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TRACKING CHANGES IN THE INTENSITY OF FINANCIAL SECTOR'S SYSTEMIC RISK

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Tracking Changes in the Intensity of Financial Sector's Systemic Risk

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Abstract

This study provides the first available estimates of systemic risk in the financial sector comprising the banking and investment fund industries during 2009Q4 -2015Q4. Systemic risk is measured in three forms: as risk common to the financial sector; as contagion within the financial sector and; as the build-up of financial sector's vulnerabilities over time, which may unravel in a disorderly manner. The methodology models the financial sector components' default dependence statistically and captures the time-varying non-linearities and feedback effects typical of financial markets. In addition, the study estimates the common components of the financial sector's default measures and by identifying the macro-financial variables most closely associated with them, it provides useful input into the formulation of macro-prudential policy. The main results suggest that: (1) interdependence in the financial sector decreased in the first three years of the sample, but rose again later coinciding with ECB's references to increased search for yield in the financial sector. (2) Investment funds are a more important source of contagion to banks than the other way round, and this is more the case for European banking groups than for Luxembourg banks. (3) For tracking the growth of vulnerabilities over time, it is better to monitor the most vulnerable part of the financial sector because the common components of systemic risk measures tend to lead these measures.

JEL Classification: C1, E5, F3, G1

Keywords: financial stability; macro-prudential policy; banking sector; investment funds; default probability; non-linearities; generalized dynamic factor model; dynamic copulas.

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Résumé non-technique

Cette étude fournit les premières estimations disponibles du risque systémique dans le secteur financier, défini comme englobant des banques au Luxembourg, leur maisons mères européennest et les sept types d'organismes de placement collectif (OPC) que les banques centrales nationales de l'Eurosystème rapportent à la Banque Centrale Européenne : fonds actions, fonds obligataires, fonds mixtes, fonds immobiliers, fonds alternatifs, autres fonds et fonds monétaires. Le risque systémique est mesuré selon trois formes: le risque commun au secteur financier, la contagion et l'accumulation de vulnérabilités du secteur financier dans le temps qui pourraient eventuellement se dénouer de manière désordonnée.

Le cadre conceptuel utilisé dans cette étude modélise explicitement l'interdépendance complexe et variable dans le temps entre les institutions financières; il permet également de répresenter les effets de contagion entre les établissements financiers situés dans différentes juridictions; il prend en compte à la fois les liens observables et les liens cachés entre les institutions financières et l'économie réelle et, enfin; il permet de fournir des projections hors-échantillon des mesures de vulnérabilités.

Le cadre conceptuel est le même que celui proposé par Jin et Nadal De Simone (2014). Premièrement, les probabilités de défaut (PD) sont estimées à partir du modèle de risque de crédit structurel de Merton (1974). Deuxièmement, l'approche de Segoviano (2006) est utilisée afin de modéliser l'interdépendance entre les banques, entre les OPC, entre les deux types d'acteurs ainsi que les effets de rétroaction (« feedback effects ») entre le système financier et l'économie réelle. Le cadre est donc utilisé pour modéliser le risque extrême ("tail risk") dans le système financier (Segoviano et Goodhart, 2009, Gorée et Radev, 2011). Troisièmement, le cadre est appliqué à une large base de données macro-financières afin d'extraire la composante commune des PDs au niveau des groupes bancaires, de leurs filiales luxembourgeoises et des OPC.

En ce qui concerne les banques luxembourgeoises et les OPC, l'étude a recours à la base de données de la Banque centrale du Luxembourg. Cette base de données est beaucoup plus riche que celles utilisées dans les études précédentes qui se basaient sur des données publiques sur les banques et en se limitant à des données de rendement sans information sur le levier des OPC ou sur leurs liens avec les banques.

Les principaux apports de cette étude sont les suivants. Tout d'abord, cette étude est, au meilleur de la connaissance des auteurs, la première application complète de l'analyse des créances contingentes (à la Gray et Malone, 2008) aux banques et OPC.

Deuxièmement, tout en suivant l'approche de Segoviano et Goodhart (2009), cette étude diffère dans plusieurs aspects importants. Compte tenu de l'absence de données concernant les credit-default swaps et les obligations de nombreuses banques ainsi que du fait que les parts des OPC ne soient pas négociées, le modèle de risque de crédit de Merton est estimé à partir des feuilles bilantaires des institutions financières comme dans Souto et al (2009), Blavy et Souto (2009), et Jin et Nadal De Simone, (2011, 2014 et 2015).

Troisièmement, cette étude identifie explicitement les liens entre les mesures du risque systémique dans le système financier et les variables macro-financières, ce qui n'a pas été fait dans la littérature empirique antérieure. Le cadre proposé identifie les variables macro-financières les plus étroitement associées au risque systémique.

Quatrièmement, en identifiant les principales variables plus étroitement associées aux vulnérabilités du système financier, le cadre proposé identifie explicitement les variables économiques et financières que les responsables de la politique macroprudentielle devraient surveiller afin de prévenir ou d’atténuer toute instabilité financière.

Enfin, et tout aussi important pour l'élaboration des politiques macroprudentielles, le cadre proposé peut fournir des prévisions hors échantillon raisonablement solides des mesures du risque systémique du secteur financier.

Les principaux résultats montrent que: 1) l'interdépendance dans le secteur financier a diminué au cours des trois premières années de la période d'échantillonnage, 2008-2011, mais a de nouveau augmenté par la suite au même temps que la BCE dénonçait une augmentation du “yield search” dans le système financier. 2) Tandis que le degré d'interdépendance entre les banques et les OPC a été très variable au cours de la période étudiée, il y a lieu d’observer une nette asymétrie dans ces interconnexions puisque les OPC représentent une source plus importante de contagion pour les banques que l'inverse, ce qui est davantage le cas pour les groupes bancaires européens que pour les banques luxembourgeoises. 3) Toutefois, alors que les vulnérabilités dans les OPC peuvent présenter un risque de contagion plus élevé pour les banques que vice-versa, il semble que, pour surveiller la croissance des vulnérabilités au fil du temps, il soit préférable de surveiller la part la plus vulnerable du secteur bancaire parce que les composants communs de mesures du risque systémique ont tendance à prendre le pas sur les mesures de risque systémique elles-mêmes. 4) Le risque systémique dans le secteur financier résultant de l'interaction entre les banques et les OPC doit être analysé non seulement du point de vue de leurs participations croisées, mais nécessite également de prendre en compte les liens indirects entre les banques et les OPC par le biais des prix du marché et des corrélations des rentabilités des portefeuilles qu'ils détiennent. 5) Les principales variables étroitement associées aux PD marginales sont similaires à celles associées aux mesures de risque systémique. Le cout de financement comme les taux d'intérêt et le spreads, et la croissance du PIB (ainsi que d'autres indicateurs de l'état de l'économie, tels que le taux de chômage) sont les variables plus etroitement associées aux mesures de risque systemique, suivie par de quantités de financement, comme la croissance du crédit.

Plusieurs enseignements pour la formulation de la politique macroéconomique peuvent être tirés de cette étude. Étant donné que l'étude lie explicitement les mesures de risque systémique à l'état de la situation macroéconomique, elle fournit un cadre pour un débat plus éclairé quant aux mesures à prendre afin de remédier à ces vulnérabilités. En tant que tel, le cadre peut aussi être utile pour l'étalonnage des instruments macroprudentiels. En outre, l'étude contribue à une mesure plus robuste du risque systémique en permettant d'évaluer les passifs éventuels découlant du système financier et, compte tenu de la condition de parité call-put intégrée dans le modèle Merton, de determiner aussi les pertes contingentes au status quo. En outre, cette étude contribue à l'élaboration de la politique macro-prudentielle en proposant un cadre pour la prévision des changements des risques systémiques financiers qui permet d'apporter une solution à la problématique selon laquelle la simple agrégation des PD marginales et leur projection dans le futur produit une mesure du risque systémique biasée vers le bas. Finalement, le cadre améliore les performances hors-échantillon de prévision du modèle en intégrant les composantes communes et idiosyncrasiques d'un large ensemble de variables macro-financières. Ceci rend le cadre utile dans les tests d'endurance du système financier.

I. Introduction and Motivation

The specific objective of this paper is to estimate measures that track systemic vulnerabilities in the financial sector over time with the intention of contributing to the formulation of macro-prudential policy. While there is no widely accepted definition of macro-prudential policy, its objective or its instruments (Galati and Moessner, 2011), in this paper, consistent with the European Central Bank's (ECB) approach, macro-prudential policy will be viewed as geared toward limiting systemic risk in order to minimize the costs of financial instability imposed on the economy (ECB, 2010a and 2010b).[1] The sources of financial instability in this study are circumscribed to those emanating from the financial sector, which comprises 30 major European banking groups, their respective 32 subsidiaries active in Luxembourg, to two 100%-owned Luxembourg banks, as well as to all seven different types of investment funds reported by the National Central Banks of the Eurosystem to the ECB.[2] Insurance companies and pension funds are not considered. Banks included in this study represent about 62% of the assets of Luxembourg's banking industry. Regarding investment funds, Luxembourg is the second largest domicile of Undertakings for Collective Investments in Transferable Securities (UCITS) in the world after the US and the third domicile of non-UCITS after Germany and France. At end-2015, Luxembourg-domiciled banks managed almost 747bn euro of assets and investment funds managed almost 3.5 trillion euro of assets. The importance of banks and investment funds for Luxembourg and the significance of the country in the financial world underpin the value of this study.

The banking sector and investment funds in Luxembourg have strong linkages.[3] Banks rely on investment funds as a source of short-term funding.[4] Money Market Funds (MMFs) are used by non-financial firms and households as a cash-management tool and some have deposit-like features.[5] Investment funds (other than MMFs) engage in 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

[1] Similarly, for the European Systemic Risk Board, 2013, macro-prudential policy seeks to safeguard the stability of the financial system.

[2] The world investment fund industry managed about 35 trillion euro of assets at the end of the third quarter of 2015. 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 US. European investment funds managed over 12.6 trillion euro at end-2015. Therefore, in the EU, total assets managed by all categories of investment funds at end-2015 represented over 85% of its GDP.

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

[4] 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).

[5] See European Systemic Risk Board (2012) for a description of the systemic risks posed by MMFs.

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 formulate and implement macro-prudential policy, it is first necessary to agree on the definition and measurement of systemic risk.[6] This paper uses Jin and Nadal De Simone (2014 and 2015) definitions of systemic risk, which combines 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). Systemic risk can take the three forms categorized by the ECB (2009): first, of a common shock that affects the financial sector as a whole and gets transmitted to the real economy, or *systematic risk*; second, of 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, of a slow build-up of vulnerabilities in the financial sector that may unravel in a disorderly manner and affect the real economy.[7] [8] Therefore, in this paper systemic risk is measured in its cross-section dimension and in its time-dimension (Bisias *et al*, 2012). 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*, 2010, Gorea and Radev, 2011). This paper studies both dimensions of systemic risk, a perspective of risk which is gathering acceptance.

This study uses Merton’s (1974) structural credit risk model to estimate implied neutral probabilities of distress (PDs).[9] To model dependence between default events and between credit quality changes statistically (Lando, 2004), 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, which has been used to model tail-risk (Segoviano and Goodhart,

[6] A seminal work in cataloguing instruments and objectives of macro-prudential policy as well as risk identification and assessment is the handbook and the flagship report of the European Systemic Risk Board (2013b, 2013c).

[7] Systemic risk in this study refers to *systemic credit risk*. There are also other sources of systemic risk, such as systemic liquidity risk, for example.

[8] See Benoit *et al*, 2015, for a recent survey of measures of systemic risk understood as “ the risk that many participants are simultaneously affected by severe losses, which then spread through the system.” This is a narrower definition than the one adopted in this study.

[9] Importantly, for macro-prudential 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 (2014), however, this study cannot use Delianedis and Geske’s (2003) model given that the length of the sample available for investment funds is binding.

2009).[10] 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). [11] For the prior correlation input into 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.[12] 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. 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 using the Generalized Dynamic Factor Model (GDFM) of Forni *et al* (2005) to link the PDs and measures of systemic risk with a large macro-financial database. 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 if the forecast is to include the idiosyncratic component and not only the common component, and it does not generate the distribution of forecasts. To address those shortcomings, this study introduces an approach similar to Jin and Nadal De Simone (2012, 2014) 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 directly from the interdependence of financial institutions, but also from the macro environment.

All these key features that matter for estimating systemic risk are not taken into account by other methodologies such as the Systemic Expected Shortfall (SES) of Acharya *et al* (2009), or the Deposit Insurance Premium of Huang *et al* (2010), which are bivariate

[10] 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.

[11] This behaviour cannot be detected from a standard correlation model (Chan *et al*, 2007).

[12] 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 currently available sample size makes it impossible.

techniques as opposed to the multivariate nature of this framework.[13] Similarly, the CoVaR methodology of Adrian and Brunnermeier (2008) is driven by the objective of determining the systemic importance of financial institutions, which the framework of this paper also allows, but it has the additional advantages of permitting the estimation of common sources of systemic risk, its latent drivers, the non-linearities and feedback effects typical of financial markets, and it does not suffer from the CoVar lack of additivity. In addition, these measures share the pitfall of not allowing to clearly identify the form of risk at play. Finally, the SES measures only the systematic risk of a firm. However, this may not be sufficient for measuring its contribution to systemic risk as the market expected shortfall may not be constant over time.

The empirical literature explicitly linking banks and investment funds is very limited, and it has normally used banks' public data and publicly available investment funds' returns covering, with some exceptions, mostly US-domiciled investment funds. Boyson *et al* (2010), defining contagion as correlation over and above the one expected from economic fundamentals, found strong evidence that large adverse shocks to funding and asset liquidity significantly increased the probability of contagion from 1990 to 2008. Acharya *et al* (20009) measured the contribution of banks and a set of non-bank financial institutions 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 also constructed in-sample and out-of-sample measures of systemic risk. Dixon *et al* (2012) analyzed the contribution of hedge funds in the US to the 2007-2008 crisis and found that while they 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, their 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 had strong linkages with MMFs. These results were broadly confirmed by Gossé and Smole (2015).

This study makes several contributions to the literature. 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 model interdependence between

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[13] In addition, the Systemic Expected Shortfall and the Deposit Insurance Premium measures require market capitalization data, and CDS data in the case of the latter measure, which in this study is only available for European banking groups.

the Luxembourg banking sector, the European banking groups they belong to and the whole Luxembourg investment fund sector. As a corollary, this study can also measure contagion across financial institutions located in different jurisdictions.

Second, while following the CIMDO approach illustrated by Segoviano and Goodhart (2009),[14] this study is different in several significant ways. Given the lack of credit-default swaps (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, (2011, 2014 and 2015).

Third, this study explicitly identifies both the observable and the latent links between measures of credit risk in the financial sector and macro-financial variables, which has not been done for the financial sector in earlier empirical literature. As a result, it identifies the macro-financial variables most closely associated with systemic risk, i.e., GDP growth, credit growth and interbank activity, which is in line with the survey in Frankel and Saravelos (2010). It also points to the relevance of measures of business confidence. As such, this study measures systemic risk taking into account the non-linearities of the financial system, the time-varying interdependence among financial institutions and the feedback effects between financial institutions and markets. In particular, this stresses that the interaction between banks and investment funds should be analyzed not only via their direct cross-holdings they display, but it requires to take into account the indirect links via the market price and return correlations of the portfolios they hold.

Fourth, by identifying the main variables more closely associated with the vulnerabilities in the financial sector, the framework explicitly pinpoints to the economic and financial variables that policymakers should monitor to preserve financial stability. The framework thus helps calibrating the macro-prudential instruments.

