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Régis Gourdel, Eduardo Maqui,
Matthias Sydow

Investment funds under stress

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Abstract

This paper presents a model for stress testing investment funds, based on a broad worldwide sample of primary open-end equity and bond funds. First, we employ a Bayesian technique to project the impact of macro-financial scenarios on country-level portfolio flows worldwide that are constructed from fund-level asset holdings. Second, from these projected country-level flows, we model the scenarios' repercussions on individual funds along a three year horizon. Importantly, we further decompose portfolio flows, disentangling the specific contributions of transactions, valuation and foreign exchange effects. Overall, our results indicate that the impact of a global adverse macro-financial scenario leads to a median depletion in assets under management (AUM) of 24% and 5%, for euro area-domiciled equity and bond funds respectively, largely driven by valuation effects. Scenario and results both present similarities to the global financial crisis. We use historical information on fund liquidations to estimate a threshold for a drop in AUM that signals a high likelihood of a forthcoming liquidation. Based on this, we estimate that 5.8% and 0.5% of euro area-domiciled equity and bond funds respectively could go into liquidation. Such empirical thresholds can be useful for the implementation of prudential policy tools, such as redemption gates.

JEL classification: F21, G15, G17, G23, G28.

Keywords: Investment funds, Bayesian model averaging, international capital flows, portfolio valuation, prudential policy.

Non-technical summary

In light of its potential contribution to systemic risk, the investment funds sector has caught the attention of regulatory institutions in recent years. In fact, empirical evidence indicates that the sector has got bigger, more risk-taking and interconnected on a global scale. Understanding the impact of macro-financial shocks on fund asset holdings and liquidations is therefore of first-order importance from a financial stability perspective, as these may ultimately translate into aggregate externalities to financial markets more broadly.

In this paper we present a model for stress testing investment funds, based on a broad world-wide sample including 47,979 equity and 34,174 bond primary open-end funds. The model is designed in two steps. The first step employs a Bayesian model averaging (BMA) technique to project the impact of macro-financial scenarios on country portfolio flows worldwide that are constructed from fund-level asset holdings. In the second step, we implement a stress propagation exercise resembling traditional top-down stress testing techniques. Our implementation models the impact of country portfolio flows, as projected in step one, at the individual fund level along a three year horizon with a quarterly frequency. Importantly, we further decompose country portfolio flows, disentangling the specific contribution of transactions, valuation and foreign exchange effects.

The contribution of our model design to stress testing investment funds is twofold. First, we refrain from assuming that funds invest only in their country of domicile or in a pre-determined geographical area. Instead, based on actual fund-level holdings we borrow from the related literature on international capital flows and focus on the international transmission of shocks to financial flows. This allows us to translate the impact of the adverse macro-financial scenario into fund liquidations via their country-level sensitivities. Second, our two-step approach models a dual propagation channel, in the spirit of FSB (2015). On one hand, the channel captures the impact of macro-financial scenarios heterogeneously, that is, accounting for funds' country exposures, compared to previous studies where exogenous shocks are induced statically and uniformly across funds (Baranova, Coen, Lowe, Noss, and Silvestri, 2017; Fricke and Fricke, 2017). On the other hand, the channel also involves the propagation to asset liquidations at the fund level, which may ultimately translate into aggregate externalities to financial stability by means of valuation effects. Future work involves the integration into system-wide stress testing frameworks.

We focus then on a subset of twelve euro area countries (EA12), to analyse fund-level effects. Overall, our results indicate that the impact of the adverse macro-financial scenario leads to a median drop in assets under management (AUM) of 24% and 5%, for EA12-domiciled equity and bond funds respectively, within the first quarter of the projection horizon. Furthermore, we empirically identify a fund threshold of 30% drop in AUM, which is a strong indicator of a forthcoming liquidation. Based on this threshold, the proportion of equity funds liquidating following the initial adverse shock is estimated at 5.8% (4.6% in terms of liquidated assets). In the case of bond funds, the ratio of fund liquidations is limited to 0.5% (0.1% in terms of liquidated assets). We also use this threshold to inform the choice of prudential policy tools, such as redemption gates.

1 Introduction

The European non-bank financial sector has seen a continuous growth in the past decade. Total assets of EU (EA) non-bank financial entities stood at €42.3 (€33.8) trillion at the end of 2017, with one-third corresponding to investment funds (ESRB, 2018b). The total assets of banks headquartered in the EU (EA) grew at a slower pace to reach €32.3 trillion (€23.5) by end 2017.[1]

Given more recent analysis in ECB (2018), not only has the investment fund sector grown bigger in the euro area, it has also become more risk-taking. In particular, investment funds reduce their holdings of highly liquid securities but increase that of lower-rated bonds. As a result they are more interconnected and vulnerable to potential shocks. While stress testing of the banking sector has been a regular feature for European supervisory authorities (CEBS since 2009 and EBA since 2011), stress testing the investment fund sector has gained attention only more recently, with several European regulatory bodies leading to progress in this area.[2]

Our analysis is related to two separate strands of the literature. First, studies related to stress testing, covering in particular portfolio rebalancing or redemptions from investment funds, including the impact of asset sales on market prices. Second, empirical work on global financial flows, in particular the investigation of the international transmission of shocks.

On the stress testing side, notable efforts have been made towards developing analytical tools to stress test investment funds in recent years. Bouveret (2017) documents liquidity stress tests for investment funds performed in various IMF FSAP studies. Using similar approaches as shown in our study, it discusses the links between the banking and investment fund sector as well as a proposal for linking bank-fund liquidity stress tests. Fricke and Fricke (2017) develop a stress testing model applied to US equity funds, incorporating the sensitivity of flows to performance as an additional shock to the established fire sales model. They conclude that systemic risk, in the sense of aggregate vulnerability to fire sales, is limited within the sector. Focusing on bond funds, Baranova, Coen, Lowe, Noss, and Silvestri (2017) assess the resilience of liquidity in European corporate bond markets by exploring the interaction between dealers and open-end investment funds participating in those markets. The authors find that investor redemptions can result in material increases in spreads in the corporate bond market. Lastly, ESMA (2019) discusses a stress simulation framework for stress testing investment funds. They apply this framework to measure funds' resiliency to investor redemption shocks. Results from a case study focusing on UCITS-regulated bond funds indicate that sufficient holdings of highly liquid assets allow funds

[1] Based on ECB Consolidated Banking Data statistics.

[2] IOSCO (FSB recommendations); ESRB (recommendation on systemic risks); EC (prudential regulation of investment firms); ESMA (entity-level stress testing and simulation-based stress test in the fund industry).

to meet investor redemptions, with the exception of high-yield funds, of which 40% would face liquidity shortfalls under large but plausible simulated shocks. They also find an overall limited price impact of fund asset sales on financial markets, with some heterogeneity between asset classes. Thus, second round effects have a smaller impact on funds' holdings than the initial redemption shock.

Recent empirical work has found that global equity and bond fund outflows can be explained by increases in financial stress and (unexpected) poor economic outlook in advanced economies. Raddatz and Schmukler (2012) find that both investors and fund managers react to country returns and crises with substantial adjustments to their investments. Their behaviour tends to be pro-cyclical, reducing their exposure to countries during bad times and increasing it when conditions improve. On the other hand, Brandao-Marques, Gelos, Ichiue, and Oura (2015) find that bond funds are more sensitive to global financial shocks and engage in "return chasing" more strongly than equity funds. For global bond fund outflows in particular, unexpected increases in inflation are an additional explanatory factor (Puy, 2016). These contributions weight heavily in our analytical framework and model design.

A number of papers have focused on the behaviour of fund investors, to study the flow-performance relationship of corporate bond funds. Goldstein, Jiang, and Ng (2017) find that US corporate bond funds exhibit a concave relationship between investor flows and fund performance, which is different from the convex pattern exhibited by equity funds. Dötz and Weth (2019) focus on funds domiciled in Germany. Their results indicate that, conditional on underperformance, the flow-performance relationship is stronger for funds with a retail investor base than those with an institutional one. In the case of illiquid funds, institutional investors are more reluctant to redeem as they internalise fire-sales driven losses.

Other papers have looked at the relationship between monetary policy and investment fund flows. Looking at the investment fund sector in the US, Feroli, Kashyap, Schoenholtz, and Shin (2014) show that monetary policy shocks can drive fund flows and flows can drive asset prices. Focusing on US bond funds, Banegas, Montes-Rojas, and Siga (2016) find that monetary policy can have a direct influence on the allocation decisions of investment fund investors. Unexpected monetary policy tightening is associated with persistent outflows from bond funds. More recently, based on a sample of funds domiciled in Luxembourg, Bubeck, Habib, and Manganelli (2018) find that ECB monetary policy announcements lead mainly to valuation effects of EA investment funds instead of an active portfolio reallocation via redemptions or injections of investors.

Figure 1 sketches the framework, under which our model for stress testing investment funds is developed. The model is designed in two steps. The first step employs Bayesian model averaging (BMA) techniques to project the impact of macro-financial scenarios on country portfolio flows constructed from fund-level asset holdings. In the second step, we implement a propagation exercise resembling traditional top-down stress testing techniques. This technical implementation models the impact of country portfolio flows, as projected in step one, at the individual fund level, along a three year horizon. We further decompose this impact, disentangling the specific contribution of transactions, valuation and foreign exchange effects in explaining the liquidation of fund assets.

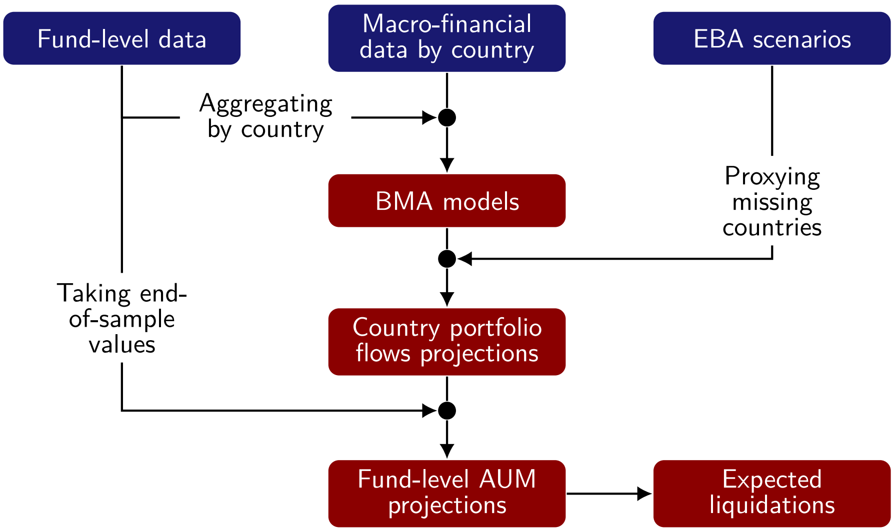


Figure 1: Overview of the investment funds stress testing framework

The analytical framework integrates multiple observational and geographical dimensions. The construction of country portfolio flows is based on a worldwide sample of (individual) equity and bond funds. Their portfolios are restricted to countries usually incorporated in global market indices, delimiting also the scope of the macro-financial scenarios, from which shocks to portfolio flows are induced. Our analysis is conducted at the fund level as well, with results for the funds that were active by the end of the sample period. This last part focuses on funds domiciled in twelve euro area countries. In the rest of the paper, we denote this set of countries as EA12, and Rest of the World (RoW) refers to all other countries.[3]

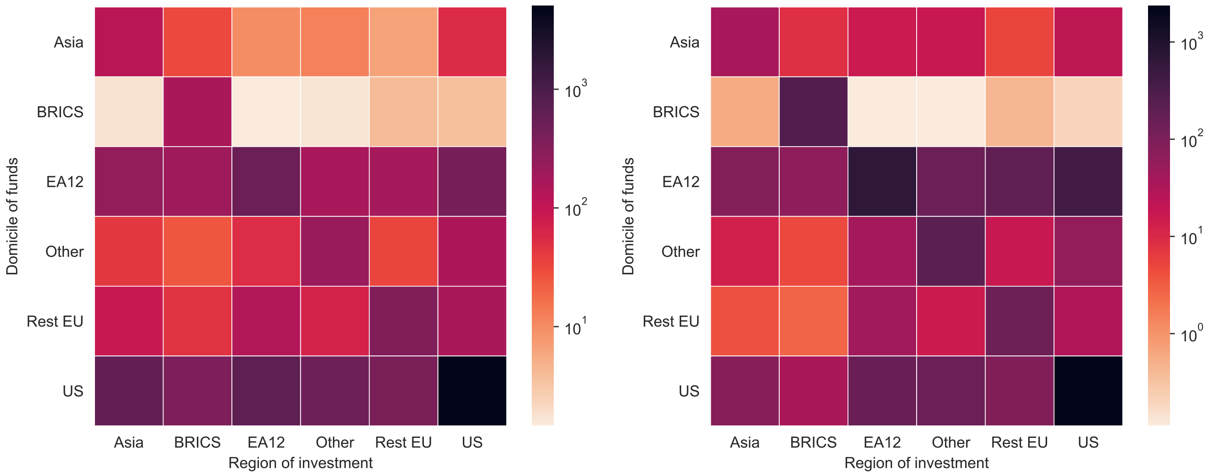
The consideration of such an integrated framework is an important feature of our analysis, which differentiates it from previous stress tests that rely exclusively on the country of domicile of funds (Mirza, Moccero, Palligkinis, and Pancaro, 2019) or their geographical investment

[3] We focus in EA12 countries as they are representative of the EA as a whole. In terms of assets under management, for example, funds domiciled in EA12 countries represent 99.9% of the EA total, both for equity and bond funds. In terms of number of funds, 99% and 99.3% of EA equity and bond funds are domiciled in EA12 countries, respectively. Countries included are: Austria, Belgium, Germany, Spain, Finland, France, Greece, Ireland, Italy, Luxembourg, Netherlands and Portugal.

focus (Baranova, Coen, Lowe, Noss, and Silvestri, 2017). These classifications suffer from over-simplification and may hamper a consolidated level of aggregation, hence biasing estimates.

For example, bond funds with the euro area declared as geographical focus still hold 20% of non-EA bonds.[4] Furthermore, a decomposition of EA-domiciled funds' AUM reveals a relatively large exposure to non-EA countries. Similarly, ECB (2017) describes prominent net bond purchases by EA funds in the US, emerging markets and the rest of the EU. Our data supports this, with significant shares of both equities and bonds invested in these economies. In this context, detaching from the domicile perspective becomes crucial when translating scenarios into country-level asset flows. Therefore, we use instead more granular portfolio information, in line with previous work on the banking sector at the ECB, e.g. Dees, Henry, and Martin (2017).

Figure 2 presents two heat maps showing holdings of equity and bond funds across different regions worldwide, with fund domiciles on the y-axis and investment areas on the x-axis. Evidence indicates that, although EA12-domiciled funds invest more in the EA12 than in any other region, there is still a large exposure to RoW countries. In the case of bond funds, for example, their portfolio of US assets is very close in size to that of EA12 assets.



(a) Equity funds

(b) Bond funds

Figure 2: Geographical distribution of funds' asset holdings in 2017Q4, in billion euros.
The region "Rest EU" includes all countries of the EU that are not in the euro area. All five countries of the BRICS are included in this region and "Asia" includes the following: Taïwan, Philippines, Singapore, Malaysia, Indonesia, Hong-Kong, South Korea and Japan. Sources: Lipper IM and authors' calculations.

With this background, we contribute to the development of stress testing tools applied to the investment fund sector in two ways. First, we refrain from using the funds' domiciles or their pre-determined geographical focus as proxies for the allocation of assets. Instead, we borrow from

[4]Value on aggregate in 2017Q4. The sample concerned includes 1027 funds.

the related literature on international capital flows and focus on the international transmission of shocks to financial flows, based on fund-level asset holdings. This allows us to translate the impact of macro-financial scenarios into fund liquidations via their individual geographical exposures.

Second, our two-step approach models a dual propagation channel, as highlighted in FSB (2015). It captures the impact of macro-financial scenarios heterogeneously, that is accounting for funds' portfolio exposures, compared to related studies that model exogenous shocks statically and uniformly across funds (Baranova, Coen, Lowe, Noss, and Silvestri, 2017; Fricke and Fricke, 2017). The propagation channel also involves the projection to asset liquidations at the fund level, which may ultimately translate into aggregate externalities to financial stability by means of valuation effects.

Our main results are summarized in table 1. The table focuses on the first quarter of the projection horizon, as it is the point at which the adverse scenario materializes most strongly. The impact of country-specific adverse macro-financial scenarios leads to median depletions in assets under management (AUM) across EA12 countries of 24% and 5%, for equity and bond funds respectively. For EA12-domiciled equity funds the drop in AUM is largely driven by the adverse impact from the RoW (15.8% drop). For EA12-domiciled bond funds this is the opposite, with a 3.2% drop originating from the EA12 region.

Furthermore, we empirically identify a fund threshold of 30% drop in AUM, which signals a high likelihood of a forthcoming liquidation. Based on this threshold, the share of equity funds liquidating following the initial adverse shock is estimated at 5.8% (4.6% in terms of assets). In the case of bond funds, the ratio of fund liquidations is limited to 0.5% (0.1% in terms of assets). This threshold can also be useful for the implementation of prudential policy tools, such as redemption gates.

