3. AN EARLY-WARNING AND DYNAMIC FORECASTING FRAMEWORK OF DEFAULT PROBABILITIES FOR THE MACROPRUDENTIAL POLICY INDICATORS ARSENAL

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ABSTRACT

The estimation of banks' marginal probabilities of default using structural credit risk models can be enriched incorporating macro-financial variables readily available to economic agents. By combining Delianedis and Geske's model with a Generalized Dynamic Factor Model into a dynamic t-copula as a mechanism for obtaining banks' dependence, this paper develops a framework that generates an early warning indicator and robust out-of-sample forecasts of banks' probabilities of default. The database comprises both a set of Luxembourg banks and the European banking groups to which they belong. The main results of this study are, first, that the common component of the forward probability of banks' defaulting on their long-term debt, conditional on not defaulting on their short-term debt, contains a significant early warning feature of interest for an operational macroprudential framework. Second, incorporating the common and the idiosyncratic components of macro-financial variables improves the analytical features and the out-of-sample forecasting performance of the framework proposed.

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1. MOTIVATION

A relatively broad characterization of the objective of macroprudential policy is to limit systemic risk so as to minimize the costs of financial instability on the economy (ECB, June 2010). The literature on financial system risk has made a distinction between three different sources of systemic risk (ECB, December 2009): first, the exposure of all financial institutions to common, simultaneous macro-financial shocks; second, the sequential contagion from an idiosyncratic shock affecting a financial institution that spreads to other financial institutions and eventually to the real sector of the economy and; third, financial imbalances that build up over time and may unravel in a disorderly manner. Limiting financial systemic risk requires having indicators that provide a measure, albeit "fuzzy", of financial stability, and a set of instruments to maintain and restore financial stability, when it is perturbed (Borio and Drehmann, 2009). Like the sources of systemic risk, indicators of systemic risk cover the cross-sectional dimension of systemic risk (e.g., Segoviano and Goodhart, 2009) and the time-dimension of systemic risk (e.g., Borio and Lowe, 2002). This paper contributes to several strands of the literature on both dimensions of systemic risk. Its objective is to develop a framework that identifies an early warning indicator of systemic risk that detects as early as possible the build up of endogenous imbalances; that recognizes exogenous shocks timely; that factors in some manner contagion among financial institutions and; that provides robust out-of-sample forecasts of probabilities of default.[1]

One of the biggest challenges for credit risk models is modelling dependence between credit quality changes and between default events. Dependence modelling is necessary to understand the risk of simultaneous defaults, the ensuing distribution of losses and their effects on financial stability. Failing

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1 *The issue of financial institutions' contributions to systemic risk is not addressed in this paper, but in an accompanying study.*

to account for dependence, therefore, underestimates potential losses (Lando, 2004). This is crucial for meaningful stress-testing exercises, for instance, as well as more generally, for the development of measures of systemic risk. To incorporate dependence, there are basically three broad approaches or mixtures of them: (1) to let probabilities of default be affected by common underlying observable variables; (2) to let probabilities of default be affected by underlying latent variables and; (3) to let direct contagion from a default event affect other firms. However, whether by using a mixture of distributions to model dependence or by using copula or network analysis, models require the estimation of marginal default probabilities as a first step. This study uses two of the structural credit risk models studied in Jin and Nadal De Simone (2011a) and Jin *et al* (2011b), i.e., Merton (1974) model and Delianedis and Geske (2003) model, to estimate implied neutral probabilities of default. To model dependence among financial institutions' default probabilities, this paper uses the Generalized Dynamic Factor Model (GDFM) of Forni *et al* (2005), which has been used extensively to exploit the information from a large dataset and also for forecasting (e.g., D'Agostino *et al,* 2011). However, as that Forni *et al* (2003) forecasting method is not easily applicable to a large number of underlying assets, and does not generate the distributions of forecasts, this paper introduces a novel approach that combines the GDFM with a dynamic t-copula to improve the GDFM forecasting capacity.

Copula theory provides an easy way to deal with (otherwise) complex multivariate modeling (Jin and Lehnert, 2011). The advantage of the copula approach is its flexibility, because the dependence structure between marginal components can be modeled in a second stage after the univariate distributions have been calibrated. The conditional dynamic t-copula is relatively easy to construct and simulate from multivariate distributions built on marginal probabilities and dependence structure. In fine, the GARCH-like dynamics in the copula variance and rank correlation offers multi-step-ahead predictions of the estimated GDFM common and idiosyncratic components simultaneously.

This study, therefore, shares the core features suggested for an appropriate measure of systemic risk according to Schwaab *et al* (2010): a broad definition of systemic risk such as the ECB's, an international focus, the incorporation of macroeconomic and financial conditions, unobserved factors, and the calculation of probabilities of defaults.

The main results and contributions of this paper to the time-dimension of systemic risk are, first, to show that the common component of the forward probability of banks' defaulting on their long-term debt, conditional on not defaulting on their short-term debt, contains a significant early warning feature of interest for an operational macroprudential framework. This is in the in the tradition recently surveyed by Frankel and Saravelos, 2010. Second, that incorporating the common and the idiosyncratic components of macro-financial variables improves the analytical features of the framework proposed, in agreement with recent work by Koopman *et al* (2010) and Schwaab *et al* (2010). Finally, and a novel contribution, the paper's framework produces robust out-of-sample forecasting of systemic risk, especially at the individual bank level.

The remainder of the study is organized as follows. Next section presents the modelling framework. Section III discusses the data, and section IV examines the empirical results. Section V concludes.

