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An Lonn Dubh: A Framework For Macroprudential Stress Testing of Investment Funds

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An Lonn Dubh: A Framework For Macroprudential Stress Testing of Investment Funds*

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Abstract

We have developed a macroprudential stress testing framework of investment funds. This framework is a tool specifically designed to engage with the Bank's data, and allows financial stability analysts to rapidly prototype stress tests. This enables the Bank to assess financial stability concerns within the investment funds sector in a targeted and timely manner. Further to the description of the architecture of the framework, we present the results of a baseline stress test, which acts as an initial implementation of the framework. These results show that contagion among investment funds is expected to be limited under normal market conditions. However, under heightened market illiquidity and increased investor sensitivity to fund returns we document the potential for significant spillovers and indirect contagion due to common asset holdings in the investment funds sector domiciled in Ireland.

1 The framework

Macroprudential stress tests are starting to play a major role in financial sector policymaking following the recent introduction of macroprudential policy frameworks (Anderson et al., 2018). These tests aim at capturing the endogenous nature of systemic risk caused by the interaction of institutions and markets in the financial system, in contrast to their microprudential counterparts which aim at investigating the resilience of individual financial institutions. Consequently, macroprudential stress tests can be used to identify risks that could have a detrimental effect on financial stability.

Financial turmoils in the recent decades showed that relatively small losses can be magnified to systemic dimensions (Haldane and May, 2011), verifying theoretical insights (Allen and Gale, 2000, Eisenberg and Noe, 2001). Macroprudential stress tests aim at capturing

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such losses, endogenously amplified through feedback and contagion effects, and investigate which features of the institutions and the system fuel them. To date, most stress tests have been used as an analytical and diagnostic tool, but well-designed stress testing frameworks can also be used in designing and calibrating macroprudential policy tools.

The stress testing methodologies developed for the banking sector are relatively advanced (Quagliariello, 2009). However, there is evidence that feedback loops also exist in market-based finance, particularly through fire sales of assets (Coval and Stafford, 2007, Shleifer and Vishny, 2011). This fact, in conjunction with the rapid expansion of market-based finance after the global financial crisis, means that there is a need to apply stress testing beyond the banking sector. The International Monetary Fund (IMF) included an expansion of the coverage of stress testing tools to non-banking financial sectors in their 2014 Financial Sector Assessment Program (FSAP) review. Bank of England recently performed a macroprudential stress test looking into how fire sales could create feedback loops in market-based finance (Baranova et al., 2017).

In Ireland, investment funds represent a large share of the financial system (Lane and Moloney, 2018), thus macroprudential stress testing of this sector is particularly important. Indeed, IMF Country Report No. 16/312, as a conclusion of the FSAP for Ireland, recommends that the Bank should "build internal capacity that would allow for more frequent stress testing with respect to market shocks for Money Market Funds (MMFs), and Investment Funds that avail of significant leverage" and conduct "more frequent liquidity stress tests [. . .] informed by security level fund holdings." In addition, Irish-based funds are externally orientated, with the vast majority of their assets being international and their liabilities held by investors outside of Ireland. Consequently, these funds are of macroprudential relevance internationally, rather than just domestically.

An Lonn Dubh[1] is a framework that develops capacity for the Bank to conduct macroprudential stress testing exercises for investment funds (including money market funds). From a practical perspective it is a software package designed to be integrated with the Bank's data and to allow fast prototyping of a wide range of stress tests in a modular and standardised way. In this way, the Bank can perform targeted simulations in a timely manner, aiding the macroprudential surveillance of the investment funds sector. The framework is based on *Black Rhino*, a general financial simulation framework. In the remainder of the section we describe the architecture and principles of *An Lonn Dubh*.

The framework's general architecture can be seen in Figure 1. *An Lonn Dubh* has a number of important features. First, the framework is modular and consists of four fundamental building blocks. The *agents* are the financial institutions involved in the stress test simulation, comprised of the relevant investment funds and potentially other market participants. The *environment* represents the macroeconomic setting in which a simulation takes place. The *dynamics* represent the behaviour of the *agents* and the *environment*, including the shocks. The *structure* represents the interconnectedness of the agents within a simulation. There is flexibility with respect to the inclusion of these modules in a particular stress test, e.g. a majority of stress tests would incorporate multiple *agents* (representing each fund in the simulation), but typically only one *environment* (representing the economy) and perhaps no *structure* (if the model does not consider network effects). Importantly, the components of the described modules are also modular, comprised of a number of specific functions.

Second, the framework is standardised. All modules within the framework have a corresponding template,[2] which ensures that all stress test implementations within *An Lonn Dubh* are consistent. In addition, features from previously implemented stress tests can easily be

[1] *The Blackbird* in English.
[2] Implemented as an abstract base class.

used in newly designed simulations, leading to economies of scale which grow over time.

Third, *An Lonn Dubh* is fully automated and integrated with the data in the Bank. Further standardisation within the framework is maintained through an automated interface to the Bank's data, meaning the framework is fully integrated with fund return data in particular. This ensures that implementations of stress testing simulations within the framework can be based on a standardised approach to data, consistent, and fast to prototype. Nonetheless, the framework is flexible enough to allow for the inclusion of other data in particular implementations, should it be necessary.

Fourth, the framework is highly flexible. While *An Lonn Dubh* is designed with investment funds in mind, it can in principle include any other institutions, making it possible to model any interactions relevant to the particular stress test simulation. For instance, Bank of England has included dealers in their recent work (Baranova et al., 2017). Our framework can also be extended to include such entities. Further, a model based on the framework can easily include the structure of the studied financial system, allowing for the inclusion of network effects. Finally, the framework is flexible enough to allow for the inclusion of macroprudential policy tools (such as liquidity management), potentially helping in designing, testing, and calibrating such tools for investment funds.

