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MACROPRUDENTIAL STRESS TESTING: A PROPOSAL FOR THE LUXEMBOURG INVESTMENT FUND SECTOR

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Macroprudential stress testing:
A proposal for the Luxembourg investment fund sector*

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Abstract

This paper assesses 'aggregate vulnerability', a measure of systemic risk, in the investment fund sector of Luxembourg by implementing a macroprudential stress testing model. While based on the proposal by Fricke and Fricke (2017), this paper focuses on the calibration of key parameters such as the flow-performance sensitivity and price impacts that are included in the model to capture the so-called 'second-round effects' of an initial adverse shock to funds' returns. According to the empirical results, limited degrees of vulnerability were found for the main fund categories such as equity funds, bond funds and mixed funds. This implies that the investment fund sector in Luxembourg does not raise any particular concern for financial stability as of November 2019. However, since the stress test was performed against a background of increased risk of a reversal in global risk premia, continued monitoring of the sector is warranted.

Keywords: investment funds; macroprudential stress test; flow-performance sensitivity; price impact; fire sales; systemic risk

JEL Classification: G11, G12, G23

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Non-technical summary

With net assets under management (AuM) amounting to more than €5 trillion as of September 2019, the investment fund sector in Luxembourg is an important component of the financial sector. As the investment fund sector remains sensitive to global developments at a time when there is elevated risk of a reversal of risk premia, the probability that vulnerabilities within the sector might trigger systemic risks may be elevated. In this context, authorities need to establish a macroprudential monitoring framework that applies to the investment fund sector.

This study proposes to assess the investment fund sector's 'aggregate vulnerability (AV)', a measure of systemic risk, by implementing macroprudential stress simulations, In this regard, this study is different from previous, traditional stress tests which have often been conducted from a microprudential perspective by fund managers for their own purposes. In particular, the adopted model includes two key parameters, the flow-performance sensitivity (FPS) and the asset price impact ratio. These parameters enable us to capture the so-called 'second round effects,' comprising impacts of additional funding shocks and asset fire sales on the funds' resilience. On the one hand, Markov regime-switching VAR models are used to calibrate the regime-dependent FPS. On the other hand, the price impact parameter is calibrated as a time-varying parameter based on the Amihud ratio.

The empirical results suggest that, during the sample period from December 2008 to November 2019, bond funds have been most vulnerable, followed by equity funds and mixed funds. As of November 2019, the results also suggest a sectoral level vulnerability of 66.7 bps under the assumption of a shock of -5% to fund returns, meaning that the sector is potentially exposed to a liquidation of 0.667% of its aggregate equity if both the stock and bond markets declined by 5%. This magnitude of global exposure may suggest that the investment fund sector is rather resilient to exogenous shocks and thus it is not likely to raise any particular concern for financial stability in Luxembourg.

However, this conclusion should be interpreted against the background of an elevated risk of a reversal in risk premia at the global level. Under such conditions, investors may be subject to a sudden increase in their degree of risk aversion, which could potentially increase the aggregate vulnerability of investment funds in Luxembourg, especially when such a change is combined with higher FPS and stronger price impacts. Therefore, continued macroprudential monitoring of the investment fund sector is warranted.

Résumé non technique

Avec un actif net sous gestion s'élevant à plus de 5 billions d'euros en septembre 2019, le secteur des fonds d'investissement au Luxembourg constitue désormais une source de financement importante pour l'économie réelle. Mais en parallèle, ceci également signifie que la probabilité que la vulnérabilité du secteur puisse provoquer des risques systémiques et donc menacer la stabilité financière soit désormais plus élevée qu'auparavant. Dans ce contexte, les autorités sont à la recherche des cadres d'analyse et outils de surveillance macroprudentiels adaptés au secteur des fonds d'investissement.

Dans ce papier, nous proposons d'évaluer la « vulnérabilité agrégée (VA) » du secteur, une mesure de risque systémique, à l'aide des tests de résilience macroprudentiels, opposés à des tests traditionnels qui ont souvent été effectués par des fonds d'investissement eux-mêmes dans une perspective microprudentielle. En particulier, le modèle proposé comprend deux paramètres clés, la sensibilité des flux aux performances (SFP) et l'impact sur les prix (i.e. ratio du changement de prix au volume de transaction), afin de tenir compte des effets de second tour (*second round effects)*. D'une part, nous utilisons des modèles de vecteur autorégressif à changement de régime markovien (MS-VAR) pour calibrer le paramètre SFP sous l'hypothèse de non-linéarité. D'autre part, nous utilisons le ratio d'Amihud afin de calibrer le paramètre d'impact sur les prix comme une série temporelle.

Les résultats empiriques suggèrent que, pendant la période de décembre 2008 à novembre 2019, les fonds obligataires ont été les plus vulnérables, suivis par les fonds d'actions et par les fonds mixtes. Pour novembre 2019, les résultats suggèrent une vulnérabilité globale du secteur de 66,7 points de base sous l'hypothèse d'un choc de -5% sur les rendements des fonds, ce qui signifie que le secteur est potentiellement exposé à une liquidation de 0,667% de ses fonds propres globaux si les marchés boursiers et obligataires reculaient de 5%. Cette ampleur de vulnérabilité globale du secteur peut suggérer que le secteur est plutôt résilient aux chocs exogènes et ne devrait donc pas poser de problème particulier pour la stabilité financière au Luxembourg.

En revanche, cette conclusion doit être interprétée dans le contexte actuel où il y a un risque élevé de renversement des primes de risque au niveau global. En effet, un tel renversement augmenterait la probabilité que les investisseurs changent subitement leur comportement de prise de risque, ce qui peut renforcer la vulnérabilité globale des fonds d'investissement, notamment lorsqu'un tel changement serait combiné avec une SFP plus élevée et un ratio du changement de prix au volume de transaction plus élevé. Par conséquent, une surveillance macroprudentielle continue du secteur des fonds d'investissement est justifiée.

1. Introduction

The global asset management industry has been rapidly expanding since the financial crisis of 2008. This expansion includes Luxembourg, which is the second largest domicile of investment funds in the world after the United States. As of September 2019, the net assets under management (AuM) of Luxembourg investment funds amounted more than €5 trillion, while it was less than €2 trillion a decade earlier. This rapid growth may pose risks to the domestic financial sector and implies that assessing the investment fund sector's resilience is an important task for macroprudential authorities.

This paper assesses the global vulnerability of the Luxembourg investment fund sector. To this end, we implement an empirical framework for macroprudential stress testing simulations, as opposed to traditional stress tests that have often been conducted from a microprudential perspective by fund managers for their own purposes. According to the ESRB (2018), microprudential stress tests usually consider fund-specific features (e.g. a fund's current investor concentration, redemption policies, and investors' profile and behaviour), and rely on assumptions on redemption levels under stress. Some advanced microprudential frameworks also take into consideration diverse risks of each individual fund. For instance, liquidity risk is either directly calculated using historical data on average daily trading volumes (e.g. for stocks) or inferred from other factors such as the total amount outstanding, credit rating, and percentage of issue held (e.g. for bonds). Market risk is often simulated by a widening of spreads, yield curve movements, and stock price shocks. Credit risk is modelled with a default and/or rating downgrade of the largest issuers in the fund, while counterparty risk is simulated by costs arising from fire sales or potential collateral calls.

Meanwhile, these traditional designs can also be transposed in a macroprudential approach when aiming to address, for instance, the question of whether the fund sector as a whole may remain resilient to adverse redemption shocks. One possible way to do so is to use aggregate variables at the sector level. Such an approach is used in some recent studies, including those by the IMF (2017), Fricke and Fricke (2017), Baranova *et al.* (2017), and ESRB (2018).

The IMF (2017) reports results of a macroprudential stress test on Luxembourg-domiciled investment funds, performed as part of their Luxembourg Financial Sector Assessment Program (FSAP). It first measures the redemption coverage ratio at the fund category level (i.e. aggregate ratio of liquid assets to net outflows) under the assumption that a large cash outflow can be triggered by redemption shocks. These ratios then serve to identify fund categories that may be the most vulnerable under adverse market conditions. In this framework, its uses two distinct measures of liquid assets ('Cash and short-term debt only' and 'High Quality Liquid Assets'), and calibrates redemption shocks either using an 'historical approach' or a 'forward looking approach'.[1] It concludes that most fixed income funds in Luxembourg are resilient to adverse redemption shocks, whereas high yield bond funds are vulnerable but to a more limited extent.

The ESRB (2018) performed a macroprudential stress simulation for the European investment fund sector. To identify investment fund categories vulnerable to significant redemption shocks, it assumes: (i) a benchmark redemption shock (a net weekly average outflow of 5% of AuM); (ii) a combination of pro-rata (80%) and waterfall (20%) selling strategies; (iii) redemption suspensions by supervisory authorities depending on the drop in fund performance (20%, 40%, 60%); and (iv) a linearity in the price response function to the volume of asset sales. It concludes that government bonds, investment grade covered bonds and equity markets would be resilient even under the most extreme cases, whereas corporate bonds and securitization markets would not be resilient, even under a milder scenario with a 5% redemption shock.

While the IMF and ESRB frameworks provide some first insights into the macroprudential design of stress tests for the investment fund sector, further improvements can be made. Indeed, the ESRB (2018) acknowledges that their framework does not take into account the so-called 'second-round effects' which may have stronger implications for financial stability than 'one-shot' impacts of initial shocks. For instance, Manconi *et al.* (2012) show that massive redemptions by investors in the bond market may trigger portfolio rebalancing at discounted prices by fund managers, and subsequently trigger a broader contagion to other markets.

Meanwhile, any successful framework designed to assess second-round effects needs to include a panel of underlying macroeconomic and financial variables related to asset fire sales, market liquidity and prices, investors' behaviour, redemption decisions, fund flows and performance. This need has also been underlined in the literature related to investment funds. For instance, Cetorelli *et al.* (2016) pointed out that large-scale redemptions from US open-ended investment funds are originally triggered by exogenous macrofinancial shocks, such as an increase in market interest rates, by passing through significant changes in assets prices. Cenedese and Mallucci (2016) also reported that equity fund outflows are essentially triggered by macrofinancial shocks (such as negative discount rate shocks), while inflows and outflows to/from bond funds in emerging markets are often determined by US interest rate shocks.

Fricke and Fricke (2017) propose a comprehensive framework for macroprudential stress testing which aims to address second-round effects when measuring investment funds' 'aggregate vulnerability' – an indicator of systemic risk proposed by Greenwood *et al.* (2015).[2] In fact, Greenwood *et al.* (2015) suggested including a 'price impact' parameter in the stress test model in order to address the effects of fire sales by banks. Fricke and Fricke

[1] Redemption shocks are calibrated at the 1% highest monthly outflows in the 'historical approach', whereas they are estimated using a regression of monthly net flows on macro-financial variables in the 'forward looking approach'.

[2] 'Aggregate vulnerability' is empirically measured differently from, but conceptually similar to, the 'CoVaR' (Adrian and Brunnermeier, 2016) or the 'SRISK' (Acharya *et al.*, 2017). See Section 2 for more detail on its definition.

