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Fire sales by euro area banks and funds: what is their asset price impact?

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Abstract

The assets under management of investment funds have soared in recent years, triggering a debate on their possible implications for financial stability. We contribute to this debate assessing the asset price impact of fire sales in a novel partial equilibrium model of euro area funds and banks calibrated over the period between 2008 and 2017. An initial shock to yields causes funds to sell assets to address investor redemptions, while both banks and funds sell assets to keep their leverage constant. These fire sales generate second-round price effects. We find that the potential losses due to the price impact of fire sales have decreased over time for the system. The contribution of funds to this impact is lower than that of banks. However, funds' relative contribution has risen due to their increased assets under management and banks' lower leverage and rebalancing towards loans. Should this trend continue, funds will become an increasingly important source of systemic risk.

Keywords: Investment funds, banks, fire sales, second-round price effects, financial contagion, financial stability.

JEL Classification: G1, G21, G23

Non-Technical Summary

The euro area investment fund sector has gained in importance since the start of the international financial crisis. As a result, regulators and policymakers alike have increasingly turned their focus to financial stability risks that could be stemming from, or amplified by this sector.

A key channel through which the investment fund sector may pose risks to financial stability is the potential for procyclical investor flows that could amplify an initial market price shock through common holdings with the banking sector. Via this channel, an initial decline in market prices depresses investment fund valuations, triggering investor redemptions. Subsequent sales of assets, which are needed to accommodate such redemptions, depress asset prices further and spill over to other sectors holding the same assets.

In this paper, we focus on the common holdings channel that exists among euro area investment funds and banks. We build a two-sector model that translates an initial bond yields shock to fire sales triggered by: *i*) a motive to keep leverage constant for both sectors; and *ii*) the need to satisfy investment fund redemptions. These sales translate into second-round price effects that affect the balance sheets of both banks and investment funds. The model allows comparing directly the systemic importance of banks and funds, the latter broken down into seven sub-sectors (equity, bond, mixed, real estate, money market, hedge funds and other funds). The model is calibrated relying mainly on the aggregate data sourced from the ECB Balance Sheet Statistics and Investment Fund Statistics over the period between 2008 and 2017. The framework allows us to evaluate the aggregate vulnerability and systemicness of euro area banks and investment funds, *i.e.*, how much does each sector loose overall and how much does it contribute to second-round price effects through fire sales, respectively.

Assuming an initial parallel shock to the yield curve, we find that the relative systemicness of investment funds (*i.e.*, their relative contribution to second-round price effects) is materially lower than that of banks, accounting for around 11% of the total in the fourth quarter of 2017. We also find that the total amount lost by second-round effects (aggregate vulnerability) has decreased for the financial system as a whole over time. Nevertheless, we find that the systemic importance of investment funds has increased significantly over time, owing to the increase in investment fund assets and the decline of bank leverage and shift towards holding more loans in recent years. Should this trend continue, funds will become an increasingly important source of systemic risk.

We also perform two policy exercises where we vary the calibrated leverage of the banking and investment fund sectors to assess how different levels of leverage in each sector affect the financial system's aggregate vulnerability. As expected, these simulations show that lower leverage implies lower aggregate vulnerability. These simulations illustrate how the framework developed in this paper can be used for policy purposes.

1. **Introduction**

The euro area investment fund sector has increased in importance since the start of the international financial crisis. Assets managed by investment funds in the euro area increased from 5.6 to 13.1 trillion euros (or by 134%) between 2008 and 2017. For comparison, assets held by credit institutions declined by 3.6% to 29.5 trillion euros over the same period. In light of the large growth of the investment fund sector, regulators and policymakers alike have increasingly turned their focus to the financial stability risks that this sector could create or amplify (International Monetary Fund, 2015; European Systemic Risk Board, 2016; Bank for International Settlements, 2018).

Procyclical investor flows represent a key channel through which the investment fund sector may pose risks to financial stability by amplifying initial market price shocks. These risks could also be magnified by the presence of common holdings with the banking sector. More specifically, an initial decline in market prices could depress investment fund valuations, triggering investor redemptions (Coval and Stafford, 2007; Ben-Rephael et al., 2011; and Lou, 2012). The subsequent assets sales necessary to accommodate such redemptions would further dampen asset prices and spill over to other sectors holding the same assets.[1] In the banking sector, an initial shock to financial assets' valuations would increase their leverage and induce them to sell assets to return to their target leverage (Adrian and Shin, 2010). These sales would further depress asset prices (Greenwood et al., 2015).

The importance of overlapping portfolios for systemic risk is well documented in the theoretical literature (Cifuentes et al., 2005; Wagner, 2011; Caccioli et al., 2014), while empirical applications have been explored separately for banks (Greenwood et al., 2015; Cont and Schaanning, 2017) and investment funds (Cetorelli et al., 2016; Fricke and Fricke, 2017). One exception is the study of Duarte and Eisenbach (2018), which focuses solely on the leverage target channel and abstracts from procyclical investor flows.

In this paper, we contribute to the literature on common holdings by assessing the potential asset price impact of fire sales by euro area funds and banks for the period between

[1] See Ellul et al. (2011) on the price impact of fire sales.

the fourth quarter of 2008 and the fourth quarter of 2017, relying on an original modelling framework which combines the banking and investment fund sectors.[2] We present a novel partial equilibrium model that translates an initial shock to bond yields into fire sales. These sales translate into second-round price effects that further decrease asset valuations and, therefore, banks' equity and funds' share values. The model combines the frameworks developed by Cetorelli et al. (2016) and Fricke and Fricke (2017) for the investment fund sector with that introduced by Greenwood et al. (2015) and extended by Duarte and Eisenbach (2018) for the banking sector. This integrated framework allows the investigation of interactions between euro area banks and investment funds triggered by an initial shock and in particular, it permits the evaluation of the subsequent fire sales. As a result, it allows the assessment of the evolution of the aggregate vulnerability of the financial system to fire sales and the systemicness of the banking and investment fund sectors over time. In this context, aggregate vulnerability is defined as the losses in the overall financial system due to the price impact of fire sales, while systemicness is defined as the contribution of each sector to the aggregate vulnerability of the system through fire-sale spill-overs. Finally, relative systemicness is defined as the ratio of systemicness over aggregate vulnerability and measures the share of a sector's contribution to the losses of the system due to the price impact of fire sales.

Importantly, to the best of our knowledge, this is the first study investigating the asset price impact of banks' and funds' fire sales in an integrated model incorporating both the leverage target and procyclical investor flows.

We compute aggregate vulnerability and systemicness at a quarterly frequency over the full sample period. For this purpose, the model is calibrated using quarterly data for the same period. In particular, we calibrate the balance sheets of the euro area banking sector and the investment fund sector relying on the data provided by the ECB Balance Sheet Statistics and Investment Fund Statistics. The procyclical relationship between the investor flows and the funds' performance, the flow-performance relationship, is estimated using fund-level data

[2] In our model, the investment fund sector is further broken down into seven sub-sectors, i.e., equity, bond, mixed, real estate, money market, hedge funds and other funds.

from Thomson Reuters Lipper IM. Finally, we compute the price impact of fire sales on equity holdings as the quarterly average of the Amihud ratio while the price impact of fire sales on bond holdings is calibrated according to values used in the literature.

This study is closely related to the paper by Cont and Schaanning (2017), which quantifies the effect of fire sales on financial institutions subject to capital, leverage and liquidity constraints in a stress scenario. However, our study relies on the more traditional leverage targeting assumption for banks (Adrian and Shin, 2010), which may be seen as the strictest constraint in the Cont and Schaanning framework, while also adding investment funds in the model and introducing investor redemptions as a response to deteriorating fund returns (Sirri and Tufano, 1998; Berk and Green, 2004).

This paper features a simulation exercise in a framework where an initial shock is amplified by procyclical investor flows and common holdings. As such, it is complementary to a related literature that develops systemic risk measures based on market prices (CoVaR and SRISK). Leading examples of this line of work include Adrian and Brunnermeier (2016) Acharya et al. (2012), Acharya et al. (2017) and Brownlees and Engle (2017). Greenwood et al. (2015) discuss the similarities in the findings of this strand of the literature with the one on common holdings. Finally, there is a complementary line of work in the literature that measures systemic risk through the interconnectedness of financial networks (Billio et al., 2012; Minoiu et al., 2015; Mezei and Sarlin, 2018; Cheng and Zhao, 2019).

Relying on our framework, we assess the effects of an initial shock to the yield curve that increases all yields by 100 bps. The source of this shock is not modelled in this paper but could stem from changes in monetary policy, credit risk, liquidity risk premia or a combination of the above.

First, we find that the aggregate vulnerability of the financial system as a whole has decreased over time. Furthermore, we find that the relative systemicness of investment funds (i.e., their relative contribution to the price impact of fire sales) is low, accounting for around 11% of the total in the fourth quarter of 2017. This result is in line with the literature concerning the United States, which suggests that the impact of adverse macro-financial shocks on equity and bond funds is rather small (Cetorelli et al., 2016; Fricke and Fricke, 2017). Nevertheless, we show that the systemic importance of investment funds has increased significantly in recent years due to the increase in investment funds' assets, the decline of bank leverage and the rebalancing of banks away from financial assets and towards loans and advances. These trends have been supported by regulatory changes (importantly, the introduction of Basel II and III), which have created strong pressures for banks to increase their capital ratios and have led to increased financial flows into investment funds to avoid banks' stricter regulatory requirements (International Monetary Fund, 2015). The growth of the investment fund sector has been driven by low interest rates and low term spreads, which have induced investors to search for higher yields, as well as the introduction of new technologies, which have lowered the barriers to entry into markets where banks once needed networks of physical branches to operate. At the same time, the significance of the banking sector declined after the crisis due to the necessary balance sheet repair and related material deleveraging.