		Baseline	Adverse global stress	Adverse EA12 stress	Adverse RoW stress
Equity	EA12 funds	0.7	-24.0	-4.5	-15.8
	RoW funds	0.6	-22.4	-0.3	-20.0
Bond	EA12 funds	0.4	-5.0	-3.2	-1.4
	RoW funds	1.3	-3.5	0.0	-2.4

Table 1: Median growth in AUM across funds, in 2018Q1, in percentage points.
The category "RoW funds" covers all funds in our sample, which are not domiciled in the EA12, including those domiciled in countries that are not stressed.
The column "Adverse global stress" corresponds to our most comprehensive stress test exercise. For the two other adverse columns, we consider the drop in AUM coming from one region only, while the assets invested elsewhere are kept constant. Sources: Lipper IM and authors' calculations.

The remainder of the paper is organised as follows. Section 2 describes the sample construction and the empirical measurements. In section 3 we provide a review of the BMA modelling approach. Section 4 specifies the propagation exercise where empirical BMA estimates are used to stress test individual funds. Then, section 5 discusses our empirical results and we conclude in section 6.

2 Sample construction and empirical measurements

The data involved in the stress testing exercise includes: i) country portfolio flows constructed from fund-level asset holdings and ii) macro-financial data and economic projections for a large set of countries worldwide.

2.1 Sample construction

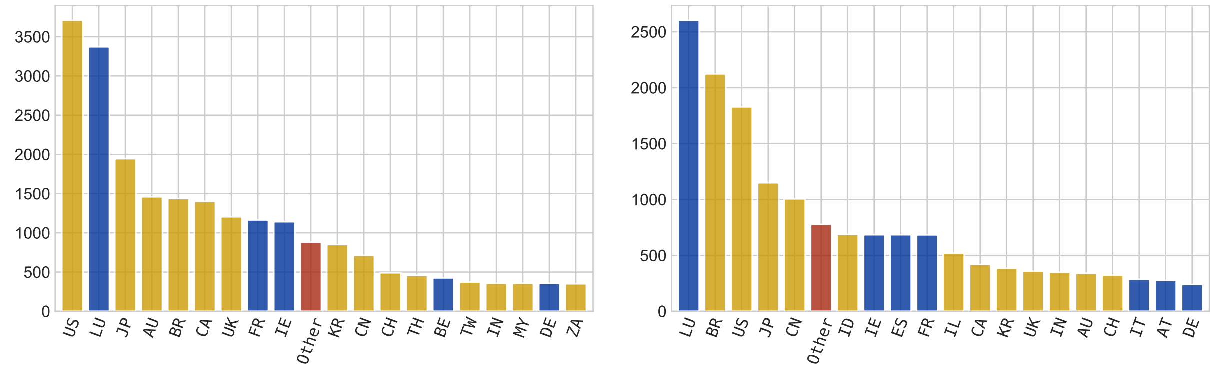
We construct a novel dataset on investment funds sourced from Refinitiv's Lipper IM database. We use fund-level portfolio information reflecting asset holdings from all primary open-end investment funds domiciled worldwide. Tables 3 and 4 in Appendix A provide descriptive statistics by country of domicile over the sample period. Our sample includes a total of 47,979 equity and 34,174 bond funds, throughout the whole sample period. This translates into 1,299,556 and 792,878 fund-quarter observations, respectively. Our sample does not only include active funds, but also merged and liquidated ones, which ensures our analysis is not affected by survivorship bias. The sample spans from 2003Q3 to 2017Q4[5] and we include all funds that have been active for at least one quarter.[6]

Figure 3 shows the number of active equity and bond funds domiciled in the top 20 countries by number of funds, reflecting the representativeness of our worldwide sample as of 2017Q4. By the end of the sample period, we cover a total of 25,440 and 17,581 equity and bond funds, respectively. Not surprisingly, several countries feature prominently, with the US, Luxembourg, Japan and Brazil sitting at the top for both equity and bond funds. Other European countries also rank highly as locations, with the UK, France and Ireland standing out in the case of equity funds, and Ireland, France and Spain in the case of bond funds. Funds domiciled outside of the 58 stressed countries (category "Other") represent a minor part of the sample.

We observe that our sample of worldwide funds is notably larger than previous studies, like

[5] The particular cut-off is due to reasonable data coverage for European funds starting from 2003Q3 within the Lipper IM database.

[6] A fund being active means that there is at least one quarter at which the fund reported a non-zero aggregated value. This particular choice as to the minimum lifetime of funds has little impact on our results. In our sample, 1.6% of equity funds were active only a year or less and they account for 0.16% of assets at most at any point in time. For bond funds they are 2.81%, representing at most 0.30% by assets at each quarter.



(a) Equity funds **(b)** Bond funds

Figure 3: Number of funds per country in our sample (top 20).
Sources: Lipper IM and authors' calculations.

Raddatz and Schmukler (2012), Brandao-Marques, Gelos, Ichiue, and Oura (2015) or Puy (2016). Also, compared to the official ECB investment fund statistics published for EA-domiciled funds, our dataset reveals a 59% minimum coverage for equity funds and 45% minimum coverage for bond funds, in terms of total assets[7], showing practically identical patterns in terms of trend. Additionally, our dataset covers the pre-crisis period, which public ECB statistics do not. Overall, our dataset contains information on a large sample of the investment funds industry, with a wide geographic coverage and different stages of the economic cycle.

In what follows, we consider only the assets which belong to the main asset class of a fund, i.e. the equity holdings of equity funds and the bonds holdings of bond funds. This is justified by historical data: on aggregate equity funds hold at least 28.3 times more equity than bonds, and bond funds hold at least 26.7 times more bonds than equity.[8]

We use information at the primary fund level as our unit of observation. Primary funds combine all different share classes (that is, shares issued with different management fees, expense ratios, investor type and investment mandate) that are available for an individual fund into a consolidated single primary fund. We find this approach reasonable, particularly for the purpose of aggregating by country, as explained in the following section. We use end-of-quarter observations, with a linear interpolation of missing information. The interpolation is done for cases of up to two consecutive missing values or at the beginning of the historical period, before 2006, where granular weights of portfolio allocations are missing.

[7] Ratio over the period with availability of the investment fund statistics, up to 2017Q4. Over the same period the median coverage is 60.9% for equity funds and 48.4% for bond funds. The maximum coverage is 67.1% for equity funds and 56.1% for bond funds.

[8] Minimum of the quarterly ratios between 2006Q4 and 2017Q4. Over the same period the median ratios between asset classes are 42.4 for equity funds and 99.0 for bond funds. The maximum ratios are 119.7 and 133.3 respectively.

Figure 4 represents the evolution of AUM comparing EA12-domiciled funds and RoW-domiciled funds at an aggregate level, for both equity and bond funds. In each panel, the plot to the left represents the number of funds in each region from 2003Q3 to 2017Q4. The plots to the right reflect the total value of assets held by EA12 and RoW funds, from a domicile perspective.

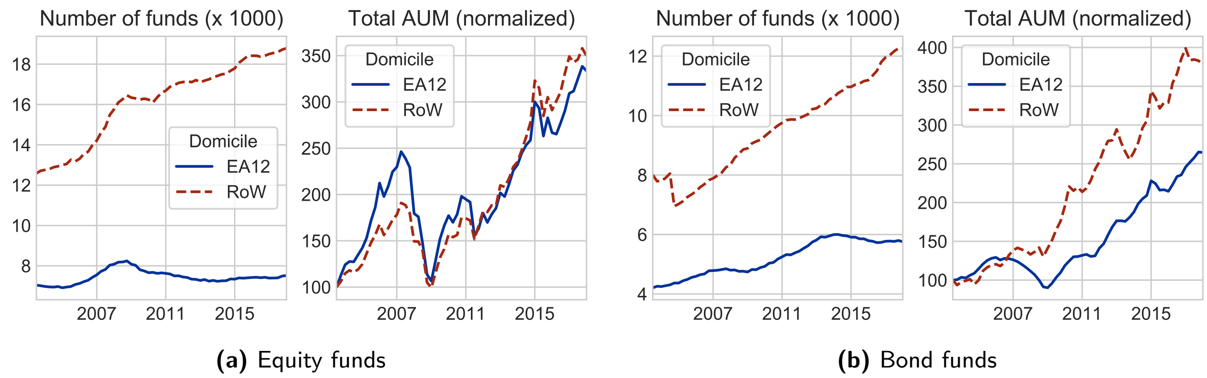


Figure 4: Evolution of the number of funds in the sample and their assets, with AUM values normalized to 100 at the beginning of the period for comparison.
Sources: Lipper IM and authors' calculations.

In line with Raddatz and Schmukler (2012) and Puy (2016), we observe two particular features characterising equity and bond fund flows in our data set: a high degree of cyclicality of country-level flows, and co-movement across countries. We observe that the number of EA12-domiciled equity funds has remained relatively unchanged since the global financial crisis, with bond funds increasing in number before stabilizing in 2013. This compares to a higher growth in the number of funds domiciled elsewhere in the world. Nonetheless, in terms of total AUM the observed growth trend in EA12 funds has been coupled to developments in funds domiciled elsewhere, although with a downward level shift. The global financial crisis has had a strong impact on equity funds, with a similar magnitude for EA12 and RoW funds. The sensitivity to the crisis has been less severe for bond funds, although bond funds in EA12 countries were more affected compared to RoW bond funds.

Unsurprisingly, our plot of equity AUM is very similar to the one done by Fricke and Fricke (2017) who restricted their study to US-domiciled equity funds. Moreover, we can extend to bond funds their observation that the market has become increasingly concentrated over the sample period, as the asset holdings have increased faster than the number of funds.

2.2 Measurement of country portfolio flows

For the purpose of estimating country portfolio flows, 58 countries are included in our analysis. These are selected based on countries usually incorporated in global market indices. In particular, we select countries included in the MSCI Europe, US, Emerging Markets and World reference indices.[9]

Building on specific fund-level asset holdings by country over time, we compute quarterly country-specific asset pools for each asset class (that is, equity and bond).[10] We then calculate aggregate country portfolio flows using an expanded version of the approach in Brandao-Marques, Gelos, Ichiue, and Oura (2015). The adjustment takes into account valuation effects, i.e. fund-level returns and additional foreign exchange effects. In the rest of this paper, country portfolio flows are sometimes referred to as "flows" for simplicity.

We fix an asset class Θ, which can be either equity or bond, and denote by $\mathrm{F}(\Theta)$ the set of dedicated funds (that is, either equity funds or bond funds). For each fund $f \in \mathrm{F}(\Theta)$ and quarter t, A_t^f denotes the total net assets of fund f at the end of t. Moreover, the portfolio of each fund comprises asset holdings invested in different countries. We decompose the value A_t^f in terms of asset types and country allocation. For a given country c, we know $\theta_t^{f,c}$ the value of assets Θ held by fund f invested in c at the end of t.

We then define the total funds' investment in country c as follows.[11] Let c be a country and t a quarter, then the value of funds' assets of class Θ invested in country c at the end of t is given by:

$$\mathrm{Inv}_t^{\Theta,c} = \sum_{f \in \mathrm{F}(\Theta)} \theta_t^{f,c} \,. \tag{1}$$

To compute country portfolio flows adjusted by valuation and foreign exchange effects, we follow the approach in ECB (2006). The percentage returns for fund f at quarter t are given by R_t^f. Since this data has no geographical granularity we have to assume that, for each fund and at each quarter, its return rate is uniform across all countries, which we can write as $\forall c, \mathrm{R}_t^{f,c} = \mathrm{R}_t^f$. It means that the assets of an individual fund are performing identically between the different countries in which it invests.[12]

[9] The 58 countries in our sample, from a portfolio perspective, are the 28 members of the European Union (including the United Kingdom) and the following: Australia, Brazil, Canada, Chile, China, Colombia, Egypt, Hong Kong, India, Indonesia, Israel, Japan, Korea, Malaysia, Mexico, New Zealand, Norway, Pakistan, Peru, Philippines, Qatar, Russian Federation, Singapore, South Africa, Switzerland, Taiwan, Thailand, Turkey, United Arab Emirates and United States.

[10] Similarly to figure 4, we can compare the evolution of assets invested in the EA12 and in the rest of the world (instead of using the domicile of the funds). We observe that, for both fund and equity, the evolution of total assets has followed a very similar pattern in the two regions.

[11] The values by portfolio are based on a subset of total AUM, and do not integrate all of what is represented in figure 4, due to incomplete reporting and investments in countries out of the exercise. Nonetheless, these discrepancies are rather marginal: in 2017Q4 for equity funds we know where 94% of assets are invested (11.0 trillion out of 11.7), and 82% for bond funds (6.4 trillion out of 5.3). These ratios are relatively stable over time for both asset classes.

Moreover, this measure is robust to country-specific structural breaks, which could arise due to changes in regulation for example. Indeed, funds of all countries are considered together, which mitigates brutal variations that could happen in one.

[12] Although this assumption may seem strong, it is reasonable since many funds are specialized. It means that,

Thus, the nominal return of a fund in c during quarter t is given by $\theta_{t-1}^{f,c} \cdot \mathrm{R}_t^f$. Summing over $\mathrm{F}(\Theta)$ and dividing by the country total, we obtain the overall funds' return rate in c, referred to as the valuation component:

$$\tilde{\mathrm{R}}_t^{\Theta,c} = \frac{\sum_{f \in \mathrm{F}(\Theta)} \theta_{t-1}^{f,c} \cdot \mathrm{R}_t^f}{\mathrm{Inv}_{t-1}^{\Theta,c}} . \tag{2}$$

Foreign exchange effects, reflecting exchange rate returns, are calculated based on the assumption that transactions take place at the quarterly average exchange rate. This feature goes beyond the approach in Brandao-Marques, Gelos, Ichiue, and Oura (2015), providing a novel extension by disentangling transaction flows from both valuation and foreign exchange effects. For quarter t, we denote by e_t^c the end-of-quarter exchange rate in country c to the euro, and by $\hat{e}_t^c$ the quarterly average exchange rate. Then, foreign exchange effects are given by summing gains before and after transactions:

$$\mathrm{FX}_t^{\Theta,c} = \frac{1}{\mathrm{Inv}_{t-1}^{\Theta,c}} \left(\frac{\hat{e}_t^c - e_{t-1}^c}{e_{t-1}^c} \times \mathrm{Inv}_{t-1}^{\Theta,c} + \frac{e_t^c - \hat{e}_t^c}{e_t^c} \times \mathrm{Inv}_t^{\Theta,c} \right) . \tag{3}$$

Foreign exchange effects are considered under the assumption that portfolio assets are denominated in the local currency corresponding to the issuer country of domicile. For example, Chilean bond/equity securities, held by a fund in its portfolio of assets, are assumed to be denominated in Chilean Peso given the entities issuing such securities are domiciled in Chile. This assumption is supported by ECB (2018), although the share of assets issued in Euro or US Dollar is non negligible for some emerging economies.

With this, unadjusted and adjusted flows are defined respectively as

$$\mathrm{Flows}_t^{\Theta,c} = \frac{\mathrm{Inv}_t^{\Theta,c} - \mathrm{Inv}_{t-1}^{\Theta,c}}{\mathrm{Inv}_{t-1}^{\Theta,c}} \qquad \text{and} \qquad \overline{\mathrm{Flows}}_t^{\Theta,c} = \mathrm{Flows}_t^{\Theta,c} - \tilde{\mathrm{R}}_t^{\Theta,c} - \mathrm{FX}_t^{\Theta,c} . \tag{4}$$

In addition, flows, partially adjusted for valuation effects or foreign exchange effects, are also computed. This is meant to provide more robustness and is necessary for the stress test projections below, in order to disentangle transactions from valuation and foreign exchange effects. More precisely, we refer to flows given by $\mathrm{Flows}_t^{\Theta,c} - \tilde{\mathrm{R}}_t^{\Theta,c}$ as valuation adjusted and to flows given by $\mathrm{Flows}_t^{\Theta,c} - \mathrm{FX}_t^{\Theta,c}$ as forex adjusted.[13]

when considering one country c, a large part of the assets invested there are held by funds which are specialized in c or a slightly broader region. Therefore, the return rates of these funds will reflect closely what we want to capture, and they will have an important weight in equation 2.

An alternative approach would be to take the growth in country-level price indexes obtained from other sources. For equity in particular, country returns from MSCI are strongly correlated with the aggregate returns of funds in our sample. This would require the same simplifying assumption than made in Raddatz and Schmukler (2012) where returns made in country c are identical for all funds f that invest there.

[13] Future work is expected to enhance our analysis by including the calculation of alternative measures. Adjusted flows could be further assessed as in Raddatz and Schmukler (2012), in order to disentangle the investor and asset

2.3 Stress testing scenario data

The set of covariates selected for the purposes of stress testing investment funds reflects the scenario narrative given by the ESRB General Board in ESRB (2018a), which was developed for the 2018 EU-wide stress test, coordinated by the EBA. For stress testing purposes other more simplistic scenarios could have been used with an aim to focus on a liquidity perspective or historical financial market stress episodes in particular. In our study, however, we refrain from this as our goal is to explicitly model a link between lower-frequency macroeconomic scenarios, country portfolio flows and fund liquidations.

The scenario for the 2018 EU-wide stress test identifies four systemic risks as representing the most material threats to the stability of the EU financial sector:

1. Abrupt and sizeable repricing of risk premia in global financial markets (that is, triggered by a policy expectation shock) leading to a tightening of financial conditions;
2. Adverse feedback loop between weak bank profitability and low nominal growth, amid structural challenges in the EU banking sector;
3. Public and private debt sustainability concerns amid a potential repricing of risk premia and increased political fragmentation;
4. Liquidity risks in the non-bank financial sector with potential spillovers to the broader financial system.

