as confidence indicators are the main drivers.

This framework tracks in advance over a couple-of-year time span a persistent increase in credit risk for the banking system in the tradition of early-warning indicators. This rise in credit risk suggests an increase in the vulnerability of the financial system. As such, the framework of this study, by separating the role of system developments from individual banks' idiosyncratic features, is an important step toward building macro-financial models of systemic risk that contain early-warning features with a realistic characterization of episodes of financial instability. This work contributes to the systemic risk literature incorporating the externalities that financial intermediaries exert on the rest of the financial system and on the economy in general by signaling out the role of common systemic forces affecting all banks and also by showing the buildup of credit risk or imbalances that increase the likelihood of default over time. It contributes to the macroprudential literature with a method to monitor systemic credit risk.

In addition, estimated measures of banking systemic credit risk reflect common distress in the banks of the system (i.e., the joint probability of default) and distress associated with a specific bank (or a set of banks) (i.e. the expected number of banks becoming distressed given that at least one bank has become distressed) and; the probability that at least one bank becomes distressed, given that a specific bank becomes distressed. This is a rich set of indicators for a macroprudential operational framework based on explicit modeling of banks' default dependence: conditional probabilities can provide insights into interlinkages and the likelihood of contagion between banks or groups of banks in the system. This should help assessing the contingent liabilities of the banking system and the expected costs of policy inaction.

Also important for macroprudential policy is the policymaker's capacity to project or forecast increases in systemic credit risk at any given point in time. This study contributes to the macroprudential literature by suggesting as well a framework for forecasting banking systemic credit risk changes. By using a dynamic CIMDO and the GDFM, it helps forecasting both the common as well as the idiosyncratic components of banking systemic credit risk measures. This remediates the well-known feature that simply aggregating banks' marginal PDs provides a downward-biased measure of banking systemic credit risk. Indeed, by incorporating the common and the idiosyncratic components of a broad set of macro-financial variables, the framework improves the analytical features and the out-of-sample forecasting performance of the model.

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Appendix I

The short-term debt (BS047) and the long-term debt (BS051) from Bloomberg can have annual, semi-annual, and quarterly frequencies, and are not consistent. Therefore, to make the data consistent, four filtering rules are applied as follows:

I. Take any zero as missing data.

II. If the annual data exist and are not equal to the semi-annual/quarterly data, then let semi-annual/quarterly data be equal to the annual data. (Take annual data as trusted).

III. If the annual data do not exist, and both the semi-annual/quarterly data and the annual data exist at the previous and the next fiscal years, but semi-annual/quarterly data are very different from the corresponding annual data at the same previous and next fiscal years, then treat the semi-annual/quarterly as missing data. (To avoid unreliable semi-annual /quarterly data)

IV. If the annual data do not exist, and annual data exist at both the previous and the next fiscal years, but they are very different from the semi-annual/quarterly data, then treat the semi-annual/quarterly data as missing data. (To avoid unreliable and too choppy semi-annual /quarterly data between the previous and the next fiscal years)

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

Appendix III. The Delianedis and Geske compound option-based credit risk model (2003)

Structural credit risk models attempt to assess the creditworthiness of a firm by modeling the evolution of the firm's asset values as a stochastic process, and by viewing bankruptcy as an endogenous random event linked to the value of the firm's assets. Debt maturity influences liquidity risk and PDs which interact in complex manners. Debt maturity is important. This is the main reason for choosing Delianedis and Geske (2003) model of credit risk. The model considers a multi-period debt payment framework to which it applies compound option theory. This enables to account for the influence of the time structure of debt on the estimated PD, and has the advantage of providing a structural conditional measure of forward PDs which can be used as an early warning measure.

Assume that a bank has long term debt, M_2, which matures at date T_2, and short term debt, M_1, which matures at date T_1. Between T_1 and T_2, the Merton model is valid as the bank's equity equals a call option giving the shareholder the right to buy the bank at the second payment date, T_2, by paying the strike price M_2. If at date T_1, the call option with the bank's value $\overline{V}$ equals at least the face value of the short term debt, M_1:

$$M_1 = \overline{V} N(k_2 + \sigma_A \sqrt{T_2 - T_1}) - M_2 e^{-r_{F_1}(T_2 - T_1)} N(k_2),$$

then, the bank can roll over its debt. So, the refinancing problem, the right to buy the simple call option of the second period by paying the strike price at the first payment date, is exactly a compound option as follows:

$$V_E = V_A N_2(k_1 + \sigma_A \sqrt{T_1 - t}, k_2 + \sigma_A \sqrt{T_2 - t}; \rho) - M_2 e^{-r_{F_2}(T_2 - t)} N_2(k_1, k_2; \rho) - M_1 e^{-r_{F_1}(T_1 - t)} N(k_1)$$

where $\rho = \sqrt{\dfrac{T_2 - t}{T_1 - t}}$, $N_2()$ is a bivariate cumulative normal distribution, and,

$$k_1 = \frac{\ln(\frac{V_A}{\overline{V}}) + (r_{F_1} - \frac{1}{2}\sigma_A^2)(T_1 - t)}{\sigma_A \sqrt{T_1 - t}}, \quad k_2 = \frac{\ln(\frac{V_A}{M_2}) + (r_{F_2} - \frac{1}{2}\sigma_A^2)(T_2 - t)}{\sigma_A \sqrt{T_2 - t}}.$$

The richness of the model allows to calculate the following risk neutral PDs: (1) the total or joint probability of defaulting at either date T_1 or date T_2, i.e., $1 - N_2(k_1, k_2; \rho)$; (2) the short-run probability of only defaulting on the short-term debt at date T_1, i.e., $1-N(k_1)$ and; (3) the forward probability held today of defaulting on the long-term debt at date T_2, conditional on not defaulting on the short-term debt at date T_1, i.e., $1-\frac{N_2(k_1,k_2;\rho)}{N(k_1)}$. Similar to the Moody's KMV iterative procedure, the Delianedis and Geske model is estimated by the two-step iterative algorithm. Regarding the maturity of the debt value, this study takes all short term obligations due in one year as a one-year maturity debt, and all long-term debt as a ten-year maturity debt.