We also perform two policy exercises where we vary the calibrated leverage of the banking and investment fund sectors to assess how different levels of leverage in each sector affect the financial system's aggregate vulnerability. As expected, these simulations show that lower leverage implies lower aggregate vulnerability. These simulations also illustrate how the framework developed in this paper can be used for policy purposes. For example, the framework could enable policy makers to quantitatively evaluate the effects of the introduction of new regulations on the asset price impact of fire sales.

Overall, our results inform the policy debate on the importance of the investment fund sector for financial stability. On the one hand, the continuing dominance of the banking sector when it comes to systemic risk justifies the focus it receives from policymakers and regulators. On the other hand, if the trends we report here continue, investment funds may become an increasingly important source of systemic risk for the financial system that will need to be scrutinised by policymakers. Overall, the diversification of funding sources for the real economy can help to distribute risks more effectively across investors and lenders and provide alternative sources of finance. However, in this context, the emergence of new vulnerabilities in the non-bank financial sector must be carefully monitored.

The rest of the paper is organised as follows. Section 2 presents the theoretical model used in this paper and Section 3 discusses the data and the calibration of the various parameters. Section 4 presents the results, discusses various robustness checks and highlights the policy relevance of our findings. In Section 5, we present the conclusions.

2. The model

We develop a three-period, partial equilibrium model that builds on the theoretical frameworks for the banking sector developed by Greenwood et al. (2015) and extended by Duarte and Eisenbach (2018), as well as on the approaches used by Cetorelli et al. (2016) and Fricke and Fricke (2017) for the investment fund sector. In particular, in this model, the financial system consists of a banking sector and seven investment fund sub-sectors. This framework can be used to study the effects of an initial market shock on banks and investment funds. In the first period, the model translates an initial market shock to bond yields into losses in bank equity and a fall in the valuation of investment fund shares due to a drop in the value of their financial assets. In the second period, fund investors react to the shock in a procyclical manner: they redeem part of their shares, forcing funds to sell assets. Moreover, both banks and funds sell financial assets to maintain a target leverage ratio. We assume that asset sales are carried out such that the weights of the assets in the banks' and funds' portfolios, including those of cash buffers, remain constant (i.e., there is no pecking order determining which part of the portfolio will be liquidated first).[3] Finally, in the third period, sales triggered by investor redemptions and leverage targeting cause second-round price effects that further depress asset valuations and therefore banks' equity and funds' share values.

Importantly, to the best of our knowledge, this is the first study investigating the impact of bank and fund fire sales in an integrated model. While Greenwood et al. (2015) only consider banks, Fricke and Fricke (2017) focus on equity funds, and Cetorelli et al. (2016)

[3] Results on the actual use of cash buffers by funds are mixed. Chernenko and Sunderam (2016) report that funds finance redemptions with their cash holdings rather than through sales of illiquid securities. Morris et al. (2017) reach the opposite conclusion for bond funds.

consider funds of all types but not banks. Thus, our model allows the investigation of the interactions between these different sectors triggered by the initial market shock to bond yields and permits the assessment of their aggregate vulnerability and systemic importance over time. However, our model is consistent with one of the specifications developed by Greenwood et al. (2015), where - in the short-term - the banking sector can only deleverage by selling financial assets, while loans, non-financial assets and remaining assets remain constant. Our framework extends the analysis of Fricke and Fricke (2017) by considering not only equity funds but seven distinct types of investment funds. We consider equity, bond, mixed, real estate, money market and hedge funds, as well as a residual 'other funds' type. Finally, we model banks and funds at the sector level instead of the single entity level. As a result, we abstract from any interaction or heterogeneity that may exist within each sector.

Before turning to the model, it is important to mention that despite its importance, the transmission channel that we model here, which operates through holdings of common assets, is not the only one that operates between funds and banks. Investment funds provide funding to banks by holding debt securities and equity and, in turn, banks invest in funds (and some other non-bank entities), making the former vulnerable to a fall in the net asset value of the latter (i.e., the value of shares in the fund). Also, within the funds universe, money market funds may effectively provide funding to the riskier hedge fund sector through broker-dealers (Infante and Vardoulakis, 2018). Moreover, there may exist direct and indirect interlinkages when banks and funds belong to the same holding company or share a common brand. These interlinkages can operate in favour or against stability. On the one hand, funds may support their parent institutions by investing in them during difficult times (Golez and Marin, 2015).[4] On the other hand, the parent entity's risk may spread directly to its subsidiaries. Alternatively, reputational damage to the image of one or more entities in the holding can affect the others indirectly through identification with the same brand.[5]

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[4] The authors discuss the implications of this link for investor protection and price discovery.

[5] Fiala and Havranek (2017) show that contagion risk from foreign owners to local banks in Eastern Europe and Turkey is substantially smaller than contagion across local subsidiaries in the same region. Similar channels could be investigated for foreign-owned investment funds. Akhter and Daly (2017) show how shocks spread across countries focusing on the experience from Australian banks being subject to risks to their US, EU or Japanese owners.

Turning to the model, there are $N + 1$ sectors, of which N are fund sub-sectors and one is the banking sector. They invest in various classes of financial assets, non-financial assets (mainly relevant for banks and real estate funds) and loans (in the case of the banking sector). Investments are financed by financial liabilities, bank equity, funds' issued shares and deposit liabilities (mostly for banks). Table 1 summarises the asset classes in both sectors and their sources of financing.

Let e_i be the bank equity or the issued fund shares/units of sector i ($i = 1, \dots, N + 1$), p_i be its financial liabilities and d_i be its deposit liabilities (the latter quantity being relevant mostly for banks). On the asset side, we denote the sum of the sector's financial assets as f_i and the sum of loans extended and non-financial assets as l_i. As mentioned, the sectors absorb the initial market shock by adjusting only the value of their financial assets (f_i).

Since assets and liabilities always match for each sector, the following holds:

$$l_i + f_i = e_i + p_i + d_i \tag{1}$$

We define the sectors' leverage as the ratio between liabilities and equity/shares:

$$b_i = (d_i + p_i)/e_i \tag{2}$$

Finally, financial assets are divided into K asset classes. $M_{\{(N+1)\times K\}}$ is a matrix collecting the weights assigned to each asset class in their portfolio (column) for each sector (row), such that $\sum_{k=1}^{K} M_{i,k} = 1$.

Table 1: Balance sheet structure of the sectors in the model

Banking sector		Investment fund sub-sectors	
Loans and non-financial assets (l_i)	Bank equity (e_i)	Non-financial assets (l_i)	Shares/units issued (e_i)
Financial assets (f_i)	Deposit liabilities (d_i)	Financial assets (f_i)	Deposit liabilities (d_i)
Debt securities		Deposits & loans	
Euro area MFIs	Financial liabilities (p_i)	*Euro area MFIs*	Financial liabilities (p_i)
Euro area government		*Euro area government*	
Euro area non-MFIs		*Euro area non-MFIs*	
Other		*Other*	
Equity		Debt securities	
Euro area MFIs		*Euro area MFIs*	
Euro area non-MFIs		*Euro area government*	
Other		*Euro area non-MFIs*	
Remaining		*Other*	
		Equity	
		Euro area MFIs	
		Euro area non-MFIs	
		Other	
		Remaining	

Notes: MFI stands for monetary financial institutions. See European Central Bank (2019) for more details.

2.1. Initial market shock to yields

In the first period, an initial market shock to yields is translated into losses in bank equity and a fall in the valuation of investment funds' shares. Let G_1 be the $K \times 1$ vector of the initial shocks to the prices of the asset classes. These asset-specific shocks translate into sector-level shocks $R_1 = MG_1$. Let $r_{i,1}$ be the shock that corresponds to sector i.

Assuming that financial liabilities remain constant in the first period, after the initial shock ($p_{i,1} = p_{i,0}$), where 0 denotes the time before the shock, the financial assets and equity/shares change as follows (we omit the index i for brevity):

$$f_1 = f_0(1 + r_1) \quad (3)$$

$$e_1 = e_0 + f_0 r_1 \quad (4)$$

Deposit liabilities (d) and loans and fixed assets (l) remain constant in all periods ($d_0 = d_1 = d_2 = d_3$ and $l_0 = l_1 = l_2 = l_3$). As mentioned above, we assume a negative shock to bond prices in this paper.

2.2. Redemptions and leverage targeting

In the second period, we assume that the negative market shock triggers investor redemptions that further decrease the value of the equity/shares of the sectors in a linear manner (as proposed by Coval and Stafford, 2007):

$$\frac{\Delta e_2}{e_1} = \gamma \frac{f_0 r_1}{e_0} \Leftrightarrow e_2 = e_1(1 + \gamma \tilde{f}_0 r_1) \quad (5)$$

where $\tilde{f}_0 = f_0/e_0$ and γ is a sector-specific sensitivity parameter, estimated in section 3.3 and assumed to be equal to zero for banks, as the concept of redemptions is not relevant for banks' capital.

Furthermore, both banks and investment funds sell assets in order to restore their leverage (b_t), i.e., to ensure that ($b_2 = b_0$). This ratio increases (i.e., $b_1 > b_0$) after the losses suffered in the first period. To restore their leverage (Adrian and Shin, 2010), banks and funds liquidate financial assets and use the proceeds to reduce financial liabilities (p_t, see Appendix A for the derivation):

$$b_0 = b_2 \Leftrightarrow \frac{d_0 + p_0}{e_0} = \frac{d_2 + p_2}{e_2} = \frac{d_0 + p_0 + (p_2 - p_0)}{e_2} \Leftrightarrow \cdots \Leftrightarrow (p_2 - p_0) = f_0 b_0 \tilde{r}_2 \quad (6)$$

where $\tilde{r}_2 = r_1 \left(1 + \gamma\left(1 + \tilde{f}_0 r_1\right)\right)$.

