4 ANNEXES

1. INSOLVENCY PROSPECTS FOR THE LUXEMBOURG NON-FINANCIAL CORPORATION SECTOR

Boubacar Diallo and Lucas Hafemann[120]

ABSTRACT

The Covid-19 pandemic has increased the importance of the topic of insolvencies of non-financial corporations (NFCs) and the potential implications for the real economy and the banking sector. This study examines the potential effects of increased insolvencies in the Luxembourg NFC sector and provides three main contributions. First, we investigate the macro-financial drivers of NFCs insolvencies in Luxembourg. Second, we directly assess the effect of the Covid-19 pandemic on different segments of the NFC sector. Third, we assess the link between NFC insolvencies and the Luxembourg banking sector. The results suggest that at the sectoral level, variables that measure sectoral activity are among the key drivers of NFC insolvencies in Luxembourg. At the macroeconomic level, GDP growth and interest rate are also found to be significant determinants of corporate insolvencies in Luxembourg. In relation to the impact of the Covid-19 pandemic on NFCs, we find that the decline in the number of insolvencies cannot be explained with pre-Covid data. These findings are consistent with the view that the supportive effects of the exceptional policy measures exceeded the adverse impact on NFC insolvencies resulting from the pandemic-related crisis. Finally, we show that NFC insolvencies are strong predictors of the number of banks' non-performing loans.

1. INTRODUCTION

This research investigates the drivers of non-financial corporation (NFC) bankruptcies in Luxembourg against the background of the Covid-19 pandemic. Understanding the key determinants of corporate bankruptcies is important from a financial stability perspective, particularly in view of a less accommodative monetary policy stance. Moreover, corporate bankruptcy has long been recognized as a macroeconomic issue, which could have adverse consequences for the broader economy. Indeed, an increase in insolvencies could potentially result in higher levels of banking stress if non-performing loans (NPL) were to increase. In addition, the increase in unemployment resulting from higher insolvencies can reduce income streams for affected households while forgone taxes and government support schemes for the unemployed can weaken sovereign balance sheets.

In view of the significant shock resulting from the Covid-19 pandemic and the subsequent effects of the lockdown measures on the non-financial corporate sector, this study looks at the potential drivers of NFC insolvencies in Luxembourg. The analysis proceeds in three steps. First, this study attempts to provide a better understanding of the main macroeconomic and financial drivers of NFC insolvencies in Luxembourg and it provides forecasts of the number of aggregate corporate insolvencies as well as by sector. Second, we investigate the effectiveness of the government support measures that were implemented during the pandemic in order to mitigate the adverse effects of the lockdown measures on the corporate sector. Finally, we look at the impact of NFC insolvencies on the Luxembourg banking sector. This is done via a model linking forecasted NFC insolvencies with the non-performing loan levels of Luxembourg banks.

120 Financial Stability and Macroprudential Surveillance Department, Banque centrale du Luxembourg

In terms of the drivers of insolvencies, we follow the literature and adopt sectoral and macroeconomic variables such as gross value added, production and employment growth, the ratio of employees' compensation to gross value added, consumption of fixed capital growth, GDP growth, the interest rate, the credit-to-GDP gap and inflation. However, to identify potential issues related to the reverse causality between these variables as drivers of insolvencies, we adopt the feasible generalized least squares (FGLS) approach and include the first lag of the dependent variable along with the first lag of the drivers as explanatory variables. This approach allows us to address the serial correlation across the variables. Our results suggest that, at the sectoral level, variables that measure sectoral activity such as growth in gross value added or production growth and the ratio of employees' compensation to gross value added are among the key drivers of NFC insolvencies in Luxembourg. Employee compensation provides insights on the cost structure of firms as it measures the degree to which employment costs translate into the production of a given output. With respect to macroeconomic variables, GDP growth and interest rate are also found to be significant determinants of corporate insolvencies in Luxembourg, while inflation is not. To further assess corporate insolvencies, we also construct the Z-score using firms' balance sheet data and the principal component analysis (PCA) to extract the appropriate weightings for the Z-score calculation. When included as an explanatory variable, we find that the Z-score is a statistically significant predictor of NFC insolvencies for firms operating in Luxembourg.

In addition, we show that forecasts which are based on the identified sectoral and macroeconomic drivers can replicate the evolution of insolvencies over time reasonably accurately. Specifically, our models forecast that 31 percent of all insolvencies occurred in the wholesale segment, followed by the construction, and accommodation and food sectors, which represented 17 and 15 percent of all insolvencies, respectively. To better assess the accuracy of our models, we apply a moving window to predict the number of insolvencies over a one-year horizon and compare the corresponding results with a random walk (RW) model.

In relation to the impact of the Covid-19 pandemic on NFC insolvencies, we compare the out-of-sample forecasts from our models with the actual number of insolvencies observed during the pandemic for the years 2020 and 2021. In comparison to the pre-pandemic period, the number of insolvencies declined by 18% in 2020 and 7% in 2021, respectively. These declines are likely attributable to the extraordinary public support measures. We find that these declines cannot be predicted using pre-crisis data. A more granular perspective suggests that those sectors most affected by the lockdown measures, such as accommodation and food services, are also the sectors with disproportionately low levels of insolvencies. These findings are consistent with the view that the supportive effects of the exceptional policy measures exceeded the adverse impact on insolvencies resulting from the pandemic-related crisis.

Finally, we look at how NFC insolvencies could impact the banking sector in Luxembourg. NFC insolvencies may have an adverse effect on banks' balance sheets through an increase in non-performing loans (NPLs). To conduct the analysis, we combine the number of insolvencies forecasted from our econometric models with the number of sectoral NPLs at the bank level. We show that NFC insolvencies are strong predictors of the amount of NPLs. Specifically, we find that an increase of one unit of insolvency in a sector is associated with a 0.84 percent increase (per number of firms in a given sector) in NPL.

The remainder of this study is organized as follows. Section 2 surveys the literature on the determinants of NFC insolvencies, their impact on the banking sector, as well as the role of the Covid-19 pandemic in driving corporate insolvencies. Section 3 introduces the data used in our analysis, and Section 4 describes the methodology. Section 5 discusses the results while Sections 6 and 7 focus on the Covid-19 pandemic and the role of the banking sector, respectively. Section 8 concludes.

2. LITERATURE REVIEW

Understanding the drivers of NFC insolvencies, particularly during times of stress, remains an important question for policy-makers as NFCs are major contributors to employment and growth. Altman (1968) introduced the first multivariate bankruptcy model using five financial indicators as predictors. These financial indicators include working capital, retained earnings, earnings before interest and tax (EBIT), the ratio of sales to total assets, and the ratio of market capitalization to total liabilities. With these financial ratios, he was then able to construct an indicator of bankruptcy called the Z-score. Moreover, Altman (2000) shows that the Z-score had an accuracy for forecasting insolvencies of 82% (94%) for the periods of 1969-1975 and 1976-1995, respectively. From the 1990s onwards, and following rapid technological innovations, more complex models emerged, including for example, neural networks for improving the logit prediction model (Fletcher and Goss (1993)). These models offer promising results by providing more accurate simulations of corporate bankruptcies compared to logit models and they offer additional options for assessing causal relationships in data (Ahn *et al.* (2000), Tseng and Hu (2010), Callejón *et al.* (2013)).

On the underlying macroeconomic factors of insolvency, Altman (1983) focuses on the determinants of corporate failure. He found that business failure is negatively affected by aggregate economic activity (measured by the gross national product i.e., GNP), money market conditions and investor expectations. Similarly, Wadhwani (1986) focuses on inflation and other macroeconomic variables for UK firms over the period 1964-1981. He shows that real wages, real prices, capital gearing, and the level of interest (both nominal and real) have statistically significant effects on NFC insolvency.

Following Wadhwani (1986), Davis (1987) studied the predictors of NFC insolvencies in the U.S., Canada and Germany. His results suggest that nominal interest rates, real input prices, real GNP and the debt to GNP ratios are significant determinants of corporate insolvency. Platt and Platt (1994) show that strong economic activity reduces the likelihood of corporate failure. According to Young (1995), real interest rate shocks, changes in the number of companies, aggregate demand, real input prices, and the nominal interest rate are the most important predictors of NFC insolvency.

Using data for Australia over the period 1974-1990, Everett and Watson (1998) find that the corporate failure rate is positively correlated with interest rates and the rate of unemployment. In a similar vein, Vlieghe (2001) analyses UK data for the period 1975-1999, and observes that the real interest rate is a significant long-run determinant of corporate bankruptcies. Virolainen (2004) argues in favor of the use of GDP, interest rates[121] and corporate sector indebtedness as explanatory variables for the default rate by emphasizing the significant and fairly robust relationship between this rate and key macroeconomic factors. Focusing on Sweden, Salman *et al.* (2011) analyze the influence of macroeconomic variables on the failure of small companies using quarterly data for the period 1986-2006. The authors find that the bankruptcy rate is negatively affected by the level of industrial activity, while the money supply, changes in GNP and the economic openness rate are positively related to the real wage.

121 The interest rate appears as the less powerful indicator. This result is justified by the sampling period being large, including two different inflation regimes.

Zikovic (2016) examines the macroeconomic elements of bankruptcies in Croatia for the period 2000-2011, concluding that interest rates, as well as industrial production, have a short-term effect on insolvencies while unemployment has a long-run effect. More recently, Anghel *et al.* (2020) investigates the response of the insolvency rate to various shocks in the economies of Romania and Spain through a structural autoregressive model using quarterly data for 2008-2016. It was found that future values of the insolvency rate are explained by past values of the interest rate in both countries as well as the retail trade index. In contrast, the influence of the investment rate on insolvency was not significant. Finally, Bellone *et al*. (2006) and Blanchard *et al.* (2012) also show that productivity has a negative and significant impact on firm exit probability.

At the sectoral level, Aleksanyan and Huiban (2016) focus on the economic and financial determinants of firm exit due to bankruptcy in the French food sector and compare them with those of other manufacturing sectors during the period 2001-2012. They demonstrate that bankruptcy risk patterns differ across food industry firms and other manufacturing firms, and that productivity and the cost of credit are important determinants of a firm's probability of going bankrupt. Mackevicius *et al.* (2018) present a cross-country analysis on the dynamics of Latvian and Lithuanian firm bankruptcy using data on more than 40,000 firms. Their work highlights that bankruptcies may materialize in larger waves during certain periods and they also outline the driving factors. In Latvia and Lithuania, the wholesale and retail repair of motor vehicles and motorcycles sector has the largest bankruptcy rate (30% on average), followed by construction firms (13% on average). They also find that private companies are more likely to initiate bankruptcy proceedings than public firms (81% versus 19%), respectively.

In the context of the Covid-19 crisis, work on the effect of government support measures has gained additional momentum. Gourinchas *et al*. (2021) and Diez *et al.* (2021) assess the role of government support in avoiding failures for small and medium sized enterprises (SMEs). Acharya and Steffen (2020) study corporate behavior by investigating the significant impact of credit risk on corporate cash holdings. Carletti *et al*. (2020) forecast the drop in profit and equity shortfall triggered by the lockdown by using a representative sample of Italian firms. They investigate the impact of the lockdown on firms' profits and estimate that a 3-month lockdown generates an aggregate yearly drop in profits of around 10% of GDP, and that 17% of firms become financially distressed.

Greenwald *et al.* (2020) show the central role of credit lines in the transmission of macroeconomic shocks and spillover effects. While credit lines increase total credit growth and have a positive impact on less constrained firms, the draw on credit by large firms leads to the tightening of lending conditions. Schivardi and Romano (2020) emphasize the high speed at which firms face liquidity shortages during the Covid-19 pandemic but argue that under the current schemes of liquidity provision, firms' liquidity remains manageable. Pagano *et al.* (2021) measure stock return response according to companies' resilience to social distancing and show that stocks of more pandemic resilient firms reflect lower exposure to disaster risk. Hanson *et al*. (2020) show that the combination of the high uncertainty with aggregate demand externalities highlights a "social value" in keeping firms alive and maintaining government support. Nevertheless, liquidity shortages may impair the long-term viability of firms.

While corporates had to adapt to be profitable during the pandemic, determining the persistence of the economic effects of Covid-19 remains important (Schivardi *et al.*, 2020). In addition, the recovery of the economy to its pre-crisis level depends on its capacity to reabsorb the decline in output. The long-lasting effects of bankruptcy, also known as the spillover effect, can amplify financial contagion to other companies, which can then affect the entire economy through its adverse impact on employment, productivity and growth.

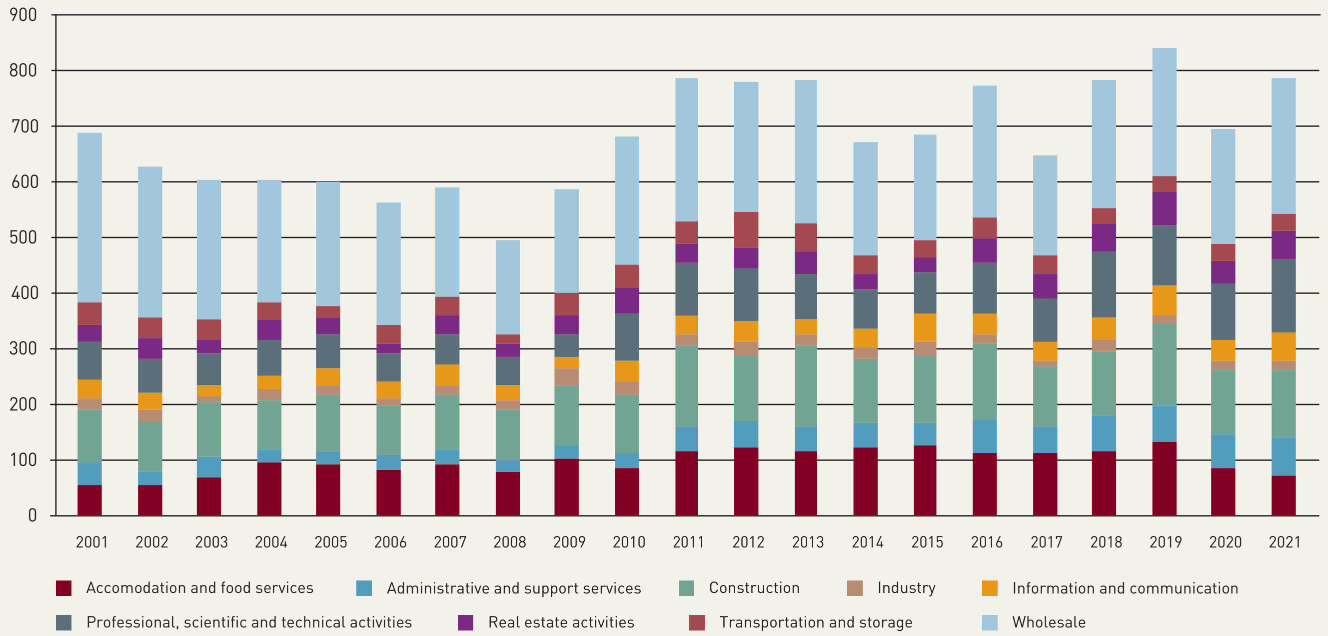
Indeed, the exceptional and unanticipated nature of the COVID-19 shock is unique for two main reasons, according to Hanson *et al*. (2020). First firms' long-run post-pandemic viability is at risk as the economic and financial recovery is linked to public health interventions in the context of an ongoing pandemic. Second, the extreme macroeconomic uncertainty due to the lack of knowledge surrounding the future path of the pandemic itself is also a unique challenge. The study highlighted different rationales behind governments' interventions. Keeping firms viable in the current environment of high macro-financial uncertainty with aggregate demand externalities has a social option value such that surviving firms exert positive spillovers on other surviving firms.

3. DATA

We first identify variables that are relevant for the solvency of firms in Luxembourg. Once these variables have been identified, we then forecast the total number of insolvencies in a given segment of the corporate sector. Hence, our main variable of interest is the total number of insolvent firms per year and sector which we obtain from STATEC.

Figure (1) displays the evolution of the number of insolvent firms in Luxembourg from 2001 until 2021. While the number of insolvent firms in Luxembourg was relatively stable until 2008, insolvencies increased following the global financial crisis and the subsequent European debt crisis. Insolvencies declined after 2013, with some fluctuation, before eventually increasing after 2017. Interestingly, the number of insolvent firms declined by 18% during the first year of the Covid-crisis. However, compared to 2020, corporate insolvencies increased by 13% in 2021. Nevertheless, they remain below the level observed in 2019.

Figure 1
Number of Insolvent Firms in Luxembourg from 2001 until 2021



Source: STATEC

To conduct the analysis, we first identify a baseline model, which we subsequently expand. The explanatory variables consist of macro variables and sector-specific variables based on the relevant literature. In the baseline model, the year-on-year (yoy) real GDP growth rate and the interest rate on NFC loans are the main macro variables that we consider. For the interest rate, we rely on a floating rate with an initial rate fixation up to one year[122]. We apply a weighted average of loans up to one million Euro and over one million Euro, respectively[123]. Using other NFC loan interest rates leads to very similar results. We take the GDP series from STATEC and the interest rate data from the BCL database.

At the sectoral level, we control for the total number of firms, the yoy growth rate of the gross value added and the ratio between the compensation of employees and the gross value added. While the first two variables are straightforward to interpret, the latter need further explanation. Compensation of employees can, to a large extent, be interpreted as fixed costs in a short-term perspective. Ideally, we would like to have these fixed costs as a share of total costs. However, as total costs are not available, we consider these fixed costs in relation to the gross value added. This variable not only allows us to identify the role of fixed costs, it also helps to estimate the effects of the government support measures, such as short-time work programs, during the Covid-crisis. The data for all three sectoral variables are taken from STATEC.

For the baseline model, we include nine sectors[124]. The number of firms is the limiting factor, so that the model covers the period from 2005 to 2021. Moreover, the number of firms is only available until 2019. For 2020 and 2021, we assume that the total number of firms per sector has not changed in comparison to 2019. This is a relatively mild assumption as the number of firms does not change significantly year on year. Indeed, the autocorrelation of the number of insolvencies per sector is 0.96.

In the non-baseline models, we analyze the effects of additional macro and sectoral variables. These macro variables include government surplus relative to GDP, yoy inflation[125], the NFC credit-to-GDP gap and two shadow short rates for the Euro area. The government surplus over GDP and the HICP inflation are directly taken from STATEC and the BCL, respectively. The BCL's narrow measure of the credit-to-GDP gap also used. The shadow short rate[126] is intended to capture the impact of the cost of financing. We focus on the shadow rates used by Wu and Xia (2017; 2019) and Krippner (2012), respectively. For additional sectoral variables, we use production growth, employment growth, and the share of micro and small firms, the share of large firms and the yoy growth rate of the consumption of fixed capital.

Finally, in terms of robustness checks, we consider balance sheet information obtained from the Bank for the Accounts of Companies Harmonized (BACH) dataset provided by the Banque de France. The BACH data contains firm information at the sector level and spans the period from 2011 to 2020 for Luxembourg. The Altman (1968) Z-score captures the most important balance sheet information that would help to forecast insolvencies. The relevant variables are working capital over total assets, retained earnings over total assets, earnings before interest and taxes (EBIT) over total assets, equity over total liabilities and sales over total assets. However, rather than applying the pre-specified weights, we use the first principal component of these five variables as an alternative weighting for the Z-score.

122 The corresponding data is taken from the BCL Website and can be accessed via https://www.bcl.lu/en/statistics/series_statistiques_luxembourg/03_Capital_markets/index.html

123 Specifically, we weight by the total number of loans.

124 The nine sectors are: Accommodation and food services, construction, information and communication, real estate activities, wholesale, administrative and support services, industry, professional scientific and technical activities, and transportation and storage.

125 Inflation levels are based on the Harmonised Index of Consumer Prices.

126 According to Krippner (2012), the shadow rate is defined as a metric for the stance of monetary policy in a zero lower bond environment.

Our approach has several advantages over the pre-specified Z-score weights. Most importantly, our weights are entirely data driven.[127] Moreover, the pre-specified weights by Altman (1968) are based on the US over the period from 1946 to 1965. In contrast, we analyze Luxembourg sectoral data over the period 2011 to 2020.

The loadings for the principal components are displayed in Table (1). Similar to Altman's (1968) Z-score that only has positive coefficients, the first principal component loads all five variables with a positive coefficient. Consequently, it can be interpreted as a variable that measures the overall health of a given sector in a given period.

Table 1:

Principal Component Weights for the Z-score calculation

VARIABLE	COMP1	COMP2	COMP3	COMP4	COMP5
EBIT/Tot. Assets	0.6727	-0.0224	0.0558	-0.1786	-0.7156
Equity/Tot. Liabilities	0.4379	-0.3403	-0.2	0.7793	0.2123
Working Capital/Tot. Assets	0.0083	0.6773	0.5682	0.4596	-0.0838
Sales/Tot. Assets	0.1367	-0.5185	0.7889	-0.1684	0.2483
Retained Earnings/Tot. Assets	0.5805	0.3951	-0.1077	-0.348	0.6117

Source: Authors' own calculations based on the BACH dataset.

4. METHODOLOGY

We first forecast the number of insolvent firms. In the analysis, we rely on two distinct models. This allows us to evaluate the robustness of our results. In its simplest form, we forecast the number of insolvencies $Insolv_{i,t}$ at time *t* and for sector *i* with sector-specific and macroeconomic variables $\boldsymbol{X}_{i,t-1}^{sector}$ and $\boldsymbol{X}_{t-1}^{macro}$, respectively, see Equation (1). We use the first lag of all variables. In the baseline model, growth in gross value added and the compensation of employees in relation to gross value added are the sector-specific variables and GDP growth and the interest rate on NFC loans are the macroeconomic variables, while the lag of the dependent variable and the lag of the number of firms are the remaining exogenous variables. Finally, the error term is given by $\varepsilon_{i,t}$.

$$Insolv_{i,t} = c + \beta_1 X_{i,t-1}^{sector} + \beta_2 X_{t-1}^{macro} + \beta_3 Insolv_{i,t-1} + \beta_4 No.Firms_{i,t-1} + \varepsilon_{i,t} \quad (1)$$

The second model is given by Equation (2). It uses the relative number of insolvent firms as the dependent variable. Thus, the number of firms in a sector is excluded from the list of exogenous variables. To obtain a forecast in terms of absolute insolvencies $\frac{\widehat{Insolv_{i,t}}}{No.Firms_{i,t}}$ is multiplied by the corresponding number of firms.

$$\frac{Insolv_{i,t}}{No.Firms_{i,t}} = c + \beta_1 X_{i,t-1}^{sector} + \beta_2 X_{i,t-1}^{macro} + \beta_3 \frac{Insolv_{i,t-1}}{No.Firms_{i,t-1}} + \varepsilon_{i,t} \quad (2)$$

127 In order to calculate the five financial ratios, we use data taken from the BACH dataset and the ratios provided within. For example, the first ratio, namely EBIT/Total assets is calculated by using ratio 35 defined as the ratio between EBIT, net turnover combined with total assets. Equity/total liabilities is determined by taking the inverse of ratio 12, which is liabilities to equity ratios. Working capital/total assets is also calculated using ratio 54, defined as operating working capital and net turnover, combined with total assets. Sales/total assets is proxied by ratio 41, defined as asset turnover ratio. Retained earnings/total assets is determined by using ratio 34, defined as the ratio between net operating profit and net turnover, combined with total assets. We then use the first principal component of these five ratios as a measure of the firm solvency captured by the Z-score. However, the Z-score with the original weights proposed by Altman (1968) leads to similar results.

To estimate models (1) and (2), we face two main issues. First, our time dimension (T) is greater than the cross-sectional dimension (N). Therefore, we cannot apply the widely used Arellano-Bond/Blundell-Bover (GMM) estimators. Second, we use the Pesaran test for cross-sectional dependence, finding that the residuals are correlated across segments of the corporate sector using the fixed effects models. To address these issues, we apply the feasible generalized least squares (GLS) approach to estimating our model following Greene (2018), Maddala and Lahiri (2006), Davidson and McKinnon (1993). This method is appropriate for panel-data linear models, in which there is the presence of AR(1) autocorrelation.

5. RESULTS

As outlined above, we base our findings on the two previous regressions. The estimates using equation 2 are shown in Table (2) while the estimates for equation 1 are shown in Table (3). Both models lead to similar results. Table (2) displays the results for all model specifications based on the share of insolvent firms as the endogenous variable and Table (3) presents the findings of the different specifications using the total number of firm insolvencies as the dependent variable.

In total, 26 different models are estimated, with different specifications for the explanatory variables as shown in the columns of Tables (2) and (3). The baseline regressions are given by column 1 in Table (2) and column 14 in Table (3), respectively. As expected, the lag of the dependent variable positively affects its current value; its coefficient is significant at one percent across all columns in both tables. The two sectoral variables, namely growth in gross value added and the ratio of compensation of employees to gross value added have the expected signs and are found to be statistically significant predictors of corporate insolvencies at the ten percent level in most specifications. While growth in gross value added is significant in 15 out of 22 cases, the ratio of compensation of employees in relation to gross value added is significant in 17 out of 26 specifications.

The macro variables also have the expected signs. GDP growth has a negative and significant impact at the one percent level, the positive coefficient of the interest rate is statistically significant at the ten percent level in 12 out of 20 specifications. Only specifications (11), (19), (20) and (24) display a negative coefficient for the interest rate, so that a positive coefficient can be found in 16 out of 20 specifications, meaning that higher funding costs make it more difficult for stressed firms to "survive".

Overall, the results of the baseline models also hold when other variables are added, see specifications (2) to (13) and (15) to (26) in Tables (2) and (3), respectively. In addition, the total number of firms is highly significant across most models that predict the number of insolvencies. The significance of the macroeconomic and sectoral variables is in line with the literature on NFC insolvencies.

Replacing the growth rate of gross value added with production growth as another variable that captures economic activity in a sector still leads to significant negative coefficients, see columns (2) and (15), respectively. Employment growth shows positive not significant coefficients in columns (3) and (16). This might be attributed to the labor stickiness (Granger 1989). Including shadow rates rather than the interest rate for NFC loans does not lead to significant parameters. However, in specification (5), the shadow rate is statistically significant at the five percent level.

In order to account for the types of firms, namely micro, small and large; specifications (6), (7), (19) and (20) of Tables (2) and (3), respectively, adjust the findings for the share of micro and small, and large firms across sectors. The coefficients associated with these variables enter insignificantly in all of the specifications.

The NFC credit-to-GDP gap and government surplus in relation to GDP have a positive, but non-statistically significant coefficient as shown for specifications (8), (12), (13), (21), (25) and (26), respectively. Nevertheless, the signs of the coefficients match expectations. An increase in credit as well as stronger government support through public spending makes insolvencies less likely. The effect of inflation is unclear from a theoretical point of view. While higher inflation levels increase the cost of input factors, it also reduces the accumulated real debt of firms. Furthermore, inflation and economic activity are positively correlated. Empirically, we observe that the latter of the two effects dominates, see columns (9) and (22). Finally, we find that the Z-score is statistically significant, in specification (11).

