CAHIER D'ÉTUDES
WORKING PAPER

N° 95

INVESTMENT FUNDS' VULNERABILITIES: A TAIL-RISK DYNAMIC CIMDO APPROACH

XISONG JIN   FRANCISCO NADAL DE SIMONE

JULY 2015

BANQUE CENTRALE DU LUXEMBOURG
EUROSYSTÈME

Investment Funds' Vulnerabilities: A Tail-risk Dynamic CIMDO Approach

Xisong Jin
Luxembourg School of Finance

Francisco Nadal De Simone
Banque centrale du Luxembourg

December 2014

Abstract

This study measures investment funds' systemic credit risk in three forms: (1) credit risk common to all funds within each of the seven categories National Central Banks report to the ECB; (2) credit risk in each category of investment fund conditional on distress on another category of investment fund and; (3) the build-up of investment funds' vulnerabilities which may lead to a disorderly unraveling. The paper uses a novel framework which combines marginal probabilities of distress estimated from a structural credit risk model with the consistent information multivariate density optimization (CIMDO) methodology and the generalized dynamic factor model (GDFM). The framework models investment funds' distress dependence explicitly and captures the time-varying non-linearities and feedback effects typical of financial markets. In addition, the estimates of the common components of the investment funds' distress measures may contain some early warning features, and identifying the macro and financial variables most closely associated with them may serve to guide macro-prudential policy. The relative importance of these variables differs from those associated with the common components of marginal measures of distress. Thus this framework can contribute to the formulation of macro-prudential policy.

JEL Classification: C1, E5, F3, G1

Keywords: financial stability; investment funds; procyclicality, macro-prudential policy; structural credit risk models; probability of distress; non-linearities; generalized dynamic factor model; dynamic copulas.

We thank the Fonds National de la Recherche (FNR), Luxembourg for its financial support. We also thank colleagues for comments received at a seminar at the Banque centrale du Luxembourg (BCL), especially Abdelaziz Rouabah and Paolo Guarda. Correspondence can be sent to: Xisong Jin, Luxembourg School of Finance, 4 rue Albert Borschette L-1246 Luxembourg, Tel: (+352) 46 66 44 5626; E-mail: xisong.jin@uni.lu; Francisco Nadal De Simone, Banque centrale du Luxembourg, 2, boulevard Royal L-2983 Luxembourg, Tel: (+352) 4774-4518; E-mail: Francisco.NadaldeSimone@bcl.lu.

Résumé non-technique

Les vulnérabilités des organismes de placement collectif : une approche dynamique d'évaluation des risques systémiques

Les fonds d'investissement sont une composante importante du secteur financier luxembourgeois avec un encours bilantaire dépassant les 3000 milliards d'euros au 30 juin 2014. Ils entretiennent des liens variés avec les établissements de crédit au niveau national et à l'étranger. Bien qu'actuellement le degré de vulnérabilité des fonds d'investissement soit compatible avec les exigences de stabilité financière, l'expérience récente lors de l'émergence de la crise financière internationale a révélé le rôle de levier que peut jouer cette composante dans la propagation des risques. Ainsi, il serait utile dans le cadre de l'institutionnalisation de la surveillance macro-prudentielle au Luxembourg de développer une batterie d'indicateurs qui puisse aider à appréhender la solidité du système financier ou de l'une de ses composantes.

Dans cette étude, nous proposons de construire des mesures de vulnérabilité pour les organismes de placement collectif (OPC) afin de contribuer efficacement à la conduite de la politique macro-prudentielle. Les mesures de vulnérabilité sont élaborées pour chaque catégorie de fonds d'investissement domiciliés au Luxembourg. Le cadre développé dans cette étude se focalise sur la mesure du risque de crédit d'importance systémique induit par des évènements peu fréquents et dont la matérialisation se traduit souvent par des pertes sociales importantes. Toutefois, il importe de souligner que les données de notre échantillon couvrent une période relativement courte ; autrement dit, elles ne nous permettent pas de produire des projections des variables de vulnérabilité et de conférer ainsi à nos mesures un caractère d'alertes avancées.

La présente étude transpose aux organismes de placement collectif le même cadre d'approche intégrée que celui appliqué précédemment par Jin et Nadal De Simone (2014) aux secteurs bancaires luxembourgeois et européen. L'objectif est de mesurer le risque de crédit systémique induit principalement par les interconnexions entre les différentes catégories de fonds d'investissement, mais aussi par l'interaction entre ces dernières et l'environnement macroéconomique.

Cette analyse englobe l'ensemble des sept types de fonds d'investissement: fonds actions, fonds obligataires, fonds mixtes, fonds immobiliers, fonds alternatifs, autres fonds et fonds monétaires. Les données bilantaires sont d'une fréquence trimestrielle et couvrent la période de décembre 2008 à juin 2013. Les dettes prises en compte sont réparties en fonction de leurs maturités initiales, c'est-à-dire selon qu'elles soient inférieures ou

supérieures à un an. Les parts des fonds émises servent d'approximation pour leurs fonds propres. Les positions des dérivés ont été consolidées.

Notre analyse consiste tout d'abord en l'estimation des probabilités de défaut (PDs) selon le modèle structurel de risque de Merton (1974). Ensuite, l'approche dite « optimisation de la densité multivariée avec information consistante » (consistent information multivariate density optimisation, CIMDO) développée par Segoviano (2006) est utilisée afin de modéliser les interdépendances linéaire et non-linéaire entre les différents types de fonds d'investissement ainsi que les effets de retour (*feedback effects*) entre la catégorie de fonds et le système financier dans son ensemble. Enfin, le cadre offert par les modèles factoriels dynamiques généralisés *(generalized dynamic factor model,* GDFM) est appliqué à une large base de données macro-financières afin d'extraire la composante commune des probabilités de défaut marginales. Ceci permet d'observer la manière dont l'ensemble des facteurs communs affectent la vulnérabilité de chaque catégorie de fonds d'investissement. Cette approche met ainsi en évidence les liens entre les mesures de vulnérabilité et les facteurs macro-économiques sous-jacents permettant ainsi d'atténuer les difficultés liées à la détermination temporelle de l'importance du risque en tant que composante des prix des actifs.

Il y a lieu de noter que le cadre adopté s'avère très adapté à l'analyse du risque de crédit sévère. Il nous a permis d'obtenir des résultats très encourageants. En premier lieu, les probabilités de défaut estimées pour chaque catégorie de fonds d'investissement sont en adéquation avec les différentes restrictions réglementaires auxquelles chaque catégorie est exposée. A titre d'exemple, les fonds alternatifs ont une tendance à présenter des probabilités de défaut plus élevées car ils sont autorisés à maintenir un levier plus important que les fonds monétaires pour lesquels seul le levier dit « technique » est permis.

Ensuite, deux mesures du risque de crédit systémique commun à tous les fonds d'investissement sont estimées : la première est la fragilité systémique des fonds d'investissement (IFSF), laquelle s'avère déterminante pour l'estimation de la probabilité qu'au moins deux catégories de fonds d'investissement soient simultanément en détresse. La seconde est l'indice de stabilité des fonds d'investissement (IFSI), lequel est destiné à mesurer l'espérance du *nombre* de fonds d'investissement qui seraient en détresse, sachant qu'un type quelconque de fonds d'investissement l'est déjà.

Il ressort de nos estimations que ces deux mesures suivent de près les changements les plus significatifs des coûts de financement, en l'occurrence les taux d'intérêt à court terme et les indices de prix des actions, ainsi que les développements macroéconomiques. Dans ce contexte, il est important de souligner que les composantes communes du risque issues des deux mesures sont corrélées négativement. Un tel résultat suggère qu'une augmentation des coûts de financement suite à un resserrement de la politique monétaire *réduirait* aussi la composante commune de l'indice de fragilité systémique des fonds d'investissement. Ceci s'explique principalement par l'incitation à une moindre prise de risque sans pour autant réduire l'apport du coût de financement à la composante commune de l'indice de fragilité.

En troisième lieu, le risque de crédit afférent à l'activité des fonds d'investissement est susceptible d'être mesuré par la probabilité conditionnelle qu'au moins une catégorie de fonds d'investissement soit en détresse (PAO) sachant qu'un type de fonds d'investissement l'est déjà. Dans ce cadre, nos résultats révèlent que le secteur des fonds d'investissement s'avère plus résilient à la détresse des fonds alternatifs et des fonds immobiliers qu'à la détresse des fonds mixtes, des fonds obligataires et des fonds d'actions. Ces résultats semblent être confirmés par une seconde mesure de contagion, en l'occurrence la matrice de dépendance (*Distress Depedence Matrix,* DDM).

De ce qui précède, il ressort que le degré de fragilité du secteur des fonds d'investissement, en termes de risque de contagion, a progressé au cours de la période de décembre 2009-décembre 2010. Depuis, une nette diminution du risque systémique est observée.

Finalement, quoique les résultats dépendent du type de fonds d'investissement, les variables macroéconomiques (notamment la croissance du PIB), ainsi que certaines variables financières, telles que l'encours du crédit à l'économie, semblent être fortement corrélées à la composante commune des probabibilités conditionnelles de détresse des fonds d'investissement au Luxembourg.

"Before we can hope to manage the risks of financial crises effectively, we must be able to define and measure those risks explicitly*." Andrew Lo*[1]

I. Introduction and Motivation

The world investment fund industry was managing about 22 trillion euro of assets at end of 2013 (Table 1).[2] This includes only investment funds organized as Undertakings for Collective Investment in Transferable Securities (UCITS), i.e., publicly offered open-ended investment funds regulated by the 2009 UCITS IV directive[3] in Europe and the 1940 Investment Company Act in the US. European investment funds organized as non-UCITS were managing over 2.9 trillion euro at end-2013.[4] In the US, Hedge Funds only managed about 1.3 trillion euro at end-2013.[5] In the EU, total assets managed by all categories of investment funds at end-2013 represented about ¾ of GDP.

After the US, Luxembourg is the second largest domicile of UCITS in the world and the third domicile of non-UCITS after Germany and France. Luxembourg-domiciled investment funds managed over 2.6 trillion euro of assets at end-2013. Worldwide, Equity, Bond and Mixed Investment Funds were the main business lines (Figure 1). In Luxembourg, Bond Investment Funds represented 37% of total assets, followed by Equity Investment Funds and Mixed Investment Funds, with shares of 29% and 22%, respectively (Figure 2). The evolution of the total number of compartments of the industry during the 2000s followed the macroeconomic cycle as measured by the output gap (Figure 3).[6]

In Luxembourg, UCITS and non-UCITS are regulated by a set of national laws that have implemented the European Commission's UCITS IV Directive, the SICAR Law of 2005, the Specialized Investment Funds Law of 2007, and the 2013 Law that implemented the

[1] Testimony Prepared for the US House of Representatives Committee on Oversight and Government Reform, November 13, 2008.

[2] Sources of statistics on investment funds are: BCL, EFAMA (2014), Investment Company Institute (2014), and TheCityUK (2013).

[3] The UCITS I directive dates back to December 1985.

[4] While non-UCITS are nationally regulated investment funds for which a classification in terms of market exposure is not possible, the European Commission's Directive on Alternative Investment Fund Managers (AIFMD) that entered into force in July 2011—Member States had time until July 2013 to transpose the Directive—creates a comprehensive regulatory a supervisory framework for non-UCITS with requirements regarding safekeeping of assets, leverage, liquidity management, management and pricing.

[5] The Dodd-Frank Wall Street Reform and Consumer Protection Act that entered into effect in July 2011, requires private pools of capital exceeding $100 million to register with the Securities and Exchange Commission as investment advisers ($150 million if they work with private funds only). For pools of capital below the threshold, registration with the state of domicile of the advisers is compulsory. Since October 2011, advisers must also report information necessary for monitoring systemic financial risk.

[6] The output gap is estimated using Corbae and Ouliaris (2006) ideal band-pass filter.

European Commission's Alternative Investment Fund Managers Directive (AIFMD). This regulatory framework is a complex set of rules regarding the type of investors who can access different categories of investment funds, the eligible investments, investment restrictions, the asset valuation approach and its frequency, permitted leverage and exposure (Table 2). Figure 4 shows leverage per investment fund's category.

Highly-leveraged hedge funds have been blamed for magnifying the crisis. For example, investment bank Bear Stearns liquidated two hedge funds that had invested in risky securities backed by subprime mortgage loans. However, Money Market Funds have also been center stage. For example, the day following the Lehman Brothers bankruptcy in September 2008, the share price of Reserve Primary Fund fell below one US dollar because the fund's holdings of Lehman-issued commercial paper became worthless. Investors swamped the fund with redemption requests, causing the fund to be closed and eventually liquidated. Withdrawal from funds grew to 144.5bn US dollar during one week, compared to 7.1bn US dollar the prior week. According to analysts at the Boston Fed, at least 20 other funds would have "broken the buck" in the US if not for direct support from fund sponsors during the financial crisis. The US Treasury also stepped in, setting up a guarantee program for MMF investors to stem redemptions at other prime money funds and to shore up the industry.

The sheer size of the world investment fund industry had prompted a large volume of research preceding the crisis. With the obvious importance of the industry heightened by the crisis, the literature has grown even further. However, the investment fund literature has not been concerned with estimating systemic credit risk in the three forms categorized by the European Central Bank (ECB), 2009: (1) credit risk common to all financial institutions; (2) credit risk in the form of contagion from a failed financial institution to the rest of the economic system and; (3) the build-up of financial institutions' vulnerabilities which may unravel in a disorderly manner. Recently, a few studies have measured systemic risk in the form of contagion or interconnectedness. In addition, the literature has mostly modeled and estimated distress[7] in two categories of investment funds, i.e., Money Market Funds and Hedge Funds. Finally, data used has often been publicly available returns and, with some exceptions, has focused on US-domiciled investment funds.

Early research that *does not use a concept of systemic risk* includes Asger *et al* (1999) who applied Cox regression analysis to determine the hazard function (conditional probability of closure) of UK unit trusts. From a purely policy perspective, Bannier *et al* (2006) studied the institutional structure of Real Estate Funds in Germany. Other similar

[7] Distress and default are used indistinctively

work concentrated on the US. Chen et al (2010) studied payoff complementarities and their impact on the fragility of US Equity mutual Funds and stressed the role of illiquidity in the vulnerability of funds. Ang *et* al (2010) used panel regression analysis in a sample of US Hedge Funds and show that changes in leverage tend to be predictable by macroeconomic factors such as funding costs and market values rather than by fund-specific characteristics. Dixon *et al* (2012) analyzed the contribution of US Hedge Funds to the 2007-2008 crisis using regression analysis and found that they were not a primary cause, although they contributed to the failure of one or more financial institutions via credit and liquidity risks. This conclusion mirrors Strömqvist's (2009) descriptive work on Hedge Funds' performance during three several periods of crisis. Finally, Schmidt *et al* (2012) analyzed runs on US mutual funds using panel regression methods and found that money tended mostly to flow out of Money Market Funds with high yields, higher prior volatility and lower expense ratios, indicating that while "hot money" chased yields, it ran from relatively more vulnerable funds.

While addressing systemic risk in a loose and incomplete form, there is a number of studies that are closely related to this research. Chan *et al* (2007) was the first study to analyze the impact of Hedge Funds on *indirect systemic risk*--defined as a series of correlated defaults among financial institutions over a short period of time. It used only returns data from the TASS database. This paper is important because it explores how the dynamic nature of Hedge Fund strategies, leverage and funds flows affected systemic risk by using a regime-switching model, with high-volatility or low-mean state probabilities as proxies for distress in the sector. Comparing their results to the rising statistics on liquidation probabilities from a logit model, the authors concluded that systemic risk was on the rise since 2004, as also argued in Jin and Nadal De Simone (2012) using measures of *direct systemic risk* in a sample of European banking groups and Luxembourg banks.

