Abstract

This study uses 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 and the generalized dynamic factor model (GDFM) supplemented by a dynamic t-copula. The financial sector comprises the banking and the investment fund industries. The framework models the financial sector components’ default dependence explicitly and captures the time-varying non-linearities and feedback effects typical of financial markets. It measures financial sector’s systemic credit risk in the three forms categorized by the European Central Bank: (1) credit risk common to the financial sector; (2) credit risk in the financial sector conditional on distress on a specific financial institution or combination of financial institutions and; (3) the buildup of banking system vulnerabilities over time which may unravel disorderly. In addition, the estimates of the common components of the financial sector’s default measures and the identification of their drivers is useful for helping to make macroprudential policy operational.

JEL Classification: C1, E5, F3, G1

Keywords: financial stability; macroprudential policy; banking sector; investment funds; procyclicality; credit risk; early warning indicators; default probability; non-linearities; generalized dynamic factor model; dynamic copulas; GARCH.

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I. Introduction and Motivation

The objective of this paper is to develop measures for tracking the systemic vulnerabilities of the financial sector over time with the intention of contributing to operationalize macroprudential policy. While there is no widely accepted definition of macroprudential policy, its objective or its instruments (Galati and Moessner, 2011), the working hypothesis in this paper is, in agreement with the European Systemic Risk Board (2013a), that the objective of macroprudential policy is to safeguard the stability of the financial system. Also consistent with the European Central Bank (ECB), macroprudential policy will be viewed as geared toward limiting systemic risk in order to minimize the costs of financial instability on the economy (ECB, 2010a and 2010b). The sources of financial instability are circumscribed to those emanating from the financial sector, which comprises banks and investment funds. Insurance companies and pension funds are not considered. Banks included in this study represent about 70% of the assets of the Grand Duchy of Luxembourg banking industry. Regarding investment funds, the Grand Duchy is the second largest domicile of UCITS in the world after the U.S. and the third domicile of non-UCITS after Germany and France. At end-2012, Luxembourg-domiciled banks managed 737.7bn euro of assets and investment funds managed almost 2.4 trillion euro of assets.

The banking sector and investment funds in Luxembourg have strong linkages. Banks rely on investment funds as a source of short-term funding. Money Market Funds (MMFs) are used by non-financial firms and households as a cash-management tool and some have deposit-like features. Investment funds (other than MMFs) engage in

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1 The world investment fund industry managed about 22 trillion euro of assets at end-2012. This includes only investment funds organized as UCITS, i.e., publicly offered open-end investment funds regulated by the UCITS IV directive of 2009 in Europe and the Investment Company Act of 1940 in the U.S.. European investment funds organized as non-UCITS managed over 2.6 trillion euro at end-2012. Therefore, in the EU, total assets managed by all categories of investment funds at end-2012 represented over ¾ of its GDP. While non-UCITS are nationally regulated investment funds for which a classification in terms of market exposure is not possible, the European Commission’s Directive on Alternative Investment Fund Managers (AIFMs) that entered into force in July 2011 creates a comprehensive regulatory and supervisory framework for non-UCITS with requirements regarding safekeeping of assets, leverage, liquidity management, management and pricing. In the U.S., Hedge Funds only managed nearly 1.2 trillion euro at end-2012. The Dodd-Frank Wall Street Reform and Consumer Protection Act that entered into effect in July 2011, requires private pools of capital exceeding $100 million to register with the Securities and Exchange Commission as investment advisers ($150 million if they work with private funds only). For pools of capital below the threshold, registration with the state of domicile of the advisers is compulsory. Since October 2011, advisers must also report information necessary for monitoring systemic financial risk.

2 See Buisson et al (2013) for a detailed analysis of the links between banks and investment funds in Luxembourg.

3 Luxembourg MMFs and other types of investment funds represented about 2% and 9% of the total funding sources of Luxembourg banks in 2012. In 2012, using a 5% percent threshold, nine banks played an important role in terms of credits received from MMFs. Conversely, three banks played an important role in the funding of MMFs in 2012 (Buisson et al, 2013).

4 See ESRB (2012) for a description of the systemic risks posed by MMFs.
maturity transformation and by providing credit funded by short-term funding and leverage, establish links not only with large banks and institutional investors, but also with households and the sovereign. These interlinkages have a strong international dimension. For example, in 2012, 90% of claims and debt securities held by Luxembourg investment funds related to foreign counterparts, of which nearly 30% were foreign banks. In addition, more than 50% of securities held by MMFs were expressed in US dollars. Therefore, systemic risk analysis requires an international dimension.

To make macroprudential policy operational, it is first necessary to agree on the definition and measurement of systemic risk. 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 events during which the financial institutions affected in the second round of effects or latter fail due to the initial shock, although they were solvent ex ante. Perotti and Suarez (2009) view systemic risk instead 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 boom periods, which become the seed of subsequent downturns (Borio et al., 2001). Thus, second-round effects and propagation are encompassed in this definition of systemic risk. From a quantitative viewpoint, systemic risk refers to financial system events that result in high losses with a small probability of occurrence and potentially harm the real economy (Drehmann and Tarashev, 2011).

As each of the above definitions is by itself incomplete, this study adopts a combined approach that brings together both the endogenous view of systemic risk of Borio et al. (2001) and the tail-risk view of the quantitative perspective of Drehmann and Tarashev (2011). Thus, systemic risk will be able to take the three forms categorized by the ECB (2009): first, as a common shock that affects the financial sector as a whole 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 affects the real economy and; third, as a slow build up of vulnerabilities in the financial sector that may unravel in a disorderly manner and affect the real economy.

Systemic risk can be viewed from a cross-section dimension as well as from a time-dimension. The former dimension is concerned with assessing default dependence across financial institutions 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,

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5 A seminal work in cataloguing instruments and objectives of macroprudential policy as well as risk identification and assessment is in the handbook and the flagship report of the ESRB (2013b, 2013c).
Gorea and Radev, 2011, Jin and Nadal De Simone, 2012). This paper studies both dimensions of systemic risk in a perspective of risk which is gathering acceptance (Bisias et al, 2012).

Regarding the measurement of systemic credit risk, this study proposes a set of indicators that when flashing red over time suggest the policymaker to look further into the drivers of systemic risk so as to decide whether to take action or not. Measurement of such a complex and time-varying phenomenon ideally requires a framework that, despite markets’ widely recognized misperceptions of risk over time, 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 / distress (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. These requirements for a systemic risk tracking and forecasting framework that can help operationalizing macroprudential policy are taxing and not easily embedded in a single model. As a result, this paper adopts an integrated framework for dealing with complex information inspired from statistics, operations research and engineering.

This study uses Merton (1974) structural credit risk model to estimate implied neutral PDs. However, as stated above, to understand the risk of simultaneous systematic defaults, the ensuing distribution of losses, and its 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). Importantly, this structure is

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6 In this study, the terms probability of default and probability of distress will be used indistinguishably. The estimated probabilities of default are risk-neutral.

7 Importantly, for macroprudential policy, 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. In contrast to Jin and Nadal De Simone (2013), however, this study cannot use Delianedis and Geske’s (2003) model given that the length of the sample available for investment funds is binding.

8 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 the dependence of PDs on them; (2) PDs depend on unobserved background variables, and credit events result in an update of the latent variables which in turn updates PDs and; (3) direct contagion from a credit event.
allowed to change as PDs change over time. Nevertheless, 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). For instance, assuming a joint Normal density function with zero correlation as prior could lead to a significant understatement of PD dependence, which becomes particularly important in period of distress when “phase-locking” behaviour most likely occurs. As a result, for the prior correlation input to the CIMDO this paper uses a simple rolling window approach; to guarantee that the correlation matrix of asset returns is symmetric and positive semi-definite, a Newton-type method is used to obtain the nearest correlation matrix to the given symmetric matrix (Qi and Sun, 2005).

A final difficulty intimately related to risk misperception over time 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, correlations are low and so are ensuing measures of interconnectedness, 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 growth, deflating assets prices and exacerbating the downturn. These regularities have led policymakers to propose “through-the-cycle” haircuts and margin requirements. Recently, Adrian et al (2013) have forcefully argued that it is leverage and not net worth that matters most for asset pricing procyclicality. Fundamentally, if risk misperceptions distort equity prices, the implied probabilities of default estimated from structural credit risk models are likely to be themselves also distorted. Similarly, as interconnectedness depends on market volatility, which is countercyclical, unconditional measures of interconnectedness or methodologies to capture latent drivers of risk should somehow be used if systemic risk is not to be underestimated during upswings. In order to deal with the asset pricing procyclicality 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 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). However, Forni et al (2003) forecasting method is not easily applicable to a large number of underlying assets simultaneously, and does not

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9 This behaviour cannot be detected from a standard correlation model (Chan et al, 2007).
10 This is an important reason to prefer Delianedis and Geske (2003) credit risk model to Merton (1974) credit risk model as the former allows the estimation of the time structure of PDs providing a sense of the impact of the time structure of leverage onto the time structure of credit risk. However, as stated above, the sample size makes it impossible.
generate the distribution of forecasts. To address those shortcomings, this paper introduces an approach similar to Jin and Nadal De Simone’s (2012 and 2013) that combines the GDFM with a dynamic \( t \)-copula to improve the GDFM forecasting capacity. This approach uncovers the tail risk or the PDs by using not only information from individual financial institutions, but also from a large data set of macro-financial variables revealing thereby not only credit risk emanating from financial institutions’ interconnectedness, but also from the macro environment. It allows tracking the macro-financial factors driving the PDs and the measures of systemic risk capturing the increase of exposures to common factors during booms, revealed during busts.

The main contributions of this study are as follows. First, and to the best of the authors’ knowledge, this study is the first comprehensive application of contingent claims analysis (as proposed by Gray and Malone, 2008) to the banking and the investment fund sectors together covering all the categories of investment funds reported to the ECB. The empirical literature explicitly linking banks and investment funds is not that large, and it has normally used banks’ public data and publicly available investment funds’ returns covering, albeit with some exceptions, mostly U.S.-domiciled investment funds. For example, Chan et al (2007) was the first study to analyze the impact of Hedge Funds on indirect systemic risk defined as a series of correlated defaults among financial institutions over a short period of time, and concluded that systemic risk was on the rising since 2004, as found in Jin and Nadal De Simone (2014) for the banking sector. Also related to this paper, Boyson et al (2010), defining contagion as correlation over and above that one expected from economic fundamentals, found strong evidence that large adverse shocks to funding and asset liquidity strongly increased the probability of contagion from 1990 to 2008 (specifically, large adverse shocks to credit spreads, the TED spread, prime broker and bank stock prices, stock market liquidity). Acharya et al (2010) measured banks’ and a set of non-bank financial institutions’ (mutual funds were excluded) contribution to systemic risk using the expected shortfall measure, which they found to be positively correlated with the institution’s leverage and marginal expected loss in the tail of the system. Billio et al (2011) proposed measures of systemic risk to capture the interconnectedness between Hedge Funds, banks, brokers and insurance companies using principal component analysis and Granger causality. They constructed in-sample and out-of-sample measures of systemic risk and found that Hedge Funds can provide early indications of systemic risk arising from a complex network of relationships among them, banks, brokers and insurance companies. Dixon et al (2012) analyzed the contribution of Hedge Funds in the U.S. to the 2007-2008 crisis and found that while Hedge Funds could have contributed to a large disruption of one or more of the core functions of the financial system due to the failure of one or more financial institutions, Hedge Funds’ contribution to the crisis was not a primary cause of it. Recently, Buisson
et al (2013) studied the linkages between investment funds and banks in Luxembourg using network analysis and concluded that despite the significance of the financial sector for the country’s economy, few domestic banks have strong linkages with MMFs.