Table 2:

Regression coefficient estimates using Share of Insolvencies as the Dependent Variable

	1	2	3	4	5	6	7	8	9	10	11	12	13
Sector-Specific Variables													
Share of insolvent firms (lag)	0.8174*** (0.0000)	0.8046*** (0.0000)	0.8268*** (0.0000)	0.8185*** (0.0000)	0.8134*** (0.0000)	0.7452*** (0.0000)	0.7618*** (0.0000)	0.8158*** (0.0000)	0.8129*** (0.0000)	0.7906*** (0.0000)	0.8056*** (0.0000)	0.8240*** (0.0000)	0.8250*** (0.0000)
Gross value added growth (lag)	-0.0001*** (0.0062)			-0.0001*** (0.0064)	-0.0001*** (0.0091)	-0.0001*** (0.0002)	-0.0001*** (0.0000)	-0.0001*** (0.0072)	-0.0001*** (0.0052)	-0.0001** (0.0119)	-0.0001*** (0.0000)	-0.0001*** (0.0073)	-0.0001*** (0.0054)
Comp. of empl. to value added (lag)	0.0000*** (0.0014)	0.0001*** (0.0003)	0.0000*** (0.0014)	0.0000*** (0.0019)	0.0000*** (0.0011)	0.0001*** (0.0001)	0.0001*** (0.0004)	0.0000*** (0.0016)	0.0000*** (0.0013)	0.0001*** (0.0002)	0.0001*** (0.0000)	0.0000*** (0.0026)	0.0000*** (0.0031)
Production growth (lag)		-0.0001*** (0.0000)											
Employment growth (lag)			0 (0.7610)										
Share micro & small firms (lag)						0,0002 (0.1328)							
Share large firms (lag)							-0,0193 (0.6173)						
Consumption of fixed capital gr. (lag)										-0.0001*** (0.0000)			
Z-score principal component (lag)											-0.0007*** (0.0000)		
Macroeconomic Variables													
GDP growth (lag)	-0.0005*** (0.0002)	-0.0006*** (0.0000)	-0.0008*** (0.0000)	-0.0004*** (0.0025)	-0.0004*** (0.0006)	-0.0005*** (0.0012)	-0.0004*** (0.0025)	-0.0005*** (0.0007)	-0.0005*** (0.0006)	-0.0005*** (0.0000)	-0.0018*** (0.0000)	-0.0005*** (0.0003)	-0.0005*** (0.0014)
Interest Rate (lag)	0.0006** (0.0195)	0.0006*** (0.0055)	0.0006*** (0.0084)			0.0010*** (0.0057)	0.0012*** (0.0008)	0,0005 (0.1323)	0,0006 (0.1028)	0.0006*** (0.0096)	-0.0009*** (0.0000)	0.0005* (0.0508)	
Shadow Rate WU Xia (lag)				0,0001 (0.2499)									0 (0,729)
Shadow Rate Wu Krippner (lag)					0.0002** (0.0229)								
NFC Credit-to-GDP gap (lag)								0 (0.8589)					
Inflation (lag)									0,0001 (0.8254)				
Government surplus to GDP (lag)												0,0001 (0.8263)	0,0001 (0.6413)
Constant	0.0020*** (0.0071)	0.0025*** (0.0005)	0.0021** (0.0115)	0.0032*** (0.0000)	0.0035*** (0.0000)	-0,0142 (0.1826)	0.0019* (0.0992)	0.0021** (0.0166)	0.0020** (0.0147)	0.0028*** (0.0002)	0.0078*** (0.0000)	0.0020** (0.0100)	0.0030*** (0.0000)

*Note: The dependent variable is the share of insolvencies in terms of number of firms at the sectoral level. The explanatory variables include the first lag of the share of insolvencies, gross value added, production and employment growth, ratio of employees' compensation to value added, consumption of fixed capital growth, the Z-score, share of micro and small and large firms all at the sectoral level. At the macroeconomic level, the first lag of GDP growth, interest rate, shadow rate, credit to GDP gap and government surplus to GDP are used. ***, **, * indicate statistical significance at the 1, 5, and 10% levels, respectively. Standard errors are displayed in parentheses.*

Table.3:

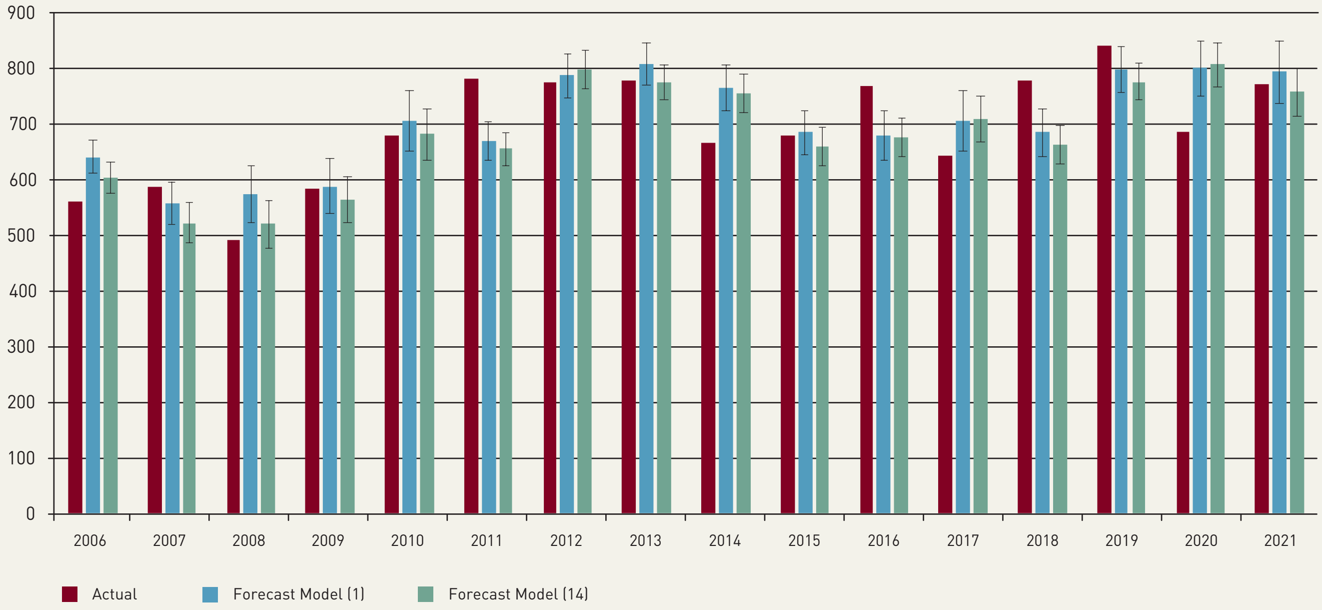
Regression coefficient estimates using No. of Insolvencies as the Dependent Variable

	14	15	16	17	18	19	20	21	22	23	24	25	26
Sector-Specific Variables													
No. of Insolvencies (lag)	0.9098*** (0.0000)	0.8920*** (0.0000)	0.9169*** (0.0000)	0.9152*** (0.0000)	0.9128*** (0.0000)	0.9258*** (0.0000)	0.9221*** (0.0000)	0.9097*** (0.0000)	0.9095*** (0.0000)	0.8996*** (0.0000)	0.9189*** (0.0000)	0.9105*** (0.0000)	0.9158*** (0.0000)
No. of firms (lag)	0.0015*** (0.0071)	0.0021*** (0.0003)	0.0013** (0.0217)	0.0014** (0.0188)	0.0015** (0.0155)	0,0011 (0.1046)	0,0011 (0.1399)	0.0016*** (0.0091)	0.0015*** (0.0071)	0.0017*** (0.0011)	0.0017*** (0.0077)	0.0015*** (0.0008)	0.0014** (0.0201)
Gross value added growth (lag)	-0,0227 (0.7740)			-0.1387* (0.0840)	-0,1313 (0.1058)	-0.1702** (0.0345)	-0.1656** (0.0462)	-0,0057 (0.9436)	-0,0186 (0.8146)	0,0335 (0.6516)	-0,0077 (0.9231)	-0,0174 (0.8265)	-0.1348* (0.0965)
Comp. of empl. to value added (lag)	0,0309 (0.1534)	0,0329 (0.1049)	0,0308 (0.1546)	0.0448** (0.0451)	0.0450** (0.0488)	0.0568* (0.0792)	0.0588* (0.0781)	0,0333 (0.1280)	0,0311 (0.1525)	0,0303 (0.1606)	-0,0003 (0.9910)	0,0306 (0.1558)	0.0449** (0.0447)
Production growth (lag)		-0.2036*** (0.0001)											
Employment growth (lag)			0,078 (0.6688)										
Share micro & small firms (lag)						0,2659 (0.2212)							
Share large firms (lag)							-798.679 (0.2983)						
Consumption of fixed capital gr. (lag)										-0.2874*** (0.0001)			
Z-score principal component (lag)											-0,4447 (0.3562)		
Macroeconomic Variables													
GDP growth (lag)	-1.8308*** (0.0000)	-1.6907*** (0.0000)	-1.9443*** (0.0000)	-1.5830*** (0.0000)	-1.6547*** (0.0000)	-2.7000*** (0.0000)	-2.6819*** (0.0000)	-1.7867*** (0.0000)	-1.7943*** (0.0000)	-1.8962*** (0.0000)	-3.8072*** (0.0000)	-1.9635*** (0.0000)	-1.6458*** -0,0001
Interest Rate (lag)	0.9847* (0.0999)	1.1974** (0.0232)	1.0293* (0.0818)			-14.512 (0.2796)	-12.885 (0.3346)	0,7183 (0.3821)	0,4124 (0.6256)	0.9114* (0.0735)	-15.932 (0.2177)	0,9423 (0.1187)	
Shadow Rate WU Xia (lag)				0,2443 (0.3954)									0,0189 (0.9445)
Shadow Rate Wu Krippner (lag)					0,4081 (0.1283)								
NFC Credit-to-GDP gap (lag)								0,0752 (0.6606)					
Inflation (lag)									0,7438 (0.3468)				
Government surplus to GDP (lag)												0,4447 (0.3562)	0,237 (0.7653)
Constant	22.838 (0.1994)	20.565 (0.1713)	23.378 (0.2031)	4.3963*** (0.0075)	4.7825*** (0.0051)	-174.404 (0.3853)	8.3470** (0.0385)	26.046 (0.2054)	20.892 (0.2483)	3.9206** (0.0128)	11.1574*** (0.0002)	21.535 (0.2218)	4.2004** (0.0178)

*Note: The dependent variable is the number of insolvencies at the sectoral level. The explanatory variables include the first lag of the share of insolvencies, gross value added, production and employment growth, ratio of employees' compensation to value added, consumption of fixed capital growth, the Z-score, share of micro and small and large firms all at the sectoral level. At the macroeconomic level, the first lag of GDP growth, interest rate, shadow rate, credit to GDP gap and government surplus to GDP are used. ***, **, * Indicate statistical significance at the 1, 5, and 10% levels, respectively. Standard errors are displayed in parentheses.*

Figure (2) shows the absolute number of forecasted insolvencies according to the baseline model and compares the out-of-sample forecast insolvencies with actual observed insolvencies. The model is unable to accurately forecast the number of insolvencies during the pandemic. In fact, 2020 marks the year with the highest overestimation of the predicted values from the actual levels. This is not surprising since the forecasts are based on pre-covid data. The fact that we forecast a high number of insolvencies in 2020 could signal that the government support measures play an important role and lead to less insolvent firms.

Figure 2
Predicted Insolvencies over time



Source: The actual data is taken from STATEC, the forecasts are authors' own calculations. Note: Error bars indicate two standard errors around the mean.

Figure (3) evaluates the cross-sectional dimension as it compares the forecasts of Model (1) and (14) with the actual results by looking at the average across the 2006 to 2020 sample. We observe that our forecasts match the actual number of insolvencies across sectors fairly well. For all three cases, the majority of NFC insolvencies occurs in the wholesale sector. Based on the actual data and Model specification (14), 31% of all insolvencies occur in this sector. This is not surprising as this is the largest sector in terms of the number of firms. The construction, and the accommodation and food sectors have the second and third highest share of insolvencies with 17% and 15%, respectively, as shown in Figure 3.

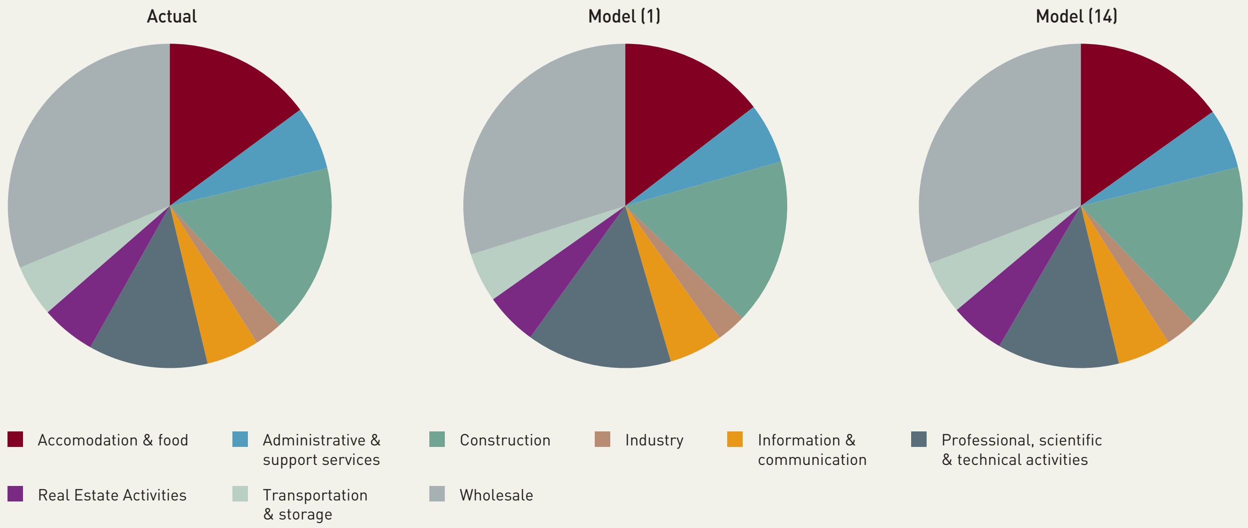
Similarly, Figure (4) shows the likelihood for a firm to become insolvent across the different sectors. The difference between Figure (4) and Figure (3) is that we now take the size of the sector into account. Again, we observe that both models forecast the share of insolvent firms quite accurately. Overall, accommodation and food services activities, followed by transportation and storage are the sectors with the highest likelihood for firms to become insolvent. These sectors are followed by construction and wholesale activities. However, firms in the real estate, as well as professional, scientific and communication sectors have the highest likelihood to remain viable.

To further assess the accuracy of our forecasting models, we evaluate them using moving window out of sample forecasts that we compare with a random walk (RW). For the moving window, we choose 2013 as the starting year for the forecast. We start by relying on the 2005 to 2012 period for forecasting insolvencies in 2013. We then add a period to forecast the dependent variable in the next year.

The benchmark that we compare our results to is a random walk. Specifically, for Model specifications (1) to (13), we assume that the share of insolvent firms has not changed in comparison to the previous

Figure 3

Year-on-Year Forecasts of Insolvencies across Sectors, Average over the period from 2006 to 2021



Source: The actual data is taken from STATEC, the forecasts are authors' own calculations.

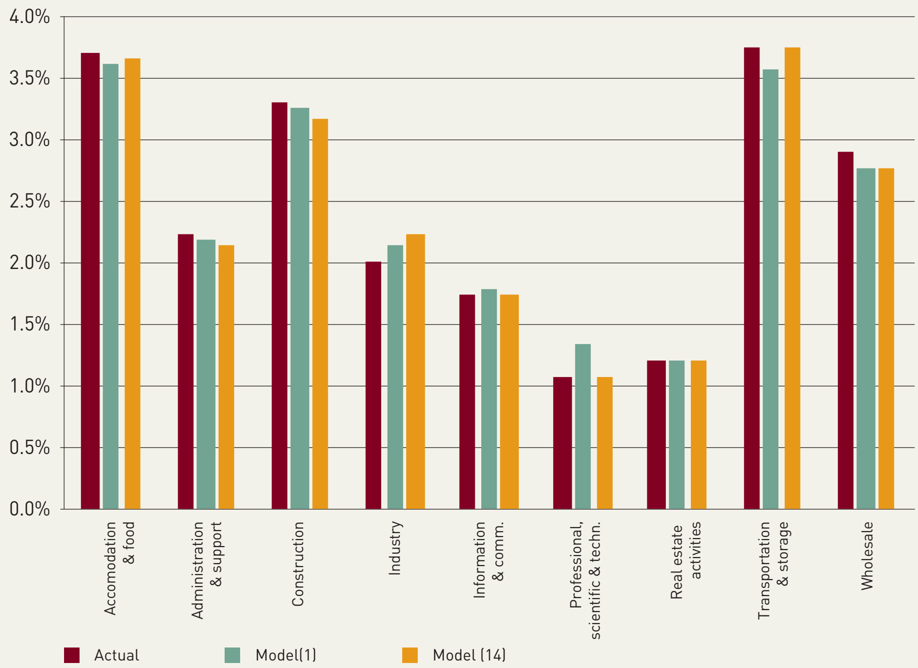
period[128]. For specifications (14) to (26), we assume that the number of insolvent firms has not changed in comparison to the previous year. We then assess our results with the root mean squared forecast error (RMSFE). We find that all models result in lower RMSFE in comparison to the random walk. According to the *t*-tests that evaluate whether the squared forecast error differs between the model and the random walk, this finding is statistically significant at the 5 percent level in 22 out of 24 models.

6. THE COVID CRISIS

During the pandemic, the relationship between economic fundamentals and NFC insolvencies may have been affected by three separate factors. First, the pandemic-related lockdown measures likely led to a decrease in sales.

Figure 4

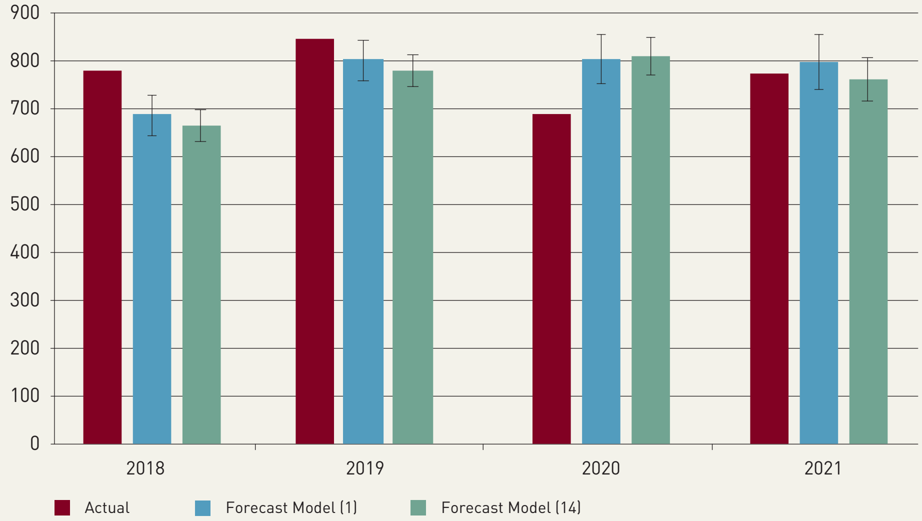
Forecasted Share of Insolvent Firms across Sectors, Average over the period from 2006 to 2021



Source: The data is taken from STATEC, the forecasts are authors' own calculations

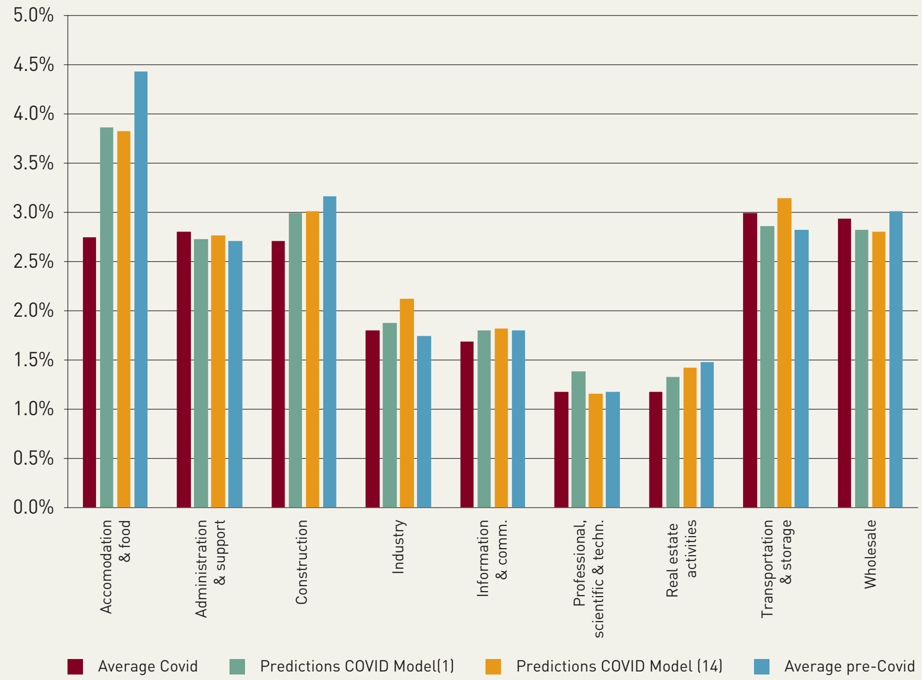
128 Other forms of random walks such as RWs with drift do not result in significantly lower RMSFE.

Figure 5
Actual and Predicted Insolvencies in the lead up to and during the COVID-Crisis



Source: The actual data is taken from STATEC, the forecasts are authors' own calculations. Note: Error bars indicate the area within two standard errors around the mean

Figure 6
Share of Insolvent Firms across Sectors during the pandemic



Source: The actual data is taken from STATEC, the forecasts are authors' own calculations. The pre-COVID period covers the years (2018 and 2019), while 2020 and 2021 are the Covid periods.

Second, the level of economic uncertainty increased significantly during the crisis[129], which could result in households experiencing less consumption choices and/or accumulating precautionary savings. Third, support schemes such as short-time work, moratoria or state-guaranteed loans were implemented. At the euro area level, the ECB launched its Pandemic Asset Purchase Programme. While the COVID-related shock may have led to an increase in the total number of insolvent firms, the exceptional support measures helped to lower insolvencies in the short to medium-term. Therefore, we analyze the impact of all these factors on the solvency of NFCs.

Figure (5) shows the evolution of insolvencies in the two years prior to the pandemic (2018, 2019) as well as the two years during the pandemic (2020, 2021). It compares these insolvencies with the forecasts from model specifications (1) and (14). Interestingly, the number of insolvent NFCs declined in 2020 by 18% relative to 2019. Although it increased by 13% in 2021 year-on-year, with the number of insolvencies remaining below pre-crisis levels.

While model specifications (1) and (14) underestimate the number of corporate insolvencies in 2018 and 2019, they overestimate the number of insolvencies during the first year of the pandemic. The relative difference between forecasted and observed data is particularly pronounced in 2020 reaching 17% for specification (1) and 18% for specification (14). The fact that the total number of insolvencies during the

129 For instance, the VSTOXX increased from 17.15 in end-January 2020 to 84.80 on 18 March 2020.

crisis is low in comparison to pre-crisis levels and model forecasts suggest that the pandemic-related policy support measures were effective in reducing the number of NFC insolvencies.

Figure (6) compares insolvencies during the pre-COVID periods 2018 and 2019 with the COVID periods 2020 and 2021, and the corresponding predictions from model specifications (1) and (14). However, in this case the focus is on the cross-sectional dimension. As shown in Figure (6), the actual number of insolvencies are relatively low across all sectors during the pandemic, namely 2020 and 2021. Using forecasts from specifications (1) and (14) during the pre-COVID periods (2018 and 2019), it is found that the accommodation and food sector has the most pronounced decline in insolvencies compared to the COVID periods (2020 and 2021). This is not surprising since this sector was one of the most affected by the lockdown measures and uncertainty. We therefore conclude that the public policy support measures were well targeted.

7. RISKS OF NON-PERFORMING LOANS FOR BANKS

In this section, we investigate the relationship between corporate insolvencies and banks' non-performing loans (NPLs). Specifically, we link forecasted insolvencies based on sectoral and macroeconomic variables obtained from model specifications (1) and (14) to sectoral non-performing loans at the bank level. This allows us to identify how banks may be exposed to NFC insolvencies due to their lending to those sectors that exhibit a higher number of insolvencies.

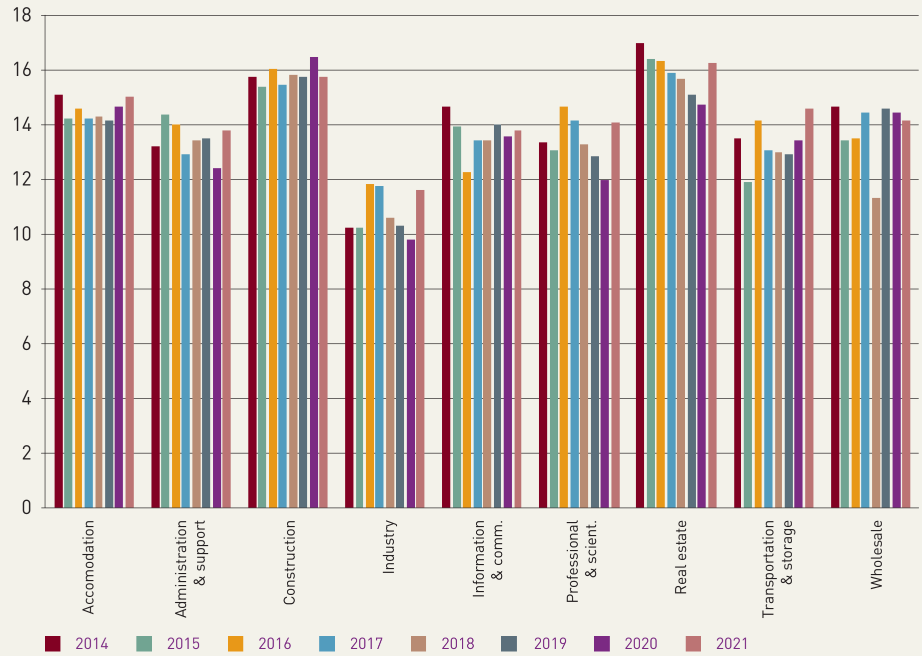
We estimate the following linear model, where *j*, *i*, and *t*, respectively refer to bank, economic sector and period.

$$\log (NPLs)_{j,i,t} = \mathrm{C} + \beta\, \widehat{Insolvencies}_{i,t} + \gamma_{j,t} + \varepsilon_t \qquad (3)$$

NPLs is the logarithm of the amounts of non-performing loans in sector *i* of bank *j* in period *t*. $\widehat{Insolvencies}_{i,t}$ is the forecasted sectoral NFC insolvencies in sector *i* during period *t*. $\gamma_{j,t}$, are bank-period fixed effects. The data used in this section cover the period 2014-2021. In Figure (7), the real estate and construction and accommodation sectors show higher levels of NPLs in logarithm during the period 2014-2021.

