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Non-alternative collective investment schemes, connectedness and systemic risk

Ramiro Losada and Ricardo Laborda

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Non-alternative collective investment schemes, connectedness and systemic risk[1]

Ramiro Losada[2] and Ricardo Laborda[3]

Abstract

This paper analyses the connectedness among non-alternative collective investment schemes and with their underlying securities markets. The results show that non-alternative collective investment schemes should not be taken as important in terms of propagation of shocks and they may play a limited role from a systemic point view, an outcome that may be confirmed by the second main result of the paper. There is not a long run relationship (cointegration) between the connectedness from non-alternative collective schemes with their underlying markets and the financial systemic risk. On the other hand, in the short run, the way that a negative shock in the financial systemic risk causes an increase in the level of connectedness is shown although the opposite cannot be said; a negative shock in the level of connectedness does not cause a rise in the measure of the financial systemic risk.

Keywords: Connectedness, investment schemes, UCITS, securities markets, systemic risk

JEL Classification: G23, G18, C53.

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2 Comisión Nacional del Mercado de Valores, c/ Edison 4, Madrid, 28006, Spain. Tel: (+34) 915 850 912. Email: rlosada@cnmv.es.

3 Centro Universitario de la Defensa, Zaragoza. Ctra. de Huesca s/n, 50090, Zaragoza, Spain. Email: rlaborda@unizar.es.

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1 Introduction

The collective investment industry is an important area of the Spanish financial economy. As well as the supply of collective investment schemes (hereafter CIS), an important investment opportunity for holders, it provides one of the major channels for public savings to be invested, helping to enhance economic growth. CIS offer important advantages over direct investment in individual securities: increased diversification, daily liquidity and professional investment management. They may also become a "spare tyre" in times of banking crisis, when firms and household can face a constrained credit supply.[1] In exchange for the benefits, investors pay fees, mainly to the investment management companies that administer the CIS.

In Europe, CIS can be divided into two categories depending on regulation: alternative CIS, which are mainly subject to the Alternative Investment Fund Managers Directive (hereafter AIFMD) and non-alternative CIS that are mainly subject to the Undertakings for the Collective Investment in Transferable Securities (hereafter UCITS) and Money Market Funds Regulation (hereafter MMFR).[2] Throughout the financial crisis, as described by the FSB (2013), it was felt that not all types of CIS are equally susceptible to runs and panic, something that the public authorities should take into account.

Regulation 1092/2010 of the European Parliament and the Council of 24 November 2010 on European Union macro-prudential oversight of the financial system and establishing a European Systemic Risk Board defines systemic risk as "*a risk of disruption in the financial system with the potential to have serious negative consequences for the internal market and the real economy*".[3] In addition, Benoit *et al.* (2017)

1 In order to diversify the sources for financing real economy projects throughout Europe, the European Commission tried to promote the Capital Markets Union (CMU). CIS are an important part of the non-bank financial economy that may allow firms to finance and support projects as they can take stakes in firms' equity or debt. CIS may be seen as one of the alternatives to banking.

2 It is important to point out that in European jurisdictions, a significant percentage of alternative CIS are regulated under the national Laws and they are closer to be considered as non-alternative UCITS ("others" category in the European Securities and Markets Authority's (ESMA) terminology), although they do not fulfil all UCITS Directive or MMFR requirements, e.g. with regard to certain guaranteed funds. AIFMD corresponds to Directive 2011/61/EU of the European Parliament and of the Council of 8 June 2011 on Alternative Investment Fund Managers and amending Directives 2003/41/EC and 2009/65/EC and Regulations (EC) No. 1060/2009 and (EU) No. 1095/2010. UCITS Directive corresponds to Directive 2009/65/EC of the European Parliament and of the Council of 13 July 2009 on the coordination of laws, regulations and administrative provisions relating to undertakings for collective investment in transferable securities. Finally, MMFR corresponds to Regulation (EU) 2017/1131 of the European Parliament and of the Council of 14 June 2017 on money market funds.

3 Regulation 1092/2010 of the European Parliament and the Council also defines the financial system as "*all financial institutions, markets, products and market infrastructures*".

recently adopted a minimal definition of systemic risk as the "*risk that many participants are simultaneously affected by severe loses, which then are spread through the system*". These authors consider different sources of systemic risk: systemic risk-taking related to the bets taken by financial institutions that are large and correlated, contagion mechanisms, which explain how losses can spillover from one part of the financial system to another and finally amplification mechanisms that capture how small shocks can end up having a significant impact.

Before the crisis, CIS were not seen as important from a systemic point of view. However, this view partially changed in 2010 when the G20 leaders requested that a series of recommendations be adopted to strengthen oversight and regulation of shadow banking (now known as non-bank financial intermediation) in order to address its potential risks for financial stability. In this regard, the Financial Stability Board (FSB) started in 2011 to evaluate these risks through an annual monitoring exercise that assesses global trends and risks in the non-bank financial intermediation system named "Global Monitoring Report on Non-Bank Financial Intermediation".[4] The main underlying idea from this FSB monitoring is that while non-banking financial intermediaries might be involved in transforming maturity/liquidity and create leverage, they may also become a source of systemic risk.

As CIS alternatives have received the attention of regulators since they may be involved in investments where there exists leverage and maturity transformation as vehicles that may enhance systemic risk, in this paper we study the potential role of non-alternative CIS as a source of systemic risk. To this end, we examine how a negative shortage in non-alternative CIS can affect the financial system by enhancing systemic risks. The aim of this paper is to try to calculate and assess the connectedness among the different types of non-alternative CIS and the securities markets where CIS managers mainly trade their portfolios. These connectedness measures envisage how much non-alternative CIS could affect other market participants through potential fire sales and how it can put them to deal with a negative externality. Likewise, connectedness measures show how a security market that faces turbulences can affect the non-alternative CIS that participate in it. A large spillover effect from non-alternative CIS on the securities they invest in may therefore constitute an unexplored source of systemic risk. To our knowledge, this paper is the first in the literature that tackles these issues.

To achieve our objectives, we draw on the recent literature (Diebold and Yilmaz, 2009, 2012, 2014, 2015), which provides a measure of interdependence or spillovers of assets returns and/or volatility based on a generalised vector autoregressive framework that takes no position with regard to how the interdependence arises. This framework provides several measures of spillover or connectedness that are related to the fraction of variance in error in H-step ahead forecasts due to shocks to another variable or variables arising elsewhere. We also consider the approach adopted by Barunik and Krehlik (2018) that describes the frequency dynamics (the short term, medium term and long term) of the connectedness by using the spectral

4 For further details of this report, see FSB (2013) which describes the main features of their annual assessment of the non-bank financial intermediation sector and FSB (2019), where the reader can find the last published report.

representation of variance decomposition based on frequency responses to shocks instead of impulse response to shocks.

Two main results can be drawn from the paper. The first is that in periods of financial distress, the connectedness among non-alternative CIS and their underlying markets increase. However, even during negative periods, the connectedness is mostly in the short run. This means that non-alternative CIS as well as securities markets process the negative shocks quickly and they are mostly translated in an increase of the contemporaneous correlation among those CIS and the assets traded in securities markets. Therefore, non-alternative CIS should not be taken as important in terms of propagation of shocks and they may play a limited role from a systemic point view. This result may be confirmed by the second main result of the paper. An analysis of how the connectedness among non-alternative CIS and securities markets with a proxy of financial systemic risk is provided which argues that there is no long run relationship between connectedness and financial systemic risk. When the short run is analysed, we see how a negative shock in the financial systemic risk causes an increase in the level of connectedness although the opposite cannot be said; a negative shock in the level of connectedness does not cause a rise in the measure of the financial systemic risk.

These results complement the views from the various of the FSB's "Global Monitoring Report on Non-Bank Financial Intermediation". We show how financial intermediaries with limited transformation of maturity/liquidity and leverage as non-alternative CIS are not an important source of systemic risk. This result can be extended for the concrete case of the fixed income collective investment schemes category.

The remainder of the paper is structured as follows. Section 2 discusses the potential role of CIS as a source of systemic risk. Section 3 describes the empirical framework. Section 4 presents the data used to study the Spanish non-alternative CIS market. Section 5 presents and discusses the results of the empirical analysis. Section 6 analyses the relationship between non-alternative CIS connectedness and systemic risk. Finally, Section 7 sets out our conclusions.

2 Collective investment schemes as potential sources of systemic risk

The non-banking financial system comprises a heterogeneous list of entity types entities which includes CIS, securities broker-dealers, securitisation entities, credit insurance providers/financial guarantors, finance companies and trust companies. They all have different characteristics and also play different economic roles. For example, as described in ESRB (2016b), market infrastructures may become an important channel for enhancing systemic risks. This is because links between financial institutions with financial market infrastructures may be a source of risk for the whole financial system as interconnectedness among entities may hinder the system's ability to reduce stress. As a result, direct and indirect contagion channels, e.g. the result of the long intermediation chains created through securitisation, can amplify common shocks. Furthermore, in a market-based financial system, many financial entities value their assets and liabilities at fair value, with systematic asset price shocks potentially transmitted instantaneously through the non-banking channel. This may have a knock-on effect as a result of deleveraging, overcrowded trades and market illiquidity (ESRB, 2016b).

In this regard, unlike bank depositors, CIS investors directly bear the losses of their investments, as CIS are effectively shared-ownership investment vehicles. In general, CIS investors own a stake proportional to the number of the CIS's shares or units that they own.[5] As mentioned earlier, from a systemic point of view, alternative CIS have received the attention of the regulator as they may be involved in investments where there is leverage and maturity transformation. Thus, along the financial crisis, alternative CIS, especially real state funds, played a role as being one of few of types of CIS that suffer from liquidity shortage. By the same token, money market funds with constant net asset value have also deserved the attention of public authorities. As shown in Schmidt *et al.* (2016), in 2008 a US money market fund with a constant net asset valuation was affected by massive redemptions which put the fund in a position where it could not meet those redemptions to the promised net asset value of $1 per unit. This event showed how such money market funds may face liquidity shortages that could be considered as runs because their investors want to redeem their positions as soon as possible but the fund cannot attend them (in game theory literature this is called first-mover advantage).

5 Nonetheless, Rajan (2006) argued that mutual funds could be subject to an agency problem. This is because mutual fund investors only have access to incomplete information and often use recent returns as an indicator to judge the fund manager's ability which may incentivise self-reinforcing fund flows. Recently, Goldstein *et al.* (2016) found evidence that corporate bond funds are especially vulnerable to run risks, as the relative illiquidity of corporate bonds benefits fund investors who sell quickly and thus fosters the first-mover advantage.

On the other hand, by regulation, non-alternative CIS have access to very limited leverage. At the same time, their portfolio must be very diversified or secured. According to ESRB (2016a), due to the characteristics of these CIS, they may help financial market in times of distress as they can assume part of excess volatility. However, it should be also pointed out that almost all non-alternative CIS offer a daily opportunity to redeem which puts pressure on the liquidity of these CIS as far as their portfolio may not be fully composed by liquid assets. The latter has arisen over the past decade; there are some types of CIS, especially fixed income funds, which have invested in assets that are considered as more illiquid in a search for yield strategy (ESRB, 2017).

Another aspect that may warrant concern is how the growth of the CIS industry may have increased herding behaviour among market participants. Brown *et al.* (2013) found evidence that managers of mutual funds have a tendency to herd based on analysts' recommendations, which can affect market prices, especially during bear markets. Moreover, the use of benchmarks and peers to evaluate CIS performance has also incentivised herding behaviour by CIS managers, what may be transferred to markets in a reduction of assets supply in periods of financial distress. This effect may be a particular challenge in markets such as corporate bonds where recent regulations seem to prevent banks or alternative CIS from supplying liquidity in times of market turmoil (IMF, 2015). At the same time, it is also important to point out that the sector of CIS is becoming more concentrated (Haldane, 2014), casting doubts about a greater fragility in this sector.[6] At the end of the day, a few managers could be in charge of a bigger portion of CIS and therefore, the CIS portfolio may become very similar. This may also have direct consequences for CIS, as due to brand effects, large redemptions in one fund may be imitated by investors of other funds managed by the same entity (IMF, 2015).

Another source that may contribute to liquidity shortage and subsequent projection in non-alternative CIS is that, as said, these vehicles are diversified in several dimensions, although their portfolio may be mostly invested in assets traded in only one secondary market, for example, the local exchange where the CIS is domiciled (Massa *et al.*, 2015). In this case, as a significant part of the portfolio's assets could be traded in one secondary market, there may be secondary effects that affect the liquidity of the whole CIS portfolio.

When one tries to assess the contribution of any financial entity to systemic risk, it can be decomposed into two complementary parts: The first consists of calculating the probability of each entity to be in a state of financial distress given negative shock. The second relates to how the liquidity and solvency distress of a financial entity or group of entities may be propagated through the entire financial system and, by extension, to the real economy.

With regard to the former, Schmidt *et al.* (2016) analysed the characteristics and drivers on US markets of the money market funds that suffered liquidity shortages during the first episodes of the financial crisis in 2008. By the same token, Martinez (2019) used the same methodology of the previous paper and extended the analysis

6 See Wendt (2015).

by including the whole field of Spanish non-alternative mutual funds during the sovereign debt crisis. He showed that the search for yield strategy leads to higher maturity transformation, which, along with the growth of this sector in the last years, increases the risk of liquidity shortage of this type of CIS when there is a framework of financial distress. These results could show how not only alternative or money market CIS are likely to be susceptible to suffering a run, although, for the time being, we are not aware of any fund which can be considered to be important that has suffered this.[7] As we said earlier, this paper tries to shed light on the second element of the potential contribution of non-alternative CIS to systemic risk, in other words how a negative shock may be propagated to other parts of the financial system. In order to do so, we try to measure the connectedness among the non-alternative CIS as well as with their main underlying secondary securities markets.

7 It should be pointed out here that there were some suspensions of subscriptions and redemptions of CIS in Spain, for example, on 27 June 2018, two mutual funds were suspended. For further details, see https://www.cnmv.es/portal/verDoc.axd?t={f99d4778-44b4-4942-a5c7-395dea5283f0}.

3 The empirical framework

This section describes the methodology used to measure connectedness. As during a financial crisis, financial market volatility generally increases and propagates across markets, we analyse the connectedness between non-alternative CIS and the securities where their managers trade by considering their volatilities. In this case, we especially focus on spillovers from shocks to the non-alternative CIS affecting the underlying securities markets where their managers trade their portfolios.

The methodology follows on from the paper by Barunik and Krehlik (2018), a follow up from the methodologies proposed by Diebold and Yilmaz (2009, 2012) based on the variance decomposition from a vector auto-regression approximating model.[8] This framework provides several measures of spillover or connectedness that are related to the fraction of the variance of error in *H*-step-ahead forecasts due to shocks to another variable or variables arising elsewhere, which is insensitive to variable ordering. The variance decomposition allows measurement of how much of the future uncertainty of one variable comes from a shock in another variable. By simply adding the shares of its forecast error coming from shocks from other assets, a spillover index can be constructed. Diebold and Yilmaz (2014) argue that this type of measures is also related to modern network theory as well as to proposed measures of systemic risk, as the expected shortfall (Acharya *et al.*, 2017) or CoVaR (Adrian and Brunnermeier, 2016).

The methodology proposed by Diebold and Yilmaz (2009, 2012) proposed a variance decomposition associated with an N-variable vector autorregression (VAR). Thus, if a covariance stationary N-variable is considered, VAR(p):

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

where $\varepsilon \sim (0, \Sigma)$ is a vector of independently and identically distributed random variables. The representation as a moving average of the vector x_t is:

$$x_t = \sum_{i=0}^{\infty} A_i \varepsilon_{t-i}$$

Where the NxN matrix of coefficients A_i follows $A_i = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \ldots + \Phi_p A_{i-p}$, with $A_i = 0$ for $i < 0$. The moving average representation of the coefficients (or other type of transformations as impulse-response functions or variance decompositions) is the main tool for the dynamics of the system. Variance decomposition allows us

8 Most of this literature focuses on the connectedness by using volatility, as it is considered as the carrier of information in standard martingale price models (Ross, 1989).

to parse the forecast error variance for each variable into parts that come from various system shocks. It makes possible to assess the fraction of the H-step-ahead error variance in forecasting x_i that is due to shocks to $x_j, \forall j \neq i$, for each *i*. As we are interesting in forecasting by means of the estimated VAR model, it is estimated by following Nicholson *et al.* (2017). They proposed an estimation method based on *lasso* (Tibshirani, 1996) suitable for prediction.[9]

In order to compute variance decompositions, orthogonal innovations are needed. However, our VAR innovations are contemporaneously correlated. One of the basic differences between the two papers by Dielbold and Yilmaz (2009, 2012) are the different methodologies they used when dealing with the orthogonality of errors. In 2009, Diebold and Yilmaz used an identification approach based on the Cholesky factorisation which was not robust enough to a different ordering of the variables that are part of the VAR model. In 2012, they tried a different approach for the identification of the model that is unaffected by ordering. This other method consists of applying the generalised VAR framework from Koop *et al.* (1996) and Pesaran and Shin (1998). For the latter approach, correlated shocks are allowed but they are appropriate weighted using the empirical observed distribution of errors. This method has its drawbacks, the most important of which is that the sum of contributions to the variance error does not necessarily add up to one. With regard to the method used to identify the model, this paper follows Diebold and Yilmaz's 2012 study.