2. THE MODELING FRAMEWORK

2.1 SELECTED MODELS TO ESTIMATE DEFAULT PROBABILITIES

In order to develop tools to measure and assess financial stability it is necessary to characterize instability. The approach taken in this paper is to apply contingent claim analysis to the measurement of credit risk. 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. In this study, Merton model (Merton 1974) is used to compute benchmark default probabilities (PDs) and distance-to-default (DD)[2], while Delianedis and Geske model (Delianedis and Geske 2003)[3] is used to compute the term structure of short- and long-run PDs for a set of Luxembourg and European banks.

For quoted financial institutions, those models are estimated by a two-step iterative algorithm similar to Moody's KMV iterative procedure[4]. 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. For the Merton model, as in Moody's KMV, debt value equals debt due in one year plus half of long-term debt.

Given that Luxembourg bank subsidiaries are not publicly quoted, an alternative approach to calculate PDs has to be followed. 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 suggesting that banks' financial statements are a crucial piece of information when forming market expectations about the probability of banks' default.[5] Regarding the estimation of volatility, although a dynamic volatility model is preferred in order to track risks more timely, most of those models require more data points than are available for Luxembourg banks. Alternatively, the RiskMetrics (RM) filter/model assumes a very tight parametric specification. The book value asset RM variance can be defined as: $h^B{}_{t+1} = (1-\xi)(\ln(V_t^B / V_{t-1}^B))^2 + \xi h^B{}_t$, where the variance forecast $h^B{}_{t+1}$ 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*, and V^B is assets' book value. To avoid calibration difficulties due to the limited sample, ξ is assumed to be same for all banks and estimated by numerically optimizing the composite likelihoods (Varin *et al*, 2011). The book-value risk neutral PDs of the Merton model and the Delianedis and Geske model can then be estimated.

2.2 THE GENERALIZED DYNAMIC FACTOR MODEL

The GDFM assumes that each time series in a large data set is composed of two sets of unobserved components: first, the common component, which is 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 component, which is specific to a particular series and orthogonal with the past, present, and future values of the common component. The common component of PDs is, therefore, best viewed as the result of the underlying unobserved systemic risk process, which is expected to be relatively persistent. The idiosyncratic component instead reflects local aspects of credit risk that while far from negligible, especially in the short term, are transient. Thus, the GDFM model applied to a large macro-financial dataset extracts the common components of marginal PDs of group banks and Luxembourg banks showing how a set of systemic factors affects both of them simultaneously, albeit with different weights. The GDFM model is estimated using the one-sided estimator proposed by Forni *et al* (2005).

2 *DD is simply the number of standard deviations that the firm is away from default.*

3 *For a bank that has long term debt which matures at date T_2, and short term debt which matures at date T_1, the model allows to calculate the following risk neutral PDs: (1) the joint probability of defaulting at either date T_1 or date T_2; (2) the short-run probability of defaulting on the short-term debt at date T_1; (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.*

4 *Duan et al, (2004) show that the KMV estimates are identical to maximum likelihood estimates (MLE).*

5 *See also Gray and Jones, 2006, for an early application of this idea.*

In this study, the data sets, beside PDs or DDs, includes market indexes and macroeconomic variables for the euro area, Belgium, Canada, Denmark, France, Germany, Greece, Japan, Netherlands, Italy, Spain, Sweden, Switzerland, United Kingdom, United States, and Luxembourg.

2.3 A DYNAMIC FORECASTING FRAMEWORK

Forni *et al* (2005) provide a good framework for multi-step-ahead predictions of the common component of credit risk. Nevertheless, the idiosyncratic (credit risk) component also plays an important role for financial instability, which cannot be neglected (see Schwaab *et al*, 2010). 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. This study introduces a novel approach to combine the GDFM with a dynamic copula. Formally, the dynamic forecasting model becomes:

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

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} is the common component, and X_t^{IC} is the idiosyncratic component. Both common and idiosyncratic components are 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 is $F(\varepsilon_{t+1}^{1}, \varepsilon_{t+1}^{2}, \ldots, \varepsilon_{t+1}^{2n})$ for i=1,2,...,2n, which includes standardized residuals from both common and idiosyncratic components and has a time-varying t-copula.[6] Using the conditional dynamic copula, it is relatively easy to construct and simulate from multivariate distributions built on marginal distributions and dependence structure[7]. Drawing on Jin and Nadal De Simone (2011a), a PD index of systemic risk is built aggregating the individual banks' PD estimates weighted by their respective implied asset values.[8]

3. 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. Market data used for estimating marginal PDs of the major European banking groups include government bond yields, the number of outstanding shares, and book value data. The macrofinancial database used for the GDFM model comprises also industrial production, employment, GPD, consumer prices, stock indices, housing prices, exchange rates, credit data. Sources are Bloomberg, DataStream, BIS, Eurostat. The market data start in May 2000 and finish in September 2011.

6 *See Patton (2006) for the definition of a general conditional copula.*
7 *See Jin and Lehnert (2011) for the dynamic conditional t-copula and forward simulation.*
8 *Weights other than asset values are used and discussed below.*

All the Luxembourg banks are unlisted, so quarterly book value data from the BCL database going back to 2003Q1 are used. 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-year maturity, short-term funding, and repos, while long term debt includes time deposits of over one-year maturity and other long-term funding.

4. EMPIRICAL RESULTS

This study estimates DDs and risk-neutral marginal PDs from two structural credit risk models, Merton (1974) model and Delianedis and Geske (2003) model, and given its objective of accounting for systemic risk, it incorporates dependence among banks' PDs by using the GDFM Model (Forni et al, 2005) with a dataset including macroeconomic and financial variables. It identifies an indicator of systemic risk that recognizes exogenous shocks timely and spots the build up of endogenous imbalances; in addition, it improves on the GDFM forecasting capacity by combining it with a dynamic t-copula.