Table (4) presents the results of the regression using bank and year fixed effects. As shown in Columns (1) and (2), the coefficient associated with forecasted insolvencies from the two baseline models enters positively and significantly at the one percent level. This suggests that insolvencies increase the number of banks' non-performing

Figure 7
Number of NPLS in logarithm across sectors and over time



Source: Authors' own calculation based on BCL data loans. Based on the coefficients in Column (1), an increase of one unit of insolvency in a sector is associated, on average, with a 0.84 percent increase per number of firms in that sector for a given bank.

Table 4:

The dependent variable is the logarithm of the amounts of non-performing loans

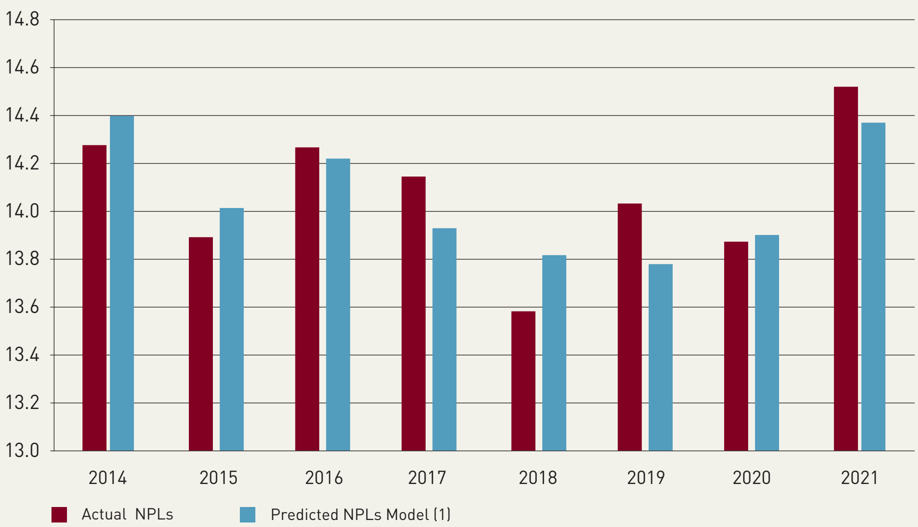
	(1)	(2)
Predicted insolvencies	0.0084*** (0.006) [0.0026]	0.0089*** (0.003) [0.0025]
Constant	13.693*** 0 [0.681]	13.653*** 0 [0.666]
Bank-fixed effects	Yes	Yes
Year Fixed effects	Yes	Yes
F-stat (p-value)	11.54*** (0.000)	13.653*** (0.000)

Source: Authors' own calculation based on BCL and STATEC data. Column (1) is based on predicted insolvencies obtained from the baseline model of equation (1) of Table (2), whereas Column (2) uses predicted insolvencies from the baseline model of equation (14) of Table (3). P-values and robust standard errors are in parentheses and brackets, respectively.

Accordingly, these two specifications can be used to estimate sectoral NPLs. As in Section 5, we use the year 2017 as the starting period for our forecasts. To assess the forecasting quality of the model, we then compare the root mean squared forecast error (RMSFE) with the random walk model RMSFE of the same years. Overall, one can see that NFC insolvencies are relatively good predictors of banks' non-performing loans in Luxembourg compared to a random walk model. Moreover, Figure (8) displays the actual annual amounts of NPLs versus those obtained using Column (1) of Table (4).

Figure 8

Predicted amounts of NPLs in logarithm based on Column (1) and Actual NPLs



Source: Authors' own calculation based on BCL and STATEC data.

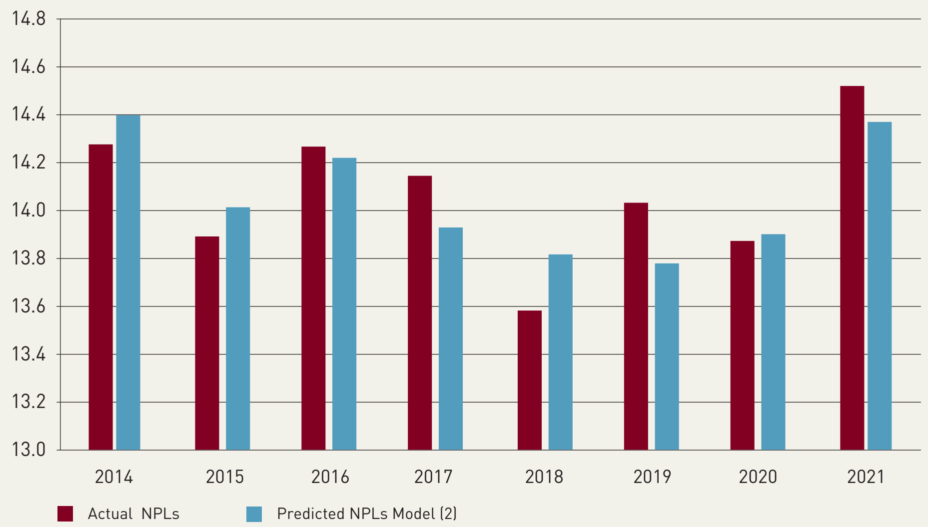
Similarly, Column (2) of Table (4) is also used to obtain predicted amounts of NPLs, which are then compared to actual amounts of NPLs as displayed in Figure (9). Finally, at the sectoral level, the forecasted NPLs obtained from the model are close to the observed data.

8. CONCLUSION

The recent and ongoing COVID-19 pandemic has generated a focus on NFCs and their role for the real economy, particularly due to the exceptional nature of the shock that affected both the supply and demand sides of the economy and the impact of the pandemic-related containment measures on the corporate sector. Moreover, significant uncertainty over developments in the NFC sector remains as the recovery still faces additional challenges including potentially higher interest rates as well as possible economic turmoil resulting from the high level of geopolitical risks.

Figure 9

Predicted amounts of NPLs in logarithm based on Column (2) and Actual NPLs in logarithm



Source: Authors' own calculation based on BCL and STATEC data

In this study, we assessed the effects of the pandemic and the related support measures on NFC insolvencies in Luxembourg and provided three contributions. First, we attempted to provide a better understanding of the main drivers of NFC bankruptcies in Luxembourg, and to forecast the number of insolvencies based on these drivers. Second, we investigated the role of the extraordinary pandemic-related support policies in mitigating corporate insolvencies in the Luxembourg NFC sector during the COVID-19 related crisis. Third, this study assesses the impact of NFC insolvencies on banks' non-performing loan levels.

The results suggest that growth in sectoral value added, employees' compensation in relation to value added, GDP growth and the Z-score are strong drivers of NFC insolvencies in Luxembourg. However, inflation, firm size and the credit gap are not found to be significant determinants of NFC insolvencies in Luxembourg. Additionally, our econometric models, based on these variables, are able to provide reasonable out-of-sample forecasts of the number of insolvencies when compared to actual observed data.

With respect to the COVID-19 related crisis, we compared the forecasts from our models with actual data, building on pre-Covid data and including the period following the initial Covid-related shock (during 2020-2021). The results suggest that the number of insolvencies during the COVID-19 pandemic is below the forecasted amount, possibly confirming the mitigating role of the Covid-related public support measures for NFCs in Luxembourg. In relation to the impact of NFC insolvencies on the banking sector, the model results suggest that an increase of one unit of insolvency in a sector is associated with a 0.84% increase in the amount banks' NPLs per number of firms in that sector.

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2. CONDITIONAL RISK MEASURES FOR ASSESSING POTENTIAL VULNERABILITY IN INVESTMENT FUNDS

Xisong Jin and John Theal[130]

ABSTRACT

We propose a diverse set of forward-looking conditional systemic risk measures (CoSR) for assessing potential vulnerabilities in the Luxembourg investment fund (IF) sector. These measures are applicable to various categories of investment funds, conditional on severe market declines, and based on a dynamic multivariate copula approach in order to calibrate shocks. We show that the measures are able to capture the non-linear time-varying dependence structure in the extreme tails of the distributions of IF returns and flows, facilitating the identification of potential spillover effects across fund categories and jurisdictions. We apply these measures to both the flows and net asset values of seven categories of investment funds in Luxembourg during the period covering 2003-2020 and find, first, that most CoSR measures under market stress in the euro area were similar to those under market stress in the United States. However, the impacts from the Chinese markets were found to be much more muted, and emerging markets could provide the benefits of diversification to Luxembourg investment funds even under significant market volatility. Second, most of the conditional systemic risk measures deteriorated around the beginning of 2020, but improved following the euro area's prompt and decisive pandemic-related policy support measures. Third, the key macroeconomic determinants of the CoSR measures include the short-term interest rate, the interest rate spread, liquidity risk and consumer confidence in the euro area.

1. INTRODUCTION

Since the Global Financial Crisis (GFC), the total assets under management (AuM) of investment funds have grown significantly. According to the European Central Bank (ECB), the total assets managed by non-money market funds in the euro area (EA) amounted to over €13 trillion in the fourth quarter of 2020.[131] When money market funds are included, the total AuM amounts to over €15 trillion, representing more than 100% of euro area GDP. In Luxembourg, as the largest investment fund centre in Europe and the second largest in the world after the US, the total net asset value (NAV) of Luxembourg-domiciled investment funds[132] has tripled since 2009, reaching over €4.9 trillion in the fourth quarter of 2020. The increase in the total NAV of investment funds can be partly attributed to valuation effects in combination with (on average) positive net inflows of investors. The low interest rate environment, banks' deleveraging and increased banking sector regulation following the GFC may also have contributed to the expansion of the non-bank financial sector globally.

The increased size of the investment fund sector has also led to increased potential for vulnerabilities, such as asset price corrections, abrupt changes in investor risk aversion and possible flight to quality behavior. These vulnerabilities may have been exacerbated with the onset of the COVID-19 pandemic in early 2020 as well as increased risk-taking related to the prolonged low interest rate environment and the high level of macro-financial uncertainty resulting from increased inflation pressures and recent geopolitical turmoil. Investors' search for yield behavior may also have amplified vulnerabilities.

130 Financial Stability and Macroprudential Surveillance Department, Banque centrale du Luxembourg.
131 The ECB publishes Euro area investment fund statistics quarterly at https://www.ecb.europa.eu/press/pr/stats/if/html/ecb.ofi2020q4~1e5f8b2d4a.en.html
132 Including Bond Funds, Equity Funds, Mixed Funds, Money Market Funds, Hedge Funds, Real Estate Funds and Other Funds.

According to ESMA (2019), the average portfolio quality of EU investors has significantly deteriorated over the past decade. Liquidity risk has also increased under more volatile market conditions. In the event of a sudden reassessment of risk premiums, faster than expected monetary policy normalization, global growth shocks, or geopolitical turmoil, investors may have an incentive to withdraw their assets from funds, in some cases leading to increased redemption pressures. Recent episodes of turmoil such as the market fluctuations observed during the onset of the COVID-19 pandemic illustrate the heightened risk environment in the financial markets. An increase in investor redemptions could increase the risk of fire sales and/or liquidity spirals resulting in potentially significant asset price revaluations across the financial system. The impact could be felt in the funding markets as well as through balance sheet and collateral channels (Adrian et al. 2016, Banegas et al. 2016, Falato et al. 2018 and Fricke and Fricke 2017).

As the GFC and the recent impact of the COVID-19 pandemic has shown, market liquidity can be procyclical and it can decrease quickly even in the most liquid segments of the market (Morris and Shin 2004 and 2017, Brunnermeier and Pedersen 2009 and an ECB Speech in November 2020). Thus, it is important to develop tools and measures to assess systemic risks in the investment fund sector, particularly due to the persistent uncertainties stemming from geopolitical factors, the coronavirus pandemic, vulnerabilities in emerging markets and heightened periods of financial market volatility driven by uncertainty.

There is a large body of literature dedicated to assessing vulnerabilities in investment funds, with various methods including the micro/macro approach, bottom-up/top-down approach, historical/scenario analysis, reduced form/structural models, first-round effects/second-round effects, system-wide/sector level, network approach/statistical methods, etc. Stress testing involves the use of an adverse scenario to assess stress in the financial system. The shocks corresponding to the adverse scenario require calibration, for which there are several approaches. The European Central Bank (ECB Technical note 2019) outlined the Financial Shock Simulator (FSS) to calibrate financial shocks for adverse scenarios as part of its stress testing framework. The FSS is used regularly by the ECB for internal and external policy analysis, including the impact assessment analysis in the Financial Stability Review. The FSS is based on a multivariate copula approach which calibrates the shocks and builds on the concepts of conditional expected returns and conditional expected shortfall. However, the non-parametric FSS requires large amounts of historical data, and the parametric FSS is based on the underlying assumption of a Gaussian distribution which implies that this approach may not fully capture tail risks.

The European Securities and Markets Authority (ESMA Economic Report 2019) has developed a framework to be used for stress simulations for the investment fund sector. The ESMA stress simulation (STRESI) framework is a simulation-based approach that combines both micro and macroprudential perspectives. This historical approach is based on the value-at-risk and expected shortfall of an empirical distribution of the variable of interest and copulas are used to calibrate the dependence between fund types. In contrast, the scenario approach takes into account the second-round effects of the price and liquidity impacts.

Greenwood, Landier and Thesmar (2015) develop a model in which fire sales propagate shocks across bank balance sheets. They describe the evolution of bank balance sheets following shocks to the value of banks' assets. For example, a bank that experiences a negative shock is likely to sell assets in order to maintain its target leverage. However, if potential buyers are limited, then asset sales depress prices and impact other banks with common exposures. Fricke and Fricke (Deutsche Bundesbank Working Paper 2017) extend the Greenwood, Landier and Thesmar (2015) fire sale model, by incorporating the flow-performance relationship as an additional funding shock. The Bank of England has developed its own system-wide stress simulation. Baranova et al. (2017) incorporate several important features of the financial system including banks and non-banks and describe how their actions may propagate and amplify stress. Farmer et al. (2020) propose a structural framework for the development of system-wide financial stress tests with multiple interacting contagion and amplification channels as well as heterogeneous financial institutions.

The Central Bank of Ireland has developed a macroprudential stress testing framework for investment funds. Shaw and Dunne (2017) employ marginal expected shortfall metrics to capture investment fund exposures to industry-wide tail events by using a novel database of investment funds reporting in Ireland. Fiedor and Katsoulis (2019) developed a framework to enable the Central Bank of Ireland to assess financial stability developments within the investment fund sector in a targeted and timely manner. Recently, Sydow et al. (ECB Working Paper 2021) presented a model of contagion propagation using a very large and granular data set for the euro area. Within a one period model, they show how the combined endogenous reaction of banks and investment funds to an exogenous shock can amplify or dampen losses in the financial system compared to results from single-sector stress testing models.

To assess the systemic risk of the investment fund sector in Luxembourg, in this study we propose a forward-looking set of systemic risk measures based on the concept of expected shortfall and probability of distress. Following the ECB's FSS, the proposed risk measures are based on a historical approach in both bottom-up and structural form. The framework uses a dynamic multivariate copula calibrate the shocks to the investment fund sector by focusing on the concepts of conditional expected returns and forward-looking conditional systemic risk (CoSR) measures. We apply this method not only to each category of investment fund in Luxembourg, but also to the aggregate investment fund sector that consists of seven categories of funds. These conditional systemic risk (CoSR) measures are able to capture the non-linear time-varying dependence structure in the extreme tails of the investment fund return and flow distributions and can identify spillover or cascade effects across securities and jurisdictions. In order to fully assess the forward-looking measures of systemic risk for Luxembourg investment funds through time, the stress analysis is applied to both the flows and NAVs of investment funds.

The main contributions of this study are as follows. First, to the best of the authors' knowledge, this study extends a set of known systemic risk measures that are usually used in the banking stability literature, i.e., the Banking Stability Index presented by Segoviano and Goodhart (2006 and 2009), the Probability of Cascade Effects proposed by Lehar (2005) and the Concentration Risk measure as in Christoffersen et al. (2012) and Jin (2018), into a new set of reduced-form measures of system risk applied to the Luxembourg investment fund sector. Similar to CoVaR in the work of Adrian and Brunnermeier (2016), our CoSR measures capture the cross-sectional dimension of systemic risk in the Luxembourg investment fund sector conditional on different market states. Second, the proposed CoSR measures are further examined in terms of components, i.e., inflow shortage effects and outflow effects in flows, as well as flow effects and market valuation effects in NAVs. Third, this paper estimates the systemic risk measures under market stress for the main systemically important countries in terms of both flows and NAVs of investment funds. In particular, it examines and compares these measures across developed markets (DMs) and emerging markets (EMs) and for the euro area, the United States and China. Finally, this paper explores the linkages between a set of macro-financial variables and the CoSR measures. By identifying the main variables associated with vulnerabilities in investment funds, the proposed approach helps to identify the economic and financial variables that may be of interest to macroprudential authorities for monitoring the risks related to investment funds in Luxembourg.

Several important facts are documented in this study for the period spanning 2003-2020. First, the proposed CoSR measures provide insights into recent developments in Luxembourg's investment fund sector. Our results suggest that the CoSR measures under market stress in the euro area were similar to those under market stress in the US and were able to accurately identify stress events, particularly common stress episodes, in the US and the EA. For comparison, the investment fund sector CoSR measures under market stress in China did not show such a high level of stress during the GFC crisis, the European multi-year debt crisis or the more recent COVID-19 pandemic. The CoSR measures for the Luxembourg investment fund sector under market stress in the EA have shown signs of deterioration since the beginning of 2020 but improved quickly following the euro area's supportive policy responses, in particular, the asset purchase programme (APP) and the new pandemic emergency purchase programme (PEPP).

Second, across the seven categories of investment funds in Luxembourg, the CoSR measures for Real Estate Funds under market stress in the US were higher than those under market stress in the EA. The outflow effects dominated in the Equity Funds, Bond Funds and Mixed Funds segments. Market valuation effects dominated in Equity Funds, Hedge Funds and Other Funds, whereas flow effects played an important role in Bond Funds, Real Estate Funds and Money Market Funds. We explain these outflow and market valuation effects in the methodology section. Furthermore, Money Market Funds served as an important source of flight-to-quality for investors during periods of market stress in both the EA and the US. In contrast, the impacts on the CoSR measures for Luxembourg investment funds from market stress in China were marginal except in the Real Estate Funds and Money Market Funds segments, where these events were mainly driven by inflow shortages and flow effects.

Third, EMs could still provide diversification benefits, in the sense of Christofferson (2012) for investment funds in Luxembourg, even under significant market stress. Specifically, the benefits are partly due to diversification of large market downturns and differences in asset classes across emerging and advanced economies. Our results also suggest that the stress in Real Estate Funds, Hedge Funds and Other Funds peaked prior to the GFC crisis, and that a significant stress episode may limit the ability of Money Market Funds to meet high levels of redemptions. We also find that Real Estate Funds, Other Funds and Money Market Funds were not affected by the COVID-19 pandemic as much as the other types of funds under stress in both DMs and EMs. However, the slow improvement in the conditional systemic risk measures towards the end of 2020 may suggest that market participants were becoming increasingly concerned about the high level of uncertainty resulting from the COVID-19 pandemic shocks on the global economy.

Finally, predictive regressions show that the CoSR measures for investment funds in Luxembourg were largely driven by short-term interest rates, interest rate spreads, liquidity risk and consumer confidence in the EA. We interpret these findings with some caution, however, as the results might be dominated by the significant episodes of stress related to the GFC of 2007-2009, the European sovereign debt crisis and the recent COVID-19 pandemic when the market was subject to frequent episodes of stress and high levels of fund flows, reflecting the significant level of uncertainty in the investment fund sector.

The remainder of the paper is organized as follows. Section 2 describes the various CoSR measures used in this study as well as the econometric approach used to assess stress in the Luxembourg investment fund sector. Section 3 explores the CoSR measures for investment funds in Luxembourg and Section 4 identifies the macroeconomic determinants of these CoSR measures for investment funds using a set of predictive linear regressions. Finally, Section 5 concludes and discusses some potential macro-prudential policy considerations.

2. METHODOLOGY

The change in net asset value (NAV) of an investment fund can be decomposed into two components: the change related to flows (i.e., flow effects or transaction effects) and the change in market valuations (valuation effects). Accordingly, the returns of the fund NAV consist of both the flow returns and the market valuation returns, derived by dividing their first difference by the NAV value of the fund in the previous month as follows:

$$R_{j,t}^{NAV} = R_{j,t}^{Flow} + R_{j,t}^{VAL}, \tag{1}$$

where $R_{j,t}^{NAV} = \frac{NAV_{j,t}-NAV_{j,t-1}}{NAV_{j,t-1}}$, $R_{j,t}^{Flow} = flow_{j,t}^{In} - flow_{j,t}^{Out}$ and $flow_{j,t} = \frac{FLOW_{j,t}}{TNA_{j,t-1}}$. $NAV_{j,t}$ is the *NAV* of fund *j* at the end of the month *t*, and $FLOW_{j,t}$ (in uppercase) is the value in euros of fund *j*'s flow (either in or out). Fund *j*'s monthly market valuation return, $R_{j,t}^{VAL}$, can be implied from the equation. We use "flow" (in lower case) for the flow ratio as defined above.

In this study, the conditional systemic risk measure of an investment fund is assessed in components. The flow risk $R_{j,t}^{Flow}$ consists of an inflow component (inflow effects), $flow_{j,t}^{In}$, and an outflow component (outflow effects), $flow_{j,t}^{Out}$, while the overall risk of $R_{j,t}^{NAV}$ can be decomposed into a flow component (flow effects), $R_{j,t}^{Flow}$, and a valuation component (valuation effects), $R_{j,t}^{VAL}$.

2.1 MEASURING SYSTEMIC RISK

To assess the systemic risk of investment funds, several CoSR measures are adopted for the events between *t* and *t+1*. The long-run CoSR measures can be expressed in a similar way for the cumulative returns between *t* and *t+T*.

2.1.1 Conditional expected shortfall (CoES)

The $\Delta CoES_{q,t+1}^{IF|market}$ is defined as in Adrian and Brunnermeier (2016) as the difference between the expected shortfall (ES) of an investment fund conditional on the market being in a tail event and the ES of the investment fund conditional on the market being in a normal state:

$$\Delta CoES_{q,t+1}^{IF|market} = CoES_{q,t+1}^{IF|R_{t+1}^{market} \leq VaR_{q,t+1}^{market}} - CoES_{q,t+1}^{IF|R_{t+1}^{market} \in VaR_{q_{norm},t+1}^{market}}, \tag{2}$$

and in euro terms:

$$\Delta^{€} CoES_{q,t+1}^{IF|market} = Size_{Euro,t}^{IF} \cdot \Delta CoES_{q,t+1}^{IF|market}, \tag{3}$$

where R_{t+1}^{IF} and R_{t+1}^{market} are returns of the investment fund and market index, respectively, between *t* and *t+1*, and $CoES_{q,t+1}^{IF|market} = -E_t\left(R_{t+1}^{IF} \middle| R_{t+1}^{IF} \leq CoVaR_{q,t+1}^{IF|market}\right)$. The negative sign is added because ES is usually defined as a positive number. $Size_{Euro,t}^{IF}$ is the NAV of the investment fund (in euros) at time t, and $CoVaR_{q,t+1}^{IF|market}$ is the value-at-risk (VaR) of the fund's return, R_{t+1}^{IF}, at confidence level *q*, conditional on market events at time *t+1*. The market events in the tail are defined as the set of R_{t+1}^{market} events falling below the $VaR_{q,t+1}^{market}$ level and the market events in the normal state are defined as the set of R_{t+1}^{market} events falling within q_{norm} – *quantiles* of its distribution. In this study, we fix the quantiles $q = 0.05$ and $q_{norm} = [0.15\ 0.85]$ for all CoSR measures.

For an investment fund sector consisting of *N* categories of investment funds, the aggregate risk measure is the weighted average of $\Delta CoES$ or the sum of $\Delta^{€}CoES$ across all categories of investment funds:

$$\Delta CoES_{q,t+1}^{IF\ sys|market} = \sum_{j}^{N} \frac{Size_{Euro,t}^{IF^j}}{TotalSize_{Euro,t}^{IF\ sys}} \Delta CoES_{q,t+1}^{IF^j|market}, \tag{4}$$

$$\Delta^{€}CoES_{q,t+1}^{IF\ sys|market} = \sum_{j}^{N} \Delta^{€}CoES_{q,t+1}^{IF^j|market}, \tag{5}$$

where $\boldsymbol{TotalSize_{Euro,t}^{IF\ sys}}$ is the total NAV of the categories of investment funds at time *t*.

2.1.2 Conditional concentration risk (CoCR)

Diversification is one way of reducing risk for investors. Different categories of investment funds give investors access to various asset classes and investment strategies whose performance may vary according to market and economic conditions. However, despite the different fund categories, there may still be an overlap of securities across funds, and price movements across different securities can also be correlated. For example, Christoffersen et al. (2014) empirically find that asset correlations have increased significantly for both DMs and EMs. The relatively similar investment strategies across funds could push cross-asset correlations higher, making funds increasingly exposed to market-wide risk and raising financial stability concerns (ECB Financial Stability Review, 2016).

In addition, the cross correlation of securities across funds is also an important channel for financial contagion with the potential to trigger asset fire sales and severe losses (e.g., Falato et al., 2018). A fire sale requires that several fund managers, each experiencing redemption pressure, contemporaneously sell common securities. Fire sales can be especially costly when there is significant overlap with the securities held by other funds experiencing outflows, as these fire sale transactions occur far from the fundamental value of the assets.

Recently, Falato et al. (2018) explore fire-sale spillovers by assessing network linkages across financial institutions using micro data for open-end fixed-income mutual funds. Fricke and Fricke (2017) extend the Greenwood, Landier and Thesmar (2015) fire sale model by incorporating a flow-performance relationship as an additional funding shock. However, both studies require data on fund holdings at the security-level, which are not available at the central bank. Since investor sentiment is most likely one of the key drivers of market anomalies like contagion (Barberis et al. 1998), we focus on investors' behavior (i.e., investment fund flows) based on the concentration risk of fund net flows among investors.

To assess the tail risk for both asset allocation and redemption pressure of investment funds, a concentration risk measure (CoCR), conditional on market events, is constructed using a value-weighted portfolio of investment funds in Luxembourg. Derived from the diversification benefits as in Christoffersen et al. (2012) and Jin (2018), the CoCR is defined as one minus the diversification benefit measure, conditional on market events:

$$CoCR_{q,t+1}^{IF\ sys|market} = 1 - \frac{\overline{CoES}_{q,t+1}^{IF\ sys|market} - CoES_{q,t+1}^{IF\ portfolio|market}}{\overline{CoES}_{q,t+1}^{IF\ sys|market} - \underline{CoES}_{q,t+1}^{IF\ portfolio|market}}, \tag{6}$$

where $CoES_{q,t+1}^{IF\,portfolio|market}$ denotes the expected shortfall with a probability threshold q of the value weighted portfolio of the investment funds, conditional on market events at *t+1*, $\overline{CoES}_{q,t+1}^{IF\,sys|market}$ denotes the weighted average of the $CoES_{q,t+1}^{IF^j|market}$ across all categories of investment funds, which is an upper bound of the portfolio CoES:

$$\overline{CoES}_{q,t+1}^{IF\,sys|market} = \sum_j^N \frac{Size_{t,Euro}^{IF^j}}{TotalSize_{t,Euro}^{IF\,sys}} CoES_{q,t+1}^{IF^j|market} \,, \qquad (7)$$

and $\underline{CoES}_{q,t+1}^{IF\,\mathrm{portfolio}|market}$ is the portfolio *CoVaR*, which is a lower bound of the portfolio *CoES*. The $CoCR_{q,t+1}^{IF\,sys|market}$ measure takes values in the interval *[0 1]*, and is increasing in the level of conditional concentration risk. Expected shortfall is additive in the conditional mean, which cancels in the numerator and denominator. By construction, CoCR does not depend on the level of conditional expected returns, and it takes into account the concentration risk arising from all higher-order moments of the distribution and not just the variance.