Another empirical research that is noteworthy is Klaus and Rzepkowsky (2009) because while not discussing systemic risk explicitly, they estimated risk spillover or contagion (i.e., the second form of systemic risk) among Hedge Funds via a logit model for failure using the large TASS database that comprises advanced and emerging market economy Hedge Funds. In the same vein, Boyson *et al* (2010) defined contagion as correlation exceeding what is justified by economic fundamentals and found strong evidence of "worst return" contagion across Hedge fund types from 1990 to 2008. Large adverse shocks to funding and asset liquidity strongly increased the probability of contagion. Billio *et al* (2011) also proposed measures of systemic risk understood as interconnectedness between Hedge Funds, banks, brokers and insurance companies using principal component analysis and Granger causality. They constructed in-sample and out-of-sample measures of systemic risk and found that Hedge Funds can provide early warnings of systemic risk arising from a complex network of relationships with banks, brokers and insurance companies. Finally, Acharya *et al* (2010) measured the contribution to systemic risk from banks and a set of non-bank financial institutions (mutual funds were excluded) modelling dependence empirically. They used a bivariate measure, the expected shortfall measure, which they found to be positively correlated with leverage at the individual institution level and marginal expected loss in the tail of the system's loss distribution.

The current paper is broader than the literature reviewed above on several counts. It studies all categories of investment funds domiciled in Luxembourg according to the business lines reported by National Central Banks of the Eurosystem to the ECB. In addition, it uses detailed investment funds' balance sheet data available to the Central Bank of Luxembourg. Beyond its contribution in terms of data coverage, this paper also contains a number of methodological innovations that have not yet been applied to research on the investment fund industry. It uses the framework developed in Jin and Nadal De Simone (2014) to estimate measures of systemic risk in the banking industry. The framework has the following main features: it applies the Merton (1974) structural credit risk model to estimate probabilities of distress and then quantifies distress dependence among categories of investment funds to capture key characteristics of systemic risk, such as interconnectedness and contagion, and non-linearities and feedback effects. Measures of systemic risk result from combining the marginal probabilities of distress estimated from Merton's model with the consistent information multivariate density optimization (CIMDO) methodology of Segoviano (2006), and the GDFM of Forni *et* al (2005). The framework estimates in-sample systemic risk and also can be extended to generate out-of-sample projections.[8] It measures systemic credit risk in the investment fund industry in three forms: (1) credit risk common to all funds; (2) credit risk in the investment fund industry conditional on distress in one or more investment fund business lines and; (3) the build-up of investment fund's vulnerabilities over time which may lead to disorderly unraveling. In addition, the estimated common components of the investment fund industry may contain early warning features, and identifying the most closely associated macro-financial variables could be useful for macro-prudential policy.

While systemic risk is limited to the investment fund industry, the framework provides encouraging results.[9] First, marginal probabilities of distress (PDs) estimated for the

[8] We call this *direct systemic* risk as opposed to *indirect systemic* risk in Chan *et al* (2007) who estimated correlation among defaults across financial institutions over a short period of time using only returns data.
[9] An accompanying paper applies the framework jointly to the banking and investment fund industries.

different categories of investment funds are consistent with their different regulatory frameworks. For example, more leveraged Hedged Funds tend to have higher PDs than Money Market Funds, which are allowed only technical leverage.

Second, Money Market Funds (and short-term Money Market Funds), which are organized as UCITS, have a relatively more frequent marked-to-market valuation, and therefore, have estimated PDs which are more closely related to the evolution of macroeconomic indicators and funding quantities, notably credit, as well as confidence indicators.

Third, the two measures of systemic risk as a result of common distress, i.e., the investment funds' systemic fragility (IFSF) indicator measuring the probability that at least two categories of investment funds become distressed, and the investment funds' systemic stability index (IFSI) measuring the expected number of categories of investment funds to become distressed given that any type has become distressed, track well major changes in funding prices, notably short-term interest rates and stock price indices ,[10] as well as macroeconomic developments. Importantly, although their common components are closely related to funding prices, confidence indicators and macroeconomic variables, they are strongly negatively correlated; this suggests that, for example, an increase in funding costs by reducing credit and activity growth, will reduce the common components of the IFSF by inducing less risk taking and will increase the common components of the IFSI because it becomes more likely that more investment funds will get distressed.

Fourth, the third measure of systemic risk, i.e., systemic risk viewed from the contagion viewpoint, is the probability that at least one (PAO) fund category becomes distressed given that another fund category has become distressed. This measure suggests that the industry was more resilient to distress in Hedge Funds and Real Estate Funds than to distress in Mixed, Bond and Equity Funds, in that order. These results are broadly confirmed by the distress dependence matrix (DDM). At the end of the sample period (2013Q2), Mixed Funds, Equity Funds and Bond Funds showed the highest systemic risk. The common component of the equally-weighted average of PAO across all investment funds' categories is strongly positively correlated with the common component of the IFSF. The two measures are therefore very useful to track the two main different forms of systemic risk.

Fifth, systemic risk understood as a slow build-up of vulnerabilities over time can be "monitored" through the common components of systemic credit risk measures, i.e., the

[10] In what follows, funding prices and funding costs are used interchangeably.

IFSF and the PAO, as Jin and Nadal De Simone (2014) show for European banking groups and their corresponding Luxembourg affiliates. The common components of the IFSF and the average PAO lead the IFSF and the average PAO, respectively, with the measures' idiosyncratic components contributing positively to systemic risk in roughly the first and third years of the sample.

Finally, while results vary across investment fund categories, the PAO common components are most closely related to macroeconomic variables (especially GDP growth) followed by funding quantities (notably credit and the credit gap). Funding costs such as interest rates, spreads and stock price indices are less related to contagion and spillovers as forms of systemic risk and more related to systemic risk measures focussed on common shocks. For instance, the PAO (proxying contagion, the second form of systemic risk) is more related to the performance of the economy, credit and leverage. Instead, the IFSF (proxying common shocks, the first form of systemic risk) is more closely linked to funding costs.

The remainder of the study is organized as follows. The next section briefly introduces the novel integrated modelling framework, explains how the Merton model is combined with the GDFM and the CIMDO, and Section III describes the systemic credit risk measures developed for the investment fund industry. Section IV discusses the data. Section V examines the empirical results. Section VI concludes.

II. Investment Funds' Systemic Risk: An Integrated Modeling Framework

This paper studies the Luxembourg investment fund industry using the systemic risk estimation framework that Jin and Nadal De Simone (2012 and 2014) applied to European banking groups and their Luxembourg affiliates. This approach to systemic risk combines Borio *et al* (2001) endogenous view of systemic risk with the quantitative Drehmann and Tarashev (2011) tail-risk view. It recognizes a fact not always addressed in the literature on investment fund distress: while the *market beta* is a sufficient statistic for static investment decisions, it is not a sufficient statistic for dynamic investment strategies such as those followed by alternative investment funds in particular.

In the investment fund industry, systemic risk can take three forms: first, a common shock that affects the whole industry and is transmitted to the real economy (*systematic risk)*; second, an idiosyncratic risk to one investment fund category that is propagated to the rest of the industry and ends up affecting the real economy; third, a slow build up of investment fund vulnerabilities that may unravel in a disorderly manner and affect the real economy. Therefore, This paper's approach covers the cross-section dimension as well as the time-dimension of systemic risk, a perspective on systemic risk that is gathering acceptance (Bisias *et al*, 2012).

Macro-prudential policy requires not only a definition of systemic credit risk in the investment fund sector, but also a means to measure that risk[11]. As suggested by Borio *et al* (2001, p. 5) "…Experience indicates that widespread financial system stress rarely arises from contagion or domino effects associated with the failure of an individual institution owing to purely institution-specific factors. More often, financial system problems have their financial roots in financial institutions underestimating their exposure to a common factor, most notably the financial/business cycle in the economy as a whole." Measurement of such a complex and time-varying phenomenon ideally requires a framework that, despite markets' widely recognized misperceptions of risk, is capable of identifying as early as possible the build-up of endogenous imbalances or the occurrence of exogenous shocks that may propagate across financial institutions and, eventually, to the real economy. At a minimum, this framework should model financial institutions' interdependence explicitly, allow for contagion across financial institutions in different jurisdictions and take into account both the links between financial institutions and among them and the real economy.

This study uses the Merton (1974) option-based structural credit risk model to estimate the implied PDs. However, to understand the risk of simultaneous systematic defaults, the ensuing distribution of losses, and the effects on financial stability, it is necessary to also model dependence between credit events. To that aim, this paper uses the Consistent Information Multivariate Density Optimizing Methodology (CIMDO) of Segoviano (2006). The CIMDO approach characterizes the whole dependence structure of financial institutions, i.e., the linear and non-linear dependence embedded in multivariate densities and has been used to model tail-risk in the banking sector and for sovereigns (Segoviano and Goodhart, 2009).[12] While this structure is allowed to change as PDs evolve over time with the economic cycle, 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, 2014). This paper uses a rolling correlation approach and adjusts the matrix to be symmetric and positive semi-definite using the Qi

[11] This study is not concerned with the tools to address systemic credit risk, but with indicators to alert the policymaker and possible form of systemic risk. It does not address macro-prudential policy implementation.

[12] Mechanisms for obtaining distress 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.

and Sun (2006) Newton-type method to obtain the nearest correlation matrix to the given symmetric matrix. This method displays fast convergence and high efficiency.

A final difficulty intimately related to risk misperception is the procyclicality of the financial system. During the business cycle upswing, perceived risk tends to be small, risk premia fall, margin requirements and haircuts decline, and leverage increases while capital requirements fall as a result of lower risk weights. Such developments reinforce the upswing.[13] Conversely, during the business cycle downswing, perceived risk rises, risk premia increase accordingly, margin requirements and haircuts rise, and financial institutions deleverage reducing credit growth, deflating asset prices and exacerbating the downturn. If risk misperceptions distort asset prices, the implied PDs from structural credit risk models are likely to be themselves also distorted. In order to deal with the procyclicality of the financial system and markets' poor assessment of systemic risk over time, the framework of this paper is completed by linking the PDs and measures of systemic credit risk in the investment fund sector with a large macro-financial database using the Generalized Dynamic Factor Model (GDFM) of Forni *et al* (2005). The GDFM has been used extensively to exploit the information from a large dataset (e.g., Kabundi and Nadal De Simone, 2011, De Nicolò and Lucchetta (2012), and D'Agostino and Giannone, 2011). This allows, by reverse engineering, to uncover the tail risk or the PDs by using not only information from investment funds, but also from a large data set of macro-financial variables revealing thereby not only credit risk emanating from funds' interconnectedness, but also from the macro environment. This allows tracking the macro-financial factors driving the PDs and measures of risk as well as the increase of exposures to common factors during booms and subsequently revealed during busts.

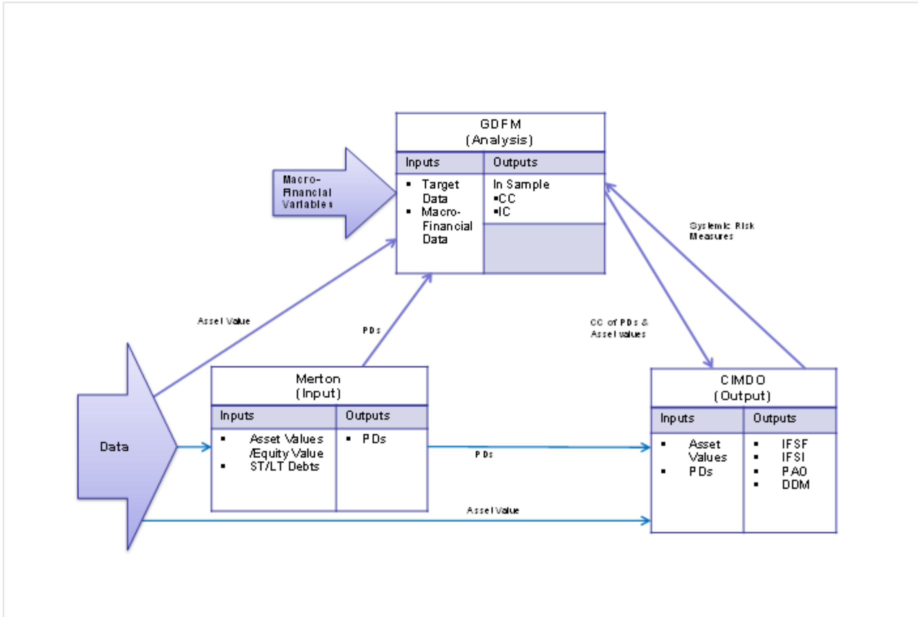
While following the Segoviano and Goodhart (2009) CIMDO approach and estimating their proposed measures of banking stability to investment funds, this study extends their work in several significant ways. First, the structural credit risk model is estimated using accounting information as in Souto *et al* (2009), Blavy and Souto (2009), and Jin and Nadal De Simone (2012 and 2014). Second, this paper explicitly links measures of credit risk in the investment fund industry to macro-financial variables. Third, the proposed framework identifies macro-financial variables most closely related to systemic risk measures, i.e., credit growth, economic activity, stock price indices and interest rate and interest rate spreads. Fourth, by identifying variables associated with investment fund vulnerabilities, the proposed framework explicitly highlights economic processes that macro-prudential policymakers may want to monitor and manage to preserve financial stability, for example, credit growth or leverage.

[13] On the procyclicality of leverage and its measurement, see Geanakoplos (2010), Adrian *et al* (2013) or Adrian and Shin (2013).

2.1. Overview of the Integrated Modeling Framework

In statistics, operations research and engineering, complex information is often broken down into several smaller, less complex and more manageable sub-tasks that can be solved by existing tools, and their solutions are then combined to solve the original problem. Sometimes, the models put together have been developed to solve specific questions in different strands of literature. This is the case with the framework proposed in this paper. The structural credit risk model of Merton (1974) assesses credit risk using option pricing. The GDFM instead is an econometric tool to perform factor analysis on large datasets and to generate forecasts. Copulas are a fundamental tool for modeling multivariate distributions and are used extensively in risk management; however, the sample-length restrictions make it impossible to adequately calibrate the assumed parametric distributions. Therefore, the CIMDO approach, based on cross-entropy, serves as an alternative to generate probability multivariate densities from partial information without having to make parametric assumptions. A few examples integrating these models already exist. De Nicolò and Lucchetta (2012) use a dynamic factor model with many predictors combined with quantile regression techniques. Alessi, Barigozzi and Capasso (2007a&b) propose two new methods for volatility forecasting, which combine the GDFM and the GARCH model and have been proved to outperform the standard univariate GARCH in most cases by exploiting cross-sectional information.

This study uses an integrated framework to measure systemic credit risk emanating from investment funds' interconnectedness and from the macro environment. To conserve space, only the key features of the novel framework are discussed below while directing the reader to the sources of its well-known components, i.e., Merton (1974) and the GDFM of Forni et al. (2005). The framework consists of three highly integrated multi-functional parts which are illustrated by the following information flow chart.