Lastly, the framework features automated quality control incorporating tools in line with the best practices in software development.[3] Further, the framework is accompanied by detailed documentation, making its use easy for new users.

In Section 2 we present the baseline model for stress testing investment funds, serving as a proof of concept and a foundation for future implementations. In Section 3 we present the results obtained through simulating the baseline model using the Bank's data on investment funds. Finally, Section 4 concludes.

2 Baseline model

We employ a model of redemptions and fire sales adapted for the investment funds sector. In particular, we apply a range of exogenous redemption shocks to the funds which forces them to sell assets at depressed prices, creating further negative fund returns and subsequent endogenous redemptions. In this sense, our model is similar to that of Baranova et al. (2017). This is a baseline model, designed to be the foundation for more complex future implementations, hence it only incorporates the minimum features required to conduct the stress test. As such, this implementation is not designed to guide policy but to provide a general overview of the sensitivity of the Irish-domiciled investment funds to stressed market conditions.

We use the Bank's data as of the end of September 2018, containing both the characteristics and holdings of investment funds. Each fund is described by a unique identifier, the category it belongs to, and whether it is an open-ended fund. There are seven categories that funds ascribe themselves to: bond, equity, hedge, money market, mixed, real estate, and other funds. Investment funds are classified as open if they allow shares redemption at any time and closed if they do not. Technically, only open funds should be subject to redemption shocks. For simplicity, we have also included closed funds in the simulation, as they represent only a small fraction (1.5 per cent) of the sector in terms of gross assets. Hence, their

[3] The framework is implemented in Python 3.7, although interface to the data uses SQL. The framework is version controlled using git. Any new release of the framework is only allowed after automated code quality review is passed, which includes tools such as pytest, Pylint, Flake8, mypy, Black, and pydocstyle.

inclusion does not have a significant impact on our results. The holdings of funds are classified as assets or liabilities, with further information including instrument type, the sector and region of the issuer, as well as the value of each position. For simplicity, in the baseline model we use gross assets. As the debt liabilities represent only thirteen per cent of gross assets across all funds, netting the assets does not qualitatively change our results and would unduly complicate the baseline model. All of the model assumptions can be relaxed in future implementations to allow for a more granular analysis.

In order to measure the price impact of asset sales, we group the assets into eighteen categories as outlined in Table 1. Specifically, debt securities are grouped by government or corporate issuer (banks, asset managers, non-financial companies (NFCs), and others). Government debt is further grouped by region (EU, UK, US, and the rest of the world (RoW)), while corporate debt is summed across all regions. The underlying assumption of this grouping is that contagion effects are expected to occur between corporate debt markets across different regions, but any sales of government debt would only be felt in the specific region. On the other hand, equities are grouped by region and summed across all sectors. We do not group by sector because the data show that equities are highly concentrated in a few of them, reducing the informativeness of such grouping. All other instrument types are not further grouped by sector or region as they represent only a small proportion of total assets. The grouping is based on the assumption that the correlations of asset prices within the specified categories would be greater than between categories. For example, equities are typically strongly correlated within regional markets. In summary, the total asset value across all funds and instrument types in September 2018 stood at just over three trillion euro, of which forty-three per cent relate to debt securities, thirty-nine per cent to equities, with the remaining eighteen per cent representing other instrument types.

With this dataset, we run the stress testing simulation. The model can be described as a cycle representing events happening at time t, usually representing a day, as shown in Figure 2. This cycle can be repeated to run up to T times, simulating T consecutive periods, and investigating t-th round effects.

The initial shock is assumed to be exogenous, and is translated as fund redemptions within a given category of funds which lead to asset sales. These are assumed to be absorbed by institutions outside of the simulation. We assume that funds attempt to retain their portfolio composition by selling assets in a pro-rata fashion as in Baranova et al. (2017), rather than using the waterfall approach by selling their most liquid assets first to satisfy redemptions. Next, in line with the academic literature, we assume that asset sales have a linear impact on asset prices. Specifically, following Greenwood et al. (2015) we assume a price impact factor of 10^{-13} for all categories except *cash instruments*, i.e. a sell-off of ten billion euro of assets in a specific category would reduce the price of these assets by ten basis points. Cash instruments are assumed to be perfectly liquid with a price impact factor of 0. Since the baseline model does not account for potential correlated shocks to investment funds outside of Ireland, the estimated fire sale impact is the marginal price impact due to the sales of Irish funds, rather than a global effect. Further analysis on the implications of different price impact factors across asset classes on the results is left for future implementations.

The reduction of asset prices in the first round leads to negative fund returns. These in turn lead to second round redemptions due to the sensitivity of investors to past returns of investment funds. In other words, investors place additional redemptions following the negative returns of funds stemming from the initial shock. Thus, shocks in each round within the model except the first are endogenous. In our baseline results below, we calibrate the flow-performance factor to 0.859, i.e. for each per cent of negative fund return the investors redeem 0.859 per cent of their investments, consistent with the findings of Goldstein et al.

(2017) and also employed by Capponi et al. (2018). Even though Goldstein et al. (2017) estimate this figure for corporate bond funds, we make the simplifying assumption in the baseline model that this number applies across all fund categories. However, the framework readily allows for unique flow-performance factors for each category and even for each individual fund within categories, which can be further examined in future implementations. The new redemptions in turn lead to further asset sales and redemptions, repeating the cycle up to period T. While the number of repetitions can be selected arbitrarily, the results become more uncertain with each round, as investors are not expected to act in a static manner over a long period.

3 Results

For the baseline model, we take the approach of reverse stress testing by identifying the market conditions under which there can be significant spillovers due to fire sales. We first present the model's results under normal market conditions, described by adequate market liquidity and moderate investors' risk aversion. Afterwards, we repeat the analysis under stressed market conditions whereby market liquidity evaporates and investors become highly sensitive to fund returns. As a result, we are able to identify the level of stress that leads to significant second round losses due to fire sales.