Second, while following the CIMDO approach illustrated by Segoviano and Goodhart (2009)\textsuperscript{11}, this study departs from theirs in several significant ways. Given the lack of CDS and bonds data for many banks as well as the fact that banks’ shares and investment funds’ parts are not traded, 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, 2013a and 2013b).

Third, this paper explicitly identifies the linkages between measures of credit risk in the financial system and macro-financial variables. As a result, the proposed framework indentifies the drivers of systemic risk, i.e., economic activity, credit growth and interbank activity, in agreement with the recent survey in Frankel and Saravelos (2010). It shows how the forces behind the evolution of marginal PDs are not necessarily the same behind the evolution of systemic risk suggesting the importance of a proper measurement of risk that takes into account the non-linearities of the financial system, time-varying interconnectedness among financial institutions and feedback effects between financial institutions and markets.

Fourth, by identifying the drivers of vulnerabilities in the financial system, the proposed framework explicitly pinpoint to the economic processes that policymakers should counter if financial instability is to be avoided, presumably after calibrating macroprudential instruments to the measures proposed.

Finally, and also importantly for policymaking, the framework also can produce robust out-of-sample forecasts of the financial sector’s credit risk measures in agreement with recent work applied to banks by Koopman et al (2010), Schwaab et al (2010) and Jin and Nadal De Simone (2014). However, due to the restrictions on the sample length imposed by the application to investment funds, as balance sheet data are only available staring in 2008Q1, this cannot be fully explored in this paper.

The main findings are the following. First, while interdependencies between banks and all investment fund types have been very dynamic over the sample period, there is a clear asymmetry in interconnections in the sense that banks’ contagion likelihood from investment funds’ distress tends to be higher than vice versa. The implication is that

\textsuperscript{11} Segoviano and Goodhart’s (2009) proposed systemic risk measures circumscribed to banks. See Jin and Nadal De Simone (2013) for an application to Luxembourg investment funds.
investment funds matter more for *systemic risk in the form of contagion* to banks than the opposite. This is relatively more in the case for European banking groups than for Luxembourg banks.

Second, in Luxembourg, interdependence in the financial sector broadly decreased in the first three years of the sample period, but rose again largely after the ECB conducted its first LTRO in December 2012, at least as measured by the Financial Stability Index (FSI). This interpretation is supported by the concomitant increase in the FSI common component. Increased interconnectedness in Luxembourg during the sample period is also present when controlling for banks’ size. Instead, the FSI of the four Domestic Systemically Important Banks (D-SIBs) gently declines over the sample period. Similarly, interconnectedness among the four worst performers European Global Systemically Important Banks (G-SIBs), notably regarding vulnerabilities associated with Equity and Bond Funds, declined during the second half of the sample. Importantly, when the worst corner of banking groups, Luxembourg banks and investment funds is considered, the interconnectedness in the financial system falls, albeit driven by idiosyncratic factors given that the FSI common component clearly increases, as stated above, likely due to the LTROs.

Third, the measure of common distress potential, the Financial System Fragility measure (FSF), increased from mid-2011 until mid-2012 largely as a result of turbulences in Europe associated with the sovereign crisis, but distress potential subsided after the second LTRO in tandem with its common component. With a one-quarter lag, the same is true of the four D-SIBs, albeit with an offsetting (negative) idiosyncratic component. At the European level, the FSF measure associated with the four G-SIBs increased after end-2012 and remained stable thereafter. Overall, common distress potential fell, however, as shown by the worst corner of G-SIBs, D-SIBs and investment funds. Therefore, it is possible to conjecture that while the LTROs were successful in reducing the common source of systemic risk as reflected in the FSF common component, the policy measure seemingly increased the interconnectedness in the financial system as reflected by the increase in the FSI common component.

Fourth, the second source of systemic risk, measured using the probability that at least one financial institution becomes distressed given that there is already one financial institution in distress (PAO), oscillated in Luxembourg during the last year of the sample with a final upward move the last quarter. However, the common component improved suggesting less contagion vulnerabilities between banks—indeed, there is a decrease in the number of size—and investment funds (except Hedge Funds and MMFs). Looking into the worst corner of the D-SIBs, it seems that LTRO operations also reduced the second source of systemic
risk (i.e., contagion risk), at least temporarily. This feature is quite visible in Luxembourg most likely as a result of the reduced funding needs of European mother companies and the ensuing impact on Luxembourg banks’ balance sheets. Regarding G-SIBs, the common component of the PAO fell, highlighting thereby the global nature of the policy measure. The Dependence Distress Matrix (DDM) confirm the above results on contagion risk. In particular, the effects of the LTROs and their temporary nature. Toward the end of the sample, contagion risk decreased when the G-SIBs are considered in contrast to what happened when the D-SIBs are considered.

Fifth, while the marginal probabilities of default of Hedge Funds have a leading-sort of behavior of systemic risk measures, especially their common components, as argued by Billio et al. (2011), this result is more general as it is also applies to the marginal probabilities of default of other types of investment funds.

Sixth, the main drivers of marginal probabilities of default are different from the main drivers of the measures of systemic risk. In particular, while credit growth and the state of the economy tend to matter relatively more for marginal probabilities of default for banks and investment funds, the cost of funding matters relatively more for systemic risk measures. Given the importance of credit growth and confidence indicators in driving banks’ vulnerabilities, as well as banks’ apparent sensitivity to preserving a stable ratio of risk to equity more than to preserving a stable ratio of risk to assets (Adrian and Shin, 2013), banks’ seem to use leveraging and deleveraging as tools to satisfy their objective of delivering a low volatility of their probability of distress.

Finally, while vulnerabilities in investment funds can pose a higher contagion risk—second source of systemic risk—on banks than the other way round, it seems that for tracking vulnerabilities growth over time—third source of systemic risk—at least during the sample period of this study, it is relatively better to monitor the worst corner of the banking industry as the common components of systemic risk measures have a latent early-warning nature.

The remainder of the study is organized as follows. Next section briefly introduces the novel integrated modelling framework, explains how to combine the Merton model and the GDFM with the CIMDO, and Section III describes systemic credit risk measures applied to the financial sector. Section IV discusses the data. Section V examines the empirical results. Section VI concludes. Appendix I summarizes the main technical features of the dynamic forecasting part of the integrated framework given that the rest of the framework is described in more detail in Jin and Nadal De Simone (2014); Appendix II describes data filtering rules and; Appendix III discusses the data sources.
II. Financial Sector 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 feasible. 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 Merton (1974) assesses credit risk using contingent claims analysis. The GDFM is instead an econometric tool to perform factor analysis on large datasets and to do forecasting. Copulas are a fundamental tool for modeling multivariate distributions and are used extensively in risk management; however, the sample-length restrictions make it impossible to adequately calibrate the assumed parametric distributions. Therefore, the CIMDO approach, 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 outperform the standard univariate GARCH in most cases by exploiting cross-sectional information.

This study uses the integrated framework to measure systemic credit risk emanating from banks and investment funds’ interconnectedness and from the macro environment developed by Jin and Nadal De Simone (2014). To conserve space, only the main, possibly less well-known features of the framework, are discussed below while directing the reader also to the sources of its well-known components, i.e., Merton (1974) and the GDFM (Forni et al 2005). The framework consists of three highly integrated multi-functional parts which are illustrated by the information flow chart in the text.

12 De Nicolò and Lucchetta’s (2012) multi-step forecasts of systemic risk indicators are based on quantile auto-regressions using the dynamic factors they estimate in a first step. While the quantile forecasts draw information from these factors, the information content in the idiosyncratic component is not captured. It is known that the idiosyncratic component also plays an important role in financial stability and cannot be neglected (see Schwaab et al, 2010). Given that the idiosyncratic component is in general autocorrelated, and therefore, can be predicted, Forni et al (2003) suggest constructing a linear forecasting model with the contemporaneous common component and the lagged idiosyncratic component. This paper uses Forni’s insight, but not his methodology, as it is not easily applicable to a large number of underlying assets simultaneously, and it does not generate the distribution of these forecasts.
First, it is better to look at the output part, the CIMDO model. In this part, the prior dependence structure information incorporated into CIMDO is exogenously estimated by a rolling window on asset returns adjusted by Qi and Sun’s (2005) nearest correlation matrix. The outputs are several important systemic credit risk measures proposed by Segoviano and Goodhart (2009) and by Radev (2012) for banks and applied here to both banks and investment funds: FSF and FSI, which measure common distress in the financial sector, the first source of systemic risk identified by the ECB (2009); DDM which measures distress between specific financial institutions (i.e., banks and or investment funds) and PAO, two measures that proxy the second source of systemic risk identified by the ECB (2009). The CIMDO approach has several important advantages. It allows the recovery of multivariate distributions from 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 as it was done using an adjusted rolling window. 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. Specifically, Segoviano and Goodhart (2009) show by Monte Carlo simulation that the CIMDO outperforms several widely used parametric distributions, i.e., the standard and conditional Normal distributions, the t-distribution, and the mixture of normal distributions, especially in the region of distress which is of interest here.

Second, the input part is Merton (1974) option-based structural credit risk model which is used to track credit risk over time. These PDs, together with asset returns, are direct inputs into the CIMDO model. However, as discussed above, risk mispricing over time suggest that full 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 GDFM combined with a dynamic t-copula; the analysis part. This part of the framework not only decomposes the indicators 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 driving the indicators, 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 risk.

13 Both copulas and quantile regressions have been extended to a dynamic environment (e.g., Patton, 2006b, Engle and Mangenelli, 2004). Like copulas, quantile regressions can provide information about the degree and structure of dependence, but in contrast to copulas, they cannot model the joint or multivariate distribution (Baur, 2013). As a result, quantile estimation and prediction rely heavily on unrealistic global distributional assumptions. Since copula-quantile regression (c-quantiles) follows immediately from the determination of the joint distribution rather than by assumption, c-quantile from copula models can deliver more robust and more accurate estimates, and dependence structure can be directly examined at a quantile level by the copula’s dependence measures (e.g., Bouyé and Salmon, 2008 and Chen et al, 2009). However, a thorough comparison between t-copula versus quantile regression techniques in the context of a GDFM is beyond the scope of this study.
The remainder of this section addresses the important point of the data source to be used for the estimation of marginal PDs. This is a crucial part of any methodology and statistical approach seeking to estimate and forecast systemic credit risk.