In this work, we do not consider ΔCoCR (i.e., the difference of CoCR) conditional on the market being in a tail event and a normal state. As CoCR is defined on the interval [0 1] via rescaling the distance between ES and VaR of a fund's portfolio by its bound range, it is difficult to interpret ΔCoCR consistently. For example, in a financial crisis period, the ΔCoCR of net flows could be very low because the CoCR conditional on the market being in a normal state during an actual crisis period is high. Nevertheless, *CoCR* measures the concentration risk of investment funds' net assets or the herding behavior and the potential fire sale pressure of funds' net flows under market stress, which could exert significant price pressure on securities far from their fundamental values.

2.1.3 Conditional stability index (CoSI)

As suggested by the banking stability index in Segoviano and Goodhart (2006 and 2009), the conditional stability index (CoSI) addresses the case in which investment funds become distressed following a common shock. Therefore, conditional on market events, the CoSI measures the expected number of fund categories that will become distressed, conditional on any one category of investment fund having become distressed. When *CoSI = 1*, the linkages across fund categories are at their minimum, conditional on market events.

Without loss of generality, the conditional stability index can be written as a system composed of three categories of investment funds *i*, *j*, and *k* as:

$$CoSI_{q,t+1}^{IF\,sys|market} = \frac{P\left(R_{t+1}^{IF^i} \le VaR_{q,t+1}^{IF^i} \middle| C(R_{t+1}^{market})\right) + P\left(R_{t+1}^{IF^i} \le VaR_{q,t+1}^{IF^j} \middle| C(R_{t+1}^{market})\right) + P\left(R_{t+1}^{IF^i} \le VaR_{q,t+1}^{IF^k} \middle| C(R_{t+1}^{market})\right)}{1 - P\left(R_{t+1}^{IF^i} \ge VaR_{q,t+1}^{IF^i} \cap R_{t+1}^{IF^j} \ge VaR_{q,t+1}^{IF^j} \cap R_{t+1}^{IF^k} \ge VaR_{q,t+1}^{IF^k} \middle| C(R_{t+1}^{market})\right)}, \qquad (8)$$

where $C(R_{t+1}^{market})$ denotes the market events, and the distress thresholds are defined in terms of the unconditional $VaR_{q,t+1}$. Alternatively, this measure could also be interpreted as a measure of contagion conditional on market events.

Similarly, $\Delta CoSI_{q,t+1}^{IF\,sys|market}$ denotes the difference between the CoSI of an investment fund system, conditional on the market being in a tail event, and the CoSI of the investment fund system, conditional on the market being in a normal state, as:

$$\Delta CoSI_{q,t+1}^{IF\,sys|market} = CoSI_{q,t+1}^{IF|R_{t+1}^{market} \leq VaR_{q}^{market}} - CoSI_{q,t+1}^{IF|R_{t+1}^{market} \in VaR_{q_{norm},t+1}^{market}}. \tag{9}$$

$\Delta CoSI$ measures the difference in the expected number of fund categories that would become distressed under two different market states. When CoSI is positive, then it is more likely that an increased amount of investment funds become distressed compared to normal market conditions.

2.1.4 Conditional probability of cascade effects (CoPCE)

Based on another common systemic risk indicator in Lehar (2005) that measures spillover effects in the banking system, the conditional probability of cascade effects (CoPCE) measures the probability that at least a certain amount of investment fund categories become distressed under a certain market condition. Thus, the CoPCE measure assesses the likelihood that a common shock is propagated through the investment fund sector.

Assuming a financial system consisting of three fund categories for illustrative purposes (i.e., *i*, *j*, and *k*), and under a given market condition, the likelihood of at least one fund category becoming distressed is calculated as follows:

$$\begin{aligned} CoPCE_{q,t+1}^{IF\,sys|market} = {} & P\left(R_{t+1}^{IF^i} \leq VaR_{q,t+1}^{IF^i} \left| C(R_{t+1}^{market})\right.\right) + P\left(R_{t+1}^{IF^j} \leq VaR_{q,t+1}^{IF^j} \left| C(R_{t+1}^{market})\right.\right) \\ & + P\left(R_{t+1}^{IF^k} \leq VaR_{q,t+1}^{IF^k} \middle| C(R_{t+1}^{market})\right) \\ & - \begin{bmatrix} P\left(R_{t+1}^{IF^i} \leq VaR_{q,t+1}^{IF^i} \cap R_{t+1}^{IF^j} \leq VaR_{q,t+1}^{IF^j} \middle| C(R_{t+1}^{market})\right) \\ +P\left(R_{t+1}^{IF^i} \leq VaR_{q,t+1}^{IF^i} \cap R_{t+1}^{IF^k} \leq VaR_{q,t+1}^{IF^k} \middle| C(R_{t+1}^{market})\right) \\ +P\left(R_{t+1}^{IF^j} \leq VaR_{q,t+1}^{IF^j} \cap R_{t+1}^{IF^k} \leq VaR_{q,t+1}^{IF^k} \middle| C(R_{t+1}^{market})\right) \end{bmatrix} \\ & + P\left(R_{t+1}^{IF^i} \leq VaR_{q,t+1}^{IF^i} \cap R_{t+1}^{IF^j} \leq VaR_{q,t+1}^{IF^j} \cap R_{t+1}^{IF^j} \leq VaR_{q,t+1}^{IF^k} \middle| C(R_{t+1}^{market})\right), \end{aligned} \tag{10}$$

where $C(R_{t+1}^{market})$ denotes the market events, and distress thresholds are defined as the unconditional $VaR_{q,t+1}^{IF^i}$. Thus, CoPCE describes the part of the distribution where distress occurs because at least one investment fund category among *i*, *j* and *k* exceed their respective distress thresholds $VaR_{q,t+1}^{IF^i}$, $VaR_{q,t+1}^{IF^j}$ or $VaR_{q,t+1}^{IF^k}$, conditional on some market events.

Similarly, $\Delta CoPCE_{q,t+1}^{IF\,sys/market}$ denotes the difference between the CoPCE of an investment fund system, conditional on the market being in a tail event, and the CoPCE of the investment fund system, conditional on the market being in a normal state:

$$\Delta CoPCE_{q,t+1}^{IF\,sys|market} = CoPCE_{q,t+1}^{IF|R_{t+1}^{market} \leq VaR_{q}^{market}} - CoPCE_{q,t+1}^{IF|R_{t+1}^{market} \in VaR_{q_{norm},t+1}^{market}}. \tag{11}$$

In our assessment of conditional systemic risk in the Luxembourg investment fund sector in Section 3, we consider cascade scenarios where at least one, two, three and five investment fund categories become distressed under a given market condition for both flows and NAVs of investment funds.[133]

2.2 A DYNAMIC FORECASTING FRAMEWORK

This section reviews the methodological and statistical approaches used to estimate and forecast fund flows, fund market valuation returns and the market index returns. First, the univariate time series prediction approach and the multivariate GARCH model are described. Second, we outline the multivariate GARCH techniques which are extended into the t-copula in order to introduce the dynamic forecasting framework. Finally, the calibration of, and simulation from, the integrated dynamic prediction framework are briefly discussed.

Redemption risk is partly associated with the liquidity risk management practices of asset managers as well as investor risk aversion. Once investors demand redemptions in excess of the level expected by the fund manager, managers will need to sell more of the underlying assets than is strictly necessary in order to meet the redemption requests. During times of reduced liquidity, fund managers may be unable to sell some of their assets, or may need to sell assets at depressed prices. This implies that when investors' outflows lead to costly liquidation by the funds, the costs would be borne largely by the remaining investors, giving rise to the so-called "first-mover advantage". This first-mover advantage can accelerate the speed of outflows.

It is well documented that flows to and from investment funds are strongly related to past performance. Previous research finds a strong relation between flows and past 12-month performance for monthly data (e.g., Ippolito 1992, Chevalier and Ellison 1997 and Sirri and Tufano 1998). We follow a benchmark regression model as in Coval and Stafford (2007).[134] However, to address the non-stationary inflow and outflow data in our sample period, an *ARIMAX (P,Q,K)* model is used to forecast fund flows (both inflows and outflows) based on past returns and lagged flows:

$$\Delta flow_{j,t} = c + \sum_{p=1}^{P} \alpha_{j,p} \Delta flow_{j,t-p} + \sum_{k=1}^{K} \beta_{j,k} R_{j,t-k}^{VAL} + \sum_{q=1}^{Q} \theta_{j,k} \varepsilon_{j,t-q} + \varepsilon_{j,t}, \quad (12)$$

where the residuals, $\varepsilon_{j,t}$, are the unexpected components of the flows.

Using monthly data, we include lagged changes in *flow*, fund market valuation returns and white noise error terms from the previous year in the regression, *ARIMAX (12,12,12)*. For each category of investment fund, we specify $\alpha_{j,P} = \sum_{p=1}^{12} \alpha_{j,p}$, $\beta_{j,P} = \sum_{k=1}^{12} \beta_{j,k}$ and $\theta_{j,q} = \sum_{q=1}^{12} \theta_{j,q}$ as the measures of the overall impacts of lagged changes in flows, returns and residuals respectively. The expected flows are calculated as the fitted values of the *ARIMAX* model.

133 Radev (2012) defines as the probability of at least two entities defaulting jointly as an unconditional systemic fragility measure.
134 Coval and Stafford (2007) forecasts fund flows based on past returns and lagged flows by the pooled regression and Fama-MacBeth (1973) regression procedure.

For simplicity, the market index return, R_t^{market}, is defined as simple return similar to $R_{j,t}^{VAL}$, and the expected $R_{j,t}^{VAL}$ and R_t^{market} are calculated as the fitted values from an *ARMA (P,Q)* model:[135]

$$R_{j,t} = c + \sum_{p=1}^{P} \alpha_{j,p} R_{j,t} + \sum_{q=1}^{Q} \theta_{j,k} \varepsilon_{j,t-q} + \varepsilon_{j,t}, \tag{13}$$

where the ARMA (12, 12) is adopted to match the information field as in the case of flows.

To deal with heteroscedasticity, we apply a multivariate GARCH model to the residual series from $\Delta flow_{j,t}$ and $R_{j,t}$ respectively. Multivariate GARCH models are multivariate extensions of the univariate GARCH model. By taking advantage of cross-sectional information within a portfolio sharing similar characteristics, multivariate GARCH models can be used to deal with noisy or constant volatility, even in the case of small sample sizes.[136]

In this study, we assume a simple multivariate model, the scalar BEKK model of Engle and Kroner (1995), which has been widely used in the literature:

$$\Sigma_t = (1 - \alpha - \beta)\Sigma + \alpha \varepsilon_{t-1} \varepsilon'_{t-1} + \beta \Sigma_{t-1}, \tag{14}$$

where Σ_t denotes the unconditional variance-covariance matrix, and ε_t are the residuals from $\Delta flow_{j,t}$ and $R_{j,t}$. The sample variance-covariance matrix, $\bar{\Sigma} = T^{-1} \sum_{t=1}^{T} [\varepsilon_t \varepsilon'_t]$, is used as an estimate of the unconditional variance-covariance matrix, Σ. The univariate volatility is conditional on the information at time t-1: $\sigma_{j,t}^2 = (1 - \alpha - \beta)\bar{\sigma}_j + \alpha_j \varepsilon_{j,t}^2 + \beta_j \sigma_{j,t-1}^2$, where the innovation process $z_{j,t} = \sigma_{j,t}^{-1} \varepsilon_{j,t}$ is independent and identically distributed $z_{j,t} \sim iid(0,1)$. We assume a different set of parameters for different investment fund categories, for example, corresponding to inflows, outflows, and market valuation returns.[137] To avoid potential high-dimensionality issues, the model is estimated using the composite likelihood method as suggested by Engle, Shephard and Sheppard (2008).

To address the dependence structure of the innovations, as in Engle, Jondeau and Rockinger (2015), we adopt the dynamic conditional t-copula which is able to capture non-linear dependencies across innovation processes very well, and is attractive from both a statistical and computational viewpoint for a large dimensional system.

The joint distribution modeled by the dynamic conditional t-copula is defined as follows[138]:

$$C(\eta_{1,t}, \eta_{2,t}, \dots, \eta_{n,t}; R_t, v_t) = T_{R_t, v_t}\left(t_{v_t}^{-1}(\eta_{1,t}), t_{v_t}^{-1}(\eta_{2,t}), \dots, t_{v_t}^{-1}(\eta_{n,t})\right), \tag{15}$$

135 For sufficient forecasting, some factor models can also be applied, e.g., Engle, Jondeau and Rockinger (2015).

136 The GARCH (1,1) model can be explored on each residual from $\Delta flow_{j,t}$ and $R_{j,t}$ respectively. However, the limited sample size like ours might not be sufficient for the estimation, resulting in too smooth or too noisy dynamics. Meanwhile, a large number of parameters might also deteriorate the out-of-sample forecasting accuracy.

137 Riskmetrics (1996) uses the exponentially weighted moving average model (EWMA) to forecast variances and covariances, the decay factor proposed by Riskmetrics is equal to 0.94 for daily data and 0.97 for monthly data. As the decay factor is not estimated but rather suggested by Riskmetrics, the model is parsimonious even for large portfolios with few data points. Nevertheless, using the same dynamics for every component in the multivariate EWMA model is difficult to justify.

138 See Patton (2012) for the definition of a general conditional copula.

where $\eta_{j,t} = \mathrm{F}_j(z_{j,t})$ for $j = 1,2,\ldots,n$, and $z_{j,t}$ are the standardized residuals from the multivariate *GARCH* model. R_t is the copula correlation matrix, and v_t is the degree of freedom. $t_{v_t}^{-1}(\eta_{j,t})$ denotes the inverse of the cumulative distribution function.

In this study, R_t is assumed to be a dynamic process through time and v_t is assumed to be constant for simplicity. However, for the standard t-copula, the assumption of one global degree of freedom parameter may be over-simplistic and too restrictive for a large portfolio. As in the multivariate GARCH model, different degrees of freedom for different groups (i.e., fund categories) can be assumed. Thus, we use a grouped t-copula in this study.

Let $Z_t \sim N_n(0, R_t)$, where R_t is an arbitrary linear correlation matrix, be independent of U, a random variable uniformly distributed on (0, 1). Furthermore, let G_v denote the distribution function of $\sqrt{v/\mathcal{X}_v^2}$. Partition $\{1,\ldots,n\}$ into m subsets of sizes $s_1,\ldots,s_m$. Let $R_t^k = G_{v_k}^{-1}(U)$ for $k = 1, \ldots, m$. If

$$Y = \left(R_t^1, \ldots, R_t^1 Z_{s_1}, R_t^2 Z_{s_1+1}, \ldots, R_t^2 Z_{s_1+s_2}, \ldots, R_t^m Z_n\right)', \tag{16}$$

then the random vector $(Y_1,\ldots,Y_s)$ has an s_1-dimensional t-distribution with v_1 degrees of freedom and, for $k = 1, \ldots, m-1$, $(Y_{s_1+\cdots+s_{k+1}}, \ldots, Y_{s_1+,\ldots+s_{k+1}})'$, has an s_{k+1}-dimensional t-distribution with v_{k+1} degrees of freedom. The grouped t-copula is described in more detail in Daul et al. (2003).

Engle (2002) proposes a class of Dynamic Conditional Correlation (DCC) models that preserve the ease of estimation of Bollerslev's (1990) constant correlation model, while allowing the correlations to change over time. These kinds of dynamic processes can also be extended into grouped t-copulas. The simplest copula correlation dynamics is the symmetric scalar model where the entire copula correlation matrix is driven by two parameters:

$$Q_t = \left(1 - \alpha^{copula} - \beta^{copula}\right)\bar{Q} + \alpha^{copula}(\tilde{z}_{t-1}\tilde{z}_{t-1}') + \beta^{copula} Q_{t-1}, \tag{17}$$

Where $\alpha^{copula} \geq 0,\ \beta^{copula} \geq 0,\ \alpha^{copula} + \beta^{copula} \leq 1$ and $\tilde{z}_{j,t} = t_{v_t}^{-1}(\eta_{j,t} = \mathrm{F}_j(z_{j,t}))$. $Q_t = |q_{ij,t}|$ is the auxiliary matrix driving the copula correlation dynamics, the nuisance parameters $\bar{Q} = E[\tilde{z}_t \tilde{z}_t']$ with sample analog $\bar{Q} = T^{-1}\sum_{t=1}^{T}[\tilde{z}_t \tilde{z}_t']$, so that R_t is a matrix of copula $q_{ij,t}$ correlations with ones on the diagonal, and $\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}}\sqrt{q_{jj,t}}}$.

Misspecification of the marginal distributions can lead to potentially significant biases in the estimation of dependence. In order to allow for flexible marginal distributions, this study does not specify marginal distributions, but adopts a semi-parametric form for the marginal distributions $\mathrm{F}_j(z_{j,t})$. The marginal densities are estimated using a Gaussian kernel for the central part of the distribution, and a parametric Generalized Pareto distribution (GP) for the two tails. Hence, the asymmetry can be captured directly by estimating the left and right tails separately. This approach is often referred to as the distribution of exceedances or peaks-over-threshold method (see McNeil 1999 and McNeil and Frey 2000 for more details).

2.3 ESTIMATION OF GROUPED T-COPULA AND SIMULATION

For calibration of, and simulation from, the grouped *t*-copula, there is no need for an explicit copula expression. The calibration of this model is identical to that of the *t* distribution except that the maximum likelihood (ML) estimation of the *m* degrees of freedom parameters has to be performed separately on each of the *m* groups. Given that the correlation between the Gaussian copula correlation $\rho_{GR} = Corr(\Phi^{-1}(\mu), \Phi^{-1}(v))$ and a t-copula correlation $\rho_{TR} = Corr(t_v^{-1}(\mu), t_v^{-1}(v))$ is almost equal to one, R_t can be well approximated by the $R_t^{Gaussian}$ from the dynamic Gaussian copula[139]. In this dynamic grouped t-copula application, a two-step algorithm is adopted, which means R_t is first estimated from the dynamic Gaussian copula, and then the v_k degrees of freedom are recovered for each group from the grouped t-copula with R_t^k fixed from the first step.

As in Engle, Shephard and Sheppard (2008), the dynamic Gaussian copula can be estimated by maximizing the m-profile subset composite likelihood (MSCL)[140] using contiguous pairs, which is tractable for large dimensional problems compared to the MCLE that requires the use of all the pairs. The composite log-likelihood is based on summing the log-likelihoods of pairs of underlying data. Each pair yields a valid (but inefficient) likelihood for α^{copula} and β^{copula}, but summing over all pairs produces an estimator which is relatively efficient and unbiased even in large-scale problems. Similarly, the degree of freedom for each group is also estimated by the MCLE using all pairs to avoid potential bias in large-scale problems.

Using conditional dynamic copulas, it is relatively straightforward to construct and simulate from multivariate distributions built on marginal distributions and a dependence structure.[141] The ARIMAX and GARCH-like dynamics of both the variance and copula correlations offers multi-step-ahead predictions of a portfolio of returns simultaneously. We adopt a one-step-ahead simulation method in this study. The CoSR measures can be easily obtained from these simulated returns of all categories of investment funds. The multi-day ahead conditional systemic risk measures can also be obtained by forward simulation over multi-periods.

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

$$C(\eta_{1,t}, \eta_{2,t}, \dots, \eta_{n,t}; R_t^{Gaussian}) = \Phi_{R_t^{Gaussian}}\left(\Phi^{-1}(\eta_{1,t}), \Phi^{-1}(\eta_{2,t}), \dots, \Phi^{-1}(\eta_{n,t})\right),$$

where $\eta_{j,t} = \mathrm{F}_j(z_{j,t})$ for $i = 1,2,\dots,n$, and $z_{j,t} \sim iid(0,1)$ are the innovations from the marginal dynamics introduced in the previous section. $R_t^{Gaussian}$ is the Gaussian copula correlation matrix. The copula correlation dynamics is similarly driven by the two parameters listed above for the t-copula. However, $\tilde{z}_{j,t} = \Phi^{-1}(\eta_{j,t} = \mathrm{F}_j(z_{j,t}))$.

140 A moment-based profile likelihood, or m-profile likelihood for short, in which the nuisance parameters are not maximum quasi-likelihood estimators but attractive moment estimators.

141 See Patton (2011& 2012) for a more detailed description of the simulation and for more discussion of the steps involved in building a copula-based model for the conditional joint distribution.

3. ECONOMIC APPLICATION

In this section, the data sets used for the investment funds are described, and the univariate model is briefly discussed. The proposed conditional dynamic grouped t-copula is applied to fund *flows* (both in and out), fund market valuation returns and market index returns. Finally, several empirical CoSR measures are estimated based on the one-step-ahead simulation, and the different CoSR measures under market stress in the EA, the US and China as well as in DMs and EMs are compared.

3.1 DATA DESCRIPTION

This study uses data from the legal reporting of "financial information" collected by the CSSF (Table 01:1)[142] for Luxembourg undertakings for collective investment (UCIs). The database covers the period from January 2003 to December 2020 and contains monthly data on Luxembourg funds' NAV and flows[143](net, in and out) for seven categories of investment funds, i.e., Equity Funds, Bond Funds, Mixed Funds, Real Estate Funds, Hedge Funds, Other Funds, and Money Market Funds. In order to assess the conditional systemic risk measures for these investment funds, the data set also includes monthly OECD market indices[144] for a number of important countries, selected by their ranking in both GDP and value of counterparts[145] of the investment funds. The considered market indices include the members of Group of Seven (G7) and other countries (i.e., the United States, Japan, Germany, United Kingdom, France, Italy, Canada, Spain and Netherlands), the seven largest emerging market countries (i.e., China, India, Brazil, Russia, Mexico, Indonesia and Turkey) and the EA19 index.

Panel A of Table 1 provides descriptive statistics for monthly flows (both in and out), flow returns and market valuation returns for seven categories of investment funds in Luxembourg, as well as the returns for DM and EM market indices from March 2003 to December 2020. The volatility cost, similar to the inverse of the Sharpe ratio, is defined as the ratio of the standard deviation to the mean of flows or returns. The volatility cost of Money Market Funds was the highest among the seven categories of investment funds, reaching 43.95 and 4.26 in market valuation returns and flow returns, respectively. The average flow returns of the seven categories of investment funds were all positive with the values for Mixed Funds, Bond Funds, Equity Funds and Money Market Funds being 1.1%, 0.9%, 0.7%, and 0.6%, respectively.

142 See Circular IML 97/136 at https://www.cssf.lu/fileadmin/files/Lois_reglements/Circulaires/Hors_blanchiment_terrorisme/iml97_136eng_amended.pdf.

143 In the 01:1 Table, net flows are called "Net units or shares issued" (line 330). It is the difference between inflows ("net proceeds from units or shares issued", line 310) and outflows ("payments made in settlement of redemptions", line 320).

144 Share price indices are calculated from the prices of common shares of companies traded on national or foreign stock exchanges. They are usually determined by the stock exchange, using the closing daily values for the monthly data, and normally expressed as simple arithmetic averages of the daily data.

145 A counterpart is supposed to be a resident of a given country if a certain investment fund has pursued economic activities in that country for at least one year.

