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Connectedness among EU investment funds: Insights from time-varying and frequency decomposition spillover indices

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Connectedness in EU investment funds: Insights from time-varying and frequency decomposition spillover indices[♦]

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Abstract

This paper investigates the financial connectedness in the EU fund industry by using the measures of interdependence of volatilities introduced by Diebold and Yilmaz (2009, 2012 and 2014) and frequency decomposition proposed by Barunik and Krehlik (2018). In order to monitor stress transmission and identify episodes of intensive volatility spillovers among different types of funds and their directional changes over time, we build a series of indices spanning from 2008 to 2020 based on a sample of more than 3,000 funds. Our empirical results suggest that government bond funds tend to receive more volatility shocks than they spread. In contrast, funds exposed to less liquid assets tend to be net transmitters of spillovers to other fund categories and they receive larger volatility spillovers than government bond funds. Based on the frequency decomposition of volatility spillovers, we show that increases in spillovers are driven mainly by medium to long-term components indicating the presence of persistence effects. Spillovers across fund categories can change markedly across periods, underlining the need for dynamic risk monitoring. Our findings call for extending the Diebold-Yilmaz framework to address correlation bias and introduce frequency decomposition.

JEL Classifications: G20, G23, G29

Keywords: Investment funds, systemic risk, volatility, risk spillovers, connectedness, frequency dynamics.

♦ The views expressed are those of the authors and do not necessarily reflect the views of the European Securities and Markets Authority. Any error or omissions are the responsibility of the authors.

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Non-technical summary

The increased integration of financial markets and the growth of the European investment fund industry over the last decade have made investment funds a key component of the EU financial system. Shocks faced by funds could propagate to other parts of the fund sector and impact financial stability, as observed during the Covid-19 market stress. Therefore, it is crucial to assess the interconnectedness within the fund sector to identify and monitor systemic risk to maintain financial stability.

Building on existing literature, this paper analyses how volatility shocks are propagated across different types of EU funds. We assess how shocks to some funds spill over to other funds, using data covering a period spanning from 2008 to 2020. Our results show that funds investing in less liquid assets (such as high yield bond funds) or using complex strategies tend to transmit shocks more than funds investing in more liquid assets (such as government bonds funds). In addition, we show that bilateral connectedness between fund categories can change over time and, for some types of funds, tend to increase during stress periods.

From a risk monitoring perspective, our measures can help analysing contagion effects within the fund sector and identify vulnerable funds (net receivers) as well as funds more likely to spread volatility to other funds. Based on our results, supervisory activities aimed at reducing systemic risk can benefit from particularly considering funds which contribute the most to the volatility in the system. Our findings could also be useful when performing system-wide stress testing.

1 Introduction

Since the Global Financial Crisis (GFC), the size of the EU asset management industry has expanded more than fivefold to reach more than EUR 30tn in 2021.[1] The sharp rise reflects valuation effects — as market valuations surged between 2008 and 2021 — and flow effects, as investors have increasingly been using funds as one of their primary savings vehicles. The development of the fund industry contributes to the diversification of the EU financial system and provides retail and institutional investors with a range of investment vehicles that can be used to gain exposures to specific asset classes (equities, bonds etc.) and different investment policies.

As investment funds play a growing role in the financial sector and in the financing of the economy, it is crucial to ensure that the asset management sector is resilient and that financial stability risks arising from funds are mitigated. Risks to financial stability can stem, among others, from liquidity mismatches and corresponding asset sales. Indeed, some funds offer daily liquidity to investors while investing in less liquid asset classes. In the event of large redemptions, fund managers might need to sell large portions of their portfolios, resulting in potential downward pressure on prices. The sales of securities by funds could then move markets due to the size of 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). Some of those risks crystallised during the COVID-19 outbreak, when funds experienced very sharp redemptions and large mark-to-market losses amid heightened levels of volatility (FSB, 2020). 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.

In that context, it is crucial to assess contagion risk within the fund sector. However, estimating contagion related to common exposures is challenging since it requires granular portfolio information, which is often not available. Alternative approaches using market-data have been proposed, such as the connectedness framework developed by Diebold and Yilmaz (2009, 2012, 2016). This type of approach uses return-based information to derive contagion indicators between entities and markets and is tractable and flexible. The Diebold and Yilmaz approach (DY thereafter) has been applied to a range of institutions, including banks (Diebold and Yilmaz, 2014; Bricco and Xu, 2019) and insurance companies (Malik and Xu, 2017), as well as markets such as sovereign CDSs (Bostanci and Yilmaz, 2020) or crypto assets (Ilyer, 2022). However, applications of the DY methodology to the fund industry have been more limited. Bouveret and Yu (2021) apply this framework to a range of US bond mutual funds and provide aggregate results by fund categories.

Our work provides several contributions. First, on the methodological side, we extend the DY methodology by addressing estimation biases arising when correlation increases, and we decompose connectedness indicators over different frequencies, following Barunik and Krehlik (2018). Second, we use connectedness indicators to identify vulnerable fund strategies (e.g. net receivers of spillovers from other funds) and fund strategies which are net spreaders of

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1 See EFAMA, Asset Management Report (2021). EFAMA considers both discretionary mandates and investment funds intended as collective investment undertakings.

shocks. Third, our results indicate that spillovers do vary significantly over time and that fund strategies, such as alternative funds, that are net receivers in calm times can become net spreaders of shocks during periods of market stress. Finally, we exploit the frequency decomposition of connectedness indicators to disentangle short-, medium- and long-term effects and find that the sharp rise in connectedness during stress events such as the Brexit referendum and the Covid-19 stress period in March 2020 was more of a medium-term nature rather than a short-term surge.

The remainder of the paper is organised as follows. Section 2 presents the literature review, while Section 3 explains the methodology adopted. Sections 4 and 5 discuss, respectively the data and the results. Finally, conclusions are offered in Section 6.

2 Literature review

A wide strand of the literature defines contagion as the transmission of shocks beyond what would be explained by fundamentals or common shocks. Masson (2004) defines spillovers as transmissions of crises that cannot be identified with observed changes in macroeconomic fundamentals. Eichengreen et al. (1996), similarly affirm that there is contagion if the probability of market disruption in a given country has risen due to shocks stemming from elsewhere when controlling for macroeconomic fundamentals.

Forbes and Rigobon (2002) argue that contagion is a significant increase in cross-market co-movements after a shock, which cannot be explained by fundamentals. They suggest that contagion and interdependencies can be distinguished by testing the significance of cross-market correlation changes; in particular, they propose a statistical methodology which corrects correlation biases due to heteroskedasticity, endogeneity, and omitted variable issues.

Baig and Goldfajn (1999) perform cross-market correlations among exchange rates, stock returns, interest rates, and sovereign bond spreads using Forbes and Rigobon (2002) methodology. They find evidence about contagion among, in particular, sovereign spreads. Andenmatten and Brill (2011) also perform the test for contagion proposed by Forbes and Rigobon (2002) to examine whether the co-movement among sovereign CDS premiums significantly increased after the beginning of the Greek debt crisis in October 2009. They conclude that in European countries both contagion and interdependence occurred. Gomez-Puig and Sosvilla-Rivero (2011) provide empirical evidence about contagion phenomena during different periods of time from 1999 to 2010 by using a database of daily frequency of yields on 10-year government bonds issued by five EMU countries (Greece, Ireland, Italy, Portugal and Spain). They apply the Granger pairwise causality test among countries and identify contagion episodes as sub-periods of significant increase in causality. Their results suggest that contagion episodes are concentrated around the first year of EMU in 1999, the introduction of euro coins and banknotes in 2002, and the global financial crisis in the late-2000s. Moreover, they also indicate that causality relationships between peripheral EMU yields have significantly risen during crises in sovereign debt markets.

Gentile and Giordano (2012) extend conventional measures of contagion by directly investigating changes in the existence and the directions of causality links among a sample of Euro area countries during the GFC and sovereign debt crises. To test for contagion, the authors apply Granger causality/VECM methodology on sovereign bond spreads and stock returns as measures of perceived country risk. Results highlight that the causality patterns have changed during the crisis periods compared to the pre-crisis ones, thus pointing out the occurrence of structural and long-term contagion phenomena among Euro area countries during the GFC and sovereign debt crises.

Engle et al. (2012) provide evidence regarding equity volatility spillovers in eight East Asian countries before, during and after the Asian Currency Crisis by using a new class of asymmetric volatility models. They underline that there are different approaches which can be followed to analyse volatility interconnectedness. The explanatory approach stems from an a priori hypothesis regarding the timing of the crisis and implies defining a dichotomous variable representing the presence of a crisis which is applied as a dependent variable of probit or logit models (Eichengreen et al.,1996, Caramazza et al., 2004, Van Rijckeghem and Weder, 2001).