As a result, the sales of financial assets of each sector (θ_2), which are determined by both redemptions and leverage targeting, are:

$$\theta_2 \stackrel{\text{def}}{=} \Delta f_2 = \Delta e_2 + \Delta p_2 \xRightarrow{p_1 = p_0} \theta_2 = \Delta e_2 + (p_2 - p_0) \xRightarrow{(5),(6)} \theta_2 = \gamma \tilde{f}_0 e_1 r_1 + f_0 b_0 \tilde{r}_2 \quad (7)$$

In matrix notation, we define a number of $(N+1) \times (N+1)$ diagonal matrices, as follows: Γ is the diagonal matrix that contains the sector-specific γ_i parameters along its diagonal. $F_{t\{N+1 \times N+1\}}$ and $\tilde{F}_{t\{N+1 \times N+1\}}$ are the matrices consisting of the sectors' financial assets and their financial assets normalised by $e_{i,t}$, respectively (with entries $f_{i,t}$ and $\tilde{f}_{i,t} = f_{i,t}/e_{i,t}$). Matrix $E_{t\{N+1 \times N+1\}}$ includes $e_{i,t}$ in its diagonal and matrix $B_{t\{N+1 \times N+1\}}$ contains the sectors' leverage, with elements $b_{i,t} = (d_{i,t} + p_{i,t})/e_{i,t}$. Finally, we stack r_1 and $\tilde{r}_2$ in column $(K \times 1)$ vectors R_1 and $\tilde{R}_2$.

Then, the sales per sector can be summarised as follows:

$$\Theta_2 = \Gamma \, \tilde{F}_0 E_1 R_1 + F_0 B_0 \tilde{R}_2 \quad (8)$$

where $E_1 = E_0 + F_0 diag(R_1)$.

This implies that the asset-class specific sales are (in amounts):

$$\widetilde{\Phi_2} = M' \, \Theta_2 = M' \, [\Gamma \, \tilde{F}_0 E_1 R_1 + F_0 B_0 \tilde{R}_2] \quad (9)$$

2.3. Second-round price effects

Finally, in the third period, the sales triggered by investor redemptions and leverage targeting cause second-round price effects that further depress asset valuations and, therefore, banks' equity and funds' share values.

In particular, we assume that these sales cause a linear price impact:

$$G_3 = L\widetilde{\Phi_2} \quad (10)$$

where L is a diagonal $K \times K$ matrix with units in percentage points per euro of sales. This additional price drop creates second round price effects at the sector level:

$$R_3 = MG_3 = MLM' \, [\Gamma \tilde{F}_0 E_1 R_1 + F_0 B_0 \tilde{R}_2] \quad (11)$$

2.4. Definitions of aggregate vulnerability, systemicness and relative systemicness

Based on the derivations above, we can now compute three indicators that measure the aggregate vulnerability, systemicness and relative systemicness of banks and investment funds in the euro area, adjusting the indicators proposed by Greenwood et al. (2015) for banks and applied to funds by Cetorelli et al. (2016) and Fricke and Fricke (2017).

Aggregate vulnerability measures the losses that the entire system suffers as a result of the price impact of fire sales, expressed as a percentage of their initial equity/shares value:

$$\widetilde{AV} = \frac{1'_N F_0 R_3}{1'_{N+1} E_0 1_{N+1}} = \frac{1'_{N+1} F_0 MLM' \, [\Gamma \, \tilde{F}_0 E_1 R_1 + F_0 B \tilde{R}_2]}{1'_{N+1} E_0 1_{N+1}} \quad (12)$$

The *systemicness* of a given sector is defined as the portion of aggregate vulnerability that is attributable to the sales of that sector:

$$S_i = \frac{1_{N+1}' F_0 M L M' \ \delta_i \delta_i{}' \ [\Gamma \tilde{F}_0 E_1 R_1 + F_0 B \tilde{R}_2]}{1_{N+1}' E_0 1_{N+1}} \qquad (13)$$

where δ_i is an N × 1 vector with a value of 1 at position i and 0 elsewhere.

Finally, we define *relative systemicness* as the ratio of *systemicness* to *aggregate vulnerability*, which measures the share of a sector's contribution to total second-round losses of the system:

$$RS_i = \frac{S_i}{\widetilde{AV}} \qquad (14)$$

3. Data and calibration

This section presents the data and calibration used to operationalise the theoretical framework and to compute the three measures presented above (aggregate vulnerability, systemicness and relative systemicness). We use quarterly data from the fourth quarter of 2008 to the fourth quarter of 2017. This section provides further insights into the following four items:

1. The construction of the sectors' balance sheets (matrices M, F_0, E_0 and B) based on aggregate euro area data;
2. The definition of the initial shock (G_1) to the prices of the various asset classes;
3. The estimation of the sector-specific sensitivity parameters that determine investor redemptions from investment funds as a response to the initial market shocks (matrix Γ);
4. The calibration of the price impact of asset sales (matrix L), i.e., the second-round price effects.

3.1. Sectors' balance sheets

We use data from ECB Balance Sheet Statistics to calibrate the balance sheets of banks and money market funds, while the balance sheets of the other sectors are calibrated using ECB Investment Fund Statistics data. The latter contains aggregate information on six euro area investment fund sub-sectors: bond, equity, mixed, hedge, real estate and a residual sector of other funds. We exclude closed-end funds from the analysis, as they do not face redemptions. Both the Balance Sheet Statistics and the Investment Fund Statistics are sourced from the ECB Statistical Data Warehouse.[6] We use non-seasonally adjusted quarterly data from the fourth quarter of 2008 to the fourth quarter of 2017, which allow us to populate matrices M, F_0, E_0 and B for each quarter in the sample.

Table 2 shows the composition of balance sheets for the sectors at the end of 2017, ignoring the regional breakdowns shown in Table 1. It can be observed that euro area banks are more than two times larger than investment funds in terms of total assets. In terms of holdings of financial assets, banks account for about 30%, which also makes them vulnerable to fire sales. Furthermore, banks are much more leveraged than funds, with equity (defined as capital and reserves) of 2.6 trillion euro supporting assets of 29.2 trillion euro. Figure B.1 in Appendix B documents the slight reduction of banks' total assets over the period examined.
The size of the euro area investment fund sector (in terms of total assets) has increased in recent years both in absolute terms and in relation to the size of the euro area banking sector, thereby triggering a debate on the relative systemic importance of the two sectors. Among investment funds, the sub-sectors with the most assets under management are equity, bond and mixed funds. Mixed funds have a potentially important role in propagating shocks since they hold sizeable amounts of both equities and bonds. A shock to either category could induce mixed funds to deleverage both asset classes, such that the class unaffected by the initial shock may also be subject to second-round price effects. Hedge funds, real estate funds and other funds also grew, but from a much lower initial size. The money market funds

[6] See European Central Bank (2017) and European Central Bank (2019) for more details on the data collection.

declined until end-2013 and have recovered somewhat since then (see Appendix B for the relevant figures).

The sectors that we analyse also hold investment fund shares on their asset side (see Table 2, column 4, “Fund shares”). For our calibrations, we treat asset-side investment fund shares as vehicles that invest with exactly the same asset allocation as the sectors for the rest of their portfolio. Therefore, we allocate the amounts invested in fund shares to the rest of the asset classes proportionally.[7]

As we analyse the impact of a market shock to yields, it is necessary to account for the fact that some of the banks’ assets are held to maturity. We approximate this portion of banks’ assets using a time series of the share of assets held to maturity by systemically important euro-area banks, calculated using SNL Financials data for the sample period. We then apply all the shocks only to the share of banks’ financial assets not held to maturity.

On a final note, all holdings of the same asset class are assumed to be homogeneous across sectors. This assumption implies that they react to market changes in the same manner and their sales are assumed to have the same price impact.

[7] This assumption is due to the fact that that no additional information is available regarding these “Fund shares”, on top of the amount invested. In particular, it is not possible to know the issuers of the shares, their investment strategies and their asset allocation.

Table 2: Sectors' balance sheets as of 2017 Q4 (billion euros)

Panel A: Assets and liabilities

	Assets		Liabilities		
	Loans & non-financial assets	Financial assets	Deposit liabilities	Financial liabilities	Bank equity/ issued shares
Equity	0	3,345	0	158	3,187
Bond	0	3,515	0	283	3,232
Mixed	1	3,104	0	204	2,901
Real estate	236	313	0	87	463
Hedge	0	448	0	77	371
Other	0	943	0	176	767
Money market	0	1,171	2	24	1,144
Funds total	238	12,839	2	1,010	12,065
Banks	21,160	8,048	20,267	6,376	2,566
Total	**21,398**	**20,888**	**20,269**	**7,385**	**14,631**

Panel B: Breakdown of financial assets

	Deposits and loans	Equities	Bonds	Fund shares	Remaining financial
Equity	97	2,821	51	237	140
Bond	176	33	2,860	217	230
Mixed	180	554	1,174	1,010	187
Real estate	81	88	11	60	73
Hedge	74	75	111	135	54
Other	160	150	281	282	70
Money market	238	1	879	41	13
Funds total	1,005	3,720	5,366	1,982	766
Banks	4	1,514	3,669	11	2,850
Total	**1,009**	**5,234**	**9,035**	**1,993**	**3,616**

Notes: The data used are not seasonally adjusted. We do not report the geographical breakdown of the asset classes that are shown in Table 1 for tractability. For investment funds, the most relevant item within remaining assets/liabilities is accrued interest receivable/payable on loans/deposits. In the case of banks, remaining assets (or liabilities) include 'other accounts receivable/payable' (ESA 2010), but also other items, such as positions in financial derivatives and accrued interest on deposits and loans.
Sources: Eurosystem's MFI Balance Sheet Statistics (for banks and money market funds) and Investment Fund Statistics (for the other fund sub-sectors).