When the model is identified, spillover indices can be computed based on the decomposition of variance that comes from forecasting one variable from the current information contained in other variables. Therefore, own variance shares can be defined as the fractions of the *H*-step-ahead error variances in forecasting x_i from shocks from x_i, for $i = 1, 2, \ldots, N$, and cross variance shares, or spillovers, as the fractions of *H*-step-ahead error variances in forecasting x_i from shock of x_j, for $i, j = 1, 2, \ldots, N, i \neq j$.[10]

If the *H*-step-ahead forecast error variance decomposition is denoted by $\theta(H)^g_{i,j}$ for $H = 1, 2, \ldots$, then:

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

where Σ is the variance matrix of the error vector ε, σ_{ii} is the standard deviation from the error term for the *i*th equation and e_i is the selection vector with one as the *i*th element and zeros otherwise. It is important to stress again that the sum of ele-

9 Nicholson *et al.* (2017) provided an R-package as well known as BigVAR that allows the methodology to be implemented very easily.

10 Readers who are interested in sources of connectedness among instrument and markets may consider studying different forecast horizons of variance decomposition. As pointed out by Diebold and Yilmaz in their 2009, 2012 and 2014 studies, variance decomposition from approximating models are a convenient approach for the empirical measures of connectedness. Diebold and Yilmaz (2009) define the measures based on assessing shares of forecast error variable in one variable due to a shock arising in another variable in the system.

ments of each row of the variance decomposition table is not necessarily equal to 1: $\sum_{j=1}^{N}\theta(H)_{i,j}^{g} \neq 1$. It is needed a normalisation of each entry of the variance decomposition in order to compute the spillover index, the normalisation is usually made by the row sum as:[11]

$$\tilde{\theta}(H)_{i,j}^{g} = \frac{\theta(H)_{i,j}^{g}}{\sum_{j=1}^{N}\theta(H)_{i,j}^{g}},$$

By means of the normalisation, $\sum_{j=1}^{N}\tilde{\theta}(H)_{i,j}^{g} = 1$ and $\sum_{i,j=1}^{N}\tilde{\theta}(H)_{i,j}^{g} = N$. In practical terms, by using this methodology what we obtain is a double entry N x N table where the pairwise relations between the considered assets are obtained, this table is known in the literature as the *"connectedness table"* (Diebold and Yilmaz, 2012).

Following the same notation, the *"pairwise directional connectedness"* from *j* to i is:

$$C_{i \leftarrow j}^{H} = \tilde{\theta}(H)_{i,j}^{g}.$$

It is important to point out that in general $C_{i \leftarrow j}^{H} \neq C_{j \leftarrow i}^{H}$, this means that total number of pairwise directional connectedness measures is $N^2 - N$.

Another measure one can be interested in is the *"net pairwise directional connectedness"*, which is defined as:

$$C_{ij}^{H} = C_{j \leftarrow i}^{H} - C_{i \leftarrow j}^{H}.$$

Instead of considering the individual elements of the connectedness table, we need to evaluate the sums by off-diagonal columns or rows in order to assess how a group of elements influences a given element and vice-versa. To do so, we first have to define M as set that contains several of the variables considered in the connectedness table. Then, *"directional connectedness from set M to i"* is defined as:

$$C_{i \leftarrow M}^{H} = \sum_{\substack{j \in M \\ j \neq i}} \tilde{\theta}(H)_{i,j}^{g},$$

and, *"directional connectedness to set M from j"* is defined as:

$$C_{M \leftarrow j}^{H} = \sum_{\substack{i \in M \\ i \neq j}} \tilde{\theta}(H)_{i,j}^{g},$$

In this literature, M usually contains all the variables except the one that is considered as the receiver or the donor of the connectedness. In former case, this would correspond to the total sum of the off-diagonal values of the row and in the latter, to the total sum of the off-diagonal values of column. As it happens with pairwise di-

11 Alternatively, it can be normalised the elements of the variance decomposition matrix by the column sum of these elements.

rectional connectedness, it may be interesting the net total effects; *"net directional connectedness between M and i"* is:

$$C_i^H = C_{M\leftarrow i}^H - C_{i\leftarrow M}^H$$

Finally, if the goal is to compute the total connectedness between two disjoint set of variables, which, in general can be of different size, then *"total connectedness between M and P"* is defined as:

$$C_{M,P}^H = \frac{1}{N}\sum_{\substack{i,j=1\\ i\neq j}}^{N}\tilde{\theta}(H)_{i,j}^g - \frac{1}{m}\sum_{\substack{i,j\in M\\ i\neq j}}\tilde{\theta}(H)_{i,j}^g - \frac{1}{p}\sum_{\substack{i,j\in P\\ i\neq j}}\tilde{\theta}(H)_{i,j}^g$$

where m is the number of element in M and p is the number of element in P. Complementarily to this measure, *"total connectedness"* of the system as:

$$C^H = \frac{1}{N}\sum_{\substack{i,j=1\\ i\neq j}}^{N}\tilde{\theta}(H)_{i,j}^g$$

Notice that the measure of total connectedness is a particular case of total connectedness between M and P where both sets are empty.

This *"connectedness table"* allows the main measures of connectedness to be calculated between the non-alternative CIS and the underlying securities markets where their managers trade their portfolios:

Connectedness table TABLE 1

	x_1	x_2	•	•	•	•	•	x_N	***From***
x_1	$\tilde{\theta}(H)_{1,1}^g$	$\tilde{\theta}(H)_{1,2}^g$	•	•	•	•	•	$\tilde{\theta}(H)_{1,N}^g$	$\sum_{\substack{j=1,\dots N\\ i\neq j}}\tilde{\theta}(H)_{1,j}^g$
x_2	$\tilde{\theta}(H)_{2,1}^g$	$\tilde{\theta}(H)_{2,2}^g$	•	•	•	•	•	$\tilde{\theta}(H)_{2,N}^g$	$\sum_{\substack{j=1,\dots N\\ i\neq j}}\tilde{\theta}(H)_{2,j}^g$
•	•	•	•	•	•	•	•	•	•
•	•	•	•	•	•	•	•	•	•
•	•	•	•	•	•	•	•	•	•
•	•	•	•	•	•	•	•	•	•
x_N	$\tilde{\theta}(H)_{1,N}^g$	$\tilde{\theta}(H)_{2,N}^g$	•	•	•	•	•	$\tilde{\theta}(H)_{N,N}^g$	$\sum_{\substack{j=1,\dots N\\ i\neq j}}\tilde{\theta}(H)_{N,j}^g$
To	$\sum_{\substack{i=1,\dots N\\ j\neq i}}\tilde{\theta}(H)_{i,1}^g$	$\sum_{\substack{i=1,\dots N\\ j\neq i}}\tilde{\theta}(H)_{i,2}^g$	•	•	•	•	•	$\sum_{\substack{j=1,\dots N\\ i\neq j}}\tilde{\theta}(H)_{N,j}^g$	$1/N\sum_{\substack{i,j=1,\dots N\\ i\neq j}}\tilde{\theta}(H)_{i,j}^g$

Source: Diebold and Yilmaz (2014).

The table shows the schematic connectedness table, which proves central to understanding the various connectedness measures and their relationships. Its main upper-left block matrix of dimension *N´N* contains the variance decompositions, called the 'variance decomposition matrix'. The connectedness table augments with a rightmost column containing row sums, a bottom row containing column sums, and a bottom-right element containing the grand average, in all cases for *i* different from *j*.

Given this framework provided by Diebold and Yilmaz (2009, 2012), Barunik and Krehlik (2018) proposed a method to decompose it in the short, medium and long term given a long horizon H. They do so by using the spectral representation of variance decomposition based on frequency responses to shocks instead of impulse response to shocks, showing how this can be used to describe frequency-dependent connectedness measures.[12] In order to implement this idea, they work out a frequency response function $A\left(e^{-i\omega}\right)=\sum_h e^{-i\omega h}A_h$ which can be obtained as a Fourier transform of the coefficients A_h, with $i=\sqrt{-1}$. Therefore, the generalised causation spectrum over frequencies $\omega\in(-\pi,\pi)$ is defined as:[13]

$$f(\omega)_{k,j}\equiv\frac{\sigma_{jj}^{-1}\left|\left(A\left(e^{-i\omega}\right)\Sigma\right)_{k,j}\right|^2}{\left(A\left(e^{-i\omega}\right)\Sigma A'\left(e^{i\omega}\right)\right)_{k,k}}$$

In this case, the row index i has been substituted by k as i is used to represent $\sqrt{-\mathrm{i}}$. It is important to point out that $\mathrm{f}(\omega)_{\mathrm{k,j}}$ is the representation of the spectrum of the kth variable at a given frequency ω due to shocks in the jth variable. As we want to obtain the variance decompositions to frequencies, $\mathrm{f}(\omega)_{\mathrm{k,j}}$ can be weighted by the frequency share of the variance of the kth variable such that:

$$\Gamma_k(\omega)=\frac{\left(A\left(e^{-i\omega}\right)\Sigma A'\left(e^{i\omega}\right)\right)_{j,j}}{\frac{1}{2\pi}\int_{-\pi}^{\pi}\left(A\left(e^{-i\lambda}\right)\Sigma A'\left(e^{i\lambda}\right)\right)_{j,j}d\lambda},$$

this variable figures out the power of the kth variable at a given frequency. This expression sums to a constant value of 2π when summing through frequencies.

Then, the cross-spectral density on the interval $d=(a,b):a,b\in(-\pi,\pi),a<b$:

$$\int_d A\left(e^{-i\omega}\right)\Sigma A'\left(e^{i\omega}\right)d\omega$$

is estimated by means of:

$$\sum_\omega \hat{A}(\omega)\hat{\Sigma}\hat{A}'(\omega),$$

for $\omega\in\left\{\left|\frac{aH}{2\pi}\right|,\ldots,\left|\frac{bH}{2\pi}\right|\right\}$, where

$$\hat{A}(\omega)=\sum_{h=0}^{H-1}\hat{A}_h e^{-2i\pi\omega/H}$$

12 The spectral representation of variance decompositions can also be viewed as a possible way of measuring causality in the frequency domain.

13 In this case the row index *i* has been substituted by *k* as *i* is used to represent $\sqrt{-1}$.

and the $\hat{A}_h$ coefficients are computed by a recursive method: $\hat{A}_0 = I$, $\hat{A}_h = \sum_{j=1}^{\max\{h,p\}} \Phi_j \hat{A}_{h-1}$, where p is the order of the VAR and $h \in \{1,\ldots,H\}$. $\hat{\Sigma} = \hat{\varepsilon}'\hat{\varepsilon} / (T - z)$, z is a correction term that depends on the specification of the estimated VAR.

The impulse response function decomposition at a given frequency is then estimated as $\hat{A}(d) = \sum_{\omega} \hat{A}(\omega)$. Thus, the estimation of the generalised variance decompositions at a given frequency is:

$$\tilde{\theta}_{kj}^{g}(\omega) = \sum_{\omega} \widehat{\Gamma_k}(\omega) \hat{f}(\omega)_{k,j},$$

where

$$\hat{f}(\omega)_{k,j} \equiv \frac{\hat{\sigma}_{jj}^{-1}\left(\left(\hat{A}(w)\hat{\Sigma}\right)_{k,j}\right)^2}{\left(\hat{A}(w)\hat{\Sigma}\hat{A}'(w)\right)_{k,k}}$$

is the estimated generalised causation spectrum, and

$$\hat{\Gamma}_k(\omega) = \frac{\left(\hat{A}(w)\hat{\Sigma}\hat{A}'(w)\right)_{k,k}}{\left(\sum_{\omega} \hat{A}(w)\hat{\Sigma}\hat{A}'(w)\right)_{k,k}}$$

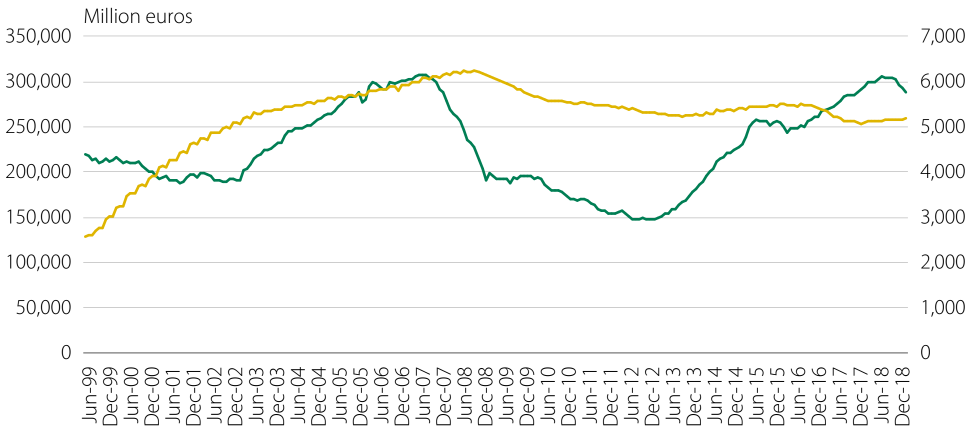
is an estimate of the weighting function.

4 Data

4.1 Stylised facts of the Spanish non-alternative collective investment schemes market: June 1999–December 2018

The non-alternative CIS considered in this paper are financial mutual funds and investment companies authorised and registered with the CNMV, the Spanish equivalent to the U.S. Securities and Exchange Commission. Real state collective investment schemes, hedge funds and foreign collective schemes marketed in Spain were not included in the analysis. We decided to remove the first two types for two reasons: they have different characteristics and they represent a small portion of the total investment in collective schemes in Spain.[14] At the end of 2018, the total assets under management (hereafter AuM) of the CIS authorised and registered with the CNMV were €290.801 billion, the real state collective investment schemes accounted for €1.058 billion, whereas hedge funds represented a figure of €2.812 billion. We did not consider foreign CIS because we do not have access to the relevant data for carrying out the analysis as they are authorised and registered with other national competent authorities.

Collective investment schemes, AuM (left axis) and number of operating vehicles (right axis)[1] FIGURE 1



Source: CNMV.

1 The number of CIS was computed considering each class of a mutual fund or investment company as a single entity.

14 Mutual funds and investment companies are open-ended CIS. This means that they allow investors to apply for the redemption of their investment against the CIS. Most of these mutual funds and investment companies are regulated according to Directive 2009/65/EC of the European Parliament and of the Council of 13 July 2009 on the coordination of laws, regulations and administrative provisions relating to undertakings for collective investment in transferable securities (UCITS). On the other hand, the excluded CIS are within the Alternative Investment Fund Management Directive and out of real state collective investment schemes and may be closed-ended.

The number of non-alternative CIS in Spain and their assets grew significantly in the period from June 1999 to December 2018. Regarding AuM, we can distinguish three different sub-periods along this whole period. As we can see in Figure 1, in the years previous to the crisis and especially from 2003, AUM went from about €200 billion to the peak of more than €300 billion in 2007. Once the crisis started, they fell by half by the end of 2012. Starting in 2013 there was a continuous growth until AuM reached again the threshold of €300 billion.

On the other hand, the number of non-alternative CIS surged from 1999 up to the beginning of the crisis. In those years, the number went from 2,500 to more than 6,000. Once the crisis started, they gradually fell to an amount slightly higher than 5,000.

Although regulatory, a large part of mutual funds and investment companies share the same regulation (UCITS Directive 2009/65/EC), also differing in two important characteristics that should be pointed out:

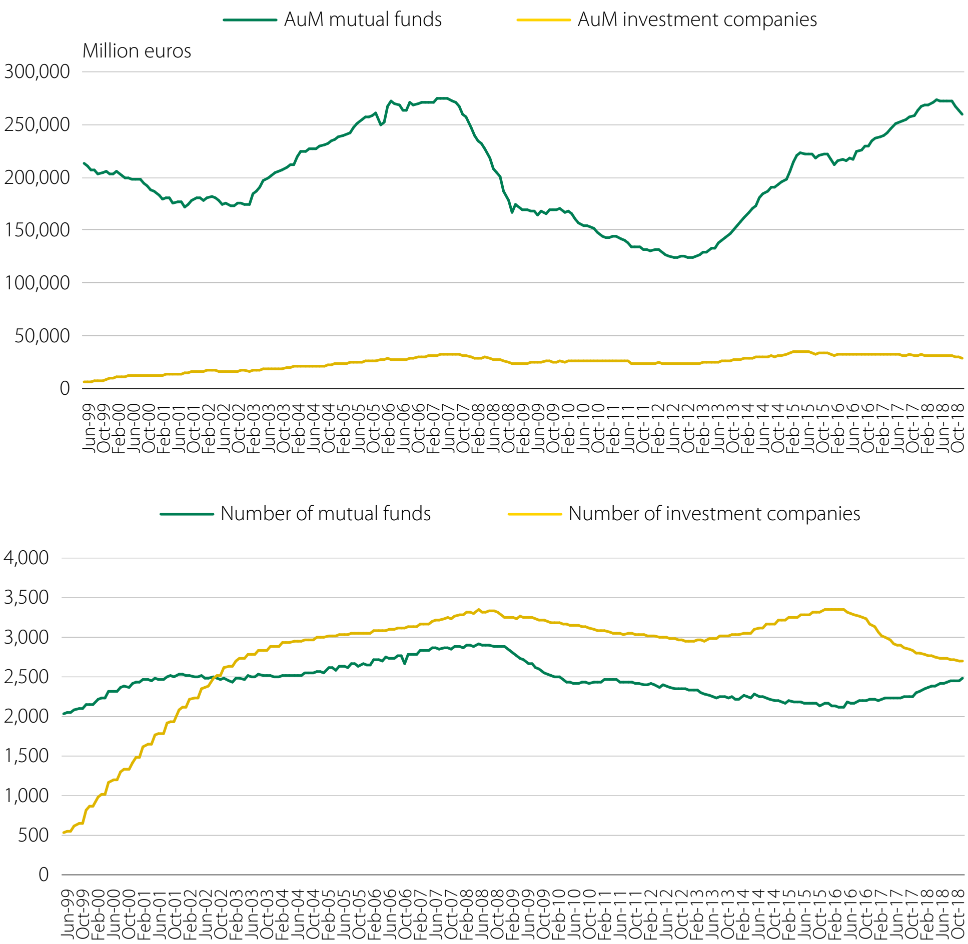
i) Mutual funds have to declare their vocation and investment strategy before they are put on the market. Investment companies enjoy more freedom and are not restricted to either a single vocation or to a close investment strategy.

ii) Mutual funds price their portfolio each day in order to make their net asset value public. Investors can therefore apply for the redemption of their investment according to the published net asset value. Investors of the investment companies may buy shares by means of the net asset value published by the Management Company or directly from a segment of the Spanish securities exchange where these companies' shares are listed and traded.[15]

Thus, the first of the differences makes investment companies more suitable for institutional investors. As we can infer from Figure 2, mutual funds are, by far, the vehicles that represent the highest portion of the CIS AuM. The number of investment companies meanwhile is higher than the number of mutual funds since 2002. The combination of both type of figures leads to mutual funds that are, in general, larger than investment companies under the criterion of AuM.