The Book Value-Based Delianedis and Geske Model

It is often argued that the estimation of structural credit risk models requires the use of market prices to be reliable. This view is not shared in this paper. First, if banks do not have liquid CDS or bond markets or are not publicly quoted, as it is the case with Luxembourg banks, an alternative approach to calculate PDs has to be followed anyway. Second, and as discussed in the text, recent policy suggestions to use "through-the-cycle" estimates of PDs, haircuts or margin requirements to deal with widely known cases of markets' mispricing of risk over time are not necessarily inconsistent with using book-value data—even at historical costs plus depreciation—to estimate PDs. Hillegeist *et al.* (2004) demonstrate that the market-based Merton's PD provides significantly more information about the probability of bankruptcy than do the popular accounting-based measures. However, Bharath and Shumway (2008) also examine the accuracy and PDs forecasting performance of the Merton model and find that most of its predictive power comes from its functional form rather than from the estimation method: the firm's asset value, its asset risk, and its leverage. In an application to Brazilian and Mexican banks, Souto *et al* (2009) and Blavy and Souto (2009), respectively, show that the book-based Merton's credit risk measures are highly correlated with market-based Merton's credit risk measures.[19] This suggests that banks' financial statements are a crucial piece of information when forming market expectations about the probability of banks' default or, at a minimum, that the alluded shortcomings of market pricing of risk are shared by book-values, and thus, book-value-estimates of PDs are not any worse than market-based estimates of PDs. Regarding the estimation of volatility, in empirical work, a dynamic volatility model is often preferred in order to track risks more timely. However, most dynamic volatility models require many more data points than are available for Luxembourg banks. The RiskMetrics (RM) filter/model instead assumes a very tight parametric specification. The book value asset RM variance can be defined as:

[19] See also Gray and Jones, 2006, for an early application of this idea.

$$h^{B}{}_{t+1} = (1-\zeta)(\ln(V_t^{\;B} / V_{t-1}^{B}))^2 + \zeta h^{B}{}_{t}$$

where the variance forecast h_{t+1}^{B} for period *t+1* is constructed at the end of period *t* using the square of the return observed at the end of period *t* as well as the variance on period *t*. Although the smoothing parameter ζ may be calibrated to best fit the specific historical returns, RiskMetrics often simply fixes it at 0.94. To avoid the calibration difficulties for our limited data points, ζ is also assumed to be same for all banks, and estimated by numerically optimizing the composite likelihoods (Varin et al, 2011), here the sum of quasi maximum likelihood functions of the estimation sample over all banks simultaneously:

$$QMLE(\zeta) = -\frac{1}{2}\sum_{i=1}^{N}\ \sum_{t=1}^{T}(\ln(h_{t,i}) + (V_{t,i}^{\;B} / V_{t-1,i}^{B})^2 / h_{t,i})$$

where N is number of banks, and there is a time series of T observations for each banks. The recursion is initialized by setting the initial σ_0^B equal to the first year book value asset volatility, and the means of quarterly assets returns in a large sample are assumed to be zeros to avoid the noises brought by the sample means to the RM variance process. The estimated value of ζ is 0.83.

In order to have a more forward-looking measure, the variance forecast $\sigma^{B}{}_{t+1}$ can be used to calibrate PDs at time t. The three book-value risk neutral PDs of the Delianedis and Geske model can be estimated by substituting V_B and σ_B into k_1 and k_2 in the Geske model. Given σ_B, the critical book value of total assets $\overline{V}^{B}$ at T_1 is calculated first. Similarly, this study takes all short term debt due in one year as a one-year maturity debt, and all long-term debt as a ten-year maturity debt.

Figure 1: Average Correlations for Luxembourg Banks and Banking Groups

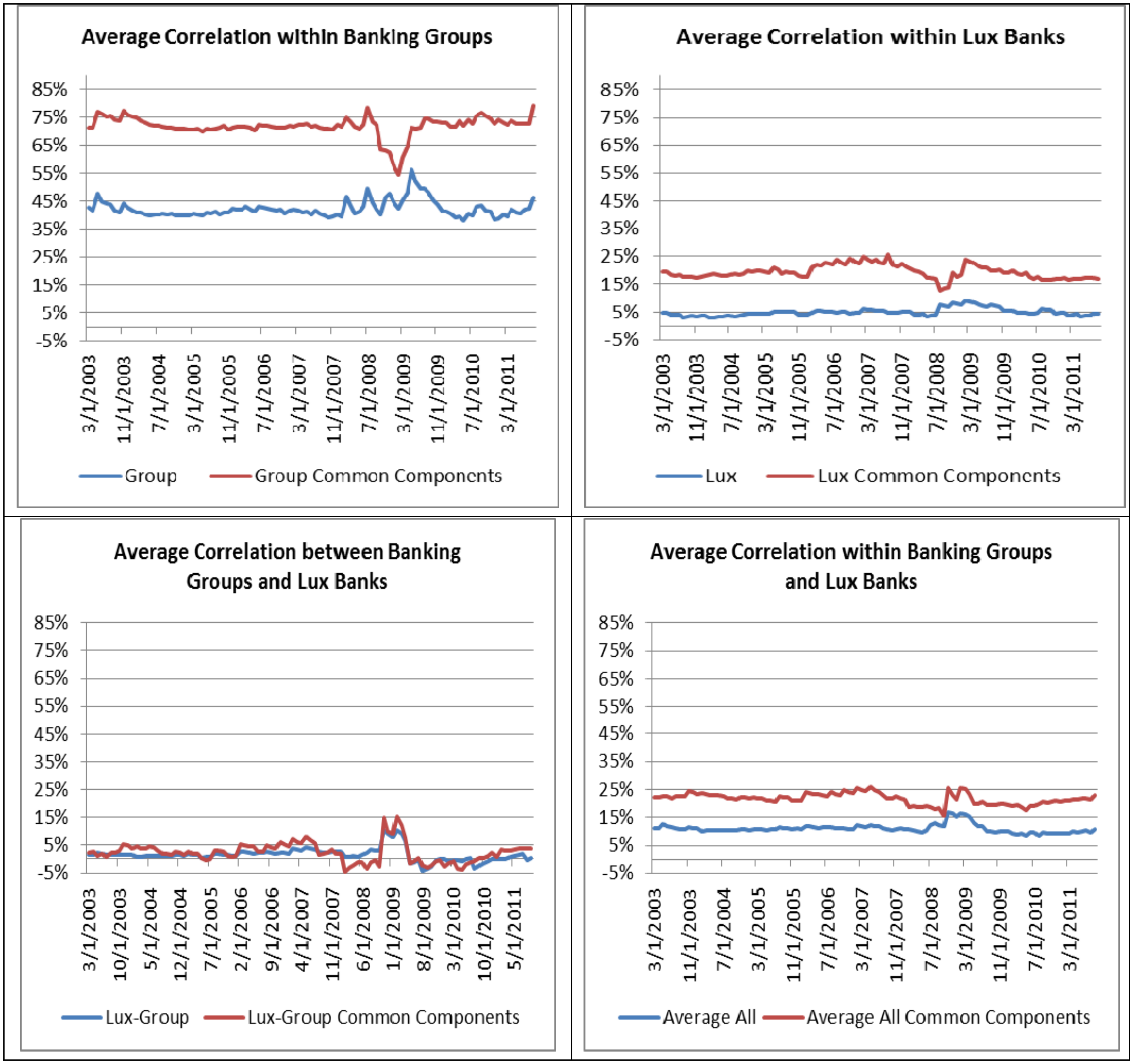

Figure 2: JPoD of the Dynamic Worst Five Banking Groups (Ranked by Total-Asset Weighted PDs)