(2017) apply the model to investment funds while adding another key parameter, 'flow-performance sensitivity (FPS)'.

The proposal of Fricke and Fricke (2017) contributes to the literature in that it is, to the best of our knowledge, the first macroprudential stress testing model that addresses second-round effects in the investment fund sector. Still, some methodological improvement can be made to better reflect the interactions between investors, funds and markets. For instance, Fricke and Fricke (2017) assume linearity in FPS, but many studies report that FPS is non-linear, time-varying or time-dependent.[3] In line with this literature, the linearity assumption is relaxed in this paper to allow for the conditional forms of the FPS. More specifically, we implement Markov regime-switching vector autoregressive (MS-VAR) models to consider the regime-dependent form of FPS (see Sections 3.1 and 4.2). As for the parameter of price impact for stocks and bonds, we consider the time-varying form using the Amihud ratio, as opposed to Greenwood *et al.* (2015) and Fricke and Fricke (2017) who consider a constant and common price impact ratio for all assets.

This paper focuses on three major fund categories (i.e. equity funds or 'EQF', bond funds or 'BOF', and mixed funds or 'MXF'), which cover around 80% of the Luxembourg investment fund sector's total AuM. The use of these three categories is motivated by lack of data for other funds, such as real estate funds and hedge funds.[4] Basic features of EQF, BOF and MXF are depicted in figures provided in the Appendix for the sample period from December 2008 and September 2019: assets under management (Figure A); relative weights in total AuM of all open-ended funds in Luxembourg (Figure B); leverage ratio defined as debt over capital[5] (Figure C); and the weights of stocks and bonds in portfolio of MXF (Figure D).

The remainder of this paper is structured as follows. Section 2 describes the macroprudential stress testing model designed for investment funds. Section 3 introduces our methodology for parameter calibration. Sections 4 and 5 describe data and report the empirical estimates of FPS and price impacts. Section 6 reports and discusses the main findings in terms of the aggregate vulnerability of the funds and the sector as a whole. Section 7 concludes.

2. The model

Following Fricke and Fricke (2017), the adopted model accounts for 'additional funding shocks' and 'fire-sales effects', triggered by an initial shock to investment funds' returns (e.g. a 5% or 10% decrease of net asset value). Considering three time periods (t, $t+1$, $t+2$), we assume the following. First, an initial shock (see Equations [1] to [4] below) arises at time t,

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[3] For more detail on the literature related to the flow-performance relationship, see Section 3.

[4] The lack of data here refers to the non-availability of daily data on trading volumes and price changes of certain types of assets, such as real estate and derivatives.

[5] The data on these variables come from Table S1.13 provided by the BCL. 'Capital' corresponds to the item 'Shares/units issued'. 'Debt' corresponds to the sum of 'Borrowings' and 'Debt securities issued'. The item 'Borrowings' includes 'Overnight borrowings', 'Borrowings with agreed maturity', 'Redeemable at notice', 'Repurchase agreements', and 'Short sales of securities'.

meaning that all 'pre-shock' variables have a time index *t-1*. Second, fund group *i* is financed with a mix of debt D_i and equity E_i, and their total assets at time *t* (i.e. $A_{i,t}$) corresponds to the sum of $E_{i,t}$ and $D_{i,t}$. Third, $B_{i,t}$ refers to fund group *i*'s leverage ratio (i.e. $B_{i,t} = D_{i,t}/E_{i,t}$)[6]. Finally, fund group *i* holds *K* assets in its portfolio at time *t*.

2.1. Initial shock at time t

Let π_t denote a *K×1* vector of net returns on *K* assets held in the portfolio of a given fund group at time *t*. Let M_t denote a *K×1* vector of *K* assets' respective weights in the portfolio at time *t*. Then, the unlevered return of the fund group at time *t*, R_t, can be defined as follows:

$$R_t = M_t'\pi_t \qquad [1]$$

This equation implies that a shock to π_t is also a shock to R_t, and that the size of R_t is determined by both π_t and M_t. For instance, if we assume a negative shock of -5% to all terms in F_t, it gives $R_t = -5\%$. In other words, if we assume a 'common' initial shock of -5% to all assets held in the fund group's portfolio, it immediately decreases the total value of the portfolio by 5%. The immediate consequences of this shock at time *t* can be expressed in terms of the fund's total assets, equity and debt, as follows:

$$A_t = A_{t-1}(1 + R_t) \qquad [2]$$
$$E_t = E_{t-1} + A_{t-1}R_t \qquad [3]$$
$$D_t = D_{t-1} \qquad [4]$$

where the time index *t-1* refers to the 'pre-shock' period.

2.2. Additional funding shock at time *t+1* captured by FPS

In order to reflect investors' behaviour in response to funds' performance, we include in the model the flow-performance sensitivity (FPS) parameter $\boldsymbol{\gamma}$.[7] In addition, as investment funds' equity and debt may have different FPS values, we distinguish between $\boldsymbol{\gamma}^E$ (FPS for equity) and $\boldsymbol{\gamma}^D$ (FPS for debt). Then, the 'additional adjustments on the liability side of the balance sheet' or the 'additional funding shock' at time *t+1* can be expressed as follows:

$$\Delta E_{t+1} = \gamma^E R_t E_t \qquad [5]$$
$$\Delta D_{t+1} = \gamma^D R_t D_t = \gamma^D R_t D_{t-1} \qquad [6]$$

From [5] and [6], we obtain $E_{t+1} = \gamma^E R_t E_t + E_t$

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[6] This definition also gives $E_{i,t-1} = A_{i,t-1}/(1 + B_{i,t-1})$ and $D_{i,t-1} = B_{i,t-1}A_{i,t-1}/(1 + B_{i,t-1})$.

[7] Fricke and Fricke (2017) include this parameter (as a fixed value) in their model, as distinguished from Greenwood *et al.* (2015).

$$E_{t+1} = E_t(1 + \gamma^E R_t) \quad [7]$$
$$D_{t+1} = D_t(1 + \gamma^D R_t) = D_{t-1}(1 + \gamma^D R_t) \quad [8]$$
$$A_{t+1} = A_t + \Delta E_{t+1} + \Delta D_{t+1} \quad [9]$$

[9] can be then written as

$$A_{t+1} = A_{t-1}\left[1 + R_t\left\{1 + \gamma^E\left(R_t + \frac{1}{1+B}\right) + \gamma^D \frac{B}{1+B}\right\}\right] \quad [10]$$

which is equivalent to

$$(A_{t+1} - A_{t-1})/A_{t-1} = R_t\left\{1 + \gamma^E\left(R_t + \frac{1}{1+B}\right) + \gamma^D \frac{B}{1+B}\right\} \quad [11]$$

Let $\tilde{R}_{t+1}$ refer to the term on the left side of [11], i.e. $(A_{t+1} - A_{t-1})/A_{t-1} \equiv \tilde{R}_{t+1}$. As this term reflects all impacts from both the initial shock at time *t* and additional funding shocks at time *t+1*, it can be called the 'adjusted portfolio return at time *t+1*'. Now, we assume that $\boldsymbol{\gamma^D}$*=0*, meaning that there is no withdrawal of debt in response to the initial shock.[8] Then, [11] is reduced to

$$\tilde{R}_{t+1} = R_t\left\{1 + \gamma^E\left(R_t + \frac{1}{1+B}\right)\right\} \quad [12]$$

Given the initial shock, [12] shows that adjusted portfolio return at time *t+1* is determined only by FPS for equity $\boldsymbol{\gamma^E}$ and the leverage ratio *B*. In other words, *ceteris paribus*, the impact of additional funding shocks on portfolio return at time *t+1* will be stronger when FPS is higher and when the leverage ratio is lower. This means that the impact of additional funding shocks will be amplified by a high FPS but mitigated by a high leverage ratio.

2.3. Second round effects at time *t+2* captured by the price impact ratio

Facing initial and additional funding shocks, investment funds could adjust their portfolios by selling (or buying) assets. This adjustment can be expressed in terms of the total amount of assets to be liquidated, which corresponds to the sum of variations of equity and debt at time *t+1* and reflecting a withdrawal of short term funding after negative shocks. However, funds also target their leverage and thus attempt to hold their portfolio weights stable when

[8] Indeed, the relevance of including $\boldsymbol{\gamma^D}$ is limited in the sense that changes in funding by debt are generally not significant in the case of investment funds, mainly due to the tight leverage constraints imposed on them. Fricke and Fricke (2017) also confirm that there is no evidence of a significant flow-performance relationship with regard to debt financing for mutual funds.

adjusting their portfolios.[9] This implies that a leverage targeting term should be added into the total amount of assets to be liquidated. In this context, the leverage targeting term can be expressed as $A_{t-1}B\tilde{R}_{t+1}$.[10] Using [5] and [6] and assuming that $\boldsymbol{\gamma}^{D}$=0, the total amount of assets to be liquidated ($\tilde{\phi}$)[11] after negative shocks can be expressed as follows:

$$\tilde{\phi}_{t+1} = \gamma^{E} E_t R_t + A_{t-1} B \tilde{R}_{t+1} \qquad [13]$$

Furthermore, this liquidation of assets (or fire sales) is likely to generate the so-called 'price impact'.[12] Combined with the amount of assets to be liquidated, the price impact is then expected to determine a fund's return at time *t+2* (i.e. $\tilde{R}_{t+2}$) as follows:

$$\tilde{R}_{t+2} = L\tilde{\phi}_{t+1} \qquad [14]$$

where ***L*** refers to the price impact ratio expressed in units of returns per euro of net sales.

2.4. Aggregate vulnerability

Using [14], the model finally defines an indicator of 'aggregate vulnerability' (AV, hereafter) of all funds within a given fund group in such a way that the indicator reflects total effects of the negative sequence relating the initial shocks (at time *t*) to asset fire sales (at time *t+2*). In line with Greenwood *et al.* (2015) and Fricke and Fricke (2017), AV is defined as follows:

$$AV_{t+2} = -\left(A_{t-1}\tilde{R}_{t+2}\right)/E_{t-1} \qquad [15]$$

This indicator measures the percentage of aggregate equity of all funds that would be wiped out by their assets liquidation (or fire sales) following initial shocks.

Finally, it is worth noting that, according to [13], [14] and [15], the amplitude of AV might mainly depend on the two parameters, $\boldsymbol{\gamma}$ and ***L***, implying that their calibration would have important implications for the results of the model. Against this background, we attempt to best calibrate these parameters using MS-VAR models and the Amihud ratio (for $\boldsymbol{\gamma}$ and ***L***, respectively).

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[9] In general, investment funds need to specify the composition of both their asset and liability sides in their sales prospectuses. Consequently, they are unlikely to deviate significantly from their proposed targets. For instance, Jiang *et al.* (2017) report that mutual funds tend to sell assets according to their liquidity pecking order during normal times, but on a pro-rata basis during times of market stress.

[10] See Greenwood *et al.* (2015) for more detail on the leverage targeting term by a bank (p.473; Assumptions 1 and 2).