The main macro-financial variables considered include: GDP, unemployment rate, HICP, residential and commercial real estate prices, stock prices, long-term rates, exchange rates, foreign demand and commodity prices, swap rates and corporate credit spread indices. Nonetheless, the availability of macro-financial variables varies across countries, in particular for non-EU or smaller countries. Each of the considered macro-financial variables has associated baseline and adverse scenario projections for EU countries and for a selection of non-EU countries. Baseline projections for EU countries are sourced from respective National Central Banks' forecasts. For non-EU countries, baseline projections are based on forecasts sourced from the IMF World Economic Outlook (WEO) as of October 2017.[14]

Projections for non-EU countries, which are in some cases not covered in the 2018 EU-wide stress test macro-financial scenario, are proxied with available country projections. We assign to missing countries the average of the projections of countries for which information is available, matched by rating proximity in 2017. The rating criterion is forward-looking and hence better

manager components. Additional measures of foreign exchange returns could take as base currency that of the funds' country of domicile and that of the fund shares' currency of denomination. This would help to shine more light on the impact of flows and foreign exchange effects.

[14] The baseline for Norway is provided by the Norges Bank.

suited than alternative approaches for scenario projections. For every country in the sample, ratings from Standard & Poor's on domestic and foreign currency are used. Ratings are converted into default rates (Witte, Debnath, and Iyer, 2018). For cases where the default rates are not available, we estimate missing information via interpolation. The overall default rate r^c for each country is computed as the average of the domestic and foreign currency default rate. The country matching works such that, if projections for country c are missing, and:

1. if other countries with projections have the same overall default rate r^c, then we impute the projections for those countries;
2. otherwise, among countries with higher default rates (that is, ratings worse than c), we consider the closest to c.

3 Modeling approach: Bayesian model averaging

In a first step, we employ a Bayesian model averaging (BMA) methodology with the aim of developing robust models, by avoiding the risk of "hand-picking" equations and therefore reducing model uncertainty (Gross and Población, 2017).

3.1 The general principle of the BMA

The BMA relies on the assumption that no single model is the only true one, and it therefore operates with a pool of models, to which weights are assigned. The individual models are combined to a posterior model using these weights, reflecting the relative performance of each model. A detailed description of the more general theoretical framework is given in Appendix B.

In our case we work with a class of linear models, such that each model can be described by a vector ϕ of coefficients. We consider a series $(\phi_i)_i$ of such models, which are contained in a set Φ. We average these models based on their posterior probabilities (see equation 17 in Appendix B), to get the expected vector of coefficients that will be our estimated model:

$$\tilde{\phi} = \sum_i \mathbb{P}(\phi_i | y) \cdot \phi_i \tag{5}$$

where y is the observable, i.e. here the historical maro-financial data.

We choose this method, combined with the linear models presented below, as it suits well the use of a scenario with a pre-determined path for exogenous variables over several periods. In comparison, models like panel VARs or GVARs would not address this as they rely on multiple endogenous variables, which does not allow for the translation of an exogenous scenario path. There is also no interest in capturing the dynamics between macro-financial variables, since these have already been taken into account in the scenario generation. Similarly, the likes of principal component analysis would be interesting but do not yield results that can be fed with such a scenario.

3.2 Determining the models

Let us first define Φ. We have a dependent variable Y, representing flows as defined in equation 4, and a set of predictor variables $(X^k)_{1\leq k\leq K}$. The predictor variables are our country-level series, such as GDP growth, unemployment, interest rates, etc. There are $K = 26$ such predictor variables in total, although the number is lower for non-EU countries as not all variables are available.

Our parameter space is built on Autoregressive Distributed Lag (ARDL) model structures, where the dependent variable is allowed to be a function of its own lags, as well as contemporaneous and possibly further lags of the set of predictor variables:

$$Y_t = \alpha + \lambda_1 Y_{t-1} + \ldots + \lambda_p Y_{t-p} + \sum_{k=1}^{K} \left(\sum_{q=0}^{p_k} \beta_{k,q} X^k_{t-q} \right) + \varepsilon_t \tag{6}$$

where p is the maximum lag of Y, p_k is the maximum lag of X^k and ε_t is the error term. The coefficients α, $(\lambda_q)_q$ and $(\beta_{k,q})_{k,q}$ constitute the parameter vector ϕ of the model.

Each model ϕ_i corresponds to a distinct subset of predictor variables $\mathscr{X}_i \subset \{X^1,\ldots,X^k\}$. In order to have non-redundant models (see equation 12 in Appendix B) we impose $\beta_{k,q} \neq 0$ for some $q \geq 0$ when $X^k \in \mathscr{X}_i$. In addition, we force the lag structures of the autoregressive part and of exogenous predictors to be "closed", that is, without gaps.[15] On the other hand, we do not impose any sign constraint.

Thus, to select ϕ_i, we compute models for all lag structures with $0 \leq p \leq 2$ and $0 \leq p_k \leq 2$ for each k. For instance, with two predictor variables, that makes a total of $3 \times 3^2 = 27$ models to estimate. For every lag structure, we employ an ordinary least squares (OLS) regression to estimate the coefficients. Then, ϕ_i is taken from the lag structure that minimizes the Bayesian Information Criterion (BIC, also called Schwarz information criterion).

A consequence is that the number of computations increases exponentially with the number of predictor variables involved. This motivates the choice of the set $(\phi_i)_i$ of models considered, by imposing a restriction on the size of $\mathscr{X}_i$. In our simulations, with a limit of four predictor variables[16], the number of models is given by $I = \sum_{j=0}^{4} \binom{K}{j}$. With $K = 26$, that makes $I = 17,902$.

[15] According to Gross and Población (2017), a setup with possible gaps leads to similar results, while considerably increasing the number of computations required.

[16] If all combinations of predictor variables were considered, the number of models would be $I = 2^K$.

3.3 Calculating the final model

Explicit values for the posterior model probabilities $\mathbb{P}(\phi_i|y)$ are required to obtain our final model. The Bayes' formula comes into play here as we have

$$\mathbb{P}(\phi_i \mid y) = \frac{f(y|\phi_i) \cdot \mathbb{P}(\phi_i)}{f(y)} \propto f(y|\phi_i) \cdot \mathbb{P}(\phi_i) \tag{7}$$

with f the density of Y, so that $f(y|\phi_i)$ is the likelihood of the model. In our case, we take $\mathbb{P}(\phi_i \mid y)$ as the BIC weight of ϕ_i, whereby $\mathbb{P}(\phi_i)$ is defined in the formula above as a function of the sample size and number of right-hand side variables. As documented in Fragoso, Bertoli, and Louzada (2018) this is the most standard approach when using non-uniform priors.[17]

Another object of interest, besides the posterior model parameters, is the probability for a particular predictor to be included in the model space, the posterior inclusion probability of a predictor variable X^k. The posterior inclusion probability is computed as the sum of the posterior model probabilities that contain the particular predictor. A predictor variable is said to be significant in the posterior model if the corresponding posterior inclusion probability exceeds the prior inclusion probability.[18]

Furthermore, we present the model structure in terms of long-run multipliers (LRM) with respect to a predictor variable X^k. The LRM of X^k is defined by

$$\text{LRM}_k = \sum_{l=0}^{\infty} \frac{\partial \mathbb{E}[Y_{t+l}]}{\partial X_t^k} = \frac{\beta_{k,0} + \ldots + \beta_{k,q}}{1 - \lambda_1 - \ldots - \lambda_p} \tag{8}$$

where the coefficients are those of the final models, with the same form as in equation 6. Moreover, the LRM is normalized by basing the LRM on normalized posterior model coefficients. A coefficient is normalized by multiplying the initial coefficient estimate by the ratio of the standard deviations of a predictor and the dependent variable. Thus, the normalized LRM of X^k is

$$\widetilde{\text{LRM}}_k = \text{LRM}_k \times \frac{\text{std}(X^k)}{\text{std}(Y)} \ . \tag{9}$$

This comes with the advantage that normalized multipliers can be compared across predictor variables within a model as well as across models (countries).

[17] See Raftery (1999) for a conceptual discussion on the use of the BIC and its comparative merits. In our simulations, whenever tested, the replacement of the BIC by the AIC has had no significant impact.

[18] Formulae regarding prior and posterior inclusion probabilities are discussed in detail in Sala-I-Martin, Doppelhofer, and Miller (2004).

3.4 Density of projected flows

The BMA, by nature, is meant to tackle the issue of model uncertainty, which is especially important in the case of high-dimensional models. Nonetheless, this leaves open the issues of coefficients' uncertainty and residual uncertainty. The posterior coefficients $\tilde{\phi}$ given by equation 5 correspond to our central simulations. As a robustness check, we estimate possible deviations from it, and also take into account the error terms of our models when we use the coefficients. More precisely, there exists a density of possible values for projected flows, from which we pick some quantiles of interest.

Let us denote by T_{proj} the projection period, from 2018Q1 to 2020Q4. Let $N \in \mathbb{N}$ be the number of simulations over which we compute the quantiles. We then generate N series of the form $(y_t^n)_{t \in T_{\text{proj}}}$, $1 \leq n \leq N$, from which we get series $(\gamma_t^p)_{t \in T_{\text{proj}}}$ for each quantile of interest p, representative of the density of projected flows. More formally, the density of projected flows is estimated as follows:

1. For every $1 \leq n \leq N$ and every model i, we draw a coefficient vector $\tilde{\phi}_i^n$ based on the posterior coefficient means ϕ_i and its associated posterior covariance matrix, assuming that the coefficients are multivariate normal. This reflects the coefficients' uncertainty.
2. For every $1 \leq n \leq N$, we have a model $\tilde{\phi}^n = \sum_i \mathbb{P}(\phi_i|y) \cdot \tilde{\phi}_i^n$ and predictor variables (X^k) available until the end of T_{proj}. So we generate a path $(y_t^n)_{t \in T_{\text{proj}}}$, following formula 6, by adding residuals $(\varepsilon_t^n)_{t \in T_{\text{proj}}}$. To do so, at any point $t \in T_{\text{proj}}$ we draw ε_t^n from a normal distribution with mean zero and standard deviation equal to the historical standard deviation of residuals under model $\tilde{\phi}^n$. This reflects the residuals' uncertainty.
3. Given a quantile $0 \leq p \leq 1$ we define a path $(\gamma_t^p)_{t \in T_{\text{proj}}}$, such that, for every $t \in T_{\text{proj}}$, γ_t^p is the quantile p of the distribution $\left\{y_t^n, 1 \leq n \leq N\right\}$.

Step 3 is repeated for different values of p, using the same pool $\left\{(y_t^n)_t, 1 \leq n \leq N\right\}$ of paths. When we refer to the 50$^{\text{th}}$ quantile however, this is the result of using directly ϕ with no simulated residuals, since it is the expected value. All the other quantiles are simulated by this algorithm.

4 Mapping projected country-level flows to the fund level

In a second step, we combine our projected country portfolio flows with the available fund-level information on country-level asset holdings. We refer to this technical implementation as a propagation exercise, as it propagates the stress from the projected country portfolio flows to the individual fund level. More precisely, we employ the projected country portfolio flows from the BMA output: the unadjusted flows $\text{Flows}_t^{\Theta,c}$, the adjusted flows $\overline{\text{Flows}}_t^{\Theta,c}$ and the partially adjusted ones. We do this for all countries c and with t taken over the projection period T_{proj}, from 2018Q1 to 2020Q4. In practice, the propagation exercise is the same for each type of flows, so for brevity of exposition we use only the unadjusted ones in this section.

Moreover, for flows there is not only one value per quarter and country that we know, but different values, which correspond to different scenarios: the baseline and adverse scenario, which relate to different exogenous paths of the same predictor variables, over T_{proj}. For the adverse scenario, we generate a density of projected flows represented by different simulation quantiles, as explained in 3.4. In the context of projected flows under the adverse scenario, we refer to the "median adverse scenario" when there is no ambiguity, i.e. the basic expected values, or the 50$^{\text{th}}$ quantile, given by the BMA. We will not precise which scenario we use in what follows as, again, the mechanism is the same for all of them.

Let t_h denote the last quarter before the projection period, i.e. 2017Q4. The last historical asset holdings $\theta_{t_h}^{f,c}$ (as introduced in 2.2) are known for every pair of fund f and country c. We assume that the flows of each country equally affect all corresponding assets of the same asset class: the assets invested in c by different funds are similarly changing. Therefore, we apply to $\theta_t^{f,c}$ the same relative flows that we found for c as a whole:

$$\forall t \in T_{\text{proj}}, \forall c, \quad \theta_t^{f,c} = \theta_{t-1}^{f,c} \cdot \left(1 + \text{Flows}_t^{\Theta,c}\right) . \tag{10}$$

Let $\psi^f = A_{t_h}^f - \sum_c \theta_{t_h}^{f,c}$ be the amount that, at the end-of-the sample period, is held by fund f but not stressed as part of the scenario, because not part of this asset class or invested in other countries. From equation 10, by combining changes since the start of the projection and summing over countries of investment we get

$$\forall t \in T_{\text{proj}}, \quad A_t^f = \psi^f + \sum_c \left(\theta_{t_h}^{f,c} \cdot \prod_{t_h < \tau \leq t} \left(1 + \text{Flows}_\tau^{\Theta,c}\right)\right) . \tag{11}$$

Our focus is then on the evolution of $A_t^f / A_{t_h}^f$, derived from equation 11, which represents the fund-level impact of projected country portfolio flows, independently of the original size of the fund. Thus, the effect of the scenario on one fund is a compound of effects in different countries, with a unique aggregation determined by the country-weights, reflecting its pre-shock investment strategy. In the next section, we study the distribution of fund-level changes in AUM, which we, in particular, distinguish by domicile for EA12 countries.

A variation of equation 11 is used to compute the effect of stress coming from one region only, as presented in table 1. In that case, the same principle is applied, but considering that flows in non-stressed countries are equal to zero in equation 11. For instance, to assess the effect of the stress in the EA12 only, we impose $\text{Flows}_t^{\Theta,c} = 0$ for any country c in RoW and any quarter $t \in T_{\text{proj}}$.

A consequence from equation 10 is that the portfolio allocation of funds is evolving. By comparing the different kinds of flows, we disentangle what is passive reallocation (i.e. valuation and foreign exchange effect) and the active rebalancing by the fund (referred thereafter as transactions). In the latter case, we do not decompose nor make explicit assumptions about the respective contributions of managers and investors, but the transactions that we capture are a compound of both.

Altogether, the cross-country heterogeneity of reallocations will change the relative country weights for each fund. This is in line with the recursive computation of country weights, which is done in Raddatz and Schmukler (2012), relying on the relative importance of returns and net flows in each country. In our method, the contribution of those different components is disentangled later on, by comparing the results obtained with different types of flows, and we add the foreign exchange effect to it.

5 Results

We present three sets of results. First, we examine the output of the BMA in terms of projected country portfolio flows. Second, we assess the impact of projected country portfolio flows on fund-level AUM.[19] Third, we translate these results into expected fund liquidations. Given our analytical framework integrates multiple observational and geographical dimensions, each set of results is selective for the purpose of presentation.

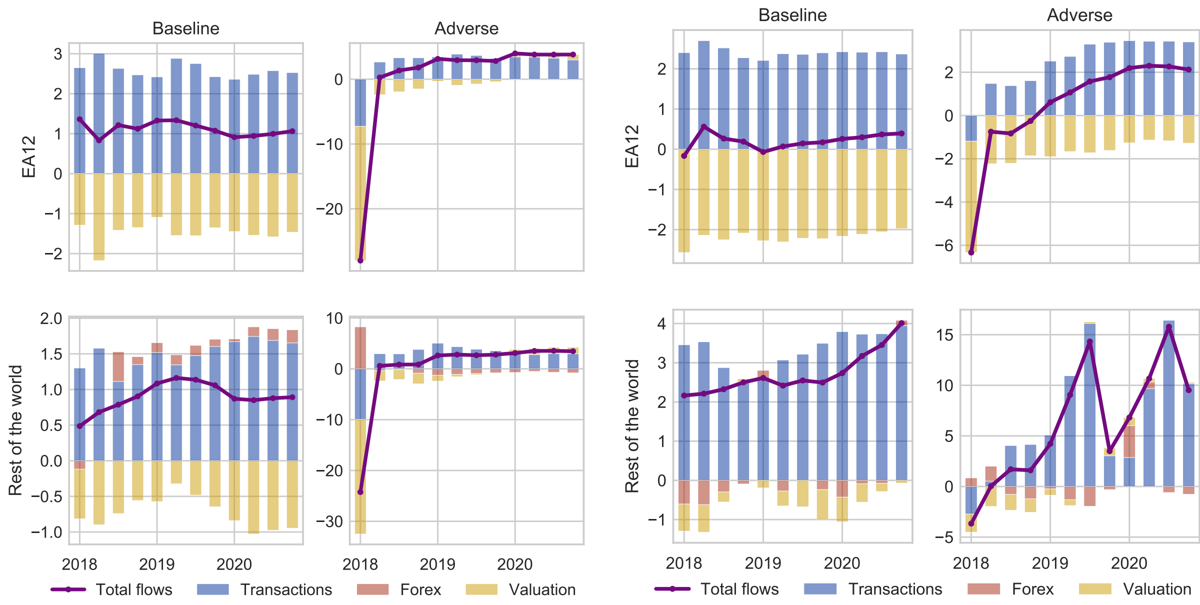
5.1 Projected country portfolio flows

We hereby present the results corresponding to step one in our modelling approach (that is, the BMA output), in terms of projected country portfolio flows. The BMA itself defines individual models for each country portfolio, which are interpreted through the lens of LRMs. LRMs and inclusion probabilities, reflecting significance levels, are presented in Appendix C. In particular, the quarterly returns on equity stock prices are a key driver of unadjusted equity flows. Short-term rates and exports also appear as relatively important predictors for equity flows when looking at EU countries. For bond flows, stock prices are also a prominent factor, although to a lesser extent than for equity. Overall, bond flows react more heterogeneously across countries. On EU

[19] Cyprus is excluded from aggregate figures and from the propagation exercise in the case of bonds as the BMA yields unrealistic estimates in this case. This is explained by a quality deficiency of the input data and its short coverage in time.

countries many other predictor variables are of importance, although sometimes only to a moderate subset: GDP growth, spread, long-term rates, short-term rates, investment, unemployment, residential property prices and inflation.