2.1. The Book-Value-Based Merton

Merton model cannot be applied directly given that the data available on banks and investment funds is based on balance sheet information. An alternative approach has to be followed to calculate PDs. Bharath and Shumway (2008) 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.14 Recently, Adrian and Shin (2013) have forcefully argued that the key state variable in applying financial frictions in asset pricing modeling is leverage. The definition of leverage that matters for asset pricing is the ratio of total assets to book equity, rather than the ratio of enterprise value to market capitalization. Similarly, Danielsson et al (2012) argue “To the extent that our focus is on the investor’s portfolio decision, the leverage should be measured with respect to the equity that is implied by the investor’s portfolio. Hence, book equity is the appropriate notion when measuring leverage embedded in portfolio choice, and not market capitalization”. This suggests that financial statements can be a crucial piece of information when forming market expectations about the probability of financial institutions’ distress. This approach is followed here. However, as shown by Adrian and Shin (2013), U.S. banks’ leverage tend to fluctuate over the cycle via changes in the size of their balance sheet in tandem with changes in total debt, and with equity being the exogenous variable (p. 4). This seems to be also the case for Luxembourg banks as the coefficient of a regression of annual changes of assets on annual changes in total debt is 98% and highly significant. In contrast, changes in leverage in the investment funds’ industry is mostly done via changes in equity following changes in total asset values, with debt being held largely exogenous. The coefficient of a regression of annual changes of assets on annual changes in equity is close to 1, and highly significant. These two forms of leveraging up can be accommodated by the framework.15

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14 See also Gray and Jones, 2006, for an early application of this idea.
15 As argued by Adrian and Shin (2013), the second form of leverage fluctuation is the closest to the way leverage fluctuates in Merton’s (1974) model where leverage fluctuates through changes in the value of assets, with notional debt held fixed. Note that a third possible form of leveraging up is via equity buybacks with total assets fixed.
The book value asset volatility is calculated by a rolling window (RW) as follows:\textsuperscript{16}

\[ \sigma_B = \sqrt{\frac{1}{N} \sum_{t=1}^{N} (\ln(V_{i,t}^B / V_{i,t-1}^B))^2} \]

where \( V_{i,t}^B \) denotes the book value of total assets at time \( t \), \( N \) represents a rolling window of four consecutive quarters. The book-value risk neutral PD\textsuperscript{17} of the Merton model can be directly estimated by:

\[ \pi_B = N\left(-\frac{\ln(V_{i,t}^B / X) + (r - \frac{1}{2} \sigma_B^2)(T-t)}{\sigma_B \sqrt{T-t}}\right), \]

where the implied book-value risk neutral distance-to-default (DD) is simply the number of standard deviations that the firm is away from default:

\[ DD_B = \frac{\ln(V_{i,t}^B / X) + (r - \frac{1}{2} \sigma_B^2)(T-t)}{\sigma_B \sqrt{T-t}}. \]

Investment funds in this paper are analyzed at an aggregate type-level and thus, the level of book-value risk neutral PD can be very low, close to zero.\textsuperscript{18} As a result, the probability of distress of banks and investment fund types in this paper is estimated subject to rescaling Merton’s DD so that the lowest possible level of \( \pi_B \) is \( 1 \times 10^{-5} \).

\section{2.2. The CIMDO Approach}

The CIMDO-approach developed by Segoviano (2006) is centered on the concept of cross-entropy introduced by Kullback (1959). It 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 the case of two financial institutions, say \( X \) and \( Y \), with their logarithmic returns represented by random variables \( x \) and \( y \), the following function can be minimized:

\textsuperscript{16} Following usual practice, quarterly volatility is annualized.
\textsuperscript{17} See Jin and Nadal De Simone, 2011a, for a detailed discussion of the differences between “actual” PDs and risk-neutral PDs. Also see the discussion regarding the level of PDs as opposed to changes in PDs regarding, especially, the absence of a broadly accepted explanation of the so called “equity risk premium”.
\textsuperscript{18} See also the discussion regarding the level of PD as opposed to changes in PD, especially, in what refers to the absence of a broadly accepted explanation of the so called “equity risk premium”.
\[ L(p, q) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} p(x, y) \ln \left( \frac{p(x, y)}{q(x, y)} \right) dx dy \]
\[ + \lambda_1 [ \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} p(x, y) dx dy - 1] \]
\[ + \lambda_2 [ \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} p(x, y) I_{[x^d, \infty)}(x) dx dy - PD^x_i ] \]
\[ + \lambda_3 [ \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} p(x, y) I_{[x^d, \infty)}(y) dx dy - PD^y_i ], \]

where \( p(x; y), q(x; y) \in \mathbb{R}^2 \) are the posterior and the prior distributions accordingly, with \( \lambda_1, \lambda_2, \) and \( \lambda_3 \) being, respectively, 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 distress \( PD_i \) for each obligor is described in the upper part of a distribution over its distress-threshold \( x^d_i \) or \( x^d_j \) respectively. The optimal solution for the posterior density is of the form:

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

This solution stresses the importance of the distress thresholds and PDs necessary for systemic risk analysis. The posterior joint density will diverge from its prior whenever one or both random variables take values above the specified cutoff values, e.g., in times of distress when more mass will be shifted toward the realizations in tails of the distribution. As mentioned above and proven in Segoviano (2006), the CIMDO-recovered distribution outperforms the most commonly used parametric multivariate densities under the Probability Integral Transformation Criterion (e.g., the standard and conditional Normal distributions, or the mixture of Normal distributions). 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). Importantly, the distress threshold is one of the central parameters of the CIMDO methodology. Following the intuition of Goodhart and Segoviano (2009), a through-time-average distress-threshold is assumed for each financial institution, which is the inverse standard Normal of its through-time-average PDs.

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.\textsuperscript{19} By construction, the CIMDO copula puts a greater emphasis on the distress region of the joint distribution. Therefore, the approach provides a robust and consistent method to estimate financial institutions’ distress dependence.

As stated above, 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 prior could lead to a significant understatement of PDs dependence. This becomes particularly important in a period of distress when “phase-locking” behaviour most likely occurs. As a result, for the prior correlation input to the CIMDO this paper uses a simple rolling window approach which is also consistent with the RW estimation of book-based Merton’s model. A Newton-type method is used to obtain the nearest correlation matrix to the given symmetric matrix to guarantee that the correlation matrix of asset returns is symmetric and positive semi-definite (Qi and Sun, 2005).

2.3. The GDFM Analysis

Following Jin and Nadal De Simone (2012), this paper uses the GDFM to examine credit risk emanating from the macro environment and from banks’ and investment funds’ interconnectedness. The GDFM of Forni et al (2005) enables the efficient estimation of the common and idiosyncratic components of very large data sets. The GDFM assumes that each time series in a large data set is composed of two sets of unobserved components.\textsuperscript{20} 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. This part, therefore, links the dynamic behaviour of PDs and systemic risk measures to the evolution of the market as described by the macro-financial information matrix.

\textsuperscript{19} 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 unavoidable fact that PDs are generated regressors.

\textsuperscript{20} This paper follows Hallin and Liska’s (2007) $log$ criterion to determine the number of dynamic factors, and Alessi, Barigozzi and Capasso (2009), who modify Bai and Ng (2002) criterion, to determine the number of static factors in a more robust manner. These tests suggest one dynamic factor and three static factors.
III. Empirical Measures of Financial Systemic Risk

The multivariate density that results from the framework proposed in this study contains all the necessary information, coherently integrated, to estimate measures of financial system systemic credit risk that are consistent with the ECB’s (2009) categorization of the three sources of systemic risk referred to above. The measures are based on Segoviano and Goodhart’s (2009) and Radev’s (2012) systemic risk measures suggested for the banking sector. However, those measures do not cover a relatively insidious manner in which 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 financial sector measure of vulnerability and the macroeconomy as the one suggested in this study. It is done here by relating marginal PDs and the proposed systemic risk measures to a broad set of macrofinancial variables that drive them by using the GDFM. This approach makes it possible to observe a few quarters in advance the buildup of vulnerabilities in the financial sector. What follows briefly reviews Segoviano and Goodhart’s and Radev’s measures adopting their terminology to avoid confusion.

3.1. The First Source of Systemic Risk: Common Distress

Two proxies of the first source of systemic credit risk, i.e., a common shock that affects the whole financial sector and gets transmitted to the real economy can be calculated. The first one is the joint Probability of Distress (JPoD) or the probability that all financial institutions become distressed. This reflects credit risk not only at the individual bank and investment fund category level, but also the linear and nonlinear interdependencies among all financial institutions. However, the JPoD is in the extreme-value theory context of this empirical study a rather excessive measure as it would imply that all the financial sector collapses simultaneously. So, this paper calculates instead an adaptation to the financial sector of the Banking System Fragility measure suggested by Radev (2012). The FSF (Financial System Fragility measure) is the CIMDO-derived probability of at least two financial institutions getting distressed jointly. Given that this is an unconditional measure, it represents the general vulnerability of the financial sector to systemic events; it represents the systemic distress potential.

Assuming for simplicity three financial institutions whose asset value processes are characterized by the random variables X, Y, and Z, the FSF measure implies summing up the following unconditional joint probabilities:

\[ FSF = P(X \geq X^*_1, Y \geq X^*_1) + P(X \geq X^*_1, Z \geq X^*_1) + P(Y \geq X^*_1, Z \geq X^*_1) + P(X \geq X^*_1, Y \geq X^*_1, Z \geq X^*_1) \]
The FSF describes the part of the posterior distribution where distress occurs because at least two among X, Y and Z go over their respective distress-thresholds $x^*_d$, $y^*_d$ or $z^*_d$.

The second measure of the first source of banking systemic risk is the FSI (Financial Stability Index). Here, while the shock is common, there is one financial institution that becomes distressed. The FSI measures the expected number of financial institutions that will become distressed conditional on any one financial institution having become distressed. When the FSI=1, the linkages across financial institutions are minimal. As the FSI increases, it means that dependence among institutions increases, for example as a result of a relatively looser monetary policy stance that entices market participants to yield search. The measure can be written as follows:

$$FSI = \frac{P(X \geq x^*_d) + P(Y \geq y^*_d) + P(Z \geq z^*_d)}{1 - P(X < x^*_d, Y < y^*_d, Z < z^*_d)}.$$  

Alternatively, this measure could be interpreted as a measure of pure contagion as well, if it were assumed that the shock is idiosyncratic. However, making an assumption about the nature of the shock is not necessary to calculate this measure.

3.2. The Second Source of Systemic Risk: Idiosyncratic Distress and Contagion

To proxy the second source of systemic risk, two measures are calculated. The first one is designed to capture distress between specific financial institutions or groups of financial institutions. This is the DDM (Distress Dependence Matrix). Pair-wise conditional PDs provide significant information about contagion and interdependencies between banks, groups of banks, types of investment funds or banks and investment funds. For example, for macroprudential policymakers it 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 conditional on MMFs defaulting, or the probability of a banking group defaulting conditional on the default of Hedge Funds. This information can be displayed in the DDM. For example, the probability of distress of financial institution X conditional on financial institution Z becoming distressed is:

$$P(X \geq x^*_d / Z \geq z^*_d) = \frac{P(X \geq x^*_d, Z \geq z^*_d)}{P(Z \geq z^*_d)}.$$
The second measure is designed to capture distress in the financial system as a result of distress in a specific bank (or groups of banks) or type of investment fund. The PAO (probability that at least one financial institution becomes distressed given that a specific bank, or group of banks, or an investment fund type has become distressed) can track 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 financial system. For instance, given market data, it is possible to study the market perception of policy measures by calculating conditional PDs and contrasting them with the FSF (Lucas et al, 2012). To follow up on the example on the LTRO program, if markets were concerned about certain institutions for reasons other than liquidity, the PAO should reflect it by not changing despite that the FSF was reduced as a result of the LTRO. This analysis is possible because all the measures come from an integrated framework, which enhances its value for macroprudential policymakers. In addition, note that the PAO measure can provide a quantitative assessment of the systemic impact of individual financial institutions, as coupled with their sizes, permit to rank them according to the implied loss given default (conditional).