[11] Under the 'usual' assumption of a positive $\boldsymbol{\gamma}$, the amount $\tilde{\boldsymbol{\phi}}$ would be positive. However, if $\boldsymbol{\gamma}$ is negative (because investors have other prevailing criteria than past performance, for instance), it is possible that $\tilde{\boldsymbol{\phi}}$ could be negative. In such cases, the absolute value of $\tilde{\boldsymbol{\phi}}$ will be used in equation [14] in order to capture the impact of $\boldsymbol{\gamma}$ on the determination of final AV as calculated in equation [15].

[12] See Section 3.2 for more detail on the concept of price impact.

3. Methodology for parameter calibration

3.1. Flow-performance sensitivity (FPS)

Fricke and Fricke (2017) assume a positive linearity in FPS (in line with Berk and Green (2004), Chen *et al.* (2010) and Cetorelli *et al.* (2016), for instance). This suggests that bad performance is followed by net outflow, whereas good performance is followed by net inflow. This assumption also implies that good and bad performance is treated symmetrically.

However, non-linearity or asymmetry in FPS is also reported in the literature. Ippolito (1992) examines the case of US mutual funds for the period between 1966 and 1984. More specifically, this paper investigate whether mutual fund investors actively react to funds' performance. He confirms that funds' net inflows are positively correlated to their performance. However, he also reports that investors react disproportionately when the expected payoffs are higher, pointing out to the existence of an asymmetry in the flow-performance relationship. According to Ippolito, this asymmetry is mainly due to high investment costs, in particular, opening and closing costs, which makes investors reluctant to move their assets from underperforming to outperforming funds unless there is disproportionate evidence of bad performance.

Asymmetry in FPS is more formally demonstrated in subsequent studies. Chevalier and Ellison (1997) find that FPS in US equity funds has a convex shape, showing that inflows increase sharply for best performing funds, whereas outflows do not increase for worst performing funds. Sirri and Tufano (1998) also find that US equity fund investors move more quickly and massively into outperforming funds than when they redeem from underperforming ones. Many other studies also confirm convexity in FPS, including Brown *et al.* (1996), Barber *et al.* (2005), Lynch and Musto (2003), Huang *et al.* (2007), Bellando and Tran-Dieu (2011)[13], and Goldstein et al. (2017).

In sum, these studies confirmed a form of non-linearity in FPS. This implies that the empirical results of any analyses based on the linearity assumption can be biased. To address such a possible bias, this paper attempts to consider a non-linear form of the FPS parameter. In particular, a conditional or regime-dependent form of FPS is considered in this paper. That is, we do not impose any restrictions on the sign or amplitude of FPS. For instance, a significantly negative estimate of FPS would reject the standard assumption of 'past performance chasing' strategy of fund investors. Such results would suggest that investors may have other prevailing criteria than (past) performance, such as diversification. To address this question, we implement Markov regime switching vector autoregressive models (MS-VAR) to estimate the flow-performance model.

Among a number of MS-VAR model specifications, two models are in particular tested and estimated: (i) specification *C*, where the constant term ($\boldsymbol{\mu}$) and coefficients ($\boldsymbol{\gamma}$ and $\boldsymbol{\beta}$) are regime-dependent, while the error term ($\boldsymbol{\varepsilon}$) is not regime-dependent; and (ii) specification *CH*, where $\boldsymbol{\mu}$, $\boldsymbol{\gamma}$, $\boldsymbol{\beta}$ and $\boldsymbol{\varepsilon}$ are all regime-dependent. Equations [16] and [17] below correspond to the equation of net inflow ratio to TNA in the 'C' and 'CH' specifications, respectively.

[13] Bellando and Tran-Dieu (2011) consider French equity mutual funds, rather than US equity funds.

$$C: \quad F_{i,t} = \mu_S + \sum_{q=1}^{k} \gamma_{q,S} R_{i,t-q} + \sum_{q=1}^{k} \beta_{q,S} F_{i,t-q} + \varepsilon_{i,t} \quad [16]$$

$$CH: \quad F_{i,t} = \mu_S + \sum_{q=1}^{k} \gamma_{q,S} R_{i,t-q} + \sum_{q=1}^{k} \beta_{q,S} F_{i,t-q} + \varepsilon_{S,i,t} \quad [17]$$

where: $\boldsymbol{R_{i,t}}$ refers to fund category *i*'s return at time *t*; $\boldsymbol{F_{i,t}}$ is net inflows into fund category *i* at time *t*, divided by its total net assets (TNA) at time *t-1*, meaning that $\boldsymbol{F_{i,t}}$ is expressed in terms of a percentage of $TNA_{i,t-1}$; the subscript *s* refers to the 'regime' or 'state' with $s \in \{1,2\}$; $\boldsymbol{\varepsilon_{i,t}}$ and $\boldsymbol{\varepsilon_{s,i,t}}$ are normally distributed error terms with $\varepsilon_i \sim N(0, \sigma^2)$ and $\varepsilon_{s,i} \sim N(0, \sigma_{s_t}^2)$, respectively. Note that, in these equations, $\boldsymbol{\gamma_{1,s}}$ (i.e., the regime-dependent coefficient of $\boldsymbol{R_1}$) represents the parameter of interest (i.e. FPS).

These equations are estimated using the so-called expectation-maximization (EM) algorithm.[14] In parallel with the estimation of the regime-dependent models, two specification tests are implemented to select the best-performing model for each fund category. First, the AIC/SBC are calculated to select the optimum number of lags for a given number of regimes. Second, the regime classification measure (RCM) of Ang and Bekaert (2002) is implemented to select the optimum number of regimes for a given number of lags. RCM is normalised between 0 and 100. If RCM = 0, the model perfectly discriminates between two regimes. If RCM = 100, the model simply assigns each regime a 0.5 chance of occurrence throughout the sample. Finally, if these specification tests lead to more than two competing models for a given fund category, the final selection is based on the parsimony principle so that the ultimately selected model corresponds to the one with the least number of parameters whose inclusion significantly improves the overall estimation performance.

3.2. Price impacts

The concept of price impact for an asset can be measured using the Amihud ratio (Amihud, 2002). Put simply, the Amihud ratio for asset ***k*** on day ***y*** is defined as the daily absolute return on asset ***k*** divided by its total trading volume (expressed in currency units) on day ***y***. Then, the monthly price impact ratio ***L*** is defined as the monthly average of the daily Amihud ratios for a given month.

Greenwood *et al.* (2015) assumed that all asset types examined in their analysis[15] have the same price impact coefficient (i.e. $L=10^{-13}$) suggesting that €1 billion of trading volume leads to a price change of 10 basis points (bps). They argued that this magnitude is comparable to empirical estimates of price impact in bond markets reported in the literature, including Ellul *et al.* (2011) and Feldhutter (2012) to name just a few.[16] However, Greenwood

[14] The EM algorithm consists of maximizing the 'updated' log likelihood function of the regime-dependent distribution of $F_{i,t}$ (i.e. $L_i = \sum_{t=1}^{T} ln\{\sum_{j=1}^{m} f(F_{i,t}|s_t, F_{i,t-1}) Pr(s_t|F_{i,t-1}, \dots, F_{i,1})\}$, where *T* is the number of observations in the data set for fund category *i*).

[15] They consider 42 asset types, including stocks and bonds; see Greenwood *et al.* (2015), p. 477.

[16] Ellul *et al.* (2011) study fire sales of corporate bonds by insurance companies, while Feldhutter (2012) examines selling pressure by comparing small and large trades of corporate bonds.

et al. (2015) acknowledged that their estimate of price impact could be an underestimate for less liquid asset classes (such as whole loans).

Fricke and Fricke (2017) also used a constant value of 4.77×10^{-6} for all funds examined in their main analysis. According to them, 4.77×10^{-6} is a typical value of the equal-weighted average price impact for investment funds. To justify their choice, they provided empirical evidence that diverse estimates of $\boldsymbol{L}$ under different specifications[17] lead to similar levels of final aggregate vulnerability for the US investment fund sector.

Further, Greenwood *et al.* (2015) and Fricke and Fricke (2017) assumed a constant and common price impact ratio for all asset types in their main analyses. However, in this paper, we assume that price impacts for stocks differ from those for bonds. In addition, we also assume that price impacts can be time-varying, time-period dependent and/or currency-dependent. These two assumptions allow us to calibrate the price impact parameter $\boldsymbol{L}$ for each type of asset (i.e., stocks and bonds) held by EQF, BOF and MXF. Section 5 provides a detailed description of our approaches to calibrating the price impact parameter for stocks ($\boldsymbol{L^S}$) and bonds ($\boldsymbol{L^B}$).

4. Monthly data and estimates of FPS

4.1. Data on fund return and net inflow

To calibrate the FPS parameter $\boldsymbol{\gamma}$, we first retrieved monthly data on net asset value per share (NAVPS), net inflow (NETINF) and total net asset value (TNA) for 2953 funds domiciled in Luxembourg for the period from December 2008 to September 2019. These data come from the *Commission de Surveillance du Secteur Financier* (CSSF)'s Table O1.1.[18] Using these data, we created two time series for each of the 2953 funds considered:

(i) '$\boldsymbol{R}$', a series of fund returns, defined as the monthly log difference of NAVPS;

(ii) '$\boldsymbol{F}$', a series of net inflow ratios, defined as NETINF at time t divided by TNA at time t-1.

In parallel, 2953 funds were classified into three categories (EQF, BOF and MXF) based on the *Banque Centrale du Luxembourg* (BCL)'s fund classification: (i) EQF comprising 1310 equity funds; (ii) BOF comprising 763 bond funds; and (iii) MXF comprising 880 mixed funds. This classification allowed us to create one aggregate series (as a simple average) for each

[17] Including specifications with (i) a constant and common value of L for all investment funds examined; (ii) constant but fund-specific values of L; (iii) time-varying and fund-specific values of L.