The predictive approach, instead, is based on selecting a set of crisis leading indicators representing economic fundamentals (Kaminsky, 1999, Kaminsky et al., 1998, Hardy and Pazarbasoglu, 1998). Moreover, they underline the variety of the methodological approaches applied in the literature to quantify spillovers: correlation analysis (Baig and Goldfajth ,1999), Garch factor model (Dungey and Martin, 2007), VAR EGARCH (In et al., 2001), Factor analysis Gjrgarch (Fernandez-Izquierdo and Lafuente, 2004), Bivariate Multi Chain Markov Switching Model (Gallo and Otranto, 2007).

Diebold and Yilmaz (2009) introduce an innovative methodology to measure contagion which does not focus on return but on volatility time series, that are represented in a VAR econometric framework. The computation of the proposed volatility spillover index relies on the Cholesky decomposition of volatility forecast error variance. The authors in the paper stress the limits of the Cholesky decomposition procedure, whose output depends on the order of the variables in the dataset, and try to overcome these issues by repeating the procedure on several permutated datasets. The proposed methodology allows for both a static and dynamic representation of interdependencies among global stock market volatilities. Diebold and Yilmaz (2012) use a generalized vector autoregressive methodology instead of Cholesky decomposition to avoid variable ordering econometric issues. The proposed approach is applied to measure spillovers across different assets (i.e., U.S. stock, bond, foreign exchange and commodities markets) during around 10 years (from 1999 to 2010). The authors show that cross-market volatility interconnections were quite limited until the global financial crisis that began in 2007 and after the collapse of Lehman Brothers in September 2008.

Diebold and Yilmaz (2016) apply the forecast variance decomposition technique to analyse interconnections among financial institutions in Europe and US in 2004-2014 years by measuring their dynamic during market crisis. From a methodological point of view, the authors show how to efficiently represent the results of variance decomposition through spillover network graphs. Demirer et al. (2017), perform a global bank connectedness analysis by using LASSO methods to avoid the dimensionality problem. Indeed, the authors estimate a high-dimensional network among the world's top 150 banks, in the 2003–2014 period. They show that equity interconnections rose correspondently to market turbulence, with sharp peaks, in particular, during the Great Financial Crisis and the subsequent European Debt Crisis. Cotter et al. (2017), develop a new methodology to analyse spillovers between the real and financial sides of the economy that employs a mixed-frequency modelling approach, which enables high-frequency financial and low-frequency macroeconomic data series to be used simultaneously. By analysing macro-financial spillovers for the US economy, the authors also show that financial markets are typically net transmitters of shocks to the real side of the economy, particularly during market disruptions.

Lastly, macro-financial spillovers are statistically associated with key variables related to financial and macroeconomic fundamentals. Barunik and Krehlik (2018) estimate interconnectedness at different frequencies, following a methodological approach which disentangles short term volatility shocks from spillovers that are persistent and transmitted for longer periods. Their approach stems from a strand of econometric literature which applies spectral decomposition to examine causality relations (Geweke, 1982, Dufour and Renault, 1988, Breitung and Candelon, 2006, Yamada and Yanfeng, 2014). Barunik and Krehlik (2018) economically justify the decomposition of volatility interconnectedness into short- and long-term components on the basis of a wide literature showing that consumption growth, which drives asset prices, can be separated into different cyclical components (Bandi and Tamoni, 2016; Ortu, Tamoni and Tebaldi, 2013). Following Dew-Becker and Giglio (2016), who set asset pricing into the frequency domain, they propose a general framework for decomposing the connectedness to any frequency band of interest. When financial markets process information quickly short-term cyclical behaviour is linked to connectedness created at higher frequencies, while shocks transmitted for longer periods are reflected by lower frequencies. This indicates that systemic risk in the longer term depends on more fundamental shifts in the investor expectations.

Barunik and Ellington (2021) develop a statistical methodology to estimate dynamic networks among economic and financial institutions which relies both on time-varying parameter VAR estimation and on the spectral decomposition setting of Barunik and Krehlik (2018). In this econometric framework a time-varying network at a given frequency band, that is at a specific time horizon, is built up. For each point of time, the output is given, therefore, by multiple short- and long-term network layers which are dynamically estimated.

3 Measuring connectedness: Empirical strategy

Previous studies have shown that crisis periods tend to be characterised by an increase in dynamic correlations and decreasing diversification opportunities (Bekaert et al., 2014; Reboredo et al., 2015; Clements et al., 2015). Moreover, only recently researchers started exploring how volatility spillovers are influenced by financial, economic and political events (see Belke et al., 2016; Baker et al., 2016b; Kelly et al., 2016). Diebold and Yilmaz (2009, 2012 and 2014) have introduced some measures of connectedness that, because of their simplicity for interpretation, help tracking the transmission of volatility shocks across assets and markets, assessing trends and studying both non-crisis and crisis episodes. The connectedness measures indicate how much of the future uncertainty associated with the systemic stress in one asset or market is due to systemic stress shocks in another asset or market. Diebold and Yilmaz (2015) have also shown how these measures of connectedness closely relate to other popular risk measures such as CoVaR (Adrian and Brunnermeier, 2008) and marginal expected shortfall (Acharya et al., 2010).

In this context, we outline the basic principles of the Diebold and Yilmaz interconnectedness method and provides some insights on how the extended framework of Barunik and Krehlík

(2018) allows to uncover the direction and the strength of volatility spillovers, and how spillovers manifests at different time horizons.

Estimating connectedness through volatility spillovers: The Diebold-Yilmaz approach

Our analysis adopts the framework developed by Diebold and Yilmaz (DY) in a series of papers (2009, 2012, and 2014). The spillover measures introduced by Diebold and Yilmaz (2009, 2012) are based on variance decomposition from vector autoregressions (VARs) that traces how much of the future error variance of a variable j is due to innovations in another variable i. More intuitively, the DY spillover measures assess how important a shock is in explaining the variations of the variables in the model, and had been employed to study spillovers in many economic and financial studies. Diebold and Yilmaz (2014) showed that the resulting indices are closely linked to the network theory and to measures of systemic risk, like the CoVaR (Adrian and Brunnermeier, 2016) or the marginal expected shortfall (Acharya et al., 2017).[2] This method relies on the notion of forecast error variance decomposition (FEVD) within the generalized VAR framework proposed by Koop et al. (1996) and Pesaran and Shin (1998) to estimate the magnitude and direction of connectedness in the time domain[3]. This process can be explained as follows. Let us describe a VAR model with n variables and p lags, which can be written as:

$$X_t = \Phi(L)x_t + \epsilon_t \qquad (1)$$

where X_t denotes a $n \times 1$ vector of endogenous variables, $\Phi(L) = \Sigma_h \Phi L^h$ is a $n \times n$ p-th order lag polynomial matrix of coefficients, L is the lag operator and ϵ_t represents a white noise error vector with zero mean and covariance matrix Σ. Assuming covariance stationarity, the process can be represented as a moving average:

$$X_t = \Psi(L)\epsilon_t = \sum_{i=1}^{\infty} \Psi_i \, \epsilon_{t-1} + \epsilon_t \qquad (2)$$

with $\Psi(L)$ being a $n \times n$ matrix of infinite lag polynomials that can be calculated recursively. Diebold and Yilmaz (2012) show that, using the generalised VAR framework of Pesaran and Shin (1998), the H-step ahead generalised FEVD, denoted $d_{ij}(H)$, can be computed as:

$$d_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=1}^{H} ((\Psi_h \Sigma)_{ij})^2}{\sum_{j=1}^{H} (\Psi_h \Sigma \Psi_h')_{ii}} \qquad (3)$$

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2 Diebold and Yilmaz (2014) discuss how the network-based connectedness measures above are related to modern measures of systemic risk. Specifically, the FROM-connectedness measure captures exposures of financial entities to systemic shocks from the network (inward spillover) in a fashion analogous to marginal expected shortfalls, while the TO-connectedness measure captures contributions of financial entities to systemic network events (outward spillover) in a fashion analogous to Delta CoVaR.