Assuming a financial system of four financial institutions for illustrative purposes (i.e., X, Y, R, and Z), and that financial institution Z becomes distressed, the measure is calculated as follows:

\[
PAO = P(X / Z) + P(R / Z) + P(Y / Z) \\
- [P(X \cap R / Z) + P(X \cap Y / Z) + P(R \cap Y / Z)] \\
+ P(X \cap R \cap Y / Z)
\]

Note that, in addition, this measure could also be used to determine the relative systemic importance of financial institutions. This measure shows the specific institution’s contribution to systemic risk through its exposure to exogenous shocks, through its role in propagating shocks via its interdependence, and by being itself subject to shocks.\(^{21}\)

3.3. The Third Source of Systemic Risk: Slow Buildup of Vulnerabilities

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

\(^{21}\) This measure would fall in the set of measures of banks’ systemic importance associated with the “contribution approach” suggested by Tarashev et al (2010).
clearly relatively more difficult to measure. As shown in Jin and Nadal De Simone (2012), the common component of Delianedis and Geske’s (2003) forward probability of default (FW PD) contains important “early warning features”. 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 identifying the economic forces driving the increase in vulnerabilities. These tend to be economic activity, credit and interbank markets activity. However, as also shown in this paper, the common components of the measures of financial systemic credit risk, i.e., the FSF, the FSI and the PAO, also contain important leading information on the build up of vulnerabilities in the financial system. Those common components can also be easily estimated and their evolution tracked over time 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, to two 100%-Luxembourg banks, as well as to all seven different types of investment funds reported by National Central Banks of the Eurosystem to the ECB: Equity Funds, Bond Funds, Mixed Funds, Real Estate Funds, Hedge Funds, Other Funds and Money Market Funds. The database contains quarterly balance sheet information starting on December 2010 and finishing on June 2013. While the length of the balance sheet data on investment funds is a binding constraint faced in this study, this is still a much richer balance sheet database than what can be found in papers estimating distress or survival in the investment funds industry, which has been circumscribed to data on returns with no information on leverage, or on some dimension of the liquidity of the portfolio, or the links with sponsoring banks.22

The macroeconomic database also includes data from 15 countries: Belgium, Canada, Denmark, France, Germany, Greece, Japan, Luxembourg, Netherland, Italy, Spain, Sweden, Switzerland, United Kingdom, and the United States. 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 data sources for market indexes and macroeconomic time series). The database comprises 258 series including three measures of credit-to-GDP gap for the

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22 As the majority of studies on some type of investment funds refer to the U.S. investment funds industry, it is pertinent to mention that before Dodd-Frank, regular filings of Hedge funds in the U.S. did not include critical information such as leverage, liquidity or the information on the portfolio, the Hedge fund’s major creditors and obligors, or the terms under which capital is committed. See footnote 1.
euro area, the UK and the US. Adding the macroeconomic variables to Merton PDs used for the Luxembourg banks, the European banking groups and the seven investment funds categories increases the database by 336 series.

All the Luxembourg banks are unlisted, so quarterly book value data from the BCL database are used. The 37 subsidiaries registered in Luxembourg represent about ⅔ 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 banking industry. For banks and investment funds, short term debt includes deposits of up to one-year maturity, short term funding, and repos, while the long term debt includes time deposits of over one-year maturity and other long term funding. For European banking groups, 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 III are used.

The use of a common accounting system allows the estimation of two sets of PDs and measures of systemic risk for the Luxembourg banks. The first set takes the assets and liabilities of the Luxembourg banking sector without excluding the links the banks have with the investment funds in different forms. The second set consolidates those links on both sides of banks’ balance sheets, i.e., in the form of credit and funding (referred to hereafter as “excl. IF”). As the pattern of behaviour is quite similar, and for conserving space, while showing both results, the discussion that follows is casted in terms of the unconsolidated version of the data with reference to the consolidated version when deemed relevant.

V. Empirical Results

This section first discusses developments in systemic risk that result from the different scenari studied. Then, it analyzes in particular the direction of contagion—the second source of systemic risk—between investment funds, Luxembourg banks and the European banking groups to which they belong. It follows a discussion of the drivers of marginal PDs and systemic risk measures. Finally, the out-of-sample forecasting capabilities of the framework are merely illustrated given that the short sample makes it impossible to perform a more robust analysis.

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23 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.
5.1. Developments in Systemic Risk

The description of systemic risk developments in Luxembourg’s investment funds and banks as well as the latter respective European parents has been done using different scenari. The set of scenari discussed has been selected among a relatively larger number of possible combinations that the flexibility of the framework allows. The choice is motivated by a combination of scenari that reasonably covers the main areas of interest for systemic risk analysis and assessment in current theoretical and policy discussions, e.g., the relative significance of contagion from the banking industry to the investment fund industry and vice versa; the role of the size of banks in systemic risk developments including the one of systemically important banks; the degree of leverage legally permitted for different investment fund types and its role in systemic risk and; the cross-border spillovers of systemic risk.

Five main scenari were used to produce the systemic risk measures discussed above. In agreement with the methodology followed in Jin and Nadal De Simone (2014), the main scenari covered include: scenario 1, the worst performing Luxembourg bank and the set of seven investment fund types, with PAO conditional on the worst performing Luxembourg bank; scenario 2, the worst-performing investment fund type, the two worst-performing Luxembourg banks and the two worst-performing European banking groups, with PAO conditional on the worst performer from these dynamically selected 5 entities; scenario 3 and 4, the worst investment fund performer and four Domestic Systemically Important Banks (D-SIBs), or four Global Systemically Important Banks (G-SIBS), respectively, with PAO conditional on the worst investment fund type performer and; scenario 5, the worst bank performer among small-, medium- and large-size Luxembourg banks and European banking groups, when investment funds are grouped into MMFs and non-Money Market Funds (NMMFs), with PAO conditional on the worst bank performer.

The systemic risk indicators as well as their common components have been estimated consolidating and not consolidating the balance sheets of the Luxembourg banks with those of the investment funds. This is possible because Luxembourg banks’ balance sheets have accounts that reflect the links between the banks and monetary and non-monetary investment funds. The results are broadly similar as can be seen below. The exception is in the PAO measure of certain scenari and will be discussed.

The FSI of scenario 1 shows a decline during the first two years of the sample, broadly speaking. However, after reaching a trough at end-2011, the FSI rose consistently until the end of the sample period (Figure 1a). This trend change coincides with the first Long
Term Refinancing Operations (LTROs) conducted by the ECB. Given that the FSI measures interdependence as a result of a shock common to the system, it seems that while the LTROs had the intended effect of reducing the cost of financing in the financial industry in Luxembourg, the policy measure also seems to have increased the expected number of financial institutions that would become distressed conditional on any one financial institution having become distressed in some scenario. When the FSI=1, the linkages across financial institutions are minimal, so the observed FSI increase signals an increase in interdependence among financial institutions: presumably, a relatively looser monetary policy stance entices market participants to yield search and thereby increases interdependence. This interpretation is supported by the simultaneous increase in the FSI common component extracted using the GDFM applied to the large macrofinancial database as well as by the reversal of the idiosyncratic component of the FSI which had been pooling down the overall measure. This interpretation is also supported by two robustness checks. First, when the scenario including European banking groups, scenario 2, is considered (i.e., a kind of worst corner of investment fund types, Luxembourg banks and European banking groups), the common component of the FSI rises significantly albeit the FSI rises only marginally driven down by its idiosyncratic component (Figure 1b). Second, scenario 3 and 4 which include the worst investment fund type and four D-SIBs or the G-SIBs, respectively, show that the FSI is stable or gently declines over the whole sample period, respectively (figures 1c and 1d). Therefore, it is possible to conclude that the FSI increases in scenarios 1 and 2 as a result of augmented interdependence at least within the more problematic banks, likely following the LTROs. However, scenario 4, which includes the four G-SIBs, displays a decreasing FSI suggesting that the increase in interdependence is localized in European banking groups other than the four G-SIBs. The flexibility of the framework is shown here once more. There is no change in interdependence among the four Luxembourg D-SIBs considered.

The measure of common distress potential in scenario 1, the FSF, oscillates somewhat until mid-2011 and then increases until mid-2012 largely as a result of turbulences in Europe associated with the sovereign crisis. However, fragility as measured by the FSF

24 On 8th December 2011, the ECB announced a number of measures to address rising funding liquidity stress in monetary and capital markets in the euro area. It announced that it would conduct two longer-term refinancing operations with a maturity of 36 months and the option of early repayment after one year, together with a reduction of the reserve ratio and measures to increase collateral availability. The LTROs would be conducted as fixed rate tender procedures with full allotment. The rate in these operations would be fixed at the average rate of the main refinancing operations over the life of the respective operation. The two allotment dates were established as 21st December 2011 and 29th February 2012, and banks requested €489.2bn and €529.5bn, respectively. See ECB (2013), for example, for an account of the evolution of funding (and market) liquidity before and after the LTROs were performed. Lucas et al (2012) have an analysis of the difference between policy measures such as LTROs that address common shocks and those that are more geared to addressing idiosyncratic shocks, very much in the spirit of this section’s discussion.
clearly decreases after the second LTRO in tandem with its common component (Figure 2a). As with the FSI, this interpretation is supported by other scenari. First, scenario 2 shows that the financial system fragility started falling after the second LTRO (Figure 2b). Second, with a one-quarter lag, the common component of the FSF of the four D-SIBs decreases while the common component of the four G-SIBs remains stable. In both scenari, the FSF increases during the second half of 2012 due to the idiosyncratic component of the FSF measure suggesting fragility concerns pertinent thereby to investment funds and their impact on G-SIBs and D-SIBs. As below in Table 3b which shows the impact of banks of distress on investment funds, it seems to be the case: both money and non-money investment funds' distress increased since mid-2012 to the end of the sample. These results support the view that the LTROs had the expected effect of a reduction in the common source of systemic risk and reduced the fragility of the financial system stemming from the banking sector.

Regarding the second source of systemic risk, i.e., contagion, the PAO measure in scenario 1 oscillated during the sample period, with a tendency to increase in 2011 vis-à-vis 2010, most likely due to the increased sovereign tensions in the euro area (Figure 3a). The PAO rose after the LTROs measures were taken despite that the PAO common component fell, in agreement with the general nature of the policy measures. With a short lag, also the idiosyncratic component of the PAO fell. This interpretation is broadly validated by other scenari results. While a similar pattern is visible when the worst investment fund type is conditionally chosen for the G-SIBs, in the case of Luxembourg’s D-SIBs, there is a very significant fall only of the idiosyncratic component of the PAO measure at the times of the LTROs (Figures 3d and 3c, respectively). The latter behavior of the PAO behavior is most likely a result of the reduced funding needs of European parent companies and the ensuing reduced funding demand reflected on Luxemburg banks’ balance sheets. Regarding scenario 2 (Figure 3b), the pattern of increased dependency in 2011 is also seen in the PAO measure. However, the measure shows a tendency to fall after the second LTRO, which surprisingly is not reflected in its common component. This implies that the idiosyncratic elements in the financial sector became relatively important. Interestingly, when the PAO with banks excluding investment funds is estimated, this risk measure and its common component do fall. As a result, given that this scenario proxies the worst corner of systemic risk, it seems that the LTRO was successful in reducing systemic risk stemming from the banking sector although the investment fund industry continued to contribute to it. This interpretation seems validated by the DDM corresponding to this scenario (see below).

Summarizing the description of developments in the different measures of systemic risk, while the LTROs were successful in reducing the common source of systemic risk as
reflected in the FSF common component, they also increased interconnectedness in some sections of the financial system as reflected by the FSI common component. Importantly, these two measures of systemic risk’s common components are strongly negatively correlated, which suggests that, for example, a reduction in funding costs will reduce the common component of the vulnerability measure FSF; however, it will increase the common component of the FSI because the fall in funding costs *ceteris paribus* will induce yield search, and more risk taking makes it more likely that more financial institutions will get distressed. Importantly, the flexibility of the framework matters for policymaking as illustrated by the decrease in interdependence of the G-SIBs at the time that European banking groups in general became more interdependent. These results indicate that monitoring G-SIBs is necessary, but not sufficient. In addition, the LTROs also seemed to have been able to reduce, albeit temporarily, the second source of systemic risk, i.e., contagion. Finally, no major differences in the pattern of the systemic risk measures are detected when investment funds’ links with the banks are excluded (see excl IF lines and their common components excl IF CC) with the exception of the scenario proxying the worst corner of systemic risk.