Finally, and importantly for policymaking, the framework can also produce robust out-of-sample forecasts of the financial sector's credit risk measures in agreement with work applied to banks by Koopman *et al* (2010), Schwaab *et al* (2010) and Jin and Nadal De Simone (2014).

The main findings of this study are the following. First, while the degree of dependence in the financial sector as measured by the Financial Stability Index (FSI) has been very

[14] Segoviano and Goodhart's (2009) proposed systemic risk measures circumscribed to banks. See Jin and Nadal De Simone (2014b) for an application to Luxembourg investment funds.

volatile over the sample period and tended to increase during the last part of the sample period, there is a clear asymmetry in dependence in the sense that banks' contagion likelihood from investment funds' distress tends to be higher than vice versa. The implication is that investment funds matter more for *systemic risk in the form of contagion* to banks than the opposite. This is relatively more the case for European banking groups than for Luxembourg banks.

Second, overall, the Financial Sector Fragility - FSF (measured as the probability that at least two financial institutions get distressed) remained high during until mid-2012, and then declined in most scenarii considered. This trend has been also clear in the common component of the fragility measure and is most likely associated to the Eurosystem successful longer-term refinancing operations with a maturity of 36 months (3YLTROs) in December 2011 and February 2012 and the following measures to increase liquidity.

Third, the second form of systemic risk - PAO (measured by the probability that at least one financial institution becomes distressed given that there is already one financial institution in distress) oscillated during the sample period, with a tendency to increase in 2011 until the second half of 2012 at least in some scenarii, most likely due to the augmented sovereign tensions in the euro area. The PAO rose after the 3YLTROs measures were taken despite a tendency of the PAO common component to fall in agreement with the general nature of the policy measure. The Dependence Distress Matrix (DDM) measure of contagion confirms these results.

Fourth, the most important macro-financial variable closely linked to the three measures of systemic risk reported tend to be funding prices (e.g., interest rates, spreads and stock price indexes), followed by variables linked to the state of the economy (e.g., GDP and unemployment), and funding quantities follow (notably credit, the credit gap and interbank lending and borrowing). However, when the fragility of the financial sector is assessed, the state of the economy is equally important as funding prices in once case or more important than funding prices in another case. It is noteworthy that these cases are those where Luxembourg banks play a relatively larger role.

Finally, while as stated above vulnerabilities in investment funds can pose a higher contagion risk on banks than the other way round (the second form of risk), it seems that for tracking the change in vulnerabilities over time (the third form of systemic risk), it is relatively better to monitor the worst corner or the tail risk of the financial sector given that the common components of systemic risk measures display a latent early-warning behavior.

The remainder of the study is organized as follows. The next section briefly introduces the integrated modelling framework and explains how to combine the Merton model and the GDFM with the CIMDO. Section III describes the systemic risk measures. 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

This study uses the integrated framework developed by Jin and Nadal De Simone (2014) to measure systemic risk emanating from banks and investment funds and their interdependence. To conserve space, only the main, possibly less well-known features of the framework, are concisely discussed below while directing the reader to the sources of its well-known components, i.e., the Merton (1974) model and the GDFM (Forni *et al* 2005).

First, it is better to look at the output part of the integrated framework, the CIMDO model. In this part, the prior dependence structure information incorporated into the CIMDO is exogenously estimated by a rolling window on asset returns adjusted by Qi and Sun's (2005) nearest correlation matrix. 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. 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 study lies. The output generated is a set of systemic risk measures originally proposed by Segoviano and Goodhart (2009) and by Radev (2012) for banks, which are applied here to both banks and investment funds: the FSF and the FSI, which measure common distress in the financial sector, the first form of systemic risk identified by the ECB (2009); the DDM which measures distress between specific financial institutions (i.e., banks and or investment funds) and the PAO, both of which proxy the second form of systemic risk identified by the ECB (2009).

Second, the input part of the integrated framework is Merton's (1974) option-based structural credit risk model, which is used to track credit risk over time. The PDs, together with asset returns, are direct inputs into the CIMDO model. However, as discussed above, given the possibility of risk mispricing over time, a final component of the proposed framework is the GDFM combined with a dynamic t-copula.[15] This part of the framework not only decomposes the systemic risk measures into two sets of unobserved components, the common component and the idiosyncratic component, but can also provide an out-of-sample forecasting of these components. The common component is best viewed as the result of the underlying unobserved systematic factors driving the measures, 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 marginal PDs 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.

2.1. The Book-Value-Based Merton

The data available on banks and investment funds for this study is purely balance sheet information. As a result, Merton's model cannot be applied directly to calculate PDs. An alternative approach has to be followed. Souto *et al.* (2009) and Blavy and Souto (2009) have shown that book-based Merton's credit risk measures are highly correlated with market-based Merton's credit risk measures.[16] Adrian and Shin (2013) have forcefully argued that the key state variable in applying financial frictions in asset pricing modeling is leverage calculated as the ratio of total assets to book equity. In addition, they show that US 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 (and for European 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

[15] Both copulas and quantile regressions have been extended to a dynamic environment (e.g., Patton, 2006a, 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 allows a direct examination of dependence structure 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.

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

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.[17] In a similar vein, Danielsson *et al* (2012) argue that "… 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 approach is followed here.

The volatility of book-value assets is calculated by a rolling window (RW) as follows:[18]

$$\sigma_B = \sqrt{\sum_{t=1}^{N} (\ln(V_t^B / V_{t-1}^B))^2}$$

where V_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[19] of the Merton model can be directly estimated by:

$$\pi_B = N(-\frac{\ln(V^B / X) + (r - \frac{1}{2}\sigma_B^2)(T-t)}{\sigma_B \sqrt{T-t}}),$$

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:

$$DD_B = \frac{\ln(V^B / X) + (r - \frac{1}{2}\sigma_B^2)(T-t)}{\sigma_B \sqrt{T-t}}.$$

Investment funds in this paper are analyzed at the aggregate type-level and thus, the level of book-value risk neutral PD can be very low, close to zero. As a result, to avoid indeterminacy within CIMDO, PDs of banks and investment fund types in this study are estimated subject to rescaling Merton's DD so that the lowest possible level of π_B is 1^{e-5}.

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

[17] 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.

[18] Following usual practice, quarterly volatility is annualized.

[19] 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 on 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".

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:

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

where PD_t^x and PD_t^y are empirically observed probabilities of distress for these two financial entities, and $p(x;y)$, $q(x;y) \in \Re^2$ are the posterior and the prior distributions accordingly, with λ_1, λ_2, and λ_3 being, 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_t for each obligor is described in the upper part of a distribution over its distress-threshold x_d^x or x_d^y, respectively. The optimal solution for the posterior density is of the form:

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

This solution stresses the importance of the distress thresholds and PDs 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 the 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. 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.[20] By construction, the CIMDO copula puts a greater emphasis on the distress region of the joint distribution providing a robust and consistent method to estimate the distress dependence of financial institutions.

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 interaction among banks, investment funds and the macro environment. 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.[21] First, there are 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, there are the idiosyncratic components,

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[20] 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.

[21] 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. Jin and Nadal De Simone (2014) discuss how the number of factors may change over time, which stresses the need to use the above-mentioned statistical tests especially when the objective is to do real-time updates of measures of systemic risk even when using the one-sided GDFM of Forni *et al* (2005). An additional technical point is that for the GDFM estimation, this paper uses the low integer of the squared root of the number of observations as suggested by Forni *et al* (2005).

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 of the integrated framework, 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.

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 sector systemic risk that are consistent with the ECB's (2009) categorization of the three forms of systemic risk referred to above. The measures based on Segoviano and Goodhart's (2009) and Radev's (2012), however, 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 in a disorderly manner. Measuring it requires a structural approach and a link between a measure of vulnerability in the financial sector and the macroeconomy as the one suggested. In this study, it is done by relating marginal PDs and the proposed systemic risk measures to a broad set of macro-financial variables that drive them by using the GDFM. This approach makes it possible to detect a few quarters in advance the build-up 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 Form of Systemic Risk: Common Distress

Two proxies of the first form of systemic 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 an adaptation to the financial sector of the Banking System Fragility measure suggested by Radev (2012). This is the Financial Sector Fragility measure (FSF). The FSF 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:

$$FSF = P\left(X \geq \chi_d^x, Y \geq \chi_d^y\right) + P\left(X \geq \chi_d^x, Z \geq \chi_d^z\right) + P\left(Y \geq \chi_d^y, Z \geq \chi_d^z\right) + P\left(X \geq \chi_d^x, Y \geq \chi_d^y, Z \geq \chi_d^z\right).$$

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^x, x_d^y or x_d^z.

The second measure of the first form of systemic risk is the Financial Stability Index (FSI). The FSI measures the *expected number* of financial institutions that will become distressed conditional on any one financial institution having become distressed as a result of a common shock.[22] When the FSI=1, the linkages across financial institutions are minimal. As the FSI increases above 1, it means that dependence among institutions increases. This can happen, for example, as a result of a relatively looser monetary policy stance that entices market participants to search for yield by moving their portfolio allocations to higher-return, higher-risk securities. The measure is:

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

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 Form of Systemic Risk: Idiosyncratic Distress and Contagion

Two measures are calculated to proxy the second form of systemic risk. The first one is designed to capture distress between specific financial institutions or groups of financial institutions. This is the Distress Dependence Matrix (DDM). 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, the probability of distress of financial institution X conditional on financial institution Z becoming distressed is:

[22] Segoviano and Goodhart (2009) discuss this same measure applied to banks. In fact, the measure was originally designed by Huang (1992) and Hartman *et al* (2001) made its first empirical application. The latter explain, using extreme value theory, why these probabilities can be interpreted as numbers.

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

The second measure is designed to capture distress in the financial sector as a result of distress in a specific bank (or groups of banks) or type of investment fund. The measure is calculated as the 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 (PAO). The PAO 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.

Assuming a financial sector 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:

$$\begin{aligned} PAO = {} & P\left(X \geq \chi_d^x / Z \geq \chi_d^z\right) + P\left(R \geq \chi_d^R / Z \geq \chi_d^z\right) + P\left(Y \geq \chi_d^Y / Z \geq \chi_d^z\right) - \\ & [P\left(X \geq \chi_d^x \cap R \geq \chi_d^R / Z \geq \chi_d^z\right) + P\left(X \geq \chi_d^x \cap Y \geq \chi_d^Y / Z \geq \chi_d^z\right) + \\ & P\left(R \geq \chi_d^R \cap Y \geq \chi_d^Y / Z \geq \chi_d^z\right)] + P\left(X \geq \chi_d^x \cap R \geq \chi_d^R \cap Y \geq \chi_d^y / Z \geq \chi_d^z\right). \end{aligned}$$

3.3. The Third Form of Systemic Risk: Slow Build-up of Vulnerabilities

As stated above, systemic risk can also manifest itself in a third, more subtle way via the build-up of vulnerabilities, often latent, over time. This form of systemic risk is clearly more difficult to measure than the other two. 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 macro-financial 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 as meaured by GDP growth, credit and interbank markets activity. However, as also shown in this paper, the common components of the measures of financial systemic risk, i.e., the FSI and the PAO, may also contain important leading information on the build-up of vulnerabilities in the financial sector.

IV. Data

This study is applied to 30 major European banking groups, to their respective 32 subsidiaries active in Luxembourg, to two 100%-owned Luxembourg banks, as well as to all seven different types of investment funds reported by the 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 2008 and finishing on December 2015. While the length of the balance sheet data on investment funds is much shorter than the one available for banks, this is still a much richer balance sheet database than what can be found in the literature 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.[23]

The macroeconomic database also includes data from 15 countries: Belgium, Canada, Denmark, France, Germany, Greece, Japan, Luxembourg, the Netherlands, Italy, Spain, Sweden, Switzerland, United Kingdom, and the United States. Market data used for the major European banking groups include government bond yields, stock price indices, industrial production, employment, GDP, consumer prices, housing prices, exchange rates, credit, 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). The database comprises 234 series including three measures of the credit-to-GDP gap for the euro area, the UK and the US. Adding the macroeconomic variables to the PDs used for the Luxembourg banks, the European banking groups and the seven investment funds categories increases the database size to 305 series.

All the Luxembourg banks are unlisted, so quarterly book value data from the Banque centrale du Luxembourg's database are used.[24] The 32 subsidiaries registered in Luxembourg represent about 55% of the total assets of the Luxembourg banking industry. When the two 100%-owned Luxembourg banks are added to the list, the database represents nearly 62% of the total assets of the banking industry. For banks and investment funds, the short-term debt includes deposits of up to one-year maturity, short term funding and repos, while the long-term debt includes time deposits with a maturity of more than one year and other long-term funding. For European banking groups, one difficulty is that short-term debt (BS047) and long-term debt (BS051) from Bloomberg have annual, semi-annual, and quarterly frequencies. To make the data consistent, four filtering rules are used as described in Appendix III.

[23] As the majority of studies on investment funds refer to the US investment funds industry, it is pertinent to mention that before Dodd-Frank, regular filings of Hedge Funds in the US did not include critical information such as leverage, liquidity, major creditors and obligors, or the terms under which capital is committed.

[24] 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.

The use of a homogeneous accounting system allows the estimation of two sets of PDs and measures of systemic risk for the Luxembourg banks. The first set considers 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 (set 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. The important point this result suggests is that systemic risk in the financial sector as a result of the interaction between banks and investment funds must be analyzed not only from the viewpoint of the direct cross-holdings they display, but requires to take into account the indirect links among banks and investment funds via the market price and return correlations of the portfolios they hold.

V. Empirical Results

This section first discusses developments in systemic risk that result from the different scenarii studied. Then, it analyzes in particular the direction of contagion—the second form of systemic risk—between investment funds, Luxembourg banks and the European banking groups to which they belong. It follows a discussion of the variables most closely associated with marginal PDs and systemic risk measures. Finally, the out-of-sample forecasting capabilities of the framework are illustrated.

5.1. Developments in Systemic Risk

Different scenarii are used to describe systemic risk developments in Luxembourg's investment funds, Luxembourg banks and their respective European parents. The set of scenarii discussed has been selected among a much larger number of possible combinations allowed by the flexibility of the framework. The choice of the scenarii is motivated by the objective of covering the main areas of interest of systemic risk analysis in current theoretical and policy discussions. For example, the chosen scenarii lend themselves to assess the relative significance of contagion from the banking industry to the investment fund industry and vice versa; to study the role of banks' size in systemic risk developments; the degree of leverage legally permitted for different investment fund types and its impact on systemic risk and; the cross-border spillovers of systemic risk.

The systemic risk measures discussed above were estimated for six scenarii:.

- 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: the worst investment fund performer and four Other Systemically Important Institutions (O-SIIs), with PAO conditional on the worst investment fund type performer;
- Scenario 4: the worst investment fund performer and four Global Systemically Important Banks (G-SIBS), with PAO conditional on the worst investment fund type performer;
- 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;
- Scenario 6: the worst or fixed investment fund performer and small-, medium- and large-size Luxembourg banks and European banking groups, with PAO conditional on the worst or fixed investment fund type performer.

Before discussing the scenario, two points are noteworthy. First, 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 feasible 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 with the exception of the PAO measure of certain scenarii, which will be discussed below.

Second, common components can be estimated using two-sided or one-sided filters corresponding to Forni *et al* (2000) and Forni *et al* (2005) methodologies, respectively. The one-sided filter is used in this paper because the objective is to perform end-of-sample estimation[25] and to illustrate the forecasting capacity of the framework. In addition, the one-sided filter provides substantial improvement over the two-sided filter when one suspects substantial cross-sectional heterogeneity in the lag structure of the factor loadings, and especially, in the common-to-idiosyncratic variance ratios (Forni *et al*, 2005). This should be kept in mind when interpreting the results.

[25] The one-sided filter lends itself more easily to track systemic risk developments in real time and is thus particularly useful for a policymaker. See Jin and Nadal De Simone, 2014 for an application.