This section discusses first the Kendall correlation of asset-weighted PDs between European banking groups and their Luxembourg affiliates. It then addresses the early-warning capabilities of the framework both at the level of banks' individual PDs and DDs, and at the level of indexes of banks' PDs and DDs. Finally, it reports results on the out-of-sample forecasting capabilities of the framework for individual PDs and for total asset-weighted PDs.

4.1 ASSET-WEIGHTED PDS [9]

As expected, there is a high degree of correlation (Kendall correlation) among European banking groups and Luxembourg banks PDs (Table 1). However, these correlations vary over time and also in sign depending on whether the short term (ST) or the long term (LT) components of PDs are considered, and on whether the common or the idiosyncratic components of PDs are considered.

During the whole sample period, correlation of PDs between both set of banks are highly significant for the whole time structure of PDs and for the common components. Interestingly, correlations are negative when the idiosyncratic components are involved, especially those of the banking groups' PDs. These results suggest that the parent banks and their affiliates are subject to bank specific factors that may diverge at a given point in time. Finding the causes of this behavior is certainly beyond the scope of this study. Nevertheless, it is possible to conjecture that this may be the result of the different business models of Luxemburg affiliates which overwhelmingly are net suppliers of liquidity to parent banks. This working hypothesis seems reasonable when the same analysis is applied to the pre-crisis period, 2004-07, the crisis period, 2008-09, and the post-crisis period, 2010-2011. It seems that it is the LT idiosyncratic components of PDs that are mostly significant and move in the opposite direction between group banks and Luxembourg affiliates during the pre-crisis period. During the crisis period, as expected, correlations increase—banks' interdependence increases (also seen in the increase of the number of significant correlations).

Finally, in the post-crisis period, there is again an increase in the importance of the idiosyncratic components which move in disparate directions at the parent and at the affiliate banks. This is more the

9 *The Kendall correlation of asset-weighted DDs between European banking groups and their Luxembourg affiliates provides the similar results as PDs.*

case with respect to the ST PDs than with respect to the LT PDs, however, which is an important difference with the pre-crisis period and possibly a reminder of the persistence of short-term solvency issues across some banking groups in Europe.

4.2 EARLY-WARNING FEATURES OF SINGLE-BANK PDS AND WEIGHTED INDEXES OF PDS

As stated above, a macroprudential policymaker is interested not only in the timeliness of measures of credit risk, but ideally would like to have some indication of the buildup of vulnerabilities in the financial system as early as possible. To assess the strength of the framework proposed in this study to that end, two approaches are followed. First, a set of Granger causality tests is performed between the common component of the estimated PDs/the macrofinancial factors and estimated PDs.[10] Second, the degree of commovement and leads and lags between the common components and estimated PDs is studied using spectral methods.

4.2.1 Granger causality tests

Table 2 summarizes the results of the Granger causality tests applied to each bank's estimated PDs. Table 2 reports ratios, which are the percentage of cases when X Granger causes Y, and Y does not Granger cause X at p-values of 1%, 5% and 10%. The ratios under common component mean that the common component Granger causes DPs and DPs do not Granger cause the common component; similarly, for DPs.[11] At the p-value of 1%, for example, the common component of the estimated DPs Granger causes banking groups Geske All PDs and DDs in 31% and 25% of the cases, respectively. It also Granger causes Luxembourg banks' PDs in 26% and DDs in 36% of the cases. The opposite is much less frequent. Importantly, the common component has a clearer anticipatory feature with respect to DDs than PDs for both banking groups and for Luxembourg banks.

The framework's best performance is with respect to the LT PDs of Luxembourg banks, i.e. the ratio is 50%. This feature is likely due to the use of book-value data for estimating Luxembourg banks' PDs, which is less timely than the information contained in share prices used for estimating banking groups' PDs. This leading information in the common component of PDs is a particularly useful feature of the proposed methodology for Luxembourg banks given that they are not quoted.

The same analysis is done for indexes of PDs weighted using proxies of some of the indicators of banks' systemic importance suggested in the literature, respectively (e.g. BCBS, 2011, and Drehmann and Tarashev, 2011). Those proxies are total assets—a proxy for *size*—and interbank lending and interbank borrowing—proxies for *interconnectedness*. Individual bank data on interbank lending and borrowing at quarterly frequency are available for Luxembourg banks only.[12] In general, the common component does not Granger cause the PDs or DDs indexes (the results are not shown to conserve space). The use of weighting schemes without dependent structure seems to hide information embedded in the common components and loadings making it more difficult to draw conclusive evidence using Granger causality tests. These weights do not seem useful to construct indices of PDs (or DDs) that could provide a meaningful early warning signal of the buildup of vulnerabilities.

10 *Jin* et al *(2011b) studied lead-lag relationships across models' PDs predictions, but had no reference to macrofinancial conditions.*
11 *Only standardized measures are displayed; non-standardized measures provide broadly the same results.*
12 *Drehmann and Tarshev (2011) propose three measures for determining banks' systemic importance. Two measures are top down: the participation approach (i.e., expected losses incurred by a given bank' non-bank creditors) and the contribution approach (i.e. expected losses from a bank's exposure to exogenous shocks, from its contribution to losses via propagation and from its idiosyncratic exposure to shocks). Another measure is bottom up, i.e. the expected losses of the whole banking system conditional on a given bank being in default. The authors show that size is a good proxy of all measures, that interbank lending proxies well the participation and the contribution approaches whereas interbank borrowing proxies well the contribution and the bottom-up approaches.*

However, the nonlinearities and feedback between PDs or DDs and their common components, make it advisable to look at matters in more detail. The leading features of the common component for Luxembourg banks' PDs can be visualized in the set of figures 1a to 1d which show asset-weighted PDs. What is of interest here is the leading behavior of the common component with respect to Luxembourg banks' estimated LT PDs. Starting in 2005 (Figure 1b) for banking groups, and in early 2006 (for Luxembourg banks), there is a clear, persistent increase in LT PDs. This suggests a buildup of credit risk long-term vulnerabilities—a fact also documented in Koopman *et al* (2010).