First, it is best to begin with the output part, i.e., the CIMDO model. In this part, the prior dependence structure information necessary for CIMDO is estimated by a rolling window on asset returns adjusted by Qi and Sun's (2006) nearest correlation matrix. The outputs are investment-fund versions of the several important systemic credit risk measures proposed by Segoviano and Goodhart (2009): the Investment Fund System Fragility measure (IFSF) and the Investment Funds Stability Index (IFSI), which measure common distress in the investment fund industry; the Distress Dependence Matrix (DDM) which measures distress between specific investment funds' categories and the Probability that At least One (PAO) investment fund category becomes distressed, which measures the distress in the system by contagion as a result of distress associated with a specific fund category. While the first two measures (IFSF and IFSI) proxy the first form of systemic risk identified by the ECB (2009), the last two measures (DDM and PAO) proxy the second form of systemic risk.[14]

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 data is limited. While this is possible without explicitly including information about the dependence structure between the assets comprising the portfolio, if such information is available, it can be easily incorporated as was done using an adjusted rolling window. In addition, the CIMDO approach describes the linear and non-linear dependencies among the

[14] See Section III for a detailed description of these measures.

variables, dependencies which have the desirable feature of being invariant under increasing and continuous transformations of the marginal distributions. Finally, and fundamentally, while the dependence structure is characterized over the entire domain of the multivariate density, the CIMDO approach appears to be more robust in the tail of the density, where the main interest of this paper lies. Segoviano and Goodhart (2009) show by Monte Carlo simulation that the CIMDO outperforms several widely used parametric distributions, i.e., the standard and conditional Normal distributions, the t-distribution, and the mixture of normal distributions, especially in the region of distress which is of interest here.

Second, the input part is the Merton (1974) option-based structural credit risk model which is used to track credit risk over time. These PDs, together with asset returns, are direct inputs into the CIMDO model. However, as discussed above, risk mispricing over time suggest that full reliance on market prices may hide the build-up of vulnerabilities and fail to deliver an adequate systemic risk measure for macro-prudential policy.

Therefore, a final component of the proposed framework is the GDFM; the analysis part, which decomposes each indicator into two unobserved components, the common component and the idiosyncratic component.[15] The common component is best viewed as the impact of the underlying unobserved systematic factors driving all indicators, and it is thus expected to be relatively persistent. The idiosyncratic component instead reflects transitory fluctuations, which may not be negligible, especially in the short term.

The remainder of this section reviews in more detail the methodological and statistical approaches used to estimate systemic credit risk in investment funds.

2.2. The Book-value based Merton model, CIMDO and GDFM

2.2.1. The Book-value Based Merton Model

The Merton model cannot be applied directly given that the data available on investment funds is limited to balance sheet information. An alternative approach has to be followed to calculate PDs. Bharath and Shumway (2008) examine the accuracy and forecasting performance of the Merton model and find that most of its predictive power comes from its functional form rather than from the estimation method: the firm's asset value, its asset risk, and its leverage. Souto *et al.* (2009) working with Brazilian banks and Blavy

[15] In Jin and Nadal De Simone (2014), this part is combined with a t-copula to generate a dynamic forecasting framework for the systemic credit risk in the banking sector. Due to the limited number of balance-sheet data points for the investment fund sector, this is not done here.

and Souto (2009) working with Mexican banks, show that the book-based Merton credit risk measures are highly correlated with market-based Merton credit risk measures.[16] Adrian and Shin (2013) forcefully argued that the key state variable in applying financial frictions in asset pricing modeling is leverage (measured as the ratio of assets to net worth or equity). They write, "…the definition of leverage that matters for asset pricing is the ratio of total assets to book equity, rather than the ratio of enterprise value to market capitalization." This suggests that investment funds' financial statements can provide crucial information to form market expectations about their distress probability. This approach is followed here. The book value asset volatility is calculated by a rolling window as follows:[17]

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

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[18] 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 domiciled in Luxembourg are analyzed at the level of investment fund category, so the level of book-value risk neutral PD can be very close to zero. Therefore, Merton's DD is rescaled so that the lowest possible level of π_B is 0.001 percent.

2.2.2. The CIMDO Approach

The CIMDO-approach developed by Segoviano (2006) is centered on the concept of cross-entropy introduced by Kullback (1959). It implies minimizing the cross-entropy objective function that links the prior and posterior distributions under a set of constraints

---

[16] See also Gray and Jones, 2006, for an early application of this idea.
[17] Following usual practice, quarterly volatility is annualized.
[18] See Jin and Nadal De Simone (2011a) for a detailed discussion of the differences between "actual" PDs and risk-neutral PDs. Also see the discussion regarding the level of PDs as opposed to changes in PDs, especially it is important to be aware that for a number of reasons, some theoretical such as the absence of a widely accepted explanation of the "equity puzzle", and some practical, such as accounting standards, it is important to concentrate the analysis on estimated PDs' ranking rather than PDs' absolute levels.

on the posterior. For example, in the case of two investment fund categories, say X and Y, with their logarithmic returns represented by random variables x and y, the following function can be minimized:

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

where $p(x;y), q(x;y) \in \Re^2$ are the posterior and the prior distributions, λ_1, λ_2, and λ_3 are the Lagrange multipliers associated with the additivity constraint and the two non-negativity constraints. 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 highlights 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. Segoviano (2006) demonstrates that the CIMDO-recovered distribution outperforms the most commonly used parametric multivariate densities under the Probability Integral Transformation Criterion (e.g., the standard and conditional Normal distributions, or the mixture of Normal distributions). In this paper, the prior distribution is assumed to be a multivariate Normal distribution to reflect the parametric assumption in Merton (1974). Importantly, the distress threshold is one of the central parameters of the CIMDO methodology. Following the intuition of Goodhart and Segoviano (2009), an average distress threshold (over time) for each investment fund category is obtained as the inverse standard Normal of its average PD over time.

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.[19] By construction, the CIMDO copula puts greater emphasis on the distress region of the joint distribution. Therefore, the approach provides a robust and consistent method to estimate investment funds' distress dependence.

As stated above, the general dependence measures calculated via the CIMDO approach are tightly related to the initial choice of correlation for the prior distribution (Gorea and Radev, 2014). Assuming a joint Normal density function with zero correlation as prior could lead to a significant understatement of investment funds' PD dependence, which seems evident in several recent studies applying the CIMDO approach. This becomes particularly important in period of distress when "phase-locking" behaviour most likely occurs.[20] As a result, this paper uses a simple rolling window approach as the prior correlation input to the CIMDO which is also consistent with the rolling window estimation of the book-based Merton model. In order to guarantee that the correlation matrix of asset returns is symmetric and positive semi-definite, Qi and Sun (2006) Newton-type method is used.

2.2.3. The Generalized Dynamic Factor Model (GDFM)

Following Jin and Nadal De Simone (2012), this paper uses the GDFM to examine credit risk emanating from the macro environment and from investment funds' interconnectedness. The GDFM of Forni *et al* (2005) enables the efficient estimation of the common and idiosyncratic components of very large data sets. The GDFM assumes that each time series in a large data set is composed of two unobserved components.[21] First, the common component, which is driven by a small number of shocks that are common to the entire panel—each time series has its own loading associated with the shocks. Second, the idiosyncratic component, which is specific to a particular variable is 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

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

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

[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).

persistent. The idiosyncratic component instead reflects local aspects of credit risk or asset value that while far from negligible, especially in the short term, are transient. This part, therefore, links the dynamic behaviour of PDs and systemic risk measures to the evolution of the market as described by the macro-financial information matrix.

III. Empirical Measures of Systemic Credit Risk

ECB (2009) defines three forms of systemic risk. The framework proposed in this study yields all the necessary information to estimate different measures of these forms of systemic risk, although limited to the investment fund industry. Segoviano and Goodhart (2009) propose two measures to capture common distress in the banking system, the Joint Probability of Distress (JPoD) and the Banking Stability Index (BSI). They propose another two measures to address distress between specific banks: the Distress Dependence Matrix (DDM), and the Probability that At least One other institution becomes distressed (PAO). However, the Segoviano-Goodhart measures do not cover another, more insidious form of systemic risk: the slow build up of vulnerabilities over time that may unravel in a disorderly manner. Therefore, this paper proposes another measure linking Merton's PD estimates with a broad set of macro-financial variables by implementing the GDFM in the CIMDO framework. What follows briefly reviews the Segoviano and Goodhart (2009) measures while slightly changing their terminology to adapt them to the investment fund industry.

3.1. The First Form of Systemic Risk: Common Distress

The first form of systemic credit risk is common distress, i.e., a common shock that affects the whole investment fund industry and propagates to the real economy. Two possible measures of this form of risk are considered. The first measure proposed by Segoviano and Goodhart (2009) is the joint Probability of Distress (JPoD) or the probability that all investment funds' categories become distressed. This reflects credit risk not only at the level of individual investment fund categories, but also linear and nonlinear interdependence among funds' categories. However, in the extreme-value theory context of this empirical study the JPoD is a rather excessive measure as it would imply that all the investment fund industry collapses simultaneously. So, instead this paper implements the Radev (2012) Banking System Fragility measure, adapting it to the investment fund industry. The Investment Fund System Fragility measure (IFSF) is the CIMDO-derived probability of *at least two* investment funds' categories simultaneously entering distress. Given that this is an unconditional measure, it represents systemic distress potential or the general vulnerability of the investment fund industry to systemic events.

For simplicity, assume three investment funds' categories whose asset value processes are characterized by the random variables X, Y, and Z. The IFSF measure is the sum of the following unconditional joint probabilities:

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

The IFSF describes the part of the posterior distribution where distress occurs because at least two among X, Y and Z exceed their respective distress thresholds x_d^x, x_d^y or x_d^z.

The Investment Fund Stability Index (IFSI) is a complementary measure of the first form of systemic risk. The IFSI measures the expected *number* of fund categories that will become distressed conditional on any one fund category entering distress. When the IFSI=1, the linkages across investment funds' categories are minimal. The IFSI is thus a measure of investment fund's dependence. As the IFSI increases, it signals that dependence among funds' categories rises. The measure can be formally written as follows:

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

The complementarity between the IFSF and the IFSI should become apparent through the analysis below of the variables most closely linked to the systematic part of both measures.

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

Two other measures proxy the second form of systemic risk. The first is designed to capture distress in the investment fund industry as a whole following distress in a specific investment fund category. The probability that at least one other investment fund category becomes distressed given that one specific investment fund category has become distressed (PAO) can capture how an idiosyncratic shock to one fund category (i.e. the Money Market Funds mentioned above) can be propagated to the rest of the financial sector and end up affecting the real economy. It is therefore an important measure for macro-prudential authorities to assess the costs of alternative policies. While conditional probabilities do not imply causation, they provide important information on interdependence in the industry. For instance, given market data, it is possible to study the market perception of policy measures by comparing conditional PDs with joint

PDs (Lucas *et* al, 2014) to disentangle the common effects of measures from their more specific effects on individual types of institution or asset classes. For illustrative purposes, assume an industry populated by four investment funds' categories (i.e., X, Y, R, and Z), and that fund category Z becomes distressed. The measure is calculated as follows:

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

This measure could also be used to rank the different funds' categories by systemic importance.

The second measure to capture contagion across categories of investment funds is the Distress Dependence Matrix (DDM). This is based on pair-wise conditional PDs. For example, macro-prudential policymakers may be interested in the PD of one category of fund conditional on another category of fund entering distress. In 2010, for example, stress in US Money Market Funds fed concerns about the whole industry and the rest of the financial system. This information can be captured by the DDM. The probability of distress of fund category X conditional on fund category Z entering distress is:

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

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

Systemic risk can also manifest itself through the build-up of vulnerabilities over time. This is clearly more difficult to measure, but an indicator can be obtained by combining the GDFM applied to a large macro-financial database with the Merton structural credit risk model within the CIMDO infrastructure. This approach can also help identify the economic forces driving the increase in vulnerabilities. For investment funds, these tend to be economic activity and the cost of funding, while for banks they are economic activity, credit growth and interbank market activity (see Jing and Nadal De Simone, 2014). As shown in the latter paper, the common components of the banking systemic credit risk measures (Joint Probability of Default, Banking Stability Index and PAO) contain leading information on the build up of vulnerabilities. In the investment fund industry, this is less clear. Only the common component of the IFSF clearly contains important leading information on the build up of vulnerabilities. The common component of the IFSI does to a lesser extent. However, given that these common components can be easily estimated, the framework in this study may serve macro-prudential policy by identifying the economic variables most closely linked to vulnerabilities. These may be useful in monitoring and eventually calibrating macro-prudential instruments.

IV. Data

This study is applied to data on all seven categories of investment funds reported to the ECB by National Central Banks: Equity Funds, Bond Funds, Mixed Funds, Real Estate Funds, Hedge Funds, Other Funds and Money Market Funds. The database contains detailed balance sheet information on investment funds from December 2008 to June 2013. Debt is broken down by initial maturity allowing the distinction between debt with a one-year maturity and debt with a longer maturity. The parts of the funds proxy their equity. The derivatives positions are netted. This is thus a much richer database than used by papers using various default probability models to estimate distress or survival in the investment fund industry. Previous studies were limited to data on returns with no information on leverage, liquidity, portfolio composition, or links with sponsoring banks.[22]

Surveillance of banking stability cannot stop at national borders, so the database of this study includes data from 14 countries besides Luxembourg: Belgium, Canada, Denmark, France, Germany, Greece, Japan, the Netherlands, Italy, Spain, Sweden, Switzerland, the United Kingdom, and the United States. Market data include government bond yields, stock price indices, industrial production, employment and GDP data, consumer prices, housing prices, exchange rates, credit data, as well as the number of outstanding shares, and book value data from Bloomberg, DataStream, BIS, Eurostat, and ECB (see Appendix I for a detailed list of data sources for market indexes and macroeconomic variables). The database comprises 258 series including three measures of credit-to-GDP gap for the euro area, the UK and the US. The Merton PDs for the different investment fund categories represent 7 additional series.

V. Results

5.1. Marginal Probabilities of Distress

To our best knowledge, this is the first systematic application of Merton's contingent claims analysis to all investment fund's categories using an internally consistent database. Therefore, it seems advisable to compare the resulting PDs to the differences

[22] Most studies of investment funds refer to the US industry. However, before Dodd-Frank regular filings of US Hedge funds did not include information on leverage, liquidity, portfolio composition, major creditors and obligors, or the terms under which capital is committed. See footnote 5.

in regulatory regime across investment funds' categories. As reflected in the literature review, leverage is closely linked to PDs. In this respect, the regulatory regime of UCITS and non-UCITS (Table 1) suggests that Money Market Funds, which are allowed only technical leverage, would have a relatively low level of PDs and would appear as the safest investment fund category. In Figure 5, Money Market Funds had close-to-zero marginal PDs during the first half of the sample period, but then their PDs started rising, largely because of persistent value losses of short-term money market paper. Real Estate Funds and Hedge Funds display relatively higher PDs since the Luxembourg Specialized Investment Fund Law of 2007 does not regulate their leverage.

Investment fund regulation also determines the valuation approach and the frequency with which it is applied. Recent experience with US Money Market Funds shows that when government guarantees made shares in US Money Market Funds similar to par-value deposits in a regular bank they became subject to runs in the same way as banks.[23] The Reserve Primary Fund "broke the buck" during the financial crisis of 2008, mostly because a flood of redemption requests followed the collapse in value of the fund's hefty investments in Lehman Brothers-issued commercial paper. The resulting panic prompted the US federal government to offer guarantees to Money Market Fund investors that their money would be returned in the event of a fund failure.

In Luxembourg, Equity Funds, Bond and Mixed Funds are mostly organized as UCITS, which are more frequently subject to mark-to-market valuation. This is reflected in the close link between the evolution of estimated PDs and funding quantities including credit growth or funding prices and macroeconomic developments. The different categories of macro-financial variables are defined below.

For each investment fund category, figure 5 also displays two indices of marginal probabilities (ignoring interdependencies): one gives equal weights across different fund category PDs (EW), and the other weights them by the value of assets managed (VW). Overall, this simple index shows an improvement in risk in the industry toward mid-2011 followed by deterioration in 2012 and a recent spike in 2013Q2.