15 https://www.bolsasymercados.es/mab/esp/SICAV/Listado.aspx.

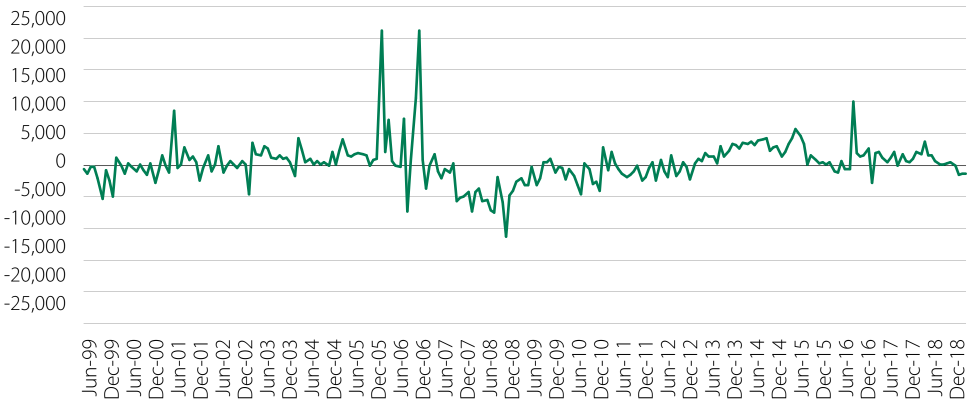
AuM and number of mutual funds and investment companies FIGURE 2



Source: CNMV.

Regarding how CIS holders behave in times of distress, Figure 3 shows monthly CIS net subscription and how there are different reactions depending on the business cycle. Over the three periods that were considered as being turbulent, there were significant negative net subscriptions. They were especially significant in the first period of the financial crisis over the period when Lehman Brother filed for bankruptcy. In that period from September 2007 to July 2009, net subscription registered negative figures in each of the months and the total amount was about €105 billion.

Monthly collective investment schemes net subscriptions FIGURE 3

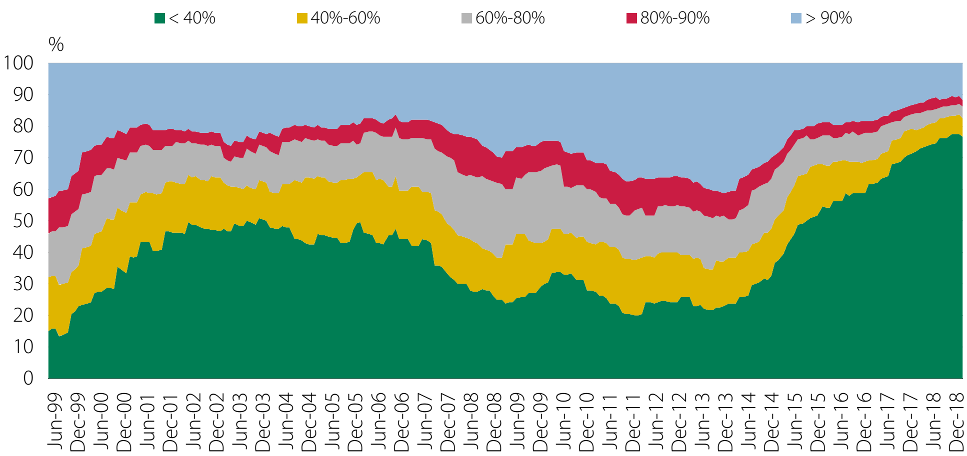


Source: CNMV.

Along with the other two unstable periods: the dot-com bubble and the sovereign debt crisis, there were also periods with negative net subscription, but their total amount was notably lower. In the first case, although there was turbulence, especially in the equity market (Ofek and Richardson, 2003), it was not translated into a recession affecting the real economy. This could have limited high negative net subscription to equity funds and other types of non-alternative CIS with a big portion of the portfolio in equity although there was no contagion of other types of CIS. In the case of the sovereign debt crisis period, negative net subscriptions were neither as large as in the first period of the financial crisis nor for so long a period. However, they did account for nearly a further €50 billion on top of the previous €105 billion. One of the reasons why the outcome of the crisis for CIS may have been less negative in the second part of the crisis is that both periods were very close, even when Spain was one of the European economies where the sovereign debt crisis was tougher. A big portion of the investors that decided to drop out of the CIS market during the early stages of the crisis did so for liquidity as well as for risk aversion reasons. The investors who remained may be seen as having been more resilient to market averse conditions.

Another important feature of this market is what the financial literature has referred to as domestic home bias (Chan *et al.*, 2005). This picks up on the fact that investors tend to invest in securities or portfolios of securities where national financial instrument are over-weighted in terms of attending to standard investment allocation models (e.g. Cooper and Kaplanis, 1986). Figure 4 shows the evolution of the weight of national financial instruments in the portfolios of Spanish CIS.

Percentage of domestic securities over total CIS AuM FIGURE 4



Source: CNMV and own calculations.

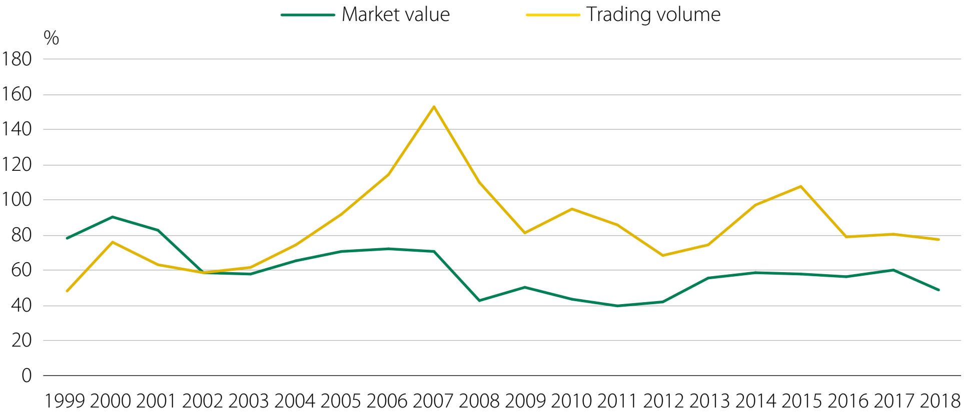
The evolution of the weighting shows how CIS portfolios are less diversified between national and international securities in times of distress. Throughout the financial crisis, it can be noticed how the percentage of CIS portfolios invested in Spanish securities was higher than in "normal" times. This effect was notably important during the sovereign debt crisis when about 35% of the total AuM were invested in CIS with portfolios comprising at least 90% of their holding in Spanish securities.

Meanwhile, from 2002 to 2007 and from 2015 to 2018, the percentage of CIS portfolios investing in international securities increased remarkably. It is important to observe how this percentage peaked in 2018, which at this point represents weak evidence that the home bias may become less important as time goes by.

It is therefore important to study the relationship between CIS and the national securities markets, and concretely, how they are interconnected. In this paper, we consider the equity and debt markets as those are the most important in the case of Spain. Figure 5 shows the market value and the trading volume that takes place over Spanish equities.[16] These figures may be considered to be in line with their European peers expect for the United Kingdom as well as the United States, which registered higher trading and market values. In the case of the trading volume, two features deserve to be focused on. The first is that it slightly increased over the considered period. The second is that the trend that it is showed is very cyclical, peaking just before the financial crisis and dropping off after it started. It only recovered after the expansive monetary policy began, although in recent years (2016-2018) it returned to low trading volumes.

16 Before MiFID I came into force, the trading of the Spanish equities took place exclusively at the official markets owned by the Spanish Stock Markets and Financial Systems (BME). Since MiFID I and later MiFID II, Spanish equities have been traded on official markets as well as on the market trading facilities such as BATS, Chi-X and Turquoise.

Spanish equity market over GDP FIGURE 5



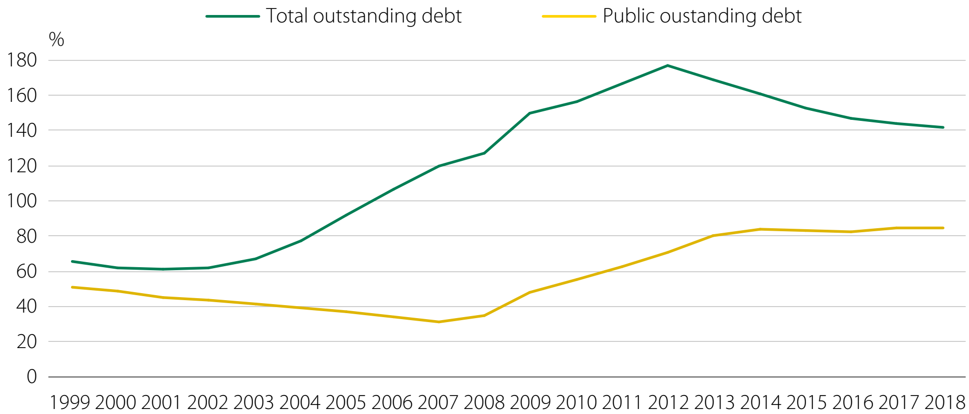
Source: CNMV and Spanish Bureau of Statistics.

Regarding the Spanish bond market, Figure 6 shows the outstanding Spanish debt issued in bonds, distinguishing between public and private debt. Thus, there are two patterns that describe this market over the past 19 years: total outstanding debt increased significantly, climbing from 60% of GDP to 140% in 2018 with a peak of almost 180% in 2012. The second pattern describes the role of public debt within total outstanding debt. Up to the beginning of the crisis, outstanding public debt decreased, while private debt increased notably as a result of the real estate boom. However, once the financial crisis kicked in, public debt grew due to continuous deficits, with a significant replacement of private debt with public debt post-2012. With respect to the size of the Spanish market compared to its European peers in terms of the outstanding debt, by the end of 2018, the Spanish market was above EU member state mean, which is about 100% of European Union GDP.

In general, investors in non-alternative CIS enjoy a high degree of diversification.[17] This allows them to bear a lower risk, in terms of volatility, than when they invest directly in the Spanish equity or bond market. Thus, in Figure 7, we can see how the weighted volatility of CIS is almost always lower than the volatility of the IBEX 35 and the IBEX Small Caps (the main indices for blue chips and small caps at the Spanish Stock Exchange) as well than for 10-year Spanish government bond (the main reference in the Spanish public debt market).

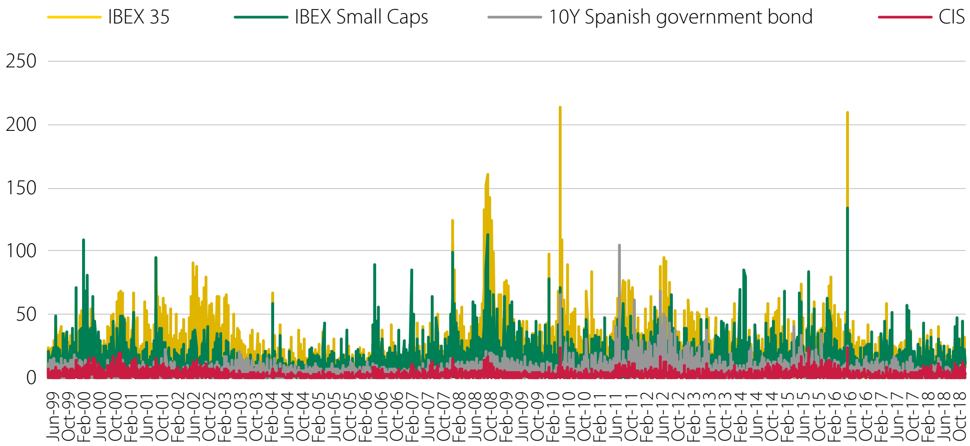
17 The UCITS and quasi-UCITS are regulated by the Collective Investment Schemes Act no. 35/2003 of 4 November and related implementing regulations transposing Directive 2009/65/EC to Spanish law. It is important to point out that under the European regulations most of the quasi-UCITS are considered as alternative CIS which fall under the category of "others".

Outstanding debt in the Spanish bond market over GDP FIGURE 6



Source: Bank of Spain and National Statistics Institute.

Annualised daily volatility FIGURE 7



Source: Bloomberg, Reuters Datastream, CNMV and own calculations.

4.2 Description of the database

The empirical application considers the Spanish non-alternative collective investment schemes as well as a representation of the equity and fixed income markets. The considered CIS are: CIS regulated under UCITS, quasi-UCITS that are regulated by the Collective Investment Schemes Act no. 35/2003 and by the Money Market Fund Regulation (MMFR). Although the quasi-UCITS can be considered as alternative from the AIFMD perspective, their characteristics are much closer to the UCITS regulation. Regarding money market funds, in Spain, this type of funds could be considered as a short term fixed income fund with risk characteristics that are not very different from UCITS either.

For the considered CIS, the original source of the data set is the CNMV, which periodically collects information as part of its duty to supervise collective investment schemes. The main data on all existing mutual funds and investment management companies were obtained on a daily basis from June 1999 to December 2018, including those that are now defunct or merged. Treating each CIS/day as a single observation, the total sample size was 37,550,747 observations, 17,550,710 of which corresponded to non-alternative mutual funds, including their different classes, with the remaining observations pertaining to investment companies. The total number of different CIS and their classes that are part of the database is 10,973: 6.960 from mutual funds and 4,013 from investment companies.

The database built for the analysis follows a two-step procedure. In the **first step**, the whole population of Spanish non-alternative CIS was considered. By means of the two main variables that characterise the non-alternative CIS in each of the days under consideration: the net asset value and the assets under management, a daily weighted volatility was computed for different categories of CIS. The CIS were grouped into five categories depending on the different profiles of their vocations: investment companies, equity funds, fixed income funds, guaranteed funds and other funds. The investment companies' category brings together all the investment companies registered with the CNMV. The equity funds category is composed by all vocations where the mutual funds own mainly a portfolio of equities, including mixed equity funds. The fixed income fund category comprises the mutual funds whose main investments are in short- and long-term fixed income, including monetary and mixed fixed income funds. The guaranteed fund category are those funds whose investment strategy consists of a structure, usually composed by a high rated bond or collection of bonds and a number or derivatives, usually over an index or a basket or assets. Finally, the other funds category covers all funds within the vocations with the more flexible investment policies within UCITS and the quasi-UCITS, this means the Global and Absolute Return vocations. Table 1 summarises the main descriptive statistics for each of these categories.

Descriptive statistics of CIS by categories TABLE 2

	Return. Mean (%)	Return. Standard deviation (%)	AuM. Mean (million euros)	AuM. Standard deviation (million euros)	Number of entities	Total number of observations
Investment companies	1.42	5.68	24,724	6,913	4,013	20,000,037
Guaranteed funds	2.16	1.97	48,585	7,918	1,907	5,005,475
Equity funds	1.69	14.43	34,473	14,582	1,872	5,419,318
Fixed income funds	1.42	0.89	101,383	26,349	2,143	4,998,729
Other funds	0.24	5.37	17,677	14,849	1,038	2,127,188

Source: Own calculations.

We can see how the fixed income funds category is the most important in terms of AuM criterion as well as the largest average funds in term of AuM. At the same time, their return/volatility was higher than in the case of the equity and other funds categories. Another feature that may deserve attention is the better performance of the investment companies compared with other funds. Given the similar volatility of the portfolios, and in many cases similar vocations (Global), the return of the former is notably higher than the latter. One of the reasons why this may happen is that the portion of institutional investors in investment companies is higher. Finally, the low return of equity funds when we consider the risk assumed by their investors should also be highlighted.

In order to compute daily volatilities and following Garman and Klass (1980), we computed the weighted by AuM daily return within each of the categories using the funds' net assets values attending to the following formula:

$$r_t^C = \sum_{i=1}^{N} \frac{AuM_{it}\left(\ln\left(nav_{it}\right) - \ln\left(nav_{it-1}\right)\right)}{\sum_{i=1}^{N} AuM_{it}}$$

where N corresponds to the number of CIS in the category. From this returns, the daily annualised volatility is determined as:

$$\sigma_t^C = \sqrt{\left(r_t^C\right)^2}\sqrt{252}$$

Therefore, we calculated five time series, one for each of the CIS categories, from 1 June 1999 to 31 December 2018 which include weekend days as well as bank holidays, with 7,154 observations.

In the **second step** of the building of the database, we combined the data from CIS with data from the Spanish underlying markets in which the CIS may invest. In the case of the equity market, we took two indices as representative: the IBEX 35 and the IBEX Small Caps. For the debt market, the representative is the on-the-run 10-year Spanish government bond.