4.2.2 Frequency-domain analysis

The test in the previous section clearly suffers from the averaging across periods typical of time-domain time series analysis, which in the presence of nonlinearities and feedback effects may mask the lead/lag relationships between common components and estimated PDs. To take that into account, this section briefly looks at the comovement between PDs and its common components using spectral methods. In particular, the coherence (squared) and the phase angle are estimated.[13] Figures 2a to 2d display the estimated coherences and phase angles between the common components and Geske ST and LT PDs for banking groups and Luxembourg banks. The complicated interrelations and feedback effects between the common components and measures of PDs evince clearly.

In general, the common components lag estimated ST PDs for banking groups only at periodicities between 1 and 2 years. Instead, the common components lead ST PDs in cycles between 2.5 years and 8 years, that is to say, roughly during the *minor* (2 to 4 years) and the *major* (4 to 8 years) business cycles' durations (NBER terminology). The common components lead LT PD during cycles of between 1.5 and 2 years and cycles of between 3 to 5 years, i.e., during most of the minor cycle and the first part of the major cycle.

In the case of Luxembourg banks, the common components lag estimated ST and LT PDs around periodicities of 1 year, and between 1.5 and 2.5 years for ST PDs and about 2 years for LT PDs. Otherwise, the common components lead ST and LT PDs at periodicities of about 3 quarters and in the longer run, at periodicities ranging between 3 and (over) 8 years for the ST PDs, and between 4 and (over) 8 years for the LT PDs.

Summarizing, the results support the leading features of information embedded in the common components at relatively high frequency (i.e., roughly 3 quarters) and at relatively lower frequency (i.e., between around 3 years and 8 years).

4.3 OUT-OF-SAMPLE FORECASTING[14]

The short number of data points available constrains a full-fledged, standard evaluation of the out-of-sample forecasting capabilities of the framework. Table 3 reports the coverage ratios, root-mean squared errors, as well as the bias, the variance and the covariance of Theil's inequality coefficient from 2010 to 2011 across all estimated Geske's PDs for banking groups and Luxembourg banks. The coverage ratio is the share of banks whose empirical simulated cdf at each of the estimated PDs is within the range of the respective quartiles. Under the null hypothesis that this forecasting framework correctly estimates the dynamics of PDs, the coverage ratio should approximate the range of quartiles if

13 *Coherence (squared) is the proportion of the variance of a series which can be explained by the other series, period (or frequency) by period (by frequency). The phase lead is the fraction of a cycle by which one series leads (lags) the other at each period or frequency. The phase lead is significant only at the periods (or frequencies) at which the coherence is significant.*

14 *The evaluation of the out-of-sample forecasting of DDs provides the similar results as PDs.*

the number of underlying banks were large enough. For example, during the first month out-of-sample forecasts, 77% of bank PDs forecasted using only the common component are within quartiles 5%-95% of the forecasted cdf of PDs. It falls to 70% at month six. When not only the common but also the idiosyncratic components are forecasted, 86% percent of the forecasted PDs fall in the quartiles 5%-95% and increases to about 88% at month six. Decomposing Theil's inequality coefficient, it seems that the improvement in forecasting ability by adding the idiosyncratic component results from an improvement in the model's capacity to replicate the degree of variance in PDs (column "Variance Proportion") and from reducing unsystematic error (column "covariance Proportion").

5. CONCLUSIONS AND MACROPRUDENTIAL POLICY IMPLICATIONS

This study develops a framework that recognizes exogenous shocks timely and identifies an early warning indicator of systemic risk that spots the build up of endogenous imbalances in advance. In addition, it provides robust out-of-sample forecasts of PDs.

It uses a two-step approach to proxy banks' default dependency. First, marginal PDs are estimated using Merton and Delianedis and Geske compound option models, the latter of which solves for the time structure of PDs. Second, the generalized dynamic factor model is applied to a large macrofinancial dataset to extract the common component of banks' marginal PDs at the banking group and at the subsidiary levels. This shows how a set of common systemic factors affect both of them simultaneously, albeit with different weights. The same framework also identifies the idiosyncratic component of banks' PDs. This two-step approach 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 can be interpreted as an increase in the vulnerability of the financial system.

By separating the role of system developments from individual banks' idiosyncratic features, this study 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 widespread imbalances over time, another interpretation of systemic risk. This study also contributes to the macroprudential literature with a method for monitoring systemic risk.

Finally, this research contributes to the macroprudential literature by suggesting a framework to forecast changes in the common and the idiosyncratic components of a large database via using a dynamic conditional t-copula. This remediates the well known feature that simply aggregating banks' marginal PDs provides a downward-biased measure of banking systemic risk. 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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Table 1

Total Asset Value Weighted PDs and PDs' Component Rank Correlation between Banking Groups and Luxembourg Banks