We start by presenting the baseline results in Figure 3, showing losses[4] as a per cent of total assets of all Irish-domiciled funds following a uniform redemption of α per cent of the assets within a given category of funds. We obtain results which are an almost linear function of the initial shock, the size of the shocked category of funds, market liquidity (price impact factor), and in the case of second round effects the sensitivity of investors to previous round fund returns (flow-performance factor).

As can be seen, the first round losses are dominant, while second round losses are negligible. As such, the magnitude of total losses across all funds is directly linked to the size of the shocked category of funds, since the larger the shocked category the larger the overall losses in the first round. Hence, bond and equity funds, which are the largest fund categories, produce the largest overall losses, while real estate funds, the smallest category, produce the smallest ones.

We further investigate the composition of the first round losses across fund categories in Figure 4 where we show the losses as a per cent of the assets of funds within each category. The plots decompose the first round losses from Figure 3 into the shocked fund category and all other categories to explain the extent to which the losses are driven by the original redemptions on the shocked category and the spillover effects on all others categories of funds. In each case, the shocked fund category suffers the largest losses while spillover losses to other categories are small (without economic significance) and only marginally increasing as a function of the shock. Overall, under standard assumptions on market liquidity and investors sensitivity to fund returns, the magnitude of spillovers, subsequent losses and redemptions is limited, even for sizeable initial redemption shocks.

Next, we investigate how this insight changes under alternative market conditions. In Figure 5 we plot first and second round losses across all Irish-domiciled funds for a range of values of the price impact factor. While second round losses remain limited compared to the first round ones for conventional values, when market liquidity evaporates they can be substantial and non-linear. The concave nature of losses is due to the interaction of the sales

[4]Fund losses are defined as changes in assets under management while fund returns are defined as changes in net asset value per share.

and the price impact applied to remaining holdings. Figure 6 breaks down the second round losses in the extreme scenario of price impact factor of 10^{-11} (i.e. a hundred million euro of asset sales leading to a change of the price of the asset of ten basis points) into the different fund categories, showing losses as a per cent of the assets of funds within each category. This figure illuminates the potential for contagion between various fund categories due to their indirect interconnectedness through common asset holdings. For example, when bond funds are shocked, the fire sale of their assets creates second round losses for MMFs that are even higher than those for bond funds. Shocks to MMFs also affect bond funds but to a lesser degree. The asymmetry is due to the asymmetry in the value of holdings of common assets between fund categories. Similarly, shocks to equity funds significantly affect hedge funds (and vice versa). Hence, under heightened market illiquidity, fire sales can cause losses to become systemic as postulated by Shleifer and Vishny (2011).

Finally, in Figure 7, we present second round losses across all Irish-domiciled funds for a range of values of the flow-performance factor representing the per cent of redemptions following one per cent of negative returns of a given fund. The price impact factor is assumed to be equal to 10^{-11} since that is the only case where second round losses are significant. We observe that second round losses remain marginally smaller than the first round ones only for the conservative parameter value of 0.5, but when the flow-performance factor becomes larger this is no longer true. As a result, when market illiquidity makes investors more risk-averse and more prone to redeem their investments, the spillover effects can exceed those due to the original redemptions. We would expect such conditions to be likely to manifest during systemic crises, for example as experienced during the run on US MMFs during the days following the default of Lehman Brothers. Market illiquidity incentivises investors to redeem first in order to avoid remaining in a fund after the manager has sold all liquid assets to satisfy redemptions. We would also expect funds with institutional investors to be more susceptible to second round effects than funds with retail investors due to greater investor sophistication.

4 Conclusions

We have reported the proof of concept of a standardised framework for fast prototyping of macroprudential stress tests of investment funds in Ireland. The presented baseline stress test highlights the usefulness of the framework for monitoring systemic risk. It underlines the importance of market liquidity and indirect interconnectedness through common asset holdings as well as investors' sensitivity to fund returns in determining the manifestation of spillovers and feedback loops in market-based finance. In future stress tests, the assumptions of the baseline model can be relaxed. For example, the framework allows for easy introduction of non-linear or stochastic functions with regards to the redemptions, asset sales, price impact, and investor sensitivity to fund returns. Further, the exogenous shock can also be applied to market prices, rather than redemptions. Finally, the framework allows for an extension of the model to include other features such as more sophisticated price discovery, macroprudential policy tools, and the incorporation of agents other than investment funds.

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Table 1: Holdings of assets of all Irish-domiciled funds in eighteen aggregate categories used in the baseline model at the end of September 2018, reported in billions of euro. Total value of assets of all funds involved in the presented stress test exceeds three trillions of euro. Bond and equity funds are the largest, each accounting for a quarter of all assets of Irish-domiciled funds. Debt securities and equities each represent around forty per cent of all assets of Irish-domiciled funds. MMFs denote money market funds. Values denoted by * removed for reasons of confidentiality. Source: Authors' calculations using Central Bank of Ireland data.