Figure 5 shows country portfolio flows and the individual contributions of its components, aggregated for EA12 and RoW countries, considering the baseline and adverse scenario developed for the EBA 2018 EU-wide stress-test.[20] Foreign exchange effects are, by design, not observed in the case of EA12-country portfolio flows. Not surprisingly, projected country portfolio flows under the adverse scenario are considerably larger compared with the baseline.



(a) Equity flows **(b)** Bond flows

Figure 5: Portfolio flows, in percentage points, over the projection horizon. "Total flows" refer to the unadjusted flows of equation 4, "Forex" and "Valuation" are as defined in equations 3 and 2 respectively, "Transactions" refer to the adjusted flows defined in equation 4. The countries in each region are weighted by their AUM, so that the flows given match the definition of subsection 2.2 when the aggregation of assets is done at the level of the whole region.
Sources: Lipper IM, ESRB EBA and authors' calculations.

In the case of equity funds, we observe a large drop in the first quarter of the projection horizon under the adverse scenario, of which more than two thirds are due to valuation effects, and a sharp reversion in the following quarter. The EA12 and RoW country portfolio flows present little differences overall, including in the first quarter under the adverse scenario. Except for this quarter, the valuation effect and transactions generally tend to offset one another, in a similar fashion for both regions. For RoW countries, the foreign exchange component is observed in the

[20] Individual country portfolio flows based on the adverse scenario are available in Appendix D.

case of equity funds under the adverse scenario, partially off-setting negative transactions in the first quarter of the projection horizon, though with a marginal impact more generally throughout the rest of the projection horizon.

For bond funds, projected country portfolio flows are smaller than in the case of equity funds. In EA12 countries, they are about four times smaller under the adverse scenario. This is primarily an embedded feature of the underlying macro-financial scenarios, though presumably it may also reflect the fact that equity prices are a driving factor weighing heavily in our models, while bond flows react more to other factors and not always in the same direction between countries. Projected RoW country portfolio flows also present more volatility throughout the projection horizon, which is likely explained due to the varied nature of assets in bond portfolio holdings. We observe a relatively small drop in the first quarter of the projection horizon for EA12 and RoW countries under the adverse scenario, mainly driven by valuation effects in the case of EA12, which reverts in the following quarters for both regions. Interestingly, for RoW flows under the adverse scenario, we observe strong positive transactions, up to more than 15%.

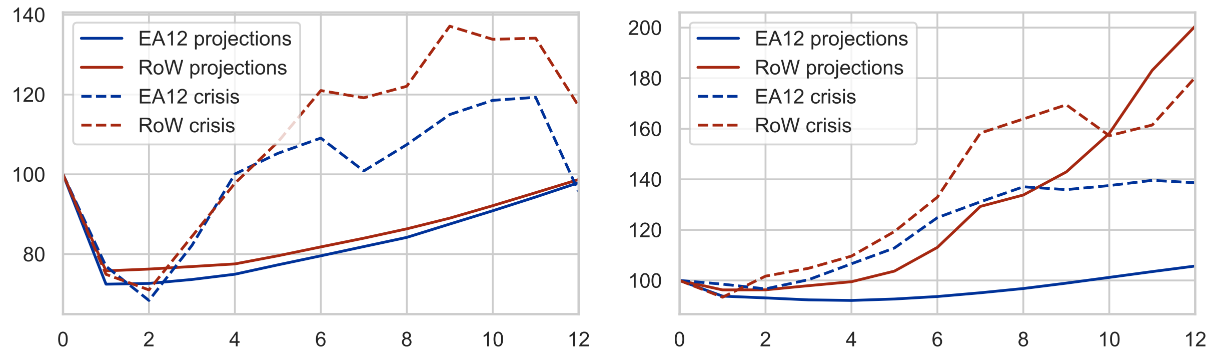
All in all, our results point to a heterogeneous impact of macro-financial scenarios. This underscores the relevance of an integrated stress testing approach considering country-specific scenarios through which shocks to fund country portfolios are induced. Potential financial stability externalities can also be inferred from these results in terms of valuation effects, in particular as valuation effects account for a large part of the drop.

To give a better idea of the meaning of these flows, we plot in figure 6 the evolution of the aggregated investment stock value under the adverse scenario. This is an integrated version of our flows results, as can be inferred from equation 4. We separate again the EA12 countries from the rest, and we compare the evolution with that of the global financial crisis, picking 2008Q3 as time 0 since the drop in AUM was the sharpest between 2008Q3 and 2008Q4.[21]

Interestingly, the drop in AUM equity is very similar under our simulations and during the crisis. Nonetheless, under our simulations we observe a slower recovery than the one observed from 2008Q4 onwards. This can be partially explained as equity AUM had been decreasing before 2008Q3 already, so this quicker recovery was actually just a bounce-back to pre-crisis values, and not really exceeding it.

In the case of bond AUM, in line with our results on flows, we observe a larger discrepancy between EA12 and RoW. The AUM was also quicker to recover during the global financial crisis, but possibly for the same reason as equity.

[21] This is observed for both bond and equity funds over our historical period, when looking at aggregate flows to both EA12 and the rest of the world.



(a) Equity

(b) Bond

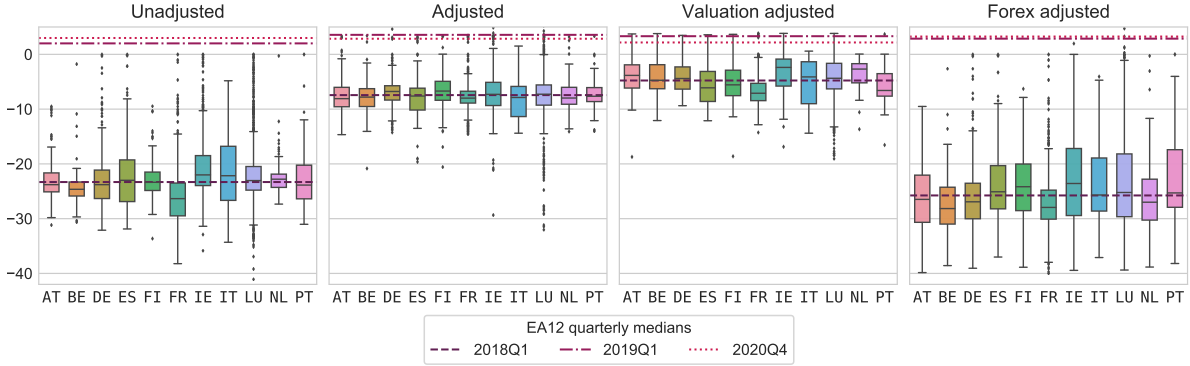
Figure 6: Aggregated AUM by country portfolio, per quarter, normalized to 100 in 2017Q4.
Comparison between projections (2017Q4 as quarter 0) and historical data of the global financial crisis (2008Q3 as quarter 0).
Sources: Authors' calculations, Lipper IM data and EBA 2018 scenarios.

5.2 Fund-level propagation

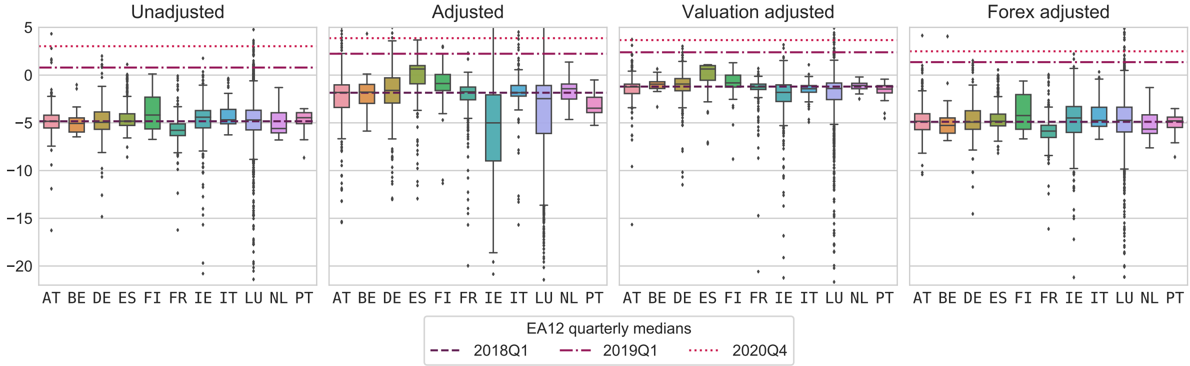
In this subsection we show the results for step two in our model design. Following the technical implementation described in section 4, we analyse the impact of country portfolio flows, as projected in step one, at the individual fund level, along a three year horizon, conditional on specific fund-level country portfolio holdings. Although our results are available for funds domiciled worldwide, we focus particularly on equity and bond funds domiciled in EA12 countries.

Figure 7 presents projected changes in AUM under the adverse scenario for individual equity and bond funds in the first quarter of the projection horizon. They are based on the different types of flows, that is, from left to right: unadjusted, adjusted, valuation and foreign exchange adjusted. Moreover, we also plot the median of changes in AUM on several quarters, over EA12-domiciled funds. Overall, the adverse macro-financial scenario channelled through country portfolio flows has a much larger impact on EA12 equity funds than on bond funds, resembling the flows projections presented in the previous subsection. The impact is more prominent at the short end of the projection horizon and it reverts in the following quarter, with a sharper reversion in the case of equity funds.

In the case of equity funds, with no flows adjustment, we observe a median drop in AUM of around 25% in the first quarter of the projection horizon. There is some heterogeneity across countries, with lower quartiles in France and Spain standing closer to 30%, and more outliers observed in the case of Luxembourg as an international financial centre. Valuation effects appear as a major component driving changes in AUM for equity funds, accounting for approximately 20% of the drop. These results are in line with Bubeck, Habib, and Manganelli (2018), where



(a) Equity funds



(b) Bond funds

Figure 7: Distributions of fund-level AUM changes in 2018Q1 under the adverse scenario, for EA12 funds grouped by domicile.
The lowest whisker is the minimum of the data points within a distance of 1.5 inter-quartile range (IQR) of the first quartile. The upper whisker is the maximum of the data points within a distance of 1.5 IQR of the third quartile. Greece is excluded as it does not have enough funds reporting at that time.
The median over all EA12 funds is computed for three selected quarters of the projection horizon and represented as horizontal lines. The scales have been harmonized for each asset class, such that some outliers may not be represented. The types of flows are defined at the end of subsection 2.2.
Sources: Lipper IM and authors' calculations.

the impact of valuation in EA investment funds is more prominent compared to active portfolio reallocation via investor transactions, at least as explained from a monetary policy channel.

For bond funds, the range of changes in AUM based on unadjusted flows is narrower than that of equity funds, with a median drop of around 5% in the first quarter of the projection horizon. We observe a lesser degree of cross-country heterogeneity compared to equity funds, but a much more prominent dispersion in the case of Luxembourg and Ireland.

5.3 Fund liquidations

In the context of prudential policy measures, we estimate in this subsection the number of fund liquidations that may occur under the adverse scenario. To estimate this number we decide on a threshold of flows below which we consider that a fund liquidates. The threshold itself is determined through back-testing on historical data, based notably on the signal-to-noise ratio of each threshold and the percentage of liquidations that it predicts. The details related to this back-testing are given in Appendix E. The selected threshold is a drop of 30% in AUM, which we apply for both bond and equity funds, and is implemented for unadjusted flows.

From a regulatory and a prudential policy perspective, different tools may be put in place to address run-like events. In AMF (2017), for example, the French financial regulator describes the use of redemption gates, to "spread out redemption requests over multiple net asset values". For instance, an illustrative monthly threshold of 20% is given to apply a gate. Although such a mechanism is not explicitly integrated in our model, our threshold analysis suggests that a 30% drop in AUM could be used as a maximum quarterly threshold to trigger prudential policy tools, such as redemption gates. This could reduce the amount of overall fund liquidations and the potential for related fire sales.

In what follows, we focus on fund liquidations based on the adverse scenario in 2018Q1, i.e. the first quarter of the projection horizon.[22] Our results - with unadjusted flows - for all funds included in the sample are summarized as follows:

- 3.4% of equity funds would liquidate, representing 1.8% of total assets,
- 3.4% of bond funds would liquidate, representing 0.6% of total assets.

In the case of equity funds, the geographical distribution of liquidations follows roughly the original distribution of funds. The difference between the ratio of funds and the ratio of assets can be interpreted as the fact that smaller funds are more affected. This could be due to the fact that they have a less diversified portfolio, meaning that if they invest mostly in a severely stressed country, their performance will plunge alike.

In the case of bond funds however, we interpret our results more cautiously. Indeed, the liquidations under the adverse scenario seem to be largely driven by Chinese assets, which makes sense since our model yields extreme results for flows in China. Thus, the difference between the ratio of funds and ratio of assets liquidated could simply reflect the fact that bond funds with a large exposure to China tend to be small on average.

We present more detailed results in table 2, looking at EA12-domiciled funds. On this set of countries, the conclusion is different: equity funds are much more affected than bond funds. Taking EA12 as a whole, we find a ratio of liquidations of 5.8% for equity funds (4.6% in terms of assets), and 0.5% for bond funds (0.1% in terms of assets) under the adverse scenario.

[22]Although some liquidations are predicted in the subsequent quarters, the number is comparatively negligible, which is in line with the results presented in the previous section, showing a rapid reversal after the shock.

For equity funds, we observe a particularly high ratio of liquidations in France (19.7%), Spain (9.9%) and Italy (9.4%) under the adverse scenario, also showing similar ratios of liquidated assets. It has to be noticed that, as we can infer from figure 7, valuation effects are a key driver of liquidations. For illustrative purposes, we apply in table 2 the same threshold to flows adjusted for valuation. Then the number of liquidations is zero for equity and negligible for bonds. Looking in particular at France, its drop in stock prices given by the scenario is important, which translates into large negative valuation effects and total flows at the country level. Then, since French funds have a lot of French assets in their portfolio they are in turn strongly affected.

	Ratio of funds liquidated (%)					Ratio of assets liquidated (%)				
Flows	unadj			valadj	-	unadj			valadj	-
Projection quantile	50	25	75	50	crisis	50	25	75	50	crisis
Austria	1.3	39.9	0.6	0.0	0.9	1.3	52.0	0.3	0.0	0.0
Belgium	3.9	36.8	0.0	0.0	2.4	8.4	37.6	0.0	0.0	1.0
Finland	3.1	33.6	0.8	0.0	0.0	0.3	34.5	0.0	0.0	0.0
France	19.7	66.3	1.0	0.0	1.4	22.8	71.0	0.2	0.0	0.2
Germany	7.8	42.0	0.0	0.0	4.5	18.4	38.6	0.0	0.0	0.1
Greece	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Ireland	1.1	22.9	0.1	0.0	3.0	0.3	24.3	0.0	0.0	0.6
Italy	9.4	37.5	4.7	0.0	0.0	11.1	33.7	8.4	0.0	0.0
Luxembourg	3.5	34.1	0.5	0.0	2.0	1.6	35.4	0.1	0.0	0.3
Netherlands	0.0	21.6	0.0	0.0	0.0	0.0	20.7	0.0	0.0	0.0
Portugal	2.3	52.3	0.0	0.0	0.0	0.6	34.1	0.0	0.0	0.0
Spain	9.9	43.4	0.0	0.0	0.0	8.6	45.0	0.0	0.0	0.0
Total EA12	5.8	37.8	0.5	0.0	1.8	4.6	36.8	0.2	0.0	0.3

(a) Equity funds

	Ratio of funds liquidated (%)					Ratio of assets liquidated (%)				
Flows	unadj			valadj	-	unadj			valadj	-
Projection quantile	50	25	75	50	crisis	50	25	75	50	crisis
Austria	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.2
Belgium	0.0	0.0	0.0	0.0	3.7	0.0	0.0	0.0	0.0	0.5
Finland	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
France	0.0	0.3	0.0	0.0	1.9	0.0	0.0	0.0	0.0	0.3
Germany	0.0	0.0	0.0	0.0	4.0	0.0	0.0	0.0	0.0	0.5
Greece	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Ireland	0.3	0.9	0.0	0.3	3.2	0.0	0.1	0.0	0.0	0.3
Italy	0.7	0.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Luxembourg	0.9	1.4	0.5	0.9	2.6	0.2	0.8	0.0	0.2	0.6
Netherlands	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Portugal	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Spain	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Total EA12	0.5	0.8	0.2	0.4	2.0	0.1	0.5	0.0	0.1	0.3

(b) Bond funds

Table 2: Results on fund liquidations.
Ratios are computed from the total number of funds active in each country, or total assets held by these funds respectively. The EA12 totals are ratios over all EA12-domiciled funds, and not an average between countries.
The projection percentiles are defined in subsection 3.4. We take the same percentiles for all countries, meaning that it does not reflect the actual percentile of the multi-country distribution, and we can expect our approach to yield results which deviate more from the median than the actual multi-country percentile would. The column "crisis" provides realised results for comparison, based on the funds in our sample which were liquidated in 2008Q4, which was the most severe part of the global financial crisis.
Sources: Lipper IM and authors' calculations.