Table 1:

Descriptive statistics of Luxembourg investment funds and market indices of other jurisdictions, including DMs, EMs

	PANEL A: SAMPLE MOMENTS								PANEL B: CORRRELATIONS							
	MEAN	STANDARD DEVIATION	VOLATILITY COST	SKEWNESS	EXCESS KURTOSIS	1ST ORDER AUTO-CORREL-ATION	LJUNG-BOX(20) P-VALUE ON FLOWS	LJUNG-BOX(20) P-VALUE ON SQUARED RETURNS	EQUITY FUNDS	BOND FUNDS	MIXED FUNDS	REAL ESTATE FUNDS	HEDGE FUNDS	OTHER FUNDS	MONEY MARKET FUNDS	AVERAGE WITH OTHER IFS
	IF Market Valuation Returns								IF Market Valuation Returns							
Equity Funds	0.007	0.04	5.66	-0.80	2.00	0.11	0.44	0.00	1.00	0.56	0.95	0.10	0.37	0.50	0.01	0.41
Bond Funds	0.002	0.01	6.74	-0.36	9.91	-0.02	0.29	1.00	0.56	1.00	0.68	0.02	0.41	0.18	0.39	0.37
Mixed Funds	0.003	0.02	5.49	-0.97	2.85	0.07	0.42	0.80	0.95	0.68	1.00	0.08	0.36	0.47	0.10	0.44
Real Estate Funds	0.004	0.02	4.30	4.68	33.75	-0.02	0.24	1.00	0.10	0.02	0.08	1.00	0.29	0.14	0.01	0.11
Hedge Funds	0.003	0.03	9.67	-0.39	17.12	-0.39	0.00	0.00	0.37	0.41	0.36	0.29	1.00	0.20	0.23	0.31
Other Funds	0.006	0.03	5.97	0.75	10.96	0.09	0.01	0.01	0.50	0.18	0.47	0.14	0.20	1.00	-0.12	0.23
Money Market Funds	0.000	0.02	43.95	0.43	1.86	-0.05	0.09	0.00	0.01	0.39	0.10	0.01	0.23	-0.12	1.00	0.10
Average	0.004	0.02	11.68	0.48	11.21	-0.03	0.21	0.40	0.50	0.46	0.52	0.24	0.41	0.34	0.23	0.28
	IF In-Flows								IF In-Flows							
Equity Funds	0.050	0.01	0.29	1.08	1.35	0.68	0.00	0.00	1.00	0.53	0.20	0.14	0.58	0.10	0.21	0.29
Bond Funds	0.055	0.01	0.20	0.51	0.21	0.61	0.00	0.00	0.53	1.00	0.28	0.08	0.41	0.20	0.18	0.28
Mixed Funds	0.032	0.01	0.34	0.80	0.60	0.56	0.00	0.00	0.20	0.28	1.00	0.16	0.19	0.18	-0.06	0.16
Real Estate Funds	0.029	0.06	2.20	6.74	56.97	-0.02	0.00	0.00	0.14	0.08	0.16	1.00	0.07	0.01	0.17	0.11
Hedge Funds	0.056	0.03	0.54	3.20	16.04	0.60	0.00	0.00	0.58	0.41	0.19	0.07	1.00	-0.01	0.05	0.22
Other Funds	0.034	0.04	1.11	5.53	48.18	0.28	0.00	1.00	0.10	0.20	0.18	0.01	-0.01	1.00	0.18	0.11
Money Market Funds	0.586	0.27	0.46	2.22	5.88	0.89	0.00	0.00	0.21	0.18	-0.06	0.17	0.05	0.18	1.00	0.12
Average	0.120	0.06	0.74	2.87	18.46	0.51	0.00	0.14	0.39	0.38	0.28	0.23	0.33	0.24	0.25	0.18
	IF Out-Flows								IF Out-Flows							
Equity Funds	0.043	0.01	0.26	1.12	1.54	0.53	0.00	0.00	1.00	0.70	0.33	0.07	0.46	0.42	0.48	0.41
Bond Funds	0.046	0.01	0.27	3.68	24.25	0.36	0.00	0.00	0.70	1.00	0.66	0.07	0.65	0.54	0.52	0.52
Mixed Funds	0.021	0.01	0.28	2.46	13.48	0.46	0.00	0.00	0.33	0.66	1.00	0.01	0.48	0.28	0.33	0.35
Real Estate Funds	0.005	0.02	3.73	8.46	79.01	0.04	0.00	0.00	0.07	0.07	0.01	1.00	0.02	-0.05	0.07	0.03
Hedge Funds	0.037	0.01	0.32	3.78	23.97	0.32	0.00	0.00	0.46	0.65	0.48	0.02	1.00	0.32	0.63	0.43
Other Funds	0.017	0.01	0.80	1.65	3.04	0.52	0.00	0.00	0.42	0.54	0.28	-0.05	0.32	1.00	0.36	0.31
Money Market Funds	0.580	0.26	0.45	2.34	6.68	0.89	0.00	0.00	0.48	0.52	0.33	0.07	0.63	0.36	1.00	0.40
Average	0.107	0.05	0.87	3.35	21.71	0.44	0.00	0.00	0.49	0.59	0.44	0.17	0.51	0.41	0.48	0.35
	IF Flow Returns								IF Flow Returns							
Equity Funds	0.007	0.01	1.53	0.20	1.41	0.62	0.00	0.00	1.00	0.50	0.38	0.02	0.42	0.10	-0.27	0.19
Bond Funds	0.009	0.01	1.27	-1.53	8.78	0.50	0.00	0.40	0.50	1.00	0.41	-0.06	0.39	0.18	-0.22	0.20
Mixed Funds	0.011	0.01	0.97	0.08	2.45	0.52	0.00	0.00	0.38	0.41	1.00	0.10	0.28	0.23	-0.14	0.21
Real Estate Funds	0.024	0.05	2.26	5.74	39.92	-0.01	0.00	0.00	0.02	-0.06	0.10	1.00	0.01	0.01	-0.08	0.00
Hedge Funds	0.018	0.03	1.73	2.52	14.55	0.60	0.00	0.02	0.42	0.39	0.28	0.01	1.00	0.06	-0.09	0.18
Other Funds	0.016	0.03	2.07	5.77	51.50	0.20	0.03	1.00	0.10	0.18	0.23	0.01	0.06	1.00	0.01	0.10
Money Market Funds	0.006	0.03	4.26	1.01	2.01	0.12	0.00	0.01	-0.27	-0.22	-0.14	-0.08	-0.09	0.01	1.00	-0.13
Average	0.013	0.03	2.01	1.97	17.23	0.37	0.00	0.21	0.31	0.32	0.32	0.15	0.30	0.23	0.03	0.11

Sources: CSSF, OECD. Calculation: BCL. Periods: March 2003 - December 2020. Notes: This table reports sample moments and average sample correlations on the monthly investment fund flows and returns. The volatility cost is defined as the ratio of standard deviation to mean of investment fund flows or returns.

Table 1:

Descriptive statistics of Luxembourg investment funds and market indices of other jurisdictions, including DMs, EMs (suite)

									AVERAGE WITHIN MARKET RETURNS	AVERAGE WITH IF IN-FLOWS	AVERAGE WITH IF OUT-FLOWS	AVERAGE WITH IF VALUATION RETURNS
				DM Returns						DM Returns		
Mean	0.005	0.044	11.145	-1.512	6.618	0.202	0.268	0.968	0.832	-0.001	-0.222	0.319
Min	0.002	0.036	6.538	-2.261	2.042	0.127	0.046	0.894	0.588	-0.381	-0.430	-0.251
Q25%	0.003	0.039	6.912	-1.864	4.635	0.175	0.172	0.911	0.771	-0.049	-0.290	0.061
Median	0.005	0.045	9.693	-1.508	6.077	0.201	0.278	0.996	0.855	0.033	-0.237	0.345
Q75%	0.005	0.048	10.669	-1.013	8.225	0.239	0.324	0.999	0.896	0.090	-0.174	0.576
Max	0.007	0.051	22.148	-0.796	12.018	0.250	0.467	1.000	0.986	0.157	0.007	0.719
				EM Returns						EM Returns		
Mean	0.012	0.058	5.321	-0.557	2.922	0.327	0.021	0.154	0.539	0.028	-0.144	0.229
Min	0.006	0.044	3.666	-1.293	0.886	0.237	0.000	0.000	0.254	-0.282	-0.293	-0.277
Q25%	0.011	0.053	4.030	-0.754	1.570	0.271	0.002	0.000	0.333	0.000	-0.205	0.093
Median	0.013	0.062	4.660	-0.644	2.925	0.324	0.012	0.000	0.603	0.062	-0.164	0.272
Q75%	0.014	0.065	4.943	-0.352	3.657	0.390	0.024	0.060	0.651	0.105	-0.065	0.405
Max	0.014	0.066	11.018	0.408	5.871	0.410	0.083	0.998	0.718	0.206	0.066	0.564

Sources: CSSF, OECD. Calculation: BCL. Periods: March 2003 - December 2020. Notes: This table reports sample moments and average sample correlations on the monthly investment fund flows and returns. The volatility cost is defined as the ratio of standard deviation to mean of investment fund flows or returns.

The skewness and excess kurtosis of flow returns were all positive except for Bond Funds, reflecting their heavy-tailed distributions. As previously stated, the investment fund sector in Luxembourg has experienced steady growth over the past decade, particularly for Bond Funds, Equity Funds and Mixed Funds as suggested by their relatively low standard deviations. Average market valuation returns were all positive, while Mixed Funds and Real Estate Funds performed better in terms of their Sharpe ratio than other categories of investment funds. The outflows were, on average, less autocorrelated, and had comparatively higher volatility cost, skewness and excess kurtosis than inflows. This may reflect the fact that investors were more sensitive to negative market information during the GFC of 2007-2009, the European multi-year debt crisis since the end of 2009, the "taper tantrum" in 2013, the Chinese stock market turbulence of 2015–2016, the China-US trade tensions since 2018 and the recent COVID-19 pandemic all contained in our sample period. The Ljung-Box (LB) test on flows and returns, and their squared values, suggest that the null hypothesis of the first 20 monthly autocorrelations being zero was rejected at the 5% significance level for most categories of investment funds.

Panel B of Table 1 shows the unconditional correlations of flows and returns during the same period. In general, the correlations between Equity Funds, Bond Funds, and Hedge Funds were higher for both returns and flows. In addition, the average correlations for outflows were higher than those for inflows, particularly for Money Market Funds. MMFs average correlation with the other six categories of investment funds was 40% for outflows, and 12% for inflows. The exception is Real Estate Funds, where the average correlation with the other six categories of investment funds was 11% for inflows and 3% for outflows. This result can be understood in the context that Real Estate Funds are less liquid than Money Market Funds, particularly during periods of financial turbulence. The low correlations of Other Funds, Money Market Funds, and Real Estate Funds with other categories of investment funds in market valuation returns and flow returns reflects their important role in relation to the benefits of diversification in reducing systemic risk (Christofferson 2012).

As regards the market indices, EMs performed better than DMs in terms of the Sharpe ratio. DMs were, on average, less autocorrelated and had comparatively higher negative skewness, excess kurtosis and cross-correlation than EMs. The market valuation returns of Luxembourg investment funds were more highly correlated with the returns of DMs than with those of EMs. This observation can likely be partly attributed to the high proportion of common asset exposures of Luxembourg investment funds to DMs. The returns of DM and EM indices were overall positively correlated with inflows and negatively correlated with outflows. However, the outflows were more sensitive to the performance of DMs than to those of EMs, while inflows into Luxembourg funds were more sensitive to the performance of EMs than to DMs.

Figure 1 shows the comparison of the cumulative performance of seven categories of investment funds in Luxembourg as well as DM and EM market indices across the same period. The NAV returns are decomposed into flow returns and market valuation returns. The NAV returns were dominated by flow effects for all categories of investment funds. Since 2015, the valuation effects became relatively stable and then more subdued for Bond Funds, Mixed Funds, Hedging Funds and Money Market Funds. In addition, the cumulative performance of funds' NAV was driven mainly by flow effects in Money Market Funds. EMs performed better than DMs as suggested by the interquartile range of their cumulative returns.

3.2 MODEL ESTIMATION

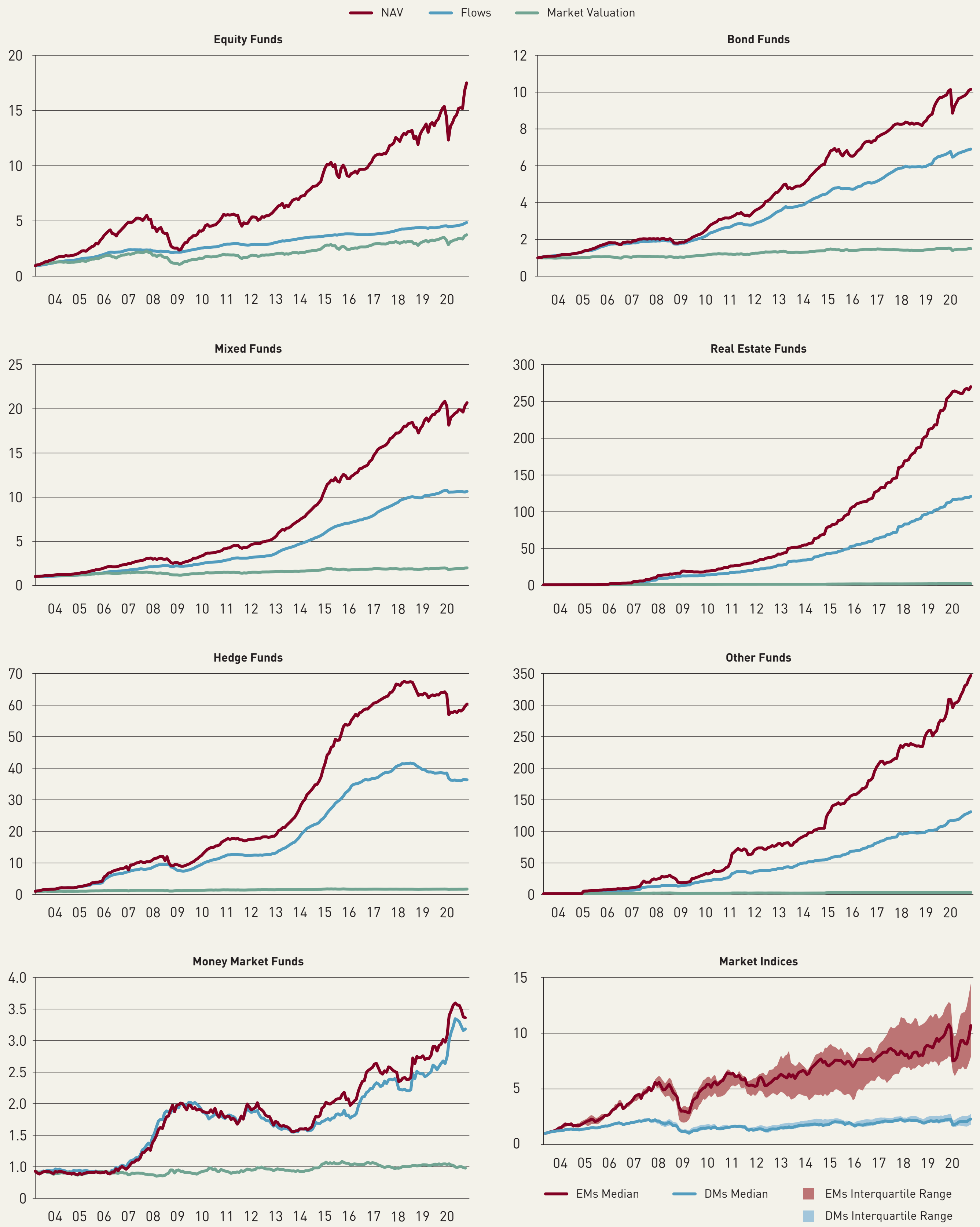
Table 2 reports the regression results of the predictive regression model for the inflows and outflows of seven categories of Luxembourg investment funds over the period spanning March 2003 to December 2020. T-statistics are computed based on the Wald test on the sum of coefficients of 12 lagged regressors. A bold coefficient value indicates significance at the 5% level, and an italic coefficient value denotes significance at the 10% level. Overall, there was a strong negative relationship between flow changes and lagged flow changes and lagged residuals, reflecting the mean-reverting property of flow changes. The changes of flows were also sensitive to lagged market valuation returns. The sum of coefficients of lagged returns, β_P, was negative and significant for Real Estate Funds and positive and significant for Other Funds in the case of outflows. However, the coefficient was significant and negative for Money Market Funds and positive and significant for Mixed Funds in the case of inflows. We adopt ARIMAX (12, 12, 12) models in this paper as previous studies, e.g., Coval and Stafford (2007), find a strong relation between flows and past 12-month performance for monthly data by testing with t statistics for each lagged return.[146]

We also apply an *ARMA(12,12)* model to the market valuation returns of each category of investment fund and to the returns of the DM and EM market indices. In general, we find a strong relation between returns and lagged residuals. The sum of coefficients of lagged returns was positive and significant for Luxembourg Equity Funds, Bond Funds, Mixed Funds and Other Funds, reflecting the aforementioned increase in the size of investment funds in the EA. With regards to the returns of the DM and EM market indices, as shown by the interquartile ranges, the responses of DMs to their lagged residuals and returns were more homogeneous than those of EMs, and the sum of coefficients of the lagged residuals (i.e., lagged returns) was more negatively (positively) significant than those of EMs.

146 In our robust tests which are not shown in this paper, based on the Wald test on the sum of coefficients of 6 lagged repressors in ARIMA(6, 6, 6), the influences from lagged returns were also significant for Hedge Funds in inflows and Equity Funds, Mixed Funds and Other Funds in outflows. The relations between flow changes and lagged returns were even stronger for Bond Funds and Mixed Funds in some sub-periods than those in the whole sample period.

Figure 1

Cumulative returns of Luxembourg investment funds and DMs and EMs market indices



Sources: CSSF, OECD. Calculation: BCL. Periods: March 2003 - December 2020.

Table 2:

Summary of ARIMAX models for Luxembourg investment fund flows and returns

	LAGGED FLOW ESTIMATE	LAGGED FLOW tSTAT	LAGGED FLOW pVALUE	LAGGED RESIDUAL ESTIMATE	LAGGED RESIDUAL tSTAT	LAGGED RESIDUAL pVALUE	LAGGED RETURN ESTIMATE	LAGGED RE-TURN tSTAT	LAGGED RE-TURN pVALUE
IF Market Valuation Return ARMA(12, 12)									
Equity Funds				**-1.22**	**42.06**	**0.00**	**0.64**	**26.88**	**0.00**
Bond Funds				**-0.60**	**24.85**	**0.00**	0.38	2.86	0.09
Mixed Funds				**-1.20**	**185.34**	**0.00**	**0.76**	**36.88**	**0.00**
Real Estate Funds				0.54	0.00	0.97	-0.37	0.10	0.76
Hedge Funds				0.14	0.01	0.91	-0.57	0.17	0.68
Other Funds				**-1.21**	**17.46**	**0.00**	**0.75**	**6.34**	**0.01**
Money Market Funds				**-1.26**	**10.34**	**0.00**	0.32	0.09	0.76
IF In-Flow ARIMAX(12,12,12)									
Equity Funds	**-2.74**	**34.23**	**0.00**	-0.63	2.03	0.15	-0.05	0.26	0.61
Bond Funds	-0.32	1.67	0.20	**-1.07**	**49.44**	**0.00**	-0.05	1.17	0.28
Mixed Funds	**-4.34**	**1 327.63**	**0.00**	0.11	0.03	0.85	**0.27**	**4.83**	**0.03**
Real Estate Funds	**-5.95**	**11 503.41**	**0.00**	**0.94**	**334.59**	**0.00**	0.08	0.01	0.94
Hedge Funds	**-3.22**	**1 429.96**	**0.00**	**-0.73**	**4.55**	**0.03**	-0.16	0.18	0.67
Other Funds	**-4.12**	**14.13**	**0.00**	-0.03	0.00	0.99	-0.06	0.15	0.70
Money Market Funds	**-0.68**	**9.56**	**0.00**	**0.63**	**44.27**	**0.00**	**-1.60**	**4.20**	**0.04**
IF Out-Flow ARIMAX(12,12,12)									
Equity Funds	**-2.66**	**11.11**	**0.00**	-0.54	0.50	0.48	0.11	0.17	0.68
Bond Funds	-3.18	0.07	0.79	-0.46	0.00	0.96	-0.06	0.00	0.99
Mixed Funds	-2.75	0.11	0.74	-1.26	2.02	0.16	0.08	0.11	0.73
Real Estate Funds	**-7.00**	**526.82**	**0.00**	0.35	0.12	0.72	**-0.69**	**4.00**	**0.05**
Hedge Funds	**-2.79**	**43.89**	**0.00**	-0.65	1.73	0.19	-0.05	0.01	0.91
Other Funds	**-4.52**	**5.31**	**0.02**	0.01	0.00	0.99	**0.20**	**7.49**	**0.01**
Money Market Funds	-0.30	0.14	0.70	0.44	0.02	0.89	-4.38	0.08	0.78
DM Return ARMA(12, 12)									
Mean				-0.73	527 497.16	0.08	0.22	9 219.82	0.21
Min				**-1.62**	**0.14**	**0.00**	**-0.75**	**0.00**	**0.00**
Q25%				**-1.40**	**8.20**	**0.00**	**0.01**	**1.69**	**0.00**
Median				**-1.36**	**44.55**	**0.00**	**0.37**	**26.30**	**0.00**
Q75%				**0.63**	**754.37**	**0.00**	0.59	118.52	0.19
Max				1.03	5 271 841.40	0.71	0.81	86 217.63	0.98
EM Return ARMA(12, 12)									
Mean				-0.37	356 204.84	0.07	0.28	23 288.71	0.18
Min				**-1.69**	**0.47**	**0.00**	**-0.38**	**0.09**	**0.00**
Q25%				**-1.62**	**13.33**	**0.00**	**-0.05**	**9.30**	**0.00**
Median				**-1.18**	**73.26**	**0.00**	**0.39**	**35.68**	**0.00**
Q75%				**1.11**	**92.10**	**0.00**	0.70	423.65	0.35
Max				1.38	2 493 150.68	0.49	0.78	16 2218.60	0.77

Sources: CSSF, OECD. Calculation: BCL. Period: March 2003 - December 2020. Notes: This table reports the parameter estimates from ARIMAX models on the monthly investment fund flows and returns. T-stats are computed based on the Wald test on the sum of coefficients of 12 lagged regressors. A bold coefficient value indicates significance at the 5% level, and an italic coefficient value denotes significance at the 10% level.

Table 3 contains the results of the multivariate GARCH estimation on the residuals from the ARIMAX model for inflows, outflows, market valuation returns, DM returns and EM returns respectively. The ARCH parameter was higher for outflows than inflows, reflecting the importance of prior innovations for outflows. The model-implied variance persistence parameters were all above 0.94, except in the case of market valuation returns of Luxembourg investment funds. The Ljung–Box (LB) test on the model residuals shows that the ARIMAX(12,12,12) models were able to capture flow and return predictability as shown in Table 1. The multivariate GARCH(1,1) models were also able to capture the strong persistence in squared flows and returns found in Table 1, except in the case of inflows to Bond Funds.[147] The skewness and kurtosis of the flow residuals were not excessive, with the exception of Hedge Funds and Other Funds, suggestive of the risk characteristics of these fund types and the subsequent need to use semi-parametric forms for the marginal distributions. The ARCH parameters for fund market valuation returns were higher than those of both DMs and EMs, reflecting the diverse asset classes held by Luxembourg investment funds. The lower skewness and higher excess kurtosis of DMs compared to EMs demonstrates the higher fat tail of the standardized residuals associated with DMs during this period.

147 In our robustness tests, which are not shown in this paper, the other lagged parameters for the AR and MA components in the ARMA models of these funds can capture volatility clustering better. However, the derived CoSR measure was almost same as those derived by 12 lags.

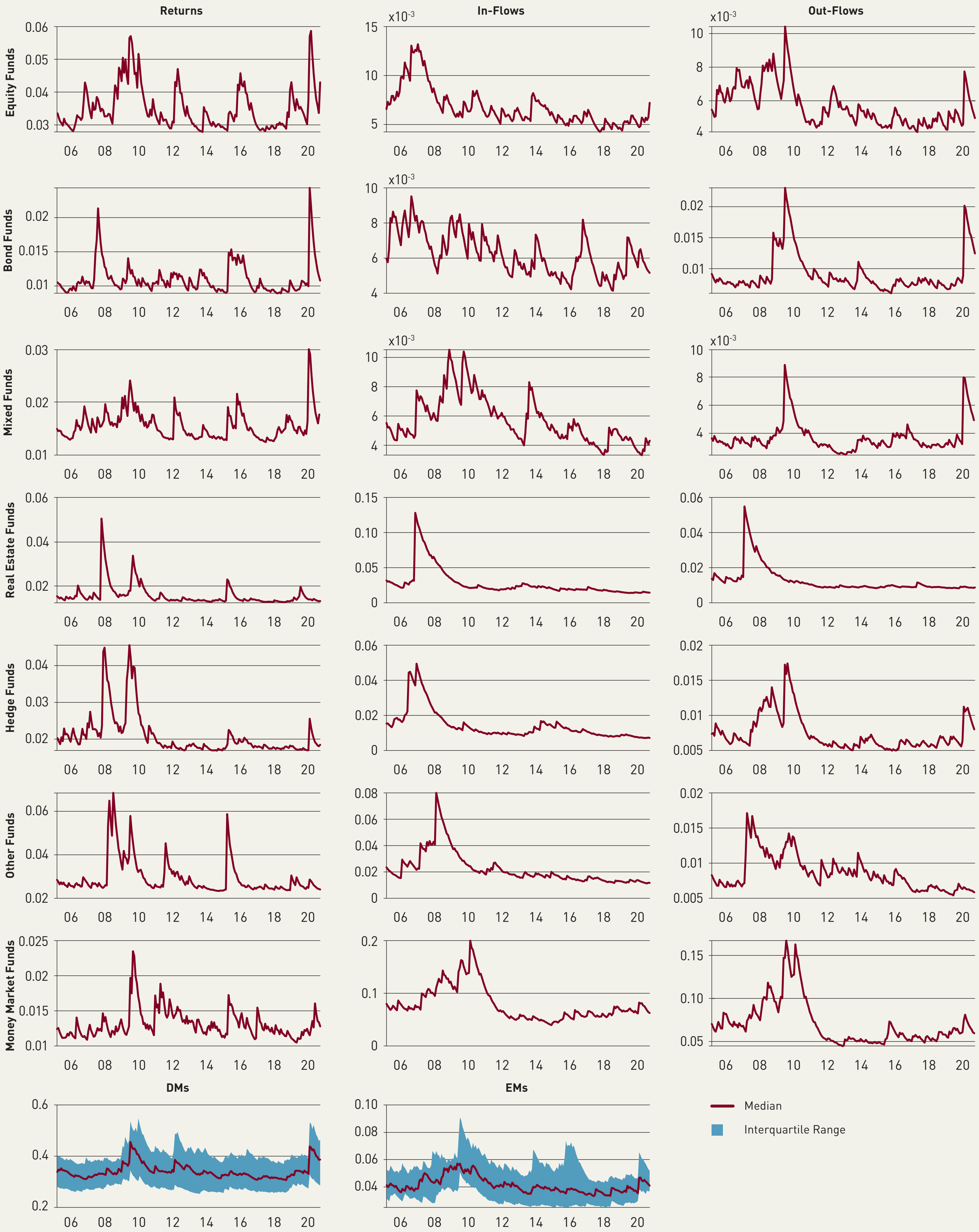
Table 3:

Summary of multivariate GARCH estimation on the residuals from ARIMAX models on Luxemburg investment fund flows and returns

	ARCH	GARCH	VARIANCE PERSISTENCE	MEAN OF STANDARDIZED RESIDUALS	STANDARD DEVIATION OF STANDARDIZED RESIDUALS	SKEWNESS OF STANDARDIZED RESIDUALS	EXCESS KURTOSIS OF STANDARDIZED RESIDUALS	1ST ORDER AUTO-CORRE-LATION	LB(20) P-VALUE ON STANDARDIZED RESIDUALS	LB(20) P-VALUE ON SQUARED STANDARDIZED RESIDUALS
IF Market Valuation Returns										
Equity Funds	0.12	0.70	0.83	0.02	1.00	0.58	9.26	0.00	0.97	0.73
Bond Funds	0.12	0.70	0.83	-0.07	0.91	-0.95	0.94	-0.07	0.87	0.00
Mixed Funds	0.12	0.70	0.83	-0.04	0.98	-0.68	1.30	-0.02	0.96	0.47
Real Estate Funds	0.12	0.70	0.83	0.02	1.01	-0.43	3.79	-0.01	0.99	1.00
Hedge Funds	0.12	0.70	0.83	0.09	1.02	1.56	10.62	0.03	1.00	1.00
Other Funds	0.12	0.70	0.83	0.10	1.08	4.35	37.69	0.08	1.00	1.00
Money Market Funds	0.12	0.70	0.83	-0.07	1.02	0.42	0.97	0.04	0.97	0.38
IF In-Flows										
Equity Funds	0.11	0.87	0.98	-0.03	1.03	1.45	10.35	0.01	0.53	0.66
Bond Funds	0.11	0.87	0.98	-0.14	0.95	0.17	0.36	-0.04	0.00	0.00
Mixed Funds	0.11	0.87	0.98	-0.07	1.01	0.30	0.49	-0.01	0.30	0.48
Real Estate Funds	0.11	0.87	0.98	-0.02	1.04	0.69	1.59	0.00	0.48	0.71
Hedge Funds	0.11	0.87	0.98	0.01	1.05	1.57	6.43	0.02	0.87	0.91
Other Funds	0.11	0.87	0.98	0.04	1.15	5.67	57.18	0.06	0.96	1.00
Money Market Funds	0.11	0.87	0.98	0.04	1.00	0.37	0.70	-0.04	0.48	0.65
IF Out-Flows										
Equity Funds	0.12	0.84	0.96	0.02	1.03	1.55	10.82	0.00	0.91	0.78
Bond Funds	0.12	0.84	0.96	-0.04	0.95	0.23	0.41	-0.03	0.52	0.18
Mixed Funds	0.12	0.84	0.96	-0.03	1.01	0.48	1.10	-0.02	0.91	0.57
Real Estate Funds	0.12	0.84	0.96	0.03	1.03	0.96	3.80	0.00	0.98	0.95
Hedge Funds	0.12	0.84	0.96	0.05	1.06	1.58	6.88	0.02	1.00	1.00
Other Funds	0.12	0.84	0.96	0.09	1.08	5.60	55.43	0.03	1.00	1.00
Money Market Funds	0.12	0.84	0.96	0.03	0.95	0.23	0.41	-0.02	0.52	0.18
DM Returns										
Mean	0.04	0.86	0.94	0.01	1.00	-0.88	3.03	0.02	0.91	0.91
Min	0.04	0.86	0.94	-0.06	0.99	-1.42	0.13	-0.04	0.69	0.52
Q25%	0.04	0.86	0.94	-0.05	1.00	-1.29	2.32	-0.01	0.89	0.96
Median	0.04	0.86	0.94	0.01	1.00	-0.76	2.97	0.02	0.93	0.98
Q75%	0.04	0.86	0.94	0.04	1.01	-0.65	4.36	0.05	0.98	0.99
Max	0.04	0.86	0.94	0.11	1.01	-0.46	5.85	0.07	1.00	1.00
EM Returns										
Mean	0.07	0.87	0.94	0.01	0.99	-0.38	0.99	-0.05	0.73	0.81
Min	0.07	0.87	0.94	-0.17	0.97	-0.65	0.33	-0.17	0.19	0.50
Q25%	0.07	0.87	0.94	-0.05	0.99	-0.58	0.72	-0.05	0.43	0.65
Median	0.07	0.87	0.94	0.01	0.99	-0.55	0.89	-0.04	0.91	0.89
Q75%	0.07	0.87	0.94	0.10	1.01	-0.17	1.36	-0.03	0.98	0.97
Max	0.07	0.87	0.94	0.14	1.02	0.19	1.73	0.03	0.99	0.98

Sources: CSSF, OECD. Calculation: BCL. Period: March 2004 - December 2020. Notes: This table reports the key descriptive statistics of parameter estimates and residual diagnostics for the multivariate GARCH model estimated on the residuals from ARIMAX models on the monthly investment fund flows and returns.