3.2. Initial shock and effect on sector performance

We now define the initial shock G_1 and its effect on the price of individual asset classes. As discussed, the shock that we consider is an upward shift in yields[8] by 100 bps, affecting bonds of all maturities, issuers and jurisdictions.[9] We assume that the other asset classes are not simultaneously affected. Thus, we identify the effects of the shock in a *ceteris paribus* manner. This yield shock is translated into a price shock by multiplying it by the calibrated modified durations of the various bond holdings.[10] These modified durations are calibrated by matching the bond holdings considered in our framework with major bond market indices retrieved from Datastream (see Appendix C for more details). For each index, we calculate the average modified duration over each quarter, using daily data. The bond holdings of money market funds are treated as separate asset classes due to their short-term nature and are thus assigned a duration of one year. This is a conservative assumption, given that this sector invests primarily in short-term securities.

3.3. Estimation of the flow-performance relationship

The deterioration in funds' performance due to the initial market shock translates into share redemption by the funds' investors, which in turn forces the various fund sub-sectors to sell assets.[11] To capture this mechanism, we model the sensitivity of investor flows to the performance of the investment fund sub-sectors in light of the considered shocks, also referred to as the flow-performance relationship.

Estimates of the flow–performance relationship are more accurate when based on fund-level information, which allows inferences to be drawn from both the temporal and the cross-

[8] Other channels which might lead to a decline in the value of the assets held by the financial system include, inter alia, rating changes, stock market changes, real estate price movements, exchange rate movements or changes in risk taking behaviour or risk premia.
[9] We are agnostic about the likelihood of this shock actually materializing. As in any stress test, our aim is to analyse the vulnerability of the system to a severe event, independently of its probability of materialising.
[10] Modified duration measures the sensitivity of a bond price to a yield change.
[11] It is important to note that "cash buffers" that could be used by funds to face redemptions, do not play a role in our framework.

sectional dimensions. As a result, we depart from the aggregate ECB data sources. For each of the seven fund sub-sectors, we extract data from Thomson Reuters Lipper IM for a sample of individual open-ended funds that are domiciled in the euro area. For each fund, we collect quarterly data on total net assets (which are by definition equal to the total value of the issued shares) and on returns. Our sample includes both active and liquidated funds to avoid potential survivorship bias in our estimations. We construct an unbalanced quarterly panel dataset which covers the period from the second quarter of 2007 to the first quarter of 2017. Flows, i.e., net subscriptions/redemptions to the funds are not observable but can be approximated as follows:

$$flow_{j,t}^{i} = \frac{e_{j,t}^{i} - e_{j,t-1}^{i}(1 + return_{j,t}^{i})}{e_{j,t-1}^{i}} \qquad (15)$$

where $e_{j,t}^{i}$ is the value of the issued shares of fund *j* that belongs to sector *i* at time *t*, $return_{j,t-k}^{i}$ is the fund-specific return for the period and $flow_{j,t}^{i}$ is the flow of fund *j* that belongs to sector *i* at time *t*, expressed as a percentage of the previous period's value of fund shares. We consider negative flows below -50% of the initial fund value and positive flows above 200% of the initial fund value to be outliers and drop them from the regression, as in Coval and Stafford (2007). In line with these authors, we run Fama and MacBeth (1973) regressions of the following specification:

$$flow_{j,t}^{i} = a^{i} + \sum_{k=1}^{4} b_{k}^{i} \cdot flow_{j,t-k}^{i} + \sum_{k=1}^{4} c_{k}^{i} \cdot return_{j,t-k}^{i} \qquad (16)$$

where $flow_{j,t}^{i}$ is defined as above and parameter c_{1}^{i} represents parameter γ_{i} in our theoretical framework capturing the sensitivity of the funds' flows to their returns and thus the short-term effects of a market shock on fund redemptions.

Table 3: Results of Fama-MacBeth regressions for analysing flow-performance relationships

	Equity funds			Bond funds			Mixed funds			Real estate funds		
	Est.		Std.error	Est.		Std.error	Est.		Std.error	Est.		Std.error
ret_{t-1} (γ_i)	0.207	***	(0.023)	0.397	***	(0.057)	0.294	***	(0.030)	-0.012		(0.024)
ret_{t-2}	0.115	***	(0.024)	0.137	**	(0.067)	0.207	***	(0.029)	0.007		(0.018)
ret_{t-3}	0.059	***	(0.021)	0.059		(0.067)	0.086	***	(0.036)	-0.052		(0.057)
ret_{t-4}	0.018		(0.020)	0.056		(0.066)	0.022		(0.030)	-0.043		(0.037)
$flow_{t-1}$	0.172	***	(0.011)	0.206	***	(0.010)	0.244	***	(0.011)	0.181	***	(0.023)
$flow_{t-2}$	0.089	***	(0.007)	0.088	***	(0.010)	0.124	***	(0.007)	0.106	***	(0.027)
$flow_{t-3}$	0.056	***	(0.006)	0.050	***	(0.006)	0.069	***	(0.007)	0.131	***	(0.028)
$flow_{t-4}$	0.046	***	(0.005)	0.039	***	(0.005)	0.055	***	(0.004)	0.120	***	(0.026)
$\log(TNA_{t-1})$	-0.002	***	(0.000)	-0.002	***	(0.000)	-0.003	***	(0.000)	-0.001	*	(0.000)
$constant$	-0.009	***	(0.002)	-0.005		(0.003)	0.001		(0.001)	0.005	**	(0.002)
No. of funds	11,949			7,700			9,957			258		
No. of quarters	37			37			37			37		
Average R^2	0.093			0.112			0.164			0.255		

	Hedge funds			Other funds			Money market funds		
	Est.		Std.error	Est.		Std.error	Est.		Std.error
ret_{t-1} (γ_i)	0.135	***	(0.037)	-0.003		(0.049)	0.990	***	(0.259)
ret_{t-2}	0.077	**	(0.035)	0.021		(0.055)	0.590	*	(0.303)
ret_{t-3}	0.017		(0.036)	0.009		(0.041)	0.132		(0.250)
ret_{t-4}	-0.024		(0.043)	-0.056		(0.048)	-0.021		(0.265)
$flow_{t-1}$	0.260	***	(0.017)	0.252	***	(0.025)	0.123	***	(0.018)
$flow_{t-2}$	0.113	***	(0.017)	0.094	***	(0.020)	0.079	***	(0.012)
$flow_{t-3}$	0.057	***	(0.011)	0.057	**	(0.026)	0.027	***	(0.011)
$flow_{t-4}$	0.037	***	(0.009)	0.135	***	(0.022)	0.061	***	(0.012)
$\log(TNA_{t-1})$	-0.002	**	(0.001)	-0.002	***	(0.000)	0.000		(0.000)
$constant$	-0.009	***	(0.003)	-0.010	***	(0.003)	-0.024	***	(0.005)
No. of funds	2202			2640			1572		
No. of quarters	37			37			37		
Average R^2	0.188			0.240			0.077		

Notes: Results of Fama-MacBeth regressions of fund flows on lagged fund flows, returns and total net assets; ***, **, * indicate significance at the 1%, 5% and 10% level, respectively. Data source: Thomson Reuters Lipper IM.

Estimating the regressions separately for each fund sector helps to capture the idiosyncrasies of the behaviour of each sector's investors. Moreover, the use of four lags for the flows and returns accounts for potential seasonal effects. Finally, the inclusion of funds' size expressed as the logarithm of total net assets controls for an important source of funds' behavioural heterogeneity. Unlike other papers in the literature, our model uses a specification that relates funds' flows to their absolute performance and not to the outperformance with respect to a benchmark (Cetorelli et al., 2016). This approach is in line with the assumption of a market-wide shock that we explore in this paper, as opposed to idiosyncratic shocks.[12] Finally, we use a linear model for simplicity, as experimenting with non-linear specifications did not lead to significantly different outcomes. Moreover, the linear approach arguably fits better when considering the absolute performance of an entity.[13]

Table 3 presents the estimates for the seven fund sub-sectors. The interpretation of the coefficient γ of the lagged returns of, for example, the equity funds is that a drop (rise) in market returns of one percent translates into an outflow (inflow) of 0.207% of the total assets of the fund in the subsequent quarter. The coefficients are statistically significant and economically meaningful for all of the sub-sectors, except real estate funds and other funds. Moreover, the magnitude of the estimated coefficients is inversely related to the volatility of the returns of a given market. For example, the sensitivity of the equity fund flows is lower than that of the bond fund flows for the same shock, as equity investors expect more volatility in their investments than bond investors. The sensitivity of the mixed fund flows lies somewhere in the middle, while money market funds (which tend to invest in short-term and safer securities) are the most sensitive. Regarding the remaining covariates, we find that past flows are positively related to current flows and that the explanatory power of both past returns and flows diminishes over time. These results point to significant procyclical dynamics induced by the behaviour of fund investors. As described above, a drop in market

[12] Ivkovic and Weisbenner (2009) find that absolute performance matters more for investor outflows, while relative performance matters more for inflows.

[13] Spiegel and Zhang (2013) argue that the flow-performance relationship is linear for models with absolute performance. Goldstein et al. (2016), on the other hand, find a concave flow-performance relationship for corporate bond funds.

returns would translate into significant investor redemptions, which would force fund managers to sell financial assets. Even in subsequent quarters there would still be outflows related to the initial market shock, *ceteris paribus*, as indicated by the positive and significant coefficients on lagged returns (Table 3). The induced asset sales would depress prices further, which would reduce once again the returns of the funds holding the assets.

3.4. Price impact

Finally, we calibrate the price impact of the sectors' sales on all relevant asset classes (matrix *L*), using a combination of our own calculations and some parameterisations as suggested in the related literature.

