Financial stability

Interconnectedness in the EU fund industry

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Summary

The COVID-19 turmoil has highlighted the risks of market-wide stress, not least for investment funds. This article assesses the connectedness among EU fixed-income funds. Our empirical results suggest high spillover effects, indicating that funds exposed to less liquid asset classes are more likely to be affected by shocks originating in other markets than funds invested in more liquid assets. Alternative funds are found to be the main transmitters of shocks, while high yield (HY) and corporate bond funds were net shock receivers during the COVID-19 market stress.

Introduction

Since the Global Financial Crisis, the size of the EU investment fund industry has expanded from EUR 5.3tn in 2008 to EUR 17.7tn in 2019. In EU, investors can benefit from the possibility of investing in a wide range of asset classes within advanced regulatory frameworks (UCITS or AIFMD).

The increasing importance of the asset management industry has also put the attention on potential financial stability risks arising from investment funds. This has been a concern during the COVID-19 outbreak as the prospects of a severe economic downturn triggered a significant deterioration of liquidity in some segments of the fixed income markets combined with large-scale investment outflows from investors in the EU investment fund industry.

Funds could present risks to financial stability through two main channels. The first one relates to liquidity mismatch, whereby some funds offer daily liquidity to investors while investing in less liquid asset classes.[112] In the event of large redemptions, fund managers might face difficulties in selling their assets, resulting in potential downward pressure on prices. The second one relates to the market footprint of funds: the sales of securities by funds could move markets owing to the size of the fund holdings compared with the absorption capacity of the market. While the action of one fund is unlikely to have an impact on markets, the simultaneous action of multiple funds could have a large impact (ESMA, 2019a).

In that context, it is crucial to assess contagion risk within the fund sector: if spillovers within the fund industry are high during stressed periods, several funds will have to sell assets at the same time, resulting in potentially large price moves and risks to financial stability. In the context of fallen angels (IG bonds downgraded to HY), ESMA (2020) shows how the sales of corporate bonds by investment funds could result in exerting downward pressure on the underlying assets.

We estimate spillovers within the EU fund industry by focusing mainly on fixed income UCITS: they account for a large share of the UCITS universe, are invested in a broad range of assets with varying degrees of liquidity, are exposed to market shocks, credit risk and are more vulnerable to change in investor sentiment.

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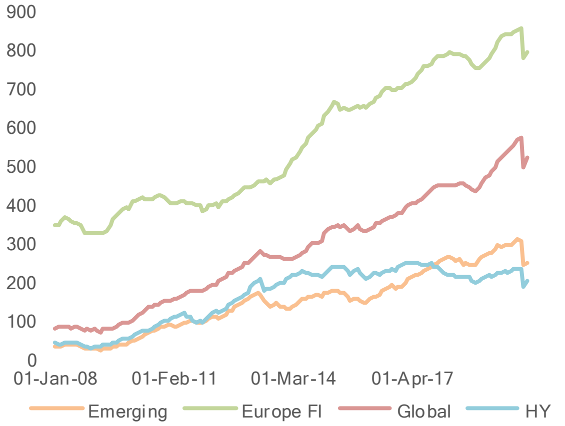
[112] Existing Union rules include specific obligations on fund management companies with respect to liquidity risk management in relation to the funds that they manage, in order to ensure that the liquidity profile of the investment of the fund is coherent with its redemption policy.

The size of the UCITS fixed income fund industry increased from around EUR 500bn at the beginning of 2008 to EUR 1,955bn at the end of January 2020 (RA.1). Over this period, the composition of the fund industry changed with an increase in the proportion of HY and EM bond funds (from 6% to 12%, and from 5% to 16% respectively). During the ongoing low interest rate environment, fixed income funds have also reduced their holdings of cash and cash equivalent assets that provide little or no income in an effort to improve returns.

At the end of March 2020, in the wake of the market turmoil triggered by the COVID-19 outbreak, the size of EU fixed income funds fell to EUR 1,700bn. With respect to the beginning of the year, fixed income net assets decreased by 12% (20% for HY and EM).

RA.1
Fixed income funds
Increase in size over time



Note: NAV of fixed income funds aggregated by style, in EUR bn.
Sources: Morningstar, ESMA.