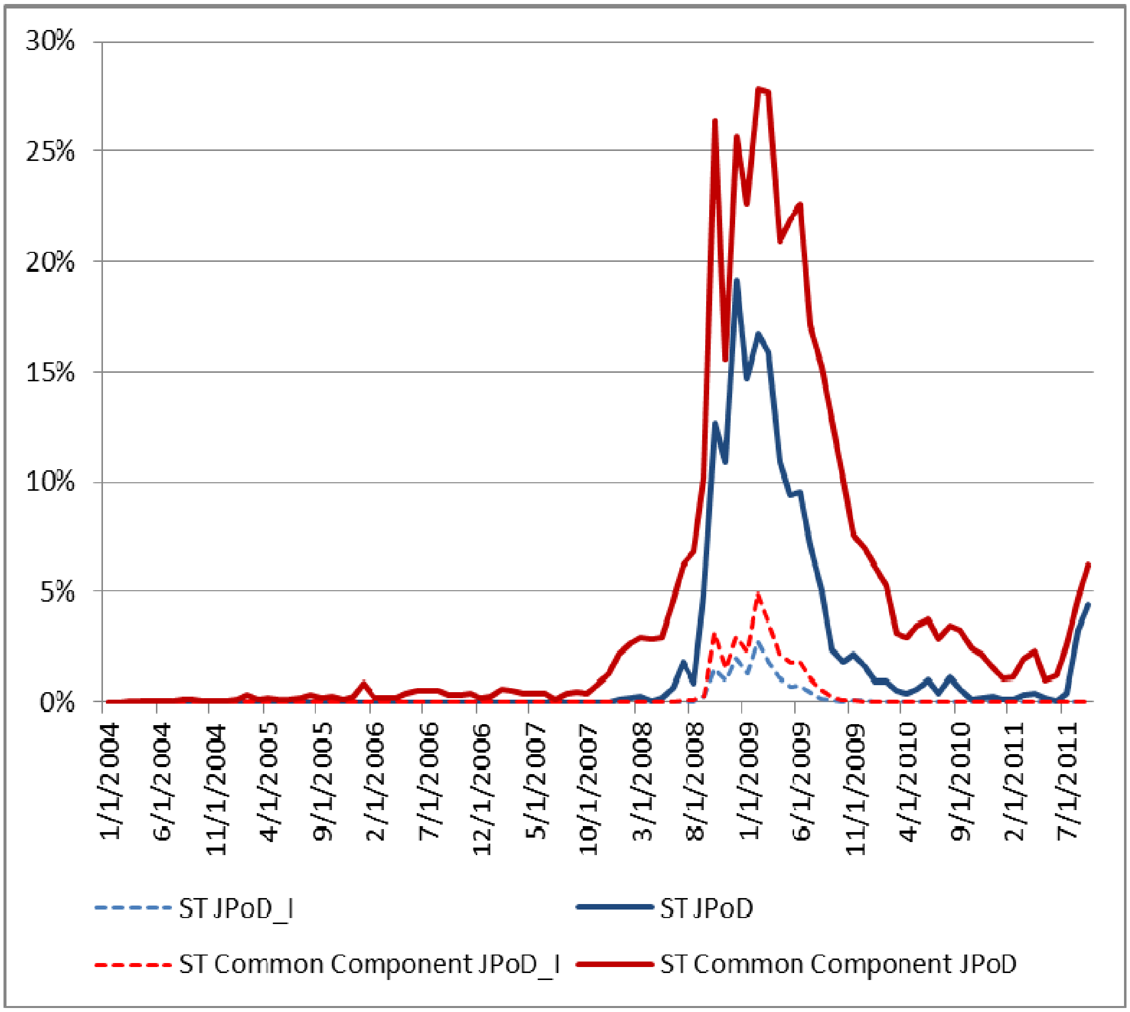

Figure 3a: Dynamic Banking Stability Measures for Banking Groups
(The Worst Five Banks Dynamically Selected by their Total-Asset Weighted PDs)

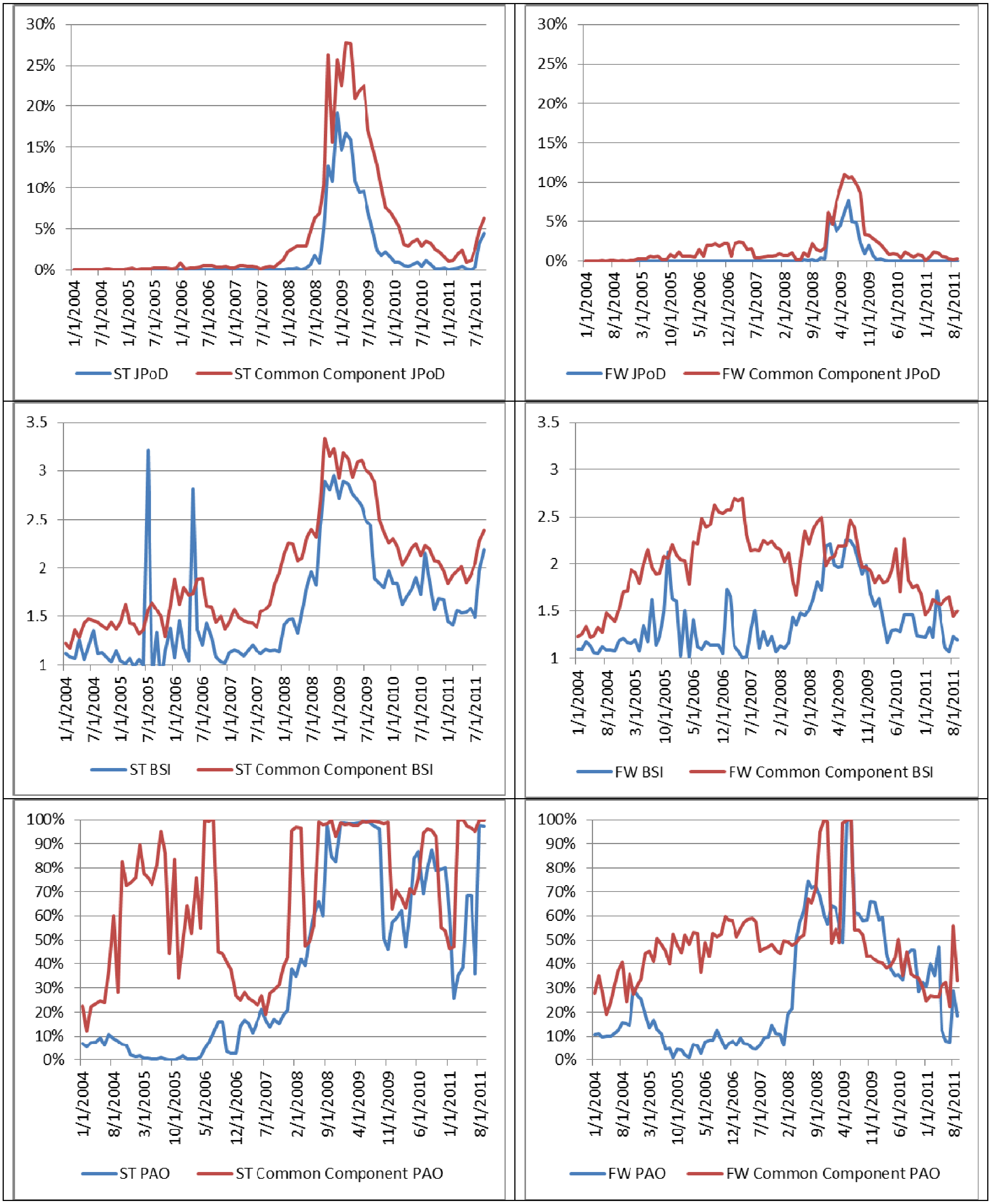

Figure 3b: Dynamic Banking Stability Measures for Lux Banks
(The Worst Five Banks Dynamically Selected by their Total-Asset Weighted PDs)