Regarding equities, the price impact is calculated as the quarterly average of the Amihud ratio, i.e., the ratio of the daily market returns over daily trade volume in euros:

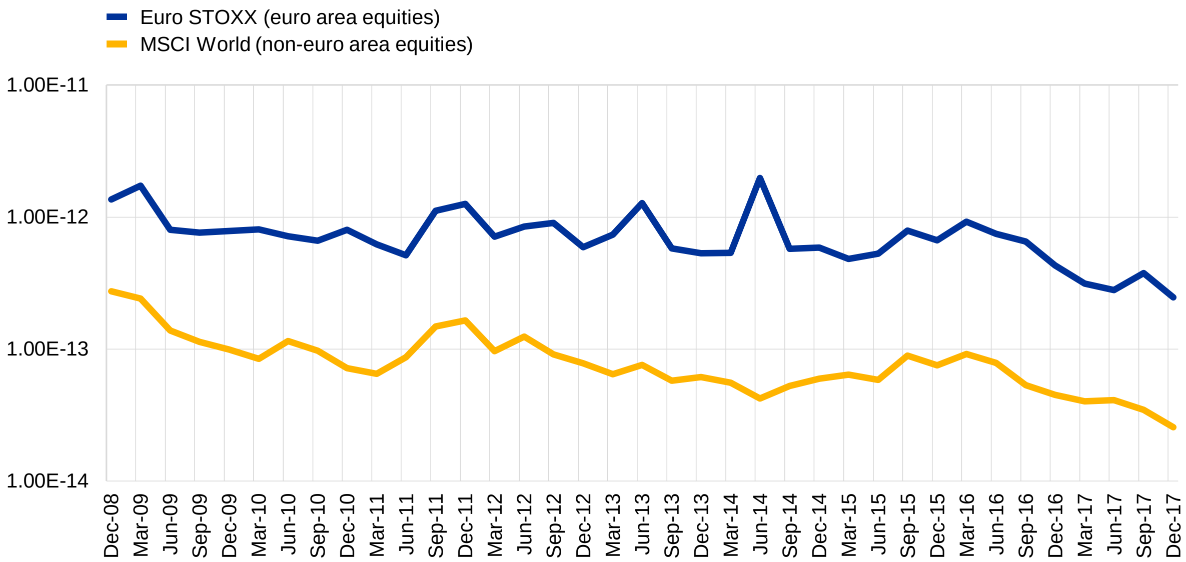
$$\mathrm{Amihud}_{k,d} = \frac{|\mathrm{Return}_{k,d}|}{\mathrm{Volume}_{k,d}} \qquad (17)$$

$$\mathrm{PriceImpact}_{k,t} = \frac{1}{D_t} \sum \mathrm{Amihud}_{k,d} \qquad (18)$$

where *k* is the asset class, *d* the day in a quarter and *t* the quarter. The interpretation of the measure is as follows. An Amihud ratio of 10^{-12} implies that 10 billion euros in sales in a given asset class lead to a price decline of 1%.

We match the euro area equity asset classes of our framework to Euro STOXX and the non-euro area classes to MSCI World and we calculate the quarterly Amihud ratio for the period of our sample. The evolution of the ratios for these indices is displayed in Figure 1. We find that the Amihud ratio of the MSCI World index peaked at the end of 2008 and then again in the second half of 2011, i.e., during the euro area sovereign bond crisis. The Amihud ratio of the Euro STOXX is much higher than that of the MSCI World, as the same volume of sales is expected to have a stronger impact on its narrower investment universe.

Figure 1: Price impact of the used stock market indices



Notes: Price impacts computed as Amihud ratios using daily data of returns and volumes following Equation (18).
Source: Own calculations based on Datastream.

Regarding corporate bond holdings, we set the price impact coefficient to 10^{-13} based on Ellul et al. (2011), who estimate fire sales from insurance companies on recently downgraded corporate bonds. Finally, we calibrate the remaining asset classes deriving implied price elasticities from information on weights assigned in the Basel III Liquidity Coverage Ratio (LCR) (as suggested by Cetorelli et al., 2016). We assign risk weights to each asset class that broadly match the ones in the LCR and estimate their price impacts using corporate bonds as a pivot asset class. Table 4 presents the risk weights that we assign to the different asset classes as derived from the Basel regulation, showing that the pivot category (the debt of non-monetary financial institutions in the euro area) has a risk weight of 35%. Hence, the price impact for the debt of monetary financial institutions in the euro area, for instance, is equal to: $\frac{60\%}{35\%} \times 10^{-13} = 1.7 \times 10^{-13}$.

Table 4: Liquidity Coverage Ratio (LCR) weights assigned to the model's asset classes

	LCR weight
Deposits & loans	
Euro area MFIs	0.00
Euro area government	0.00
Euro area non-MFIs	0.00
Other	0.00
Debt securities	
Euro area MFIs	0.60
Euro area government	0.05
Euro area non-MFIs	0.35
Other	0.35

4. Results

We run the calibrated model for each quarter from the fourth quarter of 2008 to the fourth quarter of 2017 with a shock featuring a parallel increase of 100 bps in all bond yields. The simulation is run separately for every quarter, i.e., without considering potential cumulative effects over time.[14]

Furthermore, it is important to recall that this analysis relies on a partial equilibrium model. Therefore, the results described in the following sections abstract from general equilibrium considerations. In particular, the model does not take into account possible feedback loops between the financial sector and the real economy that could amplify the effects triggered by the initial shock.[15] Additionally, the model features banks' and funds' common holdings as a contagion channel but abstracts from other possible channels, such as

[14] Cumulative effects are not analysed as fire sales, which are the main stress channel assessed with the model developed in this paper, are deemed to be extreme one-off short term contagion events. Furthermore, our framework would have to be materially redesigned and recalibrated to take cumulative effects into account. However, this goes beyond the scope of this paper.

[15] Other papers have quantified the impact of financial stress on the real sector in the euro area. For example, Mallick and Sousa (2013) find that unexpected variation in financial stress plays an important role in explaining output fluctuations.

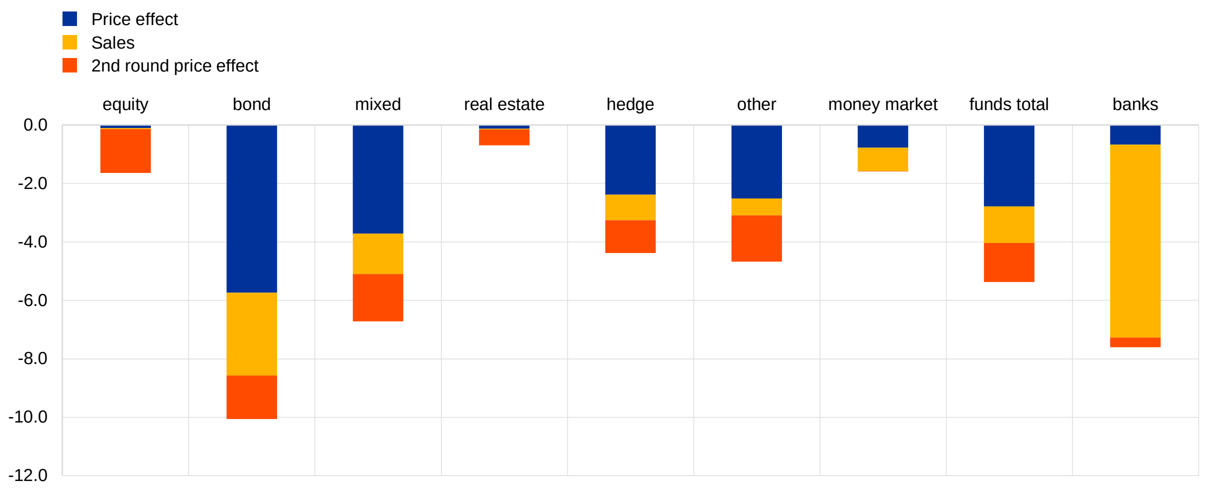
those related to bilateral exposures, which are also likely to magnify the losses induced by the initial market-price shock. Finally, the model does not include a policy authority that could intervene to dampen the negative effects of the shock.

Section 4.1 hereafter presents the main results of the simulation for the last quarter of 2017 in terms of aggregate vulnerability, systemicness and relative systemicness and discusses in detail how the model operates. Section 4.2 focuses on the evolution of aggregate vulnerability and relative systemicness over time. Section 4.3 presents a number of robustness checks and Section 4.4 illustrates possible extensions and the use of the framework for policy purposes.

4.1. Results for the last quarter of 2017

To recall, the 100 bps initial shock translates into: *i)* initial *price effects*, i.e., direct valuation losses; *ii) sales* of financial assets triggered by procyclical investor outflows (in the case of the funds) and by deleveraging of all sectors to maintain a target leverage ratio; and *iii) second-round price effects* related to these sales. Figure 2 presents these effects as a share of total sector assets for the most recent period of our sample (the fourth quarter of 2017).

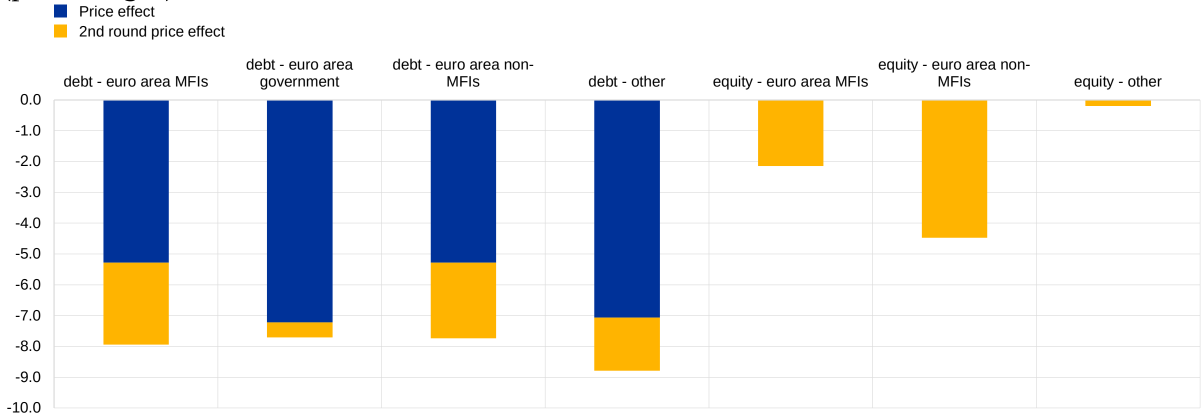
Figure 2: Effects as percentage of total assets by sector for 2017 Q4
(percentages)



Notes: The price effect has been computed based on Equation (4), the sales effect based on Equation (8) and the second-round price effect based on Equation (11).