The First Form of Systemic Risk: the FSI as a Measure of Dependence

Investment funds have a predominant role in scenario 1. When the FSI=1, the linkages across financial institutions are minimal (Segoviano and Goodhart, 2009). So, the observed FSI increase above 1 might signal an increase in dependence among financial institutions. The FSI of scenario 1 shows a slight decline during the first two years of the sample. However, it started rising to new high levels coinciding with the first and second 3YLTROs conducted by the Eurosystem in December 2011 and February 2012, respectively (Figure 1a)[26]. After peaking in June 2013,[27] the FSI followed a downward trend up to June 2014, when it started increasing again coinciding with the ECB Governing Council's decision to make the interest rate on the deposit facility negative (-0.10%). It kept rising until March 2015, coinciding with the ECB's expanded asset purchase program (APP) which encompassed a set of euro-denominated investment-grade public sector securities and integrated the existing purchase programs for asset-backed securities (ABSPP) and covered bonds (CBPP3) launched in autumn 2014. The combined monthly purchases of the program amount to 60 billion euro per month (1,140 billion euro in total) until September 2016.

Given that the FSI measures dependence among financial institutions as a result of a shock common to the system, it seems that while the 3YLTROs clearly had the intended effect of reducing the cost of financing in the financial industry as shown by the improvement in market liquidity conditions, the policy measure might have also increased dependence in the financial sector. This seems reflected in the behavior of the FSI in scenario 1 which stresses the role of investment funds in systemic risk measures.

For some time, the ECB has been stating its concern about yield search in the financial sector in a context of protracted low interest rates (e.g., ECB Financial Stability Review, November 2014, p. 8, and November 2015, p. 47). The ECB has mentioned in particular the rise in balance sheet leverage of investment funds since 2013, in particular in the

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[26] 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 enlarge the set of eligible collateral. The 3YLTROs 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 operations. The two allotment dates were established as 21st December 2011 and 29th February 2012, and banks requested 489.2bn euro and 529.5bn, respectively. See ECB (2013), for example, for an account of the evolution of funding (and market) liquidity before and after the 3YLTROs were performed.

[27] The ECB reported that during the first half of 2013, repayments of 3YLTROs represented 59% of the initial injection of central bank liquidity in the market (ECB, July 2013). Higher-than-expected repayments led to a short- lived rise in short-term interest rates.

case of hedge funds and bond funds.[28] This behavior increases correlation across asset classes rising thereby dependence among financial institutions (e.g., Dell'Ariccia *et al*, 2013). This interpretation seems supported by the trend increase in the FSI common component as well as by the reversal of the idiosyncratic component of the FSI, which had been pulling down the overall risk measure, since end-2011 until 2015.[29] This interpretation is consistent with the behavior of the FSI in other scenarii. The FSI and its common component do not display major changes over the sample period in scenarii 2 and 3, respectively Figures 1b and 1c, except during 2015 when there is a clear rise in dependence across all scenarii. Except in 2015, there was no major change in dependence in what can be considered as the worst corner of systemic risk, i.e., the two worst banking groups, the two worst Luxembourg banks and the worst investment fund (scenario 2), and among the four Luxembourg O-SIIs (scenario 3). In addition, when the four banking groups and the worst investment fund are taken into account (scenario 4, Figure 1d), the FSI and its common component fall from the last quarter of 2011 until the second half of 2013. This supports the interpretation that the increase in dependence was localized in the investment fund industry, at least until 2015, when it became more widespread.[30] This important matter clearly requires further study.

The First Form of Systemic Risk: The FSF as a Measure of Fragility

The measure of common distress potential, the FSF, displays a similar pattern across scenarii 1-3 in that it increased roughly until the second 3YLTROs, fell and then rose again transitorily during the last quarter of 2014 in scenarii 1 and 2 (Figures 2a and 2b). This suggests that fragility was overall reduced in the worst corner of the financial system represented by scenario 2. This behavior was likely due to turbulences in Europe associated with the sovereign debt crisis and its negative implications on risk premia and liquidity. It is noteworthy that the FSF common components were either stable or on a broadly declining trend, except in the case of the four Luxembourg O-SIIs, which common components increased from 2014Q2 to the end of the year (Figure 2c). The behavior of the common components of the FSF is consistent with the common shock nature of events the 3YLTROs and other policy measures intended to address.

[28] The EU bond fund sector is large (3 trillion euro), holds a significant proportion of illiquid assets and plays an important role as provider of marginal liquidity in secondary bond markets. In the less liquid non-financial corporate markets, more than 25% of debt securities outstanding were held at end-2014 by investment funds (ECB, FSR May 2015. In the much larger markets for government and bank debt securities, investment funds held 12% and 9%, respectively. Luxembourg-domiciled bond investment funds held 378bn euro at end-2014.

[29] Lucas *et al* (2012) provide an analysis of the difference between policy measures such as 3YLTROs that address common shocks and those that are more geared to addressing idiosyncratic shocks, very much in the spirit of this section's discussion.

[30] A rise in correlation across assets classes is also mentioned by the ECB in its November 2015 Financial Stability Review.

As with the FSI, this interpretation is supported by other scenarii. First, in scenario 2 the financial sector fragility started falling after the second 3YLTROs (Figure 2b). Second, with a two-quarter lag, the common component of the FSF of the four OSIIs decreased, while the common component of the four G-SIBs remained stable (Scenarii 3 and 4, Figures 2c and 2d, respectively). In scenarii 3 and 4, 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 O-SIIs.[31] As displayed below in Table 3b, which shows the impact of distress of investment funds on banks, it seems that both MMF and NMMF distress increased since mid-2012 until the end of the sample. These results support the view that liquidity-enhancing policy measures had the expected effect of reducing the common form of systemic risk and the fragility of the financial sector stemming from the banking sector.

The Second Form of Systemic Risk: The PAO as a Measure of Contagion Risk

In scenario 1, the PAO oscillated during the sample period, with a clear tendency to increase in 2011 until the second half of 2012, most likely due to the augmented sovereign tensions in the euro area (Figure 3a). The PAO rose after the 3YLTROs measures were taken despite the fact that the PAO common component fell in agreement with the general nature of the policy measure. The PAO trend and its common component have been broadly downward since them.

While a broadly similar pattern is visible in first half of the sample in scenario 2 (Figure 3b), contagion increases in the worst corner of systemic risk after 2013. In contrast to other systemic risk measures, and for this scenario only, there is a clear difference between including or excluding investment fund asset and liability holdings by banks. After the second LTROs, PAO fell in scenario 2 although the common component remained high indicating again that contagion came mostly from the investment fund industry. The same is true during 2015. This is confirmed by a large increase in the probability of distress stemming from the investment fund industry (Table 3b). As a result, it seems that the 3YLTROs was successful in reducing systemic risk stemming from the banking sector although the investment fund industry continued to contribute to it. This is addressed in more detail in the next section.

Another interesting development in the PAO is the very significant fall of the idiosyncratic component of the measure at the times of the 3YLTROs among Luxembourg O-SIIs and the worst investment fund (Scenario 3, Figure 3c).This was likely a result of the reduced

[31] Recall that these scenari include the worst investment fund.

funding needs of European parent companies and the ensuing fall in funding demand reflected in Luxemburg banks' balance sheets.

To summarize, developments in the different measures of systemic risk depict the following situation in the financial sector. First, while the 3YLTROs and other non-standard monetary policy measures were successful in reducing the common form of systemic risk as reflected in the FSF common component, they might have also increased dependence in some sections of the financial sector as reflected by the FSI common component. The common components of these two measures of systemic risk are strongly negatively correlated, especially after the second 3YLTROs. This may suggest that, for example, while a reduction in funding costs reduces the common component of the vulnerability measure FSF, it may also increase the common component of the FSI because the fall in funding costs, *ceteris paribus*, induces a search for yield and more risk taking, which makes it more likely that more financial institutions will get distressed. This point has been raised by the ECB on several occasions, as mentioned above. Second, the flexibility of the framework enhances its value for policymaking as illustrated by the decrease in dependence of the G-SIBs at the time that European banking groups in general became more dependent. These results indicate that monitoring G-SIBs is necessary, but not sufficient.[32] 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 that proxies the worst corner of systemic risk.

5.2. Contagion Risk between Investment Funds and Banks

Recently, the role of investment funds financial stability has been debated at length. Suffice it to mention the work of the Financial Stability Board (2012, 2015), the ECB in several issues of its Financial Stability Review, the IMF, and other bodies suggesting measures to strengthening the oversight and regulation of the so-called "shadow banking system". Concerns about the impact of MMFs grew worldwide, for instance, after the run on the Reserve Primary Fund in the US which "broke the buck" in 2008. This followed 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 US federal government to step in and offer guarantees to MMFs investors that their money would be returned in the event of a fund failure.[33] While discussion in the previous section highlights the role on the investment

[32] This point has been developed in Jin and Nadal De Simone (2014).
[33] See Jin and Nadal De Simone (2014b) for an application of the framework of this study to all investment fund types domiciled in Luxembourg.

funds industry in systemic risk, it is opportune to analyze contagion between investment funds and banks in more detail. Contagion can result not only from asset cross holdings, but more fundamentally from correlated price changes of the financial assets that banks and investment funds hold in their portfolios. As it is well known, those changes become more rapid and move in the same direction in times of market stress, a phenomenon known as "locking behavior". The CIMDO framework can capture these features given its dynamic nature and its capacity to account for the nonlinearities and feedback effects within the financial sector and between the financial sector and the real economy.

The scenarii chosen for this study are rich enough to provide insights into the interdependence between both types of financial entities. The systemic risk measure used in this section is the DDM. Distress is presented such that the rows of the DDM display the probability of distress of financial institutions 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 is broadly consistent with the PAO results providing a useful checking mechanism.

Several results can be discussed. First, while interdependencies between banks in Luxembourg, their parent companies in Europe and the investment fund industry have been very volatile over the sample period, there is a clear asymmetry in the patterns of the estimated statistical dependence. Results from all scenarii seem to indicate that vulnerabilities of investment funds matter more in the form of contagion to banks than the other way round. In addition, this tends to be relatively more the case for the European banking groups than for their Luxembourg affiliates.

To conserve space, only results from scenarii 1, 2 and 5 are reported. In scenario 1, the average PD of the Luxembourg bank conditional on distress in investment funds is between 2 and 3 times the average PD of investment funds conditional on distress in the Luxembourg bank (Table 1). In scenario 2, the same is true either for Luxembourg banks or for the European banking groups (Table 2). It is noteworthy that distress in investment funds clearly tends to result on a higher conditional PD for European banking groups than for Luxembourg banks. For instance, at 2015Q4, distress in the worst investment fund results in a conditional probability of distress of the first worst banking group of 99% and a conditional probability of distress of the first worst Luxembourg bank of 42%.

Scenario 5 considers MMF, NMMFs, and European banking groups, and it also classifies Luxembourg banks into small, medium and large (Tables 3a and b).[34] It is also

[34] 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

the case that distress in investment funds results in higher average PDs on banks than the opposite. At 2015Q4, distress in investment funds had an average conditional probability of distress on banks of 89% (Table 3b) while distress on banks had at that time a conditional probability of distress on investment funds of 27% (Table 3a). There is no clear pattern as to what type of investment fund is a relatively more important contagion source, however. For example, at 2013Q4, NMMFs distress had a larger impact on all banks, but at 2012Q4 the MMF had a larger impact on all banks (Table 3b).

The relatively finer granularity of scenario 5 allows separating the effect of investment funds' distress by jurisdiction and by Luxembourg bank's size. With the exception of 2014Q4, MMFs' distress is more important for Luxembourg banks—broadly independently of their size—than for European banking groups. Instead, distress in NMMFs tends to affect European banking groups relatively more. This is likely the result of Luxembourg banks' role as net providers of liquidity to their parents and the importance of MMFs for Luxembourg banks' funding. Note that medium- and large-size Luxembourg banks tend to be relatively more dependent on distress in NMMFs than small-size banks. Therefore, *size does matter* for analyzing systemic risk in Luxembourg, a result that echoes Jin and Nadal De Simone's (2014) analysis of banks' systemic risk. To further explore this important policy matter, scenario 6 was run. It includes the seven types of investment funds together with small, medium and large Luxemburg banks as well as European banking groups. 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 tend to be more vulnerable to distress in NMMFs than to distress in MMFs. The above results are confirmed.

The DDMs also confirm the PAO results on contagion. In particular, note a reduction of contagion risk stemming from the banking sector as a result of the 3YLTRs, albeit temporary, although the investment fund industry continued to contribute to it (Table 5 shows the worst corner of systemic risk). To illustrate, while the common component of the conditional PD of the banking sector fell from 23% in 2011Q4 to as low as 6% six months later, the common component of the conditional PD of the investment fund was largely stable. Also, the average conditional PD as a result of distress in the worst bank performer in Luxembourg and the worst banking group performer declined from 52% and 62% in 2011Q3, respectively, to 39% and 53% in 2011Q4, respectively, and to 42% and

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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 5 Luxembourg systemic important banks about 50% of the time. Then, banks within each size category were treated homogeneously as one bank.

53% in 2012Q2. Conditional PDs raised again later showing the temporary nature of the policy measures.

The importance of the banking sector as a source of contagion onto investment funds has risen since the end of 2013. The probability of distress in investment funds conditional on distress in banks was 7% at end-2013 and rose to 27% at end-2015 (Table 3a). This is true across banking groups and all sizes of Luxembourg banks. The conditional PD rose especially for NMMF. Similarly, the probability of distress on banks conditional on distress in investment funds increased from 53% at end-2013 to 89% at end-2015 (Table 3b). This is the case for both MMF and NMMF as sources of distress and it is also true for the conditional probability of distress on banking groups and on Luxembourg banks, independently of their size. For example, the conditional probability of distress in money market funds (non-money market funds) on banking groups rose to 84% (97%) at end-2015 from 0% (58%) at end-2013. The conditional probability of distress in money market funds (non-money market funds) on small Luxembourg banks rose to 98% (100%) at end-2015 from 27% (45%) at end-2013. The figures for large Luxembourg banks are 85% (63%) at end-2015 and 70% (86%) at end-2015.

Finally, the very much discussed role of alternative investment funds as source of contagion to the banking sector can be illustrated with the PAO from hedge funds and other funds, both in the case of the four European banking groups and the Luxembourg OSIIs (Figure 4). First, note that the PDs of both fund types display a volatile and disparate behavior during the sample period. In particular, hedge funds' PD rose since the second quarter of 2014. In contrast, other funds' PD started falling since mid-2013. Second, the systemic risk posed by both fund types as measured by PAO tends to be higher for Luxembourg OSIIs than for European banking groups.

Summarizing, DDMs show a tendency for conditional probabilities of distress stemming from distress either in the investment fund industry or the banking industry to increase in recent years. This is true independently of the investment fund type (Table 4) and the jurisdiction or size of the bank. This development is largely the outcome of an increase in correlation across asset classes following economic agents' search for yield, which the ECB has been pointing at since 2014 in its Financial Stability Review. This behavior reduces diversification possibilities and largely explains the increase in the conditional probability of distress of large Luxembourg banks, despite that they, in contrast to small- and medium-size banks, have an extended access to diversification possibilities.

5.3. The build-up of vulnerabilities over time

Measures of systemic risk and their common and idiosyncratic components, when combined with an understanding of the macro-financial variables most closely linked to their common component can be valuable tools for monitoring the build-up of systemic risk in the financial industry, as exemplified in Jin and Nadal De Simone (2015) for the investment fund industry. To that end, the same methodology applied to marginal PDs was applied in this study to the FSI, the FSF and the PAO measures of systemic risk.