The IBEX 35 index comprises the 35 most liquid shares, usually from the largest firms that are listed and traded on the Spanish stock exchange.[18] Among the regular constituents of the index, the bank sector is one of the most important as it represents about 25-40% of the all constituents' market value. The IBEX Small Caps meanwhile is an index comprising 30 firms among the smallest listed and traded on the Spanish stock exchange.[19] These small firms represent typical Spanish firm more closely and the index path can be seen as proxy of the evolution of the real economy. These two indices can therefore be taken to be complementary. Regarding the Spanish debt market, we chose to consider the main benchmark of the Spanish public debt.

In the case of the equity indices, the data on daily values were obtained from Thomson Datastream. For the 10-year government bond benchmark, the main data source

18 The IBEX 35 is an index computed according to the following formula: $I_t = I_{t-1} \, x \, \frac{\sum_{i=1}^{35} MV_{i,t}}{\left[\sum_{i=1}^{35} MV_{i,t-1} \pm J\right]}$, where I_t is value of the index at t, $MV_{i,t}$ is the market value of each of the constituents of the index and J is a coefficient used in order to adjust the market value of the constituents due to the issuance of new shares or any other corporate action that may dilute the equity value of the firm.

19 The IBEX Small Caps is also an index weighted by market value that follows the same formula as the IBEX 35, with the difference between them the criteria for choosing the constituents. One of the criteria consists of prohibiting a share to be part of the IBEX 35 and the IBEX Small Cap at the same time.

was Bloomberg. We took the daily information on prices from the 10-year bond considered as the on-run. In both cases, volatility was calculated using a similar procedure to the CIS, with the data collected for these indices not including weekend days and bank holidays. Moreover, in the case of 10-year government bond benchmark, we also excluded the volatility on the days on which the on-the-run bond changed.

The final database on which the analysis is based is made up of eight time series of volatilities, one for each of the securities markets indices and one for each of non-alternative CIS categories. In order to work out a consistent database, we excluded from the time series obtained in the first of the database the weekend days and the bank holiday. At the same time, the returns from the days after the weekend and bank holidays were recalculated for including the returns from the excluded days. Finally, we excluded the days where the on-the-run 10-year government bond changed too, meaning that the database provides a sample of 4,941 trading days. Table 3 shows the main descriptive statistics of the series:

Descriptive statistics of volatility series TABLE 3

	Volatility. Mean (%)	Volatility. Standard deviation (%)	Number of observations
IBEX 35	15.8	15.7	4,941
IBEX Small Caps	12.0	11.6	4,941
10-year Spanish government bond	5.1	5.4	4,941
Investment companies	4.8	4.7	4,941
Guaranteed funds	1.4	1.4	4,941
Equity funds	10.1	10.4	4,941
Fixed income funds	0.6	0.7	4,941
Other funds	3.3	4.3	4,941

Source: CNMV, Bloomberg and Thomson Datastream and own calculations.

The volatility of the different assets appear as expected while that of securities indices is higher than their CIS category peers due to a higher diversification and because the different portfolios become more risky as far as the portion of equity is higher. Not surprisingly, the IBEX 35 leads the table followed by the IBEX Small Caps and the equity funds category, with the fixed income funds category recording the lowest volatility.

5 Results

In this section we report the empirical results of the analysis of the connectedness between the five different types of non-alternative CIS considered in this paper (investment companies, equity funds, fixed income funds, guaranteed funds and other funds) and the main Spanish underlying securities markets where their managers trade non-alternative CIS portfolios.

The methodology described in Section 3 is applied to the Section 4.2 database that consists of eight time series of volatilities. It is important to recall that those market instruments were: IBEX 35 index, IBEX Small Caps index and the on-the-run 10-year Spanish government bond. The others are synthetic and represent different categories of Spanish non-alternative CIS: investment companies, equity funds, fixed income funds, guaranteed funds and other funds.

Table 4 shows the full-sample volatility connectedness, which is obtained through generalised variance decomposition. Each of the entries of Table 4 is the estimated contribution to the forecast error variance of one variable coming from innovations to other variable. The estimate of total volatility connectedness is based on a vector autoregression model of order 3 and generalised variance decompositions of 250-day ahead forecast errors.

Full sample connectedness table TABLE 4

	IBEX 35	IBEX SC	10-Y Bond	IC	EF	FIF	GF	OF	*From*
IBEX 35	30.4	8.5	2.2	18.6	23.1	4.6	3.3	9.3	69.6
IBEX SC	12.7	47.3	1.2	13.0	13.5	3.9	2.6	5.8	52.7
10-Y Bond	4.5	1.7	61.4	2.6	3.3	6.3	19.1	1.2	38.6
IC	15.5	7.2	1.0	25.9	21.7	8.2	3.6	16.9	74.1
EF	20.0	7.9	1.4	22.5	27.2	4.3	2.3	14.4	72.8
FIF	6.1	3.3	4.2	13.1	6.6	41.2	16.3	9.2	58.8
GF	5.0	2.5	14.4	6.5	4.0	18.3	46.3	3.1	53.7
OF	9.9	4.1	0.6	22.0	18.6	7.8	2.3	34.8	65.2
To	73.7	35.1	25.0	98.2	90.7	53.5	49.4	59.9	60.7
Net	4.1	-17.6	-13.6	24.1	17.9	-5.3	-4.3	-5.3	

Source: Own calculations.

IC = Investment Companies, EF = Equity Funds, FIF= Fixed Income Funds, GF = Guaranteed Funds, OF = Other Funds.

The first important result that emerges from Table 4 is that about 60.7% of the volatility forecast error variance in all the variables is due to connectedness or spillovers,[20] meaning that these may be considered as important on average or unconditionally in our sample.

As our main interest lies in the capacity of non-alternative CIS to affect systemic risk, we have given special attention to the fraction of the total volatility forecast error variance of the IBEX 35, the IBEX Small Caps and the on-the-run 10-year Spanish government bond explained by the non-alternative CIS volatility shocks. It is therefore important to focus on the spillovers from shocks to the non-alternative CIS volatilities to the main representative Spanish financial instrument volatility. Table 4 shows that IBEX 35 has a "from" connectedness of 69.6%, due mainly to the impact of volatility shocks to the Equity funds group (23,1%) and Investment companies group (18.6%) that almost explain the 40% of the total volatility forecast error variance of the IBEX 35. Table 4 also indicates that IBEX Small Caps has a slightly lower "from" connectedness than IBEX 35 "from" connectedness, reaching a level 52.7%, due again to the impact of volatility shocks to the Equity funds group (13%) and Investment companies group (13.5%). Interestingly, Table 4 shows the lowest spillovers from the non-alternative CIS volatility shocks to the on-the-run 10-year Spanish government bond that is especially explained by the spillover effects from the Fixed income funds (6.3%) and from the guaranteed funds category (19.1%).

It is also important to emphasise that the "to" connectedness of the Investment companies and the Equity funds categories (98.2% and 90.7%) exceeds their "from" connectedness (74.1% and 72.8% respectively) by 24.15% and 17.9% respectively. Therefore, they are net transmitters of shocks. On the other hand, Fixed income funds, Guaranteed funds and the "Other" category have negative net connectedness (-5.3%, -4.3% and -5.3%), indicating that they are net receivers of shocks. Among the market instruments (IBEX 35 index, IBEX Small Caps index and the on-the-run 10-year Spanish government bond), Table 4 indicates that only the IBEX 35 displays a slightly positive net connectedness (4.1%) while the IBEX Small Caps and on-the-run 10-year Spanish government bond have the more negative net connectedness (-17.6% and -13.6%), and consequently they are net receivers of shocks.

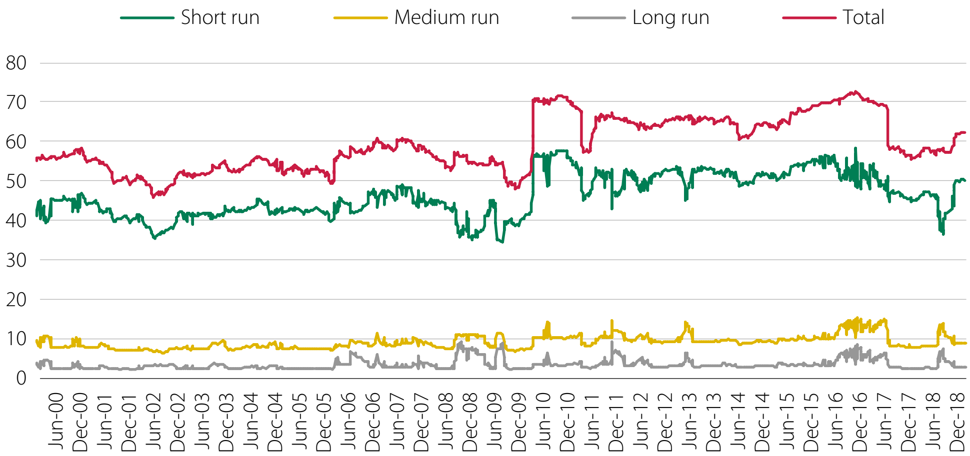
Before we can make any conclusions on whether the connectedness found can be considered to be positive or negative in terms of financial stability or any other aspect, another angle should be explored, namely how this connectedness evolves over time. This is especially important in this case as spillover volatility may be seen as positive when it helps to the price formation in the underlying markets and by extension to the pricing of CIS portfolios from the "Other" category. It may also be seen as negative when it helps to propagate negative shocks in periods of crisis.

Therefore, in the following analysis, we study the time-frequency dynamics of connectedness of system as full sample connectedness is a summary of "average" volatility connectedness dynamics that could potentially miss secular and cyclical movements in connectedness. Figure 8 shows the time dynamics of the total connectedness of system as well as the decomposition of the total connectedness into frequency

20 Annex I shows the decomposition of the connectedness measures in the short, medium and long run.

bands up to one week (corresponding to the short term), from one week to one month (corresponding to the medium term) and from one month to 250 days (corresponding to the long term), allowing us to investigate how market and non-alternative CIS risk is connected at different frequencies over time.

Total connectedness June 2000-December 2018 FIGURE 8

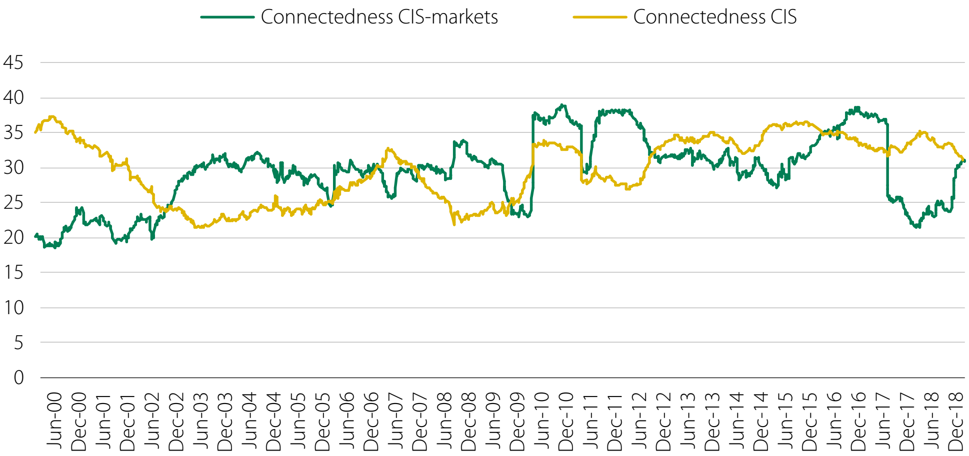


Source: Own calculations.

This figure shows that the total volatility connectedness ranges between 45% and 75% with different temporal dynamics of the eight volatilities of the system as shocks work across the system with different impact. During the burst of the tech bubble in 2000, the index reached very high levels attaining an average volatility connectedness of about 50% until mid-2002 where the index dropped below the total sample average volatility connectedness. In June 2002 the index reached the lowest level and started to increase steadily reaching a local maximum in mid-2007, due to the tightening monetary policy deployed by the U.S. Federal Reserve from mid-2006 onwards. Interestingly the index remained at quite low levels during the 2007-2009 global financial crises, but started to increase sharply during the Eurozone debt crisis in 2010-2012. The period from August 2012 onwards can be characterised by an increase in the average total connectedness of the volatilities of the market instruments and the non-alternative CIS categories as the total average connectedness is 72.4%, higher than the total unconditional average connectedness, irrespective of the cyclical movements of financial markets. This empirical finding could be considered as evidence of a more integrated system, as the spillover of the shocks across the system is stronger along that period. Finally, once the result of the Brexit referendum was known there was a drop in the total connectedness that seems to start to recover during the second half of 2018.

Figure 8 also reveals the frequency decomposition of connectedness and shows that shocks creating uncertainty in the short term are by far the main driver of total connectedness over the whole sample. Therefore, the uncertainty represented by volatility translates into non-persistent responses of investors to shocks. If we focus on the periods of high connectedness of the system, these are also driven by high-term frequency response to shocks, something that could be explained as short-term uncertainty. Although during the periods of high connectedness linked to adverse market risk conditions, there were relative peaks of long-term uncertainty, their role, in absolute terms, can be described as non-critical.

Connectedness among CIS and with securities markets FIGURE 9

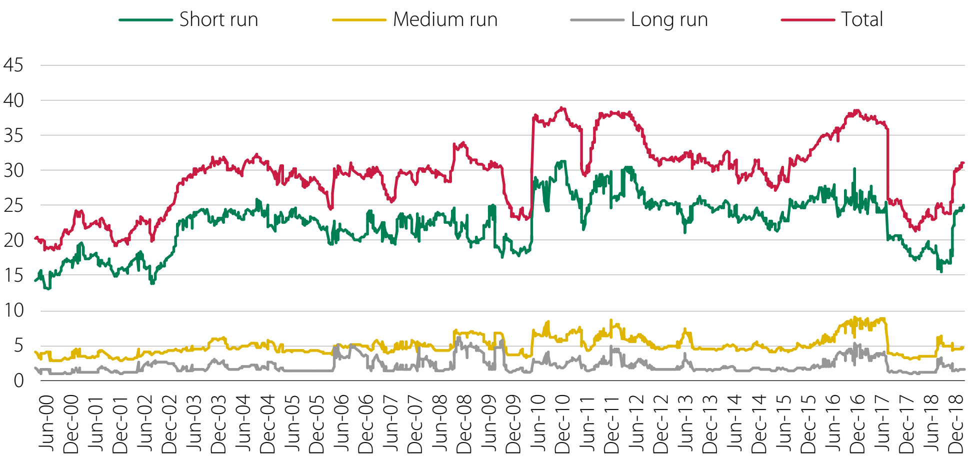


Source: Own calculations.

Given these results, the most likely explanation of the connectedness is that of it having a positive role, a sign that non-alternative CIS as well as markets process the shocks quickly, which becomes an adequate process of price formation. In distress conditions, the connectedness among CIS and with their underlying market could be said to play a limited role in terms of financial stability that does not go further than an increase in the contemporaneous correlations among assets. The results are in line with the FSB view – that financial institutions that have neither the transformation of maturity/liquidity nor the leverage as key aspects of their investment strategies have a limited impact in financial stability through financial markets.

In general, the dynamics of the total connectedness of the system behaved as expected with the exception of the periods at the beginning of financial crisis (around the Lehman bankrupt) and at the beginning of the sovereign debt crisis (around the bail-out of Greece). As can be seen in Figure 9, in these two periods the drop in the connectedness mainly came from how the volatilities between non-alternative CIS and their underlying markets interact. These two periods also share a further commonality, that when connectedness rose, it rose sharply. Therefore, in these periods the flows of volatilities between CIS seem to show a partial decoupling of the prices in securities markets with the pricing of CIS portfolios. Figure 10 may reinforce this idea as it is shown how the main driver of the connectedness between the non-alternative and securities markets is again the short run.

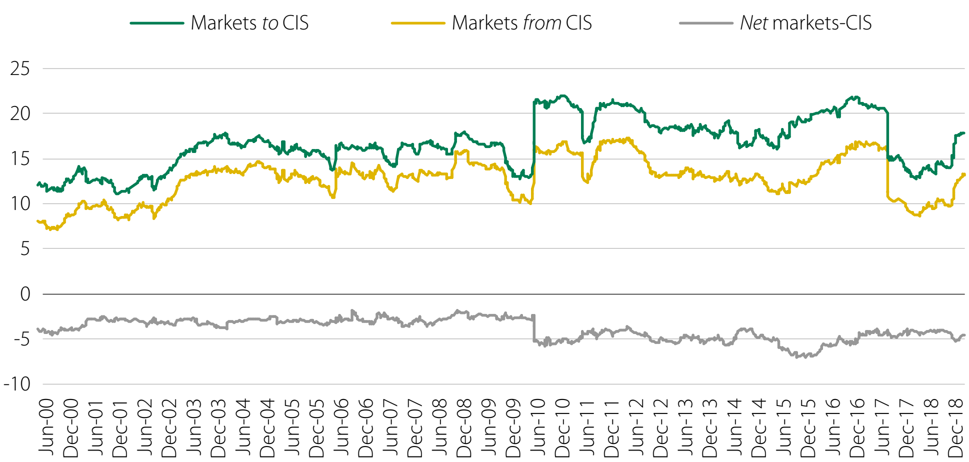
Connectedness between CIS and securities markets FIGURE 10



Source: Own calculations.