3 The generalized variance decomposition is invariant to the ordering of variables and allow to avoid *a priori* assumptions on the sequence of responses to shocks. The generalised variance decompositions does not imply a causal relationship between different variables in a system but identifies instead the associations between variables based on historical relations and correlations.

where σ_{jj} is the standard deviation of the error term of the j-th equation of the VAR, i.e. the j-th diagonal element of the Σ matrix, and Ψ_h is a matrix of moving average coefficients corresponding to the lag h. The $d_{ij}(H)$ indicates the contribution of the j-th variable to the variance of forecast error of the variable i-th at the given horizon. Since the sum of the own- and cross-variance contribution shares does not necessarily equal one, the entries of the variance decomposition matrix can be normalized by the row sum:

$$\tilde{d}_{ij}(H) = \mathrm{C}^{\mathrm{H}}_{\mathrm{i \leftarrow j}} = \frac{d_{ij}(H)}{\sum_{j=1}^{n} d_{ij}(H)} \qquad (4)$$

The normalized variance contribution $\tilde{d}_{ij}(H)$ defined above provides a measure of pairwise connectedness from j to i at horizon H in the time domain. In other words, $\tilde{d}_{ij}(H)$, which we denote as $\mathrm{C}^{\mathrm{H}}_{\mathrm{i \leftarrow j}}$, captures the extent to which the variations in i's returns or volatility can be explained by j. The pairwise connectedness from j to i can be conveniently used to build measures of the degree of connectedness among the variables in the system. Based on the generalised FEVD, the system-wide (or total) connectedness measures how important in aggregate system are spillovers and is given by:

$$Total\ spillover: C^{H} = \frac{1}{N} \sum_{i,j \neq i} \tilde{d}_{ij}(H) = \frac{\sum_{i,j=1,i \neq j}^{N} \tilde{d}_{ij}(H)}{\sum_{i,j=1,i=1}^{N} \tilde{d}_{ij}(H)} \qquad (5)$$

that is the ratio of the sum of the off-diagonal elements of the variance decomposition matrix to the sum of all its elements. Although this would be sufficient to study the total volatility spillover to understand how much of shocks to volatility spill over across major asset classes, the generalized VAR approach allow to learn about the direction of volatility spillovers. The directional connectedness FROM the system to j and the directional connectedness from j TO the system are, respectively:

$$FROM: \mathrm{C}^{\mathrm{H}}_{\mathrm{j \leftarrow .}} = \frac{1}{N} \sum_{i \neq j} \tilde{d}_{ij}(H) = \frac{\sum_{i=1,i \neq j}^{N} \tilde{d}_{ij}(H)}{\sum_{i,j=1}^{N} \tilde{d}_{ij}(H)} \qquad (6)$$

and

$$\mathrm{TO}: \mathrm{C}^{\mathrm{H}}_{\mathrm{. \leftarrow j}} = \frac{1}{N} \sum_{i \neq j} \tilde{d}_{j,i}(H) = \frac{\sum_{j=1,j \neq i}^{N} \tilde{d}_{ji}(H)}{\sum_{i,j=1}^{N} \tilde{d}_{ij}(H)} \qquad (7)$$

The set of directional spillovers represent the decomposition of total spillovers into those coming FROM (or TO) a particular source. The total net connectedness is then a measure of the spillovers emitted by j in net terms and is obtained as the difference between the two directional indices:

$$Net: C_j^H = \mathrm{C}^{\mathrm{H}}_{.\leftarrow \mathrm{j}} - \mathrm{C}^{\mathrm{H}}_{\mathrm{j}\leftarrow .} \qquad (8)$$

The sign of the net total directional connectedness illustrates if an asset class i is transmitting return or volatility shocks ($C_j^H > 0$) or receives by other variables in the system ($C_j^H < 0$). Finally, the net pairwise directional connectedness measure is then simply defined as the difference between the gross volatility shocks transmitted from market i to j and gross volatility shocks transmitted from j to i:

$$Net\ pairwise: \mathrm{C}^{\mathrm{H}}_{\mathrm{ij}} = \mathrm{C}^{\mathrm{H}}_{\mathrm{j}\leftarrow \mathrm{i}} - \mathrm{C}^{\mathrm{H}}_{\mathrm{i}\leftarrow \mathrm{j}} \qquad (9)$$

The DY approach allows the estimation of connectedness measures across entities or markets over a given time horizon which are then used to quantify contagion effects. However, during times of stress, as correlation among market variables rises, contagion measures may result biased and eventually increase as discussed by many researchers (Forbes and Rigobon, 2002; Bekaert, Harvey, and Ng, 2005). Therefore, changes in contagion measures might reflect changes in cross-sectoral correlation rather than changes from ‘true’ connectedness indicators, as explained by Baruník and Krehlík (2018).

Frequency connectedness

The DY approach can be supplemented by decomposing connectedness indicators over different time horizons. Such decomposition allows to distinguish between increases in connectedness driven by short-term components (and hence likely to dissipate quickly) and changes driven by medium to long-term components (which are more persistent). Without such a decomposition, it is challenging to assess whether connectedness among funds had increased due to short-term cyclical behaviour (such as fund shares reacting quickly to change in asset prices) or more medium-term factors (such as change in investors’ behaviour). Therefore, the frequency decomposition provides a step further in risk assessment by identifying short- and long-term changes to connectedness.

Baruník and Krehlík (2018) extend the DY framework for measuring connectedness in the frequency domain. They show that it is possible to establish a spectral representation for the variance decomposition and the connectedness measures. This representation decomposes the connectedness indicators into components at different time horizons. Given a specific frequency band ω the pairwise spillover can be estimated by:

$$(\hat{\vartheta}_d)_{jk} = \sum_{\omega} \hat{\Gamma}_j(\omega)(\hat{f}(\omega))_{j,k} \qquad (10)$$

where $(\hat{f}(\omega))_{j,k}$ is the estimated generalized causation spectrum, which indicates the strength of the relationship on given frequency:

$$(\hat{f}(\omega))_{j,k} = \frac{\hat{\sigma}_{kk}^{-1}((\hat{\Psi}(\omega)\hat{\Sigma})_{j,k})^2}{\left(\hat{\Psi}(\omega)\hat{\Sigma}\,\hat{\Psi}'(\omega)\right)_{j,j}} \qquad (11)$$

and

$$\hat{\Gamma}_j(\omega) = \frac{(\widehat{\Psi}(\omega)\widehat{\Sigma}\,\widehat{\Psi}'(\omega))_{j,j}}{\Omega_{j,j}} \qquad (12)$$

is the estimate of the weighting function in which

$$\Omega = \Sigma_{\omega}\widehat{\Psi}(\omega)\hat{\Sigma}\widehat{\Psi}'(\omega)$$

while Ψ(ω) is the discrete Fourier transform of the impulse response function (Ψ(L)) on the frequency band ω.

The connectedness measures at different time horizons can then be calculated using the spillover estimates and the sum of the connectedness indicators over different time horizons are equal to the initial DY indicator:

$$C_{\infty} = \sum_{d_s \in D} C_{d_s}^{\mathrm{F}}$$

where d_s denotes an interval over which the connectedness indicator is estimated and d_s belongs to D the set of intervals which form a partition of the interval $(-\pi,\pi)$, such that $\cap_{d_s \in D_s} d_s = \emptyset$ and $\cup_{d_s \in D_s} d_s = (-\pi,\pi)$.

4 An overview of connectedness withing the EU fund industry

Data sample

Our objective is to estimate connectedness measures within the EU fund industry. However, with around 60,000 funds in the EU, estimating connectedness indicators for such a large set of funds makes the analysis intractable. In addition, a single fund alone is unlikely to cause systemic risk given its relative size, while groups of funds are more likely to have an impact on financial stability. Therefore, we compute return indicators for each fund category in our sample, using data on individual funds within each category. Such approach aggregates fund returns based on individual data and measures funds' performance by using indices, which is standard practice in the investment fund industry. The underlying assumption is that the funds within a category are homogeneous, as they invest in assets with the same characteristics and reflect the same asset market dynamics.[4] Benoit et al. (2017) noted that system-wide connectedness, or systemic risk, is often considered a "hard-to-define-but-you-know-it when-you-see-it" concept. Generally, as summarised by Barunik and Krehlik (2018) systemic risk in literature is defined as the risk that many market participants are simultaneously affected by severe losses, which then spread through the system.

The volatility of the returns of fund indices is then used to derive the connectedness measures. Our initial sample consists of all EU-domiciled funds, equity, fixed income and multi-asset investment funds in the Morningstar database, covering a period from January 2008 and the

[4] Bouveret and Yu (2021) find that US investment funds with similar investment policies tend to have the same level of high quality liquid assets and similar portfolio exposures.

end of 2020. Information on individual fund returns is collected at weekly frequency. Funds with total net assets (TNA) below EUR 150mn (as of December 2019) and for which a 12-month track record of performance was not available have been removed.[5] Funds are split across seven fund categories: equity, mixed alternative funds and four bond fund types reflecting the diversity of fixed income funds (corporate, emerging, high yield and government bond funds).[6] Alternative funds encompass funds that hold non-traditional investment or use complex investment and trading strategies. Such strategies include taking short positions on assets and using derivatives.[7]

Panel A of Table 3 in Annex shows the number of funds in the sample, starting from close to 1,789 funds in 2008 and increasing over time to a maximum of 4,023 in 2020. Overall, at the end of 2019 our sample of funds amounts to assets under management of EUR 2.95tn and covers around 30% of the EU fund industry in terms of asset under management.[8] Given the size of the sample used, the return indices are representative of the performance and volatility of the European investment fund industry.[9] Panel B of Table 1 displays summary statistics for fund returns and total net assets (TNA) of each fund category over the considered period. For each investment fund category, we compute a value-weighted return index, where the weight is the relative size of the fund within that category:

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

where N corresponds to the number of funds per category, and fund values and returns are denominated in EUR. Figure A.1 in Annex shows the evolution of the derived investment fund indices.[10] As it can be seen, all fund indices have a similar clear upward trend and the equity fund index exhibits the largest variability over the period studied.