A truly operational macro-prudential framework should lend itself not only to measuring systemic vulnerabilities, but also to identifying the macro-financial variables most closely linked to their common components. To determine the variables most closely associated with those vulnerabilities, all macro-financial variables of the database were categorized into four classes: real variables (GDP in volume and current prices, industrial production, unemployment, the harmonized consumer price index, and agricultural and industrial property prices); funding costs (short- and long-term interest rates, spreads, foreign exchange rates, stock market price indexes, 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).

Table 6a summarizes the contribution of each of the set of macro-financial variables to systemic risk across scenarii, and Table 6b summarizes the contribution of each set of macro-financial 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 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 these factors. Thus, the common component is matched with all variables for the GDFM estimation. By using the top 50% of the absolute value of these composite loading of all factors, the Tables 6a and 6b show the weighted contribution of the all categories of variables closely associated with the common component of each systemic risk measure and PD.

This analysis of composite loadings is limited given that no estimation errors are provided. As a result, the robustness of the rankings is checked in two ways: first, by using the empirical cumulative distribution of absolute composite loadings and the proportion of variance explained that result from the GDFM, and second, by selecting a statistical cut point at 0.0001 so that absolute composite loadings resulting from the

GDFM below that cut point are treated as being not significantly different from zero. In both cases, i.e., the ranking of the variables that result from the first half of the cumulative distribution of composite loadings and the ranking that results from the composite loadings with an absolute value above the cut point, are broadly similar (they are not shown).

The most important point is that the ranking of the variables most closely associated with the common components of systemic risk measures coincides with the ranking of the variables most closely associated with the common components of marginal PDs. The most important macro-financial variable closely linked to the three measures of systemic risk reported tend to be funding prices (e.g., interest rates, spreads and stock price indexes), followed by variables linked to the state of the economy (e.g., GDP and unemployment), and funding quantities follow (notably credit, the credit gap and interbank lending and borrowing). However, there is an exception related to the form of systemic risk. When the fragility of the financial sector is assessed, the state of the economy is either equally important as funding prices (in scenario 3) or more important than funding prices (in scenario 6). These cases are those where Luxembourg banks play a relatively larger role.

These results matter for policy. Given that funding prices matter most for both systemic risk measures and PDs, especially for systemic risk measures, by affecting funding prices, monetary policy can affect the evolution of *systemic vulnerabilities* in the financial sector via the traditional channel that affects investment and consumption, and thus economic activity. As a result, a proper assessment of the contribution that monetary policy can have on financial stability requires models that measure in some manner the impact of monetary policy on systemic risk indicators.

More broadly, the results also have important implications for macro-prudential 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 funding quantities are also closely linked to systemic risk measures in the financial sector, ranking fourth after funding quantities, the state of the economy and PDs.

5.4 Out-of-sample Forecasting

Macro-prudential policymakers are interested in having as much as possible forward-looking measures of systemic risk. As it is well known, in-sample results say nothing about the out-of-sample performance of a given framework. Therefore, this section addresses the out-of-sample forecasting capabilities of the framework. The main conclusion is that even in a data-constrained environment, the framework does a reasonably good job at forecasting changes in systemic risk measures.

Following Jin and Nadal De Simone (2012, and 2014), this paper illustrates how to apply the 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' interdependence. The book-value based Merton's model considered in this study is estimated by a rolling window and is used as input into the CIMDO.[35] An AR(3) - GARCH (1,1) model is also used to track dynamic changes of both the idiosyncratic and the common components. Table 7 reports root-mean squared errors, as well as the bias, the variance and the covariance components of Theil's inequality coefficient for the FSI, the PAO and the FSF systemic risk measures for scenario 5, i.e., the one including the worst bank performer among Luxembourg banks (small-, medium- and large-size) and European banking groups, plus MMFs, NMMFs from 2013 to 2015.[36]

Looking at root-mean squared errors, it is apparent that using only the common components of the systemic risk measures for the out-of-sample forecasts generates significantly worse forecasts than using both the common components and the idiosyncratic components for the FSI and the PAO. There are no differences for the forecasting of the FSF. In general, the results indicate that idiosyncratic components play a role for measures of dependence and contagion, but not for fragility. Fragility is well described by common forces.[37] These results merit further research.

It is informative to look into the components of Theil's inequality. The variance proportions of the systematic error are made almost zero, as it is desirable, and the covariance proportion of the unsystematic forecast error become close to 1, as it is also desirable. Finally, the bias proportion of the FSI and the PAO are improved by using also the idiosyncratic components given that the average values of the simulated and "actual" series deviate less from each other as a result. This is not the case for the FSF which bias proportion does not improve. However, using the idiosyncratic components for forecasting the FSF does not deteriorate the forecast either. So, it seems advisable to use both the common and the idiosyncratic components in out-of-sample forecasting of systemic risk measures.

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[35] Instead, given their less data-constrained environment, Jin and Nadal De Simone (2012) used the BEKK model.
[36] The model is re-estimated recursively adding one period at a time and forecasting always two quarters forward.
[37] Please recall that a one-sided GDFM filter is used for estimating the GDFM model, which attributes a larger weight to the latest observations and thus captures trends in the series relatively well.

VI. Conclusions and macro-prudential policy implications

The integrated framework used in this study estimates measures of systemic risk, provides latent indications of the build-up of systemic vulnerabilities, can generate robust out-of-sample forecasts of the systemic risk measures. Given that financial stability cannot stop at national borders, it uses a set of European banking groups, beside their affiliates in Luxembourg and all types of Luxembourg investment funds. The financial sector in this study is defined as including all investment fund types domiciled in Luxembourg, banks in Luxembourg and their parent European banking groups.

The integrated framework can be described as follows. First, marginal PDs are estimated using the Merton (1974) model. Second, in contrast to other popular measures of systemic risk (e.g., Systemic Expected Shortfall or CoVar), the framework lends itself to the use of book-value data to cope with Luxembourg 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 statistical dependence among financial institutions, an important feature of systemic risk, a key feature of systemic risk that it is not shared by other approaches. Fourth, the generalized dynamic factor model applied to a large macro-financial dataset extracts the common components of financial institutions' marginal PDs illustrating how a set of common systematic factors affects banks, their mother companies and investment funds simultaneously, albeit with different weights. It brings out the links between measures of distress and their underlying, most closely associated macro-financial variables. It thus alleviates the bias on systemic risk measures stemming from the use of market prices given well-known difficulties that markets seemingly experience when it comes to pricing risk over time; this is a drawback of other systemic risk measures (e.g., Deposit Insurance Premium).

Funding prices, i.e., interest rates, spreads and stock price indexes, are the most significantly associated variables with either marginal PDs or measures of systemic risk. The state of the economy (i.e., GDP growth and unemployment) ranks second and PDs third as the type of variables most closely associated with systemic risk.

This framework contributes to the macro-prudential literature with a method to monitor financial systemic risk. It generates a monitoring toolkit that tracks changes in systemic risk in the financial sector in the sense of a build-up of vulnerabilities, part of which are latent. As such, it can be part of a larger set of indicators for the surveillance of the most insidious way in which systemic risk can arise, i.e., via a slow build-up of vulnerabilities. This way, given red-flashing indicators, policymakers could tighten the scrutiny of financial markets by, for instance, increasing the severity of the tests of the system or activating pre-existing macro-prudential 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 can be useful in the calibration of the instruments of the macro-prudential arsenal, given that it generates not only the factor loadings of the systemic risk measures, but it could also incorporate the policy instruments.

This work also contributes to the systemic risk literature by measuring at least part of the externalities that financial intermediaries exert on the rest of the financial sector and on the economy in general via signaling out the role of common systemic forces affecting all financial institutions. An important related implication of the analysis in this study is that systemic risk in the financial sector, as a result of the interaction between banks and investment funds, must be analyzed not only from the viewpoint of the direct cross-holdings they display, but requires to take into account the indirect links among banks and investment funds via market price and return correlations of the portfolios they hold.

In addition, this framework contributes to a relatively more robust measurement of the other two forms of systemic risk. First, it allows the estimation of measures of financial systemic risk that reflect common distress in the financial institutions of the system (i.e., the Financial Sector Fragility measure). Second, it allows the estimation of 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 provides a rich set of indicators for the formulation of macro-prudential policy based on explicit modeling of the default dependence of financial institutions. Conditional probabilities can provide insights into interlinkages and the likelihood of contagion or spillovers between banks or groups of banks and investment funds. This feature of the framework should help assessing the contingent liabilities emanating from the financial sector and, given the basic call-put parity condition embedded in the Merton model, the expected losses of maintaining a given policy.

Finally, and also very important for macro-prudential policy, there is the policymaker's capacity to project or forecast increases in systemic risk at any given point in time. This study contributes to the macro-prudential literature by suggesting a framework for forecasting changes in financial systemic risk. By using a dynamic CIMDO and the GDFM, the framework helps forecasting both the common as well as the idiosyncratic components of systemic risk measures. This remediates the well-known feature that simply aggregating marginal PDs and projecting them results in a downward-biased measure of systemic risk. By incorporating the common and the idiosyncratic components of a broad set of macro-financial variables, the framework improves the analytical features and the out-of-sample forecasting performance of the model. This feature of the framework makes it also useful in the stress testing of the financial sector.

From an economic and financial stability perspective, the main findings of this study support the view that systemic risk emanating from investment funds can be significant. They also point at the different importance of the direction of contagion between investment funds and banks depending on the former business lines, and the latter location and size. Finally, as signalled by the ECB, the success of monetary policy in improving funding and market liquidity conditions and the ensuing protracted period of low interest rates in the euro area may have also resulted in a search for yield increasing thereby financial institutions interdependence.

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Figure 1 - FSI Systemic Risk Measure