Interconnectedness and contagion

Interconnectedness and contagion are different concepts. Interconnectedness refers to linkages between financial institutions or markets regardless of market conditions. Contagion is defined as a significant increase in cross-market links owing to a shock occurring in one market or asset (Forbes and Rigobon, 2002; Pericoli and Sbracia, 2003).[113]

Interconnectedness analysis is usually divided into two groups depending on the type of data used: exposure-based analysis and market-based analysis. Exposure-based analyses require granular data showing the interconnectedness between institutions and markets. For example, Clerc et al. (2014) use data on CDS exposures to map the European CDS network. More recently, ESMA (2019b) uses EMIR data to estimate exposures in derivatives markets. The main advantage of exposure-based analysis is to provide a direct overview of the linkages between entities. However, data on exposures are not always available or consistent across institutions, and are not usually timely reported.

As an alternative, market-based measures of interconnectedness uncover indirect linkages between financial institutions and markets based on investor perceptions, which are reflected in prices.

There is an extensive body of literature investigating inter-market transmissions and the relationships among different financial market segments (see Bricco and Xu (2019) for an overview). The existing studies could be loosely divided into two groups, long-run cointegration approaches and short-run GARCH analyses. Cointegration analyses aim to examine the existence of stable relationships in the long run, but are not able to capture the time varying characteristics of shock spillovers when these relationships change.

Within the range of GARCH analyses, the approach developed by Diebold and Yilmaz (2009, 2012, 2014) (DY hereafter) provides a flexible framework that can be applied to investment funds and markets. This methodology allows a large number of variables to investigated simultaneously as well as the rich dynamics of spillovers to be characterized and has some appealing properties:

- Variance decompositions are used to define connectedness measures, showing how much of the future uncertainty associated with the stress in asset i is owing to stress shocks in asset j;
- These measures relate to other widely used risk measures such as CoVaR (Adrian and

[113] An exhaustive description of the different definitions of contagion is provided by Pericoli and Sbracia (2003).

Brunnermeier, 2016) and marginal expected shortfall (Acharya et al., 2017);

— They are relatively fast to adapt to changes in the data owing to their high predictive power (Arsov et al.,2013).

RA.2 provides an overview of the econometric model used to estimate volatility spillovers between markets or institutions. This framework has been used to measure dynamic connectedness across institutions such as GSIBs (IMF, 2017), or banks and insurance (IMF, 2016), as well as across markets (Gentile and Giordano, 2012).

In the next section we use the DY framework and apply it to the fund industry to estimate how EU funds are connected across fund categories in normal times, and to assess whether or not the COVID-19 crisis has led to contagion effects within EU funds.

RA.2
Estimation of interconnectedness

Overview of Diebold and Yilmaz (2012, 2014) framework

Extending their 2009 methodology, DY 2012 examine volatility spillovers by developing a revised spillover measure based on the generalized impulse response approach of Koop, Pesaran, and Porter (1996) and Pesaran and Shin (1998). The forecast error variance decompositions produced by this version are independent to variable ordering. The DY approach is based on three different measures of interconnectedness:

i) Pairwise directional connectedness (interlinkages between two entities or markets);
ii) System-wide connectedness (overall level of connectedness in the systen);
iii) System-wide directional spillovers (how individual shocks are transmitted to the system and how shocks to the system are transmitted to individual entities).

The authors use a Variance Autoregression model (VAR) based on the standard deviations of the market returns to estimate the different measures of connectedness. The VAR is then used to decompose the volatity forecast error variance: how much of the variation in the volatility of A can be explained by B?

Formally, the VAR model is given by:

$$x_t = \sum_{i=1}^{p} \Phi_i x_{t-i} + \varepsilon_t$$

where x_t is a vector of return volatility.

After estimating the VAR, the generalized forecast error variance is decomposed to identify the contribution of each variable to the other variables.

Variable j's contribution to variable i's H-step-ahead generalised forecast error variance is given by:

$$\theta_{i,j}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \Sigma A'_h e_i\right)}$$

where Σ is the covariance matrix for the error vector ε, σ_{jj} is the standard deviation of the error term for the j^{th} equation and e_i is the selection vector with one as the i^{th} element and zeros otherwise.

For the purpose of our analysis, we follow DY (2014) and perform the VAR estimation on a system of log-volatilities of financial indices with automatic selection of the LASSO penalty using cross-validation.

The connectedness measures can then be directly computed:

Total connectedness:

$C^H = \frac{\sum_{i,j=1, i\neq j}^{N} \tilde{\theta}_{i,j}^{g}(H)}{\sum_{i,j=1,}^{N} \tilde{\theta}_{i,j}^{g}(H)}$ [**System-wide** connectedness]

Example: How has connectedness across US and EU equity markets evolved over time?

Inward connectedness:

$C_{i\leftarrow \cdot}^{H} = \frac{\sum_{j=1,\, j\neq i}^{N} \tilde{\theta}_{i,j}^{g}(H)}{\sum_{i,j=1,}^{N} \tilde{\theta}_{i,j}^{g}(H)}$ [Uncertainty of *i* **FROM** the system]

Example: How does a fund category react to shocks from another segment of the fund industry?