Instrument	Sector	Region	Bond	Equity	Hedge	Mixed	MMFs	Real Estate	Other	Total
Cash instruments	All	All	45.05	29.18	50.90	23.10	68.01	1.32	55.34	272.90
Debt securities	Governments	EU	55.18	0.82	2.11	10.11	7.30	*	3.24	*
Debt securities	Governments	UK	37.50	0.27	1.70	45.04	11.86	*	158.79	*
Debt securities	Governments	US	59.01	5.25	12.46	7.46	26.66	*	3.29	*
Debt securities	Governments	RoW	63.82	0.11	0.87	3.89	1.31	0.00	0.30	70.31
Debt securities	Banks	All	87.54	2.41	1.27	11.91	233.95	*	1.46	*
Debt securities	Asset Managers	All	187.65	0.95	10.86	13.32	40.55	0.07	11.05	264.45
Debt securities	NFCs	All	114.10	2.12	4.85	10.80	22.33	0.09	4.35	158.63
Debt securities	Others	All	5.60	0.01	0.17	0.41	2.90	0.00	0.22	9.31
Equity	All	Ireland	22.12	28.25	35.57	56.48	0.75	0.68	20.12	163.97
Equity	All	UK	2.09	53.59	7.34	15.81	*	0.55	1.87	*
Equity	All	Other EU	1.82	121.07	28.44	25.47	*	1.01	3.87	*
Equity	All	US	5.73	315.99	71.53	21.00	*	1.61	5.88	*
Equity	All	RoW	2.92	247.28	42.53	21.51	0.00	0.98	5.96	321.19
Securities Borrowing	All	All	6.58	0.62	*	2.41	72.01	0.00	7.56	*
Property and land	All	All	0.00	0.00	0.00	0.00	0.00	19.56	0.00	19.56
Derivatives	All	All	5.09	16.78	18.30	7.33	*	0.00	46.15	*
Other assets	All	All	38.45	9.90	11.91	6.48	1.39	0.96	16.38	85.46
Total	All	All	740.25	834.62	*	282.52	489.42	27.05	345.82	3,020.79

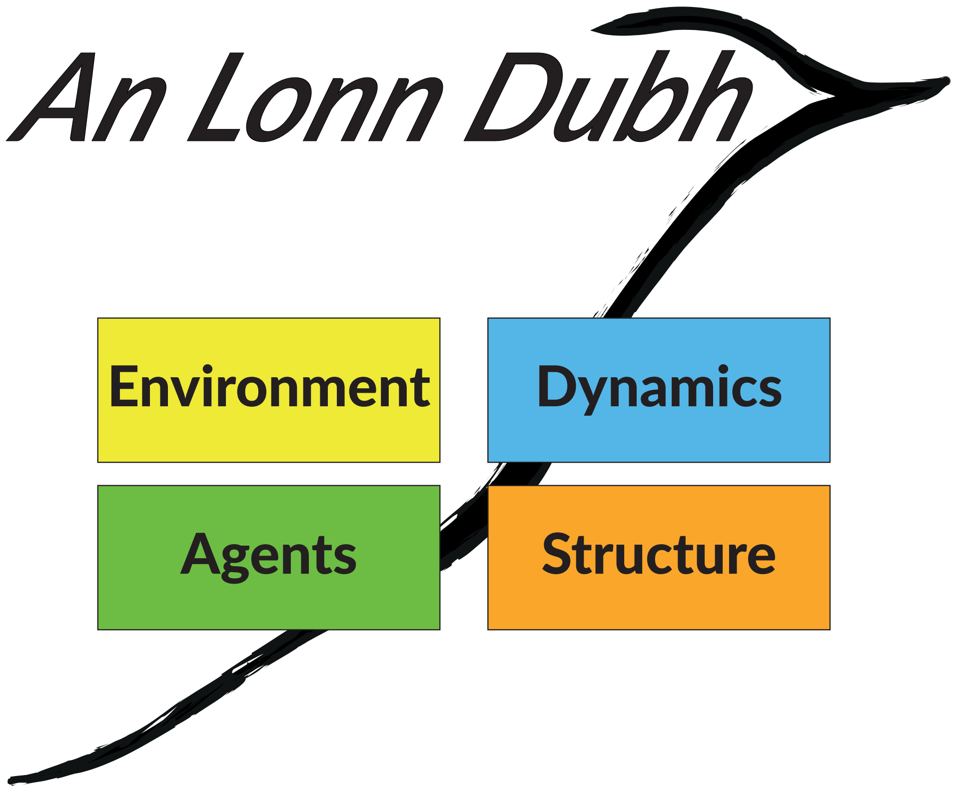

Figure 1: Structure of *An Lonn Dubh* — a framework for macroprudential stress testing of investment funds. The framework has four building blocks. *Agents* represent the modelled financial institutions, most notably the investment funds, but can also include other institutions. *Agents* have a balance sheet filled with transactions. *Environment* represents the macroeconomic situation in which the *agents* find themselves in, e.g. including measures of market liquidity. *Dynamics* represent the behaviour of the *agents* and the financial system, most notably including the economics of a given stress test and applied shocks. *Structure* represents the interconnectedness of financial institutions, allowing for the inclusion of network effects. Source: Authors' compilation.