### 5.2. Contagion Risk between Investment Funds and Banks

In recent discussions on financial stability, the role of investment funds has been debated at length. Suffice it to mention the work of the Financial Stability Board (2011, 2012) and other bodies suggesting measures to strengthening the oversight and regulation of the so-called “shadow banking system”. Both in Europe and the U.S., measures to increase the regulation and the surveillance of investment funds have proliferated. Concerns about the impact of MMFs grew worldwide, for instance, after the run on the Reserve Primary Fund in the U.S. which “broke the buck” in 2008 mostly because of a flood of redemption requests, and the fund’s hefty investments in Lehman Brothers-issued commercial paper, which plummeted in value when Lehman Brothers failed. The resulting panic prompted the U.S. federal government to step in and offer guarantees to MMFs investors that their money would be returned in the event of a fund failure. It is thus opportune to analyze contagion between investment funds and banks.

The scenari of this study are rich enough to provide insights into the interconnection between both types of financial entities. The systemic risk measure that seems particularly useful for this aim is the Distress Dependence Matrix (DDM). Distress is presented such that the rows of the DDM display financial institutions’ probability of...
distress conditional on the distress of the financial institutions reported on the columns of the DDM. The evolution of contagion as described by the average of columns and rows of the DDMs, should be broadly consistent with the PAO results and thus is useful as a checking mechanism.

Several results follow. First, while interdependencies between banks in Luxembourg, their parent companies in Europe and the investment fund industry have been very dynamic over the sample period of this study, there is a clear asymmetry in the patterns of the interconnections. From all scenarios analyzed, it seems that investment funds’ vulnerabilities matter more in the form of contagion to banks than the other way round. In addition, this seems to be relatively more the case for the European banking groups than for their Luxembourg affiliates.

To conserve space, the results of scenarios 1, 2 and 5 are only reported (Tables 1, 2 and 3a and 3b, respectively). In scenario 1, conditional on distress in investment funds, the average PD of the Luxembourg bank is between 2 and 3 times the average PD of investment funds conditional on distress in the Luxembourg bank. In scenario 2, the same is true either for Luxembourg banks or for the European banking groups. Importantly, with the exception of the DDM as of 2011Q2, it is also the case that distress in investment funds results in a higher PD for European banking groups than for Luxembourg banks.

Scenario 5 considers MMF and NMMFs, European banking groups, and it also classifies Luxembourg banks into small, medium and large. It is also the case that distress in investment funds results in higher average PDs on banks than the opposite. There is no clear pattern as to what type of investment fund is a relatively more important contagion source, however. For example, at mid-2010 and mid-2011, NMMFs distress had a larger impact on all banks, but at mid-2012 and mid-2013, distress in MMF had a large impact on banks instead.

Second, the relatively finer granularity of this scenario allows separating the effect of investment funds’ distress by both jurisdiction and by Luxembourg bank’s size. As a result, MMFs’ distress is more important (except in 2011Q2) for Luxembourg banks than for European banking groups. Instead, distress in NMMFs matters more for European banking groups. This is to be expected given the role of Luxembourg banks as net

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27 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 about 50% of the time. Then, banks within each size category were treated homogeneously as one bank.
providers of liquidity to their parents and the importance of MMFs for Luxembourg banks’ funding. However, note that large Luxembourg banks tend to be as dependent on distress in NMMFs as European banking groups. Therefore, size does matter for analyzing systemic risk in Luxembourg, a result that echoes Jin and Nadal De Simone’s (2014). To further explore this matter, scenario 6 was run; it includes the seven investment funds together with small, medium and large Luxemburg banks as well as banking groups. In general, small- and medium-size Luxembourg banks tend to be affected relatively more by distress in MMFs than by distress in NMMFs (Table 4). In contrast, large-size Luxembourg banks and European banking groups are more vulnerable to distress in NMMFs than to distress in MMFs.

Third, the DDMs confirm the PAO results on systemic risk via contagion. In particular, note a reduction of contagion risk as a result of the LTROs, albeit only temporarily, in all the Tables. To illustrate, in Table 1, the average PD as a result of distress in the Luxembourg bank fell from 31% at mid-2011 to 25% in 2012Q1 and 2012Q2. Yet, it rose to 39% at the end of the sample, 2013Q2. Similarly, in Table 2, the average PD as a result of distress in the worst bank performer in Luxembourg and the worst banking group performer, declined from 50% and 62%, respectively, at mid-2011 to 42% and 53%, respectively, at 2012Q1 and to 40% and 51% in 2012Q2. In the Luxembourg bank case, it remained at 40% at the end of the sample but rose to 57% for the European banking group. The investment fund industry fragility in terms of contagion increased during 2012 and until the end of the sample period, rising from 59% in 2012Q1 to 74% in 2013Q2, confirming the description of the PAO behavior of scenario 2 in Section 5.1 above.

In fine, the banking sector became more fragile in terms of contagion between mid-2011 and mid-2012, but it improved toward the end of the sample: the row average increased to 23% from 5%, and then declined to 13% (Table 3a). In contrast, the investment fund’s industry became more fragile in terms of contagion over the sample period, especially during the last year: the row average increased to 59% at mid-2013 from 46% at mid-2012 (Table 3b). The DDM confirms a recent increase in systemic risk in the investment fund industry, a result found in Jin and Nadal De Simone (2013).

5.3. The buildup of vulnerabilities over time

5.3.1. Latent early-warning behavior

While the estimation and follow up of the evolution of the common component of marginal PDs and asset return correlations are useful tools in a macroprudential
policymaker’s dashboard, measures of systemic risk and their common components do seem a necessity. Systemic risk understood as a slow buildup of vulnerabilities over time can be “monitored” using the common components of the measures of systemic credit risk, e.g., the FSF and the PAO in conjunction with the analysis of their drivers. Jin and Nadal De Simone (2014) provide an application of this idea to European banking groups and their corresponding Luxembourg affiliates showing how the common components of systemic risk measures often behave as proxies of “latent early warning” (endogenous) measures of systemic risk.

From a policy viewpoint, it is clearly important to address the issue of whether there is any leading behavior in the common components of risk measures. For example, Billio et al (2011), argue that the PDs of Hedge Funds have a leading-sort of behavior of systemic risk measures, especially their common components. This result is confirmed in this study. The common components of the Hedge Funds PDs lead between 1 and 5 quarters all three measures of systemic risk, and not the opposite (not shown). However, this leading behavior does not seem to be an exclusive feature of this type of investment fund. There is often a leading-sort of behavior of the common components of marginal PDs of the investment funds’ industry in general.28 Using scenario 1, for instance, the common components of the average PD of the investment fund industry lead for between 2 quarters in the case of the FSI and the FSF and for 5 quarters in the case of the PAO, and not the opposite (Figure 4). As a result, at least during the sample period of this study, even without taking into account the contribution of cross-correlation to systemic risk, the framework can contribute to monitoring risk over time.

When the contribution of cross-correlations to risk is taken into account, the capacity of the common components of systemic risk measures to behave as latent early-warning indicators manifests itself clearly. To conserve space, only the results of scenario 1 and 5 are shown. These are displayed in Figures 5 and 6, respectively. The most important aspect of the results is that while the common components of the systemic risk measures may lead the measures for up to 9 quarters in some cases (at least 2 quarters), these are the cases associated with scenario that condition on the worst performer among banks, independently of the jurisdiction. In contrast, when conditioning on the worst investment fund type performer, the common components of the systemic risk measures do not display a clear latent early-warning feature (not shown). These results were confirmed by running the same estimations for the other three scenarios that

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28 Given the short sample length available, statistical tests other than the Box and Pierce Q statistics are difficult to implement. The Q statistic is distributed approximately as a chi-square with K degrees of freedom and tests that all autocorrelation coefficients are jointly zero. Results of the test using 8 lags are shown.
condition on the worst investment fund type performer (i.e., scenari 3, 4, and 6) and are available upon request.

It is important to summarize the results so far. The results suggest that while contagion likelihood, the second source of systemic risk, is more important from the worst corner of the investment-fund industry to the banking industry and not the other way round, when it comes to the third source of systemic risk, the common components of the systemic risk measures tend to exhibit latent early-warning features when conditioning on the worst performer from the banking industry independently of the jurisdiction. The results are consistent with the main drivers of systemic risks as discussed below. This highlights the operational relevance of the framework proposed in this study, in particular the important flexibility it offers to look at the three widely-accepted sources of systemic risk in the financial industry from different perspectives, as well as to elaborate scenari on informed judgment and contribute to polishing the assessment of systemic risk.

5.3.2. Drivers of the common components of systemic risk measures

Measures of systemic risk and their common and idiosyncratic components, when combined with the drivers of their common components, can be valuable tools for monitoring the buildup of systemic risk in the investment fund industry, as exemplified in Jin and Nadal De Simone (2013). To that end, the same methodology applied to marginal PDs as well as to cross-correlations of asset returns of investment fund types, was applied to the FSI, the FSF and the PAO measures of systemic risk.

A truly operational macroprudential framework should lend itself not only to measuring systemic banking vulnerabilities, but also to identifying their drivers. To determine the drivers of those vulnerabilities, all macrofinancial variables of the database were categorized into four classes: real variables (GDP in volume and current prices, industrial production, unemployment, the HICP, and agricultural and industrial property prices); funding costs (short- and long-term interest rates, spreads, 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).

The most important point to stress is that the ranking of variables driving the common components of systemic risk measures differs from the ranking of variables driving the common components of marginal PDs. This is not surprising. On the one hand, the common components of marginal PDs of financial institutions are associated relatively
more closely with the drivers that affect the type of financial institution in question and thus its business line and the pertinent regulations. On the other hand, systemic risk measures result from a complex interaction between marginal PDs, cross-correlation of asset returns and conditional probabilities within the CIMDO framework. Therefore, in contrast to marginal PDs, systemic risk measures’ common components are affected by the nonlinearities and feedback effects that make each financial institution interact with the rest of the financial sector and the real economy in general. This point stresses the importance of modeling interdependence to properly assess the drivers of systemic risk, to measure it, and to adopt macroprudential policies that are adequately calibrated to address the vulnerabilities they intend to tackle.

Table 5a summarizes the contribution of each of the set of variables to systemic risk across scenarios, and Table 5b summarizes the contribution of each set of variables to the PDs of banks and investment fund types. The contributions are calculated in the following manner. The common component of each type of systemic risk measure or marginal PD is regressed on the three-dimensional vector of its mutually orthogonal common factors (without intercept). The multiples of the regression coefficients and each factor loading estimates from the GDFM constitute the composite loadings for each factor. Since all variables for the GDFM estimation are standardized with zero mean and unit variance, the composite loadings of all factors are simply the sum of the composite loadings of the three factors. Tables 5a and 5b show the contribution of the first and the second most significant driver per variable category to the common component of each systemic risk measure and PD by taking the absolute value of the composite loadings. The tables display the ranking using the top 50% of the absolute value of these composite loadings. This contribution analysis based on composite loadings, of course, has its own limits if not provided with estimation errors. However, in this combined modeling framework with such short sample period, the consistent estimation of statistical errors is both theoretically and empirically very difficult, if not totally impossible. As a result, the robustness of the rankings was checked in two ways: first, by using the empirical cumulative distribution of absolute composite loadings, and second, by selecting a statistical cut point at 0.0001 so that absolute composite loadings lower than the cut point are treated as being not significantly different from zero. There were no significant changes in the ranking of the drivers as a result of these checks.

The most important drivers across the three measures of systemic risk reported are macroeconomic activity followed by funding quantities (notably credit, the credit gap and interbank lending and borrowing) and funding prices (especially interest rates, the interest rate spread, and stock prices). Confidence indicators also matter albeit less frequently; confidence indicators seem to matter more when conditioning on the worst
investment fund type (i.e., scenarios 3, 4 and 6). The important point to stress is that interest rates, spreads and stock prices passed from not being important drivers of banks’ marginal PDs and from being the least important drivers of marginal PDs of all types of investment fund types—except Bond Funds—to be significant drivers of the common components of the first and second sources of systemic risk.