	Lux Geske Total	Lux Geske ST	Lux Geske LT	Lux Accumulated Common Component Total	Lux Accumulated Common Component ST	Lux Accumulated Common Component LT	Lux Accumulated Idiosyncratic Component Total	Lux Accumulated Idiosyncratic Component ST	Lux Accumulated Idiosyncratic Component LT
2004-2011									
Group Geske Total	0,51	0,50	0,45	0,47	0,45	0,66	-0,17	-0,19	-0,12
Group Geske ST	0,52	0,50	0,47	0,46	0,43	0,66	-0,15	-0,18	-0,10
Group Geske LT	0,35	0,36	0,25	0,49	0,51	0,51	-0,28	-0,30	-0,24
Group Accumulated Common Component Total	0,62	0,60	0,57	0,34	0,31	0,54	-0,03	-0,06	0,03
Group Accumulated Common Component ST	0,54	0,53	0,49	0,44	0,41	0,62	-0,14	-0,16	-0,05
Group Accumulated Common Component LT	0,50	0,50	0,42	0,17	0,19	0,35	0,12	0,09	0,12
Group Accumulated Idiosyncratic Component Total	-0,57	-0,57	-0,47	-0,28	-0,30	-0,41	-0,02	0,01	-0,05
Group Accumulated Idiosyncratic Component ST	-0,46	-0,46	-0,36	-0,42	-0,44	-0,47	0,13	0,16	0,06
Group Accumulated Idiosyncratic Component LT	-0,51	-0,49	-0,43	-0,15	-0,15	-0,34	-0,19	-0,18	-0,15

	Lux Geske Total	Lux Geske ST	Lux Geske LT	Lux Accumulated Common Component Total	Lux Accumulated Common Component ST	Lux Accumulated Common Component LT	Lux Accumulated Idiosyncratic Component Total	Lux Accumulated Idiosyncratic Component ST	Lux Accumulated Idiosyncratic Component LT
2004-2007									
Group Geske Total	-0,04	-0,04	0,10	0,09	0,01	**0,60**	-0,14	-0,08	**-0,38**
Group Geske ST	0,00	-0,01	0,14	0,06	-0,02	**0,57**	-0,09	-0,04	**-0,32**
Group Geske LT	**-0,46**	**-0,41**	**-0,37**	**0,38**	**0,32**	**0,30**	**-0,59**	**-0,55**	**-0,60**
Group Accumulated Common Component Total	**0,38**	**0,35**	**0,50**	**-0,38**	**-0,47**	0,09	**0,28**	**0,33**	**0,18**
Group Accumulated Common Component ST	0,09	0,07	**0,19**	-0,01	-0,10	**0,40**	-0,07	-0,04	-0,13
Group Accumulated Common Component LT	**0,36**	**0,34**	**0,43**	**-0,46**	**-0,47**	-0,12	**0,42**	**0,44**	**0,38**
Group Accumulated Idiosyncratic Component Total	**-0,25**	**-0,27**	**-0,25**	**0,43**	**0,41**	**0,26**	**-0,20**	**-0,21**	**-0,36**
Group Accumulated Idiosyncratic Component ST	**0,17**	0,14	**0,19**	-0,09	-0,12	0,05	**0,26**	**0,28**	0,07
Group Accumulated Idiosyncratic Component LT	**-0,37**	**-0,35**	**-0,38**	**0,53**	**0,53**	**0,20**	**-0,52**	**-0,54**	**-0,47**
2008-2009									
Group Geske Total	**0,42**	**0,38**	0,17	**0,51**	**0,38**	0,07	-0,20	**-0,30**	**0,31**
Group Geske ST	**0,44**	**0,36**	0,20	**0,53**	**0,36**	0,09	-0,21	**-0,28**	**0,34**
Group Geske LT	**0,37**	**0,48**	-0,13	**0,32**	**0,53**	-0,23	-0,10	-0,20	0,16
Group Accumulated Common Component Total	**0,45**	**0,40**	0,16	**0,52**	**0,40**	0,06	-0,17	**-0,28**	**0,30**
Group Accumulated Common Component ST	**0,46**	**0,39**	0,20	**0,55**	**0,38**	0,10	-0,19	**-0,26**	**0,35**
Group Accumulated Common Component LT	**0,41**	**0,53**	-0,14	**0,36**	**0,58**	-0,24	-0,07	-0,15	0,15
Group Accumulated Idiosyncratic Component Total	**-0,69**	**-0,78**	0,08	**-0,45**	**-0,59**	0,19	**-0,32**	-0,20	-0,03
Group Accumulated Idiosyncratic Component ST	**-0,38**	**-0,49**	0,18	-0,20	**-0,39**	**0,27**	**-0,25**	-0,17	-0,01
Group Accumulated Idiosyncratic Component LT	**-0,55**	**-0,49**	-0,17	**-0,54**	**-0,36**	-0,03	-0,20	-0,17	-0,22
2010-2011									
Group Geske Total	**0,61**	**0,61**	**0,54**	**0,42**	**0,37**	**0,49**	**0,35**	**0,35**	0,07
Group Geske ST	**0,60**	**0,60**	**0,53**	**0,42**	**0,37**	**0,45**	**0,35**	**0,35**	0,10
Group Geske LT	**0,42**	**0,42**	**0,33**	0,05	0,00	**0,42**	**0,48**	**0,50**	-0,15
Group Accumulated Common Component Total	**0,70**	**0,70**	**0,61**	**0,27**	0,22	**0,54**	**0,54**	**0,54**	0,05
Group Accumulated Common Component ST	**0,67**	**0,67**	**0,62**	**0,33**	**0,27**	**0,59**	**0,46**	**0,46**	0,02
Group Accumulated Common Component LT	**0,41**	**0,41**	**0,32**	-0,18	-0,23	**0,48**	**0,65**	**0,70**	-0,17
Group Accumulated Idiosyncratic Component Total	**-0,43**	**-0,43**	**-0,34**	0,12	0,15	**-0,50**	**-0,61**	**-0,67**	0,19
Group Accumulated Idiosyncratic Component ST	**-0,48**	**-0,48**	**-0,41**	0,05	0,08	**-0,51**	**-0,57**	**-0,63**	0,11
Group Accumulated Idiosyncratic Component LT	**-0,44**	**-0,44**	**-0,29**	0,19	0,24	**-0,45**	**-0,66**	**-0,71**	0,14

The table reports the Kendall correlation matrix of the monthly PDs and their components between banking groups and Luxembourg banks. For Luxembourg banks, monthly PDs are assumed to be same within each quarter. A bold value with underscore indicates significance at the 95% level, whereas a bold value indicates significance at the 90% level.