[18] More specifically, NAVPS corresponds to 'Net asset value per unit or share' (Line 120), and TNA to 'Total net asset value' (Line 110). NETINF corresponds to 'Net units or shares issued (or redeemed)' (Line 330), which refers to the difference between 'Net proceeds from units or shares newly issued' (Line 310) and 'Payments made in settlement of redemptions' (Line 320). More detail on the definition of these data/variables can be found in *Circular IML 97/136 as amended by Circular CSSF 08/348 (available on the CSSF website).*

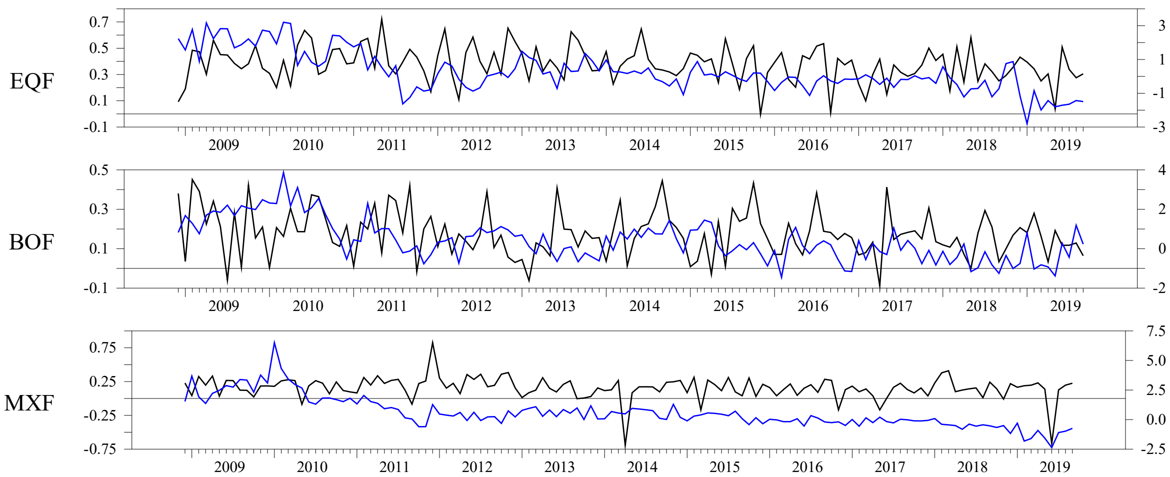
of the two variables (i.e. ***R*** and ***F***) and for each of the three categories of fund. The resulting series are depicted in Figure 1, and their descriptive statistics are provided in Table 1. On average during the sample period, EQF performed best with an average monthly return of 0.379%, followed by BOF (0.177%) and MXF (0.159%). The highest volatility in performance was shown by MXF, followed by EQF and BOF. In parallel, the highest average net inflow ratio to TNA was shown by MXF (0.581%), followed by BOF (0.428%) and EQF (0.270%). This suggests that compared to its relative size, MXF grew most steadily and rapidly during the sample period.

4.2. Estimates of the FPS parameter γ

Table A in the Appendix reports results of the MS-VAR model specification tests (i.e. AIC/SBC and RCM). Based on these results, specification 'C' with two regimes and two lags is selected for EQF, while specification 'CH' with two regimes and three lags is selected for BOF and MXF. Table 2 reports the estimation results of these models. Note that most of 'MS1' and 'MS2' estimates of FPS (i.e. $\boldsymbol{\gamma_1}$**(s=1)** and $\boldsymbol{\gamma_1}$**(s=2)** in the ***F*** column) are significant, which seems to confirm the regime-dependent conditionality in FPS for examined fund categories.

Commonly for the three fund categories, the constant term ($\boldsymbol{\mu_s}$) for ***R*** is positive and significant (at 1%) in both regimes. Meanwhile, $\boldsymbol{\mu_s}$ for ***F*** in regime 1 is positive and significant only for BOF and MXF, while that in regime 2 is negative and significant only for EQF and BOF. These common features indicate that transitions between two regimes took place depending rather on the sign of the average value of ***F*** than that of the average value of ***R.***

Figure 1. Aggregate fund return and net inflow ratio to TNA



*Notes. In each panel, the black line depicts the series of aggregate fund return (**R**; lhs), defined as monthly log difference of net asset value per share (NAVPS). The blue line plots the series of net inflow ratio to total net assets (**F**; rhs). These series are expressed in percentage points. EQF = equity funds; BOF = bond funds; MXF = mixed funds. The sample period goes from December 2008 to September 2019.*

Table 1. Descriptive statistics of aggregate fund return and net inflow ratio to TNA

Fund category	EQF		BOF		MXF	
Variables	R	F	R	F	R	F
Obs.	130	130	130	130	130	130
Mean	3.79E-01	2.70E-01	1.77E-01	4.28E-01	1.59E-01	5.81E-01
Variance	1.83E-04	1.40E-02	1.39E-04	1.04E-02	2.69E-04	1.70E-02
Skewness	-2.23E+01	5.16E+01	3.32E+01	5.93E+01	-1.67E+02	1.32E+02
Kurtosis	3.30E+01	2.14E+01	-1.73E+01	2.38E+01	1.10E+03	3.18E+02
J.-B. stat.	1.67E+02	6.01E+02	2.55E+02	7.92E+02	7.18E+04	9.27E+03
p-value (J.-B.)	4.34E+01	4.96E+00	2.79E+01	1.91E+00	1.29E-154	7.33E-19
Minimum	-1.69E-03	-2.80E+00	-8.87E-02	-1.45E+00	-6.93E-01	-2.37E+00
Maximum	7.21E-01	3.20E+00	4.51E-01	3.86E+00	8.25E-01	6.50E+00

Notes. ***R*** *refers to aggregate fund return defined as monthly log difference of net asset value per share (NAVPS).* ***F*** *refers to aggregate net inflow ratio to total net assets (TNA). R and F are expressed in percentage points. EQF = equity funds; BOF = bond funds; MXF = mixed funds. The sample period goes from December 2008 to September 2019.*

4.2.1. Estimates of γ for EQF

The estimation results in column '***F***' for EQF in Table 2 show a significantly negative estimate of $\boldsymbol{\gamma}$ in regime 1 ($\boldsymbol{\gamma}_{s=1}$=-0.0404), and a significantly positive estimate of $\boldsymbol{\gamma}$ in regime 2 ($\boldsymbol{\gamma}_{s=2}$=0.0523). On the one hand, these significant estimates (with the opposite sign to each other) confirm the regime-dependent conditionality of the FPS parameter. On the other hand, these results indicate that the 'past performance chasing' strategy of investors is confirmed in regime 2, but other criteria than performance prevail in regime 1.

4.2.2. Estimates of γ for BOF

Column '***F***' for BOF in Table 2 reports similar results to those for EQF: the estimate of $\boldsymbol{\gamma}$ is significantly positive in regime 1 (i.e. $\boldsymbol{\gamma}_{s=1}$=0.0382), while it is significantly negative in regime 2 ($\boldsymbol{\gamma}_{s=2}$=-0.0641). These estimates also confirm the regime-dependent conditionality of FPS for BOF, suggesting that BOF investors continue to chase past performance in regime 1, but not in regime 2.

4.2.3. Estimates of γ for MXF

Column '***F***' for MXF in Table 2 shows that the estimate of $\boldsymbol{\gamma}$ is positive but not significant in regime 1, while it is significantly negative in regime 2 ($\boldsymbol{\gamma}_{s=2}$=-0.0327). Hence, there is no evidence of a positive FPS for MXF, in contrast to the cases of EQF and BOF. On the contrary, investors seem to have other criteria than past performance when deciding whether to invest into or redeem from MXF.

Table 2. Flow-performance relationship estimated by MS-VAR models

Fund category	EQF		BOF		MXF	
Dep. variable	R	F	R	F	R	F
μ(s=1)	0.4218***	0.1067	0.1445***	0.8512***	0.1530***	0.1156**
μ(s=2)	0.4131***	-1.0990***	0.1230***	-0.5024***	0.2122***	-0.1078
γ_1(s=1)	0.0087	**-0.0404****	0.1652**	**0.0382*****	-0.0639	**0.0102**
β_1(s=1)	-0.2859	0.4955***	0.5682	0.3074***	-0.3012	0.4820***
γ_1(s=2)	-0.0143	**0.0523*****	-0.1389	**-0.0641*****	0.2084**	**-0.0327***
β_1(s=2)	0.8332	0.8166***	1.4067***	0.5608***	1.4668**	0.1688
γ_2(s=1)	-0.2604***	0.0649***	-0.0299	0.0250***	-0.1196	-0.0062
β_2(s=1)	0.151	0.4813***	-3.0521***	0.4579***	-0.4559**	0.1282**
γ_2(s=2)	0.0754	-0.0430*	0.3638***	0.0148	0.041	-0.0376
β_2(s=2)	1.8232***	-0.3441*	0.6148**	0.1444**	-0.3724	0.9209***
γ_3(s=1)	-	-	-0.0679	-0.0429***	-0.0583	0.0274*
β_3(s=1)	-	-	-1.5130**	0.0205	-0.4306**	0.2110***
γ_3(s=2)	-	-	0.1224	0.0482***	-0.2326**	0.0515**
β_3(s=2)	-	-	-0.0103	0.3574***	-0.7736	0.1259
σ	0.0120***	0.3342***	-	-	-	-
σ(s=1)	-	-	0.0032***	0.4380***	0.0285***	0.1107***
σ(s=2)	-	-	0.0173***	0.1144***	0.0153***	0.3946***
$\sigma_{R\text{-}F}$	0.0018		-		-	
$\sigma_{R\text{-}F}$(s=1)	-		-0.0119***		0.0045	
$\sigma_{R\text{-}F}$(s=2)	-		0.0077		0.0192	
P(1,1)	0.4084*		0.7028***		0.9273***	
P(1,2)	0.8868***		0.3241***		0.1208*	

*Notes. Specification 'C' with two regimes and two lags was selected for EQF, while specification 'CH' with two regimes and three lags was selected for BOF and MXF. This table reports estimation results of these models with two variables (R and F in percentage points). In the cases of EQF and BOF, 's=1' refers to 'regime 1' corresponding to times of better performance combined with net inflow, while 's=2' refers to 'regime 2' corresponding to times of worse performance combined with net outflow. In the case of MXF, 's=1' or 'regime 1' corresponds to times of worse performance combined with net inflow, while 's=2' or 'regime 2' corresponds to times of better performance combined with net outflow. P(1,2) reflects the estimated probability of transition from regime 2 to regime 1. P(1,1) refers to the estimated probability of no transition from regime 1. ***, **, and * refer to the 1%, 5%, and 10% significance levels, respectively.*

5. Daily data and monthly estimates of price impact *L*

To estimate the price impact ratio for stocks and bonds held by the three fund categories, daily data on changes in price and daily trading volume of stocks were retrieved from the ECB's Statistical Data Warehouse (SDW).

5.1. Price impact ratio for stocks L^S

Daily data on the historical closing price and trading volume for 24 stock indexes were retrieved from the SDW for the period from December 1st, 2008 to September 30th, 2019.[19] For a given index, a series of daily Amihud ratios was first calculated (see Section 3.2), which served to create a series of monthly price impact ratios defined as the Amihud ratios' monthly average. Repeating this process for each of the 24 indexes allowed us to create 24 series of monthly price impact ratios L_i^S (with *i* = 1,…,24).

These series were then used to create three aggregate series of price impact for stocks L^S by currency under the assumption that price impacts may differ depending on the currency in which stocks are denominated. Note that series denominated in currencies other than the euro were first adjusted[20] with the spot exchange rates against the euro so that price impacts for all stocks can be expressed in terms of euro.[21] They were then classified into three groups: (i) a 'EUR' group comprising 14 indexes (AEX Amsterdam; ASE Athens; ATX Vienna; BEL20; CAC40; DAX; EuroStoxx50; Euronext100; FTSE MIB; IBEX35; ISEQ Irish; LuxX Luxembourg; OMX Helsinki; PSI20 Lisbon); (ii) a 'USD' group comprising 4 indexes (DJ Composite; DJ Industrial Average; DJ US Banks; NASDAQ); and (iii) a 'ROW' group comprising 6 indexes (S&P Toronto; SMI Swiss; FTSE250; HSI Hong Kong; Nikkei225; KOSPI Korea). An aggregate series was created for each of the groups, i.e. $L^{S,EUR}$, $L^{S,USD}$ and $L^{S,ROW}$, representing the price impact for stocks denominated in euro, dollar and other currencies, respectively. Figure 2 depicts these series. For instance, the sample mean of the series of $L^{S,EUR}$ is 0.35%, meaning that a sale of stocks equivalent to €1 million induced a price decrease by 0.35% on average during the sample period.