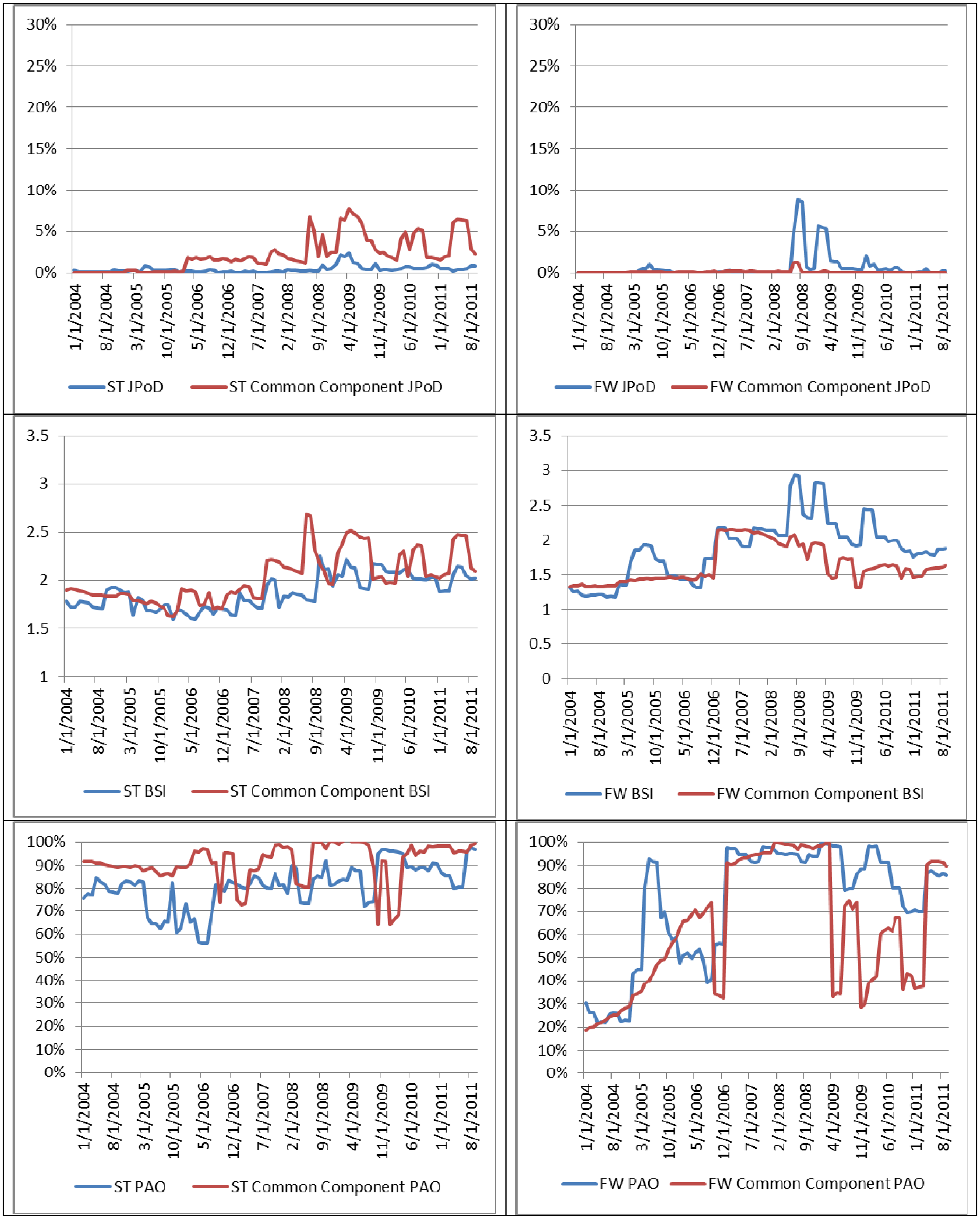

Figure 3c: Dynamic Banking Stability Measures for Lux Banks
(The Worst Five Banks Dynamically Selected by their Interbank-Lending Weighted PDs)