5 The exclusion of small funds is normally advocated in literature, see Elton, Gruber, and Blake (2001) among others. The size filter is particularly relevant for fund flows because modest dollar flows can translate into extreme percentage flows for the smallest funds

6 Alternatively to the value-weighted equity fund index, as a robustness check the analysis is conducted using indices of the Eurostoxx family. The results are similar, and can be made available upon request.

7 The fund classification adopted relies on the main Morningstar categorisation, which is based on investment funds' prospectuses and key information documents.

8 The assessment is based on EFAMA 2021 and it holds also when considering total assets at the end of 2020.

9 If a fund is liquidated at any time after being included in one of the indices, then its past returns and TNA are not excluded from the index. The data of such fund are preserved to avoid survivorship bias which can result in distorted index returns.

10 The indices are base weighted at the 1st of January 2008.

Table 1

Panel A: Category indices

Fund categories	**Alternative**	**Corporate**	**Emerging**	**Government**	**HY**	**Mixed**	**Equity**
Mean	0.029	0.055	0.060	0.057	0.081	0.062	0.114
Median	0.037	0.076	0.077	0.073	0.093	0.113	0.346
Min	-4.598	-4.845	-7.337	-2.108	-5.199	-7.277	-17.123
Max	2.182	1.623	2.443	1.749	2.534	3.162	7.866
St.D.	0.497	0.395	0.836	0.371	0.734	0.789	2.242
Skewness	-1.828	-4.095	-1.669	-0.455	-0.915	-1.872	-1.269
Kurtosis	20.134	49.696	15.693	6.351	9.690	18.665	11.171
ADF	-23.062	-19.696	-21.968	-26.187	-22.717	-23.588	-26.241

Panel B: Correlation

Fund categories	**Alternative**	**Corporate**	**Emerging**	**Government**	**HY**	**Mixed**	**Equity**
Alternative	1						
Corporate	0.7137***	1					
	(26.415)						
Emerging	0.7087***	0.7819***	1				
	(26.042)	(32.519)					
Government	0.2035***	0.4893***	0.2814***	1			
	(5.387)	(14.544)	(7.601)				
HY	0.8123***	0.8251***	0.8517***	0.1999***	1		
	(36.110)	(37.864)	(42.137)	(5.290)			
Mixed	0.8692***	0.6971***	0.7380***	0.2017***	0.7525***	1	
	(45.570)	(25.206)	(28.350)	(5.339)	(29.624)		
Equity	0.6254***	0.4288***	0.5339***	0.0541	0.4998***	0.8811***	1
	(20.774)	(12.303)	(16.367)	(1.403)	(14.958)	(48.301)	

Table 1 reports the statistical properties and correlation matrix of the value-weighted returns. As indicated in panel A, equity, mixed and HY fund categories have the highest average returns, while Alternative funds have the lowest average performance. Equity and Emerging return indices have the highest standard deviations, respectively. All the series show negative skewness, indicating a high frequency of large negative returns, and exhibit excess kurtosis, pointing to frequent extreme observations. The augmented Dickey-Fuller (ADF) tests show that all the returns series are stationary.

Panel B of Table 1 indicates that most fund categories have a highly significant positive correlation (>60%), reflecting that the underlying funds tend to co-move together. Only government and mixed funds have lower correlation, albeit significant and positive.

The value-weighted returns can then be used to estimate the corresponding volatilities and compute the connectedness indicators. The return volatilities are first estimated by filtering the indices' returns with an ARMA(1,1)-EGARCH(1,1) model. Table 2 indicates that the volatility dynamics of the indices are captured best by the EGARCH model with a T-Student distribution.[11] Model specification has been selected on the basis of chi-squared test and by minimizing the Akaike information criterion (AIC) and the Bayesian information criterion (BIC) values. The results show that average returns of the series record highly persistent volatilities as depicted by the high level of significance of GARCH parameters.

Table 2 - Volatility model estimates

Fund categories	Alternative	Corporate	Emerging	Government	HY	Mixed	Equity
μ	0,02***	0,06***	0,11***	0,06***	0,08***	0,05***	0,04
ar	-0,72***	0,40***	0,65***	0,88***	0,94***	-0,75***	0,03
ma	0,69***	-0,27***	-0,62***	-0,85***	-0,92***	0,72***	-0,13***
ω	-0,04	-0,28***	-0,08***	-0,11***	-0,05***	-0,05***	0,10
α	-0,04	-0,03	-0,067	0,012	-0,040	-0,14***	-0,20***
β	0,97***	0,88***	0,89***	0,95***	0,95***	0,93***	0,94***
γ	0,31***	0,34***	0,50***	0,21***	0,37***	0,27***	0,20***
skew	0,93***	0,86***	1,05***	0,90***	0,95***	0,78***	0,71***
shape	5,39***	6,61***	6,15***	5,18***	8,56***	6,06***	7,80***
chi-squared	16,50 (0.62)	12,94 (0,84)	11,22 (0,92)	16,98 (0,59)	14,90 (0,73)	11,28 (0,91)	13,18 (0,83)

Note: μ, ar, ma parameters refer to ARMA(1,1) specification, while α,β, and ω capture persistence in volatity; γ estimates the leverage effect tha t is return asymmetry respect to informational shocks; skew and shape allow to identify residual distribution. Chi-squared goodness of fit test, which compares the empirical distribution of the standardized residuals with the theoretical ones from the chosen density, is based on Palm (1996); in parenthesis pvalues are reported.

Connectedness in the EU fund sector: Static approach

Following the methodology described in Section 3, we examine the full sample connectedness using a third order VAR and a 100-period ahead forecasting horizon for the variance decomposition.[12] Table 2 shows the full-sample connectedness and provides a range of information. The values on the diagonal represent how much of the estimated volatility of category i is explained by idiosyncratic shocks (own-connectedness). Other values in the table show the volatility spillover impact between fund category pairs, that is how a certain type of funds contributes to the volatility level of other types of funds. The penultimate row (labelled TO) give the total directional connectedness from i to all others, indicating whether shocks to i spread to other funds. The last column (labelled FROM) shows the total directional connectedness from others to i. The last row (labelled NET) gives the difference between volatility shock transmission and reception.

On a 'gross' basis, spillover measures can be compared across fund categories to identify which categories receive the largest spillovers and which categories transmit the highest

[11] Several specifications (i.e., GARCH, APARCH, EGARCH) have been tested by considering different distributions for each model innovations (i.e., T-Student, Normal).

[12] The choice of the forecast horizon is based on Barunik and Krehlik (2018) and is in line with prevailing literature. In this approach, the selected forecast horizon does not have affect for connectedness measures. In particular, they note that the forecast horizon is an approximation factor and, as in the pure time domain, has no interpretation. Operationally, an H sufficiently high produce better approximations especially when lower frequencies are of interest.

spillovers to other funds. On a ‘net’ basis, spillover measures indicate whether funds categories are net receivers or net transmitters of volatility from/to the other fund types.

Table 3 yields a range of important results. First, own-connectedness (diagonal values) is the largest individual element in the table: the main single driver of volatility for each fund category relates to shocks directly affecting this fund category, explaining around 40% of the variance.[13] However, spillovers from other funds account for the majority of the variance at 60% across almost all fund types.[14] This implies that changes in volatility tend to be driven by shocks affecting other funds, emphasizing the importance of spillover effects. Funds with exposure to less liquid asset classes (corporate, EM, HY) or using complex strategies (alternative) tend to receive more spillovers than funds exposed to more liquid assets (equity and government). Second, spillovers from funds to other fund categories can be very large: shocks to mixed funds explain more than 30% of the variance experienced by equity funds, and alternative funds explain more than 20% of the variance experienced by HY funds. There is a high degree of variation in terms of spillovers received from others. On the one hand, government funds (and to a lesser extent equity funds) propagate shocks to other funds very mildly (with a connectedness indicator below 50%). On the other hand, alternative and mixed funds are akin to super spreaders, with volatility spillovers to other funds higher than 80%.

Table 3: Volatility spillover table

	Alternative	Corporate	Emerging	Government	HY	Mixed	Equity	**Spillovers FROM others**
Alternative	**37.9**	9.7	10.7	0.8	16.5	18.3	6.1	62.1
Corporate	14.7	**34.3**	13.2	5.1	17.5	10.7	4.4	65.7
Emerging	14.6	12.7	**35.0**	1.5	21.6	10.8	3.7	65.0
Government	8.1	12.8	5.7	**54.3**	5.4	7.9	5.8	45.7
HY	20.4	14.1	18.3	1.0	**30.7**	11.8	3.6	69.3
Mixed	19.1	7.0	9.3	0.6	10.5	**30.6**	23.0	69.4
Equity	7.8	2.4	4.1	0.2	3.7	33.0	**48.8**	51.2
Spillovers TO others	84.7	58.7	61.3	9.2	75.3	92.5	46.6	61.2
NET spillovers	22.6	-6.9	-3.7	-36.4	6.0	23.0	-4.6	

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

Finally, the last row in Table 3 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 alternative funds showing the highest shock transmission levels at 23% for both. The transmission of volatility shocks by HY bond funds appears more limited at 6%. The

[13] 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.