After discussing the total connectedness we analysed the information contained in the "directional to others" row and the "directional from others" column dynamically through the directional connectedness plots. Therefore, we analysed the directional information that is masked under the total connectedness plot. From Figure 11, it can be argued that the shocks in the volatility of the non-alternative CIS affect future volatility of the securities markets in a stronger manner than when it flows in the opposite direction. This means that the information that securities markets incorporate in trading assets from the pricing of the CIS portfolio is higher. Although, CIS portfolios are mainly composed of liquid assets, they contain certain assets which are not so liquid and which help to fix references for prices in the segment of the equity market for small caps and partly for the market of public debt (see Table 4). It is also important to point out that the net contribution of CIS to securities markets increased, as their connectedness peaked at the beginning of the financial crisis before growing significantly.

Connectedness *to from net* securities markets-CIS FIGURE 11

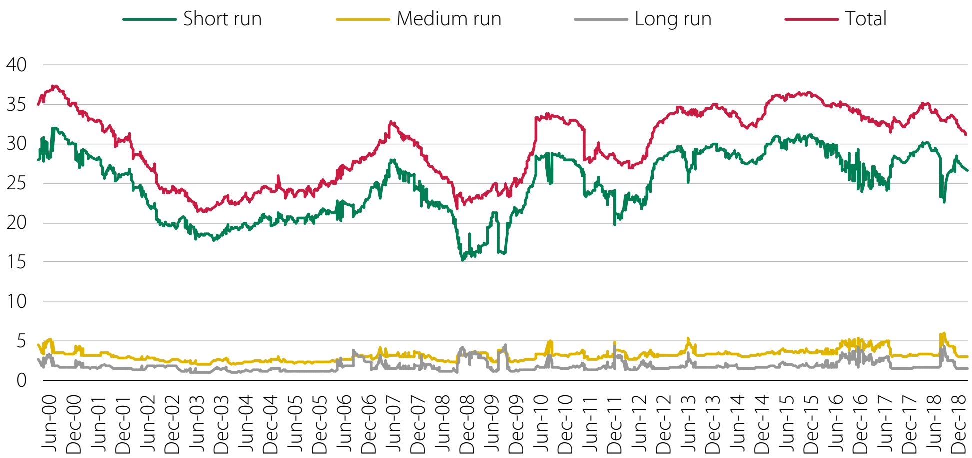


Source: Own calculations.

In order to gain a better understanding of the whole picture of connectedness, Figure 12 plots the total connectedness corresponding exclusively to the spillover from each of the categories of non-alternative CIS shocks to the other categories non-alternative CIS in the long, medium and short term. As in the other figures of this type, the connectedness among CIS categories comes mainly in the short run. Shocks from one CIS category are absorbed quickly by the other CIS. In this regard, even if one category of CIS may experience distress, as far as the other CIS categories are liquid, the other CIS could absorb negative shocks in a very short period of time. One of the main reasons why this would happen is that this type of financial institutions is mostly financed by their unit and shareholders who bear all profits and losses of the CIS portfolios.

Finally, Figure 13 provides the percentage contribution of each category of CIS to the total connectedness among CIS. In this regard, the categories of equity funds, investment funds and other funds contribute with a percentage very similar to the connectedness along the studied period. At the same time, the contributions from fixed income and guaranteed funds are more volatile, being the one from guaranteed funds always lower than the categories mentioned earlier. The percentage of contribution of the fixed income category was persistently lower as well since about June 2002 until December 2015. From that moment onwards, the percentage is comparable with the highest categories of contributors.

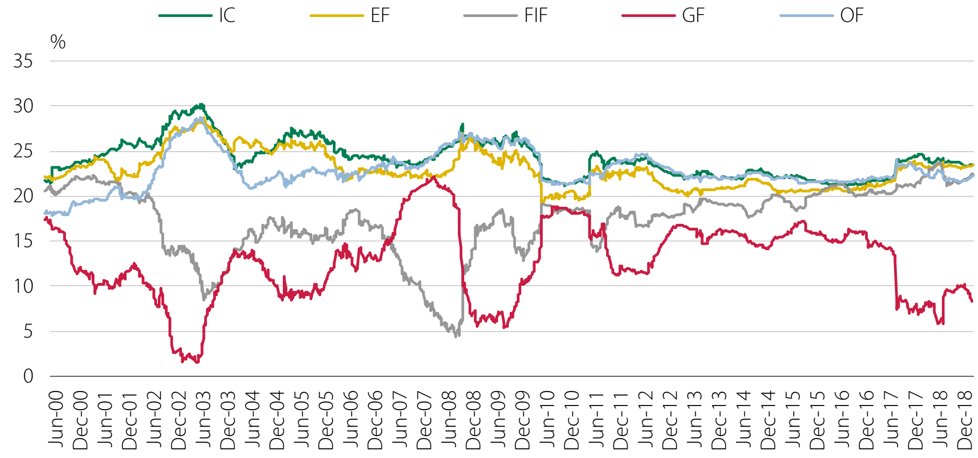
Total connectedness among CIS categories FIGURE 12



Source: Own calculations.

Percentage of contribution by category to total connectedness among CIS

FIGURE 13

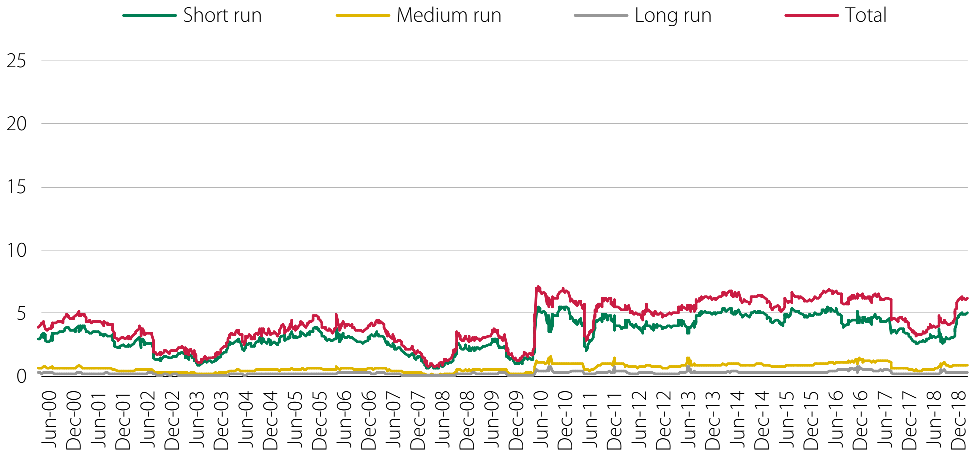


Source: Own calculations.

As a consequence of the European Central Bank monetary policy, non-alternative CIS, especially fixed income funds, have been involved in a search for yield strategy (ESRB, 2017). This has raised the concern that CIS in general, and this type of CIS in particular, have been investing in assets that are less liquid than in recent years. In order to address how this behaviour may have impacted on connectedness, we analysed the spillovers of shocks from funds of fixed income category on the financial markets and vice-versa. In this case, a very high spillover of funds with fixed income volatility shocks to the financial market volatilities would give these funds a potential role of amplifying systemic risk episodes.

Figure 14 shows that connectedness of funds of fixed income and financial markets only represent about 15% of total non-alternative CIS-market connectedness. At the same time, if we compare the pattern of the connectedness with the one from all non-alternative CIS, they are very close. It is also important to point out that after a significant drop during 2017, connectedness rose to reach a level closer to the ones disclosed during the financial crisis during 2018. However, as in the whole analysed period, most connectedness came in the short run. This trend may be interpreted as a sign that this increase in the connectedness is mainly translated in a rise of the correlation of the assets traded in the securities markets. Therefore, if the empirical evidence does not change in the future, the investment strategies of the fixed income funds will represent limited stress on the financial system.

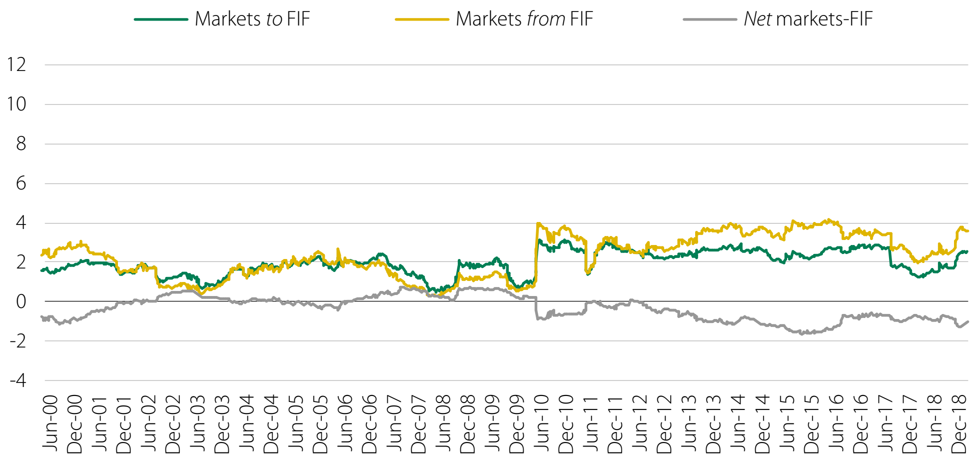
Connectedness between FIF and securities markets FIGURE 14



Source: Own calculations.

The last conclusion is in line with that shown in Figure 15. This demonstrates that net directional volatility between markets and the funds of fixed income is on average close to zero for the whole period but has become negative from the European debt crisis onwards, suggesting that funds of fixed income have become net transmitters of shocks to Spanish financial markets volatilities. This qualitatively relevant result is not so relevant from a quantitative point of view as net directional volatility is always above 2%. If we focus on the "net" connectedness during 2018, behaviour did not change with respect to previous years. It may be argued that fixed income funds mainly contribute to price formation in the securities markets and by extension they help them to enjoy better conditions as a result of being more liquid.

Connectedness *to from net* securities markets-FIF FIGURE 15

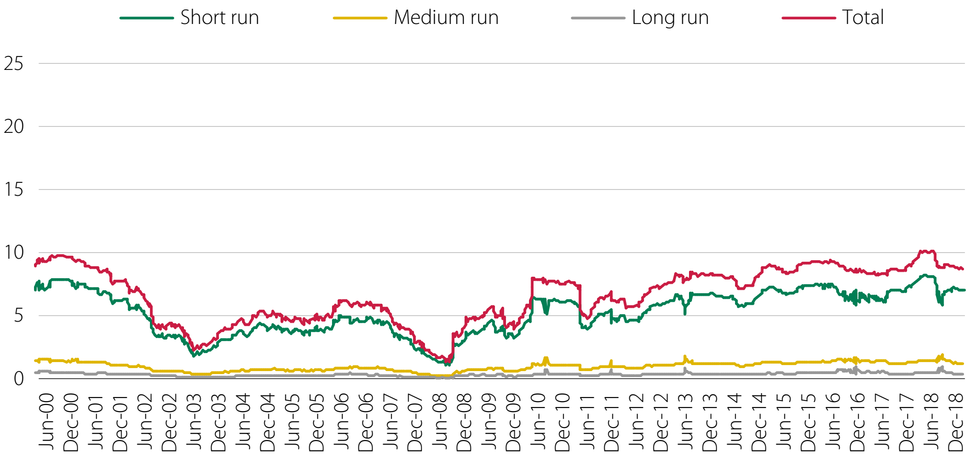


Source: Own calculations.

When we turn the analysis to focus on the relationship between fixed income funds and the other type of non-alternative CIS, we can see in Figure 16 that it is very volatile. At the beginning of the 2000s as well as in recent years, connectedness has been of great importance, representing about 20-25% of the total connectedness among non-alternative CIS (See Figure 12). Even for those periods, if we compare that figure with the percentage of AuM in these funds, the latter is higher. One of reasons for this is that this type of fund is usually made up of funds with the lowest levels of volatility. From 2003 to 2008, connectedness was persistently low, only starting to rise once the financial crisis started. In any case, the connectedness during the financial crisis was lower than the one found in the last couples of years. When connectedness is split into the short, medium and long run, it is found that most connectedness come in the short run as has been the case for all CIS.

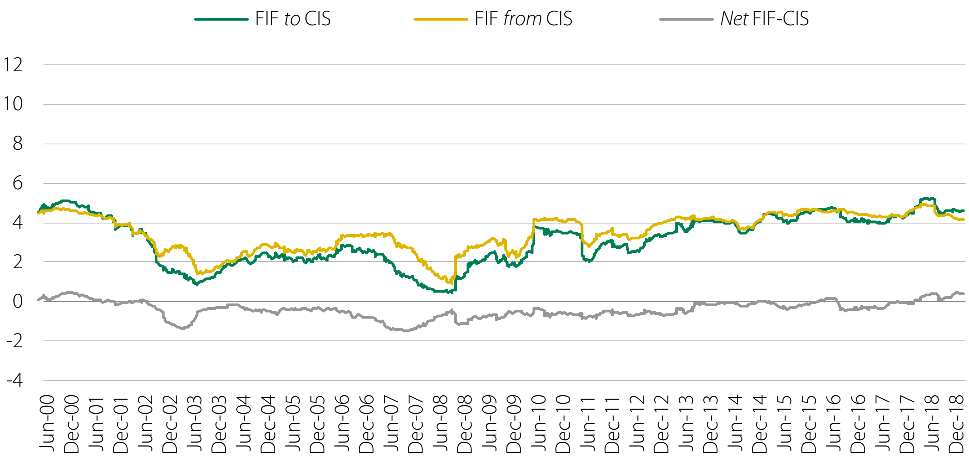
Figure 17 shows how connectedness is divided in connectedness "from", "to" and "net" with regard to fixed income funds. If we combine the results from this Figure with those from Figure 16, it can be argued that although in general the fixed income funds category is a net receiver of volatility, this situation tend to change when connectedness reaches its highest levels. Thus, the fixed income funds category became a provider of volatility for the other categories of CIS.

Connectedness between FIF and other categories of CIS FIGURE 16



Source: Own calculations.

Connectedness *to from net* FIF-CIS FIGURE 17



Source: Own calculations.

Therefore, given the current concerns over possible liquidity shortage in the fixed income category, what we can state from the perspective of connectedness is that it rose during 2018. This happened due to the connectedness between the fixed income funds and the securities markets as well as because of the connectedness between the fixed income funds with other categories of CIS. These connectedness are mostly driven by the short run, this means that there is a fast absorption of any possible shock in volatilities in terms of markets and CIS. As in the previous cases, this can be interpreted that in general this short run connectedness helps to the formation of prices in the securities markets and by extension to the pricing of CIS portfolios. From a systemic risk perspective, the rise of connectedness can be taken as an indication of a higher correlation between fixed income fund portfolios and the system's other assets and CIS, however it does pose limited risk in the long run.

In Annex 2, the reader can find Tables 14 and 15 as well as Figures 23-28. These tables and figures represent the connectedness between non-alternative CIS and several underlying securities markets from January 2008 to December 2018. In this case, apart from the three instruments considered before (IBEX 35, IBEX Small Caps and the on-the-run 10-year sovereign bond), it has been added the daily volatility of a basket of CDS from Spanish issuers.[21] We added this last instrument to try to have an indicator of the corporate bond market. From the tables and figures in the annex, we can see that apart from finding out slightly higher level of connectedness, especially when considering the spillovers between CIS and securities markets, all the qualitative results and trends remain to be similar.

Extensions and robustness checks

So far, the connectedness of the Spanish non-alternative CIS and with the national underlying national securities markets has been studied taking into account all such CIS. However, it is also interesting to explore how this connectedness evolves over time for relevant clusters of CIS. Figure 18 shows the total connectedness among non-alternative CIS and with their underlying markets from June 2000 to December 2018 for the CIS that are considered as institutional and for the CIS run by management companies owned by credit institutions.[22]

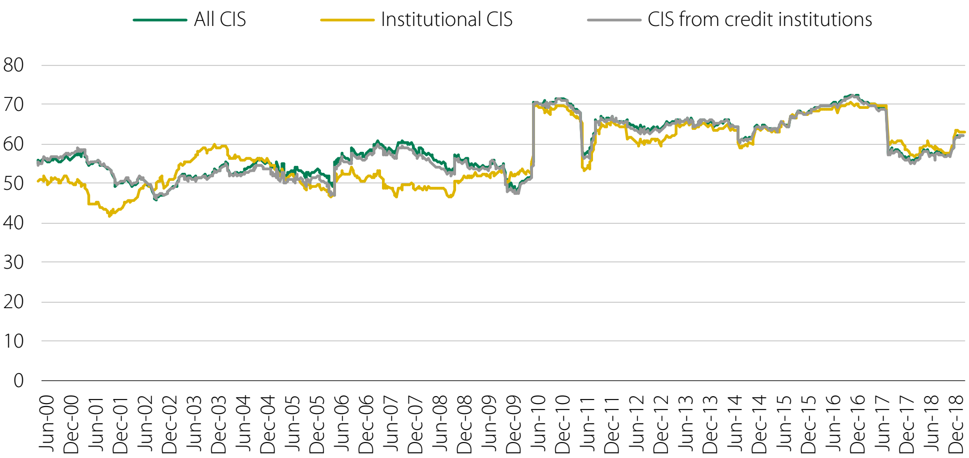
From the aforesaid Figure, it can be argued how, in general, there is no substantial difference on connectedness when institutional CIS and CIS from credit institutions are compared with the whole dataset, especially after the financial crisis started. The result from CIS from the management companies of credit institutions is

21 The number of CDS changes over the analysed period. More issuers were incorporated as soon as their CDS was available on Thomson Datastream. The basket is composed by nine issuers at the 01/01/2008 and it consisted of 17 issuers as of 31/12/2018.