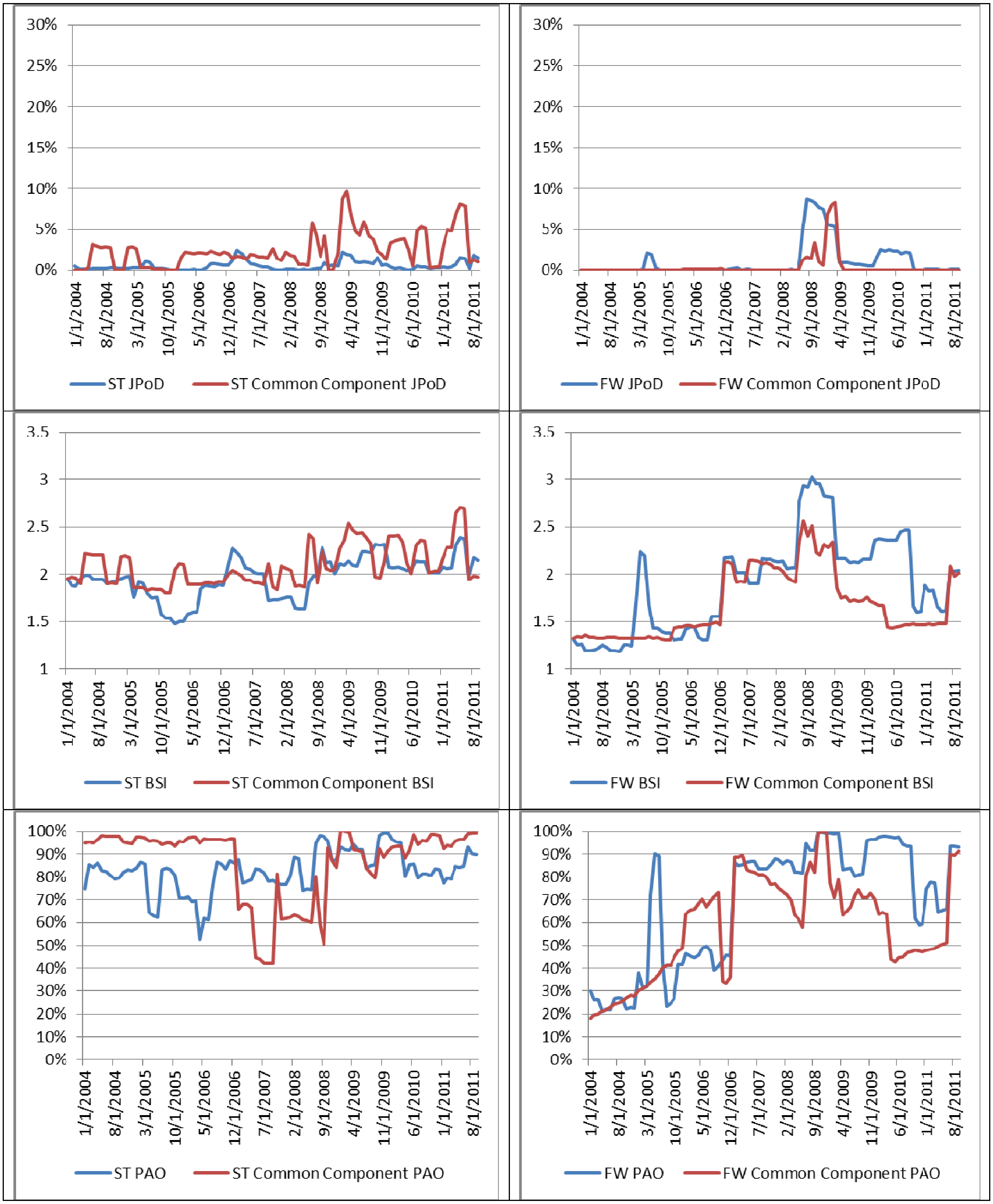

Figure 3d: Dynamic Banking Stability Measures for Lux Banks
(The Worst Five Banks Dynamically Selected by their Interbank-Borrowing Weighted PDs)