Figure 5 also shows the common components of the estimated PDs (red dashed lines). The GDFM output is used to determine how closely different variables are linked to the common components of estimated PDs. To facilitate understanding, all macro-financial

[23] While the US regulation of Money Market Funds authorizes an amortized cost method that results in par-valuation of assets, EU regulations authorize only short-term Money Market Funds to apply constant or floating net asset value (NAV). All other Money Market Funds are obliged to apply floating NAV. In addition, they must provide daily price and NAV, and the IMMFA Code of Practice stipulates escalation procedures when the value of an IMMFA fund differs from its mark-to-market valuation.

variables in the database were categorized into four classes: macroeconomic variables often associated with the business cycle (GDP in volume and current prices, industrial production, unemployment, the HICP, agricultural and industrial property prices); funding quantities (total credit, loans to households, mortgages, loans to non-financial firms, interbank lending and borrowing); funding costs (short- and long-term interest rates, foreign exchange rates, stock market prices, stock price volatility, house prices) and confidence measures (various indices of consumer and business sentiment).

Table 3 displays the contribution of each macro-financial variable category to the common components of the estimated PDs. These were calculated as follows. For each investment fund category, the common component of its PD is regressed on the three-dimensional vector of its mutually orthogonal common factors (without intercept because the GDFM uses standardized data).[24] The resulting regression coefficients are combined with each variable's factor loading from the GDFM to become the *composite loadings* for each variable.[25] Since the common factors are orthogonal and all variables are standardized with zero mean and unit variance for the GDFM estimation, the composite loadings of all factors are simply the sum of the composite loadings of the three factors. Table 3 reports the contribution of each category of macro-financial variable to the common component of the PD for each investment fund category (taking the absolute value of the composite loadings). The Table displays the top 50% of the variables as ranked by their composite loadings (in absolute value) to calculate the Total and Average in each category of variables.

This analysis of composite loadings is limited given that no estimation errors are provided. However, the short sample makes these unreliable. As a result, the robustness of the rankings is checked in two ways: first, by using the empirical cumulative distribution of absolute composite loadings 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 discussion below is based on the averages in the table given that the number of variables across categories varies.

[24] Statistical results are presented in Table A1 in Appendix II.
[25] The composite loadings measure, therefore, the combined impact of each macro-financial variable in the common components of PDs by taking into account the factor loadings of each variable and the explanatory power of each factor.

Several observations are in order. First, whether unweighted or weighted by the share of total assets managed in each fund category,[26] the largest composite loadings are associated with funding quantity variables. These are followed by macroeconomic variables, confidence measures and funding prices. However, results differ across investment funds' categories. For Money Market Funds, macroeconomic variables, funding quantities and confidence indicators matter almost equally. For Mixed Funds and Other Funds, the largest composite loadings are on funding quantities (especially credit) followed by macroeconomic variables (GDP growth and unemployment). This result is in line with findings by Jin and Nadal De Simone (2014) for the banking industry. For Bond Funds and Equity Funds, all four categories of variables are equally important. For Hedge Funds, confidence indicators have the largest composite loading. Finally, for Real Estate Funds, macroeconomic variables (notably GDP growth and unemployment) have the largest loadings.

The results have important implications for macro-prudential policy as well as for ongoing proposals for regulatory change and supervision. They seem to support proposals to monitor closely credit growth, the business cycle and its impact on leverage. As an illustration, the persistent increase of PDs in Other Funds and their steep rise in Real Estate Funds merits closer surveillance. This seems particularly the case for Other Funds as the common component of their PDs shows an unrelenting increase since the second half of 2011. The latter development seems to be largely associated with an increase in leverage (Figure 4) that, in contrast to what is reported at an EU level, is not visible in Luxembourg-registered Hedge Funds.[27]

While the common component of systemic risk measures will be discussed in more detail below, we first consider developments in the common component of the marginal PD of Money Market Funds. This common component suggests a trend increase earlier than the PD itself during the first half of the sample period. The PD estimate is pulled down by idiosyncratic factors during this period (i.e., the difference between the estimated PD and its common component), which would hinder an assessment of credit risk in this type of fund if the common forces driving PDs were not estimated simultaneously. This feature is reversed toward the end of 2011 when the changes in liquidity and valuation rules in the US mutual fund industry prompted them to reduce their exposure to European banks, causing a US dollar shortage in the EU. This shortage incited the ECB and the Fed to take policy measures which succeeded in reducing stress in the sector. Regarding Equity Funds, the common component of PDs

[26] The weighted contributions are not shown in the table.
[27] The ECB Financial Stability Review (2013) reports that the first quarter 2013 survey data of the ECB and the Fed suggest an increased use of leverage by Hedge Funds favored by low benchmark interest rates and higher risk tolerance.

follows the decrease in the distress measure closely since mid-2011. This is largely due to the upswing in the stock market. No idiosyncratic factors countered it. In general, monitoring the PD and its common component in a given investment fund category may help a policymaker track risk in the sector. This has to be complemented, however, by a thorough assessment of systemic risk in the industry.

5.2. Measures of Systemic Credit Risk

5.2.1. First form of systemic risk: common shocks

The Investment Fund Systemic Fragility measure (IFSF) tracks the probability that at least two of the seven investment fund categories will simultaneously enter distress (Figure 6). The common component of the IFSF (IFSF CC) may provide insight into the build-up of vulnerabilities over time reflecting changes in the PDs and their correlations. This is discussed more thoroughly below given that its nature is relatively more consistent with the third form of systemic risk.

The IFSF measure seems to follow major market events relatively closely (see Table A2 Appendix II for a timeline of main events during the sample period). The IFSF started receding in the second half of 2010 following the policy agreement to assist Greece, the tightening of the Stability and Growth Pact and the accord to put in place the European Stability Mechanism (ESM) for countries in distress. However, the measure took a significant upward trend in the second half of 2011 as the sovereign risk crisis worsened in an environment of weakening macroeconomic growth prospects. In 2011, euro area bank funding pressures increased markedly in specific market segments, particularly for unsecured term funding and US dollar funding. The US dollar shortage was in part the result of the reduction of US Money Market Fund exposure to European banks following the 2010 regulatory changes by the Security and Exchange Commission. This may explain the reversal of common factors which pulled down the IFSF until mid 2011.

Toward the end of 2011, the European Council and euro area governments agreed a package of measures to restore confidence and address the tensions in financial markets, including the fiscal compact, the strengthening of stabilization tools for the euro area, a more effective European Financial Stability Facility, the accelerated implementation of the ESM, and agreement on the challenges faced by Greece. In addition, the ECB decided to conduct two longer-term refinancing operations with a maturity of 36 months in response to severe market tensions that threatened the functioning of the money market and the flow of bank credit to the economy. The first operation took place in December and the second was allotted in February 2012. In the

US, the Federal Reserve re-opened swap lines with the foreign central banks to alleviate stress in money markets. These measures managed to reduce the common sources of systemic risk as reflected in a drop of the IFSF after March 2012. Finally, the upturn of the IFSF at the end of the sample may be related to the uncertainties regarding the continuation of fiscal consolidation in Portugal and tensions in Cyprus.

The Investment Fund Stability Index, IFSI (Figure 7) shows relatively small changes during the available sample. The index indicates a decrease in dependence among investment funds' categories from the end of 2010 until 2012, when it returned to levels somewhat higher than at the beginning of the sample, possibly because capital flows into euro area fixed income funds rose substantially (ECB, 2013). With a pause between mid-2011 and mid-2012, idiosyncratic factors pulled down the IFSI despite common systematic forces raising investment fund dependence (see section 5.2.3). During the last year of the sample, the increase in the IFSI may reflect a weakening macroeconomic backdrop, especially in stressed economies, prospects of further asset quality deterioration weighing on banks and investment fund sponsors as well as increased volatility in funding markets.

5.2.2. *Second form of systemic risk: idiosyncratic risk and contagion*

This section discusses two conditional probability measures of idiosyncratic risk and contagion. The first, the PAO, measures the probability that at least one other fund category becomes distressed given that one fund category—dynamically chosen to be the riskiest—has already become distressed.[28] This measure suggests that the overall investment fund industry in Luxembourg was more resilient to distress in Real Estate and Hedge Funds than to distress in Mixed, Bond and Equity Funds, in that order (Figure 8). At the end of the sample period (2013Q2), Real Estate Funds were the fund category that ranked the lowest as a source of credit risk that could spill over to the rest of the industry. Conversely, Mixed, Equity and Bond Funds entailed the highest systemic risk at the end of the sample.

The second measure of systemic risk through contagion, the DDM, is particularly useful to assess the vulnerability interdependencies among investment funds' categories. For instance, Dixon *et al* (2012) studied the contribution of Hedge Funds to systemic risk, in particular in the run-up to the crisis, and found that while Hedge Funds affected their partners (via the credit channel) and asset price spirals (the liquidity channel), they do

[28] Money Market Funds are subject to restrictions on their eligible and investment portfolios that suggest treating them as independent from other funds and thus, they are not included in the PAO measure.

not appear to have been the primary cause of the financial crisis.[29] Comparison among investment funds' categories using the DDM suggests that after the end of 2010, Hedge Funds were not a major source of systemic risk through contagion or spillover effects: Hedge Funds ranked between 4th and 6th among investment funds' categories in terms of the probability of contagion or spillover risk; this is clear from Table 4 which displays the probability of distress for each investment fund category in the row, conditional on distress in the investment fund category in the column. DDMs are calculated for mid-2010, mid-2011, mid-2012 and mid-2013.

The DDMs confirm that the systemic risk contribution of Other Funds was highest in 2010Q2 and 2011Q3. While it was lower in 2012Q2, it rose again in 2013Q2. The investment fund industry as a whole became less fragile in terms of contagion risk between 2010Q2 (45%) and 2012Q2 (35%). However, it reversed this trend at the end of the sample (43%) (see column and row averages). Contagion became more likely if any given fund category entered distress. Thus the DDM confirms a recent increase in the second form of systemic risk in the investment fund industry. This result is consistent with the estimated increased in dependence suggested by the IFSI and coincides with the rise in the first form of systemic risk suggested by the IFSF.

However, averages hide diverging evolutions. While the conditional PDs between Equity Funds and Bond Funds suggest the likelihood of contagion or spillovers increased from 69% at mid-2010 to 83% at mid-2013, the conditional PD between Mixed Funds and Hedge Funds actually fell from 68% to 36% during the same period (Table 4). In fine, Real Estate Fund distress would have the largest impact on Hedge Funds and Other Funds at the end the sample with conditional PDs around 52-53% as opposed to 27% for Bond Funds or 13% for Equity Funds. This information suggests why the DDM measure is generally considered a useful indicator of the second source of systemic risk to be regularly estimated for macro-prudential purposes.

5.2.3. *Third form of systemic risk: the build-up of vulnerabilities over time*

The common component of marginal PDs and asset return correlations may be useful tools in a macro-prudential dashboard, but measures of systemic risk and their common components seem a necessity. Systemic risk understood as a slow build-up of vulnerabilities over time can be "monitored" using the common components of the measures of systemic credit risk, e.g., the IFSF and the PAO in conjunction with the

[29] This does not negate the importance of needed reforms in the Hedge Funds industry, such as for example, improving the transparency of Hedge Funds' activities and margining practices in derivative trades; eliminating compromised risk-management incentives and; reducing the likelihood of runs on prime brokers.

analysis of their loadings as discussed above. Jin and Nadal De Simone (2014) apply this idea to European banking groups and their Luxembourg affiliates and find that the common components of systemic risk measures often behave as "early warning" indicators. In the investment fund industry, measures of systemic risk and their common and idiosyncratic components may also be valuable tools to monitor the build-up of systemic risk, especially combined with the macro-financial variables most closely linked to their common components. Therefore, the methods applied to marginal PDs and to cross-correlations of asset returns in different investment funds' categories are also applied to the IFSF, the IFSI and the PAO measures of systemic risk.

The first important point to stress is that the loadings of different variables in the common components of systemic risk will differ from their loadings in the common components of marginal PDs. On the one hand, the common components of marginal PDs are associated more closely with the variables most relevant to a given investment fund category and its regulations. On the other hand, systemic risk measures result from a complex interaction between marginal PDs, cross-correlation of asset returns and conditional probabilities within the CIMDO framework. Therefore, the common components of systemic risk measures are affected by the nonlinearities and feedback effects that link each investment fund category to the rest of the financial sector and the economy in general. This heightens the importance of modeling interdependence to measure systemic risk properly and adequately calibrate macro-prudential instruments to the vulnerabilities they intend to tackle.

Table 5 summarizes the contribution of variables to the common components of systemic risk measures. The structure is similar to that of Table 3, which reported the contributions of the variables to the common components of PDs by investment fund category. However, in Table 5 the impact of each macro-financial variable, with some exceptions, reflects mostly its factor loading. For example, factor 1 contains some additional explanatory power for the common components of the IFSF and the IFSI, but less for the PAO (Table A3 Appendix II). The common components of the IFSF and the IFSI have large loadings on funding prices, notably interest rate levels, the interest rate spread, and stock price indices, followed by confidence indicators and (closely) macroeconomic variables. The important point is that interest rate levels, spreads and stock price indices have the lowest loadings in the common component of marginal PDs for all investment funds' categories, but have the highest loadings in the common components of the first form of systemic risk. This matters for policy. For example, it seems to suggest that monetary policy can have an important direct and indirect role, via the traditional interest-rate channel as well as via what has been called the risk-taking channel[30] in the evolution of vulnerabilities in the investment fund industry. This seems to be well captured, *ceteris paribus*, by the significant (contemporaneous) negative correlation between the interest rate spread in the euro area and the common components of the IFSF and the PAO (69% and 84%, respectively).[31] Thus, if monetary policy, *ceteris paribus,* reduces the interest rate spread, the IFSF common component may tend to increase, which would be consistent with the risk-taking channel of monetary policy. A monetary policy loosening, by encouraging more risk take-up, increases the probability that at least two investment funds' categories enter distress (assuming no offsetting idiosyncratic component) (Figure 9). Moreover, the negative correlation between the common components of the IFSF and the IFSI (89%) indicates that the loosening of monetary policy, by inducing a positive effect on economic activity via the traditional interest-rate channel, makes funding less costly and reduces the expected number of investment funds' categories in distress (as captured by the IFSI).

The PAO common components load variables differently across investment funds' categories, as was also the case for PDs. However, PAO common components assign higher loadings to macroeconomic variables (4 cases out of 7) and credit growth (3 cases out of 7).

These results suggest that contagion, the second form of systemic risk, is more closely related to the performance of the economy, credit and leverage, while the first form of systemic risk is more closely related to funding costs.

So far, the analysis of the relative importance of different macro-financial variables in the common components of PDs and measures of systemic risk entailed more or less sophisticated forms of correlation analysis. For macro-prudential policy formulation, however, it seems useful to ask the question of whether there is any anticipatory behavior in the common components of systemic risk measures as reported in Jin and Nadal De Simone (2014) for the banking industry. Table 6 displays the results of several Granger-causality tests.[32] The IFSF common components, and to a lesser extent the IFSI common components tend to lead their respective systemic risk measures during the sample period, while the opposite is not the case (respective p-values are 1% and

---

[30] According to the risk-taking channel, an accommodative monetary policy by keeping interest rates low can induce economic agents to undertake relatively riskier activities in their search for a higher return (e.g., Borio and Zhu, 2008, and Altumbas et al, 2010).

[31] The *ceteris paribus* condition is appropriate as monetary policy responds to shocks common to the macro-financial variables and, therefore, it is not exogenous.

[32] All the tests use 4 lags. The estimates display no serial correlation as indicated by the Kolmogorov-Smirnov statistic at the 10% level of confidence.