5.2. Currency weights in stock portfolios

Monthly currency weights in the stock portfolios of EQF and MXF were calculated using granular data on the historical breakdown of each fund category's holdings of stocks by currency (i.e. 'EUR', 'USD' and 'ROW') covering stocks from 135 countries. Figure 3 plots the

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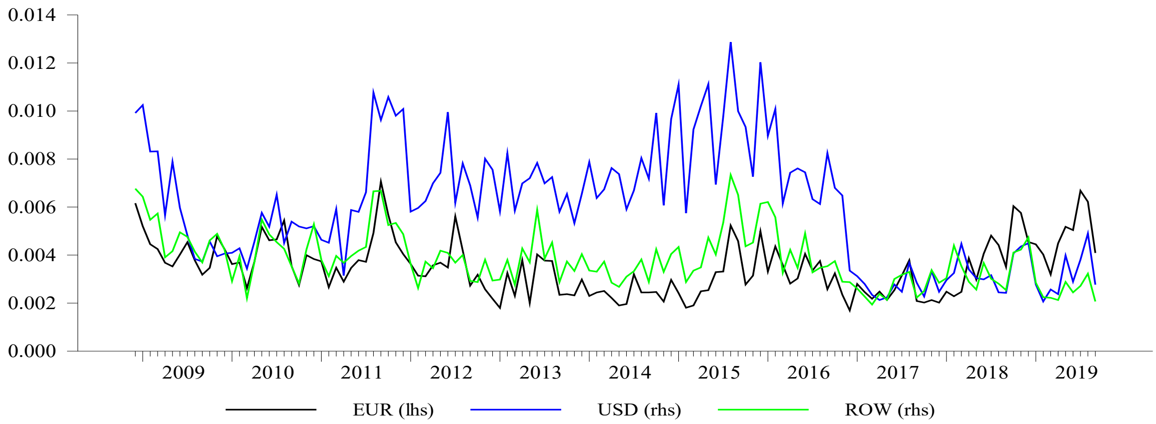
[19] Table B in the Appendix provides the list of these indexes.

[20] This means that the price impacts are multiplied by the exchange rates expressing the values of one euro in terms of the units of other currencies.

[21] The data on the exchange rates against the euro come from the ECB's Statistical Data Warehouse (SDW). Specifically, the following spot exchange rates are used: EUR/CAD, EUR/CHF, EUR/GBP, EUR/HKD, EUR/JPY, EUR/KRW and EUR/USD.

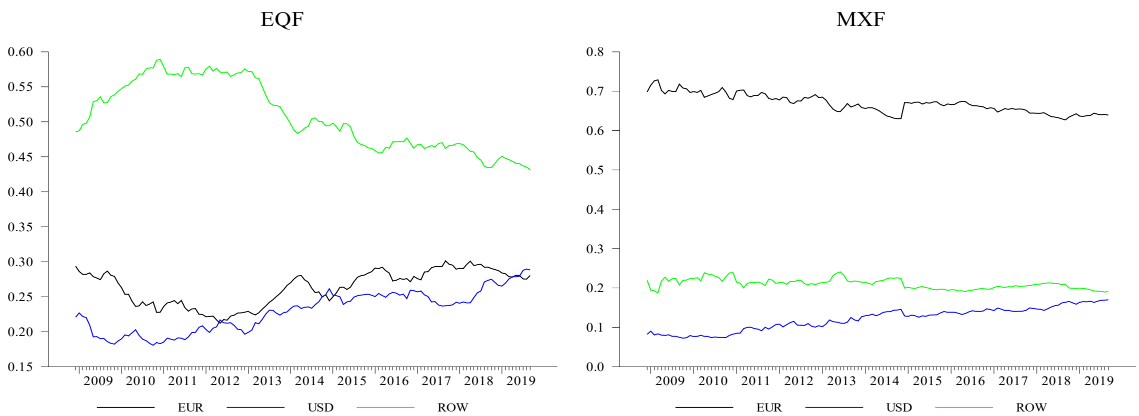
resulting series ($W^{S,EUR}$, $W^{S,USD}$ and $W^{S,ROW}$) for EQF and MXF, respectively. One interesting point is that EQF seem to prefer stocks in ROW, while MXF prefers stocks in EUR.

Figure 2. Price impacts for stocks by currency



Notes. This figure plots the series of price impact ratio for stocks (EUR = $L^{S,EUR}$; USD = $L^{S,USD}$; ROW = $L^{S,ROW}$), multiplied by 1000000, meaning that the depicted values refer to the price change ratios to a sale of stocks equivalent to €1 million. The sample period goes from December 2008 to September 2019.

Figure 3. Currency weights in stocks holding by EQF and MXF



Notes. This figure depicts the relative weights of three currencies (EUR, USD and ROW) in the aggregate portfolios of stocks of EQF and MXF. The sample covers the period from December 2008 to September 2019.

5.3. Price impact for bonds L^B

Regarding bonds, no daily data on price change and trading volume were available. As a result, the price impact parameter for bonds (***L^B***) could not be calibrated. Consequently, some reference values proposed in the literature were considered as potential proxies for the price impact ratio for bonds. For instance, Ellul *et al.* (2011) reported that the price impact of insurance companies' selling of downgraded bonds ranged between 2.5×10^{-9} and 3.5×10^{-8} for the period from 2001Q1 to 2005Q3. More recently, Langedijk *et al.* (2018) used high-frequency data on sovereign bonds from four euro member countries (Germany, Finland, Italy and Portugal) for the period from 2011:01:01 to 2012:12:31 to estimate time series of price impacts for sovereign bonds based on a mix of large and small markets with higher and lower credit quality. This time series could be an interesting proxy, but the time span is too short (2011-2012) to be relevant for our analysis.

Another interesting proposal comes from Bao *et al.* (2018). They proposed a series of time-period-dependent price impacts for downgraded bonds (from 'investment grade' to 'speculative grade') over the period from 2006:01:01 to 2016:03:31. In fact, they divided the sample period into five sub-periods: (i) Pre-crisis Period (2006:01:01 to 2007:06:30); (ii) Crisis Period (2007:07:01-2009:04:30); (iii) Post-crisis Period (2009:05:01-2010:07:20); (iv) Post-Dodd–Frank Period (2010:07:21-2014:03:31); and (v) Post-Volcker Period (2014:04:01-2016:03:31). For each of these sub-periods, a constant value of price impact is estimated: (i) 0.7×10^{-8}; (ii) 3×10^{-8}; (iii) 2.1×10^{-8}; (iv) 1.5×10^{-8}; and (v) 2.4×10^{-8}.

Among these references, the Bao *et al.* proposal seems to be the most relevant for our analysis for two reasons. First, the proposed price impact for bonds is a time-period dependent series. Second, the period considered in Bao *et al.* (2018) corresponds the best to our sample period among the proposals. However, as the sub-sample periods do not correspond exactly to our sample period, some adaptations were made. First, the value of 3×10^{-8} (for the crisis period from 2007:07 to 2009:04 in Bao *et al.* (2018)) was applied to the first sub-period from 2008:12 to 2009:04 in our analysis. Second, the value of 2.4×10^{-8} (for the post-Volcker period from 2014:04 to 2016:03 in their analysis) was applied to the last sub-period from 2014:04 to 2019:09 in our analysis. In sum, the following values were used as price impact ratio ***L*** in [14] for BOF: (i) 3×10^{-8} for 2008:12-2009:04; (ii) 2.1×10^{-8} for 2009:05-2010:07; (iii) 1.5×10^{-8} for 2010:08-2014:03; and (iv) 2.4×10^{-8} for 2014:04-2019:09.

5.4. Price impact ratio for MXF

As MXF hold a mix of stocks and bonds, both ***L^S*** and ***L^B*** should be combined with their respective weights in the global portfolio of MXF. Consequently, price impact ratio ***L*** in [14] for MXF is defined as follows:

$$L_{MXF} = \{L^S \times W^S\}_{MXF} + \{L^B \times W^B\}_{MXF} \qquad [18]$$

where: ***W^S*** and ***W^B*** refer to the weights of stocks and bonds in the global portfolio of MXF, respectively; and $\{L^S\times W^S\}_{MXF} = \{L^{S,EUR}\times W^{S,EUR} + L^{S,USD}\times W^{S,USD} + L^{S,ROW}\times W^{S,ROW}\}_{MXF}$.

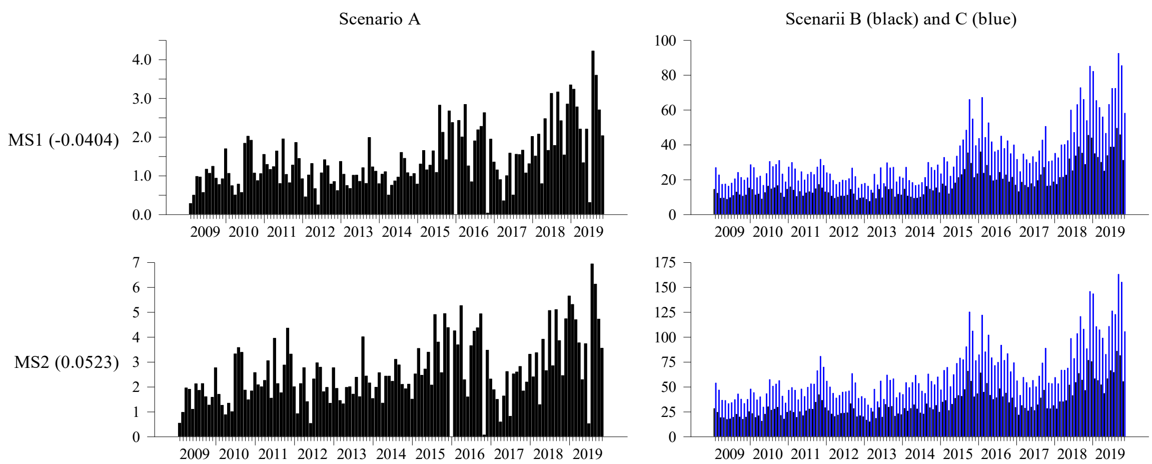
6. Results: Aggregate vulnerability under three scenarios

Aggregate vulnerability (AV_{t+2}) as defined in [15] was finally estimated under three scenarios; (i) 'Scenario A' or 'Baseline scenario', where series of original returns are introduced as $\boldsymbol{R_t}$; (ii) 'Scenario B' or '5% scenario', where an initial shock of -5% return is assumed and introduced as $\boldsymbol{R_t}$; and (iii) 'Scenario C' or '10% scenario', where an initial shock of -10% return is assumed and introduced as $\boldsymbol{R_t}$. In parallel, the regime-dependent estimates of FPS for each of the fund categories were used when estimating AV. As for the price impact ratio, $\boldsymbol{L^S}$ by currency (i.e. $\boldsymbol{L^{S,EUR}}$, $\boldsymbol{L^{S,USD}}$, and $\boldsymbol{L^{S,ROW}}$) are used for EQF and MXF, while $\boldsymbol{L^B}$ based on Bao *et al.* (2018) is used for BOF and MXF.