Figure 2
Volatilities of Luxembourg investment funds and DMs and EMs market indices



Sources: CSSF, OECD. Calculation: BCL. Period: March 2004 - December 2020.

Figure 2 shows the dynamic volatility of market valuation returns, inflows and outflows for each type of investment fund as well as the interquartile ranges for DM and EM market returns. The profiles of volatility of returns show the periods of high volatility associated with the GFC of 2007-2009, the European debt crisis around 2012, the Chinese stock market turbulence of 2015–2016 and the COVID-19 pandemic in March 2020. However, the profiles of volatility of outflows responded to these episodes of turmoil differently than those of inflows. In particular, there was no obvious reaction to the Chinese stock market turbulence of 2015–2016 and the China-US trade tensions in early 2018. On average, the volatility of EM markets was higher than those of DM markets. In contrast, the volatility of DMs during the COVID-19 pandemic increased to around the level of the GFC, although with a much shorter duration.

Table 4 reports the parameter estimates for the dynamic grouped t-copula. There are several discrepancies in the degrees of freedom (DF) across the groups. For example, the DF of EMs was higher than that of DMs, and the DF of outflows was much lower than that of inflows. This likely reflects the high tail dependence in DMs and outflows. Therefore, assuming only one global DF parameter might be over-simplistic and too restrictive for the aggregate investment fund portfolio in Luxembourg. The dependence updating parameter, α^{copula}, is 0.01, and the autoregressive parameter, β^{copula} is 0.87 with a correlation persistence of 0.89. Thus, the copula dependence is still highly dynamic.

Table 4:

Dynamic conditional grouped T-copula estimation for Luxembourg investment fund flows and returns

α	0.01	
ß	0.87	
Correlation Persistence	0.89	
	Numbers of Data Series	**DoF**
DM Returns	10	8.5
EM Returns	7	11.6
IF In-Flows	7	72.8
IF Out-Flows	7	13.2
IF Returns	7	20.0

Source: CSSF, OECD. Calculation: BCL. Period: March 2004 - December 2020. Notes: This table reports the estimation results for the dynamic conditional grouped T-copula model.

Figures 3A and 3B show the interquartile ranges of the dynamic conditional copula correlations and low tail dependence within and across groups. We reverse the sign of outflows to facilitate the interpretation of the results both for within and across groups. The t-copula generalizes the normal copula by allowing for non-zero dependence in the extreme tails[148]. The pairwise tail dependencies between groups are calculated by using the maximum of their degrees of freedom, if they are not in the same group.

The results show that the level of copula correlation and tail dependence within fund market valuation gains or between fund market valuation gains and DM/EM returns (panels on the right column) was higher than those in other cases (panels on the left and middle column). The low tail dependencies of inflows were almost zero due to the high DF. However, the dependencies of outflows were higher, on

148 This type of dependence is measured by τ^U upper tail dependence, and τ^L lower tail dependence: $\tau^L = \lim_{\zeta\to 0} \Pr[\eta_1 \le \zeta | \eta_2 \le \zeta] = \lim_{\zeta\to 0} \Pr[\eta_2 \le \zeta | \eta_1 \le \zeta] = \lim_{\zeta\to 0}(\frac{C(\zeta,\zeta)}{\zeta}$, and $\tau^U = \lim_{\zeta\to 1} \Pr[\eta_1 > \delta | \eta_2 > \delta] = \lim_{\zeta\to 1} \Pr[\eta_2 > \delta | \eta_1 > \delta] = \lim_{\zeta\to 1}(\frac{1-2\delta+C(\delta,\delta)}{1-\delta})$. Two random variables exhibit lower tail dependence, for instance, if $\tau^L > 0$. The normal copula imposes that this probability is zero. The two parameters of the t-copula, ρ_t and v_t, jointly determine the amount of dependence between the variables in the extremes. Since it is a symmetric copula, the dependence between the variables during extreme appreciations is restricted to be the same as during extreme depreciations, and is given by: $\tau_t^U = \tau_t^L = 2 - 2T_{v_{t+1}}(\sqrt{v_t + 1}\sqrt{\frac{1-\rho_t}{1+\rho_t}})$.

average, than those of inflows, and they were more volatile and more responsive to the GFC and the COVID-19 pandemic than those of both inflows and market valuation returns. The average between-correlations with DM were comparably higher than those with EM, which is consistent with the unconditional correlations found in Table 1. The copula dependencies of fund market valuation returns were also higher during 2015-2016, coinciding with increased asset price correlations (ECB, November 2016, Financial Stability Review), reflecting risk-taking behavior and interconnectedness within the investment fund sector. (see Figure 3A)

In order to fully assess the forward-looking measures of CoSR through time, the parameters of the *ARIMAX* predictive regression model, multivariate *GARCH*, grouped t-copula and marginal semi-parametric form are all fixed[149] using the values estimated from the full sample. All flows and returns are subsequently simulated one-step-ahead from March 2005 to December 2020.[150] The CoSR measures constructed in this forward-looking manner are able to reasonably predict future, rather than contemporaneous, events. (see Figure 3B)

3.3 FORWARD LOOKING SYSTEMIC RISK MEASURES OF INVESTMENT FUNDS UNDER MARKET STRESS IN THE EA, THE US AND CHINA

Figure 4A depicts the *ΔCoES* of flow returns under market stress in the US, the EA and China for each category of investment fund for the period spanning March 2005 to December 2020. The sum of inflow components and outflow components equals the ΔCoES of flow returns. The *ΔCoES* measure seems to identify major market events relatively closely, in particular, the global financial crisis (2008 – 2009) and the COVID-19 outbreak in early 2020. The profiles of ΔCoES for Luxembourg investment fund segments were similar under market stress in the US and the EA, with the exception of Real Estate Funds. This may reflect the market interconnections between the US and the EA and the idiosyncratic component of the US Real Estate Funds segment.

Considering the upper tails of ΔCoES under market stress in both the EA and the US, the impacts were strong for Bond Funds, Mixed Funds, Hedge Funds and Other Funds, and outflow effects dominated in Equity Funds, Bond Funds and Mixed Funds. However, Bond Funds and Hedge Funds were more sensitive to negative market shocks in the EA than in the US, and the impacts from the US on Real Estate Funds and Money Market Funds were, on average, marginally higher than those from the EA. It is noteworthy that the ΔCoES of Real Estate Funds and Other Funds actually peaked around the beginning of 2016, preceding the Lehman Brothers default, and Money Market Funds served as an important source of flight-to-quality under market stress in the EA and the US.

As for China, its market stress affected Luxembourg Mixed Funds, Real Estate Funds and Money Market Funds. In contrast to Other Funds, the average impacts from China on Real Estate Funds and Money Market Funds were marginally higher than those in both the EA and the US. Overall, most of the effects from China were driven by inflow shortages.

Moving to the *ΔCoES* of NAV returns as depicted in Figure 4B, ΔCoES was decomposed into a flow component and market valuation component. Like flow returns, the profiles for ΔCoES were similar under market stress in the US and the EA during the various crisis periods, including the recent COVID-19 outbreak. Market valuation effects dominated in Equity Funds, Hedge Funds and Other Funds, while flow

149 The out-of-sample estimation by expanding windows is difficult in this study because of the limited length of monthly data. Instead, by the fixed parametric form for the whole period, we can better understand or evaluate these risk measures over the observed crisis events.

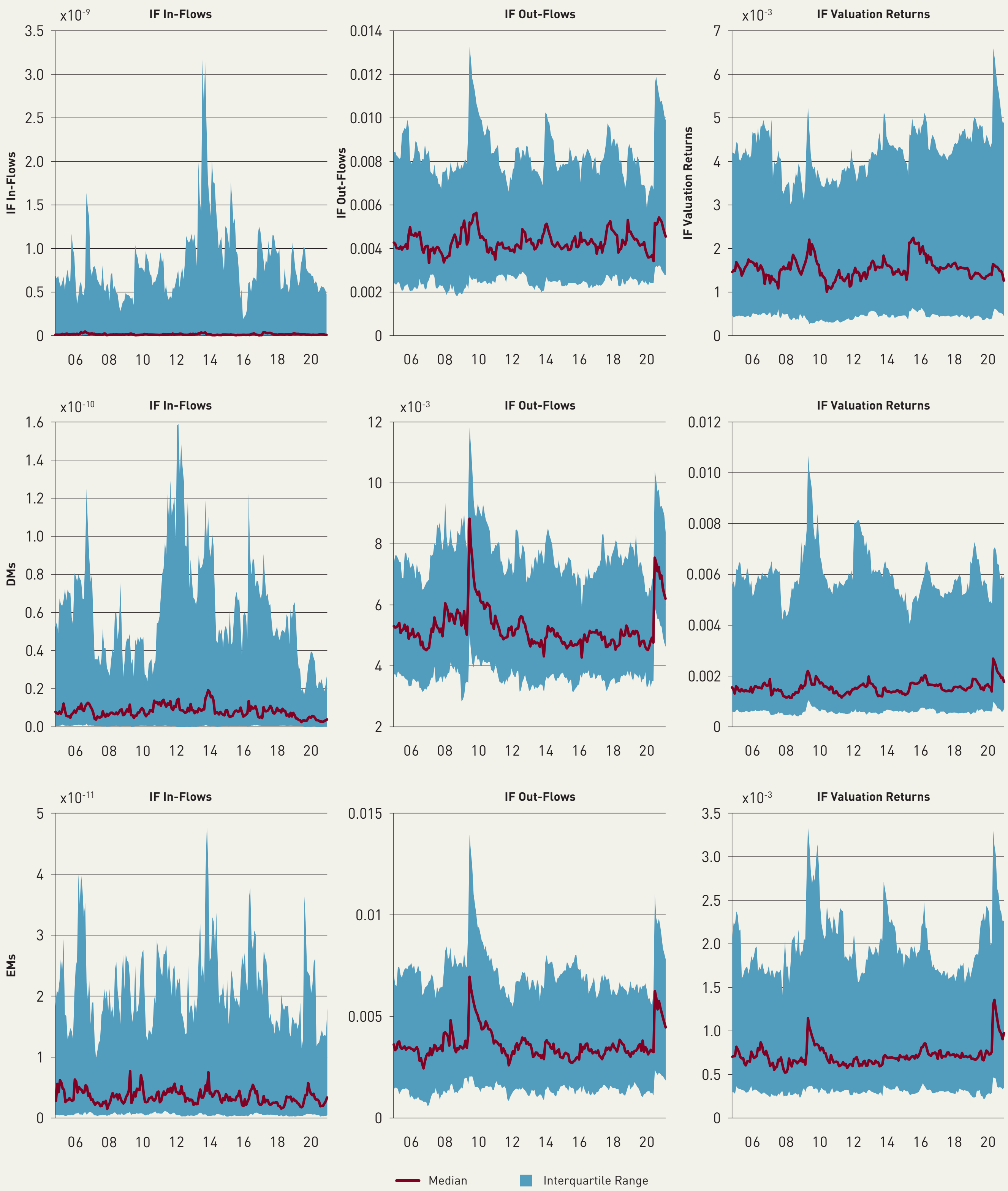
150 At each date, 35000 values of the innovations are simulated for each flow or returns over a one-month horizon.

Figure 3A

Copula correlations of Luxembourg investment funds and DMs and EMs market indices

Sources: CSSF, OECD. Calculation: BCL. Period: March 2004 - December 2020.

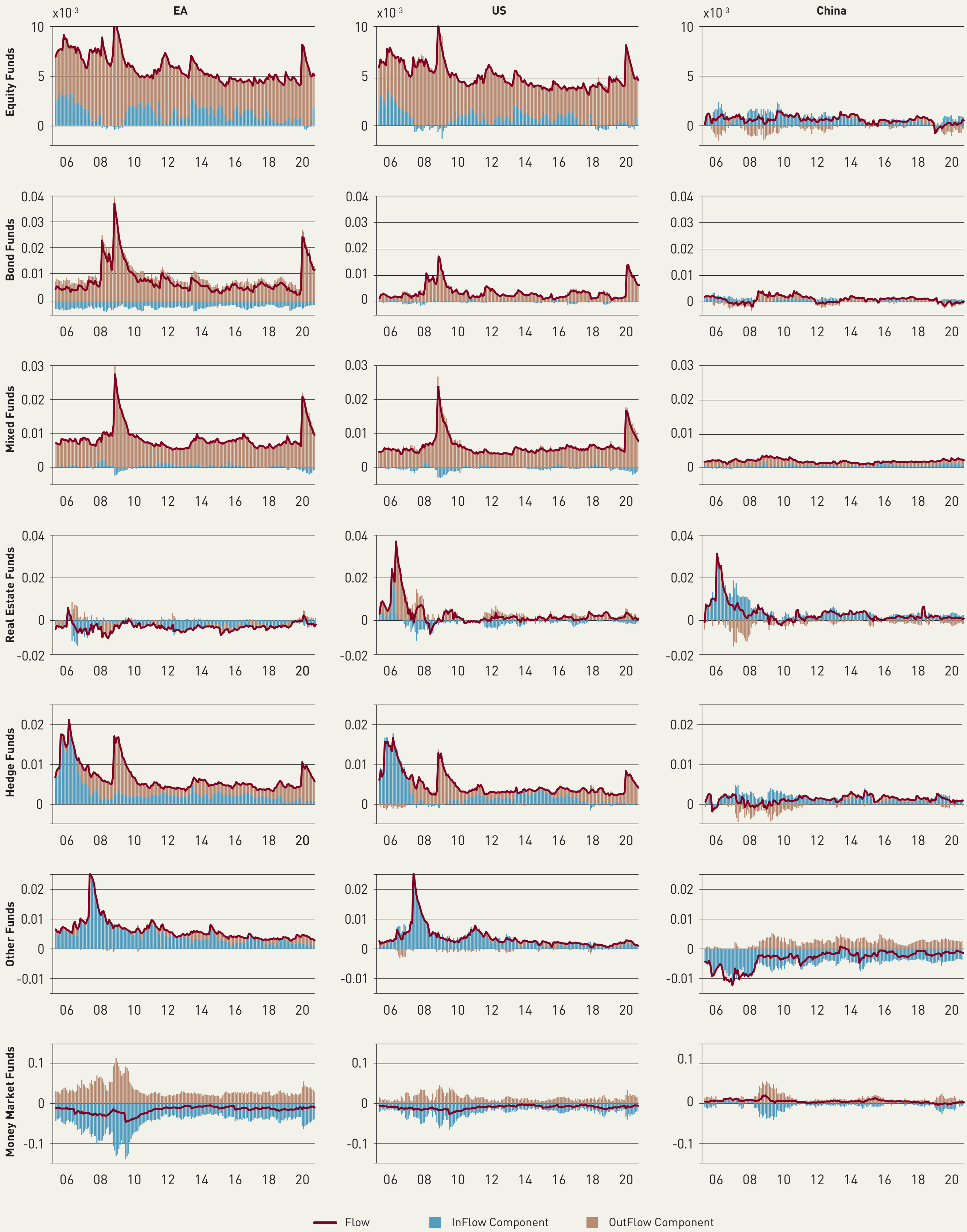
Figure 3B
Low tail dependences of Luxembourg investment funds and DMs and EMs market indices



Sources: CSSF, OECD. Calculation: BCL. Period: March 2004 - December 2020.

Figure 4A

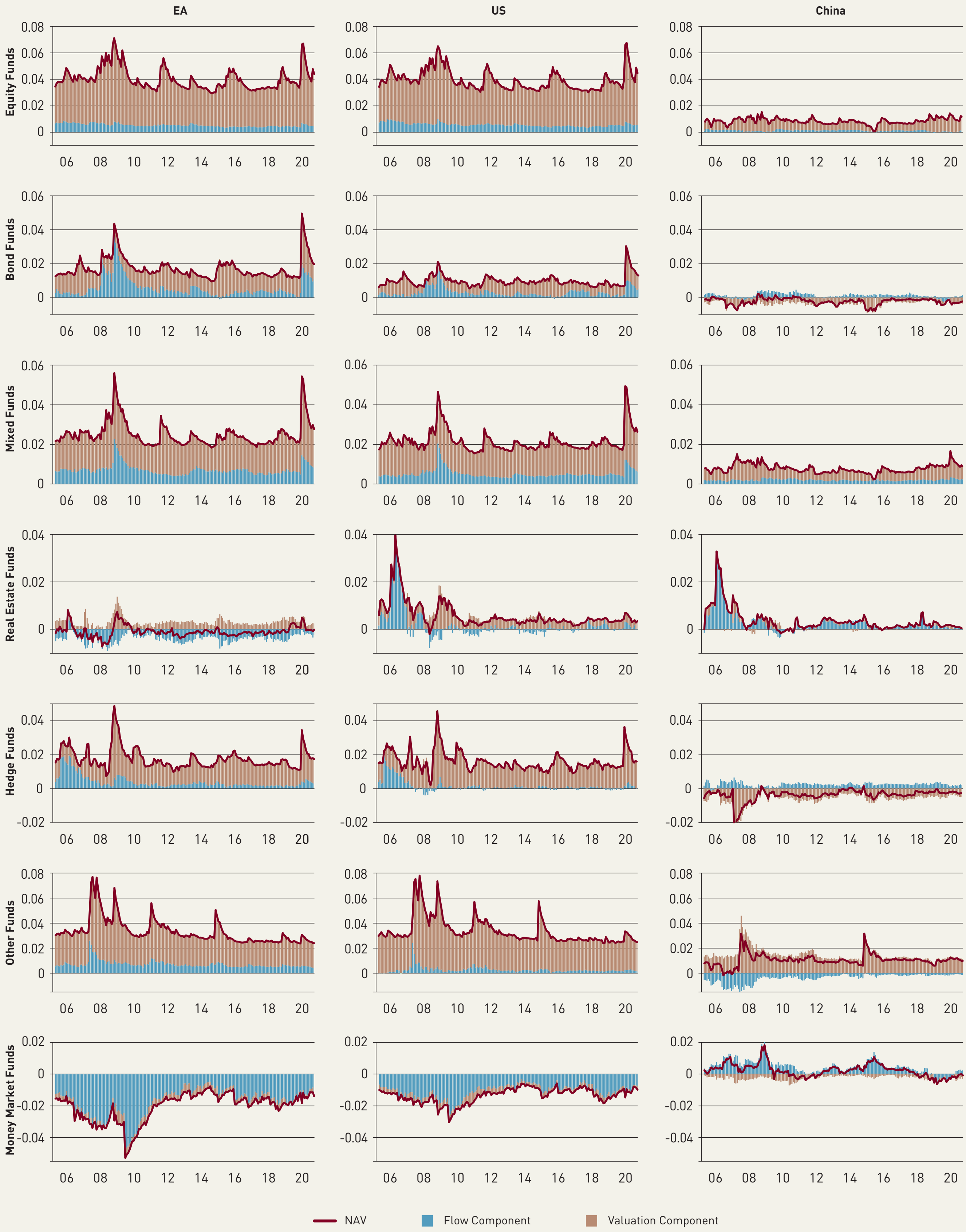
ΔCoES of Luxembourg IF flows under market stress in originating in the EA, the US and China markets



Sources: CSSF, OECD. Calculation: BCL. Period: March 2004 - December 2020.

Figure 4B

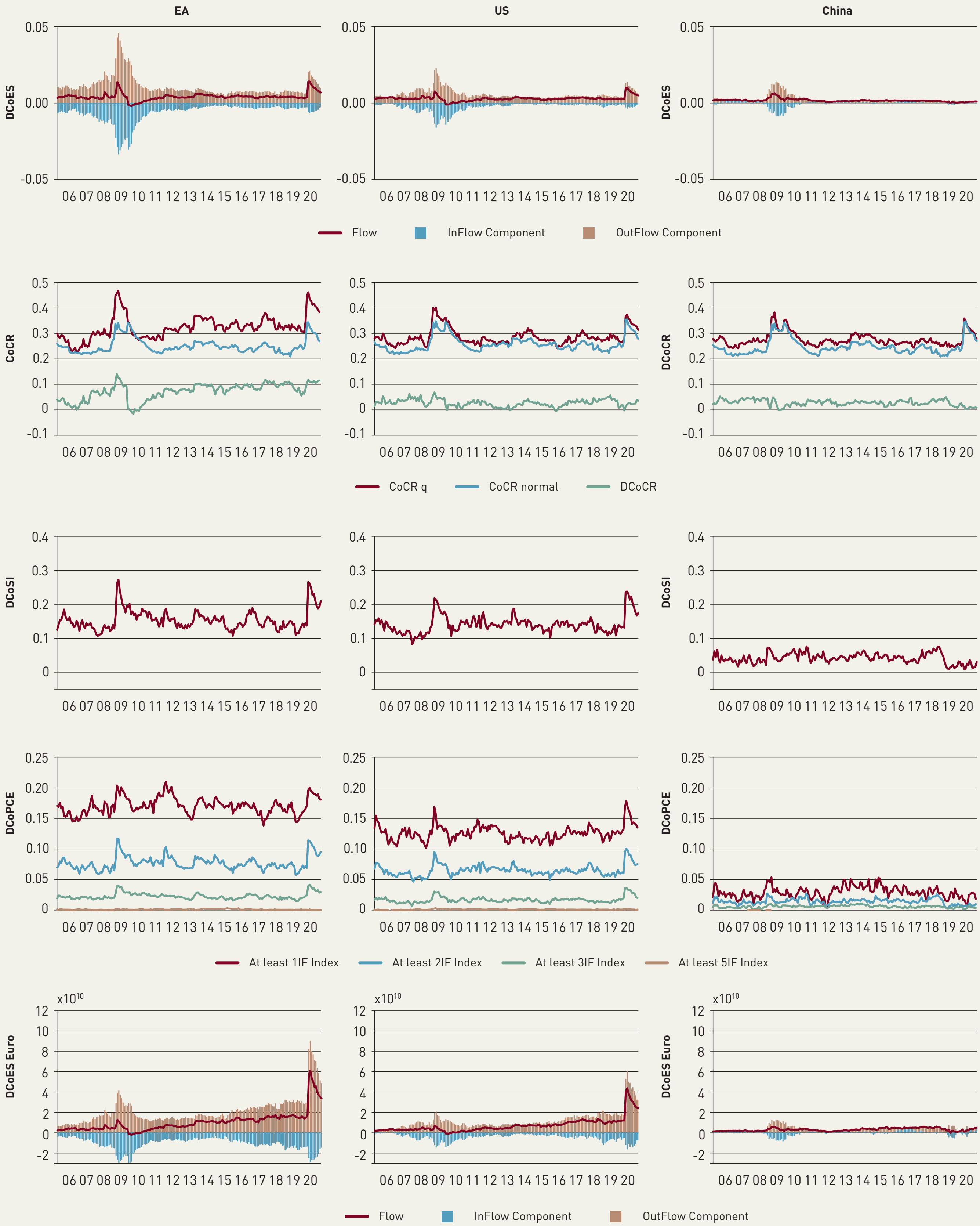
ΔCoES of Luxembourg IF NAVs under market stress originating in the EA, the US and China



Sources: CSSF, OECD. Calculation: BCL. Period: March 2005 - December 2020.