Outward connectedness:

$C_{\cdot\leftarrow i}^{H} = \frac{\sum_{j=1,\, j\neq i}^{N} \tilde{\theta}_{j,i}^{g}(H)}{\sum_{i,j=1,}^{N} \tilde{\theta}_{j,i}^{g}(H)}$ [Uncertainty of *i* **TO** the system]

Example: Which market segment contributes more to shocks in other market segments?

Net connectedness:

$C^H = C_{\cdot\leftarrow i}^{H} - C_{i\leftarrow \cdot}^{H}$ [Difference between shocks **TO** and **FROM**

Pairwise directional connectedness:

$C_{i\leftarrow j}^{H} = \tilde{\theta}_{i,j}^{g}(H)$ [Uncertainty of ***i*** related to ***j***]

Example: How is the German equity market connected to the US market?

Interconnectedness in the EU fund industry

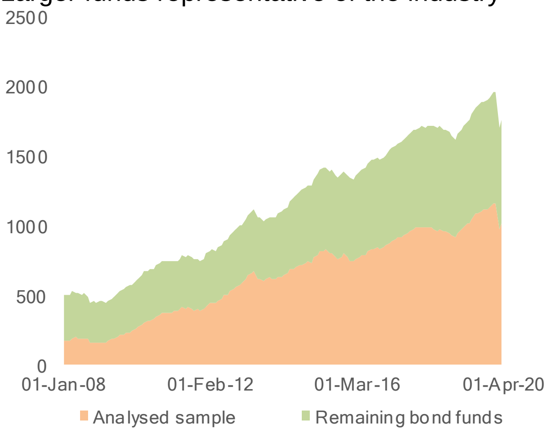
This section describes the data used for our analysis and presents results for connectedness of EU bond and multi-asset UCITS, with a special focus on recent developments during the COVID-19 market crisis.

Sample

We use a sample of UCITS fixed income and multi-asset funds sourced from Morningstar. with data from January 2008 to April 2020. Returns and fund values are sampled at a weekly frequency to avoid day-of-the-week effects. Given the diversity of fixed income UCITS, funds are split into four different categories: HY bond funds, EM bond funds, IG corporate bond funds and government bond funds. Multi-asset funds are included as they also invest in fixed income instruments. These are mixed funds that invest in both equity and bonds, and funds that apply investment strategies that are comparable to hedge funds (alternative UCITS). The latter consist of investment vehicles that may gain exposure to a variety of assets via derivatives, base their investment decisions on market valuations and the macro-economic environment, or eventually profit from changes in the credit conditions in bond markets using derivatives, such as CDS and IRDs, to hedge systematic risk in credit and interest rate markets.

The final sample includes 3,280 funds with a NAV of more than EUR 150mn and with a minimum 12-month track record of performance. Overall, bond funds used in the analysis account for a share of the EU fixed income industry varying from 35% at the beginning of 2008 to 60% in 2020 (RA.3).

RA.3
Fixed income funds' sample
Larger funds representative of the industry



Note: Representativieness of analysed sample over time, EUR bn.
Sources: Morningstar, ESMA.

For each fund category, we build a weekly value-weighted return:

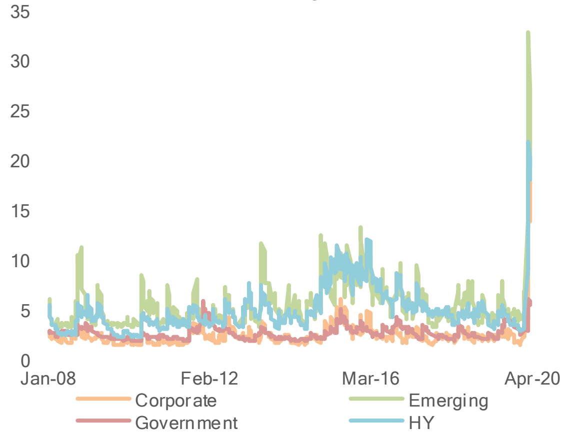
$$r_t^C = \sum_{t=1}^{N} \left(\frac{AuM_{i,t} * Return_{i,t}}{\sum_{i=1}^{N} AuM_{i,t}} \right)$$

where N corresponds to the number of funds per category, and fund values and returns are denominated in euro.

The value-weighted return can then be used to extract the corresponding volatilities and examine their spillover effects using a parsimonious model setting, which also eases the interpretation of results.