The ratio of liquidations for bond funds is considerably lower in median terms across EA12 countries. Luxembourg (0.9%), Italy (0.7%) and Ireland (0.3%) are the only ones featuring predicted liquidations. Similar results are observed based on ratios of liquidated assets.

Additionally, we present results in the case when all country flows are realised at the first quartile of their density (25^{th} percentile) and third quartile (75^{th} percentile) respectively. It is to be noted that those results are probably stronger, i.e. further from the median, than what we would observe by taking the quantiles on the actual density of AUM changes for funds, which would be computed from a multivariate distribution of country flows. Nonetheless, an analysis of our models points out that residuals are correlated across countries, so this way of using regressions' quantiles can still be interpreted as a consistent robustness check.

Finally, we look at the liquidations that occurred during the global financial crisis for comparison, providing figures on both the ratios of funds and ratios of assets liquidated in EA12 countries. These figures are for liquidations happening in 2008Q4, in line with figure 6, which was the core of the crisis. For equity funds, looking at the total over EA12 countries, there were fewer liquidations during the crisis, with a figure which is more similar to our simulated third quartile. This can be explained by the fact that, during the global financial crisis, liquidations were more evenly spreaded between quarters, with also many in the rest of 2008 and 2009, although 2008Q4 was the most acute. In our projections almost all of the liquidations occur in the first quarter of the scenario. For bond funds, there were more liquidations during the crisis based on both metrics. Bond funds that liquidated during the global financial crisis were smaller on average than those that liquidate under our adverse scenario. Overall, the aggregate figures for bond funds' liquidations are relatively low for both.

The comparison with the crisis, and the differences between the ratios of funds and ratios of assets liquidated, may also be indicative that our threshold performs correctly on average, but that in practice the size of the fund matters. For the EA, we find that 5.8% of equity funds would liquidate, and the fact that they account for 4.6% of the total assets suggests that the funds liquidated would be rather small on average. However, the same exercise on the historical data is much more striking: 1.8% of funds liquidated in 2008Q4 while they represented only 0.3% of assets. Thus, we may overestimate the extent to which large equity funds would liquidate. We reach a similar conclusion for bond funds.

More precisely, a big fund could resist a large drop, relative to its total asset holdings, whereas a smaller fund would liquidate, and this is not captured by our uniform threshold. If comforted by further evidence, then there would also be a case for policy instruments to be more granular and take this dimension into account. This is in line with the conclusion of Fricke and Fricke (2017), although they add that, in spite of being less vulnerable, large funds are still systemically more important.

6 Conclusion

We present a model for stress testing investment funds, based on a worldwide sample of equity and bond primary open-end funds and designed in two steps. The first step employs Bayesian model averaging (BMA) techniques to project the impact of adverse macro-financial scenarios on country portfolio flows constructed from fund-level asset holdings. In the second step, we implement a propagation exercise resembling traditional top-down stress testing techniques. It models the impact of country-level asset flows along a three year horizon - as projected in step one - back to the individual fund level. We further decompose this impact, disentangling the specific contribution of transactions, valuation and foreign exchange effects in explaining the liquidation of fund assets.

The contribution of our model design to stress testing investment funds is twofold. First, we refrain from using the funds' domiciles or their geographical focus as proxies for the allocation of assets. Instead, we borrow from the related literature on international capital flows, and focus on the international transmission of shocks to financial flows based on fund-level asset holdings. This allows us to translate the impact of country-specific adverse macro-financial scenarios into fund liquidations via their individual geographical exposures. Second, our two-step approach models a dual propagation channel, in the spirit of FSB (2015). On one hand, the channel captures the impact of macro-financial scenarios heterogeneously, that is, accounting for fund portfolio exposure risk and asset diversification. On the other hand, the channel also involves the propagation of asset liquidations at the fund level, which may ultimately translate into potential aggregate externalities to financial stability by means of price effects. Future work involves the integration into system-wide stress testing frameworks (Alla, Espinoza, Li, and Basurto, 2018).

Overall, our results indicate that the impact of our adverse macro-financial scenario leads to median drops in AUM of 24% and 5%, for EA12-domiciled equity and bond funds respectively, within the first quarter of the projection horizon. Based on empirical estimates resembling prudential policy tools, we find a ratio of liquidations of 5.8% for equity funds (4.6% in terms of liquidated assets), compared to bond funds where the ratio of fund liquidations is limited to 0.5% (0.1% in terms of liquidated assets) under the adverse scenario.

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A Historical data on funds' assets

	Last quarter				Whole period		
	Number of funds	Mean AUM	std of AUM	Total AUM	Number of funds	Average lifetime	Number of observations
AT	188	0.07	0.12	13.7	356	34.0	12,119
BE	425	0.10	0.23	42.8	1,447	24.0	34,714
CY	1	0.07		0.1	2	4.5	9
DE	353	0.36	1.41	128.4	760	29.5	22,449
EE	6	0.05	0.05	0.3	18	36.6	658
ES	276	0.12	0.22	33.0	687	29.8	20,500
FI	203	0.19	0.32	38.9	352	33.1	11,653
FR	1,162	0.18	0.35	203.7	2,742	29.4	80,585
GR	46	0.02	0.03	0.9	56	41.5	2,325
IE	1,102	0.34	0.87	370.3	2,183	21.8	47,641
IT	79	0.24	0.22	19.3	510	23.5	11,994
LT	5	0.01	0.01	0.0	18	26.8	483
LU	3,325	0.32	0.72	1,079.6	6,742	24.8	167,391
LV	5	0.00	0.00	0.0	12	18.7	224
MT	18	0.03	0.08	0.6	29	14.3	416
NL	157	0.33	0.55	52.2	327	25.9	8,463
PT	48	0.04	0.06	1.8	86	43.4	3,730
SI	35	0.02	0.03	0.8	47	34.2	1,606
SK	5	0.05	0.04	0.3	10	32.2	322
AE	13	0.02	0.01	0.2	20	37.0	739
AU	1,285	0.14	0.51	182.5	2,263	29.5	66,779
BG	4	0.00	0.00	0.0	4	48.2	193
BR	1,423	0.03	0.08	46.3	2,785	21.4	59,541
CA	1,175	0.27	0.57	312.1	2,549	26.4	67,224
CH	489	0.33	0.69	161.2	700	29.3	20,523
CL	132	0.03	0.03	4.0	234	25.6	5,999
CN	712	0.10	0.21	73.6	730	15.4	11,236
CO	25	0.01	0.03	0.3	32	22.2	711
CZ	17	0.05	0.05	0.9	20	40.0	801
DK	257	0.17	0.32	43.5	423	35.0	14,786
EG	32	0.00	0.00	0.1	32	35.3	1,131
HK	177	0.24	0.48	42.4	224	29.7	6,663
HU	66	0.01	0.01	1.0	101	22.5	2,276
ID	245	0.03	0.08	7.5	297	18.6	5,520
IL	288	0.03	0.05	7.2	483	25.1	12,118
IN	327	0.22	0.43	70.5	463	36.2	16,747
JP	1,934	0.09	0.37	182.4	3,388	24.8	84,024
KR	835	0.04	0.11	30.5	2,095	21.0	44,029
MX	140	0.06	0.10	8.7	154	30.5	4,696
MY	358	0.06	0.14	21.0	439	34.2	14,996
NO	158	0.37	0.63	58.4	300	34.5	10,364
NZ	77	0.06	0.08	4.7	122	21.4	2,612
PE	16	0.01	0.03	0.2	21	19.1	402
PH	58	0.06	0.11	3.7	65	21.0	1,366
PK	41	0.04	0.09	1.7	51	28.0	1,427
PL	128	0.05	0.12	6.7	177	31.9	5,640
QA	5	0.01	0.01	0.1	6	29.5	177
RU	144	0.00	0.01	0.7	333	26.7	8,896
SE	303	0.54	0.79	163.4	551	33.3	18,357
SG	122	0.08	0.17	9.7	257	32.7	8,411
TH	458	0.05	0.13	22.6	721	21.0	15,157
TR	72	0.01	0.02	0.5	84	29.2	2,454
TW	373	0.05	0.07	17.1	569	33.9	19,312
UK	1,149	0.63	1.29	719.3	2,150	31.5	67,825
US	3,705	2.15	13.84	7,967.6	6,658	32.3	215,045
ZA	348	0.09	0.24	32.1	408	27.2	11,088
Other	797	0.07	0.33	59.6	1,686	25.5	43,009
All	25,327	0.48	5.37	12,250.5	47,979	27.1	1,299,556

Table 3: Equity funds – Descriptive statistics for AUM by country of domicile.
Sample period: 2003Q3–2017Q4. AUM in billion euros and lifetime in quarters. Sources: Lipper IM data and authors' calculations.

	Last quarter				Whole period		
	Number of funds	Mean AUM	std of AUM	Total AUM	Number of funds	Average lifetime	Number of observations
AT	269	0.11	0.16	30.7	528	33.3	17,571
BE	114	0.07	0.14	8.0	348	28.5	9,935
CY	2	0.01	0.01	0.0	8	2.4	19
DE	240	0.16	0.24	37.9	507	29.6	15,024
EE	0			0.0	5	19.4	97
ES	683	0.13	0.28	85.7	1,708	25.1	42,823
FI	79	0.40	0.63	31.3	116	35.0	4,058
FR	676	0.23	0.78	156.2	1,582	27.9	44,069
GR	38	0.03	0.05	1.3	45	39.0	1,756
IE	662	0.63	2.64	415.3	1,114	20.4	22,735
IT	246	0.27	0.42	66.8	585	23.2	13,571
LT	2	0.03	0.02	0.1	5	17.6	88
LU	2,565	0.43	1.11	1,105.3	4,729	24.2	114,527
LV	9	0.02	0.01	0.1	14	22.6	317
MT	21	0.06	0.07	1.3	27	25.7	693
NL	71	0.43	1.43	30.6	128	24.5	3,132
PT	27	0.10	0.16	2.6	115	27.4	3,150
SI	4	0.01	0.01	0.1	5	26.8	134
SK	6	0.13	0.20	0.8	14	26.4	370
AE	3	0.04	0.02	0.1	4	24.0	96
AU	303	0.20	0.46	60.6	562	27.0	15,193
BG	1	0.03		0.0	1	50.0	50
BR	2,080	0.28	1.22	579.4	3,913	22.9	89,600
CA	368	0.46	1.14	168.4	588	25.7	15,126
CH	324	0.44	0.74	142.4	449	28.0	12,575
CL	124	0.11	0.16	13.7	186	23.4	4,349
CN	1,001	0.13	0.29	134.5	1,042	13.8	14,342
CO	38	0.12	0.17	4.6	45	32.4	1,460
CZ	19	0.17	0.24	3.3	26	33.4	868
DK	195	0.23	0.37	45.4	310	31.4	9,721
EG	8	0.01	0.01	0.1	8	25.1	201
HK	86	0.20	0.47	17.1	102	22.6	2,308
HU	56	0.09	0.15	5.1	79	27.9	2,207
ID	688	0.02	0.03	11.3	1,478	12.1	17,935
IL	519	0.04	0.06	21.6	812	27.2	22,053
IN	215	0.37	0.56	80.1	441	26.4	11,664
JP	1,148	0.08	0.31	90.8	1,873	25.6	47,981
KR	272	0.04	0.12	11.7	2,892	8.2	23,655
MX	174	0.13	0.28	22.8	207	29.9	6,197
MY	124	0.06	0.12	7.2	177	26.8	4,744
NO	82	0.43	0.79	35.3	127	30.9	3,928
NZ	27	0.13	0.22	3.4	45	20.4	916
PE	56	0.02	0.05	1.2	88	11.3	993
PH	60	0.04	0.14	2.7	77	31.6	2,436
PK	47	0.01	0.02	0.7	63	26.2	1,651
PL	83	0.12	0.19	9.9	104	32.3	3,362
QA	1	0.01		0.0	1	21.0	21
RU	63	0.03	0.07	1.9	102	24.9	2,543
SE	80	0.54	0.71	43.0	108	31.7	3,423
SG	46	0.20	0.27	9.1	105	26.4	2,767
TH	167	0.21	0.61	35.5	1,538	9.3	14,371
TR	73	0.02	0.04	1.5	191	15.0	2,874
TW	128	0.07	0.12	9.0	202	16.6	3,361
UK	343	0.58	0.90	198.2	553	31.7	17,528
US	1,826	1.69	7.05	3,090.9	2,842	36.3	103,077
ZA	111	0.13	0.28	15.0	127	34.1	4,325
Other	717	0.11	0.23	75.4	1,123	25.7	28,908
All	17,370	0.40	2.49	6,926.7	34,174	23.2	792,878

Table 4: Bond funds – Descriptive statistics for AUM by country of domicile.
The statistics are calculated over the 2003Q3–2017Q4 sample period. AUM in billion euros and lifetime in quarters. Sources: Lipper IM data and authors' calculations.

B Bayesian Model Averaging: a theoretical introduction

B.1 The setup of a general BMA

We start from an observable y. Given a certain class of models, we want to find a vector of parameters ϕ, corresponding to one of these models, which best describes y. We suppose that the parameters describing our model class are in a space $\Phi = \mathbb{R}^d$. For example, consider the case of a simple linear regression with intercept: $y = \alpha + \beta \cdot x + \varepsilon$. Then, $\Phi = \mathbb{R}^2$, and a model is described by a vector $\phi = (\alpha, \beta) \in \Phi$.

When searching for the model we consider ϕ as a random vector, so we take a probability measure $\mathbb{P}$ on Φ. We consider I subsets of the parameter space, denoted $\{M_i\}$, which satisfy

$$\forall (i,j) \in \{1, \dots I\}^2, i \neq j \implies \mathbb{P}(M_i \cap M_j) = 0 \tag{12}$$

and

$$\mathbb{P}\left(\bigcup_{i=1}^{I} M_i\right) = 1 \tag{13}$$

meaning that the parameter vector is almost surely in one of these subsets. We refer to $\mathbb{P}(M_i)$ as the prior model probability of M_i, and to $\mathbb{P}(M_i|y)$ as the posterior model probability.

B.2 Expectation and variance

Using equations (12) and (13), for any measurable set $A \subset \Phi$, the posterior coefficient distribution satisfies:

$$\mathbb{P}(A|y) = \sum_{i=1}^{I} \mathbb{P}(M_i|y) \cdot \mathbb{P}(A|y, M_i) \tag{14}$$

so that the expected parameters of the overall model are given by

$$\mathbb{E}[\phi|y] = \sum_{i=1}^{I} \mathbb{P}(M_i|y) \cdot \mathbb{E}[\phi|y, M_i] \,. \tag{15}$$

The parameters $\mathbb{E}[\phi|y, M_i]$ of individual equations are therefore averaged using the posterior model probabilities as weights. The posterior variance associated to this model is

$$\mathrm{Var}(\phi|y) = \sum_{i=1}^{I} \mathbb{P}(M_i|y) \cdot \mathrm{Var}(\phi|y, M_i) + \sum_{i=1}^{I} \mathbb{P}(M_i|y) \left(\mathbb{E}[\phi|y, M_i] - \mathbb{E}[\phi|y]\right)^2, \tag{16}$$

(see section 4.6 in Leamer (1978) for the proof). It means that the final variance is always larger than the average of the variances of individual models, with an additional term that depends on how close are model-specific estimations from the average one.

An advantage of this approach is that we initially restrict our computations to $\bigcup_i M_i$ but our search covers the whole convex set of $\bigcup_i M_i$, which is generally bigger. Thus, choosing the models

$\{M_i\}$ is a key intermediary step towards finding ϕ. In particular, we can define $\{M_i\}$ based on y, so as to optimize the convex set of $\bigcup_i M_i$ for the data.

B.3 Use with a finite set of models

In most cases, taking M_i as a continuous subset of the model space would be too much of a burden to be really usable. So we focus on a finite sample of models $(\phi_i)_i$, such that $\forall i, M_i = \{\phi_i\}$. To be in line with condition (13), we assume that all other vectors in Φ have a zero prior probability. Therefore, in practice there is an equivalence between M_i and ϕ_i as $\mathbb{E}[\phi|y, M_i] = \phi_i$. Thus, equation 15 simplifies into

$$\mathbb{E}[\phi|y] = \sum_{i=1}^{I} \mathbb{P}(\phi_i|y) \cdot \phi_i \ . \tag{17}$$

In the case of linear models, it is formally equivalent to averaging the results of different models with certain weights. Due to their linearity, the preferred approach is to perform the averaging on the coefficients, to then obtain a final model from which we compute the results.

C Variables and long-run multipliers

We present in table 5 the variables used in our models. All of them are available in datasets provided by ECB Statistics. To all of these variables, one of several transformations are applied, such that each transform variable is a predictor variable.

The transformations used are the following:

- Taking the growth, denoted by Gx with x the number of quarters defining the growth period.
- Taking the simple variable, or level, denoted by L.
- Taking the difference, denoted by Dx with x the number of quarters between the start and end points.