17%).[33] In contrast, for the average PAO and the PAO by investment fund category, the common components do not lead their respective PAO measures. Instead, the PAOs of Bond Funds, Mixed Funds, Other Funds and Money Market Funds appear to lead their respective common components.[34]

The common components of the IFSF improved during the first year of the sample, but deteriorated in 2011 before subsiding again after mid-2012. This behavior may be associated with major macroeconomic events that are captured somewhat earlier in the common components of the IFSF systemic risk measure. The rescue of Greece, the reinforcement of the Stability and Growth Pact and the establishment of the ESM were positive events followed by the worsening of macroeconomic prospects and the 2011 US dollar funding pressures in the euro area. The IFSF common components improved again in 2012 following the strengthening of euro area stabilization tools, a more effective European Financial Stability Facility, the accelerated implementation of the ESM, a more lasting solution to the challenges faced by Greece as well as the LTROs of the ECB and the Federal Reserve swap lines with the foreign central banks to alleviate market stress and liquidity pressures.

A policymaker monitoring investment fund vulnerabilities may be interested in tracking the variables with highest loadings in the common components of systemic risk measures. This is especially the case for measures of a common form of systemic risk (i.e., the IFSF). However, it is sometimes possible for idiosyncratic components to add to common components as was the case for the IFSF measure between 2011Q2 and 2011Q4, or for idiosyncratic components to offset common components as was the case from the beginning of the sample to end-2010. By disentangling common and idiosyncratic components in systemic risk measures, this framework may contribute to improve the identification and tracking of systemic risk vulnerabilities.

VI. Conclusions and macro-prudential policy implications

The framework developed in this study allows the estimation of systemic credit risk measures for the Luxembourg investment fund industry. It provides a possible early-warning measure of build-up in systemic vulnerabilities during the period 2008Q4-2013Q2. While out-of-sample forecasts of these systemic credit risk measures can be generated, this task requires a longer set of historical data.[35]

---

[33] A simple cross-correlation analysis suggests that the common components of the IFSF lead the IFSF measure by two quarters.
[34] The PAOs of Equity Funds and Other Funds tend to lead their respective common components with p-values of 14 and 15%, respectively.
[35] Jin and Nadal De Simone (2014) apply the same framework to forecast systemic risk in the banking sector.

The proposed framework has the following main features. First, marginal PDs are estimated using the Merton (1974) option pricing model. Second, the framework uses book-value data to compensate the lack of market data for non-publicly quoted funds. Third, the CIMDO approach of Segoviano (2006) is used to model time-varying linear and non-linear dependence among funds' categories and between investment funds and the economy. Fourth, the framework applies the generalized dynamic factor model to a large macro-financial dataset to extract the common component of investment funds' marginal PDs as well as measures of systemic risk. This reveals a set of common systematic factors affecting all variables simultaneously, albeit with different weights. The paper's approach stresses the links between measures of distress and macro-financial variables, while avoiding the pitfalls of relying only on markets which occasionally misprice risk over time. The common component of systemic risk measures carries large loadings for real economic activity and credit growth, as well as various measures of the cost of funding. This is consistent with the findings by Boyson *et al* (2010) for US Hedge Funds.

Results are encouraging. First, marginal probabilities of distress (PDs) estimated for the different investment fund categories are consistent with differences in their regulatory framework. For example, more leveraged Hedge Funds tend to have higher PDs than Money Market Funds, which are allowed only technical leverage.

Second, Money Market Funds are organized as UCITS, which have a relatively more frequent marked-to-market valuation. This is consistent with the result that their estimated PDs are more closely linked to the evolution of macroeconomic indicators, funding quantities, notably credit, and confidence indicators.

Third, the two measures of systemic risk reflecting common distress (IFSF and IFSI) track well major changes in funding prices, notably short-term interest rates, spreads, and stock price indices, and macroeconomic developments. The negative correlation between the common components of these two measures suggests that an increase in funding costs following a tightening of monetary policy, *ceteris paribus*, will reduce the common component of the IFSF by inducing less risk taking and will increase the common component of the IFSI as it becomes more likely that more investment funds' categories will enter distress.

Fourth, the measure of systemic risk viewed from the contagion viewpoint, the PAO, suggests that the industry was more resilient to distress in Hedge Funds and Real Estate Funds than to distress in Mixed, Bond and Equity Funds, in that order. These results are confirmed by the DDM. Mixed Funds, Bond Funds and Equity Funds entailed the highest systemic risk at the end of the sample period. The common component of the equally-weighted average of PAO across all investment funds' categories is strongly positively correlated with the common component of the IFSF which suggests that during the sample period, both forms of systemic risk interacted closely; thus, these measures of systemic risk from different sources are useful operational indicators.

Fifth, systemic risk understood as a slow build-up of vulnerabilities over time can be "monitored" following the common components of two measures of systemic credit risk, i.e., the IFSF and the PAO. The common components of both measures lead the actual measures by up to two quarters, with the idiosyncratic components contributing positively to systemic risk during roughly the first and third years of the sample and negatively during the second year. While results vary across investment fund categories, overall, macroeconomic variables (especially GDP and unemployment) and funding quantities (notably credit and the credit gap) are most closely associated with the common components of the PAO. Funding costs such as interest rates, spreads and stock price indices carry lower loadings. Instead, the common component of the IFSF and the IFSI carry highest loadings on funding prices, notably interest rates, the interest rate spread, and stock price indices, followed by confidence indicators and macroeconomic variables. This may suggest that monetary policy can have a direct and indirect role in the evolution of vulnerabilities in the investment fund industry via the traditional interest-rate channel by which changes in the cost of funding affect investment and economic activity and via the risk-taking channel by which it affects the level of risk that economic agents wish to take.

Therefore, this framework contributes to the macro-prudential literature on monitoring systemic credit risk. This includes, at least in the case of the common form of systemic risk, the possibility of tracking changes in systemic risk a couple quarters in advance by estimating the common components of the IFSF measure. As such, this framework may be part of a larger set of instruments for the surveillance of the most insidious form of systemic risk, i.e., a slow build-up of vulnerabilities. This way, policymakers could tighten the scrutiny of financial markets, for instance, by activating pre-existing macro-prudential instruments to cope with systemic risk or by implementing a closer risk-driven surveillance. By explicitly linking systemic risk in the investment fund industry to the state of the macroeconomy and extracting their driving forces, this paper proposes an approach that contributes to a more informed discussion of the appropriate policy measures to address the observed vulnerabilities. If at a given point in time systemic risk is most likely to result from contagion, this study suggests that a policymaker seeking to address that risk should look more closely at the performance of the economy, credit and leverage; in contrast, if systemic risk is most likely to result from a common adverse shock, acting on funding costs may be more efficient.

Results show that macroeconomic variables, funding quantitites and confidence indicators matter almost equally for Money Market Funds. Instead, for Mixed Funds and Other Funds the most closely linked variables are funding quantitities. For Bond Funds and Equity Funds, all four categories of variables are equally important. For Hedge Funds, confidence indicators have the largest composite loading. Finally, for Real Estate Funds macroeconomic variables, notably growth and unemployment, are the most closely linked. The key role of credit measures, economic activity, interest rates and confidence indicators in the evolution of investment fund vulnerabilities resembles the results obtained when applying this framework to the Luxembourg banking industry.

By separating the role of systemic and idiosyncratic developments for each fund's category, this framework contributes to building macro-financial models of systemic risk that contain some early-warning features. This work also adds to the systemic risk literature by considering the impact that a relatively less studied group of financial intermediaries may exert on the rest of the financial system and on the economy.

In addition, this framework contributes to a relatively more robust measurement of the other two forms of systemic risk identified by the ECB (for banks) by allowing the estimation of measures of investment fund systemic credit risk that reflect *common distress* in the industry (the IFSF) and *distress associated with a specific fund category that is transmitted to other categories* (the PAO and the DDM). This is a rich set of indicators for a macro-prudential operational framework based on explicit statistical modeling of investment fund distress dependence: conditional probabilities can provide insights into interdependencies and the likelihood of contagion or spillovers among funds. This should help to estimate any implied contingent liabilities originating in the investment fund industry, much as the International Monetary Fund did, for instance, for the US banking sector (International Monetary Fund, 2010). This information would be useful to estimate the expected costs of policy inaction given the detected vulnerabilities.

References

Acharya, V. V., L. H. Pedersen, T. Philippon and M. Richardson, 2010, “Measuring Systemic Risk”.

Adrian, T. and H. S. Shin, 2013, “Procyclical Leverage and Value-at-Risk”, Staff Report No. 338, *Federal Reserve Bank of New York*.

Adrian, T., E. Moench, and H. S. Shin, 2013, “Leverage Asset Pricing”, Staff Report No. 625, *Federal Reserve Bank of New York*.

Alessi, L., Barigozzi, M., and M., Capasso, 2007a, “Generalized Dynamic Factor Model + GARCH: Exploiting Multivariant Information for Univariate Prediction”, LEM Working Paper.

Alessi, L., Barigozzi, M., and M., Capasso, 2007b, “ Dynamic Factor GARCH: Multivariate Volatility Forecast for a Large Number of Series”, LEM Working Paper.

Alessi, L., Barigozzi, M., and M., Capasso, 2009, “A Robust Criterion for Determining the Number of Factors in Approximate Factor Models”, *ECORE* Discussion Paper 97.

Altunbas, Y., L. Gambacorta and D. Marques-Ibanez, 2010. "Bank Risk and Monetary Policy," *Journal of Financial Stability*, Vol. 6(3), pp. 121-129.

Ang, A., S. Gorovvy, and G. van Inwegen, 2011, “Hedge Fund Leverage”, *Journal of Financial Economics*, 102(1), pp. 102-126.

Asger, L., A. Timmermann, and D. Blake, 1999, “The Hazards of Mutual Fund Underperformance: A Cox Regression Analysis”, *Journal of Empirical Finance*, 6 (2, pp. 121—152.

Bai, J., Ng, S., 2002, “Determining the Number of Factors in Approximate Factor Models”, Econometrica 70(1), 191-221.

Bannier, C., F. Fetch, and M. Tyrell, (2006), “Open-end Real Estate Funds in Germany – Genesis and Crisis”, Discussion Papers 04/2007, *Deutsche Bundesbank*.

Bharath, S.T., and T.Shumway, 2008, “Forecasting Default with the Merton Distance to Default Model”, *The Review of Financial Studies*, 21, No 3, pp. 1339-1369.

Billio, M., M. Getmansky, A. W. Lo, and L. Pelizon, 2010, ”Econometric Measures of Systemic Risk in the Finance and Insurance Sectors”, *NBER* working paper 16223.

Bisias, D., M. Flood, A. W. Lo, and S. Valavabnis, 2012, “A Survey of Systemic Risk Analytics”, Working Paper 1, Office of Financial Research, *US Department of the Treasury*.

Blavy, R., and M. Souto, 2009, “Estimating Default Frequencies and Macrofinancial Linkages in the Mexican Banking Sector”, IMF Working Paper, WP/09/109, *International Monetary Fund*.

Borio, C., C. Furfine, and P. Lowe, 2001, “Procyclicality of the Financial System and Financial Stability: Issues and Policy Options”, BIS Papers No. 1, *Bank for International Settlements*.

Borio, C. and H. Zhu, 2008, "Capital Regulation, Risk-taking and Monetary Policy: A Missing Link in the Transmission Mechanism?," *Journal of Financial Stability*, Vol. 8(4), pp. 236-251.

Boyson, N. M., C. W. Stahel, and R. Stulz, 2010, “Hedge Fund Contagion and Liquidity Risk”, *Journal of Finance* Vol. 55 (5), pp. 1789-1816.

Chan, N., M. Getmansky, S. M. Haas, and A. W. Lo, 2007, “Systemic Risk and Hedge Funds”, *University of Chicago.*

Chen, Qi, I. Goldstein, and W. Jian, 2010, “Payoff Complementarities, Self-fulfilling Beliefs and Mutual Fund Outflows”, *Journal of Financial Economics* Vol. 98 (2), pp. 239-262.

Corbae, S. and S. Ouliaris, 2006, "Extracting Cycles from Nonstationary Data," in *Econometric Theory and Practice: Frontiers of Analysis and Applied Research,* ed.by D. Corbae, S. Durlauf, and B. Hansen (New York: Cambridge University Press).

European Economic Community, 1985, UCITS I Council Directive, 85/611/EEC, http://www.esma.europa.eu/system/files/Dir_85_611.PDF.

European Economic Community, 2009, UCITS IV, 2009/65/EC, http://www.esma.europa.eu/system/files/L_302_32.pdf.

European Fund and Asset Management Association, EFAMA, 2013, International Statistical Release.

D'Agostino, A. and D. Giannone, 2011, "Comparing Alternative Predictors Based on Large-panel Factor Models", *Oxford Bulletin of Economic Statistics* 74(2), pp. 306-326.

De Nicolò G.D. and M. Lucchetta, 2012, "Systemic Real and Financial Risks: Measurement, Forecasting, and Stress Testing", IMF Working Paper WP/12/58, *International Monetary Fund*.

Dixon, L, N. Clancy and K. B. Kumar, 2012, "Hedge Funds and Systemic Risk", *The Rand Corporation.*

Drehmann, M. and N. Tarashev, 2011, "Systemic Importance: some Simple Indicators", BIS Quarterly Review, March, *Bank for International Settlements*.

European Central Bank, "The Concept of Systemic Risk", *Financial Stability Review,* pp. 134-142, December 2009.

European Central Bank, 2013, *Financial Stability Review,* May.

Forni, M., M. Hallin, M. Lippi, and L. Reichlin, 2005, "The Generalized Dynamic Factor Model One-sided Estimation and Forecasting", *Journal of the American Statistical Association* Vol. 100, No. 471, pp. 830-840.

Geanakoplos, J., 2010, "The Leverage Cycle", in *NBER Macroeconomics Annual 2009*, V. 24, pp. 1-65, University of Chicago Press.

Gorea, D. and D. Radev, 2014, "The Euro Area Sovereign Debt Crisis: Can Contagion Spread from the Periphery to the Core?" *International Review of Economics and Finance, 30, pp. 78-100*

Gray, D. and M. Jones, 2006, "Indonesia: Selected Issues Paper, "Measuring Sovereign and Banking Risk in Indonesia: An Application of the Contingent Claims Approach", IMF Country Report No. 06/318, *International Monetary Fund*.

Gray, D. F. and S. W. Malone, 2008, *Macrofinancial Risk Analysis*, John Wiley & Sons, Ltd.

Hallin and Liska, 2007, "Determining the Number of Factors in the General Dynamic Factor Model", *Journal of the American Statistical Association*, 102, 603-617.

Hedge Funds, 2013, *TheCityUK*.

International Monetary Fund, 2010, *Financial Sector Assessment Program*.

Investment Company Factbook, 2013, *Investment Company Institute.*

Jin, X. and F. Nadal De Simone, 2012, "An Early-warning and Dynamic Forecasting Framework of Default Probabilities for the Macroprudential Policy Arsenal?", Working Paper No. 75, *Central Bank of Luxembourg*.

Jin, X. and F. Nadal De Simone, 2014, "Banking Systemic Vulnerabilities: A Tail-risk Dynamic CIMDO Approach", *Journal of Financial Stability*, 10.1016/j.jfs.2013.12.004

Kabundi, A. F. Nadal De Simone, 2011. "France in the Global Economy: A structural Approximate Dynamic Factor Model Analysis", *Empirical Economics* 41(2) pp. 311-342.

Klaus, B. and B. Rzepkowsky, (2009), "Risk Spillover among Hedge Funds. The Role of Redemptions and Fund Failures", Working Paper Series 1112, *European Central Bank*.

Kullback, S., 1959, Information Theory and Statistics, New York: *John Wiley and Sons*.

Lo, A. W., 2008, Testimony Prepared for the US House of Representatives Committee on Oversight and Government Reform, November 13, 2008.

Lucas, A., B. Schwaab and X. Zhang, 2014, "Conditional Probabilities for Euro Area Sovereign Default Risk", *Journal of Business and Economic Statistics,* 2014,Vol 32 (2), pp. 271-284.