This result matters for policy. For instance, this outcome—also found in Jin and Nadal De Simone (2013) in the investment fund industry—seems to suggest that monetary policy can have an important direct and indirect role (via the traditional channel of monetary policy effect on activity and also via the risk-taking channel) in affecting the evolution of systemic vulnerabilities in the financial sector. This effect may be underestimated when systemic risk, interdependences and vulnerabilities are not explicitly modeled given that funding prices matter relatively much less for marginal PDs than for complex measures of systemic risk.

The results also have important implications for macroprudential policy as well as for regulation and supervision. Proposals to monitor closely credit growth over the business and financial cycles, and its impact on leverage and maturity transformation seem supported by these results. As a further illustration, this seems particularly the case for Other Funds and Hedge Funds which PAOs common components show an unrelenting increase since the second half of 2011 (Figure 7). This development may be associated with an increase in leverage reported at an EU level in Hedge Funds. Notice that while Other Funds’ PDs common components also show the increase in vulnerability, this is not obvious in the case of Hedge Funds’ PDs common components. However, the systemic risk measure PAO indicates that a similar increase in vulnerability is present in Hedge Funds contemporaneously. From a financial stability viewpoint, both the second and the third sources of risk, admittedly the ones that policymaking can address directly, can be tracked by the framework proposed in this study and policy measures can be taken once the instruments have been duly calibrated.

5.4 Out-of-sample Forecasting

In-sample results say nothing about the out-of-sample performance of the proposed framework. Therefore, this section addresses its out-of-sample forecasting capabilities. However, the short number of data points available constrains a full-fledged, standard evaluation. Following Jin and Nadal De Simone (2012), this paper still show, by an

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29 The ECB Financial Stability Review (2013) reports that first quarter 2013 survey data of the ECB and the Fed suggest an increased use of leverage by Hedge Funds favored by low benchmark interest rates and higher risk tolerance.
example, how to apply their dynamic forecasting framework which combines the GDFM and a dynamic t-copula to examine systemic risk emanating from the macro environment and from investment funds and banks’ interconnectedness. The book-value based Merton model considered in this paper is estimated by a rolling window. As a result, the correlation input into the CIMDO uses a simple rolling-window approach. An AR(3) - GARCH (1,1) model is also used to track dynamic changes of both the idiosyncratic and the common components, since in the database, book-value data of Luxembourg banks and IF are actually quarterly. Table 6 reports root-mean squared errors, as well as the bias, the variance and the covariance components of Theil’s inequality coefficient across all estimated measures of systemic credit risk, the BSI, the FSF and the PAO, respectively, for scenario 5, i.e., the worst bank performer among Luxembourg banks (small-, medium- and large-size) and European banking groups, plus MMFs, NMMFs, with PAO conditional on this worst bank performer from 2012 to 2013.

Even for such a small-sample forecasting exercise, it is apparent that using only the common components of the systemic risk measures for the out-of-sample forecasts generates worse forecasts than using both the common components and the idiosyncratic components. This is especially the case for the root-mean squared errors, as they are halved, highlighting important idiosyncratic factors at work during the period and consistent with the discussion above. With regard to the components of the Theil’s inequality coefficient (i.e., bias, variance, and covariance), it seems that the improvement in the overall forecasting ability (row “Covariance Proportion”) obtained by adding the idiosyncratic component results from an improvement in the model’s capacity to reduce the systematic bias for all three measures, even at the expense of an increase of the degree of variance in PDs (column “Variance Proportion”), a feature that is due to the short sample and the difficulty in projecting the second moment as a result. This was shown not to be the case in Jin and Nadal De Simone (2012) as they work with a sample of reasonable length. Note that the addition of the idiosyncratic component also helps in reducing the unsystematic error as represented by the Covariance proportion. Therefore, even in this small sample, the proposed framework also somehow does a reasonably good job at forecasting systemic risk measure changes.

VI. Conclusions and macroprudential policy implications

The framework developed in this study estimates measures of systemic risk, provides latent early-warning indicators of the buildup systemic vulnerabilities, and with a

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30 Instead, given their less data-constrained environment, Jin and Nadal De Simone (2012) used the BEKK model.
31 The model is re-estimated recursively adding one period at a time and forecasting always two quarters forward.
reasonable sample length, can generate robust out-of-sample forecasts of them. Given that financial stability cannot stop at national borders, it uses a set of European banking groups, besides their affiliates in Luxembourg and all Luxembourg investment funds.

The framework can be decomposed as follows. First, marginal PDs are estimated using the Merton (1974) model. Second, the framework lends itself to the use of book-value data to cope with the lack of market data for non-publicly quoted banks and investment funds. Third, the CIMDO approach of Segoviano (2006) is used to model the time-varying linear and non-linear dependence among financial institutions. Fourth, the framework offered by the generalized dynamic factor model applied to a large macrofinancial dataset extracts the common component of financial institutions’ marginal PDs illustrating how a set of common systematic factors affect banks, their mother companies and investment funds 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 that markets seemingly experience when it comes to pricing risk over time. Beyond the credit gap and credit aggregates, economic activity, confidence indicators and funding prices, in that order, are important drivers of marginal PDs in the financial sector defined in this study as including all investment fund types domiciled in Luxembourg, banks in Luxembourg and their parent European banking groups. Besides confidence indicators, these insights agree with what was suggested by Borio and Lowe (2002), and by Drehmann and Tarashev (2011). The ranking of the drivers of systemic risk measures is different given that interest rates, spreads and stock prices pass from not being important drivers of banks’ marginal PDs and from being the least important drivers of marginal PDs of all types of investment fund types—except Bond Funds—to be significant drivers of the common components of the first and second sources of systemic risk. The most important drivers across the three measures of systemic risk reported are macroeconomic activity followed by funding quantities together with funding prices. This outcome suggests that a thorough assessment of the role of monetary policy in preserving financial stability may require models that make explicit the role of interest rate changes in systemic risk measures.

This framework contributes to the macroprudential literature with a method to monitor financial systemic risk. It generates a monitoring toolkit that tracks changes in systemic credit risk in the financial system in the sense of a buildup of vulnerabilities part of which are latent. As such, it could be part of a larger set of instruments for the surveillance of the most insidious way in which systemic risk can arise, i.e., via a slow buildup of vulnerabilities. This way, policymakers could tighten the scrutiny of financial markets by, for instance, increasing the severity of tests of the system or activating pre-existing
macroprudential instruments to cope with systemic risk. Given that this paper’s approach explicitly links the systemic risk measures with the state of the macroeconomy in order to extract its driving forces, it lends itself to a more informed discussion of the policy measures to address the observed vulnerabilities. In particular, the framework is useful in the unavoidable calibration of the instruments of the macroprudential arsenal.

By separating the role of system developments from individual financial institutions’ idiosyncratic features, this framework constitutes 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 also 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.

In addition, this framework contributes to a relatively more robust measurement of the other two sources of systemic risk by allowing the estimation of measures of financial systemic credit risk that reflect common distress in the financial institutions of the system (i.e., the Financial System Fragility measure) and distress associated with a specific bank (or a set of banks) or investment fund type and the probability that at least one other financial institution will become distressed as a result. This is a rich set of indicators for a macroprudential operational framework based on explicit modeling of financial institutions’ default dependence: conditional probabilities can provide insights into interlinkages and the likelihood of contagion or spillovers between banks or groups of banks in the system and investment funds. This should help assessing the contingent liabilities of the financial system and the expected costs of policy inaction.

Finally, and also very 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 as well by suggesting a framework for forecasting financial 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 systemic credit risk measures. This remediates the well-known feature that simply aggregating marginal PDs results in a downward-biased measure of 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. This feature of the framework makes it also useful in stress testing of the financial system.
References


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Appendix I: The Combined GDFM and Dynamic t-Copula: A Dynamic Forecasting Framework

Forni et al (2005) provide a good framework for multi-step-ahead predictions of the common component. Nevertheless, the idiosyncratic component also plays an important role for financial stability and cannot be neglected (see Schwaab et al, 2010). Jin and Nadal De Simone (2014) introduces a novel approach to combine the GDFM with a dynamic t-copula. First, the AR (zero mean)-GARCH model can be applied to both the common components and the idiosyncratic components of 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:

\[
X_{t+1}^F = X_{t+1}^{CC-F} + X_{t+1}^{IC-F}
\]

\[
X_{t+1}^{CC-F} = X_{t+1}^{GDF-F} + \sigma_{t+1}^{CC} e_{t+1}^{CC}
\]

\[
X_{t+1}^{IC-F} = \sum_{i=1}^{p} X_{t+1-i}^{IC} + \sigma_{t+1}^{IC} e_{t+1}^{IC}
\]

\[\sigma_{t+1}^2 = \alpha_0 + \alpha(\sigma_i e_i)^2 + \beta \sigma_i^2\]

\[e_{t+1} \sim iid(0,1)\]

\[F(e_{t+1}, e_{t+1}^2, ..., e_{t+1}^{2n}) = C_T(F_1(e_{t+1}^1), F_2(e_{t+1}^2), ..., F_3(e_{t+1}^2n); R_t, v_t),\]

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 \(F(e_{t+1}^1, e_{t+1}^2, ..., e_{t+1}^{2n})\) for \(i=1,2,...,2n\), includes standardized residuals from both the common and the idiosyncratic components and has a time-varying t-copula form.

The copula provides a robust method for a consistent estimation of dependence structures and is very flexible.\(^{33}\) In addition, the use of the conditional dynamic copula

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\(^{32}\) The input to the GDFM is a vector of stochastic covariance-stationary processes with zero means and finite second-order moments. In this paper, the standardized first difference of PDs and the log difference of asset values are exogenous inputs to the GDFM.

\(^{33}\) In addition, copulas are often relatively parsimoniously parameterized, which facilitates calibration. Correlation, which usually refers to Pearson’s linear correlation, depends on both the marginal distributions
makes it relatively easy to construct and simulate from multivariate distributions built on marginal distributions and dependence structure. The following sections explain the modelling of marginal dynamics, dynamic t-copulas, and forward simulation procedures.

1. Modelling Marginal Dynamics

Misspecification of marginal distributions can lead to dangerous biases in the estimation of dependence. Given that time series data and the common and idiosyncratic components of financial data usually reveal time-varying variance and heavy-tailedness, 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 marginal dynamics are:

\[
X_{t}^{CC} = \sigma_{t}^{CC} \epsilon_{t}^{CC}
\]

\[
X_{t}^{IC} = \sum_{i=1}^{p} X_{t-i}^{IC} + \sigma_{t}^{IC} \epsilon_{t}^{IC}
\]

\[
\sigma_{t}^{2} = \alpha_{0} + \alpha (\sigma_{t-1}^{IC})^{2} + \beta \sigma_{t-1}^{2}
\]

\[
\epsilon_{t} \sim iid(0,1),
\]

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. Since 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 \(\epsilon_{t}\) from the estimation of the marginal dynamics, the empirical cumulative distribution function (cdf) of these standardized residuals is estimated by the distribution of exceedances or peaks-over-threshold method (McNeil, 1999, and McNeil and Frey, 2000).\(^{34}\)

2. The Dynamic Conditional t-Copula

The copula of the multivariate standardized t distribution is a good candidate for the high-dimensional problem dealt with in this paper which requires non-zero dependence in the tails. The conditional dynamic t-copula is defined as follows\(^{35}\):

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\(^{34}\) The upper and lower 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. Because of our small observations, 20% thresholds are used to ensure that there are sufficient data points in the tails to conform well to a GP.