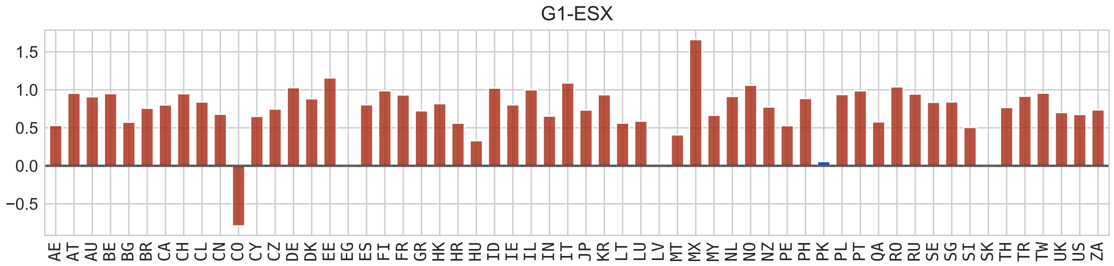
Code	Description
YER	Gross Domestic Product
ESX	Stock prices
STN	Short-term rates
LTN	Long-term rates
S-LTN	Spread (difference in LTN with Germany or with the US)
CPP	Commercial property prices
RPP	Residential property prices
URX	Unemployment rate
CPI	Consumer index prices
ITR	Investment
XTR	Exports
PCR	Real private consumption

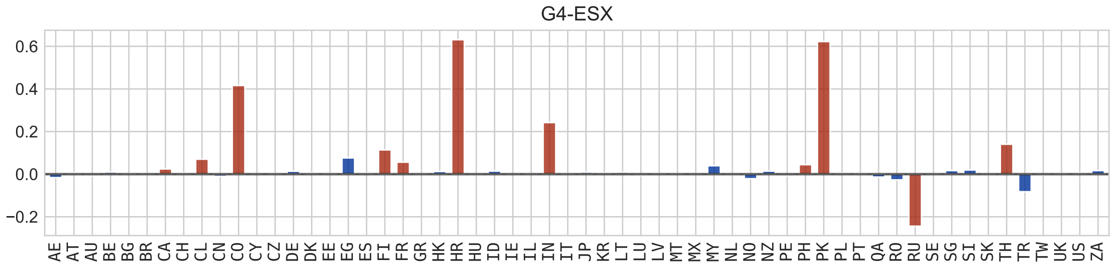
Table 5: Variables used in the simulations.

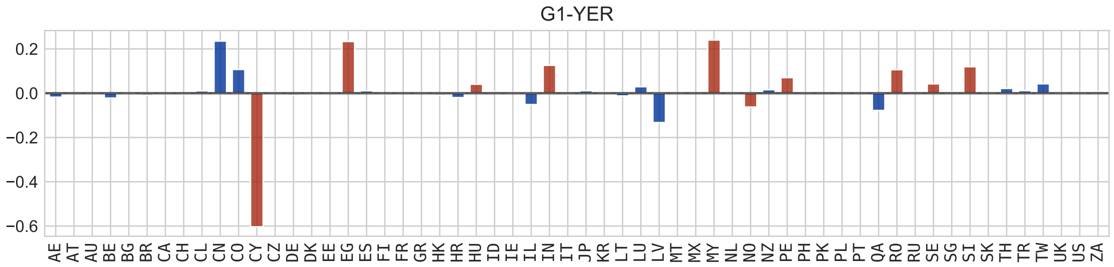
Normalized long-run multipliers are given below for each transformed variable. They combine contemporaneous and lagged coefficient estimates for a given predictor in one multiplier, and are comparable across predictor variables and across countries. Those presented here correspond to the unadjusted flows described by equation 4. The values for adjusted and partially adjusted flows are also available upon request. All the values are authors' calculations.

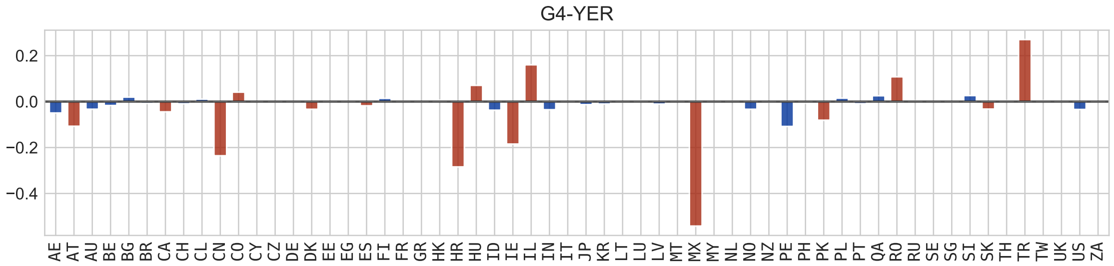
We use the colour red for countries in which the variable is significant, and blue otherwise. The significance, as defined in 3.3, is a measure less precise than the LRM itself and its information is largely already contained in the magnitude of the corresponding LRM.

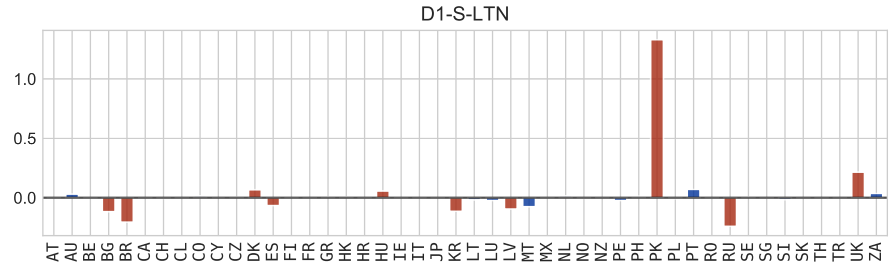
C.1 LRMs of unadjusted equity flows

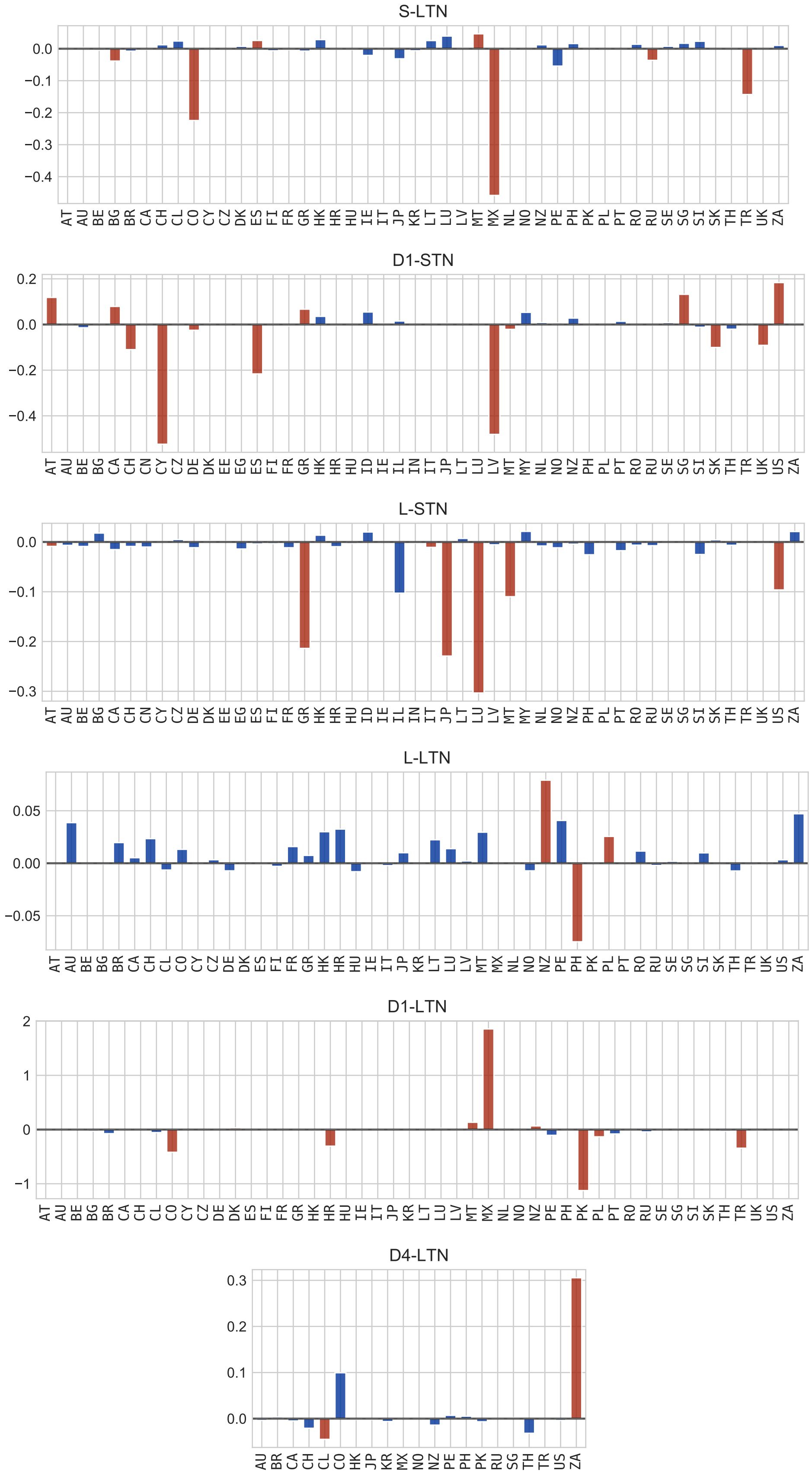


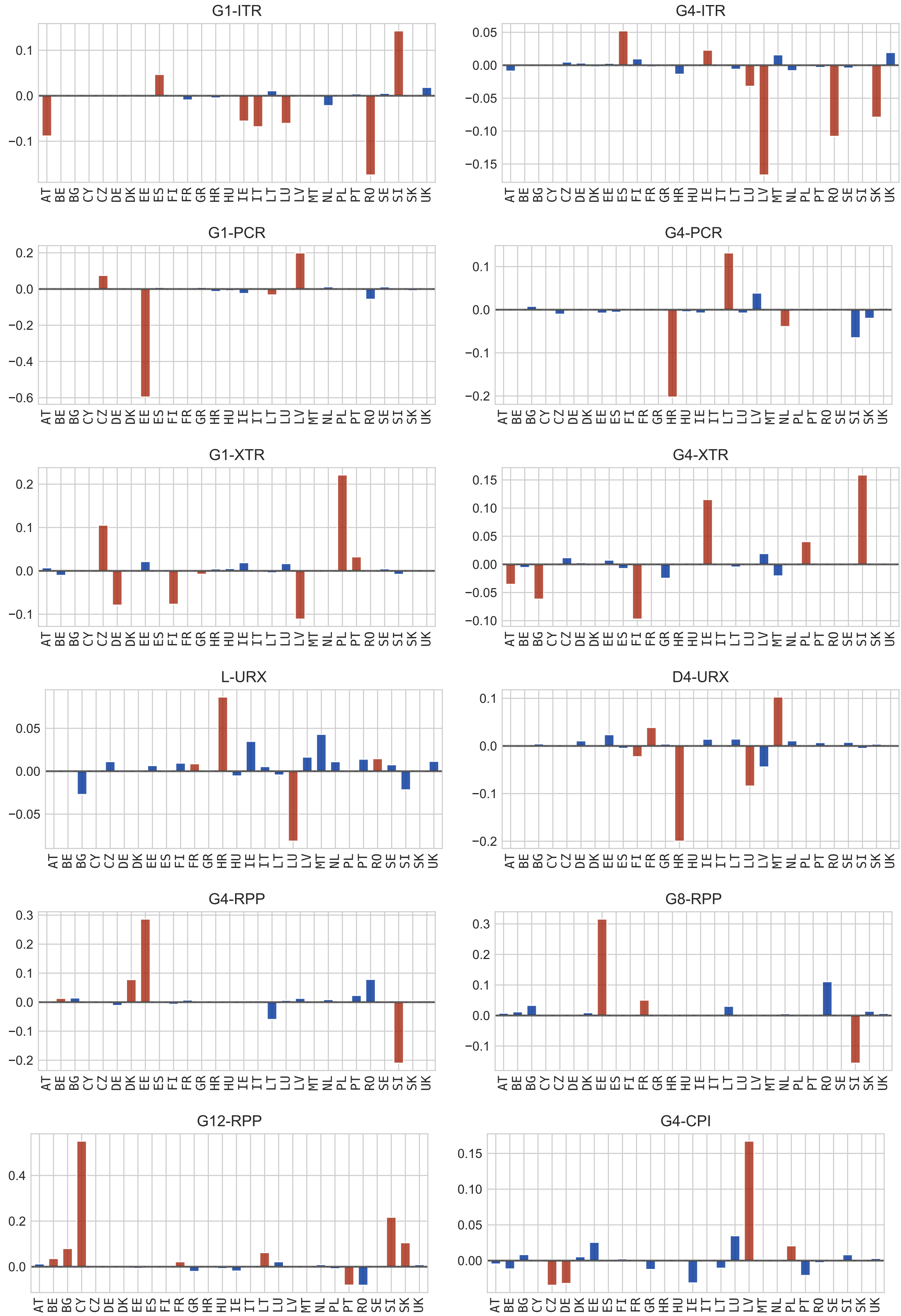




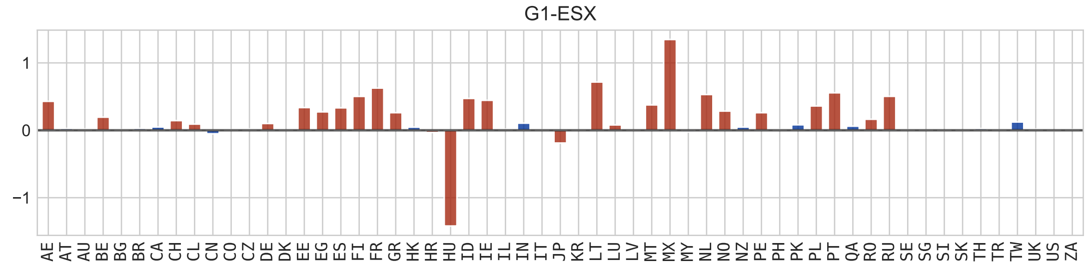


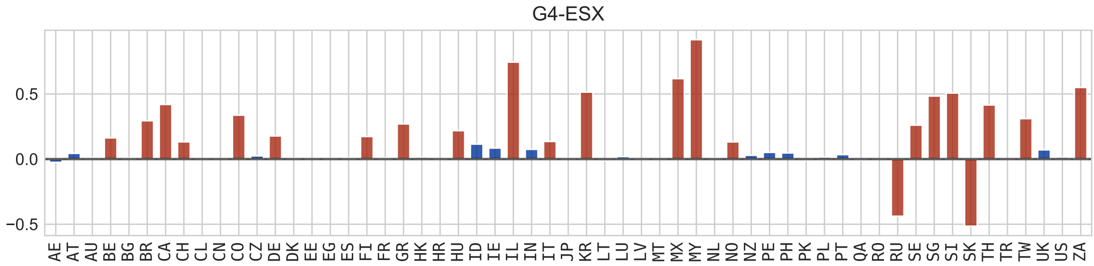


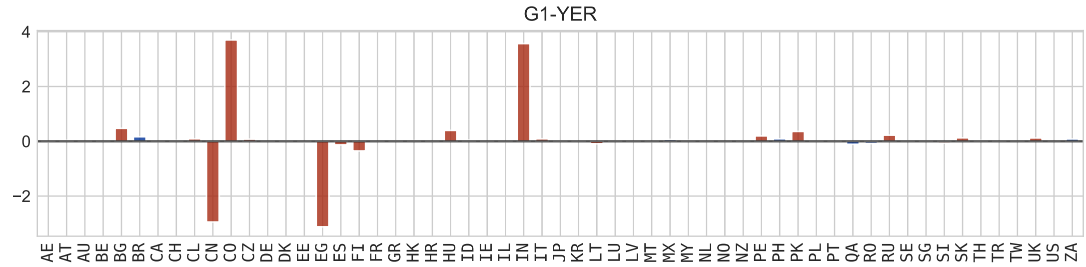

S-LTN
D1-STN
L-STN
L-LTN
D1-LTN
D4-LTN

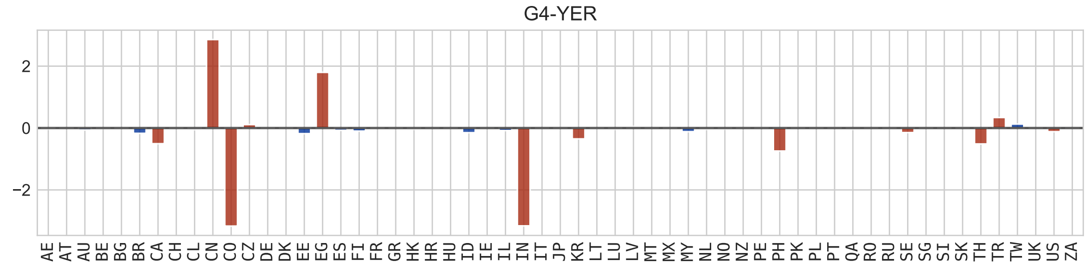

G1-ITR
0.1
0.0
−0.1
G4-ITR
0.05
0.00
−0.05
−0.10
−0.15
G1-PCR
0.2
0.0
−0.2
−0.4
−0.6
G4-PCR
0.1
0.0
−0.1
−0.2
G1-XTR
0.2
0.1
0.0
−0.1
G4-XTR
0.15
0.10
0.05
0.00
−0.05
−0.10
L-URX
0.05
0.00
−0.05
D4-URX
0.1
0.0
−0.1
−0.2
G4-RPP
0.3
0.2
0.1
0.0
−0.1
−0.2
G8-RPP
0.3
0.2
0.1
0.0
−0.1
G12-RPP
0.4
0.2
0.0
G4-CPI
0.15
0.10
0.05
0.00
AT BE BG CY CZ DE DK EE ES FI FR GR HR HU IE IT LT LU LV MT NL PL PT RO SE SI SK UK