The initial price effects of the shock are stronger for most investment funds than for euro area banks (2.8% vs 0.7% of total assets). Funds are more exposed to market risk than banks, which primarily hold loans and, to a lesser extent, non-financial assets. Moreover, the losses of the various investment fund types match their portfolio structure: bond funds are the most affected, followed by mixed funds and, to a lesser extent, hedge funds and other funds. The direct exposure of equity and real estate funds is minimal. Despite smaller initial losses, banks react with much stronger sales than funds (6.6% vs 1.2% of total assets). The target of maintaining a stable leverage ratio induces banks to sell relatively more assets than funds, despite the procyclical outflows that the latter experience. Banks' sales also dominate in absolute terms, accounting for approximately 92% of the system's total sales.

Figure 3: Effects on asset prices by asset class for 2017 Q4
(percentages)

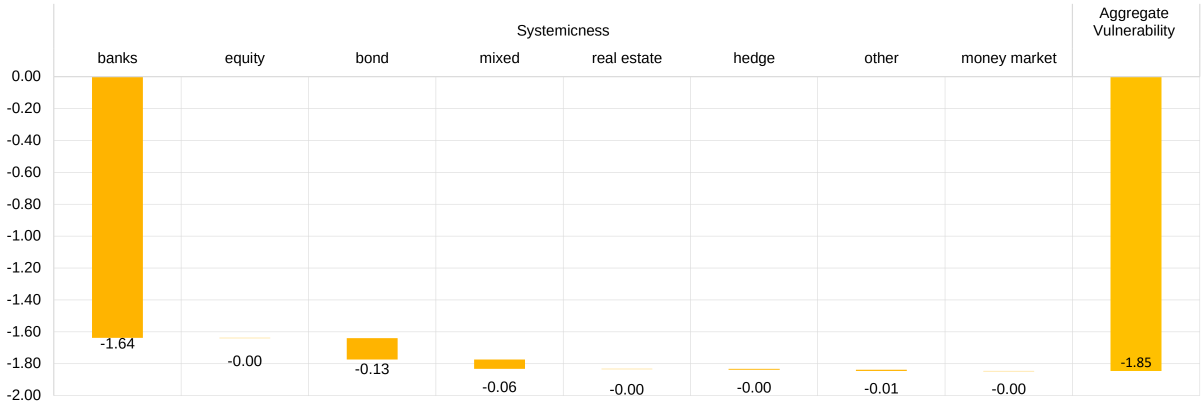


Notes: The initial price effect on asset prices is G_1, while the second round price effect has been computed based on Equation (9).

The sales generate second-round price effects that also affect equity and real estate funds, which were immune to the original shock. These funds are affected by the sales of other agents that hold both equities and bonds, such as mixed funds and banks. Overall, the observed second-round price effects are relatively sizeable for banks, as they are only slightly lower than the initial price effect. Figure 3 shows the initial and second-round price effects for various asset classes. Equities are only affected by the latter and euro area non-monetary financial institution equities are the most affected.

Figure 4 provides the aggregate vulnerability of the system and gives a breakdown of the systemicness of the various sectors. We find that the system loses 1.85% of the sum of bank equity and funds' issued shares due to second-round price effects. Bank sales contribute 1.64% to this loss while bond funds contribute 0.13%. This implies a *relative systemicness* of 88.7% for the euro area banking sector.

Figure 4: Aggregate vulnerability and systemicness of the sectors for 2017 Q4
(percentages)



Note: Aggregate vulnerability has been computed based on Equation (12) and systemicness based on Equation (13).

4.2. Results over time

We now turn to the time dimension. We apply the same shock for each quarter of the period from the fourth quarter of 2008 to the fourth quarter of 2017. This approach allows us to measure aggregate vulnerability over time and to interpret the developments in banks' relative systemicness in the context of structural changes in the euro area financial sector.

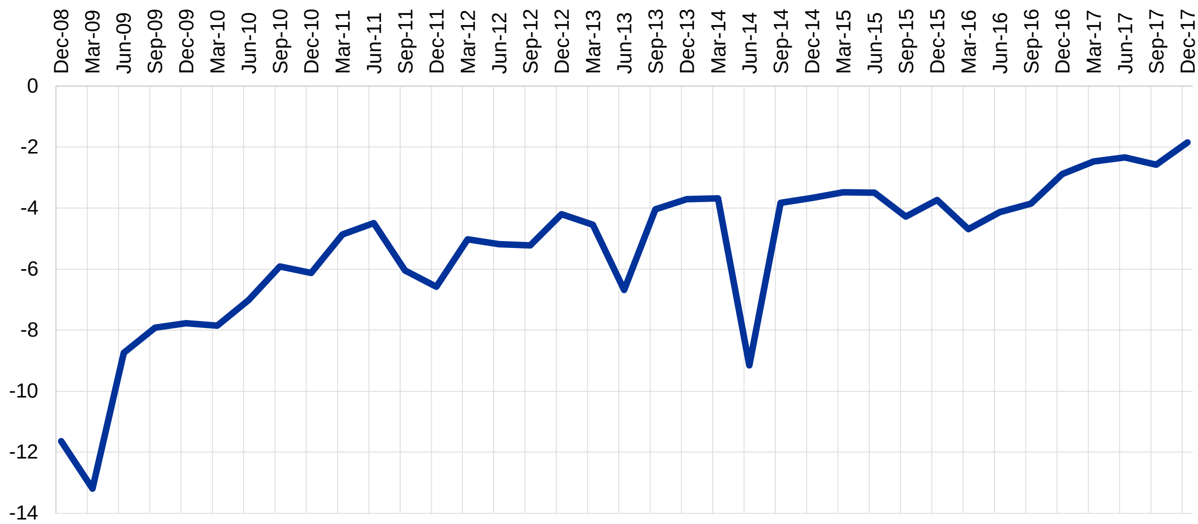
Aggregate vulnerability (i.e., the losses that banks and funds would experience due to second-round price effects) has decreased over time (Figure 5). At the same time, the relative systemicness of euro area investment funds has consistently increased over time, albeit starting from a very low initial level (Figure 6).[16] Bond and mixed funds have been the key contributors to this increase, which is consistent with their role as key sellers of assets.

The relative increase in the size of the euro area investment fund sector compared to banks, as well as the downward trend in banks' leverage, are contributing to the increased systemicness of funds (see Appendix B, Figure B.1 and Figure B.2). Moreover, banks have recently decreased their reliance on financial assets for yield, given the sizeable debt security purchases by the Eurosystem and a shift in interest towards lending to the real economy

[16] The relative systemicness of euro area investment funds is defined as the sum of the relative systemicness of the seven fund sub-sectors.

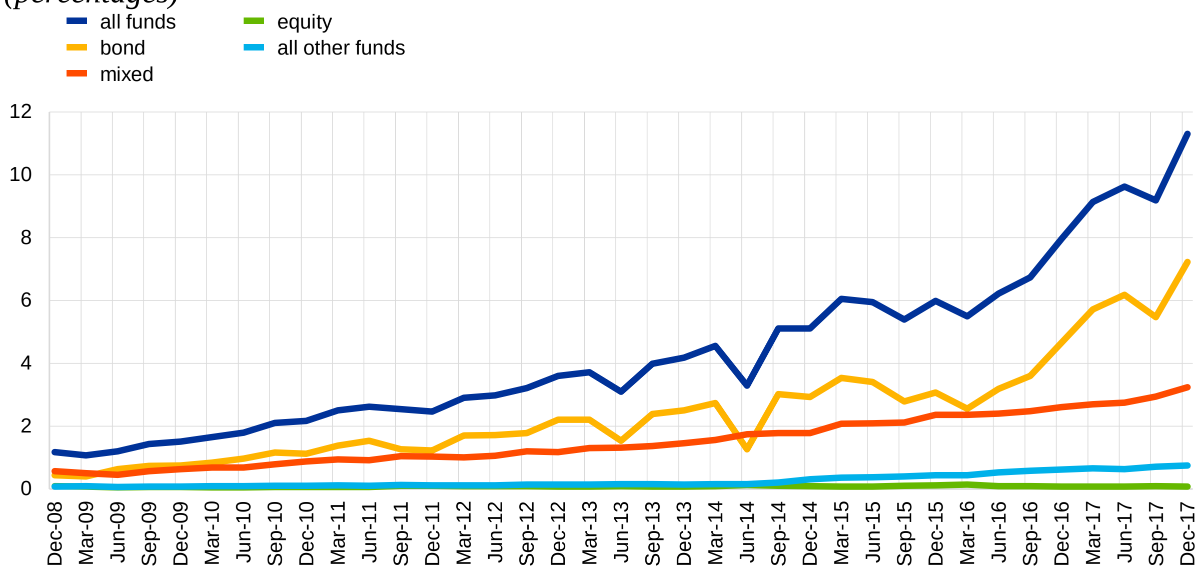
(Appendix B, Figure B.3). These factors have led to a decrease in the relative exposure of banks to the original shock and thus a reduction in the strength of their reaction.