Luxembourg, 2004, "Loi relative à la Société d'Investissement en capital à risque", "SICAR Law", http://www.cssf.lu/fileadmin/files/Lois_reglements/Legislation/Lois/LoiSICARupdate_120713.pdf

Luxembourg, 2007, "Loi relative aux fonds d'investissement spécialisés", "SIF Law", http://www.cssf.lu/fileadmin/files/Lois_reglements/Legislation/Lois/L_130207_SIF_upd_120713.pdf

Luxembourg, 2013, "Loi concernant les gestionnaires de fonds d' investissement Alternatifs", http://www.cssf.lu/fileadmin/files/Lois_reglements/Legislation/Lois/L_12071 3_GFIA.pdf

Merton, R., 1974, "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates", *Journal of Finance* 29, pp. 449-470.

Nelsen, R., 1999, "An Introduction to Copulas", Lecture Notes in Statistics 139, Springer.

Qi, H. and D. Sun, 2006, "A Quadratically Convergent Newton Method for Computing the Nearest Correlation Matrix", *SIAM. Journal of Matrix Analysis and Applications* 28(2), pp. 360–385.

Radev, D., 2012, "Assessing Systemic Fragility – A Probabilistic Perspective", Working Paper, GSEFM Frankfurt-Mainz-Darmstadt and Johannes Gutenberg University Mainz, 2012.

Segoviano, M., 2006, "Consistent Information Multivariate Density Optimization Methodology", FMG Discussion Papers #557, London School of Economics.

Segoviano, M. and C. Goodhart, 2009, "Banking Stability Measures", IMF Working Paper WP/09/04*, International Monetary Fund*

Schmidt, L., A. Timmermann, and R. Wermers, 2012, "Runs on Money Market Mutual Funds", mimeograph.

Souto, M., Tabak, B., and F. Vazquez, 2009, "Linking Financial and Macroeconomic Factors to Credit Risk Indicators of Brazilian Banks", *Banco Central do Brasil*, Working Paper No. 189.

Strömqvist, M., 2009, "Hedge Funds and Financial Crises", *Economic Review* Vol. 1, pp. 87-106.

United States Congress, 2010, "Dodd-Frank Wall Street Reform and Consumer Protection Act".

Figure 1 - Composition of World Investment Funds' Assets
(UCITS, percent)

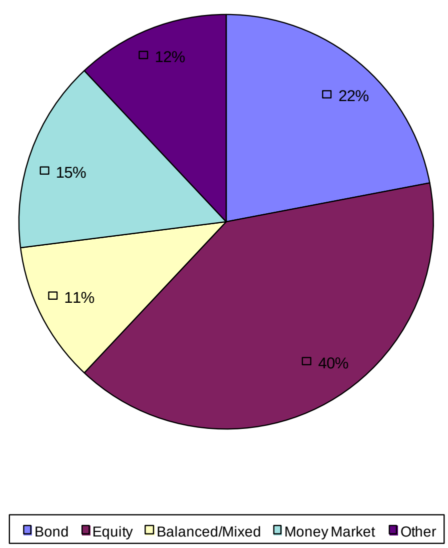


Figure 2 - Composition of Luxembourg Investment Funds' Assets
(UCITS and Non-UCITS, percent)

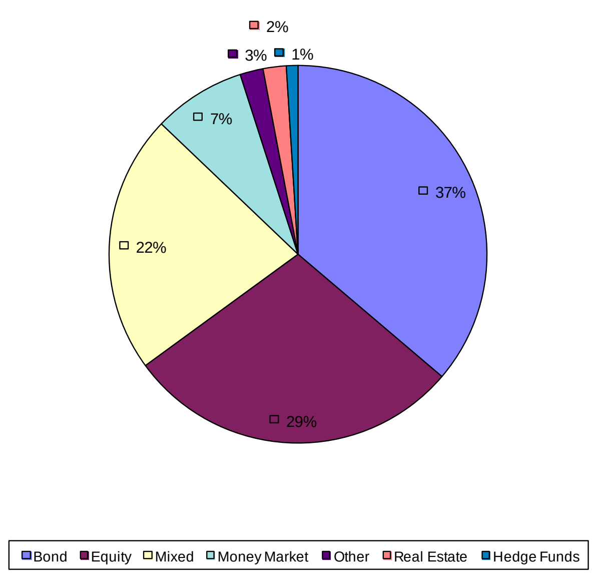


Figure 3 – Number of UCITS Compartments and the Output Gap
(annual percent change in UCITS compartments; percent)

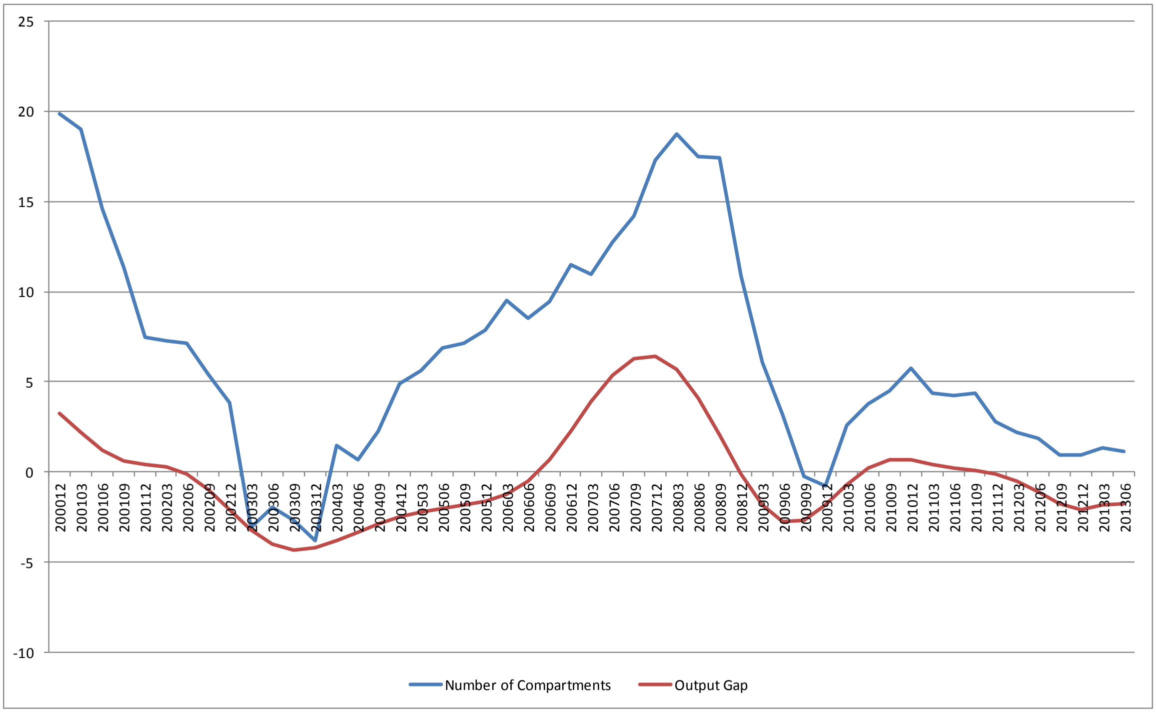


Figure 4 – Leverage by Investment Fund category
(Assets / Equity)

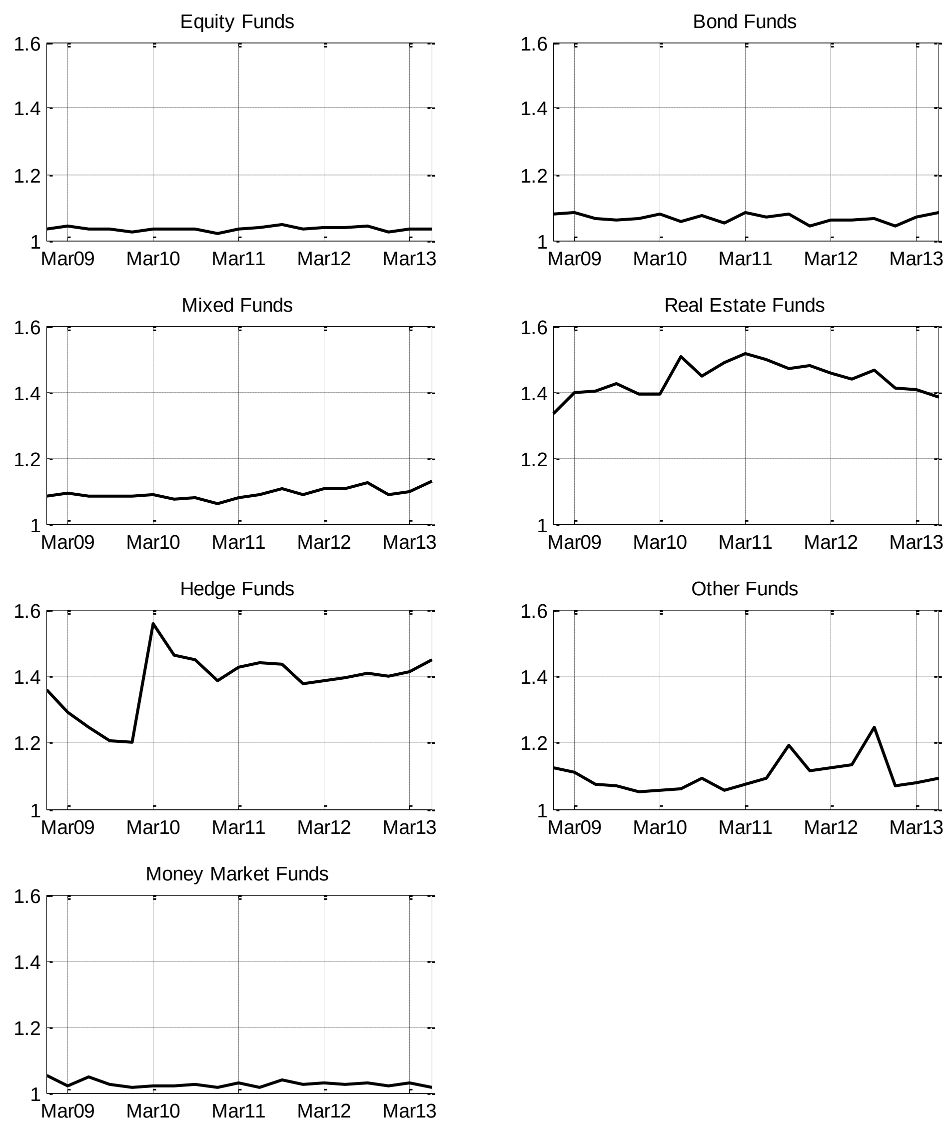


Figure 5 – Marginal Probabilities of Distress by Investment Fund category

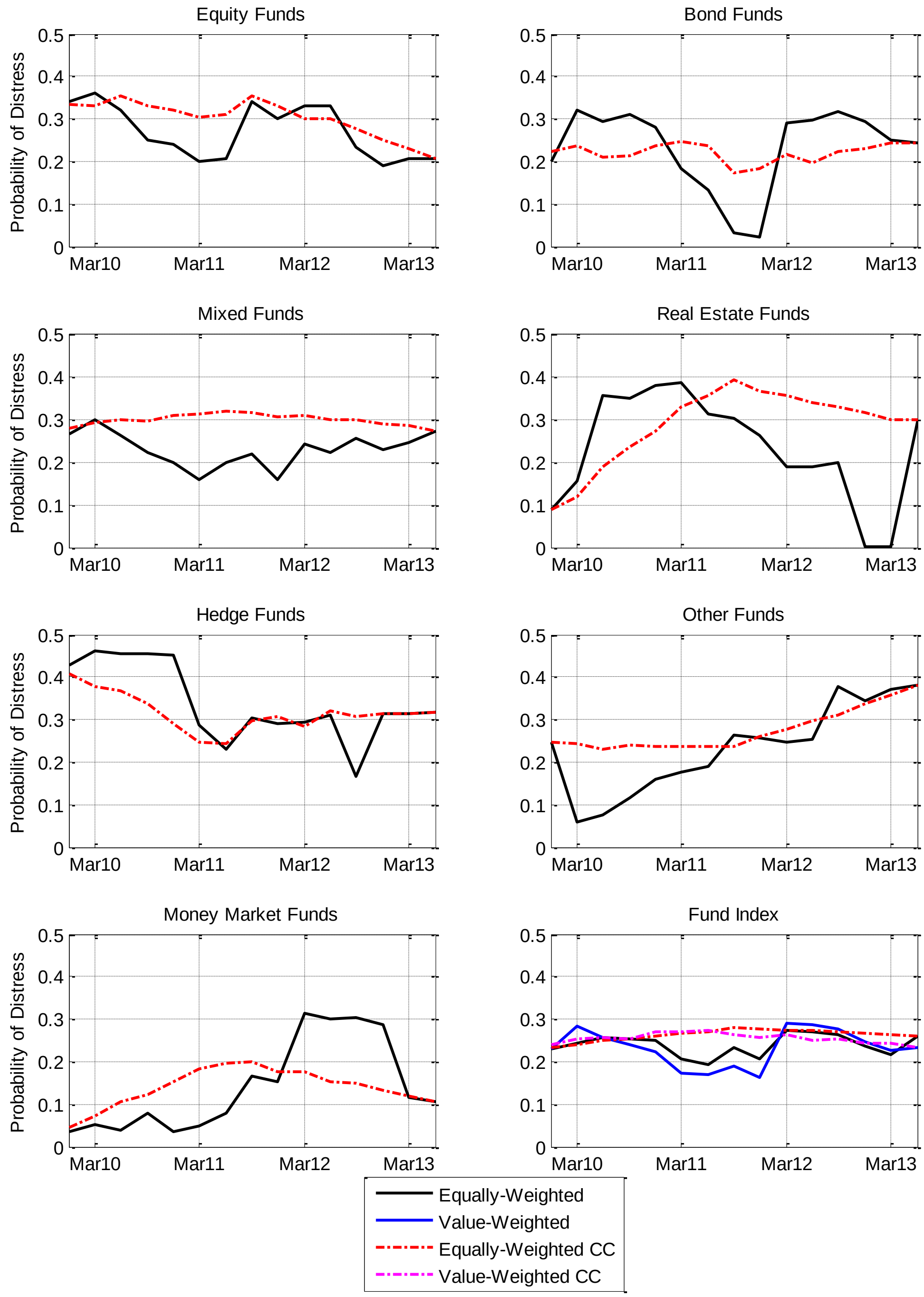


Figure 6 – Investment Fund System Fragility Measure:
Probability that at least two investment fund categories are simultaneously in distress

Figure 7 – Investment Fund Stability Index:
Expected number of funds categories entering distress
conditional on any one fund category being in distress

Figure 8 – Probability that At least One (PAO) other investment fund category becomes distressed given that one investment fund category is already in distress