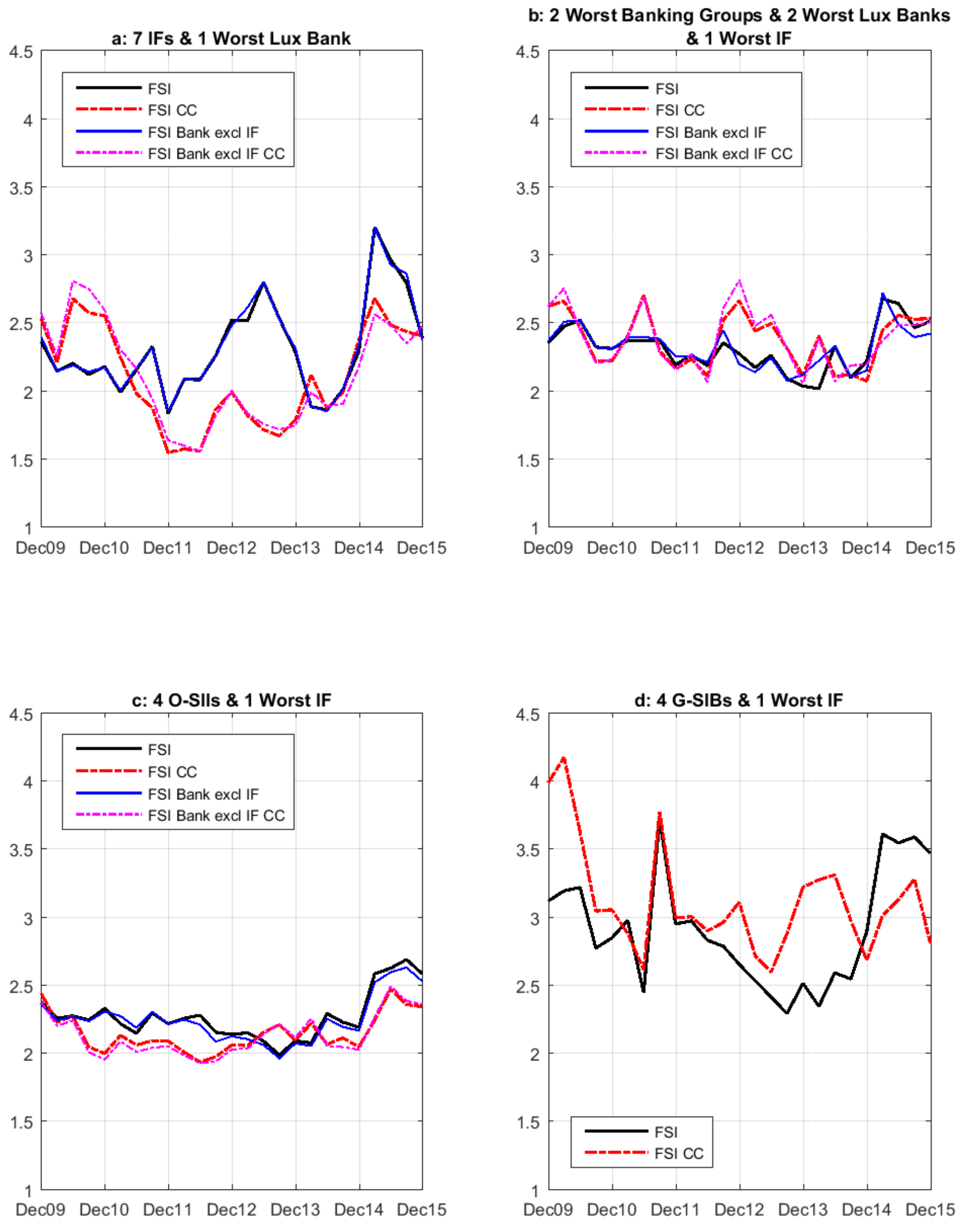

Figure 2 - FSF Systemic Risk Measure

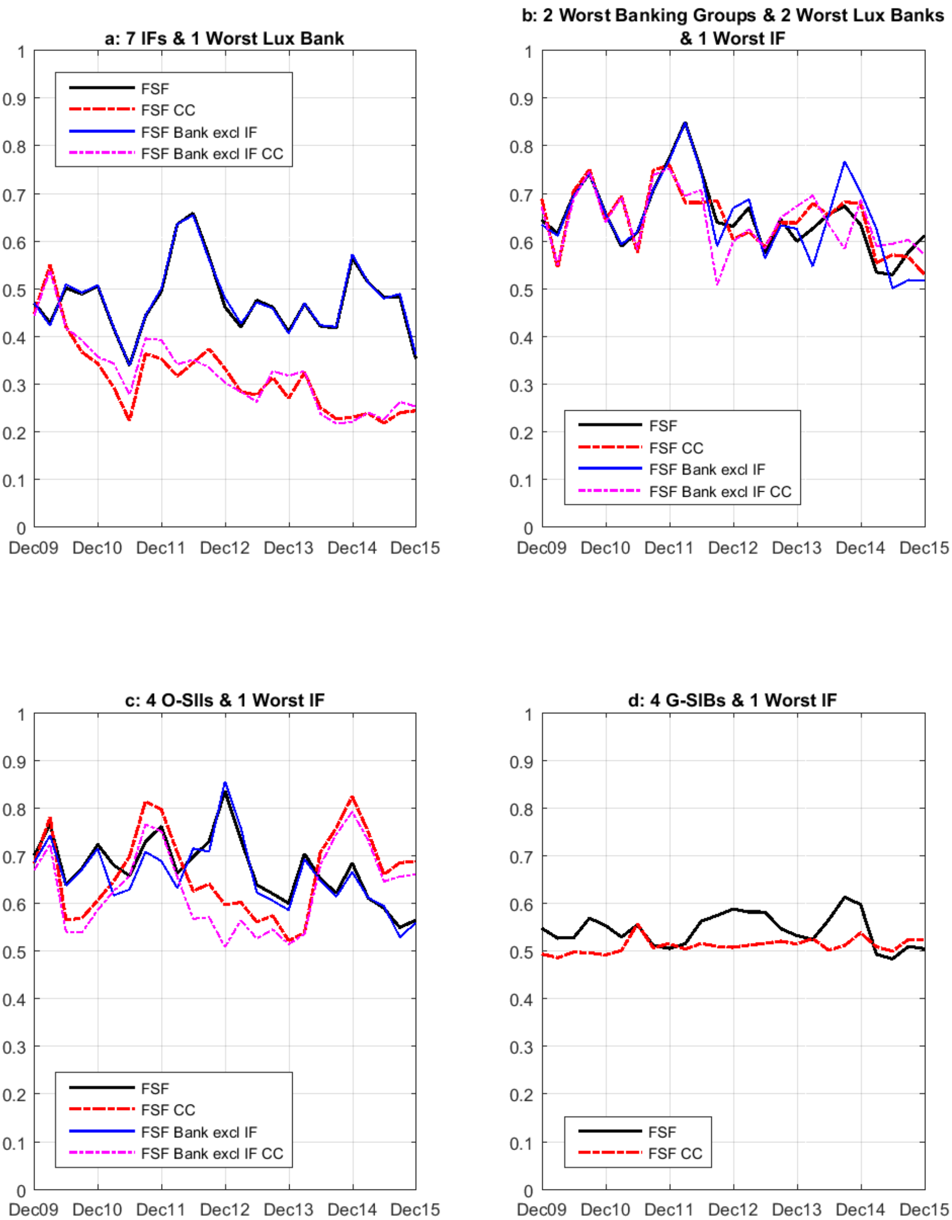

Figure 3 - PAO Systemic Risk Measure

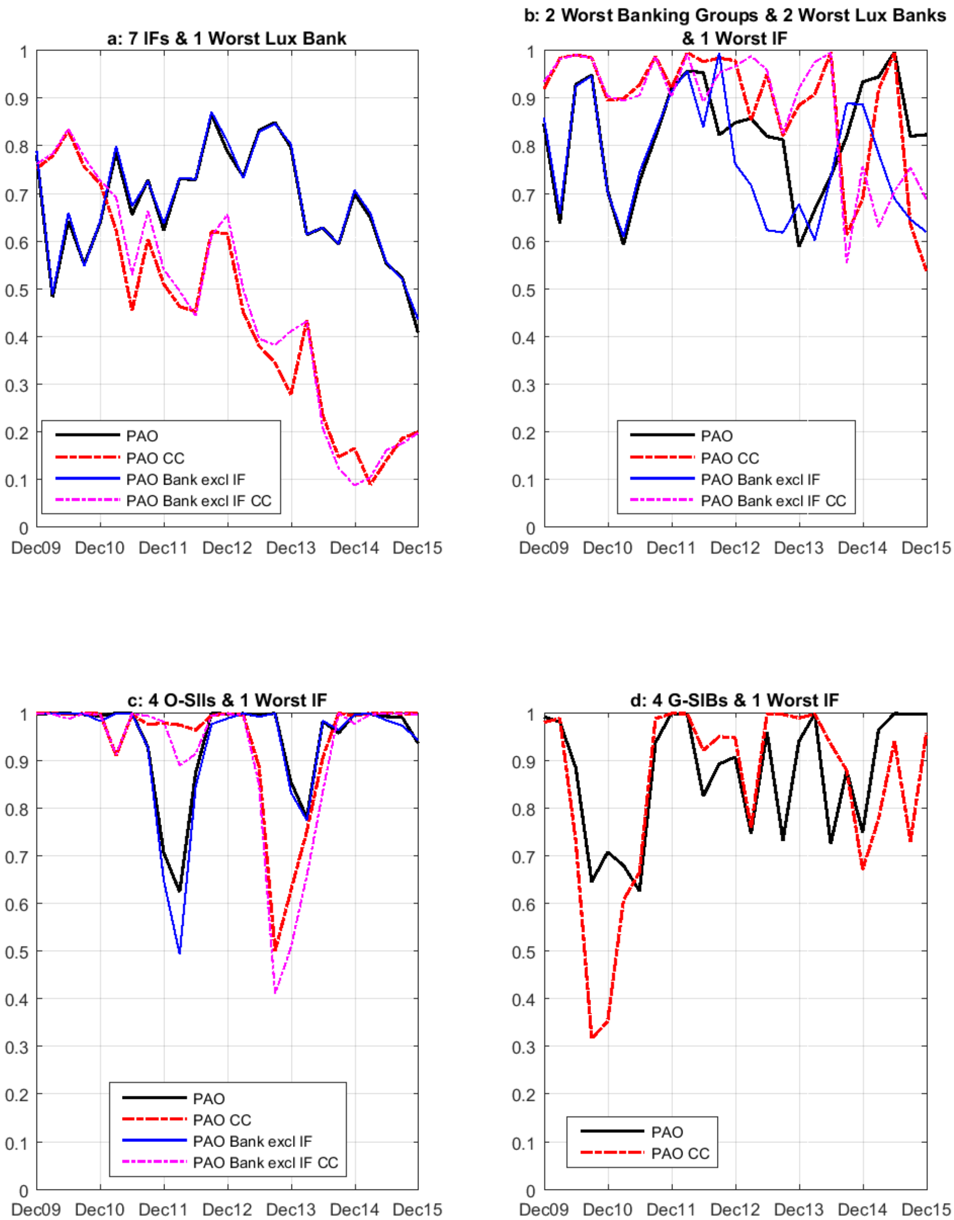

Figure 4 – PDs and PAO for Hedge Funds & Other Funds

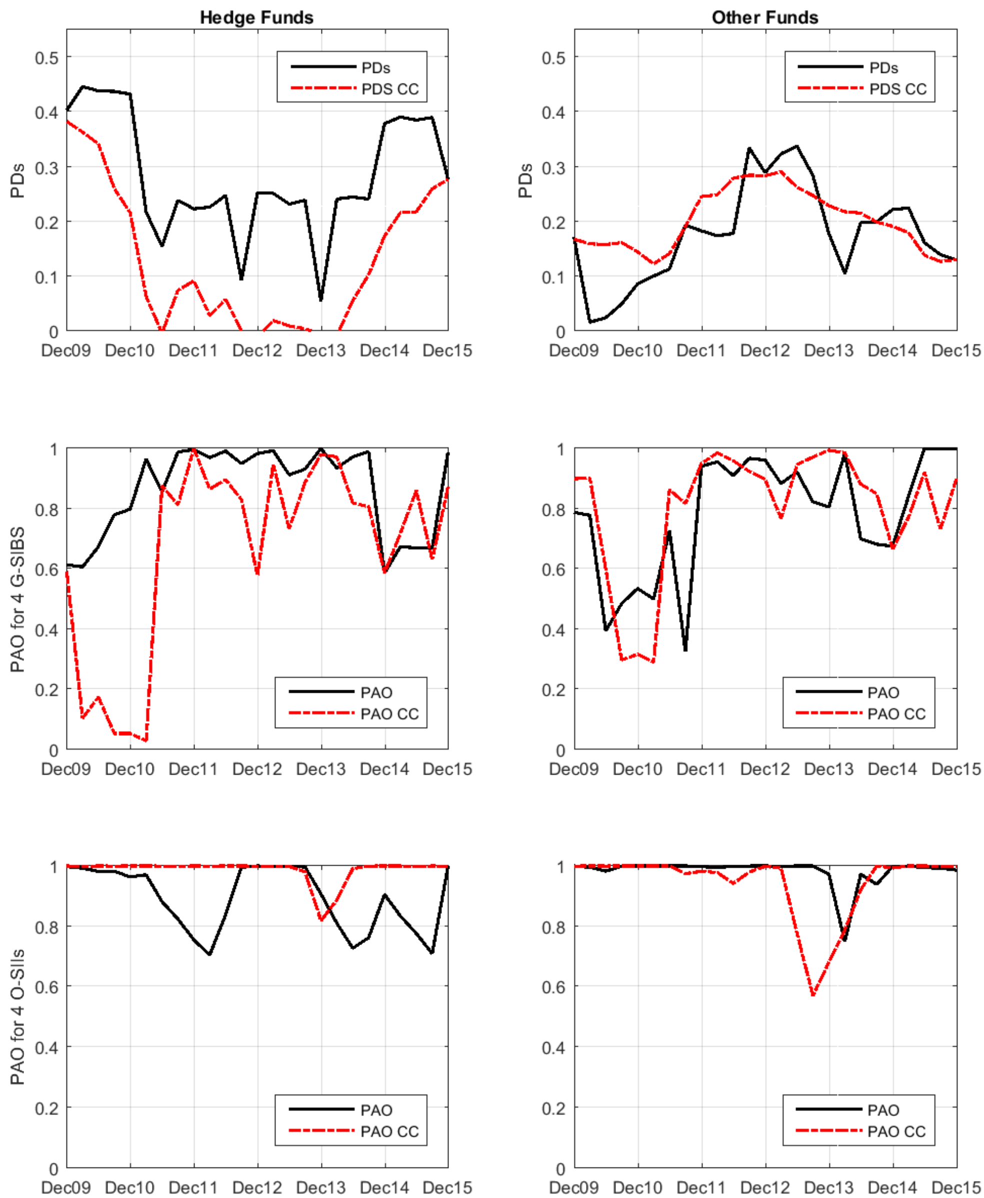

Table 1: Distress Dependence Matrices for 7 Investment Fund Types & the Worst Luxembourg Bank