Figure 5: Aggregate vulnerability over time
(percentages)



Note: Aggregate vulnerability has been computed based on Equation (12).

Figure 6: Relative systemicness of funds over time
(percentages)



Note: Relative systemicness of each fund sub-sector has been computed based on Equation (14). Systemicness of all other funds is the sum of the systemicness of hedge funds, real estate funds, money market funds and other funds. Systemicness of all funds is the sum of the systemicness of all seven fund sub-sectors.

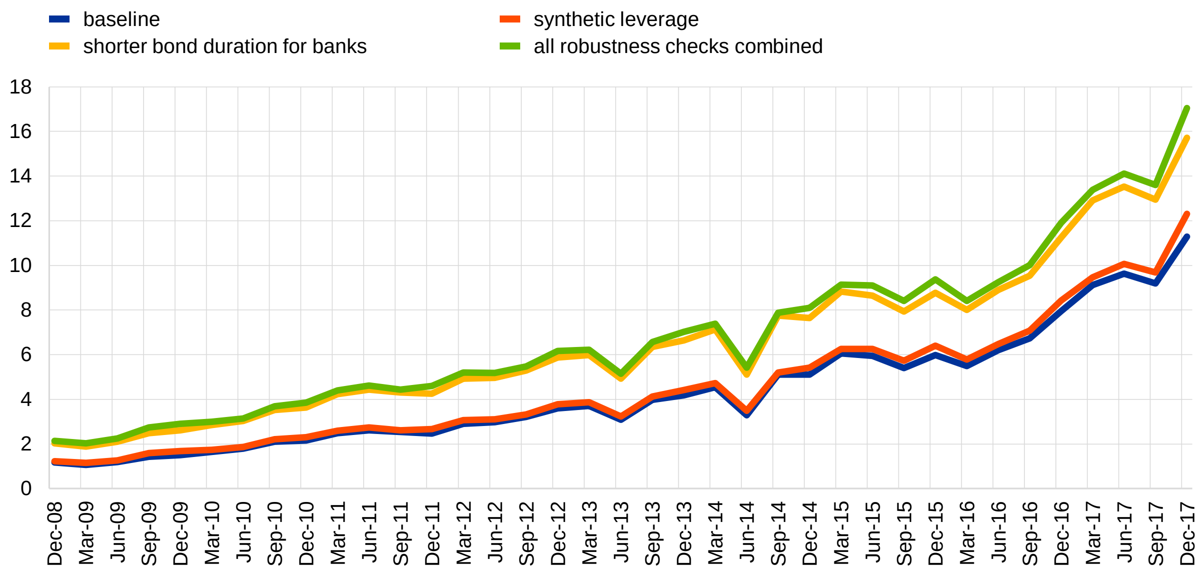
4.3. Robustness checks

Our results suggest that the euro area banking sector is of dominant but decreasing systemic importance relatively to euro area investment funds. This section assesses the robustness of our baseline findings.

First, we depart from our assumption that the common bond holdings of banks and funds have the same duration. Banks invest in securities that have one to two years lower time to maturity than investment funds (see European Central Bank, 2018). As such, we consider an alternative calibration where the duration of banks' holdings is two years shorter than that of the market indices, while the duration for investment funds remains unchanged. Figure 7 (yellow line) presents the relative systemicness of the investment fund sector under this assumption. We find that the relative systemicness of investment funds materially increases compared to our baseline scenario (Figure 7, blue line).

Figure 7: Relative systemicness of funds over time: robustness checks

(percentages)



Note: Relative systemicness of funds is the sum of the relative systemicness of the seven fund sub-sectors. The latter have been computed based on Equation (14).

Second, the fact that we cannot capture funds' synthetic leverage in our data may also lead to an overestimation of the importance of banks. Moreover, this may cause an underestimation of the true exposures of both unregulated hedge funds and the more regulated remaining sectors. To address this possibility we increase the leverage of funds in our model by increasing financial assets and liabilities so that the leverage of hedge funds is 0.5, in line with calculations by Ang et al. (2011), and the leverage of the remaining sub-sectors is at least 0.1, which is the regulatory limit for Undertakings for Collective Investment in Transferable Securities Directive (UCITS) funds. We find that increasing the investment fund leverage increases the relative systemicness of the sector, although the effects are quantitatively small (Figure 7, red line).

Overall, the results of these robustness checks indicate that the role of investment funds may be larger than what our baseline results suggest. Still, even when the effects of the various robustness specifications are combined (Figure 7, green line), they do not alter the main finding of the paper: the relative systemic importance of the euro area banking sector is much higher than that of the investment fund sector, but this dominance has decreased over the period that we examine.

4.4. Possible extensions and use of the framework for policy purposes

This section discusses how the framework developed in this study allows for several simple extensions and can be flexibly employed for various policy purposes under different assumptions.

First, the calibration of this framework is flexible and may easily be modified. This concerns, in particular, the flow-performance relationship and the price impact. The former is estimated through Fama-MacBeth regressions. However, as discussed above, there are various ways to conduct the estimation and a non-linear specification could also be used. The latter relies on Amihud ratios for equities and pivot price impacts from the literature (Cetorelli et al., 2016) for bonds. However, price impacts could be estimated more explicitly, or different estimates from the literature could be used (Cont and Schaanning, 2017). This flexibility could allow policy makers to conduct sensitivity analyses using various calibrations featuring, for example, different degrees of conservatism.

Second, a simple shock to the yield curve is assumed in this study. However, future studies could further extend this framework to use a fully-fledged macro-financial scenario, as it is typical of policy applications, such as micro- or macroprudential stress test exercises (see Budnik et al., 2019, for the latter type of exercise).

In this spirit, we present the results of an additional exercise in Table D.1 in Appendix D, in which we consider a severe drop in stock prices (-20%), in addition to our baseline shock to bond yields (+100 bps).[17] Such a scenario could materialise, for example, during a sovereign debt crisis. The additional stock market shock causes aggregate vulnerability to more than double, from 1.8% (in the baseline analysis presented in Section 4.1) to 4.3%. The

[17] This alters the initial price shock G_1, as the price of equity of euro area MFIs, euro area non-MFIs and other equity are assumed to suffer an initial decline of 20%.

relative systemicness of investment funds increases from 11.3% to 12.4%, in light of the sector's larger equity exposure.

Third, various strategies could be employed to describe how fund managers honour redemption requests, e.g., by drawing first on cash holdings. Similarly, some more complex assumptions could be introduced in the form of pecking-order strategies that bank managers follow when they are forced to sell assets. This may facilitate regulatory impact assessments by introducing regulatory tools that would affect the constraints or incentives of fund or bank managers during deleveraging.

Fourth, other assumptions could be used for the leverage target. While this study assumes a constant target at the current level, as suggested in the literature (e.g. Cont and Schaanning, 2017), different assumptions could be made based on, for example, supervisory data. Similarly, impact studies could be performed including the introduction of new regulatory leverage targets. In a similar vein, this study relies on a non-risk weighted capital ratio (the leverage ratio). Alternatively, one could use risk-weighted measures for banks (such as CET1 or T1 capital ratios). In the two policy exercises presented below it is shown how different levels of leverage of banks and funds affect their aggregate vulnerability.

Fifth, additional extensions could also be introduced. For example, this study develops an approach to estimate second-round losses due to fire sales. However, the same mechanism could easily generate third- and further-round losses (possibly until convergence). Furthermore, this model relies on aggregate data for the seven investment fund sub-sectors and the banking sector. Future studies could instead use granular, fund-by-fund and bank-by-bank data to better capture the constraints faced by individual entities and the impact per entity.

Finally, to demonstrate the validity of the framework developed in this paper as a tool for policy analysis we carry out two policy simulations in which we vary the leverage of the banking sector and investment fund sector, respectively. These exercises allow us to gauge how the same yield shock would play out differently if the considered financial sectors were more (or less) leveraged and, ultimately, to assess how different levels of leverage affect the financial system's aggregate vulnerability.[18]

In the simulations, increases (decreases) in leverage of banks and funds are implemented by increasing (decreasing) financial liabilities and decreasing (increasing) bank equity and funds' issued shares. Total assets and deposit liabilities are assumed to remain constant.

In Table D.2, we show the results of a series of model simulations for different levels of banking sector leverage. The third row in the table reports the baseline results for the actual level of leverage in the fourth quarter of 2017. An increase in bank equity as a share of total bank assets by 100 bps over the baseline would decrease the aggregate vulnerability in absolute terms by 0.2 p.p. from 1.8% to 1.6%. At the same time this reduction in leverage would reduce banks' relative systemicness from 88.7% to 87.4%. Lower bank leverage implies that banks would have to sell fewer assets in reaction to the initial yield shock, dampening the asset price impact of fire sales. The opposite effects are observed when the leverage of the banking sector increases: aggregate vulnerability becomes more pronounced and the relative systemicness of banks increases.

In Table D.3, we show the results of a series of model simulations for different levels of leverage in the investment fund sector. The fourth row in Table D.3 reports the baseline results for the actual leverage in the fourth quarter of 2017. If funds had no leverage, the aggregate vulnerability would decrease in absolute terms by 0.2 p.p. with respect to the baseline setting, which features a weighted-average ratio of fund liabilities to fund issued shares of 8.4%. At the same time, an increase in the ratio of fund liabilities to issued shares to 30% would increase the aggregate vulnerability in absolute terms by 0.4 p.p., from 1.8% in the baseline analysis to 2.3%. At the same time, funds' relative systemicness would increase substantially to 17.1% from 11.3%.

[18] Greenwood et al. (2015) conduct a similar exercise for the banking sector.

5. Conclusion

This paper investigates the evolution of the aggregate vulnerability of the financial system to fire sales and the systemic importance of euro area investment funds and banks over time. The study relies on a single, consistent novel framework where an initial shock to bond yields leads funds to sell assets to address investor redemptions, while both banks and funds sell assets to keep their leverage constant. These fire sales generate second-round price effects.