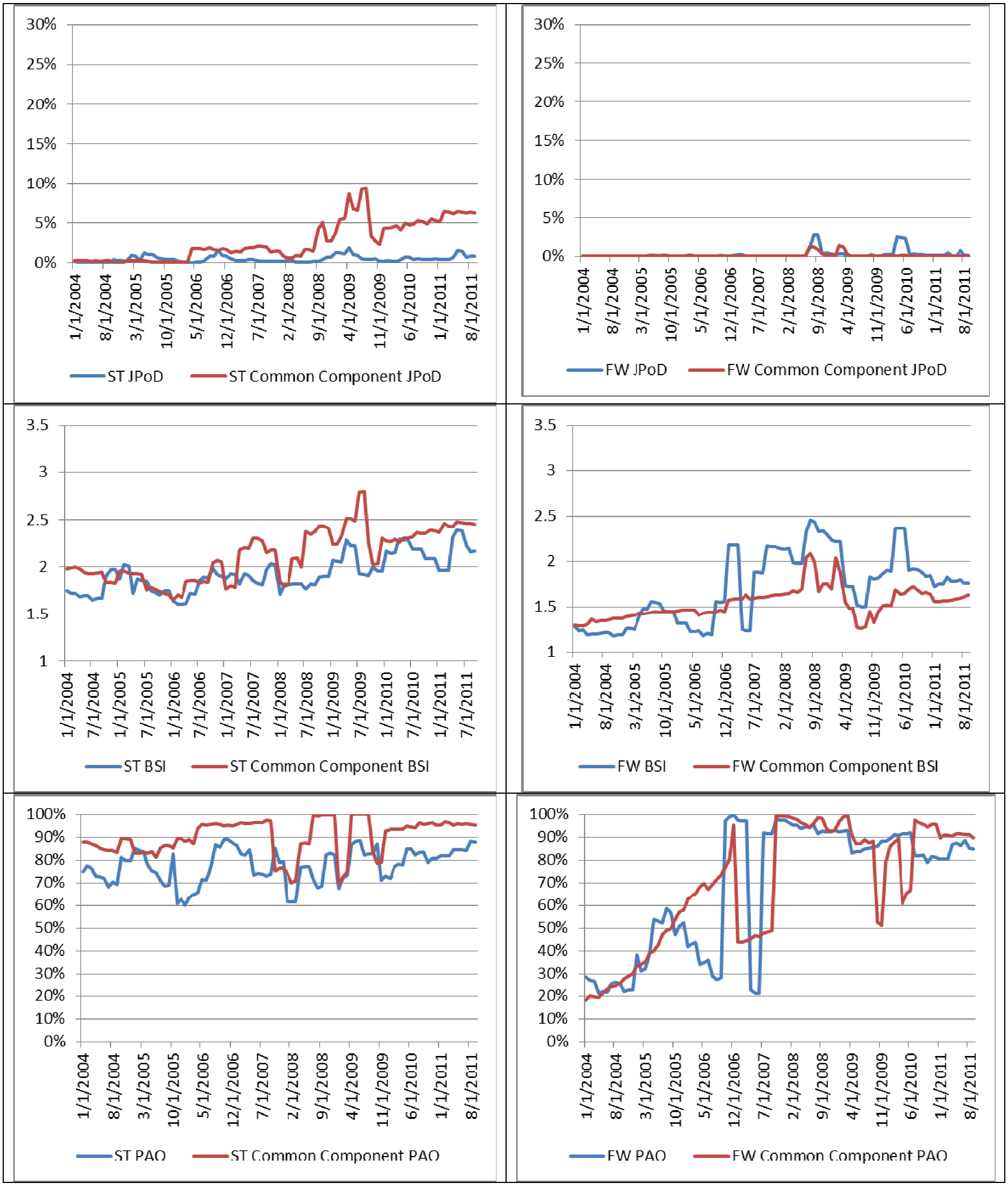

Figure 4: PDs for Luxembourg SML Size Banks and Banking Groups

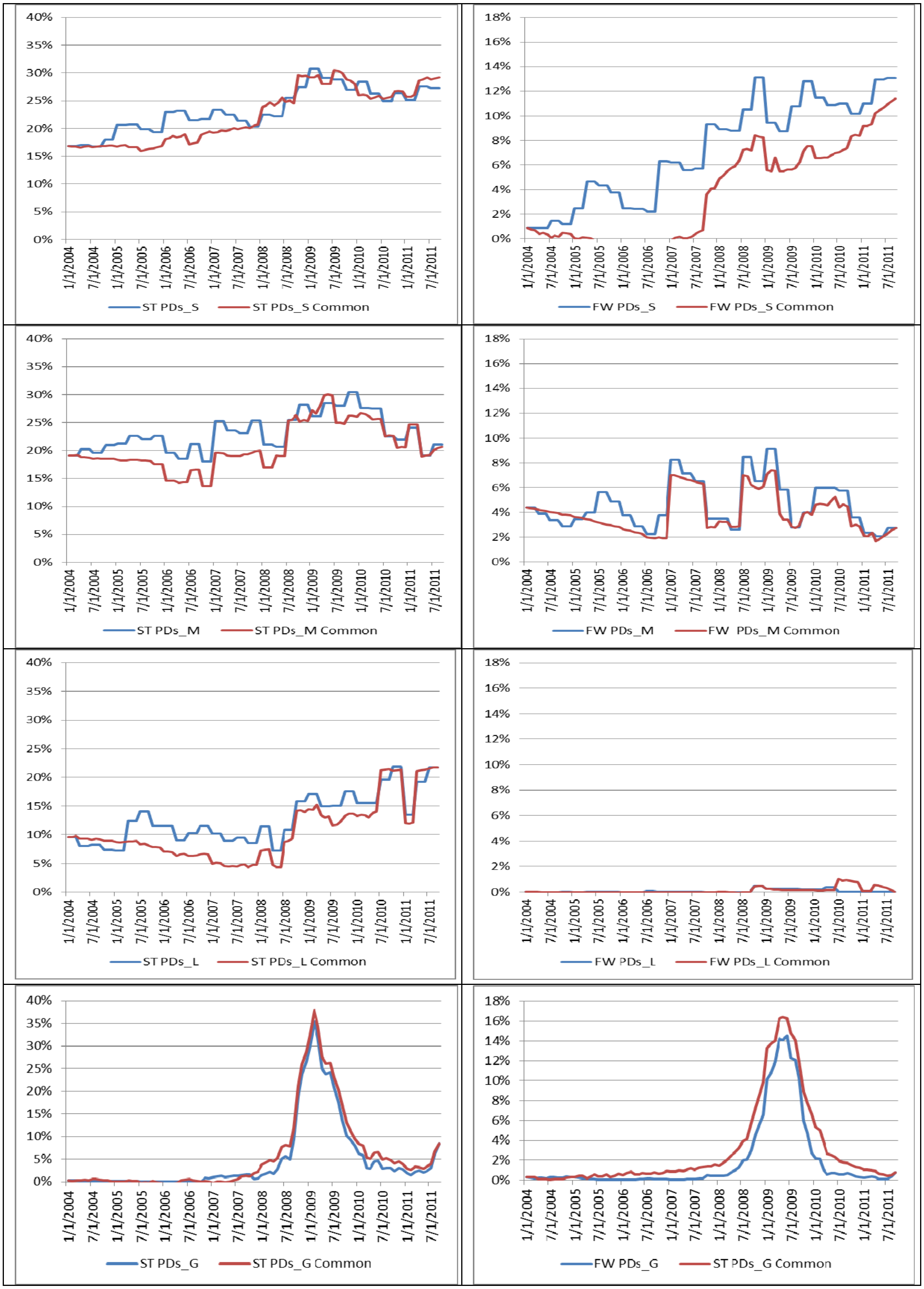

Figure 5: PAO for SML

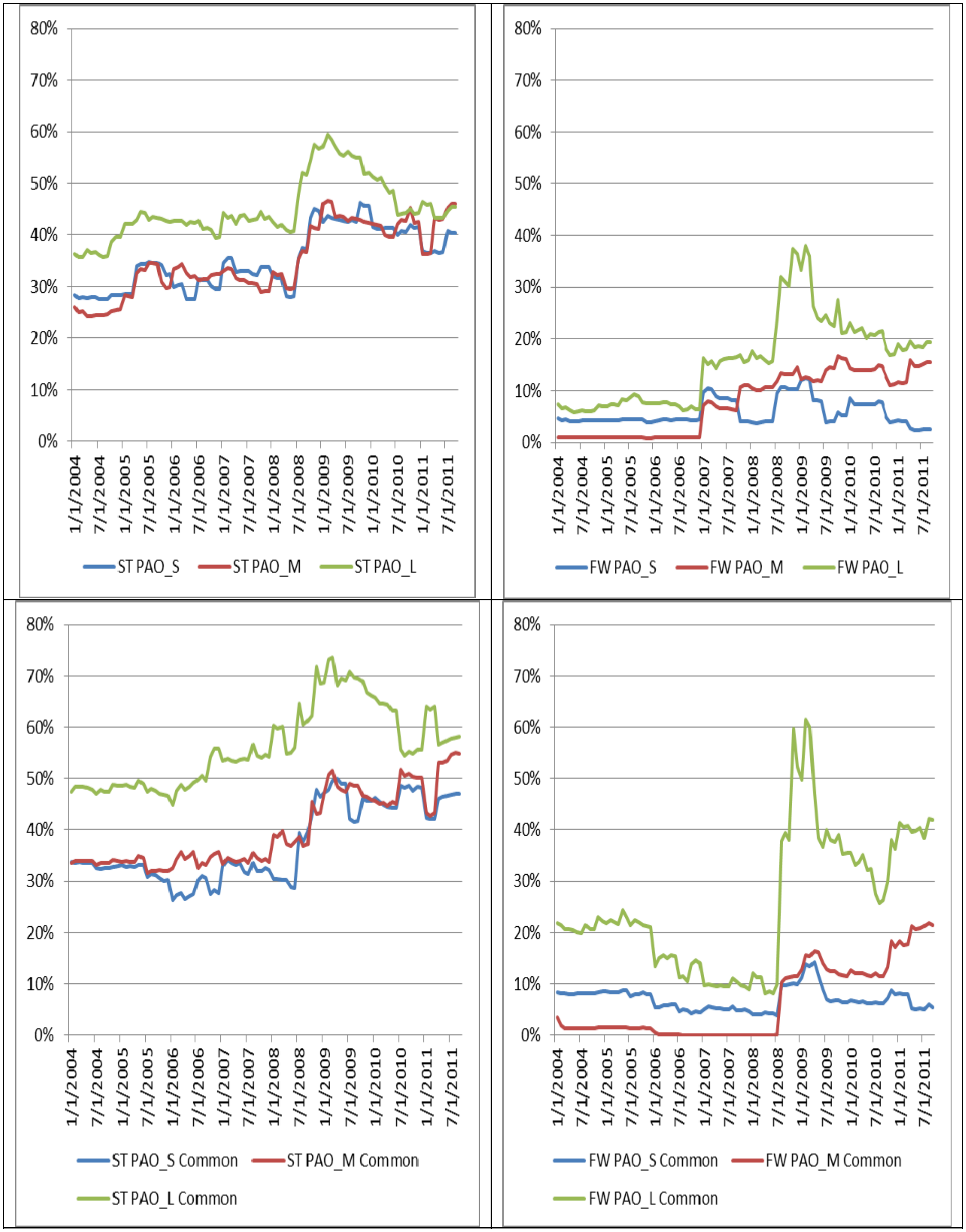

Figure 6: PAO for SML&G

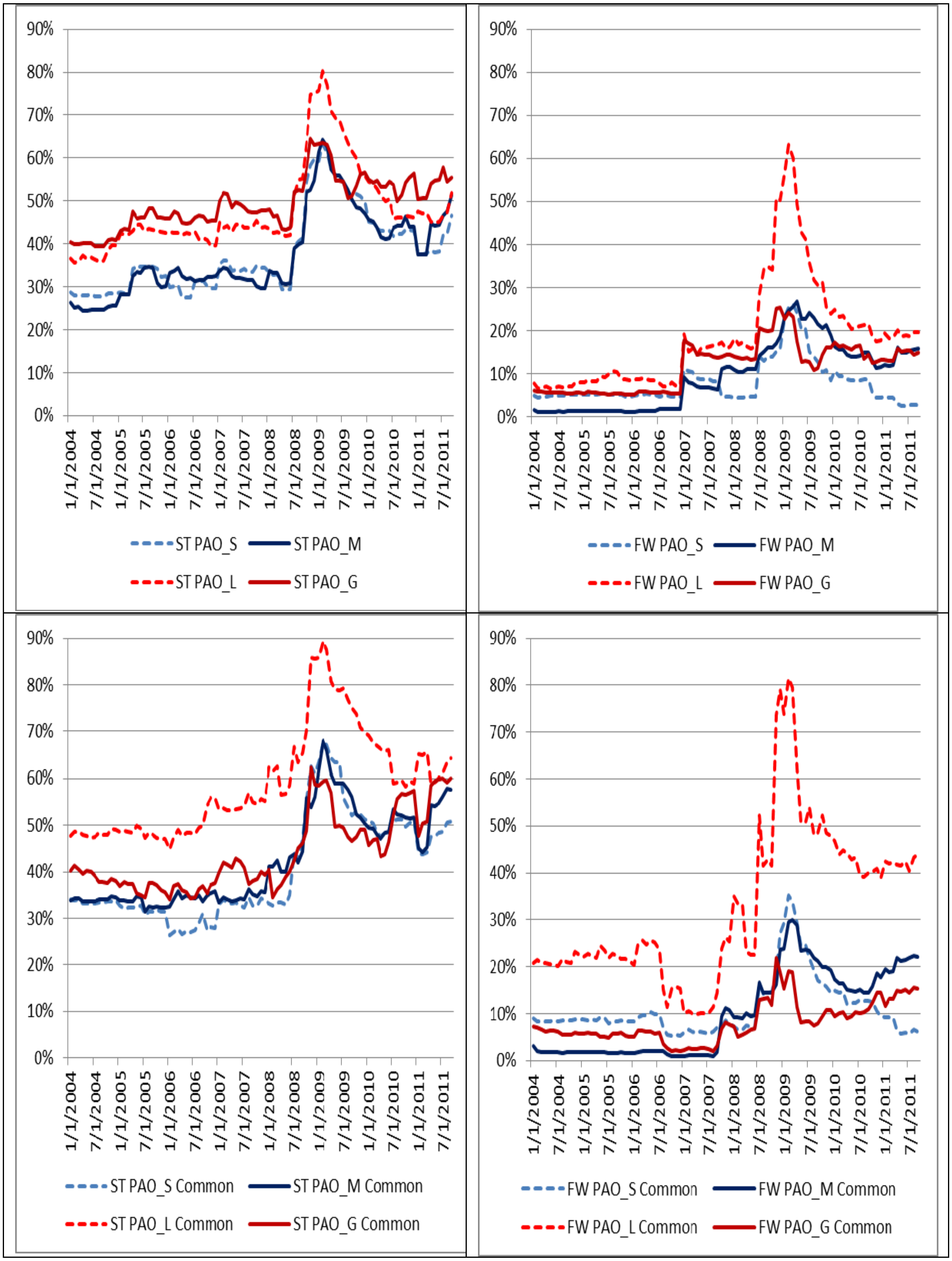

Table 1: PAO for Five Luxembourg Systemically Important Banks

	PAO at 2011Q3
Bank A	0.76
Bank B	0.76
Bank C	0.87
Bank D	0.80
Bank E	0.75

PAO: conditional probability that at least one other bank becomes distressed given that aspecific bank becomes distressed.

Table 2: Distress Dependence Matrices

	Bank A	Bank B	Bank C	Bank D	Row Average	Bank a	Bank b	Bank c	Bank d	Row Average
Q4 2007										
Bank A	1.00	0.03	0.04	0.05	0.28	0.02	0.01	0.01	0.01	0.01
Bank B	0.01	1.00	0.06	0.02	0.27	0.00	0.00	0.00	0.00	0.00
Bank C	0.03	0.12	1.00	0.15	0.33	0.01	0.01	0.01	0.01	0.01
Bank D	0.00	0.00	0.00	1.00	0.25	0.00	0.00	0.00	0.00	0.00
Column Average	0.26	0.29	0.27	0.30	0.28	0.01	0.01	0.01	0.01	0.01
Bank a	0.16	0.07	0.12	0.18	0.13	1.00	0.08	0.09	0.12	0.01
Bank b	0.56	0.56	0.52	0.52	0.54	0.40	1.00	0.40	0.35	0.01
Bank c	0.19	0.15	0.20	0.15	0.17	0.14	0.12	1.00	0.21	0.00
Bank d	0.16	0.09	0.15	0.21	0.15	0.19	0.11	0.22	1.00	0.01
Column Average	0.27	0.22	0.25	0.27	0.25	0.43	0.33	0.43	0.42	0.01
Q4 2008										
Bank A	1.00	0.83	0.90	0.94	0.92	0.84	0.72	0.76	0.75	0.77