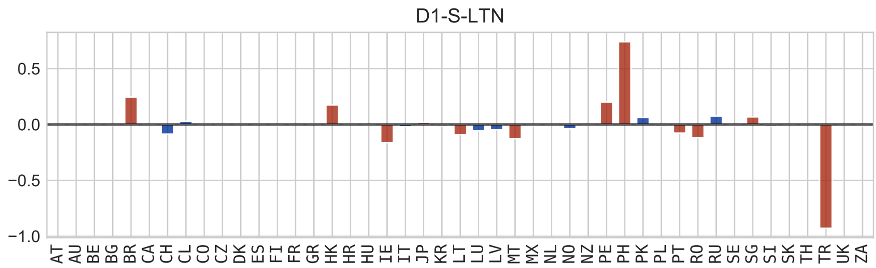
C.2 LRMs of unadjusted bond flows

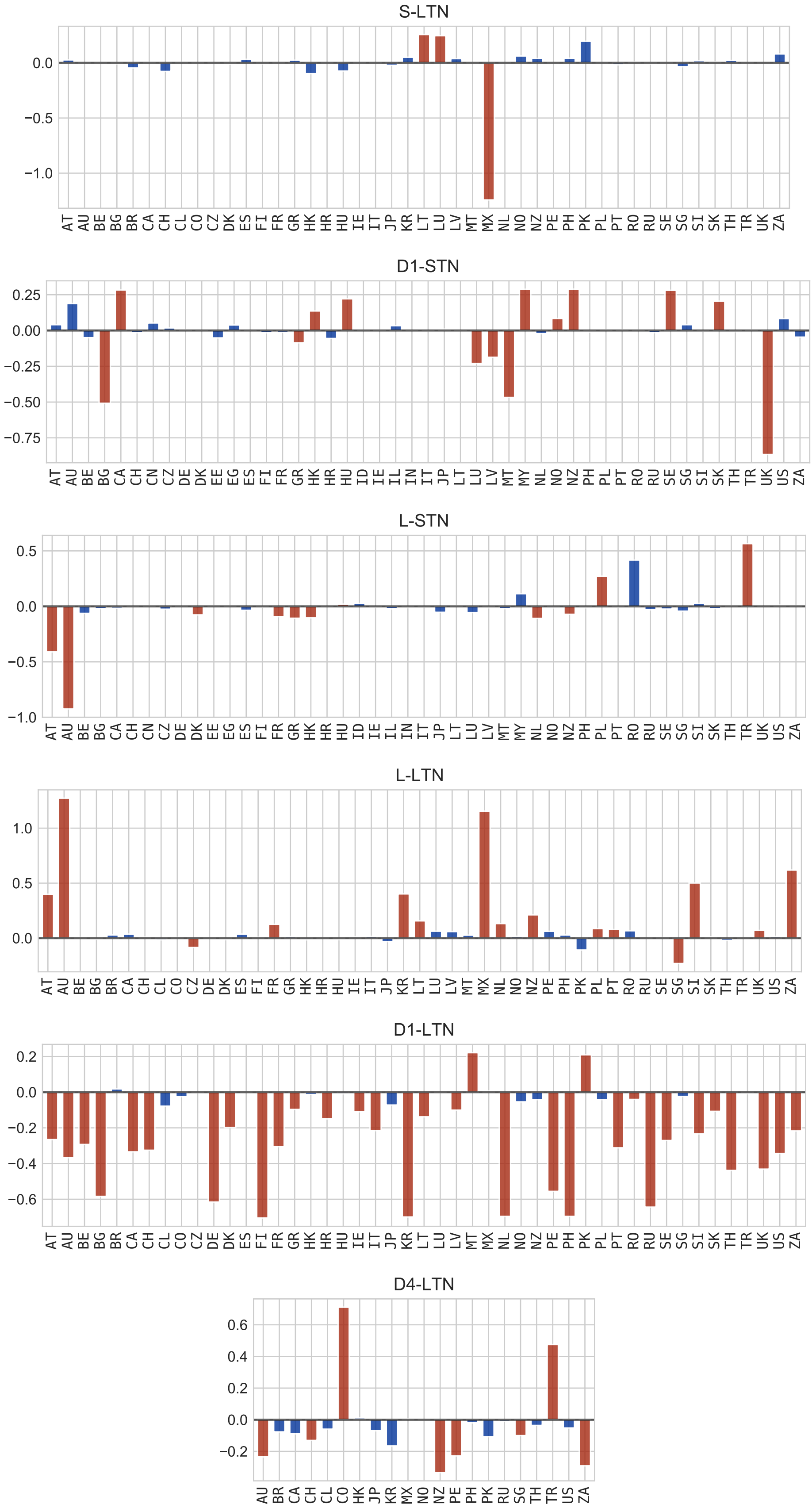


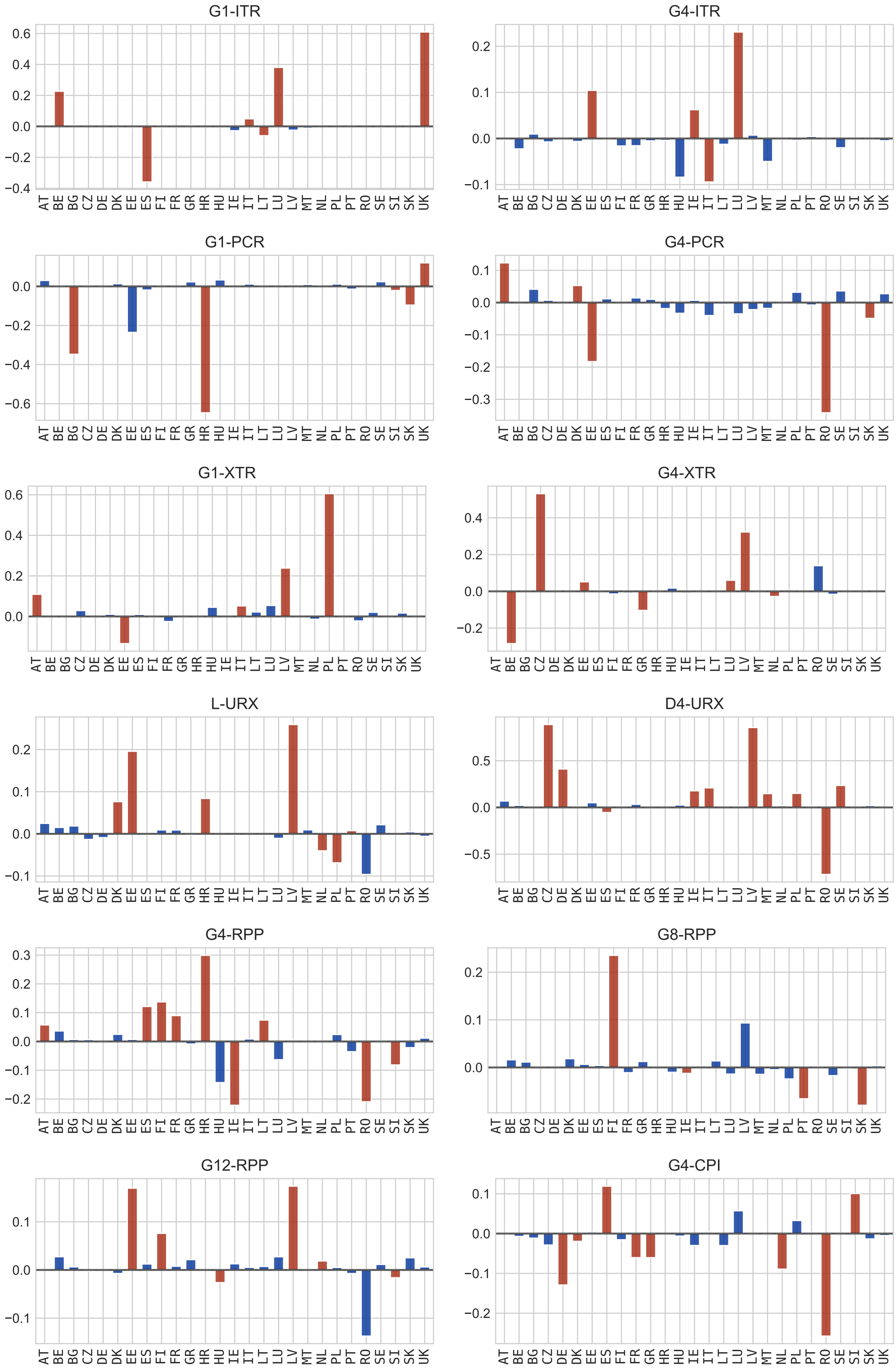









S-LTN
D1-STN
L-STN
L-LTN
D1-LTN
D4-LTN


G1-ITR
G4-ITR
G1-PCR
G4-PCR
G1-XTR
G4-XTR
L-URX
D4-URX
G4-RPP
G8-RPP
G12-RPP
G4-CPI
AT BE BG CZ DE DK EE ES FI FR GR HR HU IE IT LT LU LV MT NL PL PT RO SE SI SK UK

D Details of adverse projected flows

D.1 Flows for equity funds

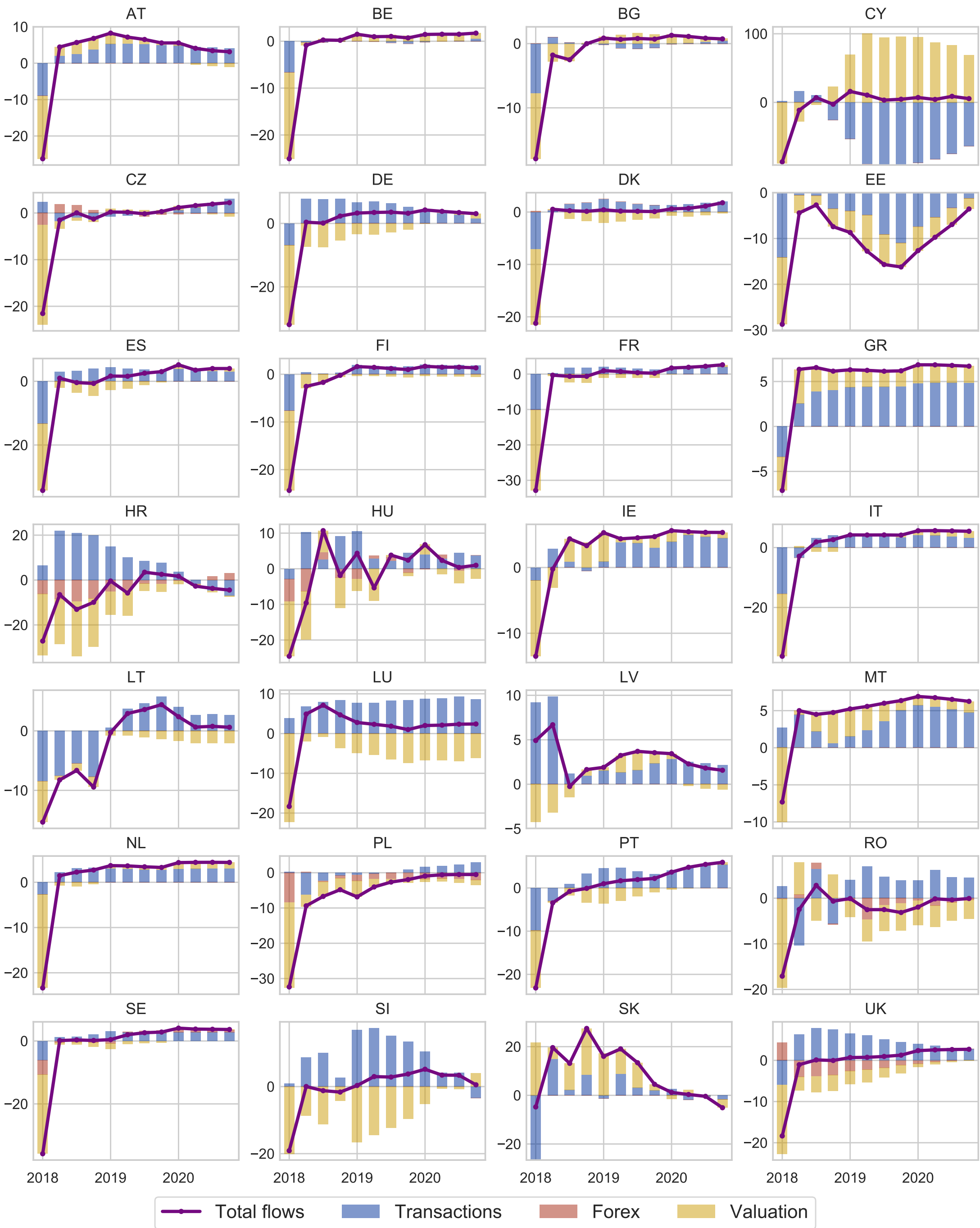


Figure 8: Projection of equity flows in EU countries under the adverse scenario, in percentage points.
Sources: authors' calculations and Lipper IM.

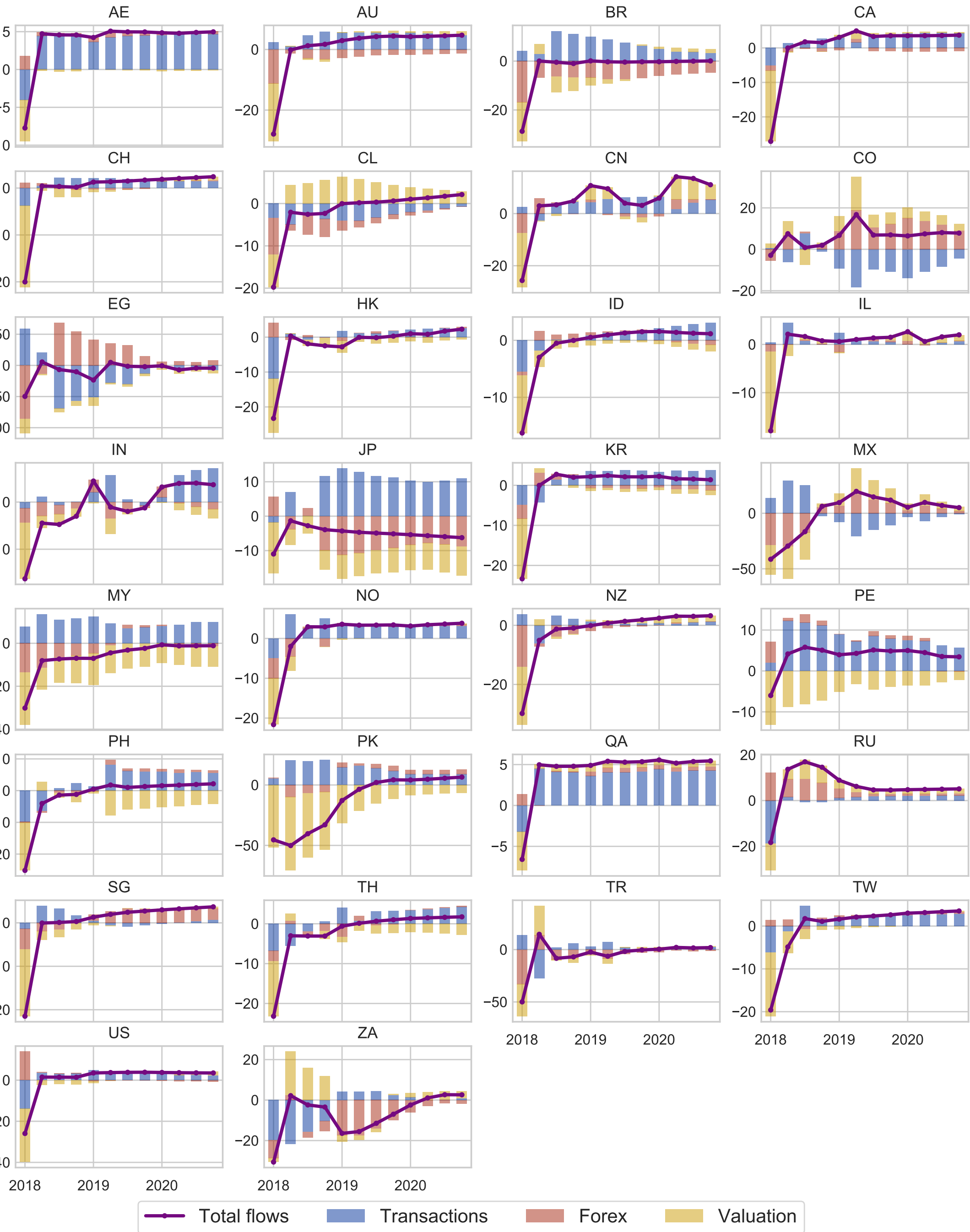


Figure 9: Projection of equity flows in non-EU countries under the adverse scenario, in percentage points.
Sources: authors' calculations and Lipper IM.