	PDs									CC PDs								
The PD in the row, given PD in the column	Equity Funds	Bond Funds	Mixed Funds	Real Estate Funds	Hedge Funds	Other Funds	Money Market Fund	Lux Bank	Row Average	Equity Funds	Bond Funds	Mixed Funds	Real Estate Funds	Hedge Funds	Other Funds	Money Market Fund	Lux Bank (Deutsche	Row Average
									Q4 2009									
Equity Funds	1.00	0.94	0.96	0.01	0.24	0.51	0.00	0.33	0.50	1.00	0.94	0.97	0.19	0.34	0.78	0.00	0.25	0.56
Bond Funds	0.41	1.00	0.56	0.01	0.06	0.13	0.00	0.17	0.29	0.38	1.00	0.49	0.12	0.12	0.29	0.00	0.09	0.31
Mixed Funds	0.65	0.88	1.00	0.01	0.20	0.40	0.00	0.28	0.43	0.65	0.82	1.00	0.23	0.33	0.76	0.00	0.25	0.50
Real Estate Funds	0.00	0.00	0.00	1.00	0.05	0.01	0.05	0.05	0.15	0.03	0.05	0.05	1.00	0.09	0.08	0.03	0.08	0.18
Hedge Funds	0.33	0.18	0.41	0.65	1.00	0.93	0.24	0.59	0.54	0.47	0.41	0.69	0.81	1.00	0.95	0.57	0.72	0.70
Other Funds	0.31	0.18	0.35	0.07	0.40	1.00	0.00	0.30	0.33	0.50	0.46	0.73	0.33	0.44	1.00	0.01	0.33	0.47
Money Market Funds	0.00	0.00	0.00	0.01	0.00	0.00	1.00	0.00	0.13	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.13
Lux Bank	0.57	0.69	0.72	0.84	0.73	0.87	0.00	1.00	0.68	0.48	0.43	0.69	0.99	0.98	0.96	0.69	1.00	0.78
Column Average	0.41	0.48	0.50	0.32	0.33	0.48	0.16	0.34	0.38	0.44	0.51	0.58	0.46	0.41	0.60	0.29	0.34	0.45
Lux Bank's effect on Investment Funds								0.25									0.25	
Investment Funds' effect on the Lux Bank									0.63									0.74
									Q4 2010									
Equity Funds	1.00	0.34	0.81	0.15	0.31	0.72	0.00	0.21	0.44	1.00	0.72	0.81	0.62	0.40	0.64	0.04	0.37	0.58
Bond Funds	0.44	1.00	0.76	0.31	0.41	0.53	0.00	0.13	0.45	0.11	1.00	0.28	0.14	0.14	0.23	0.00	0.07	0.25
Mixed Funds	0.60	0.44	1.00	0.17	0.24	0.64	0.00	0.14	0.40	0.41	0.98	1.00	0.47	0.37	0.69	0.00	0.24	0.52
Real Estate Funds	0.31	0.49	0.45	1.00	0.29	0.87	0.13	0.50	0.51	0.57	0.85	0.83	1.00	0.46	0.69	0.00	0.42	0.60
Hedge Funds	0.81	0.84	0.85	0.38	1.00	0.66	0.24	0.22	0.62	0.39	0.92	0.70	0.48	1.00	0.81	0.18	0.41	0.61
Other Funds	0.37	0.21	0.45	0.22	0.13	1.00	0.00	0.16	0.32	0.41	0.99	0.88	0.49	0.54	1.00	0.01	0.30	0.58
Money Market Funds	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.13	0.01	0.00	0.00	0.00	0.06	0.00	1.00	0.01	0.14
Lux Bank	0.63	0.30	0.57	0.73	0.25	0.93	0.13	1.00	0.57	0.80	1.00	0.99	0.99	0.92	0.99	0.05	1.00	0.84
Column Average	0.52	0.45	0.61	0.37	0.33	0.67	0.19	0.30	0.43	0.46	0.81	0.69	0.52	0.49	0.63	0.16	0.35	0.51
Lux Bank's effect on Investment Funds								0.20									0.26	
Investment Funds' effect on the Lux Bank									0.50									0.82
									Q4 2011									
Equity Funds	1.00	0.51	0.59	0.25	0.76	0.00	0.06	0.00	0.40	1.00	0.10	0.92	0.06	0.29	0.38	0.05	0.04	0.36
Bond Funds	0.01	1.00	0.03	0.01	0.01	0.01	0.00	0.00	0.13	0.00	1.00	0.04	0.05	0.00	0.03	0.00	0.02	0.14
Mixed Funds	0.22	0.50	1.00	0.19	0.33	0.06	0.00	0.06	0.29	0.18	0.16	1.00	0.07	0.02	0.13	0.00	0.03	0.20
Real Estate Funds	0.20	0.23	0.41	1.00	0.21	0.07	0.38	0.21	0.34	0.04	0.80	0.24	1.00	0.00	0.07	0.01	0.28	0.30
Hedge Funds	0.73	0.70	0.85	0.25	1.00	0.05	0.00	0.03	0.45	0.14	0.05	0.05	0.00	1.00	0.27	0.02	0.01	0.19
Other Funds	0.00	0.43	0.14	0.07	0.04	1.00	0.04	0.37	0.26	0.50	0.84	0.91	0.13	0.72	1.00	0.00	0.15	0.53
Money Market Funds	0.02	0.00	0.00	0.16	0.00	0.02	1.00	0.10	0.16	0.04	0.00	0.00	0.01	0.03	0.00	1.00	0.09	0.15
Lux Bank	0.00	0.24	0.29	0.50	0.07	0.92	0.60	1.00	0.45	0.10	0.98	0.40	1.00	0.06	0.28	0.27	1.00	0.51
Column Average	0.27	0.45	0.41	0.30	0.30	0.27	0.26	0.22	0.31	0.25	0.49	0.44	0.29	0.27	0.27	0.17	0.20	0.30
Lux Bank's effect on Investment Funds								0.11									0.09	
Investment Funds' effect on the Lux Bank									0.37									0.44
									Q4 2012									
Equity Funds	1.00	0.50	0.65	0.07	0.05	0.20	0.00	0.10	0.32	1.00	0.80	0.78	0.37	0.00	0.46	0.00	0.19	0.45
Bond Funds	0.87	1.00	0.76	0.59	0.04	0.26	0.00	0.16	0.46	0.88	1.00	0.98	0.88	0.00	0.52	0.00	0.19	0.55
Mixed Funds	0.88	0.59	1.00	0.39	0.12	0.37	0.00	0.20	0.44	0.89	1.00	1.00	0.89	0.00	0.53	0.00	0.19	0.56
Real Estate Funds	0.01	0.07	0.06	1.00	0.01	0.05	0.01	0.03	0.16	0.02	0.03	0.03	1.00	0.00	0.02	0.00	0.01	0.14
Hedge Funds	0.12	0.05	0.19	0.07	1.00	0.65	0.57	0.52	0.40	0.00	0.00	0.00	0.00	1.00	0.00	0.03	0.01	0.13
Other Funds	0.46	0.34	0.62	0.57	0.70	1.00	0.37	0.53	0.58	0.98	0.99	1.00	0.97	0.00	1.00	0.00	0.41	0.67
Money Market Funds	0.00	0.00	0.00	0.10	0.46	0.28	1.00	0.31	0.27	0.00	0.00	0.00	0.00	0.88	0.00	1.00	0.20	0.26
Lux Bank	0.41	0.38	0.61	0.59	0.97	0.93	0.71	1.00	0.70	0.65	0.57	0.57	0.57	0.29	0.66	0.33	1.00	0.58
Column Average	0.47	0.37	0.49	0.42	0.42	0.47	0.33	0.36	0.41	0.55	0.55	0.54	0.58	0.27	0.40	0.17	0.27	0.42
Lux Bank's effect on Investment Funds								0.26									0.17	
Investment Funds' effect on the Lux Bank									0.66									0.52
									Q4 2013									
Equity Funds	1.00	0.48	0.46	0.06	0.16	0.44	0.03	0.10	0.34	1.00	0.37	0.48	0.98	0.28	0.28	0.01	0.00	0.43
Bond Funds	0.24	1.00	0.42	0.07	0.01	0.26	0.05	0.08	0.27	0.98	1.00	0.96	0.97	0.41	0.75	0.03	0.03	0.64
Mixed Funds	0.36	0.67	1.00	0.21	0.15	0.64	0.00	0.21	0.40	0.99	0.76	1.00	0.98	0.40	0.59	0.01	0.03	0.60
Real Estate Funds	0.12	0.31	0.54	1.00	0.56	0.56	0.05	0.66	0.47	0.18	0.07	0.09	1.00	0.16	0.05	0.00	0.00	0.19
Hedge Funds	0.09	0.01	0.11	0.15	1.00	0.19	0.00	0.15	0.21	0.13	0.07	0.09	0.39	1.00	0.09	0.00	0.02	0.22
Other Funds	0.52	0.65	0.98	0.33	0.42	1.00	0.00	0.32	0.53	1.00	1.01	1.00	0.99	0.72	1.00	0.03	0.05	0.72
Money Market Funds	0.00	0.01	0.00	0.00	0.00	0.00	1.00	0.00	0.13	0.02	0.03	0.01	0.00	0.00	0.02	1.00	0.22	0.16
Lux Bank	0.31	0.48	0.79	0.97	0.84	0.80	0.01	1.00	0.65	0.01	0.09	0.09	0.00	0.30	0.10	0.71	1.00	0.29
Column Average	0.33	0.45	0.54	0.35	0.39	0.49	0.14	0.31	0.38	0.54	0.43	0.46	0.66	0.41	0.36	0.22	0.17	0.41
Lux Bank's effect on Investment Funds								0.22									0.05	
Investment Funds' effect on the Lux Bank									0.60									0.19
									Q4 2014									
Equity Funds	1.00	0.38	0.29	0.08	0.12	0.19	0.24	0.06	0.29	1.00	0.84	0.85	0.99	0.86	0.82	0.55	0.07	0.75
Bond Funds	0.70	1.00	0.59	0.04	0.10	0.43	0.30	0.07	0.40	0.92	1.00	0.96	1.00	0.92	0.91	0.54	0.13	0.80
Mixed Funds	0.82	0.93	1.00	0.05	0.10	0.77	0.31	0.19	0.52	0.95	0.97	1.00	1.00	0.96	0.94	0.59	0.12	0.82
Real Estate Funds	0.39	0.12	0.09	1.00	0.63	0.06	0.72	0.45	0.43	0.23	0.21	0.21	1.00	0.25	0.20	0.18	0.03	0.29
Hedge Funds	0.67	0.31	0.19	0.71	1.00	0.09	0.65	0.27	0.48	0.79	0.77	0.79	0.98	1.00	0.77	0.63	0.09	0.73
Other Funds	0.61	0.75	0.86	0.04	0.05	1.00	0.24	0.26	0.48	0.96	0.97	0.99	1.00	0.99	1.00	0.63	0.13	0.83
Money Market Funds	0.36	0.25	0.17	0.22	0.18	0.11	1.00	0.13	0.30	0.38	0.34	0.36	0.53	0.48	0.37	1.00	0.05	0.44
Lux Bank	0.44	0.28	0.47	0.65	0.34	0.58	0.62	1.00	0.55	0.18	0.30	0.28	0.30	0.24	0.29	0.21	1.00	0.35
Column Average	0.62	0.50	0.46	0.35	0.32	0.40	0.51	0.30	0.43	0.68	0.67	0.68	0.85	0.71	0.66	0.54	0.20	0.63
Lux Bank's effect on Investment Funds								0.20									0.09	
Investment Funds' effect on the Lux Bank									0.48									0.26
									Q4 2015									
Equity Funds	1.00	0.46	0.55	0.50	0.41	0.97	0.65	0.16	0.59	1.00	0.79	0.82	0.48	0.74	0.79	0.87	0.11	0.70
Bond Funds	0.45	1.00	0.75	0.15	0.71	0.72	0.83	0.27	0.61	0.71	1.00	0.96	0.59	0.84	0.95	0.94	0.15	0.77
Mixed Funds	0.62	0.85	1.00	0.40	0.70	0.98	0.96	0.24	0.72	0.75	0.97	1.00	0.60	0.85	0.97	0.95	0.15	0.78
Real Estate Funds	0.41	0.12	0.29	1.00	0.13	0.40	0.43	0.06	0.36	0.28	0.38	0.38	1.00	0.39	0.38	0.45	0.05	0.41
Hedge Funds	0.56	0.99	0.86	0.21	1.00	0.81	0.83	0.34	0.70	0.75	0.95	0.95	0.68	1.00	0.95	0.88	0.15	0.79
Other Funds	0.62	0.47	0.56	0.31	0.38	1.00	0.67	0.12	0.52	0.75	0.99	1.00	0.61	0.87	1.00	0.94	0.16	0.79
Money Market Funds	0.18	0.24	0.24	0.15	0.17	0.29	1.00	0.09	0.29	0.47	0.56	0.56	0.42	0.47	0.54	1.00	0.08	0.51
Lux Bank	0.38	0.66	0.51	0.19	0.59	0.46	0.77	1.00	0.57	0.25	0.41	0.38	0.22	0.35	0.40	0.37	1.00	0.42
Column Average	0.53	0.60	0.60	0.36	0.51	0.70	0.77	0.28	0.54	0.62	0.76	0.75	0.58	0.69	0.75	0.80	0.23	0.65
Lux Bank's effect on Investment Funds								0.18									0.12	
Investment Funds' effect on the Lux Bank									0.51									0.34

Note: These matrices present the probability of distress of the financial institutions in the rows, conditional on the financial institutions in the columns becoming distressed.

Table 2: Distress Dependence Matrices for the 2 Worst Banking Groups, the 2 Worst Luxembourg Banks, and the Worst Investment Fund Type

	PDs						CC PDs					
The PD in the row, given PD in the column	2nd Worst Banking Group	1st Worst Banking Group	2nd t Worst Lux Bank	1st Worst Lux Bank	1st Worst Investment Fun	Row Average	2nd Worst Banking Group	1st Worst Banking Group	2nd t Worst Lux Bank	1st Worst Lux Bank	1st Worst Investment Fun	Row Average
						Q4 2009						
2nd Worst Banking Group	1.00	0.84	0.34	0.52	0.98	0.73	1.00	0.98	0.34	0.47	0.99	0.76
1st Worst Banking Group	0.82	1.00	0.21	0.45	0.98	0.69	0.96	1.00	0.34	0.47	0.97	0.75
2nd t Worst Lux Bank	0.34	0.22	1.00	0.46	0.16	0.43	0.35	0.34	1.00	0.72	0.41	0.56
1st Worst Lux Bank	0.53	0.47	0.48	1.00	0.62	0.62	0.49	0.49	0.74	1.00	0.56	0.66
1st Worst Investment Fund	0.59	0.60	0.09	0.36	1.00	0.53	0.57	0.56	0.24	0.31	1.00	0.54
Column Average	0.66	0.63	0.42	0.56	0.75	0.60	0.67	0.67	0.53	0.59	0.79	0.65
Banks' effect on Investment Funds						0.41						0.42
Investment Fund's effect on Banks					0.68						0.73	
						Q4 2010						
1st Worst Banking Group	1.00	0.47	0.63	0.50	0.59	0.64	1.00	0.69	0.42	0.48	0.54	0.63
2nd Worst Banking Group	0.49	1.00	0.74	0.34	0.49	0.61	0.71	1.00	0.43	0.39	0.34	0.57
1st Worst Lux Bank	0.65	0.74	1.00	0.28	0.74	0.68	0.43	0.44	1.00	0.72	1.00	0.72
2nd Worst Lux Bank	0.55	0.35	0.29	1.00	0.48	0.54	0.50	0.40	0.74	1.00	1.00	0.73
1st Worst Investment Fund	0.28	0.22	0.34	0.21	1.00	0.41	0.04	0.02	0.07	0.07	1.00	0.24
Column Average	0.60	0.56	0.60	0.47	0.66	0.58	0.54	0.51	0.53	0.53	0.77	0.58
Banks' effect on Investment Funds						0.26						0.05
Investment Fund's effect on Banks					0.58						0.72	
						Q4 2011						
2nd Worst Banking Group	1.00	0.75	0.25	0.06	0.97	0.61	1.00	0.76	0.08	0.29	0.96	0.62
1st Worst Banking Group	0.79	1.00	0.30	0.13	1.00	0.64	0.79	1.00	0.22	0.26	1.00	0.66
2nd t Worst Lux Bank	0.26	0.30	1.00	0.77	0.11	0.49	0.08	0.21	1.00	0.76	0.08	0.43
1st Worst Lux Bank	0.06	0.13	0.74	1.00	0.00	0.39	0.27	0.24	0.72	1.00	0.24	0.49
1st Worst Investment Fund	0.49	0.49	0.05	0.00	1.00	0.41	0.39	0.38	0.03	0.10	1.00	0.38
Column Average	0.52	0.53	0.47	0.39	0.62	0.51	0.51	0.52	0.41	0.48	0.66	0.52
Banks' effect on Investment Funds						0.26						0.23
Investment Fund's effect on Banks					0.52						0.57	
						Q4 2012						
2nd Worst Banking Group	1.00	0.67	0.53	0.35	0.82	0.67	1.00	0.91	0.63	0.37	0.86	0.75
1st Worst Banking Group	0.72	1.00	0.46	0.37	0.63	0.64	0.95	1.00	0.68	0.41	0.91	0.79
2nd t Worst Lux Bank	0.60	0.49	1.00	0.40	0.98	0.69	0.68	0.70	1.00	0.75	1.00	0.83
1st Worst Lux Bank	0.38	0.39	0.39	1.00	0.30	0.49	0.35	0.36	0.65	1.00	0.63	0.60
1st Worst Investment Fund	0.43	0.31	0.45	0.14	1.00	0.47	0.30	0.30	0.32	0.23	1.00	0.43
Column Average	0.62	0.57	0.56	0.45	0.75	0.59	0.66	0.65	0.65	0.55	0.88	0.68
Banks' effect on Investment Funds						0.33						0.29
Investment Fund's effect on Banks					0.69						0.85	
						Q4 2013						
2nd Worst Banking Group	1.00	0.41	0.36	0.66	0.66	0.62	1.00	0.81	0.49	0.18	1.00	0.70
1st Worst Banking Group	0.43	1.00	0.19	0.53	0.62	0.55	0.85	1.00	0.43	0.29	0.99	0.71
2nd t Worst Lux Bank	0.44	0.22	1.00	0.32	0.65	0.53	0.56	0.47	1.00	0.59	0.35	0.59
1st Worst Lux Bank	0.72	0.55	0.29	1.00	0.36	0.58	0.19	0.28	0.52	1.00	0.01	0.40
1st Worst Investment Fund	0.22	0.20	0.19	0.11	1.00	0.34	0.11	0.10	0.03	0.00	1.00	0.25
Column Average	0.56	0.48	0.40	0.53	0.66	0.52	0.54	0.53	0.49	0.41	0.67	0.53
Banks' effect on Investment Funds						0.18						0.06
Investment Fund's effect on Banks					0.57						0.59	
						Q4 2014						
2nd Worst Banking Group	1.00	0.55	0.65	0.34	0.28	0.56	1.00	0.49	0.32	0.56	0.31	0.54
1st Worst Banking Group	0.51	1.00	0.65	0.32	0.68	0.63	0.47	1.00	0.55	0.25	0.94	0.64
2nd t Worst Lux Bank	0.72	0.77	1.00	0.23	0.77	0.70	0.35	0.62	1.00	0.03	0.61	0.52
1st Worst Lux Bank	0.38	0.38	0.23	1.00	0.40	0.48	0.59	0.27	0.03	1.00	0.27	0.43
1st Worst Investment Fund	0.13	0.33	0.31	0.16	1.00	0.39	0.16	0.50	0.29	0.13	1.00	0.42
Column Average	0.55	0.61	0.57	0.41	0.63	0.55	0.51	0.58	0.44	0.40	0.63	0.51
Banks' effect on Investment Funds						0.23						0.27
Investment Fund's effect on Banks					0.53						0.54	
						Q4 2015						
2nd Worst Banking Group	1.00	0.67	0.36	0.24	0.92	0.64	1.00	0.79	0.68	0.25	1.00	0.74
1st Worst Banking Group	0.70	1.00	0.66	0.50	0.99	0.77	0.82	1.00	0.83	0.43	0.93	0.80
2nd t Worst Lux Bank	0.40	0.71	1.00	0.80	0.65	0.71	0.76	0.90	1.00	0.51	0.81	0.80
1st Worst Lux Bank	0.27	0.54	0.82	1.00	0.42	0.61	0.28	0.47	0.52	1.00	0.23	0.50
1st Worst Investment Fund	0.49	0.50	0.31	0.19	1.00	0.50	0.53	0.47	0.38	0.11	1.00	0.50
Column Average	0.57	0.69	0.63	0.55	0.80	0.65	0.68	0.72	0.68	0.46	0.79	0.67
Banks' effect on Investment Funds						0.37						0.37
Investment Fund's effect on Banks					0.75						0.74	

Note: These matrices present the probability of distress of the financial institutions in the rows, conditional on the financial institutions in the columns becoming distressed.