22 For the purposes of this article, we defined wholesale funds as those in which the holdings are greater than 150,000 thereafter. For the case of the investment companies, the assumption was made that all of them were considered as institutional investment vehicles. In the sector as a whole, the proportion of retail funds was notably higher than that of wholesale funds. Regarding the other classification, the Spanish financial economy relies mainly on banks. Thus, we can divide this sector into two: fund management companies may belong to a credit institution or may be independent. Considering the type of management company, we would like to point out that bank fund management companies accounted for the greatest proportion of mutual funds and AuM.

not surprising since they account for most of the AuM.[23] However, the result for the index of the institutional CIS is not so straightforward, as this part of Spanish CIS market represented about 20-35% of AuM in the analysed period. One may have expected a different behaviour for this type of investors as they are considered to be as more sophisticated. However, previous papers on the Spanish CIS market, e.g., Cambon and Losada (2014), show how the institutional CIS do not present any significant different pattern in their investment behaviour in comparison with the retail segment in the fixed income funds categories. The opposite appeared in the more risky categories of CIS in which institutional investors could enjoy higher returns. As most of the institutional investors' AuM is invested in fixed income CIS categories, it could help to understand why the connectedness is not substantially different.

Total connectedness by different types of CIS FIGURE 18

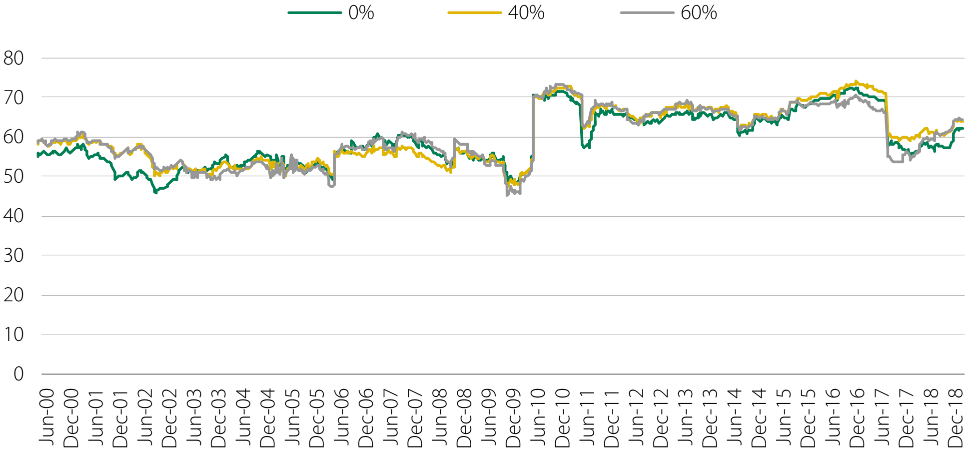


Source: Own calculations.

One may assume that as CIS hold more domestic assets, the subset of these CIS should be more interconnected among themselves and with national securities markets when they are considered on their own. However, if we look at Figure 19 is observed, the connectedness for CIS with portfolios that contain at least 40% and 60% of domestic securities assets do not show a level of connectedness that differs greatly to all Spanish non-alternative CIS. This therefore backs up the methodology used as it shows the level of connectedness embedded in the dataset irrespective of any noise that CIS with few or no domestic assets holding may cause. At the same time, as might be expected, the other conclusion that may arise is that most of the non-alternative CIS connectedness comes from the CIS with the largest positions in domestic securities.

23 See Cambón and Losada (2014).

Total connectedness by minimum percentage of domestic assets in the CIS portfolios FIGURE 19



Source: Own calculations.

Finally, we conclude this part of the analysis by exploring the robustness of the result to the choice of the parameters for the model. Figures 29-31 in Annex 3 show the total connectedness for different values for the number of lags of the predictive VAR described in Section 3 ($p = 3$, $p = 4$, $p = 5$), the number of sessions that contains the estimation windows ($w = 200$, $w = 250$, $w = 300$ sessions) and the forecast horizon ($H = 200$, $H = 250$, $H = 300$ sessions).

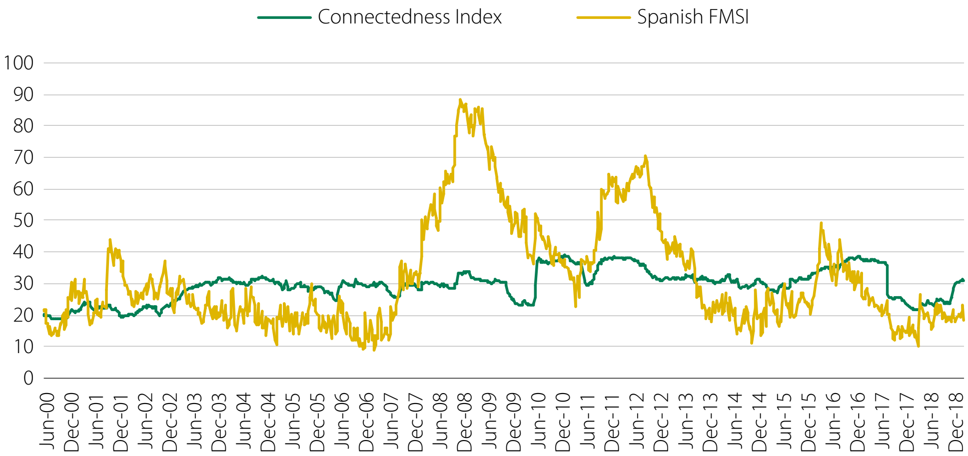
From these figures we can see how the total connectedness among non-alternative CIS and with their underlying markets barely change for the different proposed lags for the predictive lags and for the forecast horizon. However, when different estimation windows are considered (Figure 30), the paths are very similar expect for the cases of sudden drops in the measured connectedness. The drops were identified in all three cases and while their magnitudes are very close, they have been disclosed by the model later where the estimation window is wider. If we attend to the predictive power of the different models with different estimation windows, the difference is very small. Therefore, it is not easy to determine how wide the optimal estimation window should be, which can be seen as a possible limitation for this type of methodology. In this paper we kept the estimation window to 250 sessions that account for about a year, following closely Barunik and Krhelik (2018).[24]

24 In this case it is also important to argue that most of the connectedness comes from the short run (see Figure 8). In previous papers on this literature, e.g. Diebold and Yilmaz (2012, 2014), the regular windows for estimation were from 100 to 200 sessions for daily data.

6 On the relationship between non-alternative investment schemes connectedness with markets and financial systemic risk

One important question is how the connectedness index between the CIS and their underlying markets developed in this article may behave over time with respect to a stress indicator for Spanish financial markets. Estevez and Cambon (2016) developed an index that adapted the "Composite Indicator of Systemic Stress" that Hollo *et al.* (2012) proposed for the whole euro area for the Spanish market, known as the Spanish Financial Market Stress Index (FMSI). We chose the connectedness index between the CIS and their underlying markets instead of the one that sum the connectedness among CIS and from them with the underlying markets because we found more relevant the possibility that the CIS may trigger a relevant rise in systemic risk through their role within securities markets. Moreover, the main driver in the variability of the total connectedness index is how the CIS are connected with markets.[25] In Figure 20, both indices were plotted, and one may observe how the Spanish FMSI shows greater volatility.

Non-alternative CIS connectedness with markets and systemic risk indices FIGURE 20



Source: CNMV and own calculations.

In order to address the analysis of these two-time series and the impact that the length and strength of financial shocks might have, a bivariate Threshold Vector

25 Furthermore, if the Johansen test (1995) were applied to both indexes it would be found that the null hypothesis that both indexes are cointegrated cannot be rejected.

Autoregressive Model (TVAR) was applied.[26] This type of VAR models assumes that one or several state transitions are triggered when a variable reaches certain threshold levels which are determined from the data. Tsay (1998) offers the methodology to compute the thresholds embedded in the data, where the non-alternative collective schemes connectedness with market index (hereafter NACISCMI) and the FSMI are considered as endogenous variables. For this analysis, we considered weekly data for the two indices from the first week of June 2000 to the last week of December 2018 in the form of logarithms.

Before discussing whether a TVAR is an appropriate model for this data, we should first look at the properties of these time series separately. In this framework, it is important to assess if they may have the presence of unit roots:

Unit root test TABLE 5

	Augmented Dickey-Fuller unit root test	
	t-Statistic	P-value
Ln(FMSI)[2]	-2.905	0.045
Ln(NACISCMI)[1]	-3.052	0.031

Source: Own calculations.

1 NACISCMI is the acronym for denoting the non-alternative CIS connectedness with markets index.

2 FMSI is the acronym for denoting the Financial Market Stress index.

Under the Augmented Dickey-Fuller test, the null hypothesis is the presence of a unit root. From Table 5, at the 95 percent level the null hypothesis should be rejected, meaning that both indices follow stationary processes.[27]

The next step to be taken in this analysis is to determine whether it is appropriate or not to use a TVAR and where so, what is the number of thresholds that best described the data. According to the Hasen (1999) test of linearity presented in Table 6, it turns out that on the one hand, a linear VAR is rejected as the model that best describes the data; on the other hand it is found out as well that it is better a single threshold (2 regimes) for the TVAR instead of considering two (three regimes). In this type of model, the threshold delay also has to be determined. Table 4 shows how the difference between d=1 or d=2 is not important in terms of information criteria (Akaike Information Criterion (AIC) or the Bayesian Information Criterion (BIC)). Thus, we have opted to set the threshold delay as 1, meaning that the estimated threshold value of the FMSI is Ln(20.1).

The considered TVAR regression model is therefore as follows:

26 Estevez and Cambon (2016) tried to assess how the FMSI relates with Spanish real economy by studying the relationship between the FMSI and Spanish Industrial Production index in a monthly basis as well as using a bivariate TVAR with two thresholds. Their main finding was a negative Granger causality of the industrial production index as a response to shocks in the FMSI which was not found when there was a shock in the in the industrial production index.

27 See Dickey and Fuller (1979).

$$x_t = c^l + \Phi_1^l x_{t-1} + \Phi_2^l x_{t-2} + \Phi_3^l x_{t-3} + \varepsilon_t^l, if\ z_{t-1} < Ln(20.1)$$

$$x_t = c^h + \Phi_1^h x_{t-1} + \Phi_2^h x_{t-2} + \Phi_3^h x_{t-3} + \varepsilon_t^h, if\ z_{t-1} \geq Ln(20.1)$$

Where z_{t-1} is the threshold variable, x_t are the two indices in natural logarithms and the vector $\varepsilon_t^s, s = h,l$ contains the state-dependent regression errors. The number of lags of the TVAR was also determined by the AIC.

Testing the var versus tvar and the threshold delay TABLE 6

	Hansen(1999) test of linearity		
	VAR us TVAR(1)	**VAR us TVAR (2)**	**TVAR(1) us TVAR(2)**
d=1	53.324	75.117	21.793
	(0.000)	(0.000)	(0.5600)
d=2	51.574	68.676	17.10231
	(0.000)	(0.000)	(0.8000)
	Testing threshold delay (d) and threshold values		
	threshold	AIC	BIC
d=1	Ln(20.1)	-10,841	-10.701
d=2	Ln(16.0)	-10,839	-10,699

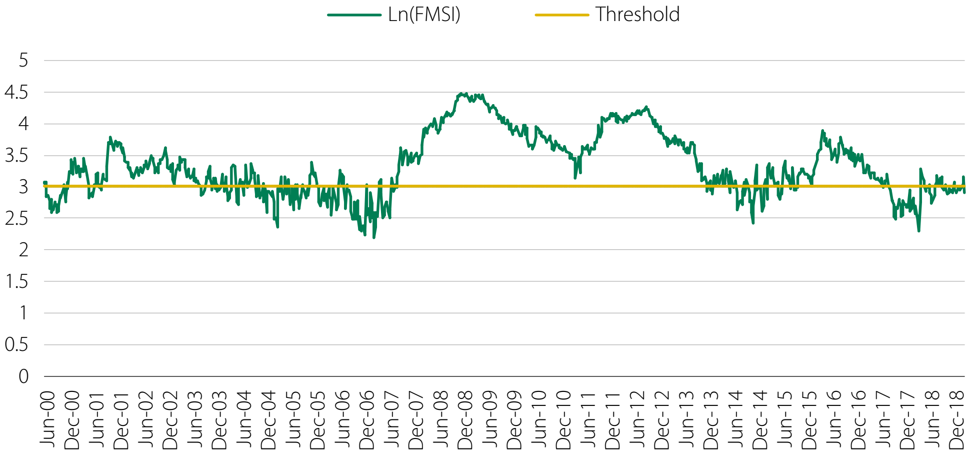
Source: Own calculations.

The Hansen test of linearity tests VAR against TVAR(1) or TVAR(2). In this case the null hypothesis is that the data follows the linear model (VAR). TVAR(1) denotes the bivariate threshold-VAR model with three lags, one threshold (two regimes) and the non-alternative investment collective schemes connectedness index and the FSMI as endogenous variables. TVAR(2) share the same characteristics as TVAR(1) but in this case two thresholds and three regimes were considered. TVAR(1) against TVAR(2) is also tested. P-values are reported in parentheses. d denotes the threshold delay and "threshold" is the threshold value computed. AIC is the Akaike information criterion and BIC is the Bayesian information criterion. Weekly data from the first week of June 2000 to the last week of June 2018.

As shown in Figure 21 the estimated threshold parameter may be interpreted as the level from which stress in the Spanish financial markets can be considered to exist.[28] Therefore, for values below the threshold level, we consider the Spanish financial markets are in a low stress environment. However, for higher values than the threshold, it is considered that the financial markets suffer from stress.

28 Estevez and Cambon (2016) analysed the relationship between the FMSI and Spanish Industrial Production index by means of a TVAR model with two FMSI-related thresholds, 26.6 and 49.0. Thus, the threshold of the analysis carried out in this paper can be considered as close to the lowest threshold they found.

Spanish FMSI and the regime from the TVAR FIGURE 21



Source: CNMV and own calculations.

Once the form of the bivariate model was determined, two important questions regarding the behaviour between these two indices arose, which sought to establish which are the long- and short-term relations between them. In other words, we would like to test whether these two indices are co-integrated and/or whether there may exist any Granger-causality.[29] In this case we should use the test for cointegration and Granger-causality adapted to specificities of threshold models: These are Seo (2006) for testing cointegration and Li (2006) for testing Granger Causality. Thus, in order to estimate cointegration, we first have to estimate a Threshold Vector Error Correction Model (TVEC) with the same characteristic as the TVAR described earlier, and given that model estimation, applying the test by Seo (2006).

Test of cointegration (TVEC) TABLE 7

Seo (2006) test of cointegration	
test-Statistic	**P-value**
38.85216	0.945

Source: Own calculations.

The null hypothesis for this Seo (2006) test is that there is no cointegration. As Table 5 shows, the null hypothesis cannot be rejected and thus there is no evidence that these two series enjoy a long-term relationship.

Table 8 offers the estimates for the parameters of the TVAR described earlier.[30] It is important to point out that the results for the FSMI and the non-alternative alternative CIS connectedness with markets index came out as similar. In this regard, both time series depend mainly on their own lags across both regimes. Therefore, it is not

29 See Granger (1969).

30 The residuals of the TVAR model do not present serial correlations. The LM test for residual correlation up to five lags was run. In this case, the null hypothesis of this test is that there is no serial correlation at lag=1,..., 5. In all the considered lags, the null hypothesis was not rejected at the confidence level of 95%.

surprising that when the Li (2006) test was applied, there was not any evidence of Granger causality. This test has as the null hypothesis that there is no Granger causality across both regimes. From Table 9, it is clear that we cannot reject the null hypothesis and they do not show a short run relationship. This final result completes the analysis for the whole considered sample and the conclusion would be that these two indices show neither co-integration nor Granger causality.

Nevertheless, these same results do not imply that there may not exist some type of relationship between the FMSI and NACISCMI in any of the two regimes. In particular, we are interested in studying possible interactions in the stress regime. One way of approaching this is to try to investigate it through the TVEC/TVAR methodology used so far; however, it may be more robust to focus on non-truncated series that are always above the estimated threshold as this subset may have different characteristics, in particular unit roots, than the ones found in the whole series.

The longest period where the FMSI is above 20.1 goes from the third week of July 2007 to the second week of October 2013, resulting in a series of 310 observations. This period picks up mainly what is known as the Great Recession where it happened: the subprime mortgages episode in the US, the collapse of Lehman Brothers and the sovereign debt crisis that affected several member states in the Eurozone.

Parameter estimates of TVAR (one threshold, two regimes) TABLE 8

	Threshold < Ln(20.1) Low stress		Threshold ≥ Ln(20.1) High stress	
	Ln(FMSI)[2]	Ln(NACISCMI)[1]	Ln(FMSI)[2]	Ln(NACISCMI)[1]
Intercept	0.497*	0.018	-0.029	0.049**
	(0.213)	(0.038)	(0.092)	(0.016)
Ln(FMSI)[2](t-1)	0.735***	0.003	0.796***	0.010
	(0.058)	(0.010)	(0.047)	(0.008)
Ln(NACISCMI)[1](t-1)	1.499***	1.101***	0.207	1.148***
	(0.442)	(0.080)	(0.202)	(0.036)
Ln(FMSI)[2](t-2)	-0.011	0.006	0.109	-0.004
	(0.056)	(0.010)	(0.060)	(0.011)
Ln(NACISCMI)[1](t-2)	-1.4016*	-0.008	-0.179	-0.0456
	(0.623)	(0.113)	(0.312)	(0.056)
Ln(FMSI)[2](t-3)	0.057	-0.008	0.115*	-0.005
	(0.049)	(0.009)	(0.045)	(0.008)
Ln(NACISCMI)[1](t-3)	-0.051	-0.1026	-0.044	-0.118*
	(0.441)	(0.079)	(0.202)	(0.036)

1 NACISCMI is the acronym for denoting the non-alternative CIS connectedness with markets index.

2 FMSI is the acronym for denoting the Financial Market Stress index.

TVAR refers to the bivariate threshold-VAR model with 3 lags, one threshold (two regimes) and the natural logarithm of Spanish FMSI and the natural logarithm of non-alternative collective investment schemes connectedness index. High stress regime occurs when the ln(FMSI) is equal to or above 3. Low stress regime occurs when the ln(FMSI) is lower than 3. Percentage of observations in each regime: 27.6% (low-stress) and 72.4% (high stress). Weekly data from the first week of June 2000 to the last week of December 2018.