6.1. Equity funds

Figure 4 plots the estimated series of AV for EQF, and Table 3 provides their respective summary statistics. The left panels of Figure 4 plot AV under scenario A, while the right panels contrast AV under scenario B with AV under scenario C. AV under scenarios B and C are much higher than AV under scenario A, which confirms the severity of the adverse scenarios. In parallel, the upper panels of Figure 4 plot AV based on $\boldsymbol{\gamma}_{\mathrm{MS1}}$ (=-0.0404), while the lower panels depict AV based on $\boldsymbol{\gamma}_{\mathrm{MS2}}$ (=0.0523). Note that AV based on $\boldsymbol{\gamma}_{\mathrm{MS2}}$ are higher than AV based on $\boldsymbol{\gamma}_{\mathrm{MS1}}$, which can be partly explained by the fact that the absolute value of the MS2 estimate is greater than that of the MS1 estimate. In addition, the negative MS1 estimate might reduce the total amount of assets to be liquidated (i.e. $\boldsymbol{\tilde{\phi}}$ as shown in equation [13]), which might in turn decrease AV. Table 3 shows that, when based on $\boldsymbol{\gamma}_{\mathrm{MS2}}$, the highest AV is measured at 6.95 bps under scenario A, while it is at 85.9 bps (or 163 bps) under scenario B (or C).

Figure 4. Aggregate vulnerability of EQF



Notes. This figure plots six series of estimated AV for EQF, based on two MS estimates of FPS ('MS1' and 'MS2') under three scenarios (A, B, C), expressed in basis points. The results cover the period between February 2009 and November 2019.

Table 3. Summary statistics of AV for EQF

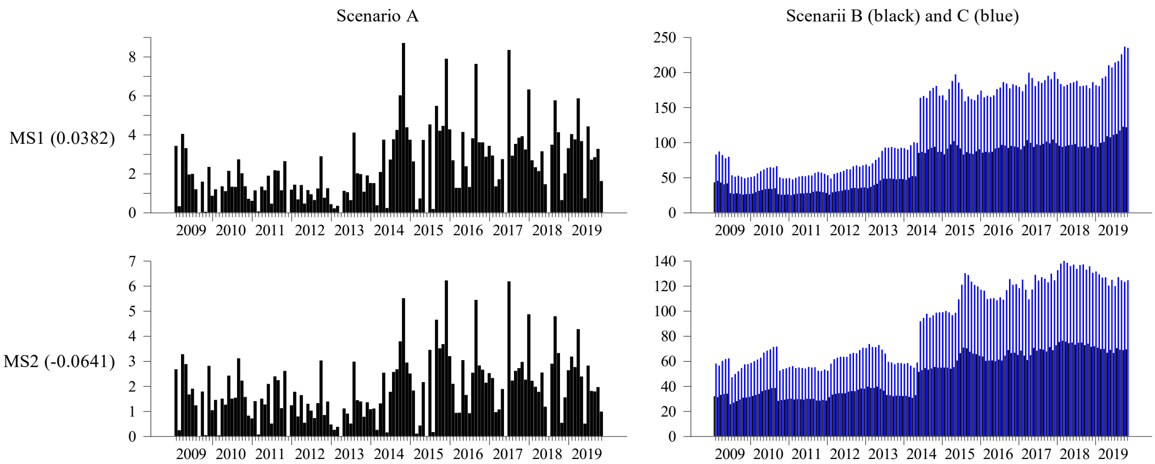
Scenario	FPS	Obs.	Mean	Min.	Fract.90	Fract.95	Max.
A	MS1	128	1.43E+00	-8.49E-03	2.53E+00	2.85E+00	4.23E+00
	MS2	128	2.63E+00	-1.54E-02	4.49E+00	5.03E+00	**6.95E+00**
B	MS1	128	1.82E+01	7.62E+00	3.32E+01	3.78E+01	4.96E+01
	MS2	128	3.40E+01	1.51E+01	5.60E+01	6.46E+01	**8.59E+01**
C	MS1	128	3.39E+01	1.41E+01	6.20E+01	7.06E+01	9.26E+01
	MS2	128	6.46E+01	2.88E+01	1.07E+02	1.23E+02	**1.63E+02**

Notes. This table provides summary statistics of the estimated series of AV for EQF under three scenarios (A, B, C) expressed in basis points. The sample period goes from February 2009 and November 2019.

6.2. Bond funds

Figure 5 plots the estimated series of AV for BOF. Its left panel depicts AV under scenario A, while the right panel plots AV under scenarios B and C. In particular, the right panels show that AV sharply rose during mid-2014. This jump can be partly accounted for by the increase in the time-period dependent price impact ratio for bonds $\boldsymbol{L^B}$ (from 1.5×10^{-8} to 2.4×10^{-8}; see Section 5.3). In parallel, the upper panels plot AV based on $\boldsymbol{\gamma}_{\mathrm{MS1}}$ (=0.0382), while the lower panels depict AV based on $\boldsymbol{\gamma}_{\mathrm{MS2}}$ (=-0.0641). AV based on $\boldsymbol{\gamma}_{\mathrm{MS1}}$ are higher than those based on AV based on $\boldsymbol{\gamma}_{\mathrm{MS2}}$, which is mainly due to the fact that $\boldsymbol{\gamma}_{\mathrm{MS1}}$ is positive (increasing $\widetilde{\boldsymbol{\phi}}$ leading to higher AV) and that $\boldsymbol{\gamma}_{\mathrm{MS2}}$ is negative (decreasing the absolute value of $\widetilde{\boldsymbol{\phi}}$ leading to lower AV). Summary statistics of AV for BOF are provided in Table 4. When based on $\boldsymbol{\gamma}_{\mathrm{MS1}}$, the highest AV is measured at 123 bps and 237 bps under scenarios B and C, respectively, which are much higher than that under scenario A (8.70 bps).

Figure 5. Aggregate vulnerability of BOF



Notes. This figure depicts six series of estimated AV for BOF, based on two MS estimates of FPS ('MS1' and 'MS2') under three scenarios (A, B, C), expressed in basis points. The results cover the period between February 2009 and November 2019.

Table 4. Summary statistics of AV for BOF

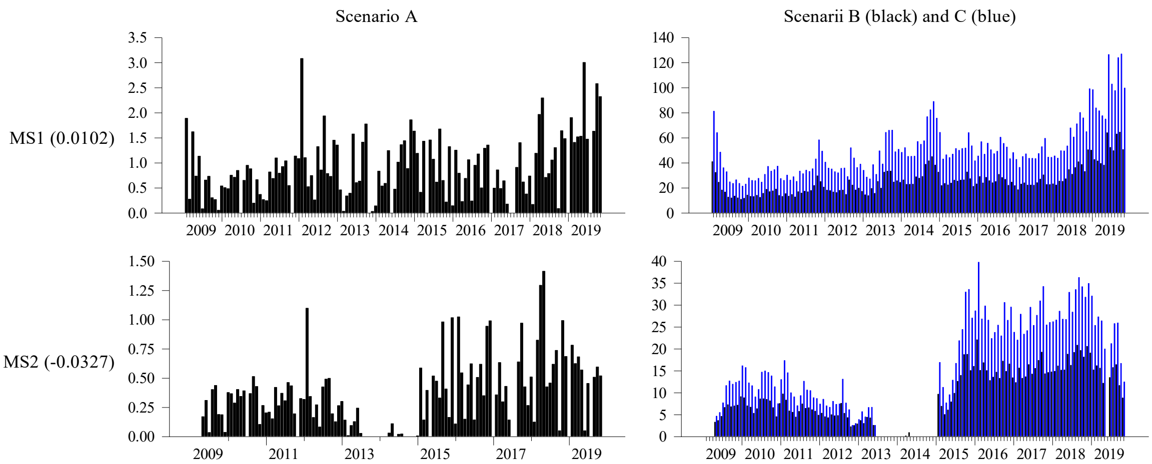
Scenario	FPS	Obs.	Mean	Min.	Fract.90	Fract.95	Max.
A	MS1	128	2.32E+00	-1.73E+00	4.31E+00	5.83E+00	**8.70E+00**
	MS2	128	1.86E+00	-1.36E+00	3.29E+00	4.52E+00	6.22E+00
B	MS1	128	6.58E+01	2.49E+01	9.95E+01	1.06E+02	**1.23E+02**
	MS2	128	4.98E+01	2.56E+01	7.13E+01	7.42E+01	7.63E+01
C	MS1	128	1.26E+02	4.73E+01	1.92E+02	2.05E+02	**2.37E+02**
	MS2	128	9.07E+01	4.71E+01	1.30E+02	1.36E+02	1.40E+02

Notes. This table provides summary statistics of the estimated series of AV for BOF under three scenarios (A, B, C), expressed in basis points. The sample period goes from February 2009 and November 2019.

6.3. Mixed funds

Figure 6 plots the estimated series of AV for MXF, and Table 5 provides their summary statistics, respectively. The left panels of Figure 6 depict AV under scenario A, while the right panels plot AV under scenarios B and C. Upper panels plot AV based on γ_{MS1} (=0.0102), while lower panels depict AV based on γ_{MS2} (=-0.0327). Similar to the case of BOF, AV based on γ_{MS1} are higher than AV based on γ_{MS2}, mainly due to the fact that γ_{MS1} is positive while γ_{MS2} is negative. Table 5 shows that, when based on γ_{MS1}, the highest AV is 3.09 bps under scenario A, which is much lower than those under scenario B (64.5 bps) or scenario C (127 bps).

Figure 6. Aggregate vulnerability of MXF



Notes. This figure plots six series of estimated AV for MXF, based on two MS estimates of FPS ('MS1' and 'MS2') under three scenarios (A, B, C), expressed in basis points. The results cover the period between February 2009 and November 2019.