D.2 Flows for bonds funds

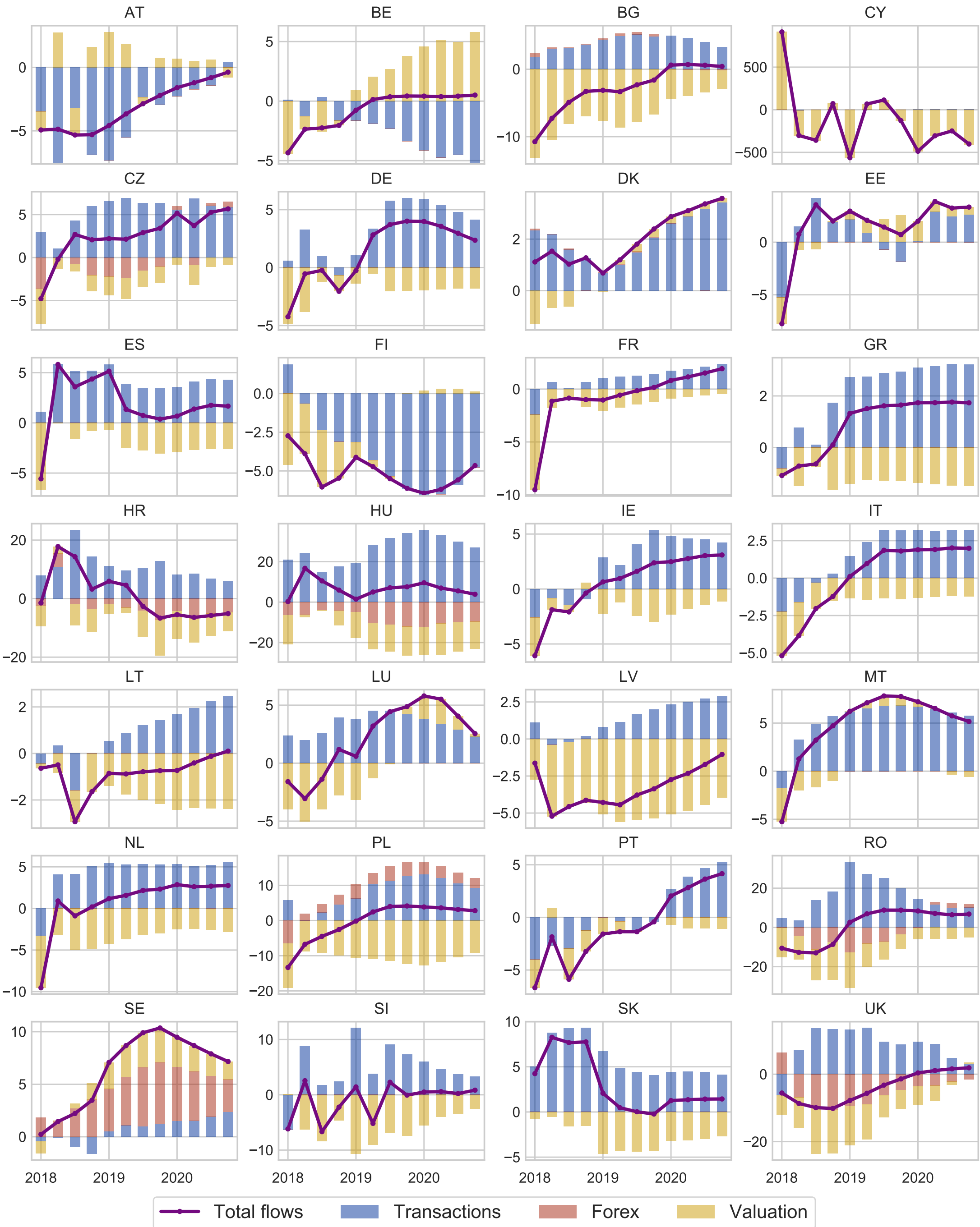


Figure 10: Projection of bond flows in EU countries under the adverse scenario, in percentage points.
Sources: authors' calculations and Lipper IM.

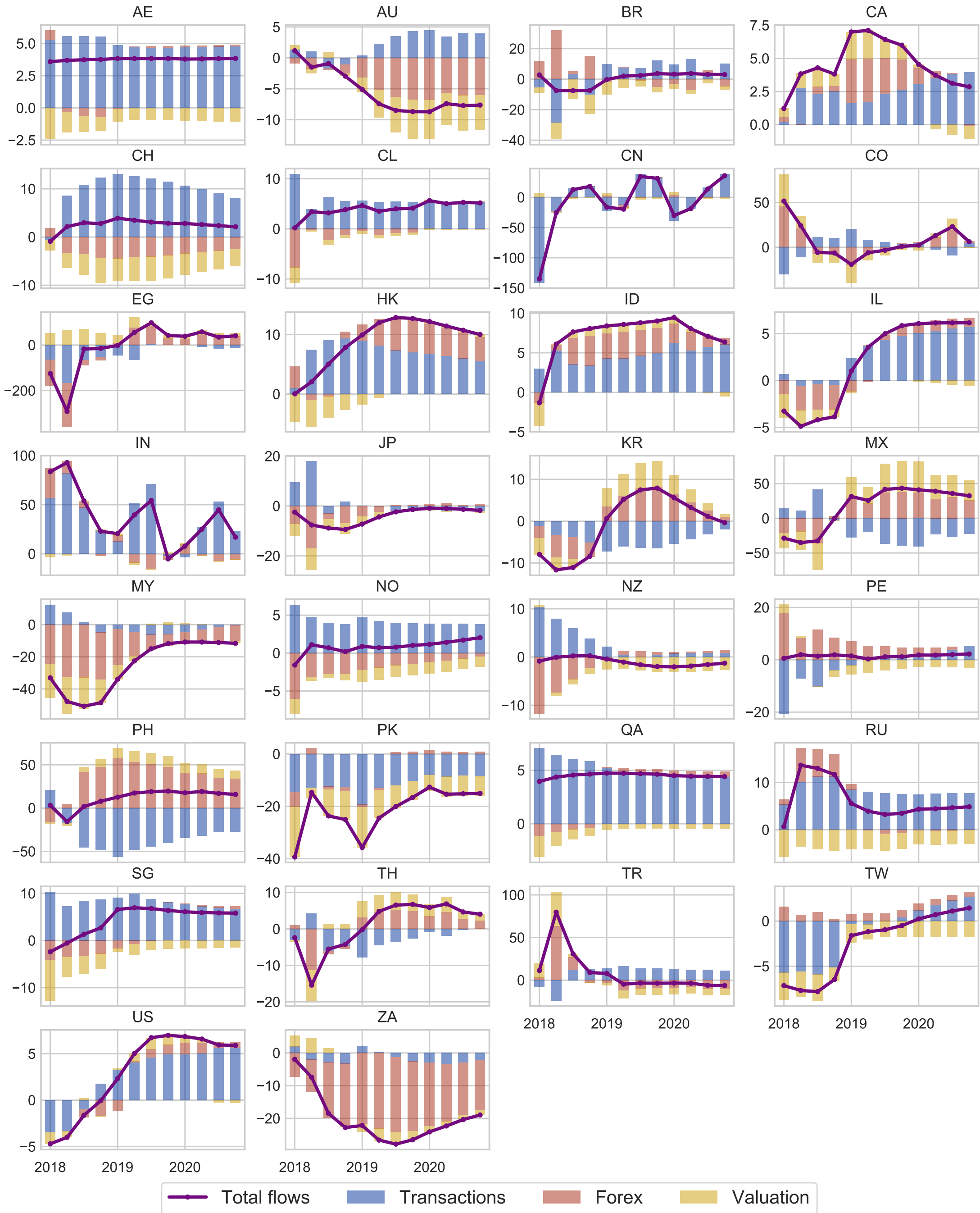


Figure 11: Projection of bond flows in non-EU countries under the adverse scenario, in percentage points.
Sources: authors' calculations and Lipper IM.

E Signal-to-noise ratio

Following ECB (2007) we use a signal-to-noise ratio to identify what is a good predictor of forthcoming fund liquidations. The core idea is that a signal is emitted when a fund exhibits bad results, a criterion based on a common threshold. We can decompose the observations as follows:

	Liquidation	No liquidation
Signal issued	A	B
No signal	C	D

such that the share of predicted cases of liquidation is $\frac{A}{A+C}$ and the share of good signals is $\frac{A}{A+B}$.

The signal-to-noise ratio is then defined as

$$\text{StNR} = \frac{A}{A+C} \cdot \frac{B+D}{B},$$

which "compares the share of predicted cases of liquidation to the proportion of bad signals or noise in no liquidation situations [...] and is neutral with respect to the relative frequency of cases of liquidation" (ECB, 2007). The count of A,B,C,D in our tests is done over a rolling window of one year, and we identify a value as StNR_t where t is the last quarter of the time period used. After comparison of different primary variables of interest, we chose to base our implementation on unadjusted quarterly flows, which at the fund level is the simple growth in AUM.

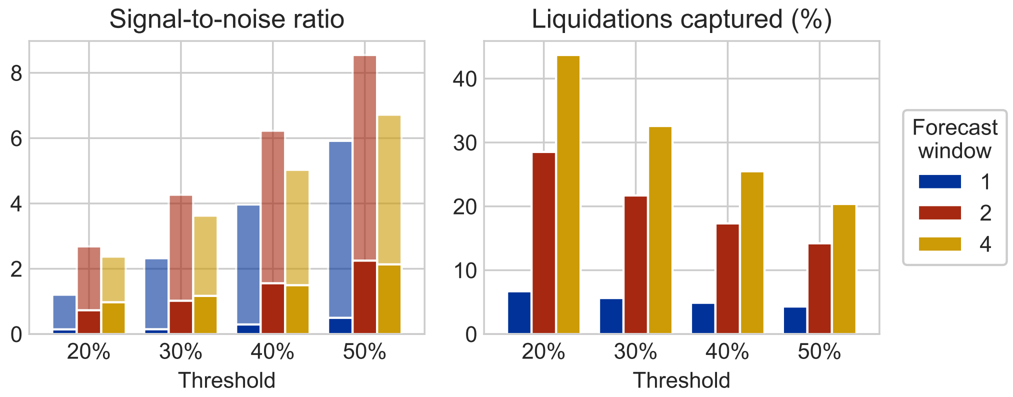
To formalize this, we compute quarterly series $(s_t^f)_t$ of Booleans for each fund, such that

$$\forall (f,t),\ s_t^f = \begin{cases} 1 & \text{if } \frac{A_{t+1}^f - A_t^f}{A_t^f} < \vartheta \\ 0 & \text{otherwise} \end{cases}$$

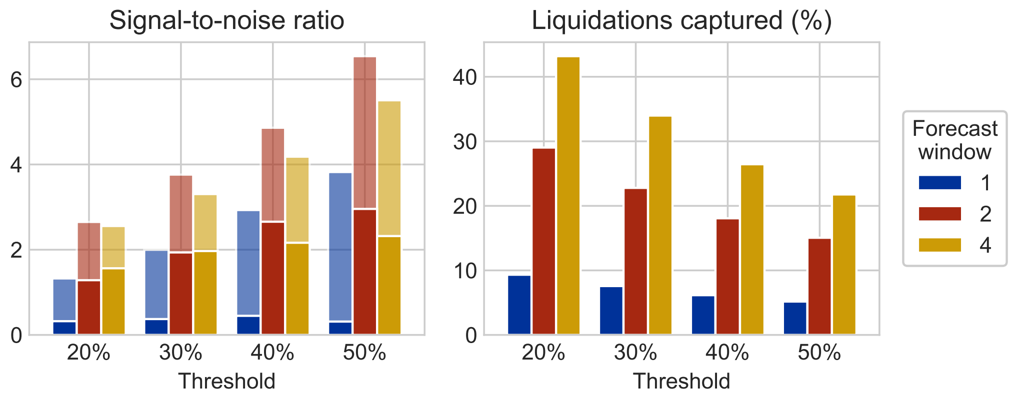
with ϑ the threshold, and we say that a signal is issued when $s_t^f = 1$. This leaves the following parameters:

- *The threshold ϑ.* The signal will be emitted when the change in the last quarter is below the threshold. So it needs to be fixed to enable the computation of the signal.
- *The size of the forecast window.* In the most basic setting, we consider that a signal is "correct" if and only if the corresponding fund liquidates in the same quarter. By extending the growth window we consider that a signal is also correct if the fund liquidates in the next quarter (with a forecast window of two quarters), or in the following year (with a forecast window of four). This does not need to be fixed and is only indicative of how to interpret the results.

We show the influence of these two parameters in figure 12. The first plot for each asset class is a comparison of the signal-to-noise ratio, taking its minimum over the time period, with varying thresholds and forecast windows. The second one is a complementary approach which compares the share of liquidations captured by our signal, that is $\frac{A}{A+C}$ only. Indeed, in addition to having a "correct" signal, we want one that is likely to capture many of the liquidations that would happen.



(a) Equity



(b) Bond

Figure 12: Signal-to-noise and share of liquidations captured, with different parameters.
The signal-to-noise ratio bars present the minimum (solid colour) and median (transparent), over the period from 2002Q4 to 2018Q1, computed on a rolling window of one year. The threshold is given in percentage of the drop in asset values, e.g. 30% corresponds to a return of -0.3. The forecast window is given in number of quarters. Source: Lipper IM and author's calculations.

We can make the following observations:

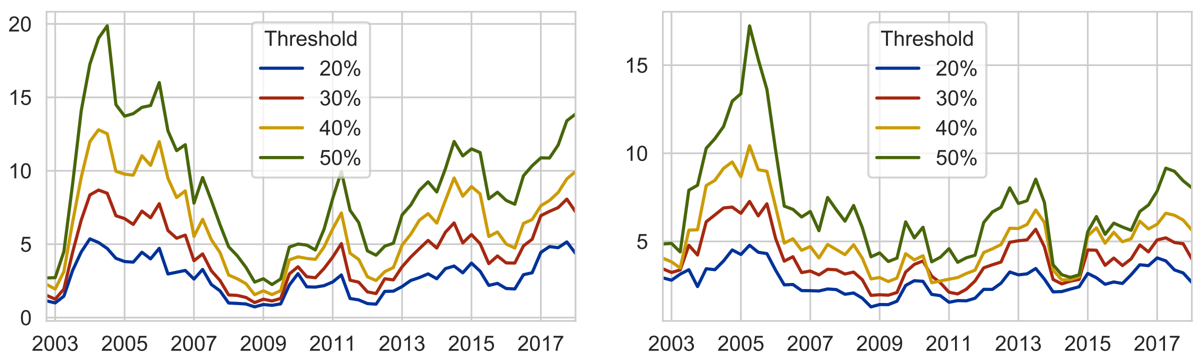
- The signal-to-noise ratio grows with the threshold: the more selective our signal is, the less noise we get. Since the ratio $\frac{A}{A+C}$ decreases, it means that $\frac{B}{B+D}$ decreases even faster.
- On the choice of the threshold, there is a trade-off between the signal-to-noise ratio and the share of liquidations captured. The more selective we are, the fewer liquidations we get.
- The forecast window matters as well. A forecast window of two quarters exhibits a higher signal-to-noise ratio than those of one or four quarters.

  On the share of liquidations, a forecast window of two quarters is significantly better than one. The four-quarter window is also slightly better than two, but with a less sensible difference and an interpretation maybe biased by later events.

This motivates our choice of a threshold of a 30% decrease in AUM, and a interpretation of it on a 2 quarters window: when a signal is emitted for one quarter, then the fund is likely to liquidate on that same quarter or in the next one.

Additionally, we plot in figure 13 the signal to noise ratio over time for different thresholds, with other parameters fixed. In particular, it appears to be much lower in times of crisis, meaning that there is a drop in the quality of our indicator and the minimums plotted in figure 12 are representative of the ratio in a crisis scenario.

This drop goes along with a contraction of indicators using different thresholds: in 2010 the difference between the 20% threshold and the 50% one is smaller than in normal times, like 2017 (the beginning of the period is less likely to be representative of what is normal because of a smaller number of liquidations reported). A possible interpretation of this goes as follows: during crises, many funds experience very bad performances, resulting in large outflows. Thus, there is a large increase in the number of signals. The number of funds that liquidate does increase as well but not to the same extent, because many of them still have decent results compared to the rest of the sector at that time. Therefore, the realised signal-to-noise is expected to be closer to that of 2009 than 2017, with a relatively small difference between the 30% and 40% thresholds.



(a) Equity

(b) Bond

Figure 13: Signal-to-noise ratio over time for different thresholds, with a forecast window of two quarters and a rolling window of one year.
The threshold is given in percentage of the drop in asset values, e.g. 30% corresponds to a return of -0.3. The forecast window is given in number of quarters. Source: Lipper IM and author's calculations.

To put these results in perspective it is also worth considering that not all funds liquidate because of bad performance. For instance if only 60% do so, it means that there is an upper limit of 60% of liquidations that we capture with our indicators. Lastly, we use quarterly returns, which are efficient to capture liquidations following a short period of intense stress, which is our case.

But we cannot predict the liquidations that result from a continuous decline over a longer period of time. For instance a fund with a drop of 20% for three consecutive quarters would be very likely to liquidate, but it is off the radar with our quarterly threshold of 30%.

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We are thankful to Christos Symeonidis for excellent research assistance, Brian Golden and Peter McQuade for helpful discussions and Marco Gross for valuable advice. We would also like to thank participants of ECB DG-R, DGMF and DG-I internal seminars, ESRB Task Force on Stress Testing meetings as well as Banque de France and CNMV seminars for their comments. The views presented in this paper are those of the authors alone, and do not represent the views of the European Central Bank or the Eurosystem.

Régis Gourdel
European Central Bank, Frankfurt am Main, Germany; email: regis.gourdel@ecb.europa.eu

Eduardo Maqui
European Central Bank, Frankfurt am Main, Germany; email: eduardo.maqui_lopez@ecb.europa.eu

Matthias Sydow (corresponding author)
European Central Bank, Frankfurt am Main, Germany; email: matthias.sydow@ecb.europa.eu

Postal address 60640 Frankfurt am Main, Germany
Telephone +49 69 1344 0
Website www.ecb.europa.eu

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