Bank B	0.51	1.00	0.79	0.69	0.75	0.49	0.47	0.50	0.41	0.47
Bank C	0.49	0.70	1.00	0.81	0.75	0.54	0.42	0.49	0.46	0.48
Bank D	0.38	0.46	0.61	1.00	0.61	0.49	0.31	0.37	0.40	0.39
Column Average	0.60	0.75	0.82	0.86	0.76	0.59	0.48	0.53	0.51	0.53
Bank a	0.46	0.44	0.55	0.65	0.53	1.00	0.35	0.48	0.51	0.59
Bank b	0.39	0.41	0.42	0.42	0.41	0.35	1.00	0.30	0.29	0.48
Bank c	0.21	0.23	0.25	0.25	0.24	0.25	0.15	1.00	0.26	0.41
Bank d	0.13	0.12	0.15	0.18	0.14	0.17	0.09	0.16	1.00	0.35
Column Average	0.30	0.30	0.34	0.38	0.33	0.44	0.40	0.49	0.51	0.46
Q1 2012										
Bank A	1.00	0.76	0.78	0.80	0.84	0.75	0.72	0.78	0.68	0.41
Bank B	0.25	1.00	0.64	0.65	0.64	0.17	0.25	0.24	0.16	0.41
Bank C	0.26	0.63	1.00	0.85	0.68	0.19	0.25	0.25	0.19	0.43
Bank D	0.02	0.05	0.07	1.00	0.29	0.02	0.02	0.02	0.02	0.41
Column Average	0.38	0.61	0.62	0.82	0.61					0.41
Bank a	0.26	0.18	0.20	0.26	0.23	1.00	0.20	0.27	0.28	0.44
Bank b	0.55	0.58	0.58	0.59	0.58	0.45	1.00	0.47	0.40	0.58
Bank c	0.07	0.07	0.07	0.06	0.07	0.07	0.06	1.00	0.10	0.31
Bank d	0.22	0.16	0.19	0.25	0.20	0.27	0.17	0.34	1.00	0.44
Column Average	0.28	0.25	0.26	0.29	0.27	0.45	0.36	0.52	0.45	0.44

These matrices present the probability of distress of the bank in the row, conditional on the bank in the column becoming distressed.
Banks with an upper case letter are European banking groups and banks with a lower case letter are their respective Luxembourg subsidiaries.