Table 2

Granger Causality Test between Common Components and DPs for Each Banks

	AT P-VALUE OF 1%		AT P-VALUE OF 5%		AT P-VALUE OF 10%	
	COMMON COMPONENT	PDS	COMMON COMPONENT	PDS	COMMON COMPONENT	PDS
Group Geske All	0,31	0,13	0,41	0,13	0,44	0,13
Group Geske ST	0,28	0,19	0,28	0,16	0,34	0,16
Group Geske LT	0,28	0,21	0,28	0,21	0,34	0,21
Group DD	0,25	0,00	0,41	0,00	0,56	0,00
Lux Geske All	0,26	0,08	0,28	0,05	0,31	0,05
Lux Geske ST	0,21	0,08	0,28	0,05	0,28	0,05
Lux Geske LT	0,50	0,03	0,42	0,08	0,44	0,06
Lux DD	0,36	0,00	0,41	0,00	0,44	0,00

This table reports the ratios according to Granger Causality test at the p-values of 1%, 5% and 10% respectively. The measures are ranked by calculating the ratio of the times X Granger causes another measure Y and Y does not Granger causes X to the number of the available banks for banking groups and Luxembourg banks. The ratios under Common Component mean that the Common Component Granger causes PDs and PDs does not Granger causes the Common Component; similarly, for PDs. The standardized measure is constructed by (x-mean(x))/std(x).

Table 3

Geske DP Forecast Evaluation for Banking Groups and Luxembourg Banks

	Coverage Ratio									RMS Error	Bias Propor-tion	Variance Propor-tion	Coviance Propor-tion
	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%				
Common Component													
1th Month	0,770	0,659	0,566	0,482	0,401	0,324	0,246	0,165	0,085	0,027	0,004	0,015	0,981
2nd Month	0,724	0,607	0,501	0,412	0,342	0,271	0,200	0,133	0,067	0,038	0,004	0,019	0,977
3rd Month	0,709	0,566	0,462	0,376	0,316	0,246	0,187	0,119	0,060	0,044	0,010	0,025	0,965
4th Month	0,705	0,559	0,457	0,383	0,314	0,242	0,181	0,124	0,063	0,051	0,016	0,028	0,956
5th Month	0,707	0,555	0,461	0,379	0,310	0,238	0,180	0,122	0,059	0,057	0,015	0,027	0,958
6th Month	0,704	0,563	0,456	0,381	0,316	0,251	0,186	0,125	0,065	0,063	0,014	0,026	0,960
Common & Idiosyncratic Component													
1th Month	0,857	0,773	0,689	0,596	0,503	0,404	0,310	0,220	0,115	0,031	0,004	0,014	0,981
2nd Month	0,854	0,747	0,649	0,568	0,475	0,381	0,300	0,207	0,108	0,042	0,005	0,015	0,980
3rd Month	0,864	0,748	0,649	0,554	0,467	0,369	0,274	0,184	0,093	0,047	0,010	0,016	0,974
4th Month	0,870	0,751	0,649	0,555	0,469	0,377	0,282	0,188	0,105	0,055	0,015	0,018	0,967
5th Month	0,874	0,753	0,647	0,556	0,475	0,382	0,288	0,190	0,095	0,061	0,012	0,014	0,973
6th Month	0,875	0,759	0,648	0,549	0,463	0,374	0,284	0,191	0,095	0,066	0,011	0,012	0,977

The table reports the coverage ratios, root mean square erros, and the proportions of bias, variance, and covariance respectively from 2010 to 2011 across all Gesk's DPs for both banking groups and luxembourg banks. The coverage ratio is the proportion of banks whose empirical cdf (simulated) at each of the observed DPs are within the range of quantiles.

Figure 1 (a)
Asset Weighted DP Index, Accumulated Common Component and Forecasts for Banking Groups - (Geske ST)

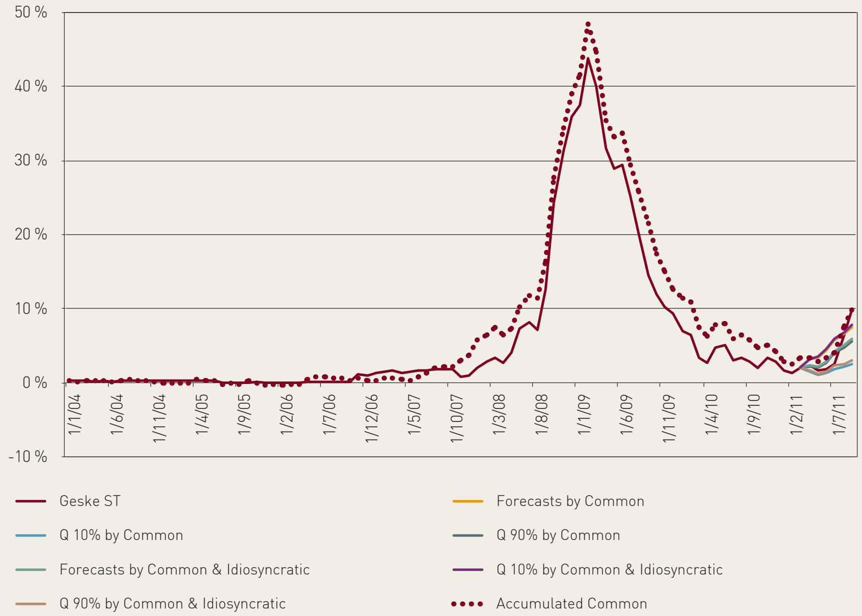

Figure 1 (b)
Asset Weighted DP Index, Accumulated Common Component and Forecasts for Banking Groups - (Geske LT)