Table 3a: Distress Dependence Matrices for MMF, NMMF, Banking Groups, Small, Medium and Large Luxembourg Banks

	PDs					CC PDs				
The PD in the row, given PD in the column	Banking Groups	Small Lux Banks	Medium Lux Banks	Large Lux Banks	Row Average	Banking Groups	Small Lux Banks	Medium Lux Banks	Large Lux Banks	Row Average
					Q4 2009					
Money Market Funds	0.00	0.00	0.01	0.00	0.00	0.00	0.01	0.01	0.01	0.01
Non-Money Market Funds	0.47	0.21	0.15	0.21	0.26	0.43	0.24	0.29	0.22	0.29
Column Average	0.24	0.11	0.08	0.11	0.13	0.21	0.12	0.15	0.11	0.15
					Q4 2010					
Money Market Funds	0.00	0.01	0.01	0.00	0.01	0.02	0.09	0.18	0.01	0.08
Non-Money Market Funds	0.24	0.05	0.25	0.23	0.19	0.15	0.20	0.07	0.27	0.17
Column Average	0.12	0.03	0.13	0.11	0.10	0.09	0.14	0.13	0.14	0.12
					Q4 2011					
Money Market Funds	0.02	0.11	0.00	0.08	0.05	0.10	0.30	0.32	0.05	0.19
Non-Money Market Funds	0.19	0.00	0.09	0.01	0.07	0.15	0.00	0.01	0.10	0.07
Column Average	0.11	0.05	0.05	0.05	0.06	0.12	0.15	0.17	0.08	0.13
					Q4 2012					
Money Market Funds	0.00	0.46	0.47	0.16	0.27	0.00	0.45	0.44	0.01	0.22
Non-Money Market Funds	0.37	0.03	0.00	0.24	0.16	0.21	0.00	0.00	0.21	0.11
Column Average	0.19	0.25	0.24	0.20	0.22	0.11	0.22	0.22	0.11	0.16
					Q4 2013					
Money Market Funds	0.00	0.01	0.02	0.01	0.01	0.01	0.20	0.15	0.19	0.14
Non-Money Market Funds	0.13	0.11	0.10	0.16	0.12	0.14	0.00	0.00	0.00	0.04
Column Average	0.06	0.06	0.06	0.09	0.07	0.08	0.10	0.08	0.10	0.09
					Q4 2014					
Money Market Funds	0.25	0.69	0.09	0.11	0.28	0.03	0.22	0.19	0.08	0.13
Non-Money Market Funds	0.26	0.24	0.25	0.11	0.22	0.27	0.43	0.39	0.31	0.35
Column Average	0.25	0.47	0.17	0.11	0.25	0.15	0.32	0.29	0.19	0.24
					Q4 2015					
Money Market Funds	0.11	0.12	0.12	0.10	0.11	0.11	0.12	0.12	0.03	0.09
Non-Money Market Funds	0.49	0.48	0.42	0.28	0.42	0.27	0.47	0.47	0.14	0.34
Column Average	0.30	0.30	0.27	0.19	0.27	0.19	0.30	0.30	0.08	0.22

Note: These matrices present the probability of distress of the financial institutions in the rows, condiitonal on the financial institutions in the columns becoming distressed.

Table 3b: Distress Dependence Matrices (Reverse) for MMF, NMMF, Banking Groups, Small, Medium and Large Luxembourg Banks

	PDs			CC PDs		
The PD in the row, given PD in the column	Money Market Funds	Non-Money Market Funds	Row Average	Money Market Funds	Non-Money Market Fun	Row Average
			Q4 2009			
Banking Groups	0.06	0.98	0.52	0.00	1.00	0.50
Small Lux Banks	0.19	0.46	0.32	0.47	0.59	0.53
Medium Lux Banks	0.71	0.31	0.51	0.34	0.66	0.50
Large Lux Banks	0.11	0.47	0.29	0.52	0.52	0.52
Column Average	0.27	0.56	0.41	0.33	0.69	0.51
			Q4 2010			
Banking Groups	0.19	0.61	0.40	0.13	0.50	0.31
Small Lux Banks	0.77	0.14	0.46	0.61	0.89	0.75
Medium Lux Banks	0.54	0.67	0.60	0.99	0.24	0.62
Large Lux Banks	0.12	0.62	0.37	0.06	0.95	0.50
Column Average	0.40	0.51	0.46	0.45	0.65	0.55
			Q4 2011			
Banking Groups	0.11	1.00	0.55	0.29	0.90	0.60
Small Lux Banks	0.58	0.01	0.30	0.97	0.00	0.49
Medium Lux Banks	0.03	0.44	0.23	0.96	0.03	0.49
Large Lux Banks	0.47	0.04	0.25	0.14	0.60	0.37
Column Average	0.30	0.37	0.33	0.59	0.38	0.49
			Q4 2012			
Banking Groups	0.00	0.96	0.48	0.00	0.92	0.46
Small Lux Banks	0.91	0.08	0.50	1.00	0.00	0.50
Medium Lux Banks	0.98	0.01	0.49	1.00	0.00	0.50
Large Lux Banks	0.34	0.66	0.50	0.02	0.89	0.45
Column Average	0.56	0.43	0.49	0.50	0.45	0.48
			Q4 2013			
Banking Groups	0.00	0.58	0.29	0.06	0.99	0.53
Small Lux Banks	0.27	0.45	0.36	0.75	0.00	0.37
Medium Lux Banks	0.89	0.46	0.67	0.66	0.01	0.34
Large Lux Banks	0.70	0.86	0.78	0.87	0.00	0.44
Column Average	0.47	0.59	0.53	0.59	0.25	0.42
			Q4 2014			
Banking Groups	0.88	0.86	0.87	0.15	0.67	0.41
Small Lux Banks	0.83	0.24	0.54	0.99	0.98	0.98
Medium Lux Banks	0.31	0.86	0.59	1.00	0.99	0.99
Large Lux Banks	0.48	0.44	0.46	0.42	0.82	0.62
Column Average	0.63	0.60	0.61	0.64	0.86	0.75
			Q4 2015			
Banking Groups	0.84	0.97	0.91	0.83	0.53	0.68
Small Lux Banks	0.98	1.00	0.99	0.99	0.98	0.99
Medium Lux Banks	0.95	0.90	0.92	1.00	1.00	1.00
Large Lux Banks	0.85	0.63	0.74	0.24	0.31	0.27
Column Average	0.90	0.87	0.89	0.77	0.70	0.74

Note: These matrices present the probability of distress of the financial institutions in the rows, conditional on the financial institutions in the columns becoming distressed.

Table 4: Distress Dependence Matrices for Banking Groups, Small, Medium and Large Luxembourg Banks, and Investment Fund Types

	PDs								CC PDs							
The PD in the row, given PD in the column	Equity Funds	Bond Funds	Mixed Funds	Real Estate Funds	Hedge Funds	Other Funds	Money Market Funds	Row Average	Equity Funds	Bond Funds	Mixed Funds	Real Estate Funds	Hedge Funds	Other Funds	Money Market Funds	Row Average
								Q4 2009								
Banking Groups	1.00	0.93	0.97	0.01	0.44	0.69	0.07	0.59	1.00	1.00	1.00	0.37	0.54	0.87	0.00	0.68
Small Lux Banks	0.47	0.34	0.47	0.52	0.92	0.99	0.20	0.56	0.56	0.47	0.66	0.98	1.00	0.88	0.52	0.72
Medium Lux Banks	0.36	0.13	0.29	0.23	0.68	0.72	0.69	0.44	0.65	0.53	0.73	0.85	1.00	0.91	0.39	0.72
Large Lux Banks	0.46	0.40	0.49	0.67	0.89	0.96	0.11	0.57	0.51	0.43	0.62	0.99	1.00	0.85	0.53	0.71
Column Average	0.57	0.45	0.56	0.36	0.73	0.84	0.27	0.54	0.68	0.61	0.75	0.80	0.89	0.88	0.36	0.71
								Q4 2010								
Banking Groups	0.66	0.60	0.64	0.11	0.60	0.33	0.20	0.45	0.67	0.49	0.55	0.59	0.20	0.48	0.12	0.44
Small Lux Banks	0.29	0.02	0.15	0.53	0.21	0.43	0.78	0.35	0.76	0.92	0.91	0.85	1.00	0.94	0.65	0.86
Medium Lux Banks	0.47	0.86	0.60	0.48	0.75	0.44	0.54	0.59	0.28	0.25	0.24	0.02	0.49	0.31	0.99	0.37
Large Lux Banks	0.82	0.35	0.70	0.62	0.41	0.88	0.10	0.55	0.66	0.99	0.95	0.97	0.96	0.95	0.07	0.79
Column Average	0.56	0.46	0.52	0.44	0.49	0.52	0.40	0.48	0.59	0.66	0.66	0.61	0.66	0.67	0.46	0.62
								Q4 2011								
Banking Groups	1.00	0.90	0.85	0.48	0.95	0.29	0.09	0.65	1.00	0.50	0.92	0.39	0.50	0.75	0.28	0.62
Small Lux Banks	0.02	0.04	0.14	0.27	0.09	0.65	0.67	0.27	0.01	0.07	0.00	0.09	0.50	0.08	0.99	0.25
Medium Lux Banks	0.36	0.49	0.57	0.08	0.53	0.82	0.03	0.41	0.22	0.01	0.05	0.00	0.63	0.20	0.95	0.29
Large Lux Banks	0.00	0.35	0.28	0.37	0.15	0.92	0.56	0.38	0.33	0.97	0.60	0.99	0.43	0.58	0.14	0.58
Column Average	0.34	0.45	0.46	0.30	0.43	0.67	0.33	0.43	0.39	0.39	0.39	0.37	0.52	0.40	0.59	0.43
								Q4 2012								
Banking Groups	1.00	0.85	0.93	0.24	0.29	0.41	0.00	0.53	0.91	0.89	0.87	0.81	0.11	0.82	0.00	0.63
Small Lux Banks	0.03	0.19	0.16	0.83	0.57	0.64	0.92	0.48	0.01	0.00	0.00	0.00	1.00	0.00	1.00	0.29
Medium Lux Banks	0.12	0.00	0.07	0.17	0.64	0.36	0.98	0.34	0.00	0.00	0.00	0.00	1.00	0.00	1.00	0.29
Large Lux Banks	0.60	0.62	0.69	0.45	0.72	0.78	0.33	0.60	0.93	0.81	0.81	0.59	0.25	0.72	0.06	0.60
Column Average	0.44	0.41	0.46	0.42	0.56	0.55	0.56	0.49	0.46	0.42	0.42	0.35	0.59	0.39	0.51	0.45
								Q4 2013								
Banking Groups	0.74	0.30	0.64	0.43	0.91	0.72	0.00	0.54	0.97	1.00	0.99	0.98	0.74	0.97	0.04	0.81
Small Lux Banks	0.29	0.53	0.57	0.81	0.26	0.56	0.25	0.47	0.00	0.00	0.00	0.00	0.24	0.01	0.79	0.15
Medium Lux Banks	0.27	0.74	0.39	0.27	0.03	0.29	0.86	0.41	0.01	0.01	0.00	0.00	0.23	0.03	0.80	0.16
Large Lux Banks	0.69	0.99	0.77	0.27	0.06	0.65	0.66	0.58	0.02	0.04	0.02	0.00	0.30	0.09	0.85	0.19
Column Average	0.50	0.64	0.59	0.45	0.32	0.56	0.44	0.50	0.25	0.26	0.26	0.25	0.38	0.28	0.62	0.33
								Q4 2014								
Banking Groups	0.72	0.94	0.83	0.20	0.45	0.72	0.90	0.68	0.62	0.64	0.59	0.64	0.48	0.55	0.13	0.52
Small Lux Banks	0.13	0.11	0.10	0.29	0.14	0.08	0.81	0.24	0.93	0.94	0.96	0.99	1.00	0.95	0.99	0.97
Medium Lux Banks	0.83	0.94	0.98	0.09	0.31	0.99	0.37	0.65	0.97	0.98	0.99	1.00	1.00	0.98	1.00	0.99
Large Lux Banks	0.37	0.44	0.56	0.32	0.06	0.75	0.49	0.42	0.83	0.87	0.85	0.91	0.83	0.80	0.53	0.80
Column Average	0.51	0.61	0.62	0.22	0.24	0.64	0.64	0.50	0.84	0.86	0.85	0.89	0.83	0.82	0.66	0.82
								Q4 2015								
Banking Groups	0.99	0.80	0.93	0.72	0.74	0.98	0.79	0.85	0.83	0.70	0.73	0.28	0.64	0.69	0.77	0.66
Small Lux Banks	0.99	0.96	0.98	0.63	0.86	1.00	0.97	0.92	0.97	1.00	1.00	0.74	0.99	1.00	0.98	0.95
Medium Lux Banks	0.74	1.00	0.90	0.40	0.99	0.85	0.95	0.83	1.00	1.00	1.00	0.78	0.99	1.00	0.99	0.97
Large Lux Banks	0.52	0.83	0.63	0.24	0.74	0.59	0.84	0.63	0.31	0.53	0.42	0.21	0.48	0.44	0.33	0.39
Column Average	0.81	0.90	0.86	0.50	0.83	0.85	0.89	0.81	0.78	0.81	0.79	0.50	0.78	0.78	0.77	0.74

Note: These matrices present the probability of distress of the financial institutions in the rows, conditional on the financial institutions in the columns becoming distressed.

Table 5: Distress Dependence Matrices for the 2 Worst Banking Groups, the 2 Worst Luxembourg Banks, and the Worst Investment Fund Type