Table 5. Summary statistics of AV for MXF

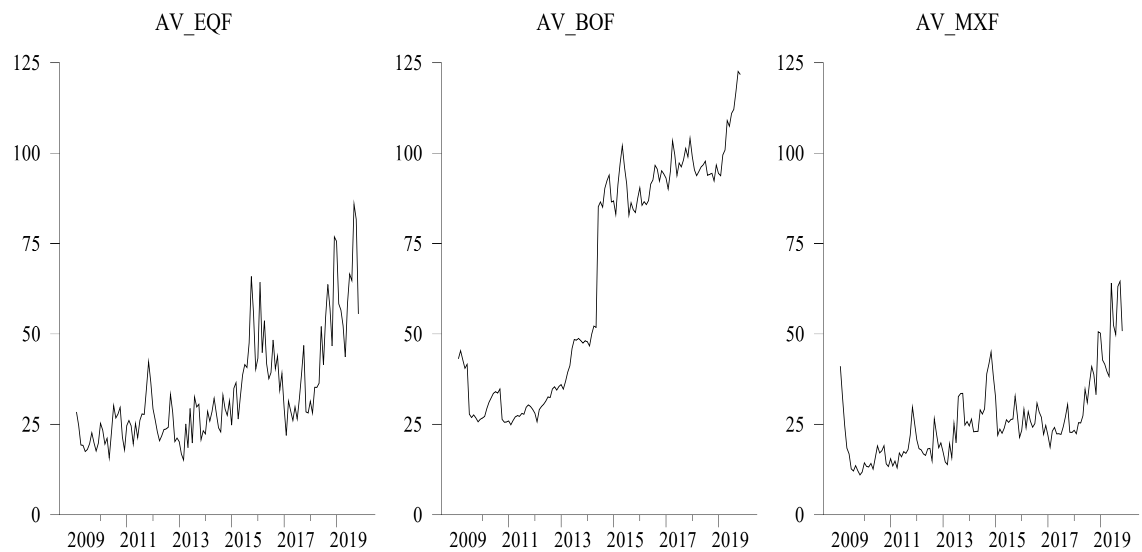
Scenario	FPS	Obs.	Mean	Min.	Fract.90	Fract.95	Max.
A	MS1	128	7.66E-01	-6.74E+00	1.63E+00	1.93E+00	**3.09E+00**
	MS2	128	2.96E-01	-2.43E+00	7.02E-01	9.89E-01	1.42E+00
B	MS1	128	2.55E+01	1.10E+01	4.00E+01	5.01E+01	**6.45E+01**
	MS2	128	8.47E+00	-1.12E+01	1.70E+01	1.90E+01	2.21E+01
C	MS1	128	5.01E+01	2.15E+01	7.85E+01	9.83E+01	**1.27E+02**
	MS2	128	1.39E+01	-2.55E+01	3.01E+01	3.34E+01	3.98E+01

Notes. This table provides summary statistics of the estimated series of AV for MXF under three scenarios (A, B, C), expressed in basis points. The sample period goes from February 2009 and November 2019.

6.4. Comparison of AV across fund categories

As discussed above, positive ***γ***-based AV is higher than negative ***γ***-based AV for each category of fund. In parallel, it is clear that scenario B is more plausible than scenario C. This suggests that the positive ***γ***-based AV under scenario B can qualify as the 'most relevant' AV from a macroprudential perspective for each of the three categories of fund. Figure 7 plots these series for a comparison across fund categories. It shows that BOF have been the most vulnerable during the sample period, followed by EQF and MXF.

Figure 7. Comparison of AV: EQF vs. BOF vs. MXF

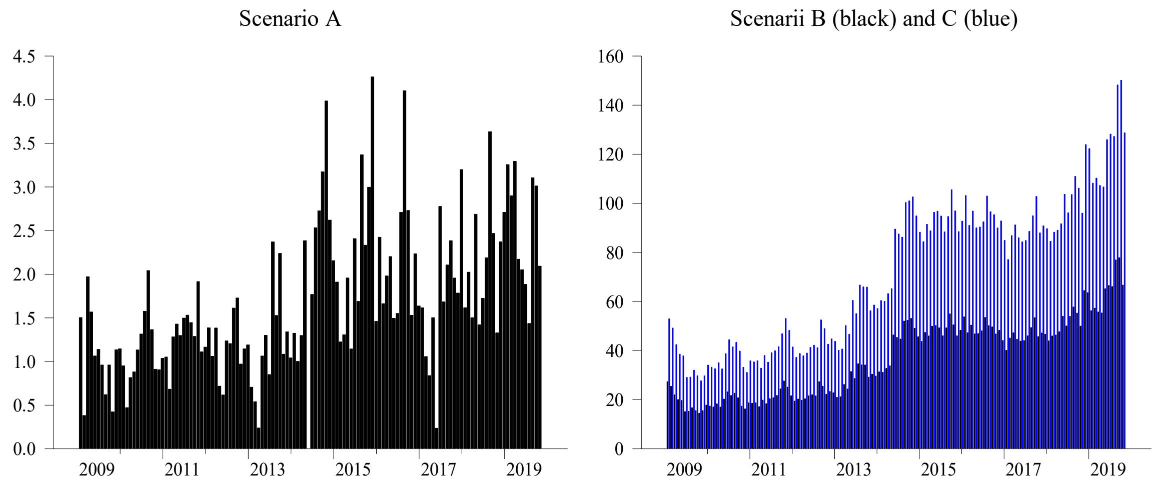


Notes. This figure depicts the positive γ-based AV under scenario B (-5% shock) for each of the three categories of fund (EQF, BOF and MXF). The sample period goes from February 2009 to November 2019.

6.5. Global aggregate vulnerability (GAV)

We now combine the series of positive **γ**-based AV for each category of fund to define a global indicator of aggregate vulnerability (GAV) for the investment fund sector of Luxembourg as a whole. We also take into account each fund category's respective weights in the sector's total AuM (see Figure B in the Appendix) when estimating GAV under the three scenarios (A, B and C). Figure 8 depicts the resulting series of GAV, and their summary statistics are provided in Table 6.

Figure 8. GAV of the investment fund sector in Luxembourg



Notes. This figure depicts the series of global aggregate vulnerability (GAV) estimated under three scenarios, A (baseline), B (-5% shock to aggregate fund return) and C (-10% shock to aggregate fund return). The sample period goes from February 2009 to November 2019.

Table 6. Summary statistics of GAV of the investment fund sector in Luxembourg

Scenario	Obs.	Mean	Min.	Fract.95	Max.	2009/02	2019/11
GAV_A	130	1.69E+00	-1.26E-01	3.23E+00	4.26E+00	1.50E+00	2.09E+00
GAV_B	130	3.72E+01	1.45E+01	6.41E+01	7.78E+01	2.74E+01	**6.67E+01**
GAV_C	130	7.16E+01	2.77E+01	1.23E+02	1.50E+02	5.30E+01	1.29E+02

Notes. This table provides summary statistics for the estimated series of GAV under scenarios A (baseline), B (-5% shock to aggregate fund return) and C (-10% shock to aggregate fund return). The sample period goes from February 2009 to November 2019.

On average during the sample period, GAV was around 1.69 bps under scenario A, suggesting that the investment fund sector in Luxembourg has not been subject to shocks that precipitated any periods of significant vulnerability. The average GAV under scenarios B and C is 37.2 bps and 71.6 bps, respectively. This seems to indicate that the sector's exposure to severe shocks has been rather limited. Other statistics for the GAV series, such as the 95[th] percentiles or maximum values, also seem to confirm the sector's limited vulnerability.

When looking at the GAV series' dynamic, one may conclude that the investment fund sector of Luxembourg has not been meaningfully vulnerable to external shocks to the funds' returns. However, it is worth noting that the sector's global vulnerability is progressively increasing. As of November 2019, GAV is 66.7 bps under scenario B, suggesting that the investment fund sector is exposed to a liquidation of 0.667% of the sector's aggregate equity if the stock and bond markets were to decline by 5%.

7. Conclusion

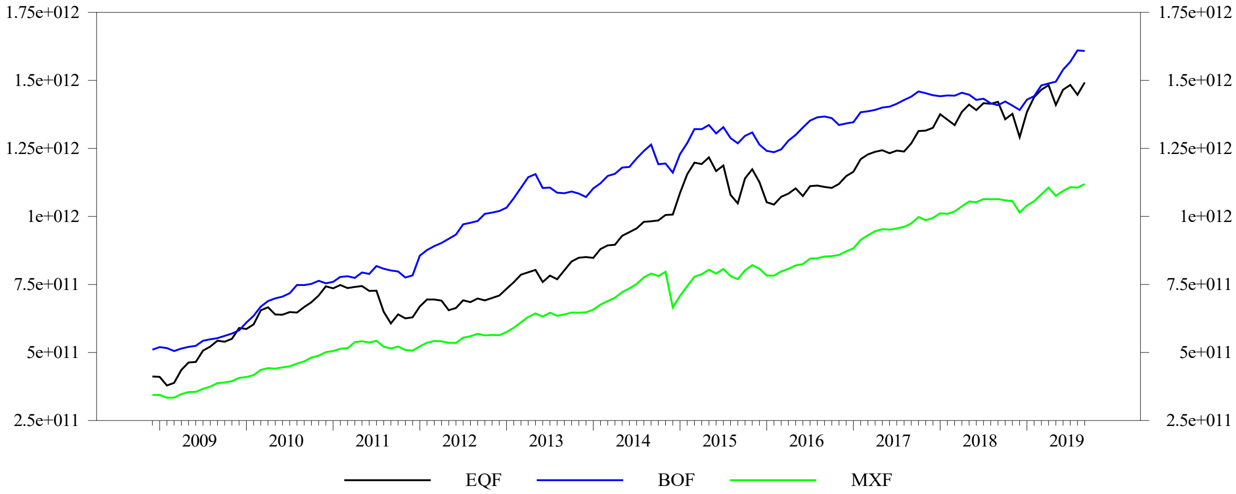
This paper assesses the aggregate vulnerability (AV) of the investment fund sector of Luxembourg by implementing a macroprudential framework for stress testing under the assumption of initial adverse shocks to fund returns. Following Greenwood *et al.* (2015) and Fricke and Fricke (2017), two key parameters, flow-performance sensitivity (FPS) and asset price impacts, are included in the stress test model. Further, this paper extends the analysis by adopting non-linear methods of calibration for the key parameters in an attempt to better capture the effects of the negative sequence relating initial shocks to additional funding shocks and fire sales.

The empirical results suggest that bond funds have been the most vulnerable, followed by equity funds and mixed funds. The results also suggest a sector-level vulnerability of 66.7 bps under scenario B, as of November 2019, suggesting that the sector was potentially exposed to a liquidation of 0.667% of its aggregate equity if both the stock and bond markets declined by 5%.

The estimated magnitude of global exposure can be considered rather limited, consequently suggesting that the investment fund sector is sufficiently resilient to exogenous shocks and that it is not likely to raise any particular concern for financial stability in Luxembourg. However, this conclusion should be interpreted against the background of an elevated risk of a reversal in risk premia at the global level. Under such conditions, investors may be subject to a sudden increase in their degree of risk aversion, which could potentially increase the aggregate vulnerability of investment funds in Luxembourg due to higher FPS and stronger price impacts. Continued macroprudential monitoring of the investment fund sector is therefore warranted.