Figure 5A

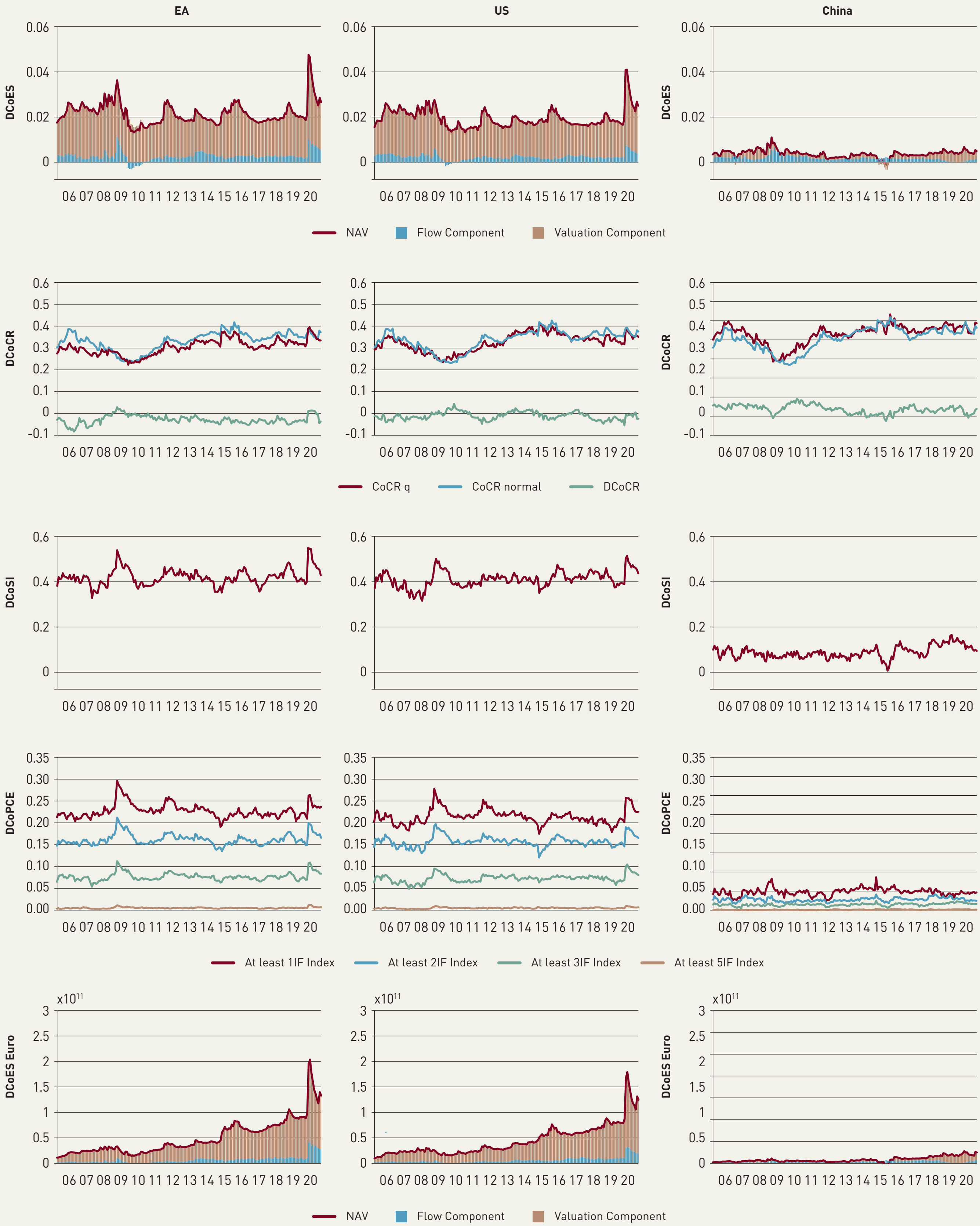
CoSR measures of Luxembourg IF flows under market stress originating in the EA, US and China



Sources: CSSF, OECD. Calculation: BCL. Period: March 2005 - December 2020.

Figure 5B

CoSR measures of Luxembourg IF NAVs under market stress originating in the EA, the US and China



Sources: CSSF, OECD. Calculation: BCL. Period: March 2005 - December 2020.

effects played an important role in Bond Funds, Real Estate Funds and Money Market Funds. The effect on Mixed Funds, resulted from a combination of both effects. As for Hedge Funds and Other Funds, flow effects were stronger under market stress in the EA than in the US. This might reveal that investment tended to flow out of Luxemburg investment funds following market stress in the EA.

The ΔCoES of Real Estate Funds under market stress in the EA was not so high during the GFC of 2007-2009 or the European sovereign debt crisis, compared with their ΔCoES under market stress in the US and China. Regarding China, except for Real Estate Funds and Other Funds, the impacts on other categories of investment funds were noticeably different from those in the EA and the US, especially during the GFC. Furthermore, compared with the flow shortages under market stress in China, the impact on Money Market Funds under market stress in both the US and the EA might reflect the flight-to-quality behavior of investors selling what they perceived to be higher-risk investments. This suggests a reversal in risk appetite, as investors seek less risk and, consequently, lower profits.

To address the structure dependence among these investment funds, the CoSR measures of all seven categories of investment funds are further examined. Figure 5A depicts the CoSR measures of flow returns for the Luxembourg investment fund sector. On average, the CoSR measures under market stress in the EA and US were higher and coincided with the GFC of 2007-2009, the European sovereign debt crisis and the COVID-19 pandemic more than those for China, since they did not impact the Chinese financial markets. For Luxembourg-domiciled investment funds, both outflow and inflow components of *ΔCoES* were stronger under market stress in the EA than those in the US and China. With the increase in the total NAVs of investment funds, $\Delta^{€}CoES$, which was dominated by the outflow components, increased significantly over time and particularly during the COVID-19 pandemic (especially under market stress in the EA).

As discussed previously, *CoCR* is defined on the [0 1] interval via rescaling the distance between the ES and the VaR of a fund's portfolio. The *CoCR* of net flows conditional on a market being in a normal state during the crisis period was also high. Thus, *ΔCoCR* was actually low during the GFC and the COVID-19 pandemic in the US and the EA. In order to interpret the concentration risk consistently, we treat *CoCR* as a measure of asymmetric herding behavior and potential fire sale pressure, which could exert significant price pressure on securities far from their fundamental value under market stress. This measure seems to have tracked the various crises well. However, the impacts from market stress in China were also strong.

The *CoSI* measures the expected number of investment fund categories that would become distressed conditional on a certain market state. The *ΔCoSI* increased significantly during the GFC and the COVID-19 pandemic under market stress in the EA and US, and were generally higher under market stress in the EA than in the US.

As for *ΔCoPCE*, we consider cascade scenarios under which at least one, two, three and five investment fund categories become distressed simultaneously under given a given market condition. The differences between these cascade effects captures the marginal contributions of these investment funds to systemic stress. The cascade effects of at least five categories of investment funds were much lower than others, and were almost flat around zero. This reflects that redemption effects could be stabilized by increased diversification across these seven categories of investment funds. The cascade or spillover effects declined slowly after 2012 but increased sharply following the COVID-19 pandemic under market stress in both the EA and the US. The profile for China was different, as the cascade effects on flows actually increased under the "taper tantrum" in 2013, and decreased during the Chinese stock market turbulence of 2015-2016. They were also observed during the GFC and the COVID-19 pandemic.

Turning to the CoSR measures of NAV returns for the investment fund sector as shown in Figure 5B, except for *CoCR* which focuses on the concentration risk of these investment funds, all other measures under market stress in both the EA and the US tracked the main crisis events during this period. On average, these CoSR measures under market stress in the EA were similar to those under market stress in the US, and the impacts from China being much more muted. Nevertheless, the concentration risk *CoCR* under market stress in China was similar to that under stress in the EA and the US. Furthermore, the *ΔCoES* under market stress in the EA and the US was dominated by market valuation effects, and flow effects also increased significantly during the GFC crisis and the COVID-19 pandemic.

The *Δ€CoES* under market stress in the EA and the US kept increasing with the growing size of investment funds in Luxembourg and this measure peaked at the onset of the COVID-19 pandemic. The cascade effects of NAV returns were much higher than those of flow returns, likely as a result of the market valuation effects. All CoSR measures under market stress in the EA began to increase from the beginning of 2020 and declined quickly upon the prompt policy responses in the euro area, in particular, the asset purchase programme (APP) and the pandemic emergency purchase programme (PEPP). However, the slow decline in systemic risk levels towards the end of 2020 could be interpreted as a sign that market participants were becoming increasingly concerned about the cumulative impact of the sequence of the COVID-19 pandemic shocks on the global economy.

3.4 Forward-looking systemic risk of investment funds under market stress in DMs and EMs

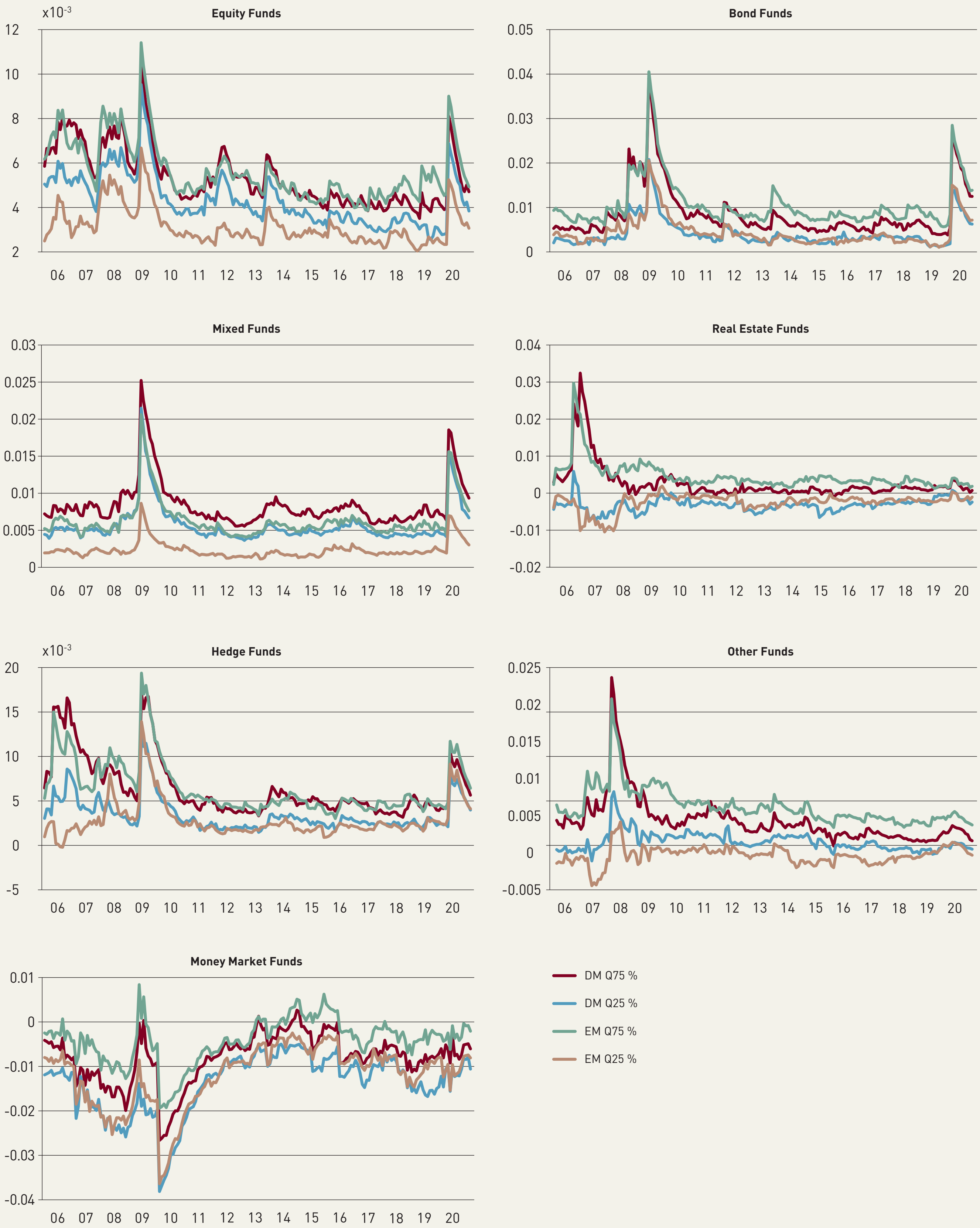
In this section, nine DMs including the G7 countries and the five largest European countries and seven largest emerging market countries were selected to assess market stress due to DMs and EMs, respectively. Other DMs and EMs are not considered in this study as Luxembourg investment funds have less direct exposure to those markets. We do not construct any DM index or EM index, but treat each country's market index separately.[151] It is also noticed that the market stress in each country might be driven by a common market risk scenario. However, in this study, we do not assess market stress resulting from the idiosyncratic components of each country's market index.

Figure 6A depicts the interquartile ranges of *ΔCoES* of flow returns under market stress in DMs and EMs for each category of investment fund from March 2005 to December 2020. The interquartile ranges of *ΔCoES* in DMs were roughly higher than those in EMs especially at the lower bound (i.e. the 25th percentile) for all categories of investment funds except for Bond Funds, Real Estate Funds and Money Market Funds, for which the impacts from EMs were, on average, stronger than those from DMs. Real Estate Funds, Other Funds and Money Market Funds were not affected as much as the other funds by the COVID-19 pandemic under market stress in both DMs and EMs. As shown by the 75th percentile for both DMs and EMs, the stress in Real Estate Funds and Hedge Funds peaked around early 2006 with stress in Other Funds following in 2007. It might suggest that the flows of Real Estate Funds, Hedge Funds and Other Funds were more sensitive to negative market information. As for the *ΔCoES* of NAV returns as shown in Figure 6B, the results were similar to those for flows. However, the measures captured the market valuation effects during certain periods, for example, during the Chinese stock market turbulence of 2015–2016. The interquartile ranges of DMs were higher than those of EMs especially for the 25th percentile for all categories of investment funds except for Real Estate Funds and Money Market Funds. It is worth noting that significant market stress could limit Money Market Funds' ability to meet investors' redemptions as was the case during the GFC. Overall, EMs could still provide

151 The distribution of the CoSR measures for these major economies shows that the highest CoSR measures were from the EA. However, these country market indices are highly correlated as they are exposed to common market-based risks (including interest rate risk, equity risk, currency risk, commodity risk, etc.).

Figure 6A

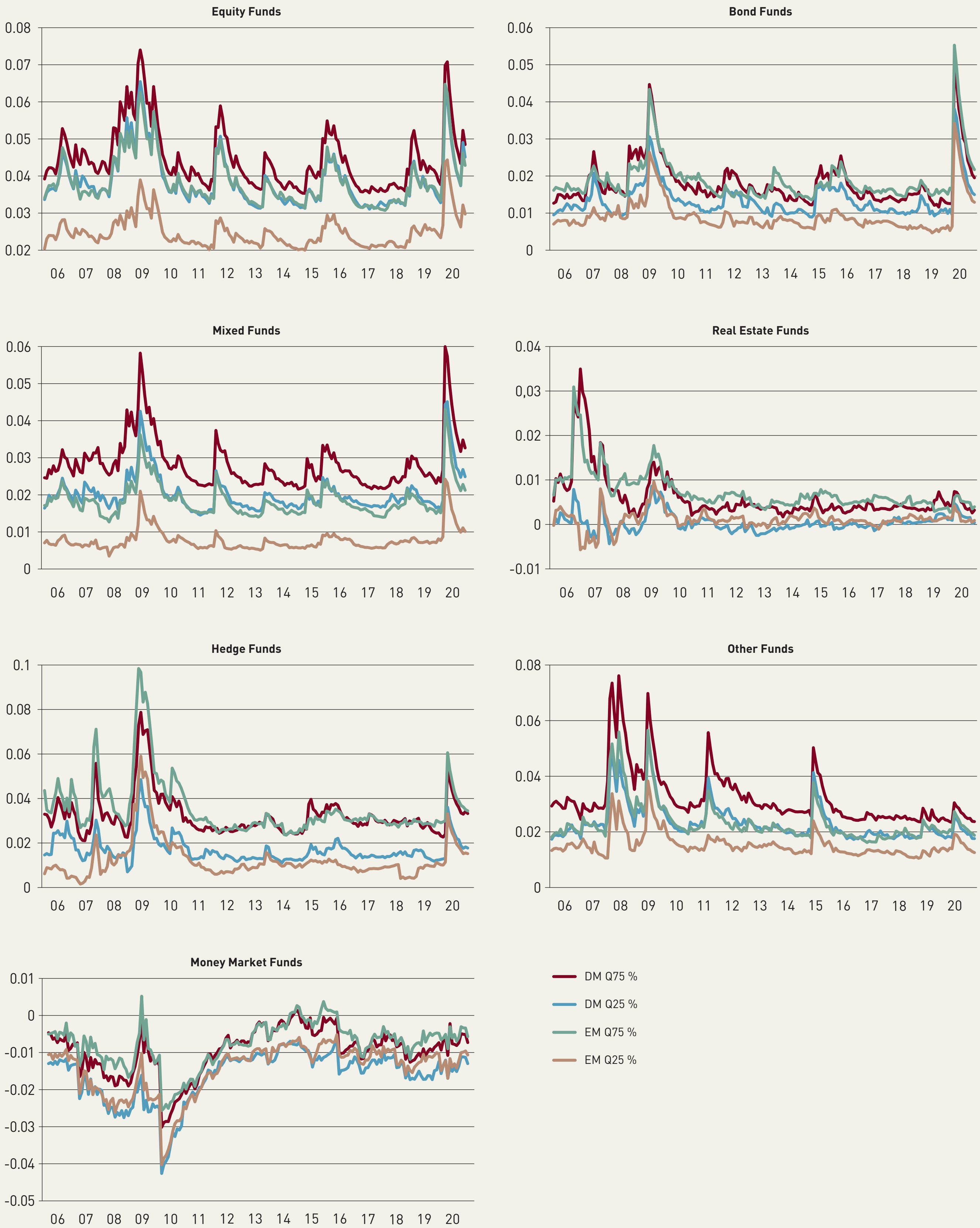
Interquartile ranges of ΔCoES of Luxembourg IF flows under market stress originating in DMs and EMs



Sources: CSSF, OECD. Calculation: BCL. Period: March 2005 - December 2020.

Figure 6B

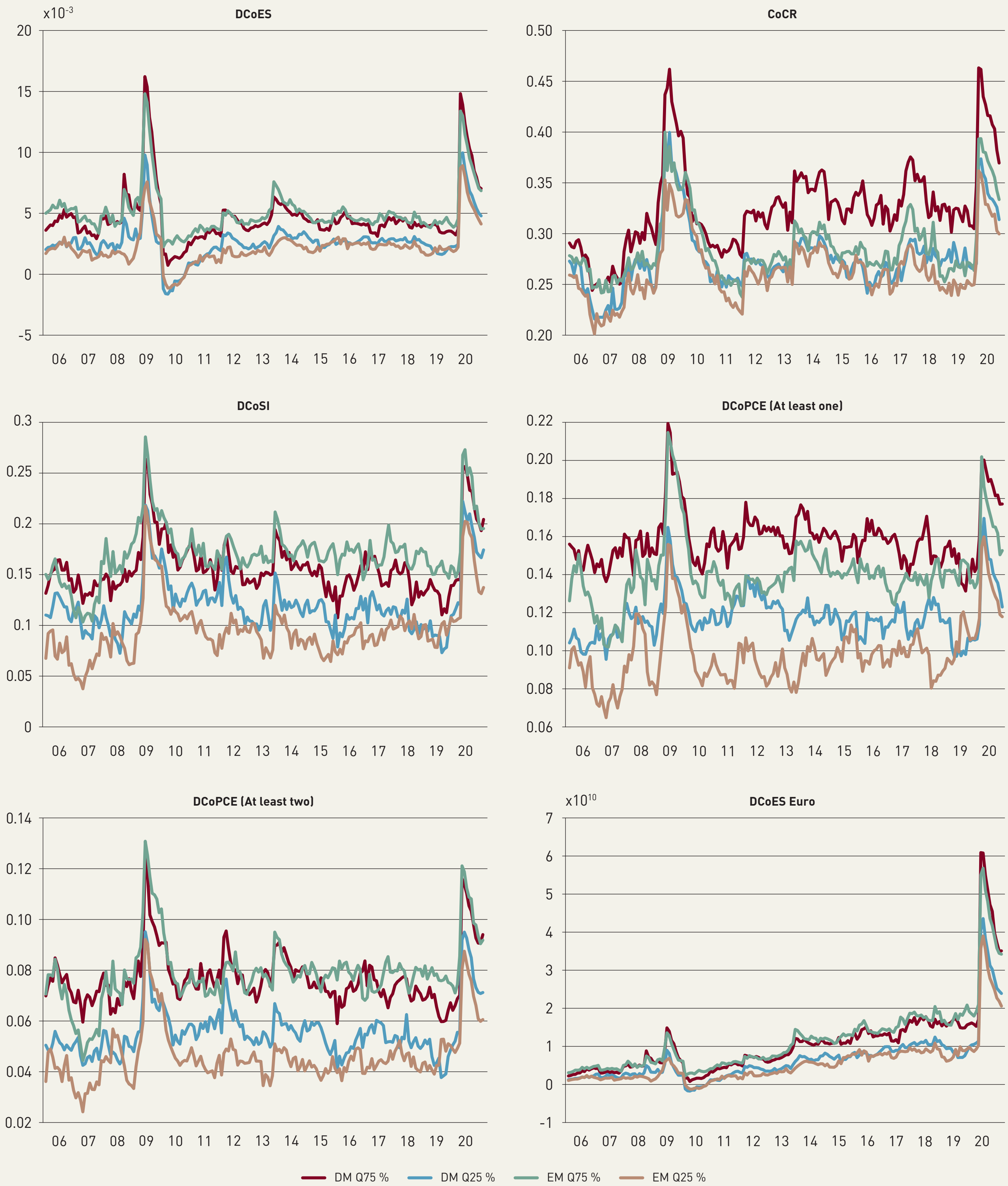
Interquartile ranges of ΔCoES of Luxembourg IF NAVs under market stress originating in DMs and EMs



Sources: CSSF, OECD. Calculation: BCL. Period: March 2005 - December 2020.

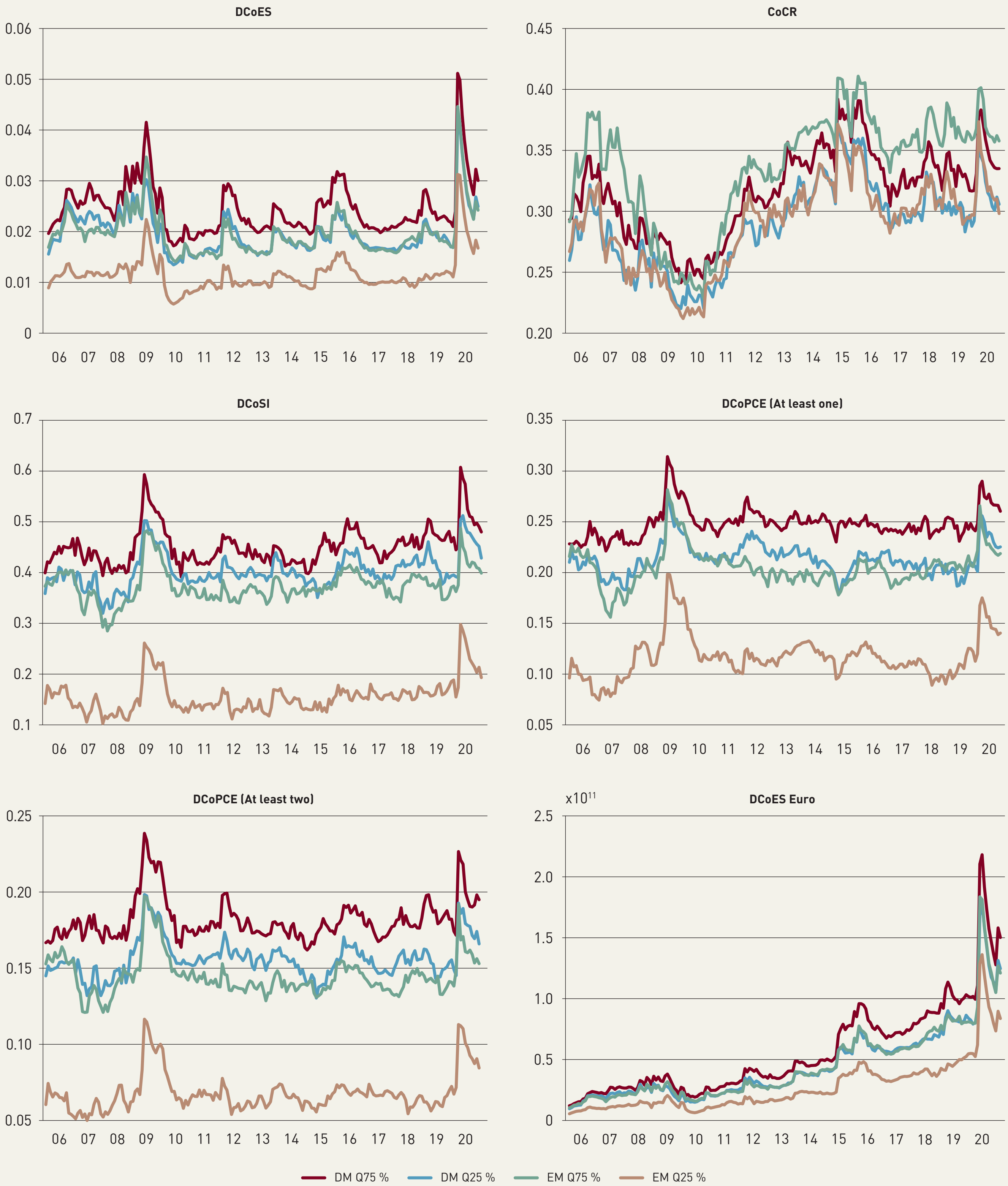
Figure 7A

Interquartile ranges of CoSR measures of Luxembourg IF flows under market stress originating in DMs and EMs



Sources: CSSF, OECD. Calculation: BCL. Period: March 2005 - December 2020.

Figure 7B
Interquartile ranges of CoSR measures of Luxembourg IF NAVs under market stress originating in DMs and EMs



Sources: CSSF, OECD. Calculation: BCL. Period: March 2005 - December 2020.

diversification benefits for the Luxembourg investment fund sector, particularly during significant market stress episodes, thereby helping to attenuate the risk of redemptions.

Figure 7A depicts the six CoSR measures for flow returns. Overall, but with some variation, the interquartile ranges of DMs were all higher than those of EMs, especially at the lower 25th percentile. With the exception of $\Delta^{€}CoES$, which increased persistently since 2010, all risk measures have remained low since the GFC. All measures experienced a sharp upturn in early 2020, coinciding with the onset of the COVID-19 pandemic. As for NAV returns, as depicted in Figure 7B, the concentration risk measure for EMs was at least as high as for DMs on average. For the other measures, the impacts from DMs were still stronger than those from EMs. It can be seen that all risk measures under market stress in both DMs and EMs increased during the COVID-19 pandemic.

4. ECONOMIC DETERMINANTS OF FORWARD-LOOKING CONDITIONAL SYSTEMIC RISK MEASURES

It is well documented that both market uncertainty and search for yield behavior of investors that tend to be more exposed to less liquid, and thus riskier, assets contribute to changes in investment fund flows and NAV. Various studies report increasing exposures of investment funds to emerging markets and the corporate bond market. Ananchotikul and Zhang (2014) find that the short-run dynamics of the portfolio flows to emerging markets are driven mostly by global "push" factors. Goldstein, Jiang and Ng (2017) find that the outflows of corporate-bond mutual funds are sensitive to bad performance much more than their inflows are sensitive to good performance. Kroencke, Schmeling and Schrimpf (2015) show that global asset reallocations of US fund investors have a strong factor structure, with two factors accounting for more than 90% of the overall variation. The first factor captures switches between US bonds and equities. The second reflects reallocations from the US to international assets. Reallocations of both retail and institutional investors show return-chasing (i.e., search for yield) behavior. Institutional investors tend to reallocate portfolios towards riskier, high-yield fixed income segments, consistent with a search for yield.

In an effort to better understand the CoSR measures of investment funds discussed this paper, the linear predictive regressions of the CoSR measures on various macroeconomic determinants are investigated as follows:

$$CoSR_{j,t} = c + \alpha_j CoSR_{j,t-1} + \sum_{n=1}^{N} \gamma_{j,k} Macrofactors_{n,t-1} + \varepsilon_{j,t}. \tag{18}$$

The selected macroeconomic variables include a set of macro variables which are reasonable metrics of the state of the economy in the EA and the US, respectively, as well as measures of market uncertainty and liquidity risk.