*** Significance at 0.1%.

** Significance at 1%.

* Significance at 5%.

Test of granger causality (TVAR) TABLE 9

	Li (2006) test of Granger causality	
	Test-Statistic	P-value
	2.0587	0.724

Source: Own calculations.

As in the previous analysis, we firstly have to study the properties of the each of their time series on their own, especially the possible presence of unit roots:

Test of unit roots for a crisis period TABLE 10

	Augmented Dickey-Fuller unit root test	
	t-Statistic	P-value
Ln(FMSI)[2]	-2.597	0.095
Ln(NACISCMI)[1]	-1.497	0.534

Source: Own calculations.

1 NACISCMI is the acronym for denoting the non-alternative CIS connectedness with markets index.

2 FMSI is the acronym for denoting the Financial Market Stress index.

The test of unit roots shown in Table 10 indicates that neither index follows a stationary process over this crisis period. At 95% percentage of significance for both series, it cannot be rejected that the null hypotheses have a unit root. Given that both series follow a random path, the appropriate tests for cointegration and Granger causality should be applied. On the basis of the results when the whole dataset was considered, both series can be assumed to be modelled linearly.

In order to test cointegration, the Johansen test (1995) is applied to a bivariate vector error correction model (VEC). By using the AIC, it was determined that the optimal number of lags for the estimated VEC should be 3. The null hypothesis of the Johansen test is that there are no more than *r* cointegrating relations. Therefore, we are testing a model with only two endogenous variables, if there were cointegrated, it should be rejected the null hypothesis when $r = 1$. Table 9 reports the results from the Johansen test and it is found the FSMI and the NACISCMI are not cointegrated either in the considered crisis period and they do not maintain a relation in the long term.

Test of cointegration (VEC) TABLE 11

	Jonhansen test (1995)	
	Trace-Statistic	P-value
r = 0	8.134	0.451
r = 1	0.185	0.667

Source: Own calculations.

Being non-cointegrated does not necessarily imply that these two time series do not have a relationship in the short term. We then tested the results of the estimation of a vector autorregresive model (VAR) to see whether there is any Granger-causal relationship between the two, the FMSI and NACISCMI. A VAR model with four lags was estimated and as it can be deemed that both series have a unit root, the Granger causality should be tested following the procedure developed in Toda and Yakamoto (1995):[31]

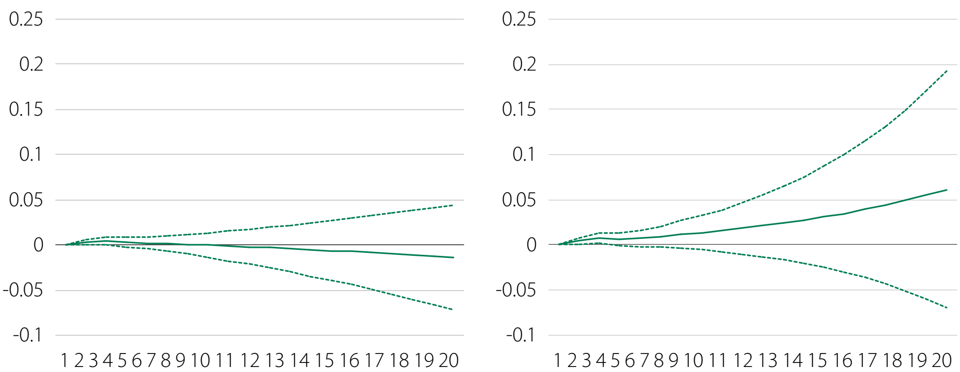
Test of granger causality (VAR) TABLE 12

	Chi-Statistic	P-value
Dependent variable : NACISCMI	9.349	0.053
Dependent variable: FMSI	0.545	0.969

Source: Own calculations.

For this test, the null hypothesis is that one of the variables (the independent variable) does not Granger-cause the dependent variable. Table 10 outlines the result of the tests for both variables, showing that the null hypothesis is about to be rejected when the NACISCMI is the dependent variable at 95% of significance. When the dependent variable is the FMSI, the null hypothesis is not rejected. It is also important to point out that if the crisis period is restricted to one of the periods where the FMSI was higher (from the third week of January 2008 to the second week of November 2012, where the FMSI was persistently above 50), Granger-causality results are clearer in the sense that the null hypothesis is rejected when NACISCMI is the dependent variable (p-value = 0.017). When the dependent variable is FSMI the null hypothesis is not rejected as in the extended crisis dataset.

Impulse response functions (IRS) of the NACISCMI to shocks in the FSMI from VAR models FIGURE 22



Source: Own calculations.

The figure on the left is the impulse response function of the VAR with 4 lags with the FSMI and NACISCMI as endogenous variables for the data from the third week of July 2007 to the second week of October 2013. In this period, the FSMI is always above 20.1. The figure on the right is the impulse response function of the VAR with 4 lags with the FSMI and NACISCMI as endogenous variables for the data from the third week of January 2008 to the second week of November 2012. In this period, the FSMI was persistently above 50.

31 Although the AIC recommended using three lags, this specification has problems of errors serial correlation. This problem is corrected by estimating a VAR with four lags.

Once the Granger-causality has been calculated, it is also important to determine the sign of response of the NACISCMI to shocks in the FSMI over time. Figure 22 shows the impulse responses function for the two crisis periods analysed previously. The figure on the left is the impulse response function of the period from the third week of July 2007 to the second week of October 2013 in which we can see that the response is not strong and it is positive for the first session and becomes negative from session 9 onward. The figure on the right is the impulse response function for the period where FSMI is persistently above 50, the response in this case is stronger and always positive.

Therefore, the main conclusions that can be taken from this section is that these two indices are not cointegrated and do not maintain a relationship in the long run. However, when the whole analysed period is considered there does not exist a Granger causality, there is evidence that as a crisis becomes deeper the FSMI Granger causes the non-alternative CIS connectedness with market indices (NACISCMI). Furthermore, the response of the NACISCMI to shocks in FSMI becomes stronger and more positive as the potential crisis is deeper. At the end of the day, it can be argued that non-alternative CIS do not cause an increase in the systemic risk through their connectedness with securities markets. Only the connectedness increases in the short run due to the increase of systemic risk. Then, the results from this section are in line with those obtained in Section 5 where connectedness among non-alternative CIS and with their underlying securities markets was analysed in depth.

7 Conclusions

In recent years, several international bodies (G20, FSB, ESRB or IMF) have started to focus on how financial institutions other than banks may contribute to systemic risk. This paper has tried to shed light on the role that non-alternative CIS may play on this regard. Specifically, the way that shocks from this type of investment vehicles can potentially be propagated through the financial system has been assessed. This analysis has been carried out by means of the level of connectedness among non-alternative CIS and with their underlying equity and debt markets.

Empirical analysis was applied to the Spanish of non-alternative CIS which comprises UCITS and quasi-UCITS investment schemes. Such financial vehicles constitute almost the whole collective investment market in Spain. Their regulation requires that most of the assets that they hold are very liquid, significantly limiting their ability to leverage. Two main results came out from the analysis: firstly that in periods of financial distress, connectedness among non-alternative CIS and their underlying markets rises notably. However, even in these negative periods, connectedness is mainly produced in the short run. This means that non-alternative CIS as well as securities markets quickly process negative shocks and they are mostly transferred as an increase of the contemporaneous correlation among those CIS and the assets traded in securities markets. Non-alternative CIS are therefore not an important source in terms of propagation of shocks although they may play a limited role from a systemic point view. At the same time, when the financial markets run periods of non-distress, connectedness is mainly in the short run as well, which can be seen as a sign of the contribution of the CIS to the price formation in the securities markets. This result can be extended for the concrete case of fixed income collective investment schemes category which is currently at the crux of the debate.

This latter outcome is complemented by the second main result of the paper. An analysis of how the connectedness among non-alternative CIS and securities markets and financial systemic risk is carried out. By means of this analysis, it is clear that there is no relationship in the long run (cointegration) between connectedness and financial systemic risk. When the short run is analysed, we can see how a negative shock in the financial systemic risk causes an increase in the level of connectedness although the opposite cannot be said; a negative shock in the level of connectedness does not cause a rise in the measure of the financial systemic risk.

In the FSB's different versions of their "Global Monitoring Report on Non-Bank Financial Intermediation", it is argued that financial institutions with a business model of maturity/liquidity transformation and/or leverage are susceptible to being systemically important. We complement this view by showing how financial intermediaries with limited transformation of maturity/liquidity and leverage as non-alternative CIS are not an important source of systemic risk.

It is also important to point out other results from the analysis of connectedness among CIS and with their underlying securities markets. By this token, in general terms, there is evidence that non-alternative CIS contribute more information to the price formation in the securities than the information CIS receive from market in order to price their portfolios. When we disaggregate among different categories of CIS, it can be seen that their behaviour is mixed. Equity funds as well as Investment companies extract more information to price their portfolios than the information they provide to securities markets. The opposite is the case when fixed income, guaranteed and global and absolute return funds were considered.

The results and conclusions presented were tested against different assumptions of the empirical model used as were more technical assumptions such as the number of lags in the specification of the model or different forecast horizons, where we found similar results. We also explored data subsets in order to examine the connectedness among non-alternative CIS and with the markets by different types of final investors: institutional of clients of credit institution or by CIS with portfolios more concentrated in the Spanish securities markets. In the former we found similar outcomes when we considered the connectedness of the CIS from different types of investors. For the case of the CIS run by management companies of credit institutions, finding similar results is not surprising since they represent most of this market. In the case of CIS held by institutional investors, one may expect different behaviour. However, this type of investor behaviour does not differ from retail investors in the fixed income funds categories (Losada and Cambon, 2014) which represent the majority of their investment in CIS. For the latter analysis, we considered the connectedness produced by only CIS with a portfolio with percentages of domestic securities above certain thresholds, in this case 40% and 60%. The analysis showed that the level of connectedness was very similar in comparison with the case where the whole population of non-alternative CIS was considered. This consistency gives support to the methodology used as it picks up the connectedness regardless of the noise from the CIS with few domestic assets.

On 1 March 2019, the regulation that created the Spanish macroprudential authority was published which empowered it with macroprudential tools regarding financial institutions, including CIS. In particular, this regulation sought to strengthen the liquidity of CIS portfolios. From a point of view of the potential contagion to securities markets, this paper shows evidence that any negative shock from CIS can be absorbed by the market with limited consequences as far as systemic risk is concerned, apparently meaning that, as long as the current conditions regarding CIS and securities market are maintained, no further measures in the liquidity of CIS' portfolios are needed.

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Annex I

Short, medium and long run connectedness tables TABLE 13

Short run connectedness: 1 to 5 days

	IBEX 35	IBEX SC	10-Y Bond	IC	EF	FIF	GF	OF	*From* ABS	*From* WTH
IBEX 35	19.2	4.7	1.2	11.2	13.8	2.8	2.0	5.4	41.2	62.7
IBEX SC	7.6	30.5	0.7	7.8	8.1	2.4	1.6	3.5	31.8	48.3
10-Y Bond	2.5	0.9	39.6	1.4	1.8	3.9	12.2	0.7	23.4	35.5
IC	10.2	4.4	0.7	17.8	14.6	5.7	2.5	11.1	49.1	74.8
EF	11.9	4.3	0.8	13.8	16.7	2.6	1.4	9.0	43.9	66.8
FIF	4.9	2.7	3.4	10.6	5.3	33.3	13.1	7.5	47.5	72.2
GF	3.7	1.9	10.9	4.9	2.9	14.3	36.5	2.3	40.8	62.1
OF	5.4	2.2	0.3	11.9	10.1	4.2	1.2	18.9	35.4	53.9
***To* ABS**	46.2	21.1	18.0	61.7	56.6	36.1	34.0	39.4	39.1	
***To* WTH**	70.4	32.1	27.4	93.9	86.2	54.9	51.7	59.9		59.6

Medium run connectedness: 5 to 20 days

	IBEX 35	IBEX SC	10-Y Bond	IC	EF	FIF	GF	OF	*From* ABS	*From* WTH
IBEX 35	6.7	2.2	0.6	4.3	5.4	1.0	0.8	2.3	16.4	77.4
IBEX SC	3.1	10.9	0.3	3.1	3.3	0.9	0.6	1.4	12.7	59.7
10-Y Bond	1.2	0.5	14.4	0.7	0.9	1.6	4.6	0.3	9.7	45.6
IC	3.2	1.7	0.2	4.9	4.3	1.6	0.7	3.4	15.0	70.6
EF	4.8	2.0	0.3	5.1	6.2	1.0	0.6	3.2	17.0	79.8
FIF	0.9	0.5	0.6	1.9	1.0	5.9	2.3	1.3	8.5	39.8
GF	1.0	0.5	2.5	1.1	0.8	2.9	7.2	0.5	9.3	43.6
OF	2.5	1.0	0.2	5.5	4.7	2.0	0.6	8.7	16.4	77.1
***To* ABS**	16.6	8.2	4.7	21.7	20.2	10.9	10.1	12.5	13.1	
***To* WTH**	78.0	38.8	22.1	102.2	95.0	51.4	47.5	58.7		61.7

Long run connectedness: 20 to 250 days

	IBEX 35	IBEX SC	10-Y Bond	IC	EF	FIF	GF	OF	*From* ABS	*From* WTH
IBEX 35	4.4	1.7	0.4	3.1	3.9	0.7	0.5	1.7	12.0	91.9
IBEX SC	2.0	5.9	0.2	2.0	2.2	0.6	0.4	1.0	8.3	63.5
10-Y Bond	0.8	0.3	7.4	0.5	0.6	0.9	2.4	0.2	5.5	42.3
IC	2.1	1.1	0.2	3.2	2.8	1.0	0.4	2.4	10.0	76.2
EF	3.4	1.5	0.2	3.6	4.3	0.7	0.4	2.2	12.0	91.7
FIF	0.3	0.2	0.2	0.6	0.3	2.0	0.8	0.4	2.8	21.7
GF	0.4	0.2	1.0	0.5	0.3	1.1	2.6	0.2	3.6	27.9
OF	2.0	0.8	0.1	4.5	3.8	1.6	0.5	7.2	13.5	102.9
***To* ABS**	10.9	5.8	2.3	14.8	14.0	6.5	5.4	8.1	8.5	
***To* WTH**	83.8	44.3	17.6	112.9	106.6	49.7	41.0	62.2		64.8

Source: Own calculations.

IC = Investment Companies, EF = Equity Funds, FIF= Fixed Income Funds, GF = Guaranteed Funds, OF = Other Funds.

Annex II

Full sample connectedness table TABLE 14

	IBEX 35	IBEX SC	10-Y Bond	CDS Corp	IC	EF	FIF	GF	OF	*From*
IBEX 35	26.6	8.9	2.4	3.6	16.9	20.5	3.9	4.0	13.2	73.4
IBEX SC	12.8	39.4	1.3	2.1	13.2	14.2	3.5	2.3	11.0	60.4
10-Y Bond	4.7	1.6	50.7	4.1	3.3	3.5	6.9	22.1	3.1	49.3
CDS Corp	8.2	3.0	4.7	58.6	5.1	7.1	2.5	6.3	4.4	41.3
IC	14.4	7.7	1.4	2.0	23.0	18.9	8.9	3.8	20.0	77.1
EF	18.2	8.8	1.6	2.9	19.9	24.8	3.6	2.4	17.6	75.0
FIF	5.0	2.9	4.8	1.5	14.0	5.2	35.6	16.2	14.7	64.3
GF	5.6	2.2	16.7	4.1	6.4	3.9	17.3	38.1	5.9	62.1
OF	11.4	6.4	1.9	2.0	18.8	15.4	9.2	4.6	20.7	69.7
To	80.3	41.5	34.8	22.3	97.6	88.7	55.8	61.7	89.9	63.6
Net	6.9	-18.9	-14.5	-19.0	20.5	13.7	-8.5	-0.4	20.2	

Source: Own calculations.