[14] Government funds are the only category for which own-connectedness is larger than spillovers from other funds. This indicates that such funds tend to be more isolated from shocks affecting the fund industry, Which is consistent with flight to safety behaviour.

remaining fund types display a negative level of net connectedness, indicating that they are net receivers of volatility shocks. Additionally, following the approach of BK (2018), we also consider the static spillover index at different frequency bands to study the varying degree of persistence stemming from shocks with a heterogeneous frequency. We decompose connectedness across three different time horizons: (i) short term (up to one month), (ii) medium term (one to six months) and (iii) long term (more than six months). This decomposition of the static connectedness assessed over the whole sample indicates that shocks of a longer-term nature have a more persistent effect on funds and tend to lead to higher propagation within funds.[15]

5 An overview of connectedness withing the EU fund industry

Dynamic total and frequency connectedness

The full-sample connectedness table covers the entire sample period and thus does not capture the dynamics of connectedness. In this section, we revisit the DY indicators across three perspectives: (i) time varying connectedness, (ii) time varying connectedness with a correlation correction and (iii) frequency decomposition of the time varying connectedness indicators.

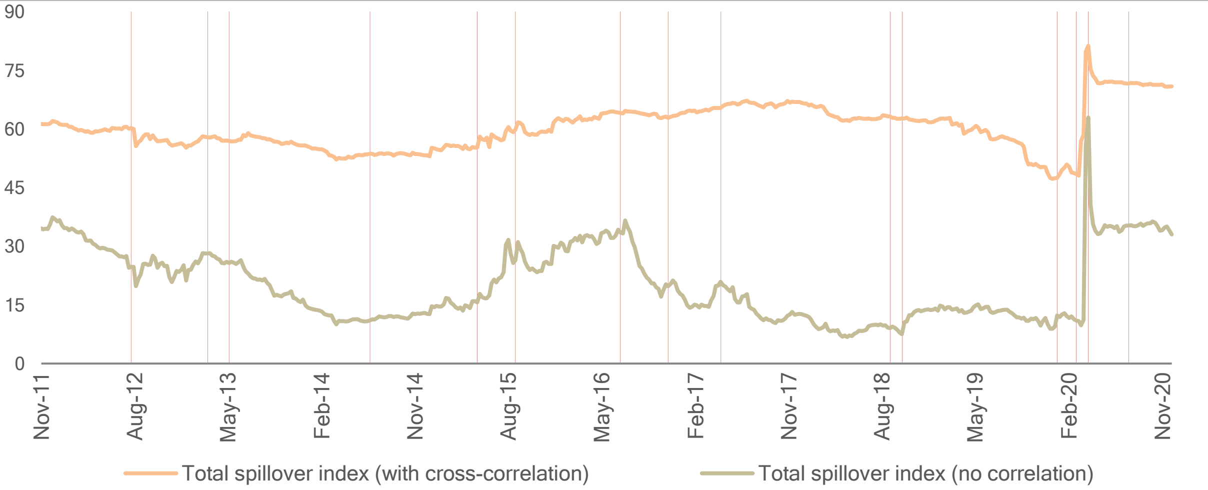
In order to study how systemic risk in the investment fund industry has changed over time, a rolling sample framework is used to create a dynamic total spillover index and assess the variation of volatility spillovers within the system over time as in DY(2012) and BK(2018).[16] Figure 1 illustrates the time dynamics of the total volatility spillover indices estimated with and without cross-sectional correlation. The horizontal axis accounts for the time factor and the vertical axis for the total spillover levels, and the data points plotted in the graph refer to each estimation window and its position corresponds to the end of each window.[17]

The classic dynamic volatility spillover index in Figure 1, which includes contemporaneous correlations appears relatively high and stable during most the analysed period, oscillating between 61.4% and 71% from October 2011 to November 2020.[18] The peak between March and April 2020 shows the large contagion effects associated with the COVID-19 market turmoil: while overall spillovers had been declining since 3Q17, spillovers shot up in March 2020 to reach their highest levels observed (from 48.6% to 81.5%). After March 2020, the spillover index plateaus at a higher level than observed before the crisis. However, as noted by many researchers (see among others Forbes and Rigobon, 2002; Bekaert, Harvey, and Ng, 2005), high levels of contemporaneous correlations may ultimately bias the assessment of contagion effects. To address this potential bias, we follow the approach suggested by Baruník and

[15] These additional results are available upon request.
[16] In line with literature, we used a 200-week rolling window.
[17] For example, the first window starts from 5 January 2008 and ends in 10 October 2011. The total connectedness calculated for this window is about 61% (34% when cross-correlations are removed), and this number's position is October 10, 2011, that is the first date in the figure.
[18] Dynamic and static results are not materially different despite the fact that the VAR estimated over the whole sample may smooth the results when there is time variation in the relationship between the variables. For example, consider a situation where the sample is split into two parts of a similar length. In one, shocks to the first variable have a positive impact on the second variable, while in the other their impact is negative of comparable magnitude. If the VAR is estimated separately in each sub-sample, the magnitude and the sign of these impacts is detected, and the connectedness measure would reflect the existent relationship. However, the VAR estimated over the whole sample attempts to fit both sub-samples simultaneously, averaging the positive and negative impact of the variables on each other.

Krehlík (2018) by adjusting the correlation matrix of VAR residuals by the cross-sectional correlations.

Figure 1: Total volatility spillover index (DY, 2012)



Note: Dynamic volatility connectedness, DY (2012) total spillover index. Figure 1 represents the total connectedness computed on a moving window with a length of 200 weeks.Vertical lines represent main events, from left to right: 1) “Whatever it takes” statetment, 2) EU equity markets and DoW make new all time high, 3) ECB cuts rates, 4) oil price starts declining, 5) Brexit referendum announced, 6) EU stock market collapse, 7) world stocks tumble as Britain votes for EU exit, 8) global bonds sold off after U.S. presidential election and new record highs in US and EU stock indexes, 9) GBP soared after Britain called a snap election for June, 10) SP500 at record high (longest bull run), 11) beginning of trade tensions, 12) UK leaves the EU, 13) COVID-19 crisis, 14) support programmes announced at G20, 15) ECB announces a €750B stimulus agreement.

When accounting for the effect of cross-sectional correlations, the structure of the total dynamic connectedness changes drastically. First, levels of connectedness are lower when correlation is taken into account, indicating that part of the increase in connectedness captured in the traditional approach is due to higher correlations across volatility measures rather than a ‘true’ increase in volatility. Second, the measure of connectedness presents a steep upward trend after the announcement of the Brexit referendum and starts declining after the vote. Third, similarly to the traditional measure, the index attains its historical high at the end of 1Q20 with the COVID-19 outbreak, with an increase of 52 percentage points.

The scenario of greater connectedness emerging at the onset of the pandemic crisis is consistent with the idea of agents generally repricing risk across market and asset classes due to the materialised vulnerability of the economy to exogenous shocks. The total spillover index sharply declines than after the G20 announced massive support programmes. The higher degree of connectedness variability over time indicates that a high degree of volatility in one segment of the fund industry is not necessarily transmitted to the other all the time. This result implies that there are periods where the system connectedness is low and information propagates more slowly across different markets, reflecting opportunities for portfolio diversification.

Our findings from the investment fund sector support the more general view that systemic risk in financial markets rise drastically during periods of heightened financial turmoil and economic uncertainty, showing in this respect the impact of the COVID-19 crisis, and indicate that the true dynamics of connectedness can be strongly influenced by contemporaneous correlations across different market segments.

As discussed above, the main reason to investigate how connectedness among different segment of the investment fund industry varies across frequencies is its strong heterogeneity. Investment funds interact and operate at diverse time horizons, reflecting different mandate, strategy, the respective market development as institutional and regulatory constraints.

Therefore, the presence of linkages with various degrees of persistence underlying systemic risk can be reasonably assumed so that shocks can propagate through markets producing heterogeneous responses over different investment horizons.

Figure 2 depicts the dynamics of total volatility connectedness into three different frequency bands based on Barunik and Krehlik (2018). In other words, the true dynamics of the overall time-varying volatility spillover indices obtained removing contemporaneous correlation in Figure 2 is broken down into the higher, medium and lower frequencies. The simple sum of the indices in Figure 2.B provides the time-varying total spillover index. In this respect, the decomposition enabled by frequency connectedness serves to further a deeper understanding of the sources of connectedness. The largest share of volatility shock transmission can be attributed to the medium- and long-term component of the decomposed original spillover index, while the level of the short-term volatility shocks plays a minor role.