\(^{35}\) See Patton (2006b) for the definition of a general conditional copula.
\[
C(\eta_1, \eta_2, \ldots, \eta_n, R_\eta, v_\eta) = T_{R_\eta, v_\eta}(t_{v_\eta}^{-1}(\eta_1), t_{v_\eta}^{-1}(\eta_2), \ldots, t_{v_\eta}^{-1}(\eta_n)),
\]

where \( \eta_n = F_n(\varepsilon_n) \) for \( i=1,2,\ldots,n \), and \( \varepsilon_i \sim iid(0,1) \), are the innovations from the marginal dynamics introduced in the previous section. \( R_\eta \) is the rank correlation matrix, and \( v_\eta \) is the degrees of freedom. \( t_{v_\eta}^{-1}(\eta_n) \) denotes the inverse of the \( t \) cumulative distribution function. \( R_\eta \) and \( v_\eta \) can be assumed to be a 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’s (1990) 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:

\[
Q_i = (1 - \alpha - \beta) \bar{Q} + \alpha_{dec}(\varepsilon_{i-1}, \varepsilon_{i-1}^*) + \beta_{dec}Q_{i-1},
\]

where \( \alpha_{dec} \geq 0, \beta_{dec} \geq 0, \alpha_{dec} + \beta_{dec} \leq 1 \), \( \varepsilon_i = t_{v_i}^{-1}(\eta_n = F_n(\varepsilon_n)) \), \( Q_i = |q_{ij,t}| \) is the auxiliary matrix driving the rank correlation dynamics and the nuisance parameters \( \bar{Q} = E[\varepsilon_i^* \varepsilon_i^*] \) have a sample analog \( \bar{Q} = T^{-1} \sum_{t=1}^{T} \varepsilon_i^* \varepsilon_i^* \), so that \( R_\eta \) is a matrix of rank correlations \( q_{ij,t} \) with ones on the diagonal, \( \rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t} q_{jj,t}}} \).

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, \( R_\eta \) can be well approximated by the Gaussian rank correlation from the dynamic Gaussian Copula (Bouye et al, 2000). For convenience, this study adopts a two-step algorithm for estimation which means that \( R_\eta \) is estimated from the dynamic Gaussian copula first by maximizing composite likelihood (Shephard and Sheppard, 2008)\(^{36} \), and then, with \( R_\eta \) fixed, the degrees of freedom are recovered from

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\(^{36}\) 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
the t-copula. In this paper, to avoid the known estimation difficulties of high-dimensional t-copulas, m-profile subset composite likelihood (MSCL) \textsuperscript{37} are maximized using contiguous pairs. The degrees of freedom for the t-copula are the 50th quantile of all degrees of freedom derived from pairwise t-copulas.

3. 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 $\epsilon_{t+1}^{im}, \ldots, \epsilon_{t+1}^{im}$ 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 $\mu_{t+1}^{ik}, \ldots, \mu_{t+1}^{im}$ by setting $\mu_{t+1}^{ik} = t_{v_{t+1}}(\epsilon_{t+1}^{ik})$, where $k=1,\ldots,m$, is the total paths of the simulation, and $i=1,\ldots,n$, is the number of components;
2. Obtain $\epsilon_{t+1}^{i1}, \ldots, \epsilon_{t+1}^{im}$ by setting $\epsilon_{t+1}^{ik} = F_{i}^{-1}(\mu_{t+1}^{ik})$, where $F_{i}$ is the empirical marginal dynamics distribution for component $i$;
3. Obtain $z_{t+1}^{i1}, \ldots, z_{t+1}^{im}$ by setting $z_{t+1}^{ik} = \epsilon_{t+1}^{ik} \sigma_{t+1}^{i}$, where $\sigma_{t+1}^{i}$ is the forecast standard deviation using a GARCH (1,1) model for component $i$;
4. Obtain $X_{t+1}^{i1}, \ldots, X_{t+1}^{im}$ by setting $X_{t+1}^{ik} = \bar{\lambda}_{t+1}^{i} + z_{t+1}^{ik}$, where $\bar{\lambda}_{t+1}^{i}$ 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 $t+1$.

Several-period predictions can be obtained in the same way. For PDs, the idiosyncratic and common components are derived from the standardized first difference of the PDs. The simulated cumulative PDs have to be truncated by $\text{Max}(DP_{t}^{\text{Simulated}}, 0)$. This forward simulation approach, therefore, integrates the one-sided forecasting features of the GDFM into the dynamic t-copula framework.
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 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)
Figure 1 - FSI Systemic Risk Measure

a: 7 IFs & 1 Worst Lux Bank

b: 2 Worst Banking Groups & 2 Worst Lux Banks & 1 Worst IF

c: 4 Lux Banks & 1 Worst IF

d: 4 Banking Groups & 1 Worst IF
Figure 2 - FSF Systemic Risk Measure

a: 7 IFs & 1 Worst Lux Bank
b: 2 Worst Banking Groups & 2 Worst Lux Banks & 1 Worst IF
c: 4 Lux Bank & 1 Worst IF
d: 4 Banking Groups & 1 Worst IF
Figure 3 - PAO Systemic Risk Measure

a: 7 IFs & 1 Worst Lux Bank

b: 2 Worst Banking Groups & 2 Worst Lux Banks & 1 Worst IF

c: 4 Lux Bank & 1 Worst IF

d: 4 Banking Groups & 1 Worst IF
Figure 4 - Leads and Lags Between Systemic Risk Measures of 7 Investment Fund Types and the Worst Luxembourg Bank, and the Common Components of Equal-Weighted Investment Fund PDs
Figure 5 - Leads and Lags Between Systemic Risk Measures and their Common Components for 7 Investment Fund Types and the Worst Luxembourg Bank
Figure 6 - Leads and Lags Between Systemic Risk Measures and their Common Components for MMF, NMMF and the Worst Bank
Figure 7 – PDs and PAO for Other Funds / Hedge Funds
(Scenario includes 4 Banking Groups)
Table 1: Distress Dependence Matrices for 7 Investment Fund Types & the Worst Luxembourg Bank

<table>
<thead>
<tr>
<th>The PD in the row, given PD in the column</th>
<th>Equity Funds</th>
<th>Bond Funds</th>
<th>Mixed Funds</th>
<th>Real Estate Funds</th>
<th>Money Market Funds</th>
<th>Lux Bank</th>
<th>Lux Bank's effect on Investment Funds</th>
<th>Row Average</th>
<th>CC PDs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Equity Funds</td>
<td>1.00</td>
<td>0.74</td>
<td>0.98</td>
<td>0.15</td>
<td>0.39</td>
<td>0.42</td>
<td>0.00</td>
<td>0.00</td>
<td>0.32</td>
</tr>
<tr>
<td>Bond Funds</td>
<td>0.65</td>
<td>1.00</td>
<td>0.84</td>
<td>0.27</td>
<td>0.41</td>
<td>0.80</td>
<td>0.00</td>
<td>0.00</td>
<td>0.21</td>
</tr>
<tr>
<td>Mixed Funds</td>
<td>0.72</td>
<td>0.70</td>
<td>1.00</td>
<td>0.15</td>
<td>0.30</td>
<td>0.45</td>
<td>0.00</td>
<td>0.23</td>
<td>0.44</td>
</tr>
<tr>
<td>Real Estate Funds</td>
<td>0.17</td>
<td>0.36</td>
<td>0.24</td>
<td>1.00</td>
<td>0.20</td>
<td>0.83</td>
<td>0.33</td>
<td>0.32</td>
<td>0.43</td>
</tr>
<tr>
<td>Money Market Funds</td>
<td>0.66</td>
<td>0.78</td>
<td>0.69</td>
<td>0.28</td>
<td>1.00</td>
<td>0.84</td>
<td>0.22</td>
<td>0.26</td>
<td>0.59</td>
</tr>
<tr>
<td>Other Funds</td>
<td>0.04</td>
<td>0.08</td>
<td>0.06</td>
<td>0.07</td>
<td>0.05</td>
<td>1.00</td>
<td>0.00</td>
<td>0.04</td>
<td>0.17</td>
</tr>
<tr>
<td>Money Market Funds</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.01</td>
<td>0.00</td>
<td>1.00</td>
<td>0.00</td>
<td>0.13</td>
<td>0.00</td>
</tr>
<tr>
<td>Lux Bank</td>
<td>0.66</td>
<td>0.46</td>
<td>0.59</td>
<td>0.52</td>
<td>0.30</td>
<td>0.50</td>
<td>1.00</td>
<td>0.53</td>
<td>0.56</td>
</tr>
<tr>
<td>Column Average</td>
<td>0.48</td>
<td>0.52</td>
<td>0.55</td>
<td>0.30</td>
<td>0.33</td>
<td>0.64</td>
<td>0.20</td>
<td>0.30</td>
<td>0.41</td>
</tr>
</tbody>
</table>

Note: These matrices present the probability of distress of the banks in the row, conditional on the 7 investment funds in the column becoming distressed.
Table 2: Distress Dependence Matrices for the 2 Worst Banking Groups, the 2 Worst Luxembourg Banks, and the Worst Investment Fund Type

<table>
<thead>
<tr>
<th>The PD in the row, given PD in the column</th>
<th>PDs</th>
<th>CC PDs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2nd Worst Banking Group</td>
<td>1st Worst Banking Group</td>
</tr>
<tr>
<td>Q2 2010</td>
<td>1.00</td>
<td>0.89</td>
</tr>
<tr>
<td>Q2 2011</td>
<td>1.00</td>
<td>0.85</td>
</tr>
<tr>
<td>Q1 2012</td>
<td>1.00</td>
<td>0.88</td>
</tr>
<tr>
<td>Q2 2012</td>
<td>1.00</td>
<td>0.94</td>
</tr>
<tr>
<td>Q2 2013</td>
<td>1.00</td>
<td>0.88</td>
</tr>
</tbody>
</table>

Note: These matrices present the probability of distress of the banks in the row, conditional on the 7 investment funds in the column becoming distressed.
Table 3a: Distress Dependence Matrices for MMF, NMMF, Banking Groups, Small, Medium and Large Luxembourg Banks

<table>
<thead>
<tr>
<th>The PD in the row, given PD in the column</th>
<th>PDs</th>
<th>CC PDs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Banking Groups</td>
<td>Small Lux Banks</td>
</tr>
<tr>
<td>Money Market Funds</td>
<td>0.00 0.01 0.01 0.00</td>
<td>0.00 0.01 0.00</td>
</tr>
<tr>
<td>Non-Money Market Funds</td>
<td>0.40 0.04 0.27 0.17</td>
<td>0.22</td>
</tr>
<tr>
<td>Column Average</td>
<td>0.20 0.03 0.14 0.09</td>
<td>0.11</td>
</tr>
<tr>
<td>Money Market Funds</td>
<td>0.02 0.01 0.05 0.00</td>
<td>0.02</td>
</tr>
<tr>
<td>Non-Money Market Funds</td>
<td>0.12 0.06 0.01 0.15</td>
<td>0.08</td>
</tr>
<tr>
<td>Column Average</td>
<td>0.07 0.04 0.03 0.07</td>
<td>0.05</td>
</tr>
<tr>
<td>Money Market Funds</td>
<td>0.02 0.52 0.45 0.12</td>
<td>0.28</td>
</tr>
<tr>
<td>Non-Money Market Funds</td>
<td>0.45 0.00 0.03 0.22</td>
<td>0.18</td>
</tr>
<tr>
<td>Column Average</td>
<td>0.23 0.26 0.24 0.17</td>
<td>0.23</td>
</tr>
<tr>
<td>Money Market Funds</td>
<td>0.00 0.09 0.13 0.08</td>
<td>0.07</td>
</tr>
<tr>
<td>Non-Money Market Funds</td>
<td>0.29 0.10 0.11 0.26</td>
<td>0.19</td>
</tr>
<tr>
<td>Column Average</td>
<td>0.15 0.10 0.12 0.17</td>
<td>0.13</td>
</tr>
</tbody>
</table>