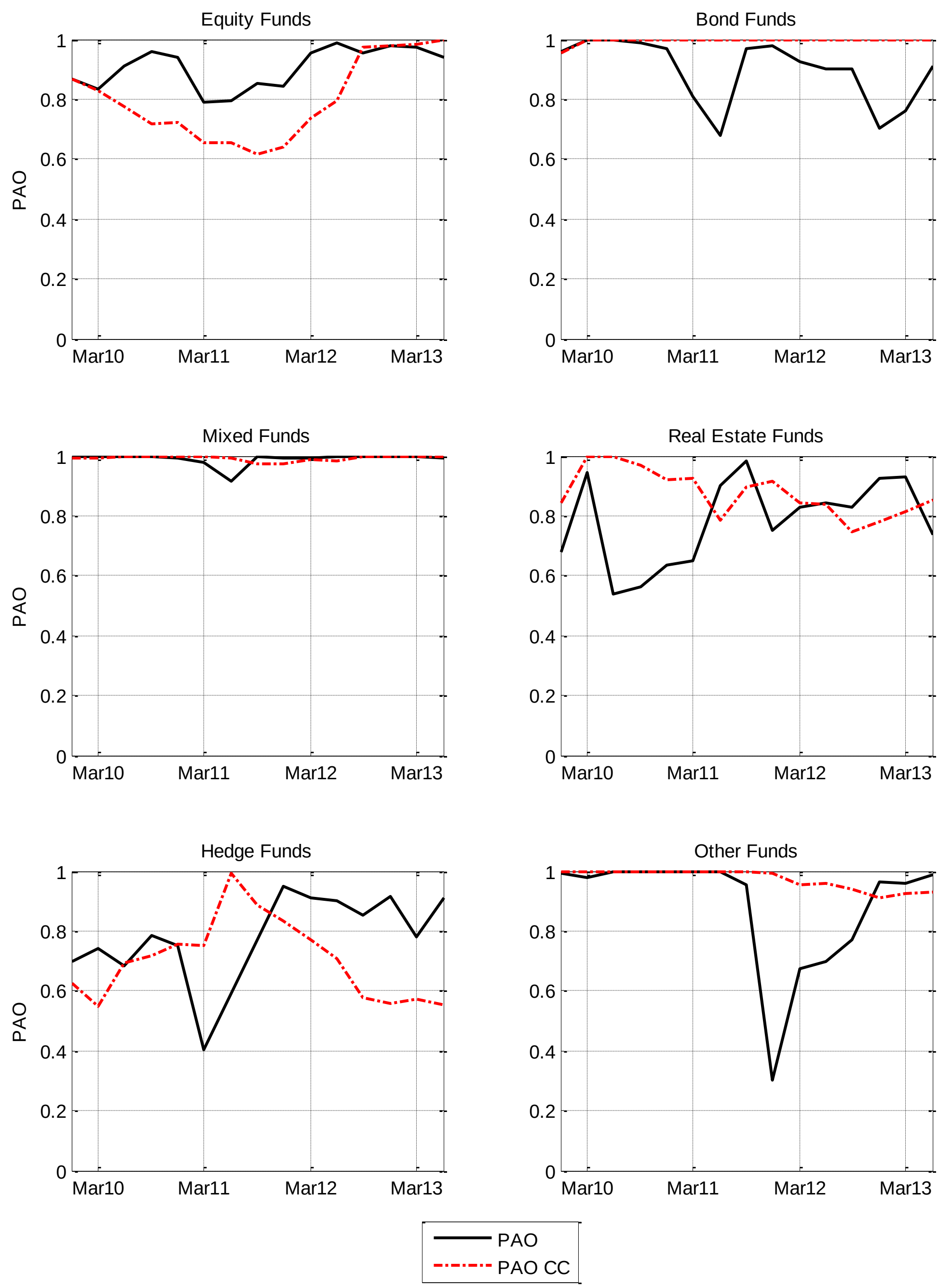


Figure 9 - Interest Rate Spread and the IFSF Common Component

Table 1 - Total Assets of the World Investment Fund Industry
(billion euro, end-2013)

	UCITS [1]		Non-UCITS [2]	Overall
	Assets	Share	Assets	Assets
United States	10889	50.0	1341	12050
Luxembourg	2198	10.1	418	2615
France	1111	5.1	415	1525
Ireland	1044	4.8	300	1344
United Kingdom	863	4.0	258	1121
Germany	278	1.3	1127	1404
Switzerland	288	1.3	69	357
Sweden	198	0.9	2	200
Italy	156	0.7	53	209
Denmark	86	0.4	99	186
Rest of Europe	645	3.0	182	827
Rest of the World	4034	18.5	n.a.	n.a.
TOTAL	21790		4264	26053

Sources: BCL, European Fund and Asset Management Association, Investment Company Institute, TheCityUK.
[1] Includes funds-of-funds assets.
[2] For the U.S., it only includes hedge funds' assets.

Table 2 - Selective Investment Fund Regulatory Features

Investment Funds	Main Legal Framework	Investors	Eligible investments and investment restrictions	Valuation approach	Valuation frequency	Leverage	Exposure	Currency derivatives
UCITS	Parts I and V, UCITS IV Directive, 2010	All	Global limits and diversification, concentration, counterparty limits; cannot be guarantors					
Short-term Money Market Funds				NAV at amortized cost or market value	Daily	Only technical	No	Only for hedging
Money Market Funds				NAV at market value	Daily	Only technical	No	Only for hedging
Non-UCITS	Part II, UCITS IV Directive, 2010 AIFMD Directive, 2013	All	No restriction on type of asset Diversification required per investment strategy	Market value if available or realizable value if market quote not available	Monthly (in principle)	Borrowing < 25% of net assets	Allowed	Yes, but in prospectus
Specialized Investment Funds (SIF)	Specialized Investment Funds Law, 2007	Well-informed investors	No restrictions of type of assets Diversification of risk is required (CSSF 07/309)	Fair value	Yearly	Not regulated	Allowed	Allowed; regulations on diversification apply
Real Estate Funds	Part II, UCITS IV Directive, 2010 or	All	All real estate, < 20% of net assets	Realizable value of assets	When units issued or redeemed; yearly	< 50% value all properties	Allowed	Yes, but in prospectus
	Specialized Investment Funds Law, 2007	Well-informed investors	All real estate, < 30% of gross assets	Fair value (unless prospectus differs)	Yearly	No maximum	Allowed	Allowed; regulations on diversification apply
Private Equity Funds	Part II, UCITS IV Directive, 2010 or	All	< 20% of net assets in any one company	Market value if available or realizable	Monthly (in principle)	Not regulated	Allowed	Yes, but in prospectus
	Specialized Investment Funds Law, 2007	Well-informed investors	< 30% of gross assets	Fair value (unless prospectus differs)	Yearly	Not regulated	Allowed	Allowed; regulations on diversification apply
	or SICARs Law, 2005	Well-informed investors	Not subject to risk spreading regulation	Fair value	Yearly	Not regulated		Allowed
Hedge Funds	Parts I and V, UCITS IV Directive, 2010 or	All	No restriction on type of asset Diversification required on long security positions	Market value, or realizable value	Twice a month	Only technical	Allowed; restrictions apply	Allowed; restrictions apply
	Part II, UCITS IV Directive, 2010 or	All	No restriction on type of asset Diversification required on long security positions	Market value, or realizable value	Monthly (in principle)	Allowed; restrictions apply	Allowed; restrictions apply	Allowed; restrictions apply
	Specialized Investment Funds Law, 2007	Well-informed investors	< 30% of gross assets in one issuer	Fair value (unless prospectus differs)	Yearly	Not regulated	Allowed; restrictions apply	Allowed; restrictions apply

Table 3: Contribution of Variables to Common Components of PDs by Investment Fund Category

(Top 50%, Absolute Composite Loading)

Equity Funds

Category	Factor 1		Factor 2		Factor 3		All Factors	
	Total	Average	Total	Average	Total	Average	Total	Average
Macroeconomy	5.5%	0.2%	8.6%	0.1%	18.6%	0.3%	18.7%	0.4%
Funding Prices	23.8%	0.3%	3.3%	0.1%	6.4%	0.2%	22.8%	0.4%
Funding Quantities	1.7%	0.2%	1.8%	0.1%	7.0%	0.3%	8.3%	0.4%
Confidence	1.3%	0.2%	0.4%	0.1%	1.9%	0.3%	0.4%	0.4%
PDs	0.3%	0.2%	0.2%	0.1%	0.6%	0.2%	0.8%	0.4%

Bond Funds

Category	Factor 1		Factor 2		Factor 3		All Factors	
	Total	Average	Total	Average	Total	Average	Total	Average
Macroeconomy	2.7%	0.1%	11.7%	0.2%	7.1%	0.1%	10.3%	0.2%
Funding Prices	11.4%	0.1%	4.5%	0.1%	2.5%	0.1%	13.6%	0.2%
Funding Quantities	0.8%	0.1%	2.4%	0.1%	2.7%	0.1%	3.4%	0.2%
Confidence	0.6%	0.1%	0.5%	0.1%	0.7%	0.1%	1.3%	0.2%
PDs	0.1%	0.1%	0.2%	0.1%	0.2%	0.1%	0.2%	0.2%

Mixed Funds

Category	Factor 1		Factor 2		Factor 3		All Factors	
	Total	Average	Total	Average	Total	Average	Total	Average
Macroeconomy	1.4%	0.0%	20.5%	0.3%	30.2%	0.5%	34.7%	0.5%
Funding Prices	6.0%	0.1%	7.9%	0.2%	10.4%	0.3%	15.0%	0.4%
Funding Quantities	0.4%	0.0%	4.3%	0.2%	11.4%	0.5%	13.8%	0.6%
Confidence	0.3%	0.0%	0.9%	0.2%	3.1%	0.4%	2.3%	0.5%
PDs	0.1%	0.0%	0.4%	0.2%	0.9%	0.3%	1.0%	0.5%

Real Estate Funds

Category	Factor 1		Factor 2		Factor 3		All Factors	
	Total	Average	Total	Average	Total	Average	Total	Average
Macroeconomy	0.1%	0.0%	23.5%	0.4%	2.7%	0.0%	24.5%	0.4%
Funding Prices	0.5%	0.0%	9.0%	0.2%	0.9%	0.0%	8.2%	0.2%
Funding Quantities	0.0%	0.0%	4.9%	0.3%	1.0%	0.0%	5.0%	0.3%
Confidence	0.0%	0.0%	1.0%	0.2%	0.3%	0.0%	1.3%	0.2%
PDs	0.0%	0.0%	0.4%	0.2%	0.1%	0.0%	0.4%	0.2%

Hedge Funds

Category	Factor 1		Factor 2		Factor 3		All Factors	
	Total	Average	Total	Average	Total	Average	Total	Average
Macroeconomy	3.6%	0.1%	6.5%	0.1%	14.0%	0.2%	17.4%	0.3%
Funding Prices	15.6%	0.2%	2.5%	0.1%	4.9%	0.2%	12.5%	0.2%
Funding Quantities	1.1%	0.1%	1.4%	0.1%	5.3%	0.2%	3.7%	0.3%
Confidence	0.9%	0.1%	0.3%	0.1%	1.4%	0.2%	2.0%	0.4%
PDs	0.2%	0.1%	0.1%	0.1%	0.4%	0.1%	0.2%	0.2%

Other Funds

Category	Factor 1		Factor 2		Factor 3		All Factors	
	Total	Average	Total	Average	Total	Average	Total	Average
Macroeconomy	1.4%	0.0%	2.5%	0.0%	15.9%	0.2%	15.6%	0.2%
Funding Prices	6.0%	0.1%	1.0%	0.0%	5.5%	0.2%	7.2%	0.2%
Funding Quantities	0.4%	0.0%	0.5%	0.0%	6.0%	0.2%	6.3%	0.3%
Confidence	0.3%	0.0%	0.1%	0.0%	1.6%	0.2%	1.2%	0.2%
PDs	0.1%	0.0%	0.0%	0.0%	0.5%	0.2%	0.4%	0.2%

Money Market Funds

Category	Factor 1		Factor 2		Factor 3		All Factors	
	Total	Average	Total	Average	Total	Average	Total	Average
Macroeconomy	0.1%	0.0%	7.3%	0.1%	18.1%	0.3%	20.8%	0.3%
Funding Prices	0.5%	0.0%	2.8%	0.1%	6.3%	0.2%	6.6%	0.2%
Funding Quantities	0.0%	0.0%	1.5%	0.1%	6.8%	0.3%	6.0%	0.3%
Confidence	0.0%	0.0%	0.3%	0.1%	1.9%	0.3%	1.8%	0.3%
PDs	0.0%	0.0%	0.1%	0.1%	0.6%	0.2%	0.6%	0.2%

Table 4: Distress Dependence Matrices

The PD in the row, given PD in the column	PDs								CC PDs							
	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
								Q2 2010								
Equity Funds	1.00	0.75	0.97	0.23	0.45	0.48	0.00	0.56	1.00	0.94	0.92	0.48	0.41	0.82	0.00	0.65
Bond Funds	0.69	1.00	0.84	0.38	0.50	0.82	0.00	0.60	0.55	1.00	0.70	0.55	0.42	0.83	0.00	0.58
Mixed Funds	0.80	0.75	1.00	0.25	0.39	0.52	0.00	0.53	0.78	1.00	1.00	0.58	0.47	0.91	0.00	0.68
Real Estate Funds	0.26	0.45	0.33	1.00	0.27	0.84	0.00	0.45	0.26	0.49	0.36	1.00	0.51	0.56	0.00	0.45
Hedge Funds	0.65	0.77	0.68	0.35	1.00	0.82	0.00	0.61	0.42	0.74	0.58	1.00	1.00	0.82	0.00	0.65
Other Funds	0.11	0.21	0.15	0.18	0.14	1.00	0.00	0.26	0.54	0.91	0.71	0.69	0.52	1.00	0.00	0.62
Money Market Funds	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.14	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.14
Column Average	0.50	0.56	0.57	0.34	0.39	0.64	0.14	0.45	0.51	0.73	0.61	0.61	0.47	0.71	0.14	0.54
								Q2 2011								
Equity Funds	1.00	0.30	0.49	0.48	0.07	0.63	0.00	0.43	1.00	0.63	0.58	0.41	0.72	0.63	0.00	0.57
Bond Funds	0.19	1.00	0.37	0.19	0.02	0.26	0.00	0.29	0.47	1.00	0.72	0.64	0.75	0.97	0.00	0.65
Mixed Funds	0.47	0.56	1.00	0.46	0.19	0.76	0.00	0.49	0.61	1.01	1.00	0.76	0.97	1.00	0.00	0.76
Real Estate Funds	0.73	0.44	0.72	1.00	0.49	0.98	0.00	0.62	0.47	0.99	0.84	1.00	0.81	0.98	0.00	0.73
Hedge Funds	0.08	0.03	0.22	0.36	1.00	0.28	0.00	0.28	0.58	0.80	0.74	0.56	1.00	0.78	0.00	0.64
Other Funds	0.58	0.37	0.73	0.59	0.23	1.00	0.00	0.50	0.48	0.98	0.73	0.64	0.74	1.00	0.00	0.65
Money Market Funds	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.14	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.14
Column Average	0.44	0.39	0.50	0.44	0.28	0.56	0.14	0.39	0.52	0.77	0.66	0.57	0.71	0.76	0.14	0.59
								Q2 2012								
Equity Funds	1.00	0.58	0.89	0.34	0.67	0.17	0.00	0.52	1.00	0.60	0.73	0.27	0.07	0.24	0.00	0.41
Bond Funds	0.53	1.00	0.85	0.24	0.23	0.44	0.00	0.47	0.39	1.00	0.61	0.50	0.00	0.40	0.00	0.41
Mixed Funds	0.59	0.62	1.00	0.15	0.31	0.21	0.00	0.41	0.72	0.92	1.00	0.48	0.01	0.42	0.00	0.51
Real Estate Funds	0.19	0.14	0.13	1.00	0.13	0.00	0.00	0.23	0.30	0.86	0.55	1.00	0.11	0.74	0.00	0.51
Hedge Funds	0.62	0.23	0.44	0.22	1.00	0.16	0.00	0.38	0.07	0.00	0.01	0.10	1.00	0.27	0.00	0.21
Other Funds	0.13	0.36	0.24	0.00	0.12	1.00	0.00	0.26	0.23	0.59	0.41	0.64	0.25	1.00	0.00	0.45
Money Market Funds	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.14	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.14
Column Average	0.44	0.42	0.51	0.28	0.35	0.28	0.14	0.35	0.39	0.57	0.47	0.43	0.20	0.44	0.14	0.38
								Q2 2013								
Equity Funds	1.00	0.70	0.60	0.13	0.09	0.39	0.00	0.42	1.00	0.79	0.75	0.56	0.04	0.53	0.00	0.52
Bond Funds	0.83	1.00	0.69	0.27	0.10	0.41	0.00	0.47	0.93	1.00	0.90	0.72	0.03	0.58	0.00	0.59
Mixed Funds	0.79	0.77	1.00	0.41	0.31	0.61	0.00	0.56	0.98	1.00	1.00	0.78	0.04	0.63	0.00	0.63
Real Estate Funds	0.19	0.33	0.45	1.00	0.49	0.42	0.00	0.41	0.80	0.88	0.86	1.00	0.02	0.60	0.00	0.59
Hedge Funds	0.14	0.12	0.36	0.52	1.00	0.62	0.00	0.39	0.07	0.03	0.04	0.02	1.00	0.27	0.00	0.20
Other Funds	0.71	0.64	0.85	0.53	0.74	1.00	0.00	0.64	0.97	0.90	0.89	0.76	0.33	1.00	0.00	0.69
Money Market Funds	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.14	0.00	0.00	0.00	0.00	0.00	0.00	1.00	0.14
Column Average	0.52	0.51	0.57	0.41	0.39	0.49	0.14	0.43	0.68	0.66	0.63	0.55	0.21	0.52	0.14	0.48

Note: These matrices present the probability of distress of the 7 investment funds in the the row, conditional on the investment funds in the column becoming distressed.