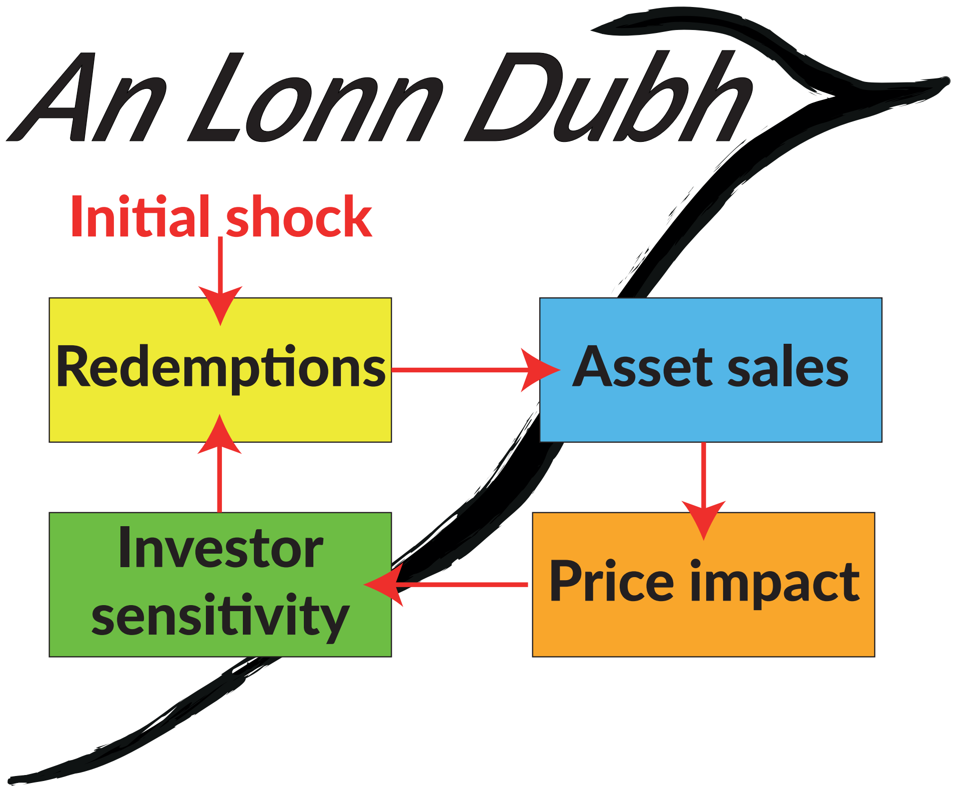

Figure 2: High-level structure of the baseline model. The simulation starts with an exogenous initial shock, i.e. redemption requests for certain investment funds. These redemptions create asset sales, which are proportional to the size of the redemptions and the proportion of the asset categories on the fund's balance sheet, as we assume investment managers wish to retain their portfolio composition. These asset sales are absorbed by institutions outside the simulation, and generate a price impact depending on the size of the aggregate sales of a given category of assets. The price impact leads to negative returns of affected funds, prompting investors to issue further redemption requests. These requests start the next round of the model, instead of the exogenous initial shock. Source: Authors' compilation.

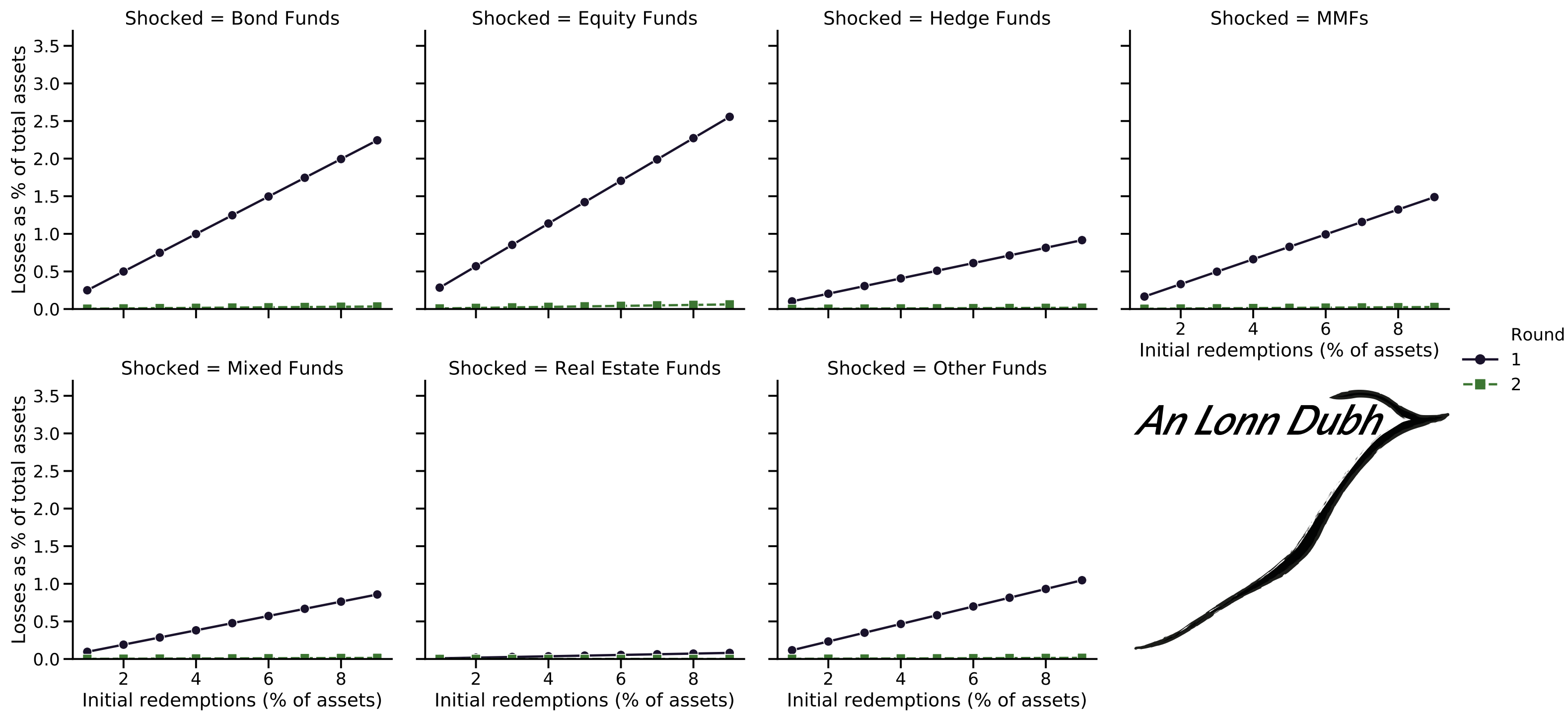

Figure 3: Aggregate losses as per cent of assets of all Irish-domiciled funds following a uniform redemption shock to a category of funds (shock to each category of funds presented as a separate subplot). Losses shown for $T = 2$ rounds of redemptions, where redemption shocks for the second round stem from investors' sensitivity to fund returns from the previous round. Losses stemming from the first round are the largest, while second round losses are negligible. The losses to all funds following a shock to a given category are a function of the shock, with the slope dependent on the share of assets of funds within that category in assets of all Irish-domiciled funds. MMFs denote money market funds. Source: Authors' calculations using Central Bank of Ireland data.