IC = Investment Companies, EF = Equity Funds, FIF= Fixed Income Funds, GF = Guaranteed Funds, OF = Other Funds

Short, medium and long run connectedness tables TABLE 15

Short run connectedness: 1 to 5 days

	IBEX 35	IBEX SC	10-Y Bond	CDS Corp	IC	EF	FIF	GF	OF	*From* ABS	*From* WTH
IBEX 35	17.3	5.2	1.4	2.3	10.4	12.5	2.4	2.5	8.0	44.7	65.0
IBEX SC	8.0	26.4	0.8	1.3	8.2	8.7	2.2	1.5	6.8	37.6	54.5
10-Y Bond	2.7	0.9	33.2	2.6	1.9	2.0	4.4	14.3	1.8	30.6	44.5
CDS Corp	5.6	2.1	3.6	46.4	3.5	4.9	1.8	4.8	3.0	29.3	42.6
IC	9.5	4.9	0.9	1.3	16.0	12.7	6.5	2.7	14.0	52.4	76.1
EF	10.7	4.9	0.9	1.7	11.8	14.7	2.2	1.4	10.4	44.1	64.0
FIF	4.1	2.4	3.9	1.2	11.3	4.2	28.8	13.1	11.9	52.1	75.6
GF	4.2	1.7	12.7	3.1	4.9	2.9	13.6	29.9	4.5	47.6	69.0
OF	7.7	4.4	1.0	1.2	15.1	12.0	7.4	2.6	17.5	51.5	74.7
***To* ABS**	52.5	26.6	25.1	14.6	67.2	60.0	40.5	42.8	60.5	43.3	
***To* WTH**	76.2	38.6	36.5	21.2	97.6	87.1	58.8	62.3	87.8		62.9

Medium run connectedness: 5 to 20 days

	IBEX 35	IBEX SC	10-Y Bond	CDS Corp	IC	EF	FIF	GF	OF	*From* ABS	*From* WTH
IBEX 35	5.6	2.1	0.6	0.8	3.8	4.6	0.9	0.9	3	16.7	83.4
IBEX SC	2.9	8.5	0.3	0.5	3	3.3	0.8	0.5	2.5	13.8	69.7
10-Y Bond	1.3	0.4	11.8	1	0.9	0.9	1.7	5.2	0.8	12.2	61.5
CDS Corp	1.8	0.6	0.8	9	1.1	1.5	0.5	1.1	0.9	8.3	41.9
IC	3	1.7	0.3	0.4	4.4	3.8	1.6	0.7	3.8	15.3	77.0
EF	4.3	2.2	0.4	0.7	4.6	5.8	0.8	0.6	4.1	17.7	89.1
FIF	0.7	0.4	0.7	0.2	2	0.8	5.1	2.3	2.1	9.2	46.6
GF	1	0.4	2.9	0.7	1.1	0.7	2.7	6	1	10.5	52.2
OF	2	1	0.7	0.5	2.3	2.1	1.2	1.3	2	11.1	74.9
***To* ABS**	17	8.8	6.7	4.8	18.8	17.7	10.2	12.6	18.2	12.8	
***To* WTH**	88.5	47.2	31.3	23.4	103.6	96.5	53.5	60.7	91.5		66.2

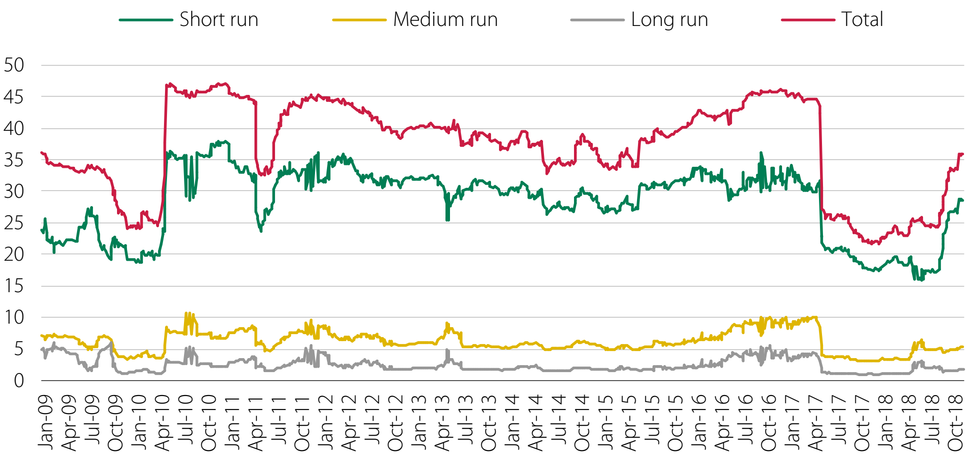
Long run connectedness: 20 to 250 days

	IBEX 35	IBEX SC	10-Y Bond	CDS Corp	IC	EF	FIF	GF	OF	*From* ABS	*From* WTH
IBEX 35	3.7	1.6	0.4	0.5	2.7	3.4	0.6	0.6	2.2	12	107.7
IBEX SC	1.9	4.5	0.2	0.3	2	2.2	0.5	0.3	1.7	9.1	81.5
10-Y Bond	0.7	0.3	5.7	0.5	0.5	0.6	0.8	2.6	0.5	6.5	57.9
CDS Corp	0.8	0.3	0.3	3.2	0.5	0.7	0.2	0.4	0.5	3.7	34.4
IC	1.9	1.1	0.2	0.3	2.6	2.4	0.8	0.4	2.2	9.3	83.6
EF	3.2	1.7	0.3	0.5	3.5	4.3	0.6	0.4	3.1	13.3	119.8
FIF	0.2	0.1	0.2	0.1	0.7	0.2	1.7	0.8	0.7	3	27.6
GF	0.4	0.1	1.1	0.3	0.4	0.3	1	2.2	0.4	4	35.2
OF	1.7	1	0.2	0.3	1.4	1.3	0.6	0.7	1.2	7.2	82.0
***To* ABS**	10.8	6.2	2.9	2.8	11.7	11.1	5.1	6.2	11.3	7.6	
***To* WTH**	97.4	56.5	25.8	24.5	114.7	108.5	48.8	53.0	100.4		70.0

Source: Own calculations.

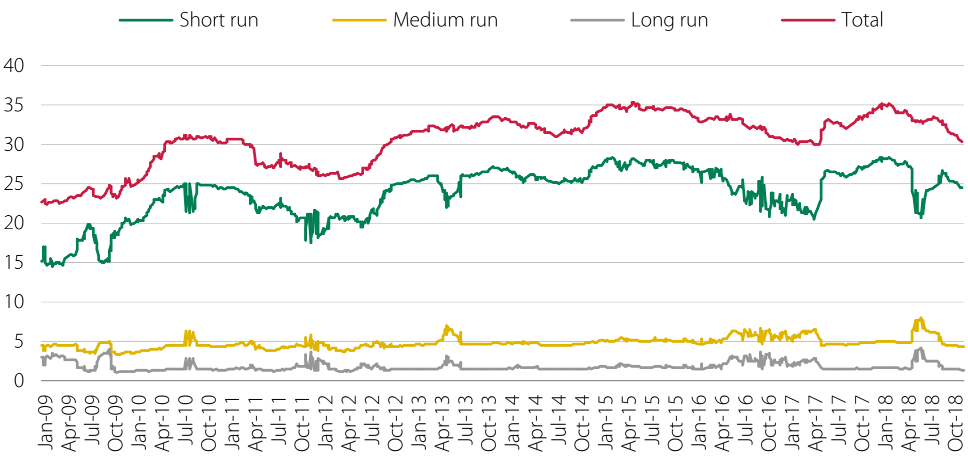
IC = Investment Companies, EF = Equity Funds, FIF= Fixed Income Funds, GF = Guaranteed Funds, OF = Other Funds.

Connectedness between CIS and securities markets FIGURE 23



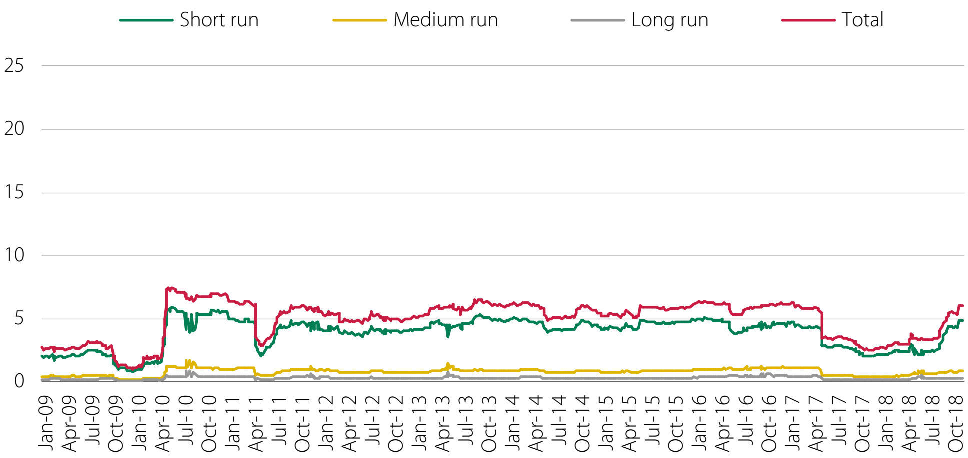
Source: CNMV.

Total connectedness among CIS categories FIGURE 24



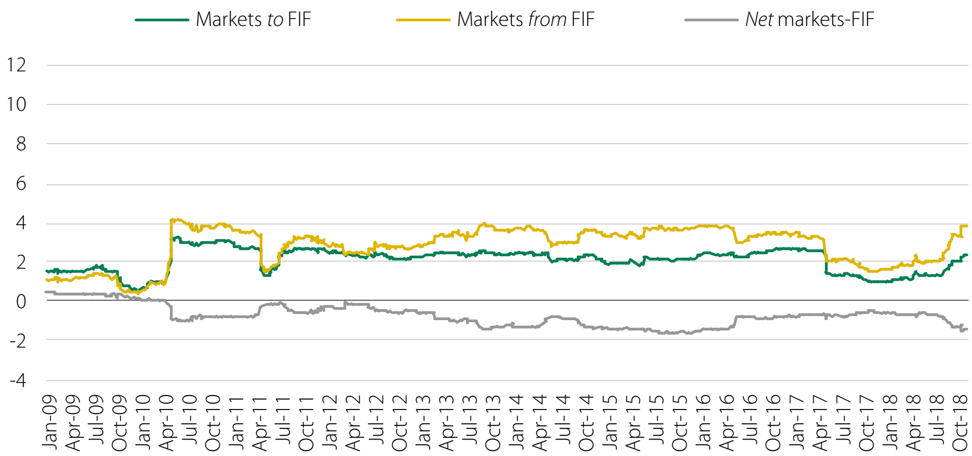
Source: Own calculations.

Connectedness between FIF and securities markets FIGURE 25



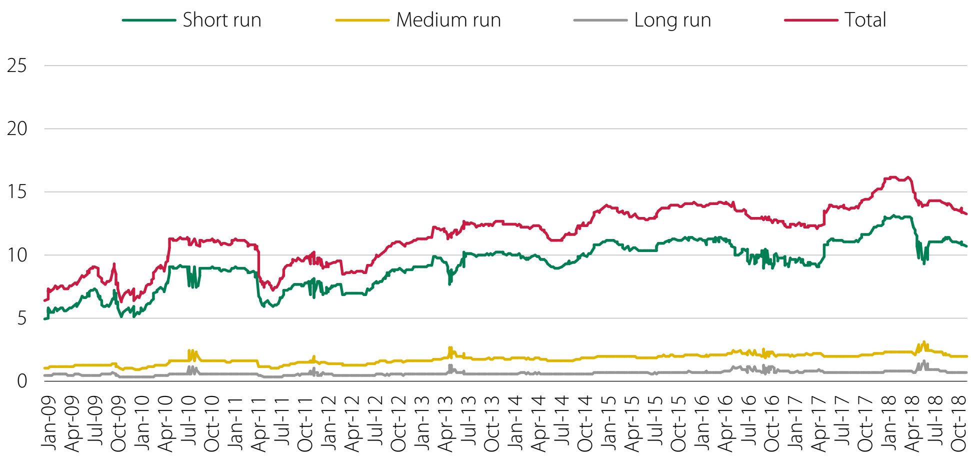
Source: Own calculations.

Connectedness *to from net* securities markets-FIF FIGURE 26



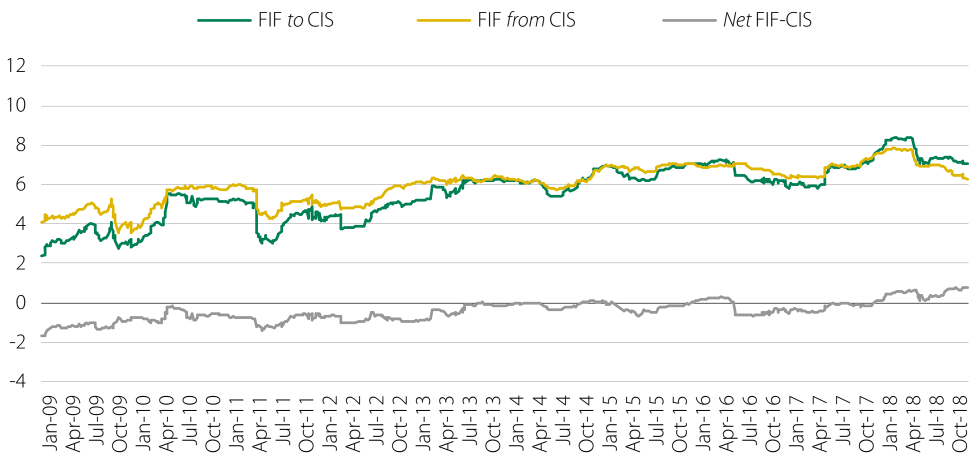
Source: Own calculations.

Connectedness between FIF and other CIS categories FIGURE 27



Source: Own calculations.

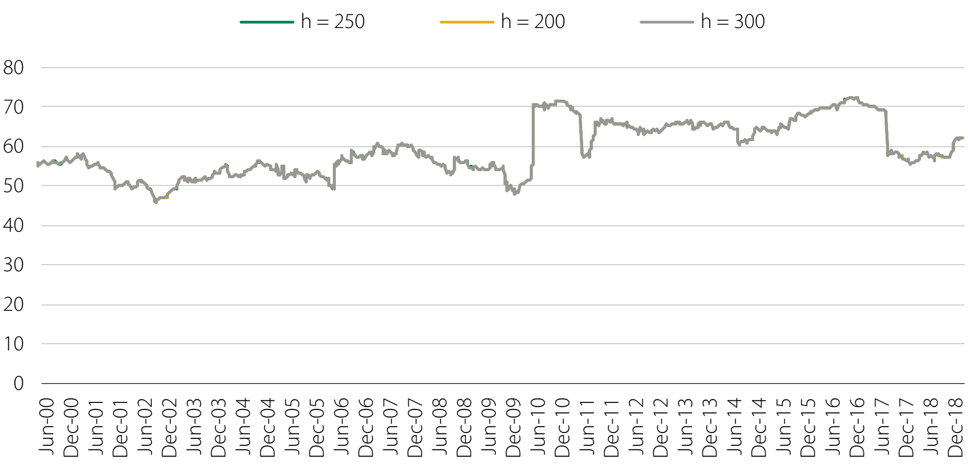
Connectedness *to from net* FIF-CIS FIGURE 28



Source: Own calculations.

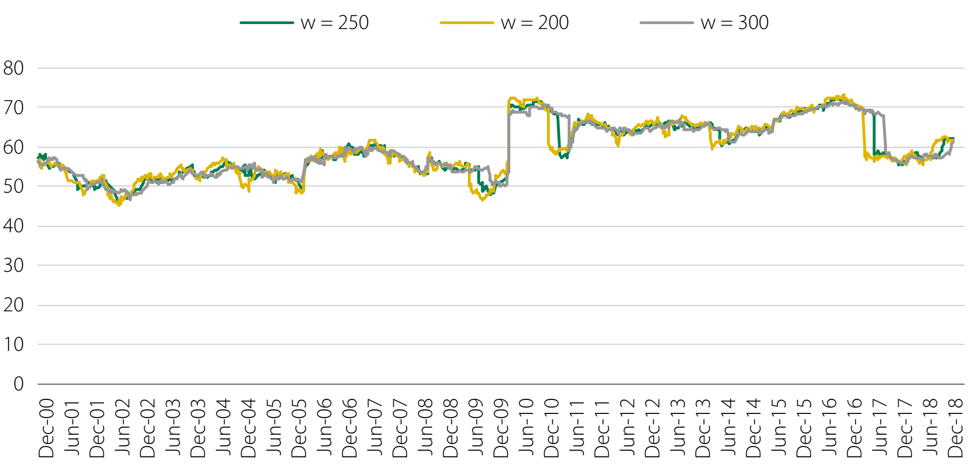
Annex III

Total connectedness by different forecast horizons FIGURE 29



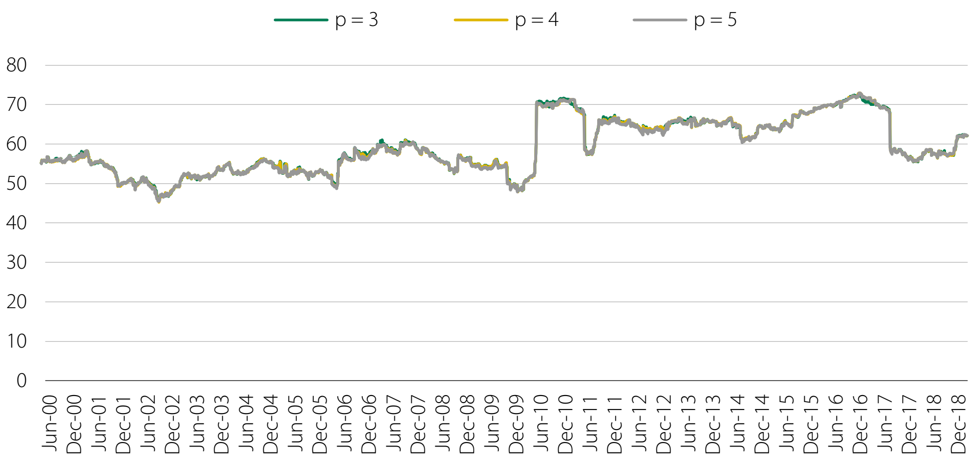
Source: Own calculations.

Total connectedness by different estimation window width FIGURE 30



Source: Own calculations.

Total connectedness by different number of lags of the predictive VAR FIGURE 31



Source: Own calculations.