The return volatilities are first estimated by filtering the weekly value-weighted fund returns and the Eurostoxx600 with an ARMA(1,1)-GARCH(1,1) model. The returns are then annualised (RA.4)

RA.4
Annualised return volatilities
Extreme movements during COVID-19 crisis



Note: Annualised volatility of fixed income funds, in %.
Sources: Consob, ESMA.

Connectedness across EU funds

The volatility connectedness table estimated following DY (2012, 2014) provides an overview of the average spillover effects across the analysed fund categories over the considered period (RA.5). The estimates of spillovers allow to assess to which extent volatility shocks spread from one fund category and which funds are more likely to receive them.

Table RA.5 displays the following types of connectedness for our sample across the entire period from 2008 to 2020:

- Own-connectedness: the fraction of the estimated volatility of category i that is owing to its own shocks, hence representing the own-connectedness of each fund category. This is represented by the elements on the diagonal of the table (i.e. i = j), e.g. for corporate bond funds this is 34.0%.
- Shock transmission – directional spillover TO others
- Shock receiver – directional spillover FROM others
- Net spillovers – difference between shock transmission and shock reception.

Typically, own-connectedness is the largest individual elements in the table. However, the total directional connectedness, the aggregated connectedness FROM others or TO others, tends to be much larger.

RA.5
Volatility spillover table

	Alternative	Corporate	Emerging	Government	HY	Mixed	Eurostoxx 600	Directional spillovers from others
Alternative	35.9	10.8	10.1	1.1	17.5	18.7	5.9	64.1
Corporate	13.8	34.0	13.0	6.1	18.0	11.1	3.9	66.0
Emerging	12.9	13.6	33.4	2.2	20.5	12.4	5.0	66.6
Government	5.4	15.6	6.1	58.4	4.9	6.1	3.5	41.6
HY	18.8	15.1	17.4	1.3	30.7	13.0	3.8	69.4
Mixed	18.8	9.3	10.0	1.4	11.9	29.9	18.7	70.1
Eurostoxx600	7.8	3.1	5.9	0.7	4.0	30.0	48.5	51.5
Directional spillovers to others	77.5	67.5	62.4	12.8	76.9	91.3	40.8	61.3
Net spillovers	13.5	1.5	-4.2	-28.8	7.6	21.2	-10.7	

Note: Connectedness table of the full sample, in %.
Source: Consob, ESMA.

The total connectedness, or spillovers, for the entire period of analysis indicates the degree of connectedness of the system. As shown in the bottom right corner of RA.5, total connectedness, is 61%, pointing to a high level of interconnectedness in the EU bond fund market. In other words, around 61% of the volatility forecasted can be attributed to spillovers among the different fund categories. The remaining 39% is explained instead by idiosyncratic and external shocks.

The methodology adopted enables us to learn about the direction of volatility spillovers across fund strategies and the stock market. Directional spillovers help to further uncover the transmission mechanism, as we can decompose the total spillovers into those coming FROM (shock reception) or going TO (shock transmission) a particular asset class in the system.

The values in the last column of RA.5, i.e. the total directional FROM connectedness, are the share of volatility shocks received by each of the six categories and the stock index FROM other fund types.[114] The total directional FROM connectedness ranges between 51.6% and 70%, showing that for all fund strategies a relatively high share of variance comes from other markets. In particular, funds exposed to less liquid asset classes (HY, EM or corporate bonds funds) are the most affected by the volatility shocks in other investment funds. In contrast, only 40% of government bond funds volatility is explained by stress from other fund categories.

The values in the ‘Spillover TO’ row of RA.5 represent the total directional connectedness transmitted from each fund type TO the others. These spillovers differ substantially across fund types. The analysis suggests that mixed, alternative and HY funds are the highest transmitters of spillovers. Government bonds funds appear again at the other end of the spectrum: they seem to transmit relatively little spillovers to other fund categories.

Finally, the last row in RA.5 provides the net total directional connectedness, which results from the difference between total connectedness TO other funds and total connectedness FROM other funds. Mixed, alternative, HY and corporate funds tend to be net transmitters of shocks to the system as their net total connectedness is positive over the reference period with mixed and

[114] The total directional FROM connectedness is equal to 100% minus the own share of the total forecast error variance by definition and represent the percentage of the forecast-error variance that come from other markets.