Overall, connectedness is driven by shocks creating uncertainty in the long-term. Its initial downward trend correlates with the EU sovereign debt crisis, when a series of measures were taken by the ECB to stabilise the EU financial system and the economy, then connectedness increases in mid-2014 when oil price dropped beyond levels justified by economic fundamentals driven by receding geopolitical concern.[19] During the period comprised between the announcement of a Brexit referendum and UK vote to leave the EU, long-term connectedness rise, diverging substantially from medium-term component. Later on, both components first aligned, then slightly increased together with global trade tensions and finally shot-up with the COVID-19 market turmoil. These situations are accompanied by bullying stock markets and volatility episodes. These results indicate that the persistency of investors' responses to shocks depends on the uncertainty about the financial system and the economic situation. As observed also by Barunik and Kocenda (2019), a high level of system connectedness driven by low frequency responses to shock translates into long-term uncertainty driving systemic risk.

Net directional volatility connectedness

The total volatility spillovers index provides an overview of how the volatility contagion among the investment fund indices spreads in the system, but it does not tell us much about the role of single fund types within the system. The analysis of *net* volatility spillovers allows to distinguish between types of investment funds that can be labelled as volatility spillover receivers or transmitters. A positive net directional spillover that a given variable is a net transmitter of spillovers to all the others. Vice versa, a negative value means that the variable is a net receiver of volatility spillovers from others.

Figure 3 shows the time-varying net directional return and volatility spillovers across all the variables of the system calculated using the pure time-domain. Fund indices exhibits different patterns and degree of time variation and the effect of the COVID crisis is well pronounced for all fund types. For government bonds funds, we find a clear net volatility receivers role, meaning that for them the level of volatility spillovers received FROM others is systematically higher than the one TO others.

Alternative funds are net volatility shock transmitters during periods of uncertainty, like the Brexit process, and turn positive again February 2020. Prior to the COVID-19 market turmoil, equity funds display an opposite pattern and appear injecting the main part of the volatility in

[19] See, Giglioli, Herman and Swiston (IMF, 2017) and World Bank 2018 Global Economic Prospects.

the considered system over the first part of the sample period, up to end of 2014.[20] The mixed fund index is instead always positive reaching the maximum positive spillovers at the beginning of the series, following the development of the sovereign debt crisis, and at the onset on the COVID crisis.

[20] According to Diebold and Yilmaz (2015), the total volatility TO connectedness tends to be higher either when a variable is central the selected system or it has been subject to frequent volatility shocks over the period, or both cases.

Figure 2: frequency decomposition of total connectedness (BK, 2018)

Note: Frequency decomposition of dynamic volatility connectedness based on Baruník and Krehlík (2018) total spillover index at different frequency bands. Figure 2 represents total connectedness at different frequency bands computed on a moving window with a length of 200 weeks.Vertical lines represent main events, from left to right: 1) "Whatever it takes" statetment, 2) EU equity markets and DoW make new all time high, 3) ECB cuts rates, 4) oil price starts declining, 5) Brexit referendum announced, 6) EU stock market collapse, 7) world stocks tumble as Britain votes for EU exit, 8) global bonds sold off after U.S. presidential election and new record highs in US and EU stock indexes, 9) GBP soared after Britain called a snap election for June, 10) SP500 at record high (longest bull run), 11) beginning of trade tensions, 12) UK leaves the EU, 13) COVID-19 crisis, 14) support programmes announced at G20, 15) ECB announces a €750B stimulus agreement.

The level of the HY fund index emerges instead as stable uncertainty source for almost the entire sample period, switching to a negative direction only at the end of February 2020. Similarly, in times of stress and market uncertainty, funds focusing on investment grade bonds become net receivers of volatility shocks. This result appears particularly relevant considering that HY and IG corporate bond funds may have less capacity to absorb shocks due to potential liquidity mismatches.

Connectedness network results

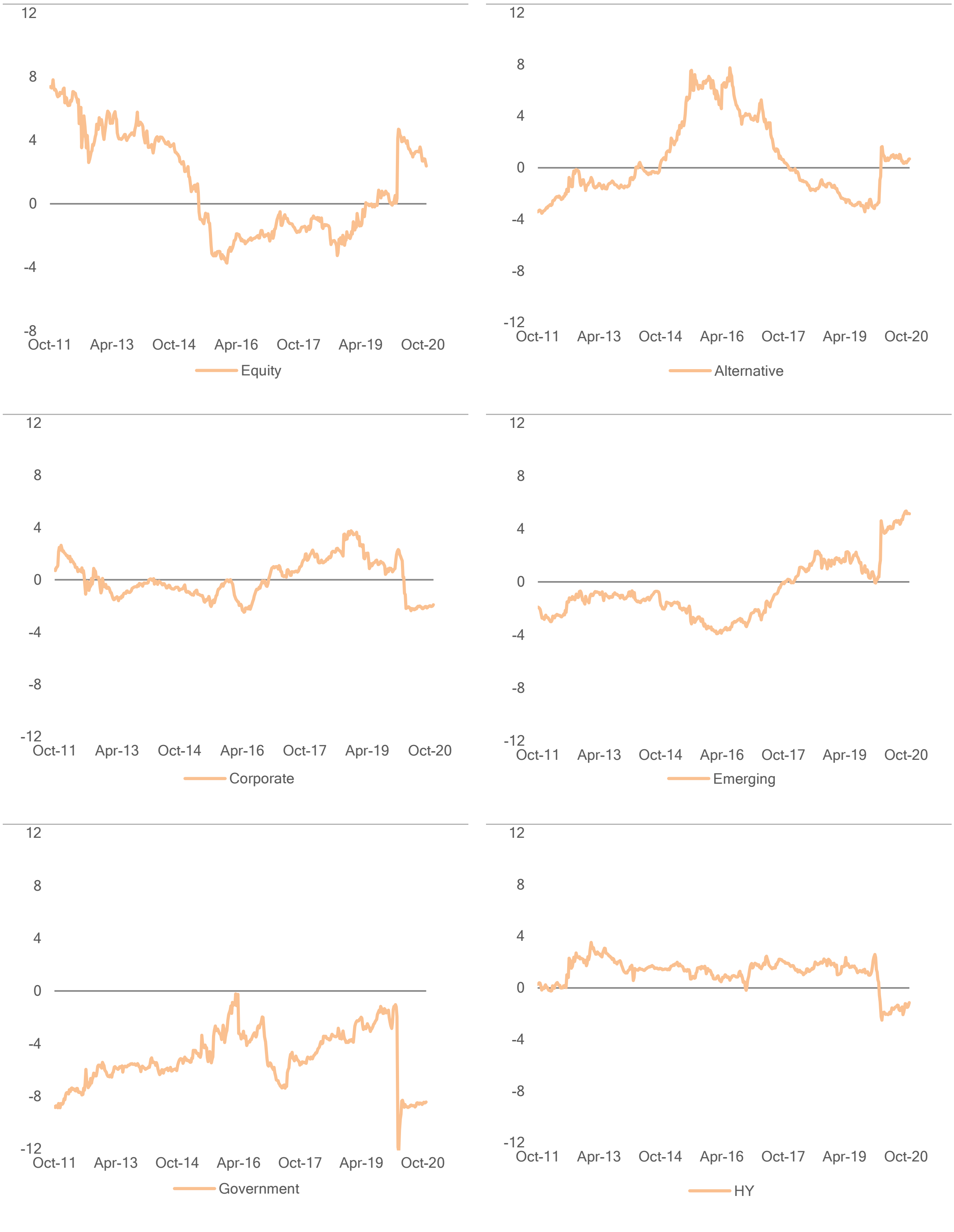
Figure 4 provides a network visualization of directional connectedness within the fund sector using the net spillover values. The full set of net pairwise directional connectedness is displayed in Figure A.2 in Annex. Looking at the whole sample period analysed it appears that equity, government, IG corporate and emerging bond funds are net receivers of shocks from other funds. In particular, government bond funds are the largest net shock receviers. While government funds receive less spillovers from other funds (45%), the volatility shocks they transmit to others are by far the lowest. This implies that, since government funds are *ceteris paribus* more likely to withstand shocks (due to the high liquidity of their assets and a more stable investor bases), they increase the resilience of the fund sector.

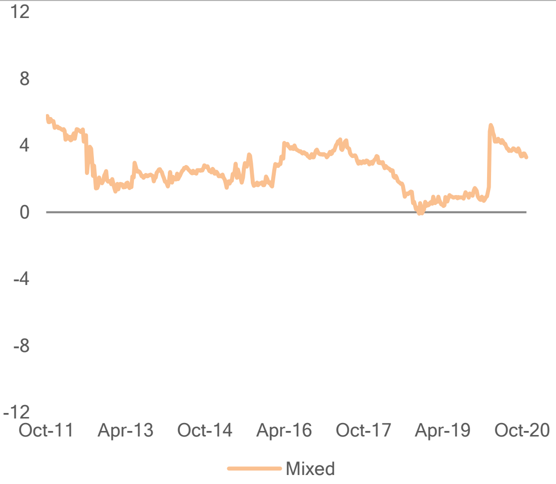
In contrast, corporate bond funds receive high spillovers from others (65%) and transmit high spillovers to others (59%). As indicated above, corporate funds are net receiver of shocks, their exposures to less liquid asset classes can make them less able to withstand shocks than government bond funds.