Table 3a: CIMDO-copula JPoD Forecast (Median) Evaluation for Banking Groups and Luxembourg Banks

	Q 5%-95%	Q 10%-90%	Q 15%-85%	Q 20%-80%	Q 25%-75%	Q 30%-70%	Q 35%-65%	Q 40%-60%	Q 45%-55%	RMS Error	Bias Proportion	Variance Proportion	Covariance Proportion
	Common Component												
	Coverage Ratio												
1th Month	0.359	0.297	0.203	0.156	0.125	0.109	0.047	0.031	0.016	0.045	0.385	0.176	0.439
2nd Month	0.469	0.375	0.297	0.234	0.203	0.172	0.078	0.063	0.031	0.046	0.457	0.204	0.339
3th Month	0.516	0.375	0.297	0.219	0.141	0.078	0.078	0.031	0.016	0.051	0.509	0.256	0.235
4th Month	0.578	0.328	0.203	0.188	0.172	0.125	0.094	0.078	0.016	0.052	0.527	0.299	0.174
5th Month	0.578	0.422	0.297	0.250	0.172	0.125	0.125	0.094	0.016	0.056	0.509	0.329	0.162
6th Month	0.703	0.438	0.359	0.313	0.219	0.141	0.094	0.078	0.063	0.062	0.443	0.335	0.222
	Common and Idiosyncratic Components												
1th Month	0.906	0.813	0.656	0.563	0.500	0.484	0.375	0.250	0.063	0.013	0.035	0.084	0.881
2nd Month	0.891	0.766	0.688	0.578	0.500	0.375	0.297	0.141	0.063	0.017	0.136	0.118	0.746
3th Month	0.906	0.813	0.766	0.703	0.531	0.391	0.281	0.172	0.094	0.022	0.192	0.169	0.639
4th Month	0.844	0.797	0.703	0.609	0.500	0.188	0.156	0.094	0.047	0.026	0.212	0.202	0.585
5th Month	0.875	0.766	0.625	0.500	0.391	0.313	0.203	0.125	0.031	0.031	0.230	0.269	0.501
6th Month	0.828	0.703	0.625	0.516	0.406	0.313	0.219	0.156	0.078	0.042	0.179	0.307	0.514

The table reports the coverage ratios, root mean square errors, and the proportions of bias, variance, and covariance, respectively, from 2010 to 2011 across all JPoD from CIMDO-copula for both banking groups and Luxembourg banks. The coverage ratio is the proportion of banks whose empirical cdf (simulated) at each of the estimated JPoD are within the range of quantiles.

Table 3b: CIMDO-copula BSI Forecast (Median) Evaluation for Banking Groups and Luxembourg Banks

	Q 5%-95%	Q 10%-90%	Q 15%-85%	Q 20%-80%	Q 25%-75%	Q 30%-70%	Q 35%-65%	Q 40%-60%	Q 45%-55%	RMS Error	Bias Proportion	Variance Proportion	Covariance Proportion
	Common Component												
	Coverage Ratio												
1th Month	0.328	0.234	0.219	0.156	0.094	0.094	0.047	0.031	0.016	0.241	0.590	0.005	0.405
2nd Month	0.344	0.281	0.250	0.219	0.188	0.172	0.125	0.047	0.031	0.243	0.464	0.000	0.536
3th Month	0.359	0.328	0.297	0.250	0.203	0.125	0.094	0.094	0.047	0.238	0.451	0.004	0.545
4th Month	0.391	0.297	0.250	0.203	0.156	0.141	0.109	0.031	0.016	0.232	0.405	0.011	0.584
5th Month	0.328	0.297	0.234	0.125	0.109	0.094	0.078	0.078	0.047	0.259	0.320	0.019	0.661
6th Month	0.391	0.313	0.234	0.172	0.141	0.094	0.047	0.047	0.031	0.256	0.357	0.025	0.618
	Common ans Idiosyncratic Components												
1th Month	0.906	0.750	0.734	0.609	0.531	0.375	0.313	0.188	0.094	0.115	0.001	0.000	0.998
2nd Month	0.859	0.734	0.625	0.563	0.422	0.344	0.297	0.172	0.094	0.156	0.000	0.001	0.999
3th Month	0.875	0.734	0.625	0.484	0.438	0.344	0.297	0.219	0.094	0.156	0.006	0.004	0.990
4th Month	0.891	0.766	0.563	0.422	0.375	0.344	0.234	0.188	0.125	0.155	0.010	0.006	0.983
5th Month	0.906	0.719	0.547	0.469	0.422	0.328	0.250	0.188	0.141	0.179	0.023	0.009	0.967
6th Month	0.891	0.719	0.641	0.500	0.406	0.328	0.313	0.219	0.109	0.183	0.045	0.015	0.940

The table reports the coverage ratios, root mean square errors, and the proportions of bias, variance, and covariance, respectively, from 2010 to 2011 across all BSI from CIMDO-copula for both banking groups and Luxembourg banks. The coverage ratio is the proportion of banks whose empirical cdf (simulated) at each of the estimated BSI are within the range of quantiles.

Table 3c: CIMDO-copula PAO Forecast (Median) Evaluation for Banking Groups and Luxembourg Banks

	Q 5%-95%	Q 10%-90%	Q 15%-85%	Q 20%-80%	Q 25%-75%	Q 30%-70%	Q 35%-65%	Q 40%-60%	Q 45%-55%	RMS Error	Bias Proportion	Variance Proportion	Covariance Proportion
	Common Component												
	Coverage Ratio												
1th Month	0.266	0.141	0.063	0.063	0.047	0.000	0.000	0.000	0.000	0.230	0.500	0.029	0.470
2nd Month	0.391	0.297	0.234	0.156	0.109	0.078	0.047	0.031	0.000	0.228	0.499	0.015	0.486
3th Month	0.531	0.328	0.250	0.188	0.141	0.109	0.031	0.031	0.031	0.248	0.429	0.006	0.565
4th Month	0.578	0.422	0.281	0.219	0.141	0.125	0.109	0.078	0.047	0.246	0.411	0.001	0.588
5th Month	0.703	0.438	0.281	0.188	0.141	0.109	0.094	0.078	0.031	0.268	0.318	0.002	0.680
6th Month	0.656	0.422	0.313	0.219	0.172	0.141	0.141	0.063	0.063	0.271	0.306	0.004	0.691
	Common and Idiosyncratic Components												
1th Month	0.906	0.797	0.641	0.516	0.438	0.281	0.188	0.141	0.109	0.118	0.000	0.011	0.989
2nd Month	0.891	0.781	0.641	0.516	0.422	0.297	0.250	0.156	0.063	0.145	0.010	0.029	0.960
3th Month	0.859	0.766	0.641	0.547	0.453	0.359	0.281	0.203	0.094	0.150	0.025	0.050	0.925
4th Month	0.906	0.781	0.734	0.578	0.484	0.359	0.266	0.156	0.047	0.156	0.036	0.047	0.917
5th Month	0.891	0.719	0.625	0.578	0.484	0.359	0.266	0.172	0.078	0.186	0.042	0.061	0.896
6th Month	0.844	0.688	0.594	0.547	0.484	0.406	0.281	0.188	0.047	0.201	0.044	0.088	0.868

The table reports the coverage ratios, root mean square errors, and the proportions of bias, variance, and covariance, respectively, from 2010 to 2011 across all PAO from CIMDO-copula for both banking groups and Luxembourg banks. The coverage ratio is the proportion of banks whose empirical cdf (simulated) at each of the estimated PAOs are within the range of quantiles.