	PDs						CC PDs					
The PD in the row, given PD in the column	2nd Worst Banking Group	1st Worst Banking Group	2nd t Worst Lux Bank	1st Worst Lux Bank	1st Worst Investment Fun	Row Average	2nd Worst Banking Group	1st Worst Banking Group	2nd t Worst Lux Bank	1st Worst Lux Bank	1st Worst Investment Fun	Row Average
						Q1 2011						
2nd Worst Banking Group	1.00	0.97	0.74	0.33	0.49	0.71	1.00	0.85	0.44	0.34	0.45	0.61
1st Worst Banking Group	0.96	1.00	0.71	0.33	0.52	0.70	0.85	1.00	0.41	0.41	0.71	0.68
2nd t Worst Lux Bank	0.76	0.73	1.00	0.40	0.43	0.67	0.43	0.40	1.00	0.76	0.49	0.62
1st Worst Lux Bank	0.35	0.35	0.41	1.00	0.98	0.62	0.35	0.42	0.78	1.00	0.85	0.68
1st Worst Investment Fund	0.13	0.14	0.11	0.25	1.00	0.33	0.14	0.22	0.16	0.26	1.00	0.35
Column Average	0.64	0.64	0.60	0.46	0.68	0.60	0.55	0.58	0.56	0.55	0.70	0.59
Banks' effect on Investment Funds						0.16						0.19
Investment Fund's effect on Banks					0.61						0.62	
						Q2 2011						
1st Worst Banking Group	1.00	0.85	0.67	0.37	0.37	0.65	1.00	0.73	0.79	0.59	0.39	0.70
2nd Worst Banking Group	0.84	1.00	0.66	0.39	0.34	0.65	0.73	1.00	0.63	0.67	0.79	0.76
1st Worst Lux Bank	0.70	0.70	1.00	0.46	0.35	0.64	0.76	0.61	1.00	0.71	0.52	0.72
2nd Worst Lux Bank	0.40	0.42	0.47	1.00	1.00	0.66	0.58	0.66	0.73	1.00	0.95	0.79
1st Worst Investment Fund	0.10	0.10	0.09	0.27	1.00	0.31	0.11	0.22	0.15	0.27	1.00	0.35
Column Average	0.61	0.62	0.58	0.50	0.61	0.58	0.64	0.64	0.66	0.65	0.73	0.66
Banks' effect on Investment Funds						0.14						0.19
Investment Fund's effect on Banks					0.51						0.66	
						Q3 2011						
2nd Worst Banking Group	1.00	0.93	0.30	0.40	0.93	0.71	1.00	0.98	0.25	0.28	0.99	0.70
1st Worst Banking Group	0.93	1.00	0.35	0.34	0.85	0.69	0.99	1.00	0.24	0.27	0.99	0.70
2nd t Worst Lux Bank	0.30	0.35	1.00	0.50	0.14	0.46	0.23	0.23	1.00	0.68	0.06	0.44
1st Worst Lux Bank	0.40	0.34	0.50	1.00	0.59	0.57	0.26	0.25	0.68	1.00	0.30	0.50
1st Worst Investment Fund	0.55	0.50	0.08	0.35	1.00	0.50	0.40	0.40	0.03	0.13	1.00	0.39
Column Average	0.64	0.62	0.44	0.52	0.70	0.58	0.58	0.57	0.44	0.47	0.67	0.54
Banks' effect on Investment Funds						0.37						0.24
Investment Fund's effect on Banks					0.63						0.58	
						Q4 2011						
2nd Worst Banking Group	1.00	0.75	0.25	0.06	0.97	0.61	1.00	0.76	0.08	0.29	0.96	0.62
1st Worst Banking Group	0.79	1.00	0.30	0.13	1.00	0.64	0.79	1.00	0.22	0.26	1.00	0.66
2nd t Worst Lux Bank	0.26	0.30	1.00	0.77	0.11	0.49	0.08	0.21	1.00	0.76	0.08	0.43
1st Worst Lux Bank	0.06	0.13	0.74	1.00	0.00	0.39	0.27	0.24	0.72	1.00	0.24	0.49
1st Worst Investment Fund	0.49	0.49	0.05	0.00	1.00	0.41	0.39	0.38	0.03	0.10	1.00	0.38
Column Average	0.52	0.53	0.47	0.39	0.62	0.51	0.51	0.52	0.41	0.48	0.66	0.52
Banks' effect on Investment Funds						0.26						0.23
Investment Fund's effect on Banks					0.52						0.57	
						Q1 2012						
2nd Worst Banking Group	1.00	0.88	0.10	0.09	1.00	0.61	1.00	0.91	0.40	0.15	1.00	0.69
1st Worst Banking Group	0.89	1.00	0.16	0.10	0.95	0.62	0.91	1.00	0.49	0.20	0.99	0.72
2nd t Worst Lux Bank	0.09	0.15	1.00	0.88	0.01	0.43	0.37	0.46	1.00	0.63	0.34	0.56
1st Worst Lux Bank	0.09	0.10	0.88	1.00	0.01	0.41	0.13	0.18	0.61	1.00	0.12	0.41
1st Worst Investment Fund	0.57	0.53	0.01	0.00	1.00	0.42	0.32	0.32	0.12	0.04	1.00	0.36
Column Average	0.53	0.53	0.43	0.42	0.59	0.50	0.55	0.57	0.52	0.40	0.69	0.55
Banks' effect on Investment Funds						0.28						0.20
Investment Fund's effect on Banks					0.49						0.61	
						Q2 2012						
2nd Worst Banking Group	1.00	0.75	0.36	0.19	0.75	0.61	1.00	0.77	0.54	0.24	0.52	0.61
1st Worst Banking Group	0.79	1.00	0.27	0.05	0.65	0.55	0.81	1.00	0.39	0.11	0.66	0.59
2nd t Worst Lux Bank	0.39	0.28	1.00	0.71	0.79	0.63	0.57	0.39	1.00	0.72	0.68	0.67
1st Worst Lux Bank	0.19	0.04	0.65	1.00	0.30	0.44	0.22	0.09	0.63	1.00	0.37	0.46
1st Worst Investment Fund	0.38	0.31	0.37	0.15	1.00	0.44	0.05	0.06	0.06	0.04	1.00	0.24
Column Average	0.55	0.48	0.53	0.42	0.70	0.54	0.53	0.46	0.53	0.42	0.65	0.52
Banks' effect on Investment Funds						0.30						0.06
Investment Fund's effect on Banks					0.62						0.56	
						Q3 2012						
2nd Worst Banking Group	1.00	0.82	0.48	0.49	0.64	0.69	1.00	0.91	0.51	0.34	0.92	0.74
1st Worst Banking Group	0.82	1.00	0.53	0.24	0.77	0.67	0.91	1.00	0.53	0.38	0.84	0.73
2nd t Worst Lux Bank	0.50	0.56	1.00	0.41	0.97	0.69	0.52	0.54	1.00	0.88	0.81	0.75
1st Worst Lux Bank	0.34	0.17	0.27	1.00	0.13	0.38	0.30	0.33	0.76	1.00	0.45	0.57
1st Worst Investment Fund	0.34	0.42	0.51	0.10	1.00	0.47	0.21	0.19	0.18	0.12	1.00	0.34
Column Average	0.60	0.59	0.56	0.45	0.70	0.58	0.59	0.60	0.60	0.54	0.80	0.62
Banks' effect on Investment Funds						0.34						0.17
Investment Fund's effect on Banks					0.63						0.75	
						Q4 2012						
2nd Worst Banking Group	1.00	0.67	0.53	0.35	0.82	0.67	1.00	0.91	0.63	0.37	0.86	0.75
1st Worst Banking Group	0.72	1.00	0.46	0.37	0.63	0.64	0.95	1.00	0.68	0.41	0.91	0.79
2nd t Worst Lux Bank	0.60	0.49	1.00	0.40	0.98	0.69	0.68	0.70	1.00	0.75	1.00	0.83
1st Worst Lux Bank	0.38	0.39	0.39	1.00	0.30	0.49	0.35	0.36	0.65	1.00	0.63	0.60
1st Worst Investment Fund	0.43	0.31	0.45	0.14	1.00	0.47	0.30	0.30	0.32	0.23	1.00	0.43
Column Average	0.62	0.57	0.56	0.45	0.75	0.59	0.66	0.65	0.65	0.55	0.88	0.68
Banks' effect on Investment Funds						0.33						0.29
Investment Fund's effect on Banks					0.69						0.85	

Note: These matrices present the probability of distress of the financial institutions in the rows, conditional on the financial institutions in the columns becoming distressed.

Table 6a - Summary of Drivers of the Common Components of Systemic Risk Measures

	Scenario	Macroeconomy	Fund Prices	Funding Quantities	Condidence	PDs
FSI	7 IFs, 1 Lux Bank - Dynamic Bank	26.7	45.6	7.7	0.9	19.1
	2 BGs, 2 Lux Banks, 1 IF - Dynamic	19.2	45.0	6.4	0.7	28.7
	4 O-SIIs,1 IF - Dynamic IFs	28.6	40.9	10.1	3.9	16.5
	4 G-SIBs, 1 IF - Dynamic IFs	20.5	45.6	13.0	2.6	18.3
	MMF, NMMF, SML Lux Banks, BG - Dynamic Banks	22.7	65.2	7.9	2.2	2.0
	SML Lux Banks, BG, 1IF - Dynamic IFs	44.8	39.8	12.2	0.0	3.1
FSF	7 IFs, 1 Lux Bank - Dynamic Bank	25.3	42.1	12.8	2.0	17.8
	2 BGs, 2 Lux Banks, 1 IF - Dynamic	19.3	45.3	7.6	6.1	21.8
	4 O-SIIs,1 IF - Dynamic IFs	33.1	33.3	9.4	1.5	22.7
	4 G-SIBs, 1 IF - Dynamic IFs	20.8	41.5	15.1	4.8	17.8
	MMF, NMMF, SML Lux Banks, BG - Dynamic Banks	20.6	58.7	16.7	0.7	3.4
	SML Lux Banks, BG, 1IF - Dynamic IFs	47.6	30.2	17.3	2.8	2.1
PAO	7 IFs, 1 Lux Bank - Dynamic Bank	17.7	52.0	11.1	0.9	18.3
	2 BGs, 2 Lux Banks, 1 IF - Dynamic	20.6	41.6	14.5	1.2	22.1
	4 O-SIIs,1 IF - Dynamic IFs	27.6	44.5	11.3	1.3	15.3
	4 G-SIBs, 1 IF - Dynamic IFs	29.6	41.4	10.3	3.4	15.3
	MMF, NMMF, SML Lux Banks, BG - Dynamic Banks	21.3	62.2	11.3	2.3	2.8
	SML Lux Banks, BG, 1IF - Dynamic IFs	33.6	44.2	16.7	0.5	5.0
	Average	26.6	45.5	11.7	2.1	14.0

Note: Table 6b reports the weighted contribution of each set of macro-financial variables to the PDs of banks and investment fund types (percent).

Table 6b - Summary of Banks and Investment Funds' PD Drivers

	Financial Institution	Macroeconomy	Fund Prices	Funding Quantities	Condidence	PDs
PDs	Luxembourg banks	31.1	36.0	12.1	2.5	18.3
	European banking groups	17.0	47.3	6.6	3.8	25.4
	Equity Funds	30.5	46.7	9.7	0.9	12.2
	Bonds Funds	22.8	44.8	9.4	0.4	22.6
	Mixed Funds	22.6	44.9	11.2	0.8	20.4
	Real Estate Funds	53.4	23.4	7.8	4.0	11.4
	Hedge Funds	37.7	30.5	10.7	1.7	19.5
	Other Funds	40.3	33.3	8.1	4.7	13.6
	Money Market Funds	23.2	47.3	10.2	0.6	18.7
	Average	30.9	39.4	9.5	2.1	18.0

Note: Table 6a reports the weighted contribution of each of the set of macro-financial variables to systemic risk across all scenarii (percent).

Table 7: CIMDO Copula BSI Forecast (Median) Evaluation for banking group index and Luxembourg bank index and worst IF (among MMF & Non-MMF)

	Common Component		Common & Idiosyncratic Component	
	1th Quarter	2nd Quarter	1th Quarter	2nd Quarter
		FSI		
RMS Error	0.17	0.37	0.23	0.32
Bias Proportion	0.10	0.12	0.02	0.03
Variance Proportion	0.21	0.08	0.01	0.00
Coviance Proportion	0.69	0.80	0.97	0.97
		PAO		
RMS Error	0.09	0.09	0.05	0.03
Bias Proportion	0.04	0.11	0.02	0.08
Variance Proportion	0.31	0.19	0.06	0.00
Coviance Proportion	0.65	0.70	0.92	0.92
		FSF		
RMS Error	0.04	0.10	0.05	0.09
Bias Proportion	0.02	0.00	0.02	0.02
Variance Proportion	0.14	0.06	0.01	0.00
Coviance Proportion	0.84	0.94	0.97	0.98

Note: The table reports the coverage ratios, root mean square erros, and the proportions of bias, variance, and covariance respectively from 2013 to 2015 across all BSI, PAO and FSF from CIMDO Copula for banking group index and luxembourg bank index and worst IF(among MMF & Non-MMF).

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

Forni *et al*'s GDFM (2005) provides a good framework for multi-step-ahead predictions of the generalized common component $X_t^{i,CC}$ of a vector process X_t^i. Nevertheless, the idiosyncratic component $X_t^{i,IC}$ also plays an important role for financial stability and cannot be neglected (see Schwaab *et al*, 2010). Jin and Nadal De Simone (2014) introduce a novel approach to combine the GDFM[38] 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 in the vector process X_t^i. Then, a dynamic t-copula is used to glue together the standardized residuals or innovations from those components. Formally, the dynamic forecasting model becomes:

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

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

[38] The input into 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 into the GDFM.

The t-copula provides a robust method for a consistent estimation of dependence structures and is very flexible.[39] In addition, the use of the conditional dynamic t-copula makes it relatively easy to construct multivariate distributions using marginal distributions and dependence structure and to simulate from them. The following sections explain the modelling of marginal dynamics, dynamic t-copulas, and forward simulations.

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:

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

The model is estimated by Quasi-Maximum Likelihood. The best AR (p) - GARCH (1,1) model 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 macro-prudential policy. Given the standardized i.i.d. residuals ε_t from the estimation of the marginal dynamics, the empirical cumulative distribution function (cdf) of these standardized residuals is estimated by the distribution of exceedances method (McNeil, 1999, and McNeil and Frey, 2000).[40]

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 [41]:

[39] 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 and the copula, and it is not a robust measure given that a single observation can have an arbitrarily high influence on it.
[40] The upper and lower 10% thresholds of the residuals are reserved for each tail to ensure that there are sufficient data points in the tails to conform well to a GP. 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 a maximum likelihood procedure.
[9] See Patton (2006b) for the definition of a general conditional copula.

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

where $\eta_n = F_n(\varepsilon_n)$ for i=1,2,...,n, and $\varepsilon_t \sim iid(0,1),$ are the innovations from the marginal dynamics introduced in the previous section. R_t is the rank correlation matrix, and v_t is the degrees of freedom. $t_{v_t}^{-1}(\eta_n)$ denotes the inverse of the t cumulative distribution function. R_t and v_t can be assumed to be constant, or dynamic processes 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:

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

where $\alpha_{dcc}\geq 0,\beta_{dcc}\geq 0,\alpha_{dcc}+\beta_{dcc}\leq 1$, $\varepsilon_t^{*}=t_{v_t}^{-1}(\eta_n=F_n(\varepsilon_n))$, $Q_t=|q_{ij,t}|$ is the auxiliary matrix driving the rank correlation dynamics and the nuisance parameters $\bar{Q}=E[\varepsilon_t^{*}\varepsilon_t^{*'}]$ have a sample analog $\bar{Q}=T^{-1}\sum_{t=1}^{T}\varepsilon_t^{*}\varepsilon_t^{*'}$, so that R_t is a matrix of rank correlations $q_{ij,t}$ with ones on the diagonal, $\rho_{ij,t}=\dfrac{q_{ij,t}}{\sqrt{q_{ii,t}}\sqrt{q_{jj,t}}}$.

Given that the correlation between the Gaussian rank correlation $\rho_{GR}=Corr(\Phi^{-1}(u)\Phi^{-1}(v)$ and a t-copula rank correlation $\rho_{TR}=Corr(t_v^{-1}(u)t_v^{-1}(v)$ is almost equal to one, R_t can be well approximated by the $R_t^{Gaussian}$ from the dynamic Gaussian Copula (Bouye *et al*, 2000). For convenience, this study adopts a two-step algorithm for estimation which means that R_t is estimated from the dynamic Gaussian copula first by maximizing composite likelihood (Shephard and Sheppard, 2008)[42], and then, with R_t fixed, the degrees of freedom are recovered from the t-copula. To avoid the

[42] The composite likelihood method is based on summing up the quasi-likelihood of all subsets. Each subset yields a valid quasi-likelihood, but this quasi-likelihood is only mildly informative about the parameters. By summing up many subsets, it is possible to construct an estimator which has the advantage of not making necessary the inversion of large dimensional covariance matrices, and avoid a significant downward bias.

known estimation difficulties of high-dimensional t-copulas, m-profile subset composite likelihood (MSCL)[43]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 $\varepsilon_{t+1}^{*i1},...,\varepsilon_{t+1}^{*im}$ for each component from the n-dimensional *t* distribution with zero mean, forecast correlation matrix R_{t+1} , and degrees of freedom v_{t+1} to obtain $\mu_{t+1}^{i1},...,\mu_{t+1}^{im}$ by setting $\mu_{t+1}^{ik}=t_{v_{t+1}}(\varepsilon_{t+1}^{*ik})$, where *k=1,...,m*, is the total number of paths of the simulation, and *i=1,...,n*, is the number of components;
2. Obtain $\varepsilon_{t+1}^{i1},...,\varepsilon_{t+1}^{im}$ by setting $\varepsilon_{t+1}^{ik}=F_i^{-1}(\mu_{t+1}^{ik})$, where F_i is the empirical marginal dynamics distribution for component *i*;
3. Obtain $z_{t+1}^{i1},...,z_{t+1}^{im}$ by setting $z_{t+1}^{ik}=\varepsilon_{t+1}^{ik}\sigma_{t+1}^{i}$, where σ_{t+1}^{i} is the forecast standard deviation using a GARCH (1,1) model for component *i*;
4. Obtain $X_{t+1}^{i1},...,X_{t+1}^{im}$ by setting $X_{t+1}^{ik}=\lambda_{t+1}^{i}+z_{t+1}^{ik}$, where λ_{t+1}^{i} is the forecast mean using an AR (p) model for the idiosyncratic component *i*, and the prediction of the common component using Forni *et al* (2005);
5. Finally, sum the predicted idiosyncratic and common components at *t+1*.

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 $Max(DPs^{Simulated},0)$. This forward simulation approach, therefore, integrates the one-sided forecasting features of the GDFM into the dynamic t-copula framework.

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[43] MSCL is a moment-based profile likelihood, or m-profile likelihood for short, in which the nuisance parameters are not maximum quasi-likelihood estimators, but attractive moment estimators due to the relative easiness of their estimation.

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)

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