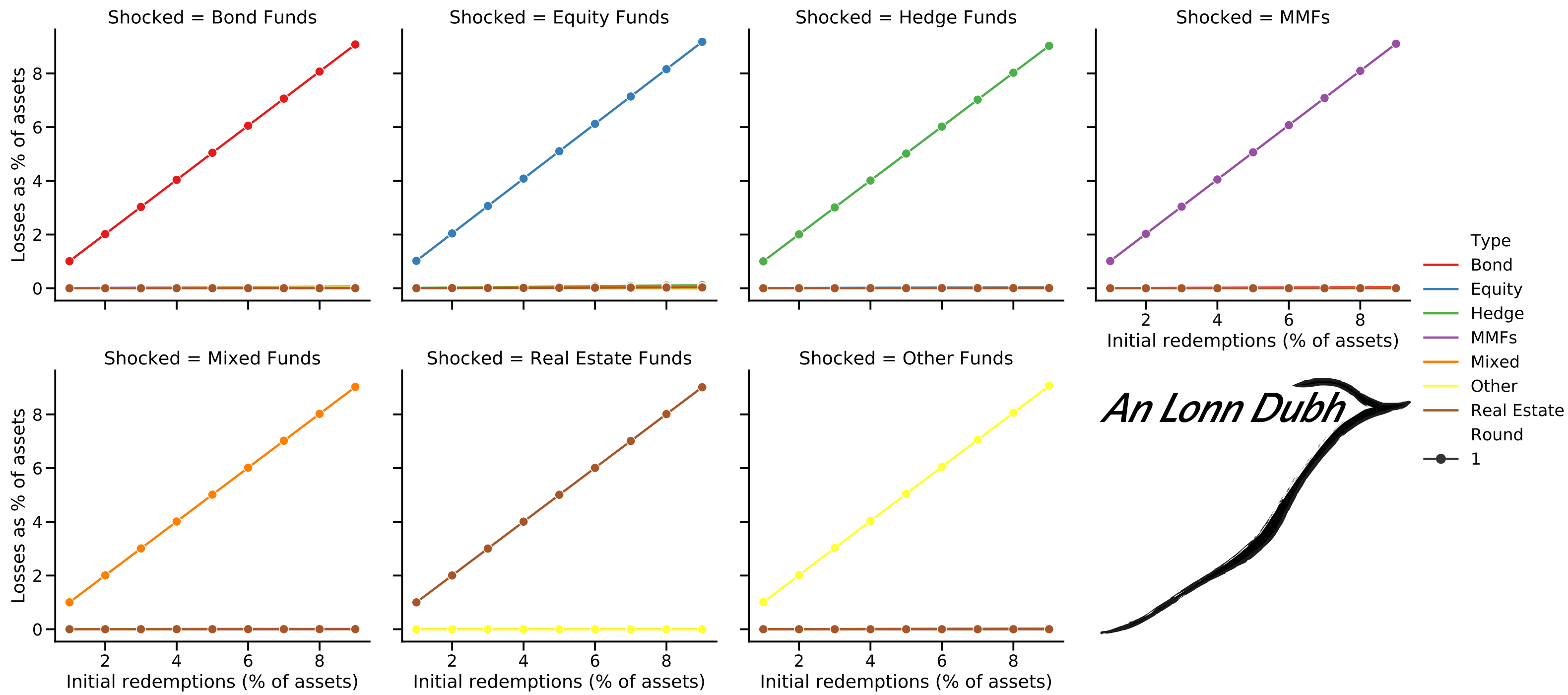

Figure 4: Losses as per cent of assets of a category of Irish-domiciled funds (losses for each category shown as a separate colour) following a uniform redemption shock to a category of funds (shock to each category of funds presented as a separate subplot). Losses shown only for the first round of redemptions for clarity of presentation, but results for subsequent rounds of redemptions are qualitatively comparable. The results show that under standard assumptions on market liquidity and investors' sensitivity to fund returns from previous rounds, there are no significant spillovers between categories of funds. It substantiates that the slopes of results shown in Figure 3 stem from the ratio of assets of funds within a given category in all Irish-domiciled funds. MMFs denote money market funds. Source: Authors' calculations using Central Bank of Ireland data.