Note: These matrices present the probability of distress of the investment funds in the row, conditional on the Luxembourg banks in the column becoming distressed.
Table 3b: Distress Dependence Matrices (Reverse) for MMF, NMMF, Banking Groups, Small, Medium and Large Luxembourg Banks

<table>
<thead>
<tr>
<th></th>
<th>PDs</th>
<th></th>
<th></th>
<th>CC PDs</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Money Market Funds</td>
<td>Non-Money Market Funds</td>
<td>Row Average</td>
<td>Money Market Funds</td>
<td>Non-Money Market Funds</td>
</tr>
<tr>
<td>The PD in the row, given PD in the column</td>
<td></td>
<td>Banking Groups</td>
<td>Small Lux Banks</td>
<td>Medium Lux Banks</td>
<td>Large Lux Banks</td>
<td>Column Average</td>
</tr>
<tr>
<td>Q2 2010</td>
<td></td>
<td>0.18</td>
<td>0.78</td>
<td>0.48</td>
<td>0.03</td>
<td>0.92</td>
</tr>
<tr>
<td>Q2 2011</td>
<td></td>
<td>0.48</td>
<td>0.65</td>
<td>0.57</td>
<td>0.12</td>
<td>0.83</td>
</tr>
<tr>
<td>Q2 2012</td>
<td></td>
<td>0.04</td>
<td>0.98</td>
<td>0.51</td>
<td>0.08</td>
<td>0.86</td>
</tr>
<tr>
<td>Q2 2013</td>
<td></td>
<td>0.00</td>
<td>0.74</td>
<td>0.37</td>
<td>0.00</td>
<td>0.99</td>
</tr>
</tbody>
</table>

Note: These matrices present the probability of distress of the banks in the row, conditional on the investment funds in the column becoming distressed.
Table 4: Distress Dependence Matrices for Banking Groups, Small, Medium and Large Luxembourg Banks, and Investment Fund Types

<table>
<thead>
<tr>
<th>The PD in the row, given PD in the column</th>
<th>PDs</th>
<th>CC PDs</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Equity Funds</td>
<td>Bond Funds</td>
</tr>
<tr>
<td>Banking Groups</td>
<td>0.88</td>
<td>0.64</td>
</tr>
<tr>
<td>Small Lux Banks</td>
<td>0.09</td>
<td>0.08</td>
</tr>
<tr>
<td>Medium Lux Banks</td>
<td>0.39</td>
<td>0.66</td>
</tr>
<tr>
<td>Large Lux Banks</td>
<td>0.37</td>
<td>0.35</td>
</tr>
<tr>
<td>Column Average</td>
<td>0.43</td>
<td>0.43</td>
</tr>
</tbody>
</table>

**Q3 2010**

| Banking Groups                           | 0.50 | 0.94 | 0.51 | 0.45 | 0.11 | 0.44 | 0.46 | 0.49 | 0.96 | 0.79 | 0.77 | 0.64 | 0.73 | 0.78 | 0.10 | 0.68 |
| Small Lux Banks                          | 0.56 | 0.03 | 0.43 | 0.59 | 0.74 | 0.58 | 0.38 | 0.47 | 0.03 | 0.12 | 0.13 | 0.27 | 0.09 | 0.16 | 0.89 | 0.24 |
| Medium Lux Banks                         | 0.01 | 0.22 | 0.18 | 0.04 | 0.65 | 0.06 | 0.57 | 0.25 | 0.22 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 | 0.17 |
| Large Lux Banks                          | 0.98 | 0.53 | 0.91 | 0.98 | 0.44 | 0.99 | 0.07 | 0.70 | 0.70 | 1.00 | 0.99 | 1.00 | 0.98 | 1.00 | 0.00 | 0.81 |
| Column Average                           | 0.51 | 0.43 | 0.51 | 0.52 | 0.49 | 0.52 | 0.37 | 0.48 | 0.47 | 0.48 | 0.47 | 0.48 | 0.45 | 0.49 | 0.50 | 0.48 |

**Q3 2011**

| Banking Groups                           | 1.00 | 0.74 | 0.99 | 0.36 | 0.86 | 0.31 | 0.05 | 0.61 | 0.99 | 0.60 | 0.77 | 0.28 | 0.20 | 0.21 | 0.10 | 0.45 |
| Small Lux Banks                          | 0.00 | 0.10 | 1.00 | 0.50 | 0.19 | 0.57 | 0.97 | 0.33 | 0.02 | 0.00 | 0.00 | 0.20 | 0.99 | 0.40 | 1.00 | 0.37 |
| Medium Lux Banks                         | 0.27 | 0.02 | 0.10 | 0.16 | 0.66 | 0.58 | 0.86 | 0.38 | 0.08 | 0.00 | 0.00 | 0.05 | 0.98 | 0.22 | 1.00 | 0.33 |
| Large Lux Banks                          | 0.22 | 0.74 | 0.50 | 0.27 | 0.07 | 0.88 | 0.25 | 0.42 | 0.02 | 0.26 | 0.15 | 0.56 | 0.84 | 0.79 | 0.87 | 0.50 |
| Column Average                           | 0.37 | 0.40 | 0.40 | 0.32 | 0.44 | 0.59 | 0.53 | 0.44 | 0.27 | 0.22 | 0.23 | 0.27 | 0.75 | 0.40 | 0.74 | 0.41 |

**Q3 2012**

| Banking Groups                           | 0.66 | 0.88 | 0.69 | 0.52 | 0.16 | 0.43 | 0.00 | 0.48 | 1.00 | 1.00 | 1.00 | 0.81 | 0.22 | 0.90 | 0.00 | 0.70 |
| Small Lux Banks                          | 0.23 | 0.12 | 0.40 | 0.57 | 0.93 | 0.67 | 0.89 | 0.55 | 0.02 | 0.00 | 0.01 | 0.03 | 0.92 | 0.15 | 1.00 | 0.30 |
| Medium Lux Banks                         | 0.36 | 0.18 | 0.14 | 0.01 | 0.20 | 0.20 | 0.93 | 0.29 | 0.01 | 0.00 | 0.00 | 0.00 | 0.82 | 0.04 | 1.00 | 0.27 |
| Large Lux Banks                          | 0.80 | 0.58 | 0.76 | 0.35 | 0.64 | 0.83 | 0.86 | 0.69 | 0.55 | 0.59 | 0.57 | 0.65 | 0.55 | 0.70 | 0.28 | 0.55 |
| Column Average                           | 0.51 | 0.44 | 0.50 | 0.36 | 0.48 | 0.53 | 0.67 | 0.50 | 0.39 | 0.40 | 0.39 | 0.37 | 0.63 | 0.45 | 0.57 | 0.46 |

Note: These matrices present the probability of distress of the banks in the row, conditional on the 7 investment funds in the column becoming distressed.
### Table 5a - Summary of Drivers of the Common Components of Systemic Risk Measures

<table>
<thead>
<tr>
<th>Scenario</th>
<th>FSI</th>
<th>FSF</th>
<th>PAO</th>
</tr>
</thead>
<tbody>
<tr>
<td>1  7 IFs and the Worst Lux Bank - PAO for the Worst Lux Bank</td>
<td>FQ</td>
<td>FP</td>
<td>CF</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>FQ, MA</td>
</tr>
<tr>
<td>2  the 2 Worst BGs, the 2 Worst Lux Banks, and the Worst IF - PAO for the</td>
<td>FQ</td>
<td>MA, CF</td>
<td>FP</td>
</tr>
<tr>
<td>Worst of these selected 5</td>
<td></td>
<td></td>
<td>FQ</td>
</tr>
<tr>
<td>3  4 D-SIBs and the Worst IF - PAO for the Worst IF</td>
<td>FP</td>
<td>MA</td>
<td>CF</td>
</tr>
<tr>
<td></td>
<td></td>
<td>MA</td>
<td>MA</td>
</tr>
<tr>
<td>4  4 G-SIBs and the Worst IF - PAO for the Worst IF</td>
<td>FQ</td>
<td>CF</td>
<td>MA</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>CF</td>
</tr>
<tr>
<td>5  MMF, NMMF, the Worst Bank of SML Lux Banks and BG - PAO for the Worst</td>
<td>MA</td>
<td>CF</td>
<td>MA</td>
</tr>
<tr>
<td>Bank</td>
<td></td>
<td></td>
<td>MA</td>
</tr>
<tr>
<td>6  SML Lux Banks, BG, and the Worst IF - PAO for the Worst IF</td>
<td>MA</td>
<td>FQ</td>
<td>MA</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>FQ, MA, CF</td>
</tr>
</tbody>
</table>

### Table 5b - Summary of Banks and Investment Funds' PD Drivers

<table>
<thead>
<tr>
<th>Financial Institution</th>
<th>FSI</th>
<th>Second</th>
</tr>
</thead>
<tbody>
<tr>
<td>Luxembourg banks</td>
<td>FQ</td>
<td>CF</td>
</tr>
<tr>
<td>European banking groups</td>
<td>MA</td>
<td>FQ</td>
</tr>
<tr>
<td>Equity Funds</td>
<td>FQ</td>
<td>MA</td>
</tr>
<tr>
<td>Bonds Funds</td>
<td>MA, FP</td>
<td>FQ</td>
</tr>
<tr>
<td>Mixed Funds</td>
<td>FQ</td>
<td>MA</td>
</tr>
<tr>
<td>Real Estate Funds</td>
<td>MA</td>
<td>FQ</td>
</tr>
<tr>
<td>Hedge Funds</td>
<td>CF</td>
<td>MA</td>
</tr>
<tr>
<td>Other Funds</td>
<td>FQ</td>
<td>MA</td>
</tr>
<tr>
<td>Money Market Funds</td>
<td>MA, FQ, CF</td>
<td>FQ</td>
</tr>
</tbody>
</table>
Table 6: CIMDO Copula BSI Forecast (Median) Evaluation for Banking Groups Index and Luxembourg Banks Index and Worst Investment Fund (among MMFs & NMMFs)

<table>
<thead>
<tr>
<th></th>
<th>Common Component</th>
<th>Common &amp; Idiosyncratic Component</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1st Quarter</td>
<td>2nd Quarter</td>
</tr>
<tr>
<td><strong>BSI</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RMS Error</td>
<td>0.13</td>
<td>0.12</td>
</tr>
<tr>
<td>Bias Proportion</td>
<td>0.78</td>
<td>0.54</td>
</tr>
<tr>
<td>Variance Proportion</td>
<td>0.15</td>
<td>0.03</td>
</tr>
<tr>
<td>Coviance Proportion</td>
<td>0.07</td>
<td>0.43</td>
</tr>
<tr>
<td><strong>FSF</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RMS Error</td>
<td>0.09</td>
<td>0.09</td>
</tr>
<tr>
<td>Bias Proportion</td>
<td>0.91</td>
<td>0.85</td>
</tr>
<tr>
<td>Variance Proportion</td>
<td>0.05</td>
<td>0.00</td>
</tr>
<tr>
<td>Coviance Proportion</td>
<td>0.04</td>
<td>0.15</td>
</tr>
<tr>
<td><strong>PAO</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>RMS Error</td>
<td>0.13</td>
<td>0.14</td>
</tr>
<tr>
<td>Bias Proportion</td>
<td>0.87</td>
<td>0.45</td>
</tr>
<tr>
<td>Variance Proportion</td>
<td>0.06</td>
<td>0.17</td>
</tr>
<tr>
<td>Coviance Proportion</td>
<td>0.07</td>
<td>0.38</td>
</tr>
</tbody>
</table>

The table reports the root mean square errors and the proportions of bias, variance, and covariance, respectively, from 2012Q1 to 2013Q2 across all BSI, FSF and PAO from CIMDO copula for the banking group index, the Luxembourg bank index and the worst investment fund (among MMFs & NMMFs).