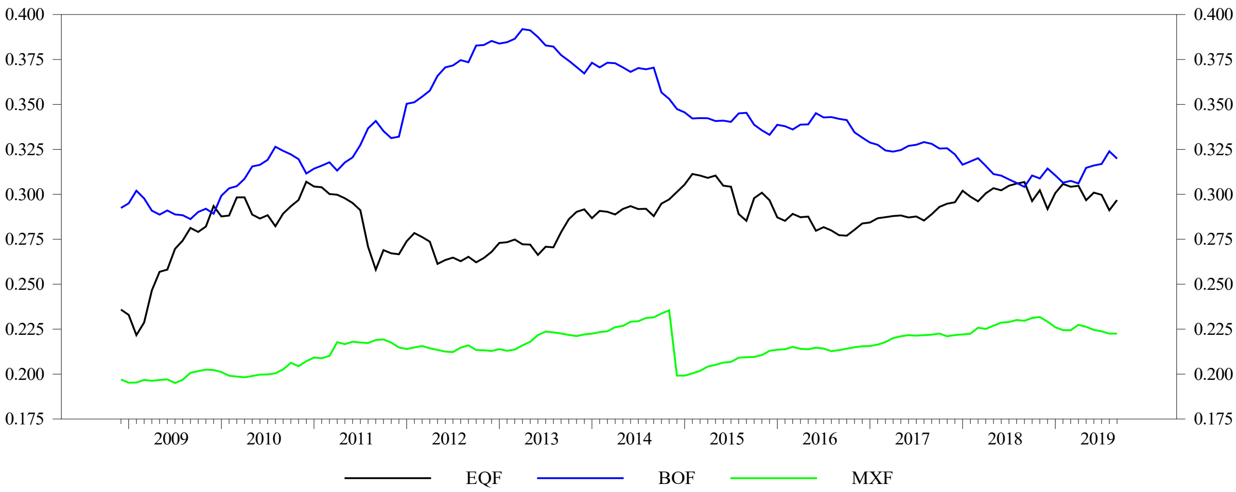
Appendix

Figure A. Assets under management (in euro)



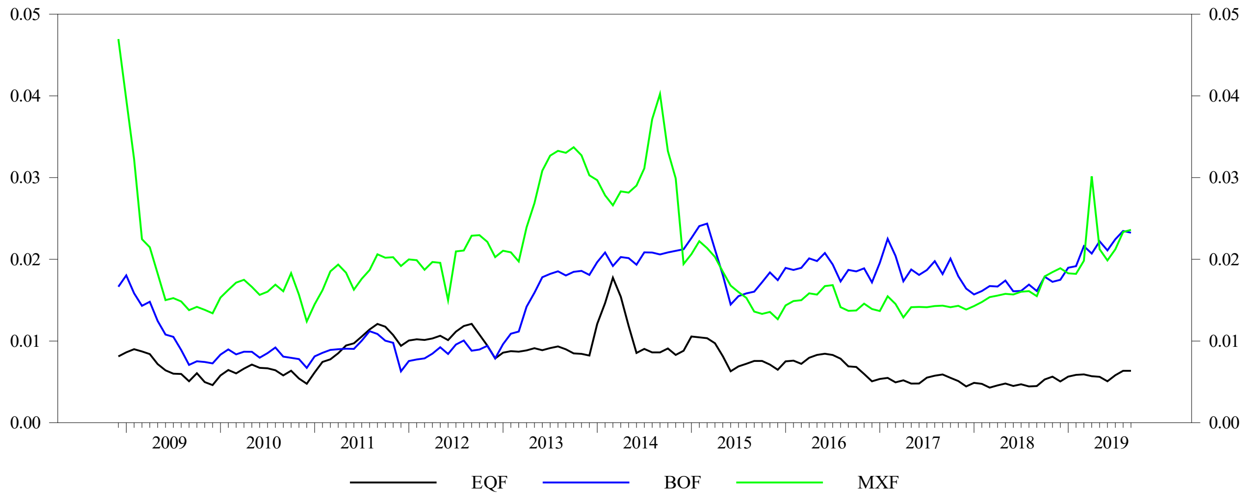
Notes. This figure depicts assets under management of EQF, BOF and MXF in absolute value (in euro). EQF = equity funds; BOF =bond funds; MXF = mixed funds. The sample period goes from December 2008 to September 2019.

Figure B. Relative weights in total AuM of all funds in Luxembourg



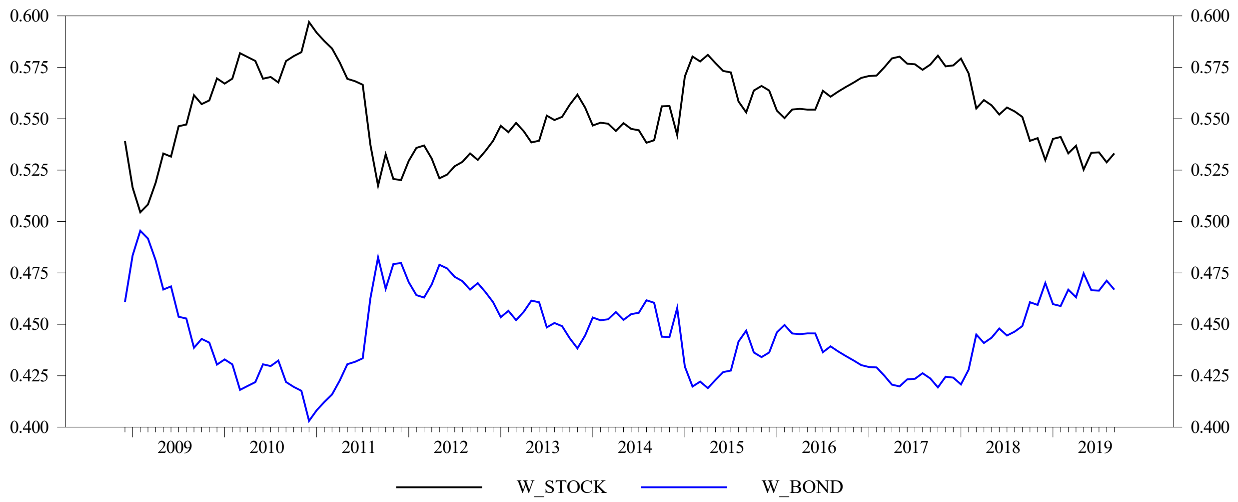
Notes. This figure depicts the relative weights of EQF, BOF and MXF in total assets under management of all open-ended funds in Luxembourg. EQF = equity funds; BOF =bond funds; MXF = mixed funds. The sample period goes from December 2008 to September 2019.

Figure C. Leverage ratio



Notes. This figure depicts the leverage ratio of EQF, BOF and MXF, defined as debt over capital. EQF = equity funds; BOF =bond funds; MXF = mixed funds. The sample period goes from December 2008 to September 2019.

Figure D. Relative weights of stocks and bonds in the portfolio of MXF



Notes. This figure depicts the relative weights of stocks and bonds in the portfolio of mixed funds (MXF). The sample period goes from December 2008 to September 2019.

Table A. MS-VAR model specification tests:
AIC/SBC for optimal number of lags and RCM for optimal number of regimes

Fund category	EQF			BOF			MXF		
Specification \ Test	AIC	SBC	RCM	AIC	SBC	RCM	AIC	SBC	RCM
MS(2)-C(1)	1.24	1.84	59	0.99	1.59	26	0.91	1.51	2
MS(2)-CH(1)	1.05	1.65	21	0.9	1.5	33	NA	NA	24
MS(2)-C(2)	1.19	2.07	50	0.85	1.72	15	0.84	1.72	8
MS(2)-CH(2)	1.15	2.02	26	0.52	1.39	4	1.16	2.04	46
MS(2)-C(3)	1.18	2.33	7	1.03	2.18	44	1.25	2.4	3
MS(2)-CH(3)	1.04	2.19	9	0.78	1.93	30	1.24	2.39	24

Notes. MS(2) refers to MS-VAR model with two regimes. 'C' and 'CH' correspond to Equations [16] and [17], respectively. The numbers in parentheses after 'C' or 'CH' refer to the number of lags. AIC refers to the Akaike information criterion. SBC refers to the Schwarz information criterion or the Bayesian information criterion (BIC). RCM refers to the regime classification measure of Ang and Bekaert (2002). EQF = equity funds; BOF =bond funds; MXF = mixed funds. The sample period goes from December 2008 to September 2019.

Table B. Stock indexes used in the calibration of the price impact parameter for stocks $\boldsymbol{L^S}$

Index number	**Country, Currency and Index name**	**SDW* code**
INDEX_01	World (all entities), Euro, Euronext 100 Index	FM.B.A1.EUR.RT.EI._N100
INDEX_02	Belgium, Euro, Belgium BEL 20 Index	FM.B.BE.EUR.RT.EI._BFX
INDEX_03	Canada, Canadian dollar, Standard and Poors Toronto Stock Exchange Composite Index	FM.B.CA.CAD.RT.EI._GSPTSE
INDEX_04	Switzerland, Swiss franc, Swiss Market Index (SMI)	FM.B.CH.CHF.RT.EI._SSMI
INDEX_05	Spain, Euro, Spain IBEX 35 Index	FM.B.ES.EUR.RT.EI._IBEX
INDEX_06	Finland, Euro, Nordic Exchange OMX Helsinki Price Index	FM.B.FI.EUR.RT.EI._OMXHPI
INDEX_07	France, Euro, France CAC 40 Index	FM.B.FR.EUR.RT.EI._FCHI
INDEX_08	United Kingdom, UK pound sterling, Financial Times Stock Exchange (FTSE) Mid 250 Index	FM.B.GB.GBP.RT.EI._FTMC
INDEX_09	Greece, Euro, Athens Stock Exchange Main General Index	FM.B.GR.EUR.RT.EI._ATG
INDEX_10	Hong Kong, Hong Kong dollar, Hong Kong Stock Exchange HANG SENG Index (HSI)	FM.B.HK.HKD.RT.EI._HSI
INDEX_11	Ireland, Euro, Irish Stock Exchange ISEQ Overall Index	FM.B.IE.EUR.RT.EI._ISEQ
INDEX_12	Italy, Euro, FTSE Milan Stock Exchange MIB	FM.B.IT.EUR.RT.EI._FTMIB
INDEX_13	Japan, Japanese yen, Nikkei 225 Index	FM.B.JP.JPY.RT.EI._N225
INDEX_14	Korea, Republic of, Korean won (Republic), Korea Stock Exchange KOSPI Index	FM.B.KR.KRW.RT.EI._KS11
INDEX_15	Luxembourg, Euro, Luxembourg Stock Exchange LuxX Index	FM.B.LU.EUR.RT.EI._LUXX
INDEX_16	Netherlands, Euro, Amsterdam Exchanges Index	FM.B.NL.EUR.RT.EI._AEX

INDEX_17	Portugal, Euro, Lisbon PSI 20 Index	FM.B.PT.EUR.RT.EI._PSI20
INDEX_18	Euro area (changing composition), Euro, Vienna Stock Exchange Austrian Traded Index	FM.B.U2.EUR.RT.EI._ATX
INDEX_19	Euro area (changing composition), Euro, German Stock Exchange DAX Index	FM.B.U2.EUR.RT.EI._GDAXI
INDEX_20	Euro area (changing composition), Euro, Dow Jones Eurostoxx 50 Index	FM.B.U2.EUR.RT.EI._STOXX50E
INDEX_21	United States, US dollar, Dow Jones Composite Index	FM.B.US.USD.RT.EI._DJA
INDEX_22	United States, US dollar, Dow Jones Industrial Average Index	FM.B.US.USD.RT.EI._DJI
INDEX_23	United States, US dollar, Dow Jones US Banks Index	FM.B.US.USD.RT.EI._DJUSBK
INDEX_24	United States, US dollar, Nasdaq Index	FM.B.US.USD.RT.EI._NDX

*Notes. * SDW refers to the ECB's Statistical Data Warehouse.*

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