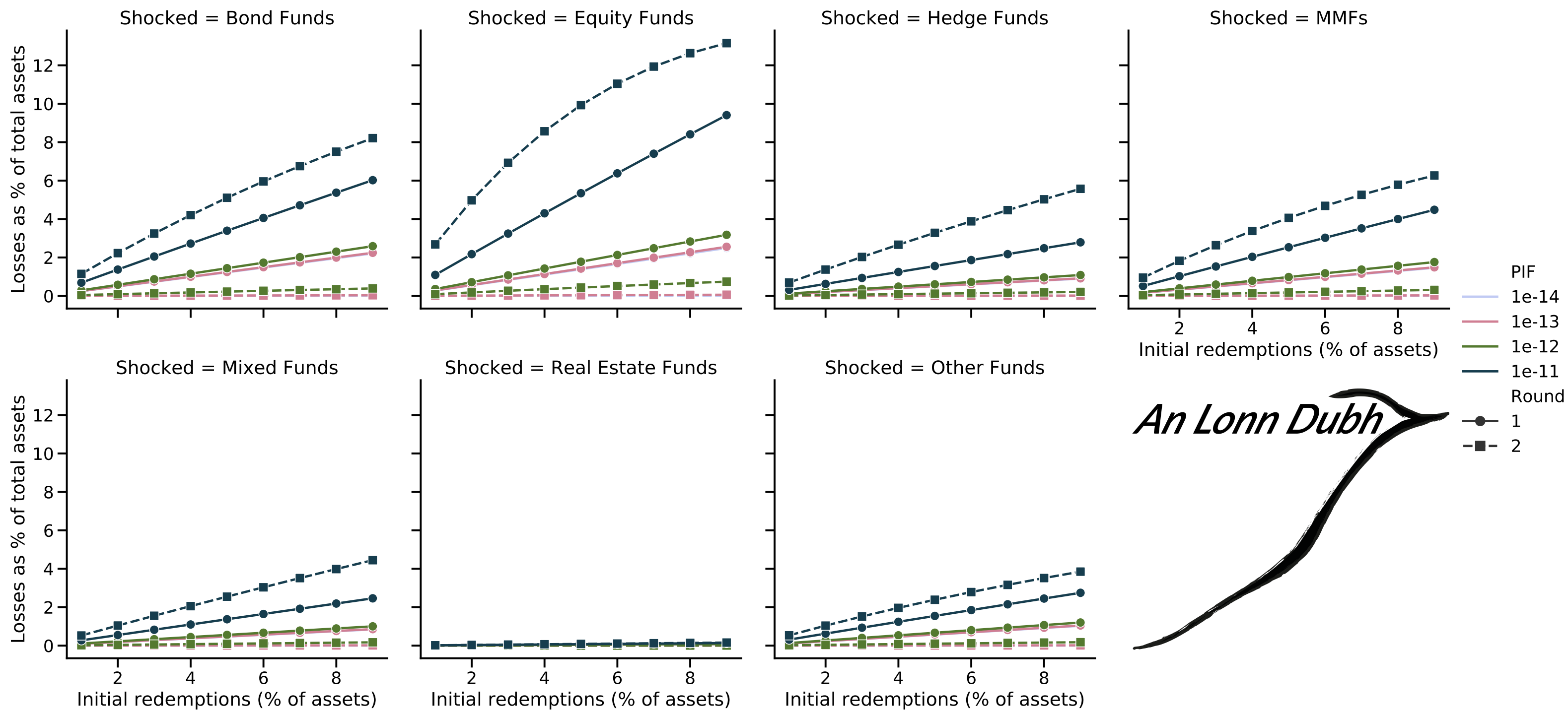

Figure 5: Aggregate losses as per cent of assets of all Irish-domiciled funds following a uniform redemption shock to a category of funds (shock to each category of funds presented as a separate subplot). Losses shown for $T = 2$ rounds of redemptions, where redemption shocks for the second round stem from investors' sensitivity to fund returns from the first round. Losses shown for various values of price impact factor (PIF, representing the decrease in price following one euro of sales in a given category of assets). While for the standard assumption on market liquidity (PIF equal to 10^{-13}) we do not observe large spillover effects, these are negatively related to market liquidity. We find that for market liquidity smaller by two orders of magnitude there are significant second round losses. MMFs denote money market funds. Source: Authors' calculations using Central Bank of Ireland data.