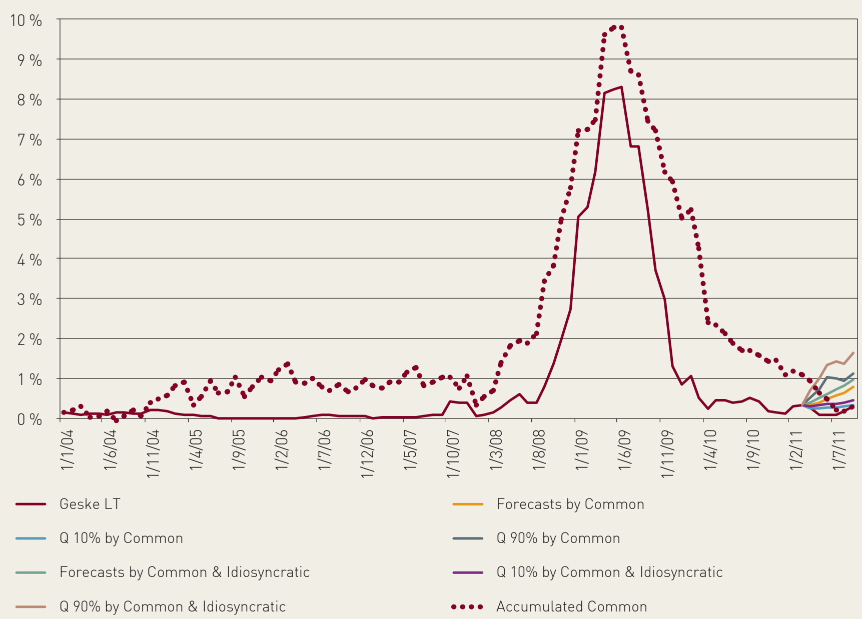

Figure 1 (c)

Asset Weighted DP Index, Accumulated Common Component and Forecasts for Luxembourg Banks - (Geske ST)

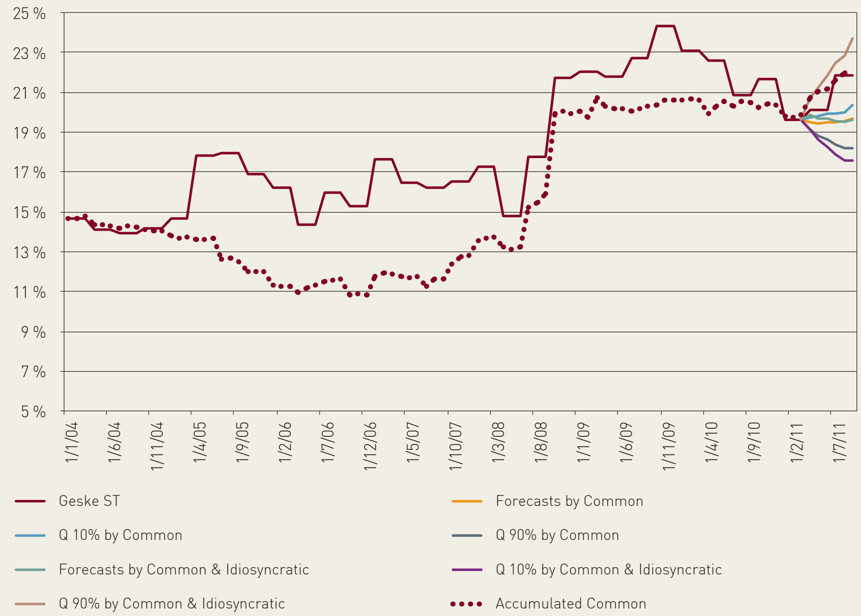

Figure 1 (d)

Asset Weighted DP Index, Accumulated Common Factor and Forecasts for Luxembourg Banks - (Geske LT)

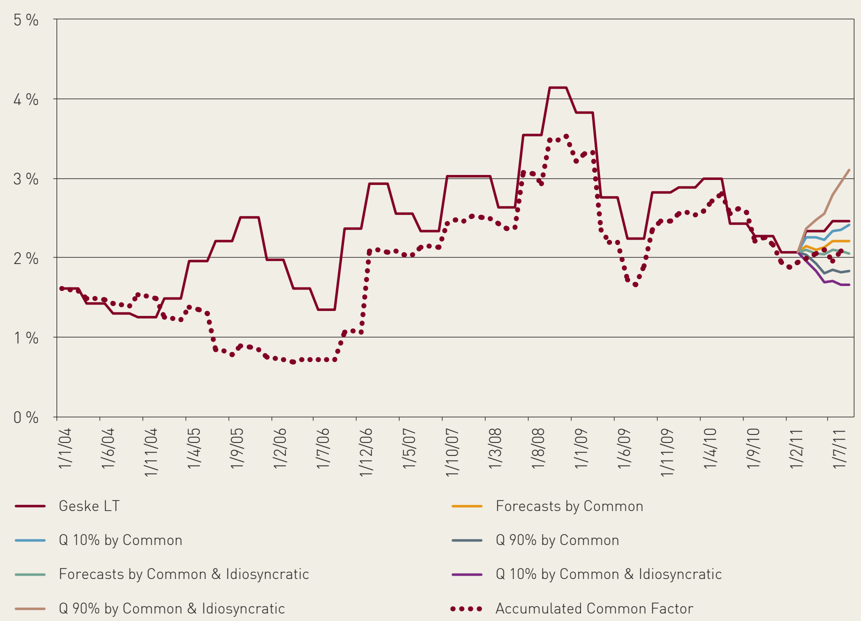

Figure 2 (a)
Coherence and Phase Angle between Common Components and Banking Groups' PDs
Geske Short Term