More precisely the set of explanatory variables considered in this paper consists of[152]:

- Short-term interest rates: 3-month short-term interest rates
- Interest rate spreads: 10-year interest rates minus 3-month interest rates
- Liquidity spreads: 3-month Libor rates minus 3-month US T-bill rates for the US or 3-month Euribor rates minus 3-month Germany T-bill rates[153] for the EA
- Log business confidence index
- Log consumer confidence index
- Log volatility index: VSTOXX for the EA or VIX for the US
- One-year log returns of market price index

All macroeconomic variables are obtained from Bloomberg, the BIS, Eurostat, the OECD and the ECB. In order to compare the predictability of the macroeconomic variables for the EA and the US, the business confidence index and consumer confidence index are all taken from the OECD. We only consider the CoSR measures for investment funds under market stress in the EA.

Table 5A reports the regression results of the CoSR measures of flow returns for the period of March 2005-December 2020. Regressions are run with Newey-West robust standard errors using a Bartlett kernel. As regards the EA macroeconomic variables, all of the variables were significant in *ΔCoES* at the 5% level, except for market volatility and business confidence. It suggests that under weak economic conditions (e.g., low short-term interest rates and interest rate spreads, high liquidity spreads, and low consumer confidence) resulted in portfolio rebalancing, flow risk would be high in the next period. The market returns also played a significant role in $\Delta^{\epsilon}CoES$ as NAVs were determined by the overall market performance. In addition, as shown by *CoCR*, these explanatory variables underscored the "herding behavior" of investors driven either by search-for-yield behaviour or fire sales under market stress. The *ΔCoSI*, which focuses on the expected number of distressed fund categories, was mainly driven by liquidity spreads, interest rate spreads, business confidence and market returns. Finally, for the cascade effects as measured by *ΔCoPCE*, under a scenario in which at least one investment fund category becomes distressed, it was driven solely by market volatility. In contrast, only market returns were weakly significant for *ΔCoPCE* where at least two investment fund categories become distressed. The regression results of these CoSR measures on macro variables from the US and EU suggest that the CoSR measures were dominated by the EA macro variables.

152 The EUR/USD exchange rate is not included in the set of explanatory variables as it is driven endogenously by some considered explanatory variables and it is not significant in our separate robust test.

153 This spread represents the European equivalent of the TED spread, which is the difference between the interest rates on interbank loans and on short-term government debt ("T-bills"). Market participants look at this difference as a proxy for short-term liquidity risk. Clearly, it cannot be excluded that the proxy also captures some credit risk, and one could even argue an implicit government guarantee. However, the correlation between this measure and other proxies for liquidity also used in the literature, such as Euribor-OIS 3M spread, is almost 94%.

Table 5A:

Macroeconomic determinants of Luxembourg IF Flow CoSR measures under market stress in the EA

	DCoES			CoCR			DCoSI			DCoPCE (AT LEAST 1)			DCoPCE (AT LEAST 2)			DCoES EURO		
	ESTIMATE	tSTAT	pVALUE	ESTIMATE	tSTAT	pVALUE	ESTIMATE	tSTAT	pVALUE	ESTIMATE	tSTAT	pVALUE	ESTIMATE	tSTAT	pVALUE	ESTIMATE	tSTAT	pVALUE
Constant	0.0683	1.579	0.114	0.678	1.304	0.192	1.203	1.937	0.053	0.032	0.117	0.907	0.387	1.548	0.122	-8.18E+09	-0.106	0.916
Lagged	**0.7439**	**12.067**	**0.000**	**0.881**	**23.101**	**0.000**	**0.713**	**11.167**	**0.000**	**0.758**	**16.191**	**0.000**	**0.712**	**11.264**	**0.000**	**8.38E-01**	**12.302**	**0.000**
EA Short-term Interest Rates	**-0.0001**	**-2.148**	**0.032**	-0.002	-1.239	0.215	-0.001	-1.067	0.286	0.000	-0.874	0.382	-0.001	-1.271	0.204	**-6.56E+08**	**-1.986**	**0.047**
EA Interest Rates Spread	**-0.0008**	**-2.477**	**0.013**	**-0.008**	**-3.279**	**0.001**	-0.004	-1.588	0.112	0.000	-0.291	0.771	-0.001	-1.335	0.182	-1.91E+09	-1.556	0.120
EA Liquidity Spreads	*0.0011*	*1.840*	*0.066*	*0.006*	*1.635*	*0.102*	0.012	1.503	0.133	0.002	1.006	0.315	*0.004*	*1.299*	*0.194*	4.87E+08	0.699	0.485
EA Log Business Confidence Index	0.0005	0.073	0.942	0.072	0.674	0.500	**-0.254**	**-2.223**	**0.026**	0.049	1.037	0.300	-0.042	-1.087	0.277	-1.65E+10	-0.752	0.452
EA Log Consumer Confidence Index	*-0.0156*	*-1.821*	*0.069*	-0.218	-1.424	0.155	-0.004	-0.032	0.975	-0.051	-0.744	0.457	-0.040	-0.690	0.490	1.63E+10	0.633	0.526
EA Log Volatility Index	0.0008	0.844	0.399	0.012	1.299	0.194	0.011	0.882	0.378	*0.005*	*1.628*	*0.103*	0.004	0.942	0.346	4.21E+09	1.068	0.285
EA 1-year log Return of Market Price Index	**0.0032**	**2.825**	**0.005**	0.020	1.432	0.152	*0.029*	*1.803*	*0.071*	0.002	0.447	0.655	0.008	1.575	0.115	*6.45E+09*	*1.689*	*0.091*
R-squared	0.81			0.88			0.73			0.73			0.70			0.91		
Constant	-0.0161	-0.391	0.696	1.042	1.187	0.235	-0.076	-0.090	0.928	0.500	1.172	0.241	0.140	0.494	0.621	-2.64E+11	-1.684	0.092
Lagged	**0.7833**	**13.119**	**0.000**	**0.883**	**22.399**	**0.000**	**0.762**	**14.108**	**0.000**	**0.762**	**16.094**	**0.000**	**0.733**	**12.921**	**0.000**	**8.40E-01**	**13.575**	**0.000**
US Short-term Interest Rates	**-0.0003**	**-2.523**	**0.012**	**-0.004**	**-2.854**	**0.004**	-0.002	-1.510	0.131	-0.001	-1.230	0.219	*-0.001*	*-1.619*	*0.105*	**-9.13E+08**	**-2.116**	**0.034**
US Interest Rates Spread	**-0.0005**	**-2.459**	**0.014**	**-0.005**	**-3.039**	**0.002**	-0.002	-0.801	0.423	0.000	-0.591	0.555	-0.001	-0.900	0.368	*-1.43E+09*	*-1.719*	*0.086*
US Liquidity Spreads	0.0011	1.499	0.134	0.006	1.234	0.217	0.008	0.902	0.367	0.001	0.507	0.612	0.003	0.755	0.450	5.64E+08	0.643	0.520
US Log Business Confidence Index	-0.0024	-0.187	0.852	-0.264	-1.418	0.156	-0.080	-0.393	0.694	-0.057	-0.745	0.456	-0.040	-0.606	0.545	-1.80E+10	-0.571	0.568
US Log Consumer Confidence Index	0.0057	0.529	0.597	0.042	0.190	0.850	0.095	0.579	0.562	-0.045	-0.731	0.465	0.011	0.196	0.845	7.36E+10	1.488	0.137
US Log Volatility Index	0.0008	1.002	0.316	0.009	0.810	0.418	0.014	1.231	0.218	0.003	1.030	0.303	0.005	1.290	0.197	4.61E+09	1.218	0.223
US 1-year log Return of Market Price Index	**0.0033**	**2.675**	**0.007**	**0.032**	**2.156**	**0.031**	0.021	1.309	0.190	0.008	1.402	0.161	0.009	1.600	0.110	*6.83E+09*	*1.681*	*0.093*
R-squared	0.81			0.88			0.73			0.73			0.70			0.91		

Sources: BIS, Bloomberg, CSSF, ECB, Eurostat, OECD. Calculation: BCL. Period: March 2005 - December 2020. Notes: This table reports the regression results of the conditional systemic risk measures of IF flow returns under market stress in the euro area. Regressions are run in levels with Newey-West robust standard errors using a Bartlett kernel. A bold coefficient value indicates significance at the 5% level, and an italic coefficient value denotes significance at the 10% level.

Table 5A:

Macroeconomic determinants of Luxembourg IF Flow CoSR measures under market stress in the EA (continued)

	DCoES			CoCR			DCoSI			DCoPCE (AT LEAST 1)			DCoPCE (AT LEAST 2)			DCoES EURO		
	ESTIMATE	tSTAT	pVALUE	ESTIMATE	tSTAT	pVALUE	ESTIMATE	tSTAT	pVALUE	ESTIMATE	tSTAT	pVALUE	ESTIMATE	tSTAT	pVALUE	ESTIMATE	tSTAT	pVALUE
Constant	0.1096	0.991	0.322	1.716	1.063	0.288	1.096	0.737	0.461	1.222	1.947	0.051	0.886	1.348	0.178	-1.48E+11	-0.539	0.590
Lagged	**0.6770**	**7.885**	**0.000**	**0.881**	**18.980**	**0.000**	**0.679**	**9.570**	**0.000**	**0.739**	**15.890**	**0.000**	**0.692**	**9.909**	**0.000**	**8.03E-01**	**10.482**	**0.000**
EA Short-term Interest Rates	**-0.0007**	**-1.995**	**0.046**	-0.004	-1.130	0.258	-0.007	-1.536	0.125	-0.002	-1.118	0.263	*-0.003*	*-1.680*	*0.093*	*-9.36E+08*	*-1.653*	*0.098*
EA Interest Rates Spread	**-0.0010**	**-2.229**	**0.026**	*-0.013*	*-1.729*	*0.084*	-0.009	-1.536	0.124	-0.001	-0.689	0.491	*-0.004*	*-1.671*	*0.095*	-1.58E+09	-1.352	0.176
EA Liquidity Spreads	*0.0006*	*1.624*	*0.104*	0.008	1.272	0.203	0.008	1.171	0.241	0.000	-0.033	0.974	0.002	0.725	0.468	1.88E+08	0.214	0.830
EA Log Business Confidence Index	0.0133	1.557	0.120	*0.153*	*1.637*	*0.102*	**-0.328**	**-1.958**	**0.050**	0.096	1.337	0.181	-0.021	-0.355	0.722	1.21E+09	0.050	0.960
EA Log Consumer Confidence Index	**-0.0470**	**-2.538**	**0.011**	**-0.404**	**-1.990**	**0.047**	-0.250	-1.167	0.243	0.001	0.012	0.990	-0.123	-1.457	0.145	-3.26E+10	-1.083	0.279
EA Log Volatility Index	0.0006	0.674	0.500	0.003	0.291	0.771	0.015	1.099	0.272	0.001	0.298	0.766	0.002	0.495	0.621	1.82E+09	0.760	0.448
EA 1-year log Return of Market Price Index	**0.0045**	**2.828**	**0.005**	0.004	0.155	0.877	0.018	0.741	0.459	-0.009	-1.024	0.306	0.003	0.375	0.708	*7.46E+09*	*1.647*	*0.100*
US Short-term Interest Rates	0.0005	1.598	0.110	0.005	0.941	0.347	0.008	1.462	0.144	0.001	0.627	0.530	*0.003*	*1.624*	*0.104*	8.59E+07	0.141	0.888
US Interest Rates Spread	0.0003	1.083	0.279	0.008	1.062	0.288	0.007	1.177	0.239	0.002	0.716	0.474	*0.003*	*1.611*	*0.107*	-4.28E+08	-0.523	0.601
US Liquidity Spreads	0.0008	1.134	0.257	-0.008	-1.080	0.280	0.009	0.949	0.343	0.000	-0.064	0.949	0.002	0.557	0.577	6.92E+08	0.615	0.538
US Log Business Confidence Index	0.0069	0.471	0.637	-0.315	-1.442	0.149	0.275	1.138	0.255	**-0.217**	**-2.226**	**0.026**	-0.025	-0.265	0.791	1.96E+10	0.554	0.580
US Log Consumer Confidence Index	0.0022	0.101	0.920	0.191	0.595	0.552	0.060	0.185	0.853	-0.139	-1.170	0.242	-0.024	-0.180	0.858	4.13E+10	0.715	0.474
US Log Volatility Index	0.0009	1.331	0.183	0.013	1.138	0.255	0.004	0.395	0.693	0.003	0.668	0.504	0.004	1.045	0.296	3.97E+09	1.425	0.154
US 1-year log Return of Market Price Index	-0.0012	-1.051	0.293	0.025	0.978	0.328	0.016	0.597	0.550	*0.018*	*1.838*	*0.066*	0.010	1.090	0.276	-6.23E+08	-0.176	0.860
R-squared	0.83			0.89			0.75			0.74			0.71			0.92		

Sources: BIS, Bloomberg, CSSF, ECB, Eurostat, OECD. Calculation: BCL. Period: March 2005 - December 2020. Notes: This table reports the regression results of the conditional systemic risk measures of IF flow returns under market stress in the euro area. Regressions are run in levels with Newey-West robust standard errors using a Bartlett kernel. A bold coefficient value indicates significance at the 5% level, and an italic coefficient value denotes significance at the 10% level.

Moving to the regression results of the CoSR measures for NAV returns for the EA macro variables shown in Table 5B, with the exception of market volatility, other EA macro variables were significant for at least one of these measures. *Δ€CoES* was driven by short-term interest rates and interest rate spreads, while *ΔCoES* was also well explained by the interest rate spread and market returns. In addition, liquidity spreads played an important role in *ΔCoSI* and *Δ€CoPCE*. The concentration risk, *CoCR* captured the search-for-yield behavior of investors under market stress driven by short-term interest rates, interest rate spreads, consumer confidence, business confidence and market returns. When these CoSR measures were regressed on US macro variables, in contrast to flow returns, the number of significant variables increased (e.g., consumer confidence). However, the EA macroeconomic variables remained the primary determinants when considering all macro variables from both the EA and the US. It is interesting to note that the signs of some significant US macro variables were opposite of those of the EA. This was the case, for example, for the short-term interest rates, the interest rate spread and business confidence index and likely reflects the risk transmission mechanism, which is not further explored in this study.

Table 5B:

Macroeconomic determinants of Luxembourg IF NAV CoSR measures under market stress in the EA

	DCoES			CoCR			DCoSI			DCoPCE (AT LEAST 1)			DCoPCE (AT LEAST 2)			DCoES EURO		
	ESTIMATE	tSTAT	pVALUE	ESTIMATE	tSTAT	pVALUE	ESTIMATE	tSTAT	pVALUE	ESTIMATE	tSTAT	pVALUE	ESTIMATE	tSTAT	pVALUE	ESTIMATE	tSTAT	pVALUE
Constant	0.016	0.200	0.841	0.060	0.175	0.861	0.466	0.700	0.484	0.676	2.025	0.043	0.283	1.084	0.278	-4.75E+11	-1.545	0.122
Lagged	**0.669**	**8.217**	**0.000**	**0.802**	**17.300**	**0.000**	**0.761**	**16.162**	**0.000**	**0.616**	**6.825**	**0.000**	**0.697**	**8.726**	**0.000**	**8.50E-01**	**12.551**	**0.000**
EA Short-term Interest Rates	0.000	0.882	0.378	**-0.003**	**-3.189**	**0.001**	-0.002	-1.185	0.236	0.000	-0.306	0.759	0.000	-0.689	0.491	**-2.30E+09**	**-2.080**	**0.038**
EA Interest Rates Spread	**-0.002**	**-2.383**	**0.017**	**-0.006**	**-2.309**	**0.021**	*-0.005*	*-1.644*	*0.100*	-0.001	-0.779	0.436	*-0.002*	*-1.616*	*0.106*	*-5.22E+09*	*-1.628*	*0.104*
EA Liquidity Spreads	0.001	1.204	0.229	-0.002	-0.588	0.556	**0.013**	**2.110**	**0.035**	**0.008**	**2.538**	**0.011**	**0.005**	**2.363**	**0.018**	-8.21E+08	-0.524	0.600
EA Log Business Confidence Index	0.000	-0.017	0.986	**0.133**	**2.238**	**0.025**	-0.012	-0.110	0.913	-0.053	-1.165	0.244	-0.007	-0.190	0.849	-2.21E+10	-0.369	0.712
EA Log Consumer Confidence Index	-0.004	-0.195	0.846	*-0.136*	*-1.744*	*0.081*	-0.072	-0.536	0.592	-0.078	-1.420	0.156	-0.046	-0.998	0.318	1.21E+11	1.308	0.191
EA Log Volatility Index	0.004	1.344	0.179	0.009	1.163	0.245	0.008	0.571	0.568	0.004	0.858	0.391	0.003	0.706	0.480	1.19E+10	1.270	0.204
EA 1-year log Return of Market Price Index	*0.004*	*1.820*	*0.069*	**0.017**	**2.014**	**0.044**	0.008	0.504	0.614	0.002	0.390	0.697	-0.001	-0.127	0.899	1.04E+10	1.087	0.277
R-squared	0.78			0.89			0.73			0.81			0.78			0.95		
Constant	-0.003	-0.021	0.983	-1.111	-1.920	0.055	-1.052	-1.011	0.312	0.642	1.604	0.109	0.030	0.078	0.938	-1.67E+12	-2.419	0.016
Lagged	**0.738**	**9.641**	**0.000**	**0.874**	**28.372**	**0.000**	**0.743**	**14.986**	**0.000**	**0.657**	**8.482**	**0.000**	**0.678**	**8.137**	**0.000**	**8.45E-01**	**12.416**	**0.000**
US Short-term Interest Rates	0.000	-0.785	0.432	**-0.002**	**-1.992**	**0.046**	-0.003	-1.558	0.119	**-0.001**	**-2.044**	**0.041**	*-0.001*	*-1.644*	*0.100*	-2.50E+09	-1.853	0.064
US Interest Rates Spread	*-0.001*	*-1.779*	*0.075*	-0.002	-1.172	0.241	-0.004	-1.589	0.112	*-0.001*	*-1.797*	*0.072*	**-0.001**	**-2.050**	**0.040**	*-3.75E+09*	*-1.668*	*0.095*
US Liquidity Spreads	*0.001*	*1.836*	*0.066*	0.001	0.318	0.750	0.011	1.366	0.172	0.005	1.312	0.190	0.004	1.417	0.157	-2.08E+08	-0.128	0.898
US Log Business Confidence Index	-0.024	-0.699	0.485	0.018	0.155	0.876	0.107	0.444	0.657	-0.023	-0.293	0.770	0.013	0.174	0.862	2.73E+10	0.326	0.744
US Log Consumer Confidence Index	0.024	0.747	0.455	*0.227*	*1.782*	*0.075*	0.137	0.720	0.472	*-0.103*	*-1.684*	*0.092*	-0.012	-0.233	0.816	*3.30E+11*	*1.886*	*0.059*
US Log Volatility Index	0.003	1.362	0.173	0.010	1.459	0.145	0.014	1.042	0.297	0.006	1.304	0.192	0.006	1.461	0.144	1.53E+10	1.559	0.119
US 1-year log Return of Market Price Index	**0.006**	**2.052**	**0.040**	**0.020**	**1.923**	**0.054**	-0.003	-0.202	0.840	0.002	0.334	0.738	-0.002	-0.334	0.738	1.13E+10	1.165	0.244
R-squared	0.77			0.89			0.74			0.81			0.79			0.95		

Sources: BIS, Bloomberg, CSSF, ECB, Eurostat, OECD. Calculation: BCL. Period: March 2005 - December 2020. Notes: This table reports the regression results of the conditional systemic risk measures of IF NAV returns under market stress in the euro area. Regressions are run in levels with Newey-West robust standard errors using a Bartlett kernel. A bold coefficient value indicates significance at the 5% level, and an italic coefficient value denotes significance at the 10% level.

Table 5B:

Macroeconomic determinants of Luxembourg IF NAV CoSR measures under market stress in the E (continued)

	DCoES			CoCR			DCoSI			DCoPCE (AT LEAST 1)			DCoPCE (AT LEAST 2)			DCoES EURO		
	ESTIMATE	tSTAT	pVALUE	ESTIMATE	tSTAT	pVALUE	ESTIMATE	tSTAT	pVALUE	ESTIMATE	tSTAT	pVALUE	ESTIMATE	tSTAT	pVALUE	ESTIMATE	tSTAT	pVALUE
Constant	0.140	0.692	0.489	-0.029	-0.027	0.979	-0.310	-0.197	0.844	1.784	2.409	0.016	0.806	1.503	0.133	-1.25E+12	-2.041	0.041
Lagged	**0.609**	**7.081**	**0.000**	**0.748**	**12.507**	**0.000**	**0.696**	**11.795**	**0.000**	**0.552**	**6.651**	**0.000**	**0.596**	**7.107**	**0.000**	**8.08E-01**	**11.313**	**0.000**
EA Short-term Interest Rates	*-0.001*	*-1.674*	*0.094*	**-0.007**	**-2.025**	**0.043**	-0.005	-0.952	0.341	-0.003	-1.591	0.112	*-0.003*	*-1.669*	*0.095*	**-2.76E+09**	**-1.679**	**0.093**
EA Interest Rates Spread	**-0.003**	**-2.957**	**0.003**	**-0.011**	**-2.190**	**0.029**	-0.004	-0.604	0.546	0.000	-0.026	0.979	-0.001	-0.653	0.514	**-5.79E+09**	**-2.055**	**0.040**
EA Liquidity Spreads	0.001	0.830	0.406	-0.003	-0.541	0.589	0.014	1.463	0.143	*0.005*	*1.785*	*0.074*	*0.004*	*1.655*	*0.098*	1.52E+09	0.541	0.589
EA Log Business Confidence Index	*0.031*	*1.606*	*0.108*	**0.330**	**3.025**	**0.002**	0.154	1.053	0.292	0.043	0.647	0.517	*0.088*	*1.813*	*0.070*	1.45E+10	0.259	0.795
EA Log Consumer Confidence Index	**-0.079**	**-2.542**	**0.011**	**-0.518**	**-2.907**	**0.004**	**-0.660**	**-2.736**	**0.006**	-0.145	-1.582	0.114	**-0.236**	**-2.826**	**0.005**	-6.41E+10	-1.075	0.282
EA Log Volatility Index	0.002	1.091	0.275	-0.003	-0.378	0.705	0.002	0.166	0.868	-0.001	-0.217	0.828	-0.003	-0.607	0.544	1.85E+09	0.376	0.707
EA 1-year log Return of Market Price Index	**0.008**	**2.135**	**0.033**	**0.038**	**2.189**	**0.029**	0.028	1.250	0.211	0.004	0.506	0.613	0.003	0.387	0.699	1.06E+10	1.073	0.283
US Short-term Interest Rates	**0.001**	**2.123**	**0.034**	0.005	1.284	0.199	0.005	0.753	0.452	0.002	0.913	0.361	0.002	1.217	0.224	7.72E+08	0.504	0.614
US Interest Rates Spread	0.001	1.431	0.152	*0.007*	*1.698*	*0.089*	0.002	0.250	0.802	0.000	0.163	0.870	0.001	0.474	0.636	3.24E+08	0.155	0.876
US Liquidity Spreads	0.000	-0.108	0.914	-0.001	-0.228	0.820	0.002	0.167	0.868	0.004	1.094	0.274	0.001	0.397	0.692	-2.59E+09	-0.863	0.388
US Log Business Confidence Index	-0.004	-0.126	0.899	-0.043	-0.235	0.815	0.138	0.478	0.632	-0.122	-1.137	0.256	-0.069	-0.782	0.434	6.14E+10	0.902	0.367
US Log Consumer Confidence Index	0.021	0.444	0.657	0.245	1.000	0.318	0.449	1.199	0.230	-0.145	-1.021	0.307	0.052	0.473	0.636	*2.51E+11*	*1.666*	*0.096*
US Log Volatility Index	*0.003*	*1.804*	*0.071*	**0.017**	**2.411**	**0.016**	0.017	1.389	0.165	0.007	1.510	0.131	**0.009**	**2.443**	**0.015**	**1.62E+10**	**2.000**	**0.046**
US 1-year log Return of Market Price Index	-0.003	-0.957	0.339	-0.025	-1.316	0.188	-0.031	-1.338	0.181	0.001	0.117	0.907	-0.004	-0.597	0.551	6.26E+08	0.076	0.939
R-squared	0.80			0.90			0.75			0.82			0.80			0.96		

Sources: BIS, Bloomberg, CSSF, ECB, Eurostat, OECD. Calculation: BCL. Period: March 2005 - December 2020. Notes: This table reports the regression results of the conditional systemic risk measures of IF NAV returns under market stress in the euro area. Regressions are run in levels with Newey-West robust standard errors using a Bartlett kernel. A bold coefficient value indicates significance at the 5% level, and an italic coefficient value denotes significance at the 10% level.

Overall, the CoSR measures were driven mostly by the EA macroeconomic variables,[154] and the predictive regressions provide some support for the findings relative to short-term interest rates, interest rate spreads, liquidity risk, consumer confidence and market returns in the EA. The results seem to be dominated by the GFC of 2007-2009, the European sovereign debt crisis and the recent the COVID-19 pandemic when the market was under stress and investors' portfolios were more correlated.

154 In a separate robust test, we regress the CoSR measures under market stress in the US on the same set of macro variables from both the EA and the US. We find that the EA macroeconomic variables were still the dominant determinants compared with those of the US.

5. CONCLUSIONS AND MACRO-PRUDENTIAL POLICY IMPLICATIONS

In this paper, a set of measures for assessing systemic risk in the Luxembourg investment fund sector is proposed. The framework is based on a dynamic multivariate copula approach, which calibrates the shocks by focusing on the conditional expected returns and forward-looking conditional systemic risk measures not only for each category of investment fund but also for the investment fund sector (consisting of seven categories of investment funds).

We show that the CoSR measures were similar, on average, under market stress in the EA as those in the US, while the impacts from China are much more muted. However, the impacts from China on the concentration risk in both flows and NAVs were also strong, reflecting the increasing global market share of the Chinese equity markets. Our results suggest that all CoSR measures under market stress in the EA deteriorated since the beginning of 2020, but improved quickly upon the EA prompt and decisive policy support. Nevertheless, the deceleration in the improvement of systemic risk towards the end of 2020 could be interpreted as a sign that market participants were becoming increasingly concerned about the cumulative impact of the persistence of COVID-19 pandemic shocks on the global economy. The interactions between these CoSR measures and macroeconomic variables also shed light on the links between fund flows and market valuation effects, market uncertainty, macroeconomic risks and financial distress.

The framework provides a possible addition to the financial stability toolkit for assessing risks in the investment fund sector. In addition, this study provides the basis for a monitoring toolkit that can track changes in systemic risk in the investment fund sector, with a view to identifying the build-up of vulnerabilities. Given that this paper's approach explicitly links the systemic risk measures with the state of the macroeconomy, it can help to facilitate a more informed assessment of the policy responses to rising stress in investment funds.

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