Table 5 : Contribution of Variables to Common Components of Systemic Risk Measures
(Top 50%, Absolute Composite Loading)

IFSF

Category	Factor 1		Factor 2		Factor 3		All Factors	
	Total	Average	Total	Average	Total	Average	Total	Average
Macroeconomy	4.91%	0.15%	3.92%	0.06%	3.44%	0.05%	4.95%	0.17%
Fund Prices	21.07%	0.26%	1.51%	0.04%	1.19%	0.04%	21.87%	0.27%
Funding Quantities	1.54%	0.15%	0.82%	0.05%	1.29%	0.05%	1.38%	0.15%
Confidence	1.17%	0.17%	0.17%	0.03%	0.35%	0.05%	1.51%	0.19%
PDs	0.27%	0.13%	0.07%	0.04%	0.11%	0.04%	0.35%	0.12%

IFSI

Category	Factor 1		Factor 2		Factor 3		All Factors	
	Total	Average	Total	Average	Total	Average	Total	Average
Macroeconomy	3.94%	0.12%	7.73%	0.12%	6.36%	0.09%	6.77%	0.19%
Fund Prices	16.90%	0.21%	2.98%	0.07%	2.20%	0.07%	18.20%	0.25%
Funding Quantities	1.24%	0.12%	1.62%	0.09%	2.39%	0.10%	2.59%	0.17%
Confidence	0.94%	0.13%	0.34%	0.07%	0.66%	0.09%	1.56%	0.20%
PDs	0.22%	0.11%	0.15%	0.07%	0.19%	0.06%	0.00%	0.00%

PAO of Equity Funds

Category	Factor 1		Factor 2		Factor 3		All Factors	
	Total	Average	Total	Average	Total	Average	Total	Average
Macroeconomy	1.26%	0.04%	59.63%	0.90%	20.41%	0.30%	59.91%	0.95%
Fund Prices	5.43%	0.07%	22.99%	0.56%	7.06%	0.23%	24.52%	0.61%
Funding Quantities	0.40%	0.04%	12.48%	0.69%	7.68%	0.32%	18.71%	0.78%
Confidence	0.30%	0.04%	2.60%	0.52%	2.11%	0.30%	1.76%	0.88%
PDs	0.07%	0.03%	1.13%	0.56%	0.62%	0.21%	1.83%	0.61%

PAO of Bond Funds

Category	Factor 1		Factor 2		Factor 3		All Factors	
	Total	Average	Total	Average	Total	Average	Total	Average
Macroeconomy	1.19%	0.04%	42.52%	0.64%	44.15%	0.66%	58.72%	0.88%
Fund Prices	5.12%	0.06%	16.39%	0.40%	15.28%	0.49%	23.69%	0.68%
Funding Quantities	0.37%	0.04%	8.90%	0.49%	16.61%	0.69%	22.09%	0.96%
Confidence	0.29%	0.04%	1.86%	0.37%	4.56%	0.65%	3.55%	0.71%
PDs	0.07%	0.03%	0.80%	0.40%	1.35%	0.45%	1.57%	0.78%

PAO of Mixed Funds

Category	Factor 1		Factor 2		Factor 3		All Factors	
	Total	Average	Total	Average	Total	Average	Total	Average
Macroeconomy	3.26%	0.10%	22.38%	0.34%	16.27%	0.24%	22.76%	0.42%
Fund Prices	13.99%	0.17%	8.63%	0.21%	5.63%	0.18%	19.15%	0.38%
Funding Quantities	1.02%	0.10%	4.68%	0.26%	6.12%	0.26%	8.22%	0.41%
Confidence	0.78%	0.11%	0.98%	0.20%	1.68%	0.24%	2.06%	0.34%
PDs	0.18%	0.09%	0.42%	0.21%	0.50%	0.17%	0.39%	0.39%

PAO of Real Estate Funds

Category	Factor 1		Factor 2		Factor 3		All Factors	
	Total	Average	Total	Average	Total	Average	Total	Average
Macroeconomy	2.11%	0.07%	3.96%	0.06%	4.08%	0.06%	3.89%	0.11%
Fund Prices	9.04%	0.11%	1.53%	0.04%	1.41%	0.05%	9.79%	0.13%
Funding Quantities	0.66%	0.07%	0.83%	0.05%	1.54%	0.06%	1.53%	0.10%
Confidence	0.50%	0.07%	0.17%	0.03%	0.42%	0.06%	0.91%	0.11%
PDs	0.12%	0.06%	0.07%	0.04%	0.13%	0.04%	0.00%	0.00%

PAO of Hedge Funds

Category	Factor 1		Factor 2		Factor 3		All Factors	
	Total	Average	Total	Average	Total	Average	Total	Average
Macroeconomy	0.45%	0.01%	21.42%	0.32%	3.15%	0.05%	23.01%	0.32%
Fund Prices	1.94%	0.02%	8.26%	0.20%	1.09%	0.04%	7.10%	0.21%
Funding Quantities	0.14%	0.01%	4.48%	0.25%	1.19%	0.05%	4.61%	0.24%
Confidence	0.11%	0.02%	0.93%	0.19%	0.33%	0.05%	1.27%	0.21%
PDs	0.02%	0.01%	0.40%	0.20%	0.10%	0.03%	0.37%	0.18%

PAO of Other Funds

Category	Factor 1		Factor 2		Factor 3		All Factors	
	Total	Average	Total	Average	Total	Average	Total	Average
Macroeconomy	1.60%	0.05%	19.87%	0.30%	3.50%	0.05%	17.75%	0.31%
Fund Prices	6.88%	0.08%	7.66%	0.19%	1.21%	0.04%	12.53%	0.23%
Funding Quantities	0.50%	0.05%	4.16%	0.23%	1.32%	0.05%	4.08%	0.27%
Confidence	0.38%	0.05%	0.87%	0.17%	0.36%	0.05%	0.70%	0.23%
PDs	0.09%	0.04%	0.37%	0.19%	0.11%	0.04%	0.40%	0.20%

Table 6: Granger Causality

	Common components lead			Financial stability measures lead		
	F(2,4)	p value	Maximum gap	F(2,4)	p value	Maximum gap
IFSF	81.71	0.01	0.37	0.75	0.64	0.34
IFSI	5.04	0.17	0.27	2.45	0.31	0.39
PAO Average	0.96	0.57	0.36	0.30	0.30	0.37
PAO Equity Funds	2.42	0.31	0.38	6.29	0.14	0.41
PAO Bond Funds	0.63	0.69	0.30	8.88	0.10	0.12
PAO Mixed Funds	1.03	0.55	0.20	80.26	0.01	0.23
PAO Real Estate Funds	0.80	0.62	0.36	1.15	0.51	0.39
PAO Hedge Funds	0.97	0.56	0.39	5.88	0.15	0.37
PAO Other Funds	0.05	0.99	0.17	41.85	0.02	0.13
PAO Money Market Funds	0.94	0.57	0.40	12.07	0.08	0.34

Four lags were used in all tests. The serial correlation test uses the Kolmogorov-Smirnov statistic; the approximate rejection limit at 10% confidence level is 0.43 for the null hypothesis that the residuals are white noise.

Appendix I: 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 II

Table A1 : Statistics of the Common Components of PDs Regressed on GDFM's Common Factors **(without intercept)**

Equity Funds

	Estimate	SE	t-Stat	p-Value
Factor 1	0.04	0.00	2.105E+16	0.00
Factor 2	0.02	0.00	3.65142E+15	0.00
Factor 3	0.04	0.00	1.06834E+16	0.00

Bond Funds

	Estimate	SE	t-Stat	p-Value
Factor 1	-0.02	0.00	-1.19304E+16	0.00
Factor 2	0.02	0.00	5.16228E+15	0.00
Factor 3	0.02	0.00	4.66022E+15	0.00

Mixed Funds

	Estimate	SE	t-Stat	p-Value
Factor 1	0.01	0.00	4.35533E+15	0.00
Factor 2	0.04	0.00	6.39381E+15	0.00
Factor 3	0.06	0.00	9.40585E+15	0.00

Real Estate Funds

	Estimate	SE	t-Stat	p-Value
Factor 1	0.00	0.00	-4.33112E+14	0.00
Factor 2	-0.05	0.00	-1.06239E+16	0.00
Factor 3	0.01	0.00	1.10908E+15	0.00

Hedge Funds

	Estimate	SE	t-Stat	p-Value
Factor 1	0.03	0.00	8.25589E+15	0.00
Factor 2	0.01	0.00	3.43119E+15	0.00
Factor 3	-0.03	0.00	-5.11169E+15	0.00

Other Funds

	Estimate	SE	t-Stat	p-Value
Factor 1	-0.01	0.00	-1.00172E+16	0.00
Factor 2	-0.01	0.00	-3.266E+15	0.00
Factor 3	-0.03	0.00	-1.12204E+16	0.00

Money Market Funds

	Estimate	SE	t-Stat	p-Value
Factor 1	0.00	0.00	6.29348E+14	0.00
Factor 2	-0.02	0.00	-2.94453E+15	0.00
Factor 3	0.04	0.00	1.37904E+16	0.00

Table A2: Timeline of events

15-Jan-09	ECB cuts interest rates by 50 bp
5-Mar-09	ECB cuts interest rates by 50 bp
2-Apr-09	ECB cuts interest rates by 25 bp
7-May-09	ECB cuts interest rates by 25 bp
7-May-09	ECB launches one-year refinancing operations
4-Jun-09	ECB launches first covered bond program
2-Dec-09	EU to create new supervisory authorities
27-Jan-10	ECB to end US dollar euro swap
25-Mar-10	EU offers support to Greece
23-Apr-10	Greece seeks financial support
2-May-10	Loan package to Greece agreed
10-May-10	ECB reintroduces US dollar euro swap and starts Securities Market Program
7-Jun-10	The European Financial Stability Facility is established
30-Jun-10	The ECB ends the covered bond program
5-Aug-10	EC, ECB and IMF support Greece's economic program
21-Nov-10	Ireland seeks financial support
28-Nov-10	New mechanism for countries in financial distress
7-Dec-10	Irish economic package agreed
16-Dec-10	ESRB is set up
16-Dec-10	Go-ahead for the European Stability Mechanism
1-Jan-11	EU supervisory bodies established
3-Mar-11	ECB announces details of refinancing operations
31-Mar-11	ECB praises Irish decision to strengthen banks
6-Apr-11	Portugal requests activation of aid mechanism
7-Apr-11	ECB raises interest rates by 25 bp
17-May-11	EC Council approves aid to Portugal and sets conditions
7-Jul-11	ECB raises interest rates by 25 bp
15-Jul-11	Stress tests results published
21-Jul-11	EU leaders discuss the crisis and support financial stability
15-Sep-11	ECB announces additional US dollar liquidity provision measures
6-Oct-11	ECB announces second covered bond program
26-Oct-11	EU leaders agree on additional measures
3-Nov-11	ECB cuts interest rates by 25 bp
8-Dec-11	ECB lowers interest rates 25bp and announces measures to support bank lending
22-Dec-11	ECB allots 489bn euro to 523 banks in the first 36-month LTRO
9-Feb-12	ECB approves eligibility criteria for additional credit claims
21-Feb-12	EU agrees on second aid package to Greece
1-Mar-12	EU leaders sign fiscal compact
3-Jan-12	ECB allots 530bn euro to 800 banks in the second 36-month LTRO
27-Jun-12	Spain and Cyprus seek financial support
29-Jun-12	EU agrees on creating a European banking supervisory mechanism
20-Jul-12	Eurogroup grants financial assistance to Spanish banking sector
9/6/2012	ECB announces technical features of outright monetary transactions
12-Sep-12	EC proposes new powers for the ECB
12-Dec-12	ECB reinstates Greek bonds as collateral
25-Mar-13	Europgroup reaches agreement of future macroeconomic adjustment program for Portugal
2-May-14	ECB reduces interest rates and reinstates Cypriot bonds as collateral
28-Jun-13	Cypriot bonds are suspended

Table A3: Statistics of the Common Components of Sytemic Risk Measures Regressed on GDFM's Common Factors **(without intercept)**

IFSF

	Estimate	SE	t-Stat	p-Value
Factor 1	0.04	0.01	3.26	**0.00**
Factor 2	-0.01	0.04	-0.23	0.82
Factor 3	-0.01	0.02	-0.36	0.72

IFSI

	Estimate	SE	t-Stat	p-Value
Factor 1	-0.03	0.01	-2.10	**0.04**
Factor 2	0.02	0.05	0.33	0.74
Factor 3	0.01	0.03	0.50	0.62

PAO of Equity Funds

	Estimate	SE	t-Stat	p-Value
Factor 1	0.01	0.01	1.54	0.12
Factor 2	0.12	0.04	3.09	**0.00**
Factor 3	0.04	0.03	1.41	0.16

PAO of Bond Funds

	Estimate	SE	t-Stat	p-Value
Factor 1	0.01	0.01	0.63	0.53
Factor 2	0.09	0.06	1.41	0.16
Factor 3	0.09	0.07	1.45	0.15

PAO of Mixed Funds

	Estimate	SE	t-Stat	p-Value
Factor 1	-0.03	0.01	-2.18	**0.03**
Factor 2	0.05	0.04	1.18	0.24
Factor 3	0.03	0.02	1.74	**0.08**

PAO of Real Estate Funds

	Estimate	SE	t-Stat	p-Value
Factor 1	0.02	0.02	0.85	0.39
Factor 2	-0.01	0.07	-0.12	0.91
Factor 3	-0.01	0.07	-0.12	0.90

PAO of Hedge Funds

	Estimate	SE	t-Stat	p-Value
Factor 1	0.00	0.02	-0.21	0.83
Factor 2	-0.04	0.05	-0.85	0.40
Factor 3	0.01	0.04	0.15	0.88

PAO of Other Funds

	Estimate	SE	t-Stat	p-Value
Factor 1	0.01	0.02	0.80	0.43
Factor 2	-0.04	0.04	-1.07	0.28
Factor 3	-0.01	0.04	-0.21	0.83

BANQUE CENTRALE DU LUXEMBOURG

EUROSYSTÈME

2, boulevard Royal
L-2983 Luxembourg

Tél.: +352 4774-1
Fax: +352 4774 4910

www.bcl.lu • info@bcl.lu