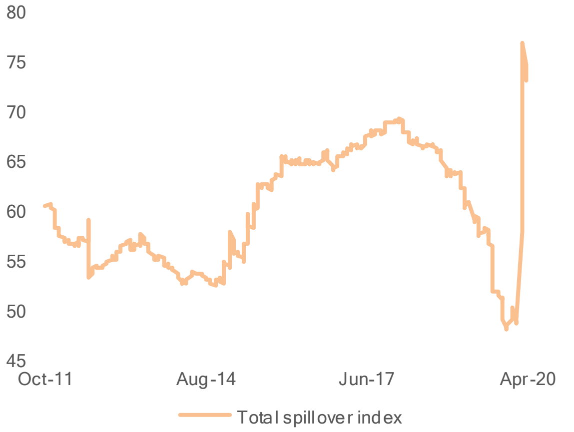
alternative funds showing the highest shock transmission levels at 21% and 14% respectively. The shock transmission of HY and corporate bond funds appears more limited at 8% and 2% respectively. The remaining bond fund types display a negative level of net connectedness, indicating that they are net receivers of shocks.

Time varying spillover indices

The full-sample connectedness table covers the entire sample period and thus does not capture the dynamics of connectedness. A rolling sample framework can be used to create a dynamic total spillover index and assess the variation of volatility spillovers within the system over time.[115]

The dynamic total spillover index shows that large contagion effects occurred in March 2020: while overall spillovers had been declining since 3Q17, spillovers shot up in March 2020 to reach their highest levels observed (RA.6).

RA.6
Dynamic total volatility spillover
Historical maximum in March 2020

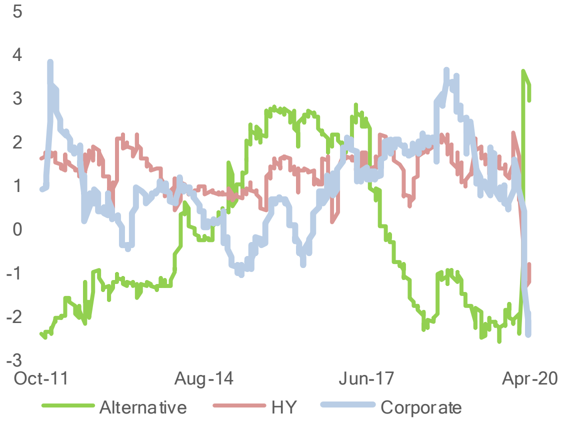


Note: Total dynamic connectedness among EU fixed income funds, mixed funds, funds pursuing alternative-like strategies and Eurosotxx600, in %.
Sources: Consob, ESMA.

The net dynamic directional spillover indices show whether different types of bond funds have tended to be shock transmitters (value >0%) or receivers (value <0%) over the sample period.

The analysis indicates that UCITS pursuing alternative strategies were shock receivers for a large period of time, especially from around mid-2017 to early 2020. However, they became shock transmitters, i.e. their contribution to the propagation of shocks increased drastically, at the start of the COVID-19 related market turmoil (RA.7). Such high effects could be related to the use of derivatives by alternative funds: liquidity deteriorated quickly in the derivative markets amid high volatility. As funds faced mark-to-market losses on their derivatives positions, they also experienced significant variation margins on those positions, which required funds to raise cash by drawing on their buffers or by selling assets, thereby affecting markets. The net contribution to volatility of HY and IG corporate bond funds somehow shows an opposite pattern as well as a lower degree of variation over the analysed period. Both HY and corporate bond funds were shock transmitters during most of the sample period, however they became shock receivers at the start of the COVID-19 related market turmoil in early 2020.

RA.7
Net dynamic directional spillovers
HY and corporate net receiver during crisis



Note: Net dynamic directional spillovers to others, in %.
Sources: Consob, ESMA.

Conclusion

This article aimed to assess the level of connectedness among EU fixed income funds using a methodological framework based on Diebold and Yilmaz (2012, 2014) that allows to identify which type of funds are shock receivers and shock transmitters.

This has been partly motivated by the acute market stress faced by investment funds during the COVID-19-related market turmoil in March 2020, with high outflows and valuation uncertainty, which has shown that different

[115] In line with prevailing literature, we used a 200-week rolling window (corresponding to about 4 years) with a 10-week-ahead forecasting horizon to capture the dynamics of spillovers.

segments of the EU fund industry can face stress at the same time.

Our empirical results, based on data covering the period from 2008 to 2020 point to high spillover effects, indicating that funds exposed to less liquid asset classes are more likely to be affected by shocks originating in other markets. The evolution of the spillover indices during the COVID-19 market stress suggests that alternative UCITS on average acted as transmitters of shocks, while HY and corporate bond funds tended to be net receivers.

Going forward, this framework can be used for monitoring stress transmission and identifying episodes of intense spill overs within the EU fund industry.

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