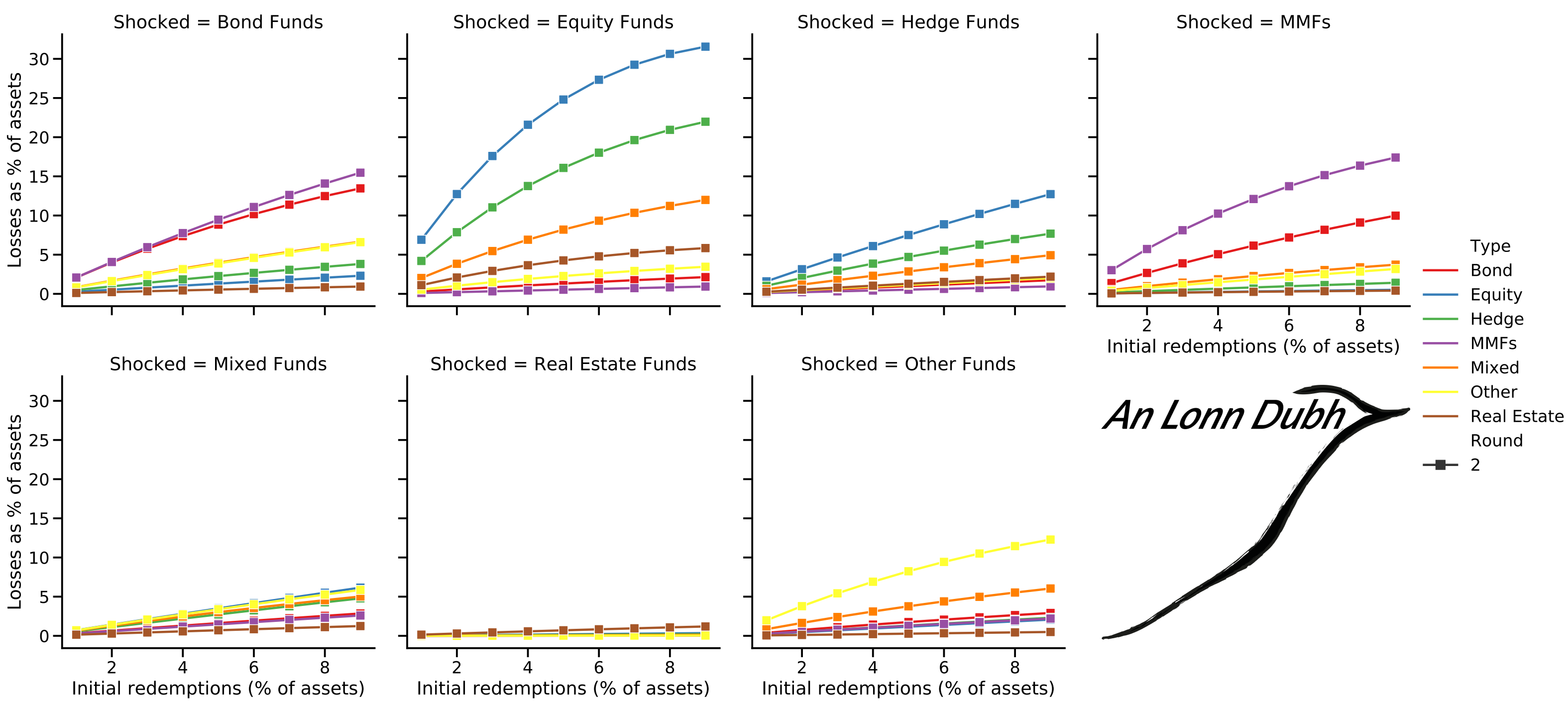

Figure 6: Losses as per cent of assets of a category of Irish-domiciled funds (losses for each category shown as a separate colour) following a uniform redemption shock to a category of funds (shock to each category of funds presented as a separate subplot) under significant market illiquidity (price impact factor of 10^{-11}). Losses shown only for the second round of redemptions related to the sensitivity of investors to losses from the first round for clarity of presentation, but results for the first round are qualitatively comparable. The results show that under significant market illiquidity there are spillovers between categories of funds. In particular, shocks to bond funds seem to significantly affect money market funds. The spillovers from shocks to money market funds to bond funds are significant, but not as pronounced. Shocks to equity funds seem to significantly affect hedge funds, and vice versa. MMFs denote money market funds. Source: Authors' calculations using Central Bank of Ireland data.

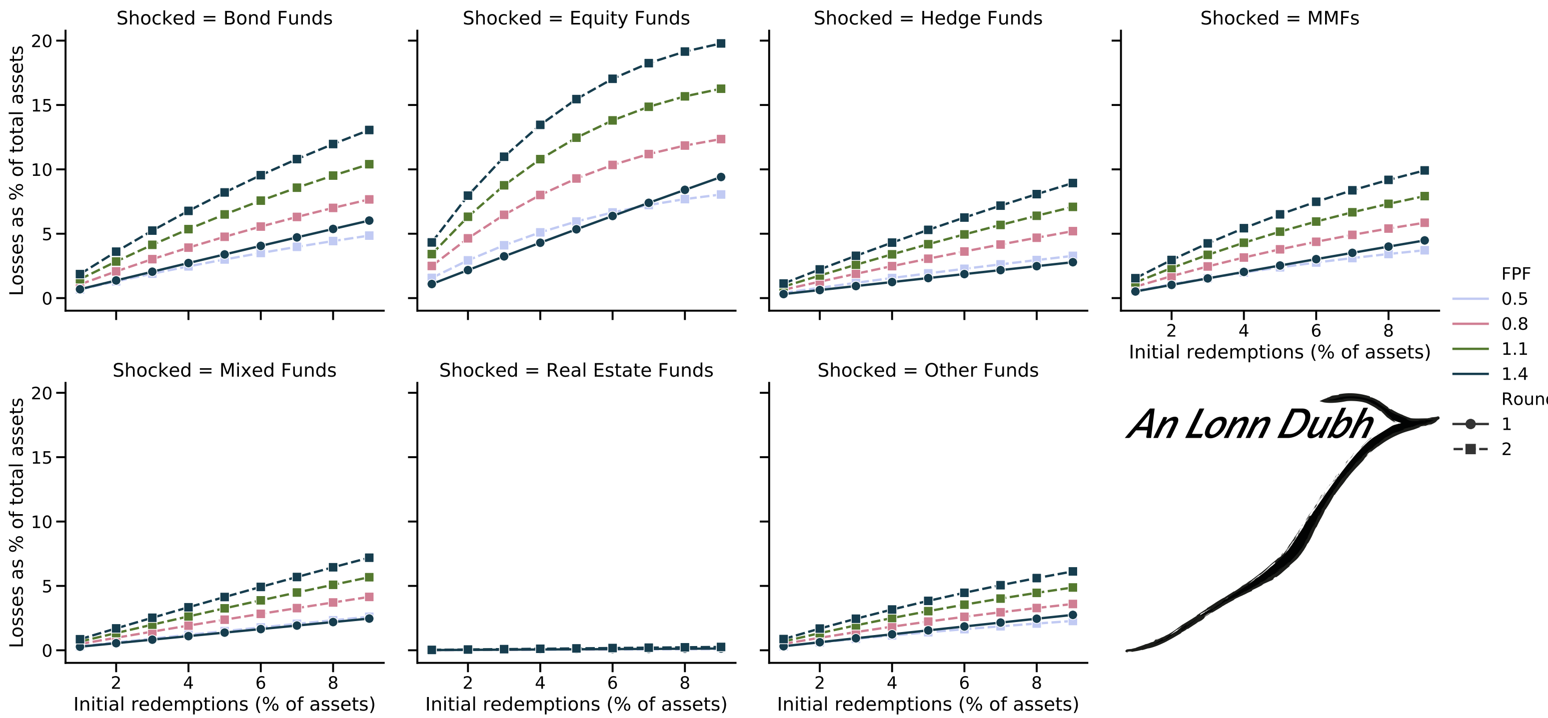

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Figure 7: Aggregate losses as per cent of assets of all Irish-domiciled funds following a uniform redemption shock to a category of funds (shock to each category of funds presented as a separate subplot). Losses shown for $T = 2$ rounds of redemptions, where redemption shocks for the second round stem from investors' sensitivity to fund returns from the first round. A price impact factor of 10^{-11} is assumed, i.e. significant market illiquidity. Second round effects for various values of flow performance factor (FPF, representing the per cent of redemptions following one per cent of negative returns of a fund) are shown. First round effects do not depend on this factor, thus only one line is plotted. While the conservative assumption on the sensitivity of redemptions to fund returns (FPF equal to 0.5) leads to second round losses being smaller than the original losses, this result depends on the value of the flow performance factor, and for values of 0.8 and upwards second round losses become larger than first round losses. MMFs denote money market funds. Source: Authors' calculations using Central Bank of Ireland data.