Finally, mixed and alternative funds are net transmitters of spillovers to other funds. Mixed funds transmit spillovers mainly to equity funds (thickest edge), government funds and to a lesser extent to HY and corporate bond funds. Alternative funds are net transmitters of shocks towards all funds as well, with their largest spillovers to government bond funds.

Given that our sample period covers more than ten years, we also estimate the net spillover measures over four different subperiods, with a focus on the Brexit referendum and on the Covid-19 crisis of March 2020. Our first period covers 2011 up to April 2015 (one year before Brexit), the second period ranges from May 2015 to June 2016 and includes the Brexit referendum, the third period ranges from July 2016 up to mid-February 2020 and the fourth period is from mid-February 2020 up to July 2020.

Figure 3: Net volatility connectedness





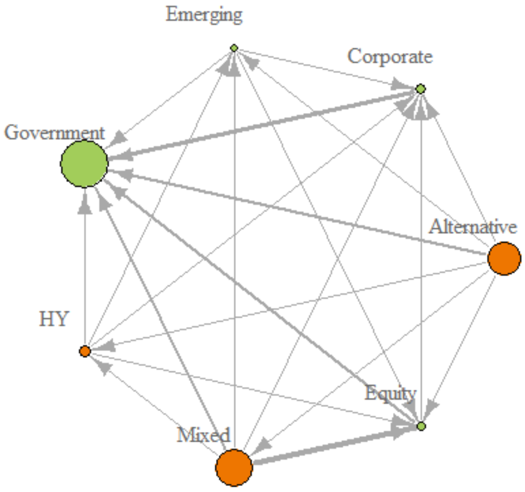
Note: Dynamic net directional volatility connectedness based on Diebold and Yielmaz (2012). The dynamic net directional volatility connectedness measures results from the difference between the directional TO spillovers from directional FROM spillovers. Positive (negative) values of the net directional volatility connectedness indicate that the corresponding fund category is a net transmitter (receiver) of volatility connectedness to (from) the system.

Figure 4 conveys some important messages. First, some fund categories are net receivers or transmitters of shocks throughout the different periods: government funds are always net receivers and mixed funds are always net transmitters. Second, for all other fund categories, they can switch between being net transmitters and net receivers of spillovers over time. Third, net spillovers change over time (as indicated by the change in the size of the nodes). For example, alternative funds were net receivers before Brexit and net spillovers were low (small node), then around the Brexit referendum, alternative funds became the largest net transmitter of spillovers to other funds (large orange node in Figure 4.B).

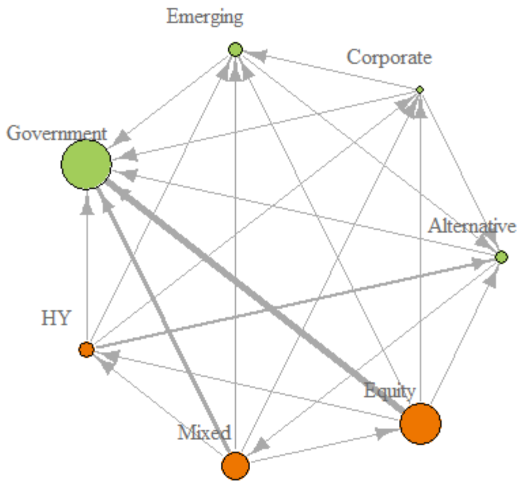
Looking at the acute stress observed during the COVID-19 crisis, Figure 4.D indicates that three types of funds were net receivers of shocks during the period. Government bond funds were net receivers, as with all other periods. Corporate and HY bond funds were net receivers of shocks from almost all other fund categories. Since such funds have less highly liquid assets than government bond funds, spillovers are likely to have a larger impact on those funds.

Figure 4: Network Analysis of Pairwise Net Spillovers

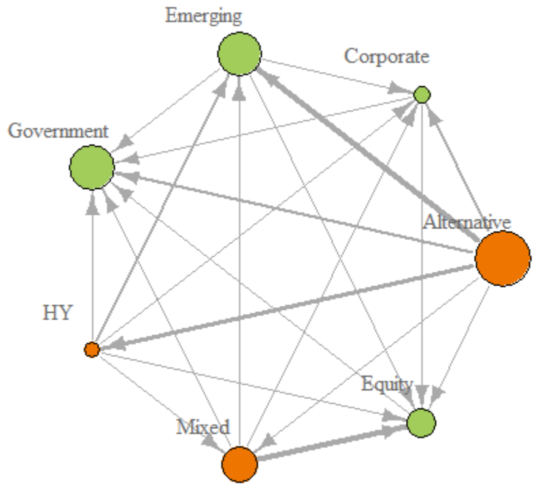
A. Whole sample



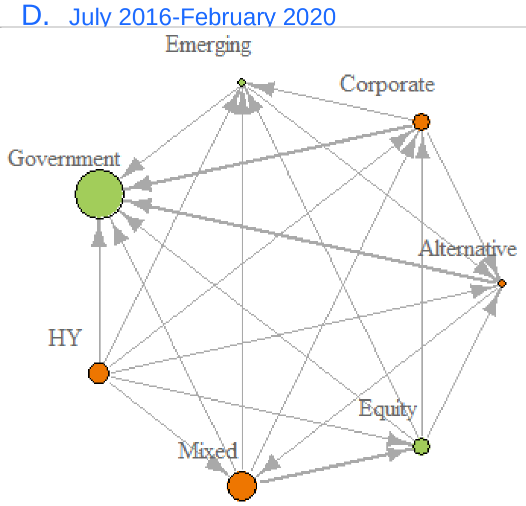
B. October 2011-April 2015



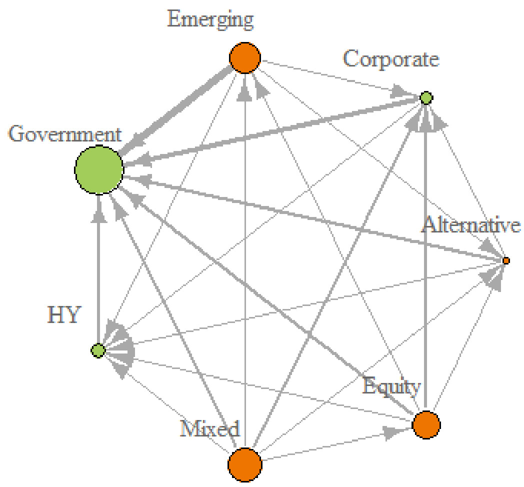
C. Brexit



D. July 2016-February 2020



E. February 2020-July 2020



Note: Network representation of the average net pairwise direction volatility connectedness based on Diebold and Yilemaz (2012). The size of the nodes corresponds to the absolute value of net spillovers (to/from each one of the other variables in the system); orange is used for fund categories which are net spreaders of shocks (positive net spillovers) and green for categories which are net receivers (negative net spillover). The thickness of the edges is based on the value of the net bilateral spillovers (i.e. thicker edges correspond to stronger net pairwise connectedness).

6 Conclusion

This paper builds upon the existing literature on volatility spillovers across financial assets and markets and examines the degree of connectedness across different types of EU funds investing in fixed income instruments and equity funds, using both a time-domain and a frequency domain framework.

By applying the methodology introduced by Diebold and Yilmaz (2009, 2012 and 2014) and Barunik and Krehlik (2018), our analysis quantifies the transmission and the direction of volatility shocks across different categories of funds during crisis and non-crisis periods.

We find that spillovers from funds account for the majority of the variance, underlining the value in analysing contagion across fund categories. Overall, we find that funds exposed to less liquid assets (such as HY, corporate and EM bond funds) tend to receive more volatility spillovers from other fund categories than funds exposed to more liquid assets (equity or government bond funds). Alternative funds and mixed funds transmit financial stress in terms of volatility shocks to other fund categories more than other liquid funds such as equity or government bond funds. Regarding net spillovers, mixed, alternative and to a lesser extent HY funds are net volatility shocks transmitters, while other fund categories are net receivers, in particular government bond funds which are net receiver of shocks.

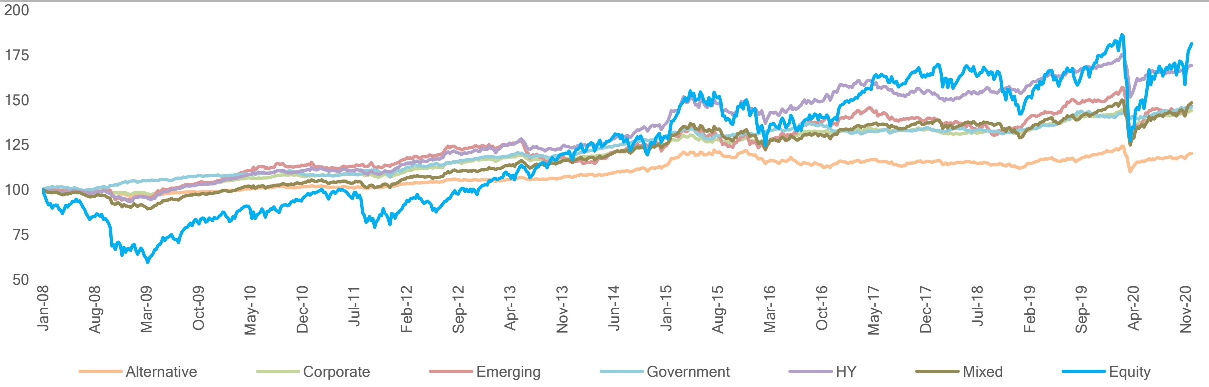
From a time series perspective, we show that the total spillover index varies over time, and when controlling for correlation bias, spillovers increase around stress periods such as the Brexit referendum in 2016 or the March 2020 COVID-19 related market stress. Using a frequency decomposition, changes in spillover stem mainly from medium and long-term components, indicating persistence effects.