Using this model, we find that the aggregate vulnerability of the financial system to fire sales has decreased in the euro area in the last decade. However, second-round price effects due to fire sales are significant and have an impact on the holdings of all financial entities considered in this analysis, whether or not they were affected by the initial yield shock. Importantly, we find that banks contribute much more to fire sales and, thus, to second-round price effects, given their size and leverage. At the same time, the systemic importance of funds has increased substantially over time. This was, first and foremost, driven by bond and mixed funds due to the material growth of their assets under management. A strong reduction in bank leverage and banks' shift towards holding more loans on their balance sheets has contributed to the decreased relative importance of banks' sales.

This framework could be used for sensitivity analyses, stress tests using a comprehensive scenario and the assessment of policy measures. We illustrate some of these applications by implementing some simulations that focus on extending the initial shocks and varying the level of leverage of the banking sector and the investment fund sector.

Finally, this framework could also be extended in some important dimensions related to the use of more granular data, the calibration of model parameters, the assumptions around leverage targeting and the approach to modelling redemptions.

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Appendix A: Derivation of financial asset sales in period two of the model

$$b_0 = b_2 \Leftrightarrow \frac{d_0 + p_0}{e_0} = \frac{d_2 + p_2}{e_2} = \frac{d_0 + p_0 + (p_2 - p_0)}{e_2} \Leftrightarrow$$

$$\Leftrightarrow (p_2 - p_0) = (d_0 + p_0)\left(\frac{e_2 - e_0}{e_0}\right) \overset{(2)}{\Leftrightarrow} (p_2 - p_0) = b_0(e_2 - e_0) \overset{(5)}{\Leftrightarrow}$$

$$\Leftrightarrow (p_2 - p_0) = b_0\big(e_1\big(1 + \gamma \tilde{f}_0 r_1\big) - e_0\big) \overset{(4)}{\Leftrightarrow}$$

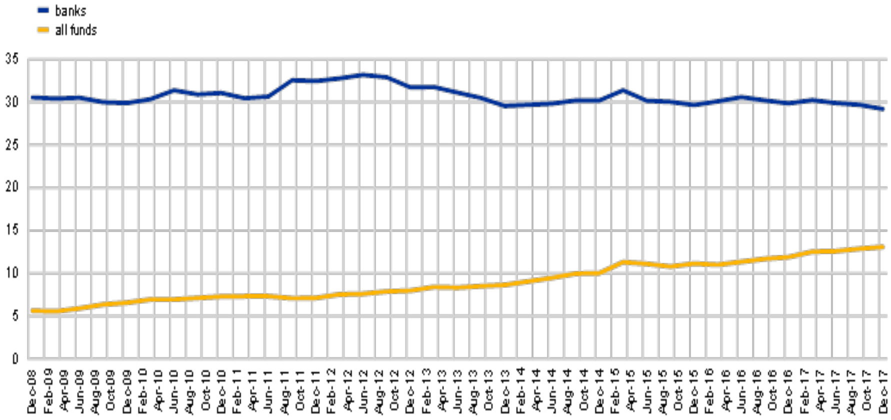
$$\Leftrightarrow (p_2 - p_0) = b_0\left((e_0 + f_0\, r_1)\big(1 + \gamma \tilde{f}_0 r_1\big) - e_0\right) \Leftrightarrow$$

$$\Leftrightarrow (p_2 - p_0) = b_0\big(\gamma f_0 r_1 + f_0 r_1 + \gamma f_0 r_1 \tilde{f}_0 r_1\big) = b_0 f_0 r_1 (1 + \gamma + \gamma \tilde{f}_0 r_1) \overset{\text{def}}{=} b_0 f_0 \tilde{r}_2.$$

Appendix B: Total assets of euro area banks and funds

Figure B.1: Total assets of euro area banks and investment funds

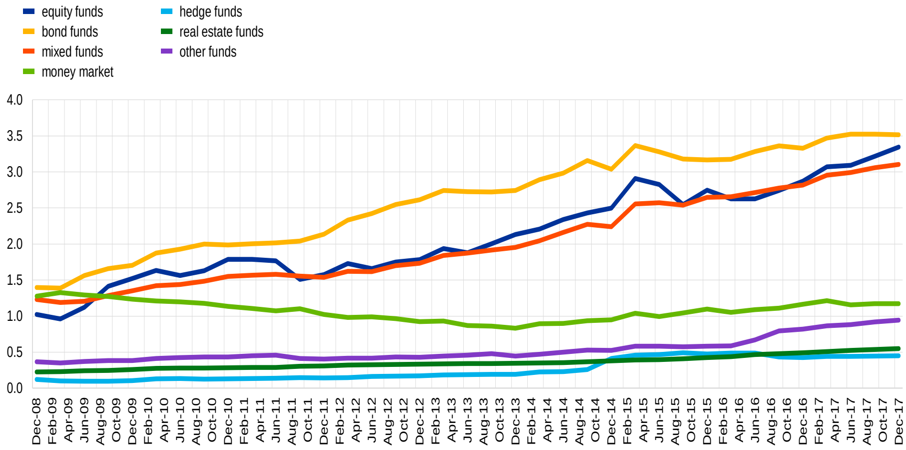
(EUR trillion; Dec. 2008-Dec. 2017)



Sources: Eurosystem's MFI Balance Sheet Statistics (for banks and money market funds) and Investment Fund Statistics (for other fund sub-sectors).

Figure B.2: Assets under management of euro area investment fund sub-sectors

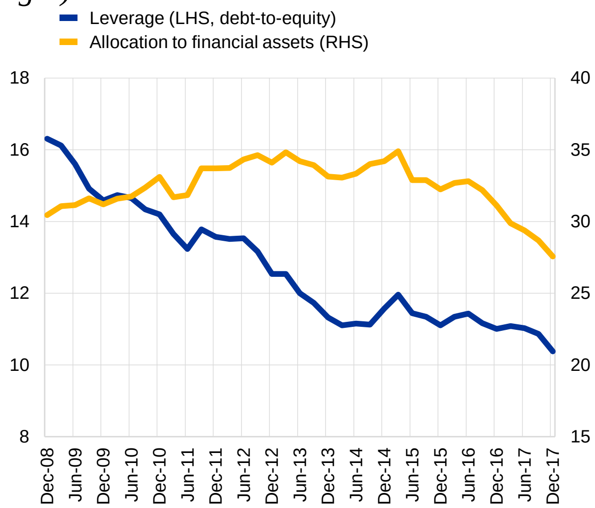
(EUR trillion; Dec. 2008-Dec. 2017)



Source: Eurosystem's MFI Balance Sheet Statistics (for money market funds) and Investment Fund Statistics (for other fund sub-sectors).

Figure B.3.: Banks' leverage and allocation to financial assets

(percentages)



Source: Eurosystem's MFI Balance Sheet Statistics.

Appendix C: Matching between the model's asset classes and market indices

The table below shows the method used for matching the model's equity and bond holdings with market indices. This matching method is used to calibrate the durations employed to calculate the initial price shock ('duration' in the third column). It is also used to calculate the Amihud ratios that are used for the calibration of the price impact ('price impact' in the third column) of equity holdings.

Table C.1: – Model classes and market indices

Asset class	Index	Use
Debt – euro area MFIs	Barclays Euro-Aggregate: Corporates EUR	duration
Debt – euro area government	Barclays Euro Government EUR	duration
Debt – euro area non-MFIs	Barclays Euro-Aggregate: Corporates EUR	duration
Debt – other	Barclays Global Aggregate Ex Euro Aggregate USD	duration
Equity – euro area MFIs	Euro STOXX	price impact
Equity – euro area non-MFIs	Euro STOXX	price impact
Equity – other	MSCI World	price impact

Appendix D: Further extensions

Table D.5: Exercise considering a 20% fall in stock market prices – 2017 Q4

Aggregate vulnerability	Systemicness of banks	Systemicness of funds	Relative systemicness of banks	Relative systemicness of funds
-4.3%	-3.8%	-0.5%	87.7%	12.4%

Table D.2: Policy runs for different levels of bank leverage – 2017 Q4

Bank equity to total assets ratio	Bank liabilities to equity ratio	Aggregate vulnerability	Systemicness of banks	Systemicness of funds	Relative systemicness of banks	Relative systemicness of funds
7.8%	11.8%	-2.1%	-1.9%	-0.2%	89.9%	10.1%
8.3%	11.0%	-2.0%	-1.8%	-0.2%	89.2%	10.7%
8.8%	10.4%	-1.8%	-1.6%	-0.2%	88.7%	11.3%
9.3%	9.8%	-1.7%	-1.5%	-0.2%	88.1%	11.9%
9.8%	9.2%	-1.6%	-1.4%	-0.2%	87.4%	12.6%

Note: The results of the baseline simulation carried out assuming the bank leverage of 2017 Q4 are reported in the row highlighted in grey.

Table D.3: Policy runs for different levels of fund leverage – 2017 Q4

Issued fund shares to total assets ratio	Fund liabilities to issued shares ratio	Aggregate vulnerability	Systemicness of banks	Systemicness of funds	Relative systemicness of banks	Relative systemicness of funds
76.9%	30.0%	-2.3%	-1.9%	-0.4%	82.9%	17.1%
83.3%	20.0%	-2.1%	-1. 8%	-0.3%	85.6%	14.4%
90.9%	10.0%	-1.9%	-1.7%	-0.2%	88.5%	11.5%
92.2%	8.4%	-1.8%	-1.6%	-0.2%	88.7%	11.3%
100.0%	0.0%	-1. 7%	-1.5%	-0.1%	91.6%	8.4%

Note: The results of the baseline simulation carried out assuming the fund leverage of 2017 Q4 are reported in the row highlighted in grey.

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