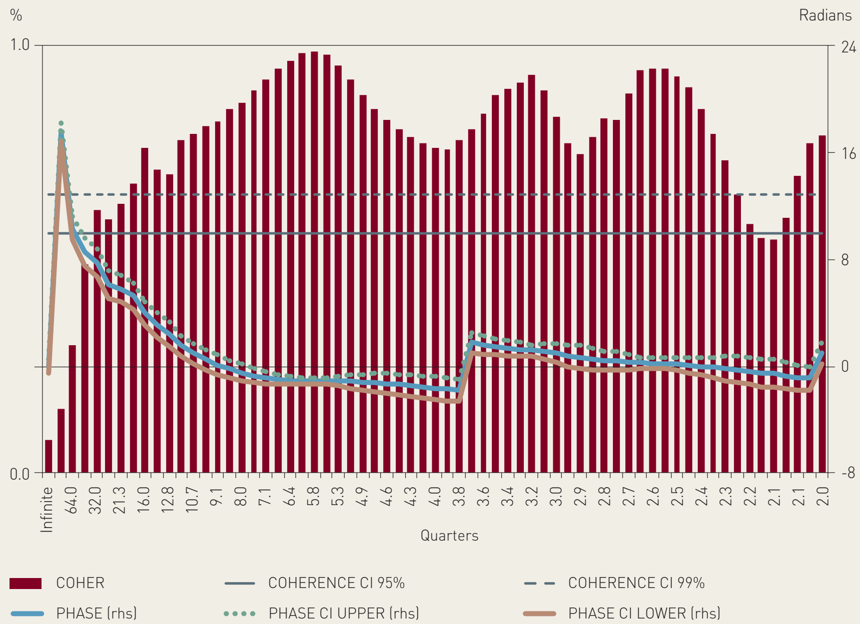

Figure 2 (b)
Coherence and Phase Angle between Common Components and Banking Groups' PDs
Geske Long Term

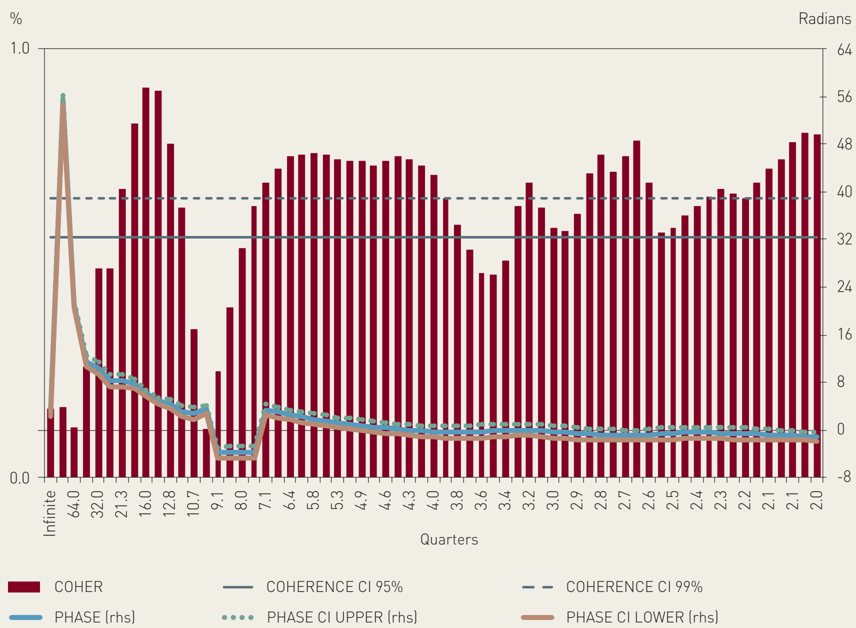

Figure 2 (c)

Coherence and Phase Angle between Common Components and Luxembourg Banks' PDs Geske Short Term

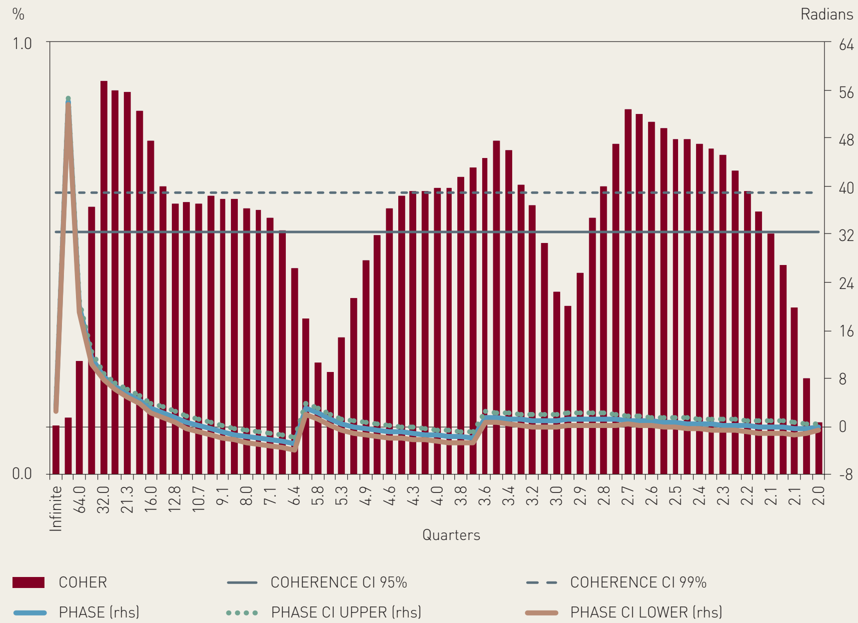

Figure 2 (d)

Coherence and Phase Angle between Common Components and Luxembourg Banks' PDs Geske Long Term