Finally, we show that bilateral connectedness between fund categories can change over time. For example, alternative funds were net receivers of spillovers before Brexit, while around the referendum they became net transmitters of spillovers, along with a substantial increase in absolute interconnectedness.

Overall, our results provide insights into contagion effects within the fund industry. From a risk monitoring perspective, our measures can help analysing contagion effects within the fund sector and identify vulnerable funds (net receivers) as well as funds more likely to spread volatility to other funds. Therefore, supervisory activities aimed at reducing systemic risk can benefit from particularly considering investment funds which contribute the most to the volatility in the system as analysed in our study. Our findings could also be useful when performing system-wide stress testing. Instead of assuming a constant correlation between funds' returns and volatility, our analysis shows that during stress periods, spillovers tend to increase sharply, even adjusting for changes in cross-sectional correlations, potentially amplifying shocks across the fund sector.

7 Annex

Figure A.1: Investment fund indices



Note: Time trend of investment und indices over the sample period from January 1, 2008 to November 28, 2020. Indices The indices are base-weighted at the 1st of January 2008.

Table 3

Panel A: Number of funds

Fund category	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Alternative	80	104	132	156	185	208	239	270	314	344	374	390	426
Corporate	140	167	177	204	222	241	264	277	283	298	319	328	335
Emerging	93	95	112	125	138	154	168	180	188	201	220	233	328
Government	73	77	82	87	91	91	96	100	101	105	107	116	129
HY	173	186	215	238	270	300	320	344	364	386	411	424	539
Mixed	620	678	732	777	819	859	918	982	1,050	1,120	1,155	1,168	1426
Equity	610	628	646	668	688	703	725	750	772	794	812	833	840

Panel B: Total Net Asset

Fund category	Eur bn	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Alternative	*Mean*	1.15	1.04	0.98	0.75	0.82	0.82	1.30	0.91	0.89	0.97	0.95	0.91	0.66
	Median	0.53	0.51	0.48	0.40	0.36	0.39	0.63	0.40	0.38	0.43	0.43	0.41	0.34
Corporate	*Mean*	0.76	1.12	0.74	0.66	0.75	0.75	0.76	1.13	0.82	0.81	0.73	0.88	0.82
	Median	0.41	0.61	0.42	0.34	0.39	0.37	0.37	0.61	0.38	0.41	0.38	0.46	0.40
Emerging	*Mean*	0.87	1.59	1.09	0.84	0.98	0.78	0.81	0.77	0.78	0.99	0.92	1.11	0.81
	Median	0.43	0.76	0.56	0.45	0.52	0.41	0.45	0.38	0.40	0.47	0.41	0.54	0.39
Government	*Mean*	0.98	0.96	0.89	0.75	0.78	0.79	0.83	0.83	0.78	0.89	0.75	0.90	0.68
	Median	0.55	0.50	0.45	0.43	0.43	0.46	0.54	0.54	0.47	0.57	0.49	0.52	0.42
HY	*Mean*	1.09	1.12	1.18	1.16	1.23	1.25	1.91	1.33	1.34	1.38	1.02	1.37	0.89
	Median	0.43	0.43	0.43	0.40	0.42	0.41	0.68	0.43	0.44	0.48	0.40	0.48	0.41
Mixed	*Mean*	0.77	0.69	0.68	0.61	0.60	0.63	0.71	0.80	0.78	0.84	0.81	0.90	0.75
	Median	0.34	0.31	0.31	0.28	0.27	0.30	0.31	0.35	0.34	0.37	0.36	0.40	0.31
Equity	*Mean*	0.32	0.41	0.44	0.34	0.39	0.51	0.55	0.67	0.61	0.70	0.59	0.65	0.60
	Median	0.16	0.21	0.23	0.18	0.21	0.26	0.30	0.34	0.32	0.39	0.34	0.36	0.33

Panel C: Funds' returns

Fund category	%	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
Alternative	*Mean*	-0.7	0.67	0.05	0.24	-0.12	-0.54	0.44	0.36	1.1	-0.21	-0.65	0.13	0.14
	Median	-0.07	0.36	0.06	0.19	-0.07	-0.37	0.29	0.18	0.93	-0.12	-0.49	0.25	0.12
Corporate	*Mean*	-0.23	-0.3	0.03	0.52	0.29	-0.41	-0.45	-0.27	0.26	-0.05	0.01	-0.02	0.21
	Median	0.14	-0.31	-0.1	0.53	0.18	-0.43	-0.03	-0.23	0.24	-0.04	0.02	-0.07	0.20
Emerging	*Mean*	0.7	-0.14	0.41	0.54	-0.51	0.24	-0.61	-2.47	-0.18	0.4	0.38	0.57	0.30
	Median	0.45	-0.11	0.46	0.45	-0.63	0.33	-0.69	-2.8	-0.29	0.47	0.4	0.52	0.17
Government	*Mean*	1.29	0.02	-0.42	0.36	0.11	0.25	0.18	-0.11	0.42	0.14	0.28	-0.47	0.14
	Median	1.25	0.01	-0.44	0.37	0.08	0.28	0.15	-0.12	0.47	0.1	0.29	-0.54	0.15
HY	*Mean*	-1.08	0.71	-0.59	1.01	-0.22	0.48	0.55	-0.08	-0.15	-0.1	-0.03	0.2	0.25
	Median	-0.91	0.34	-0.52	1.05	-0.06	0.43	0.4	-0.14	0.06	-0.06	-0.02	0.23	0.21
Mixed	*Mean*	-2.04	-0.08	0.69	1.14	-0.05	-1.22	1.1	-1.8	-0.12	0.17	-2.05	0.64	0.35
	Median	-1.48	-0.1	0.55	1.12	-0.09	-1.18	0.99	-1.75	0.05	0.05	-1.84	0.47	0.30
Equity	*Mean*	-1.02	0.66	0.31	-0.23	0.36	0.40	0.14	0.25	0.07	0.22	-0.26	0.48	0.09
	Median	-0.98	1.04	0.58	-0.15	0.58	0.49	0.58	0.39	0.24	0.24	0.01	0.53	0.49

Figure A.2: Net pairwise directional Connectedness

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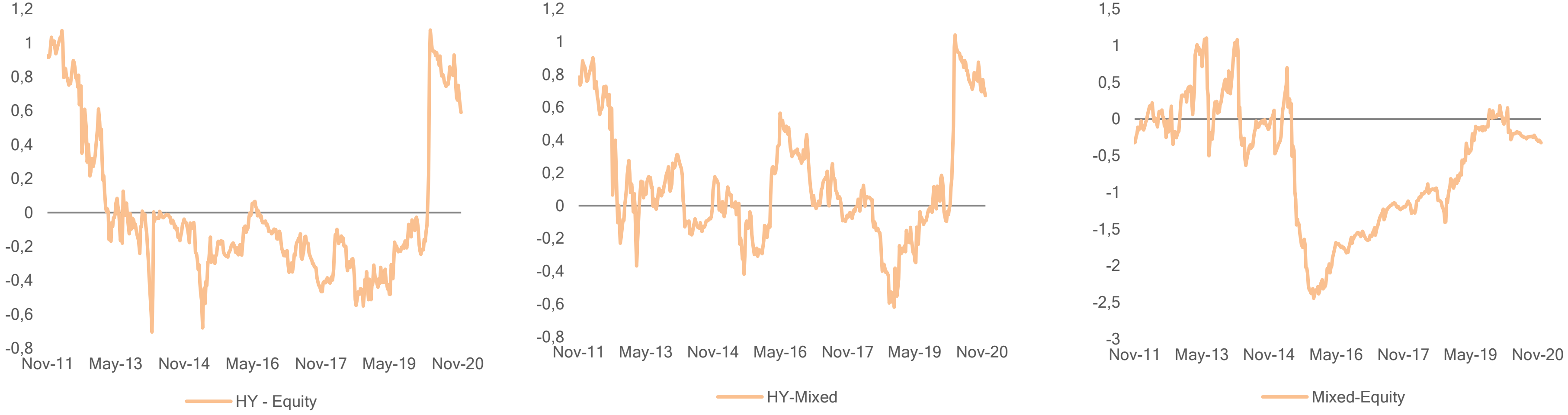

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