Network Effects of Portfolio Rebalancing by Global Bond Funds

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February 20, 2024

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Abstract

We study the impact of an exogenous shock on portfolios of global funds investing in emerging market (EM) sovereign government bonds, examining the network of interconnections among these funds and their role in transmitting losses. Leveraging a quasi-natural experiment surrounding the Argentinian primary presidential elections in August 2019, which led to a significant loss for funds invested in Argentinian debt, we employ a difference-in-difference research design to explore the subsequent portfolio rebalancing and selling pressure propagation through cross-holdings of EM sovereign bonds. Our findings reveal that the initial portfolio losses prompt discretionary sales of other EM sovereign bonds by affected funds, creating spillover effects on peer global funds. Utilizing a modified Coval-Stafford pressure metric, we quantify exposure-induced bond sales or purchases by affected "peer" funds and demonstrate their significant impact on bond returns. This study contributes to the literature on open-ended mutual funds, shedding light on peer selling pressure dynamics and the contagion effects that may arise from portfolio rebalancing in the context of unexpected shocks. The results underscore the importance of understanding network interconnections among funds for financial stability considerations.

JEL Classification: G11, G15, G23

Key words: Mutual funds, Fire-sales, Sell Pressure, Peer Pressure, Sovereign Default

1 Introduction

The highly accommodative monetary policies implemented in the aftermath of the global financial crisis spurred investors to seek higher yields (e.g., Becker and Ivashina, 2015; Choi and Kronlund, 2017). Consequently, given the low yields in advanced economies, coupled with appealing global economic growth, investors have progressively augmented their exposure to a diverse range of fixed-income strategies in emerging markets. A prominent trend involves the substantial increase in assets under management by global fixed-income funds, which form multi-country bond portfolios. The International Monetary Fund reports that since 2008 these funds nearly doubled their assets under management to about $1 trillion which constitutes 10 percent of the global bond investment fund sector (Cortes and Sanfilippo, 2020).[1] Within this group of funds, the assets managed by funds that focus on EM sovereign bonds have surged seven-fold, accounting for up to 19 percent of total assets for the average fund. Notably, approximately 98 percent of EM open-ended bond funds are actively managed (Shek, Shim, and Shin, 2018; Hui, 2019).

A possible reversion of this trend raises concerns about vulnerabilities for investors and borrowers as well as potential contagion effects across markets. For instance, Jotikasthira, Lundblad, and Ramadorai (2012) have documented the evidence of contagion resulting from equity funds domiciled in advanced economies liquidating their holdings of emerging markets equities. Recent literature explores the connectedness of mutual funds through the network of shared securities holdings and finds that the actions of a group of funds could exert a significant influence on market dynamics, ultimately affecting broader asset classes and funds. The phenomenon of portfolio rebalancing by funds, especially when conducted at discounted prices, has been shown to induce pressure on other funds and asset prices (e.g., Falato, Hortaçsu, Li, and Shin, 2020; Fricke and Wilke, 2023).

In this paper, we exploit the exogenous shock that generated a significant loss for portfolios of funds investing in emerging market (EM) sovereign government bonds. We show that the inherent network of interconnections among these funds functions as a mechanism for transmitting losses, potentially magnifying, and redistributing vulnerabilities associated with fire sales. These sales may arise either from the necessity to fulfill investor redemptions on the liability side or from

[1]According to the Bank of International Settlements (BIS) the total dollar-denominated debt of non-banks by emerging market economies stood at $3.6 trillion in 2017.

discretionary sales by active fund managers exceeding those mandated by investor redemptions (e.g., Shek, Shim, and Shin (2018)).

In examining the influence of funds' exposure to an adverse shock on their portfolio rebalancing, potential confounding arises if funds that are affected by the shock endogenously choose the level of their exposure based on their expectations and unobservable investment opportunities during the shock. To mitigate this issue in our study, we adopt a difference-in-difference research design on portfolios of international bond funds that were invested in sovereign government bonds of Argentina around the Argentinian primary presidential elections in August 2019. The unanticipated results of these elections precipitated the departure of a pro-market president and subsequently culminated in the nation's sovereign default in May 2020 when it failed to pay around $500 million in interest on its already delayed bond debt. The fortuitous nature of the election outcome in our study introduces a substantial element of randomness into the distribution of funds' pre-election exposure allowing for a causal estimation of the impact of the affected funds' post-shock portfolio rebalancing and selling pressure propagation through cross-holdings of other emerging market sovereign bonds with unaffected funds. We use rich microdata on multi-country open-ended bond funds with portfolios encompassing positions in both advanced and emerging markets. In our sample, the majority of global bond funds are domiciled in Luxemburg (33 percent of funds) and the U.S. (27 percent of funds) – the largest fund families by the number of mutual funds being Amundi, Fidelity, PIMCO, BlackRock, and Invesco (See Tables A.4 and A.2 in the Appendix).

The Argentinian context serves as an apt context for our investigation. Despite Argentina's historical recurrence of eight sovereign defaults, the latest occurring in 2001, the nation experienced a successful reentry into the international debt markets from 2016 through 2018. During this phase, Argentina raised $56 billion from international bond funds and other financial institutions, with our study specifically concentrating on the 'Macri bonds' named after the pro-market president who in 2016 settled the 14-year $4.65 billion cash payment to its main holdout creditors.[2] These 'M-bonds' were issued under New York law and were denominated in the US dollars and Euro. However, the unforeseen outcome of the presidential primaries in 2019 triggered an immediate reassessment of

[2] `https://www.bloomberg.com/news/articles/2016-02-29/argentina-reaches-4-65-billion-deal-with-main-holdouts`

the sovereign default probability of Argentine debt, leading to a sudden and steep depreciation in the prices of these sovereign bonds.

The results of our empirical investigation reveal that the initial portfolio loss of exposed funds due to Argentina leads to discretionary sales of other EM sovereign bonds and cash hoarding by managers of these funds, without significant flows by ultimate fund investors. As demonstrated by Morris, Shim, and Shin (2017), this strategic move serves the dual purpose of discouraging redemptions and expanding the pool of liquid assets available for potential sales to fulfill future redemption requests. During times of stress, funds may choose to reallocate their investments into assets that are either less risky or more liquid. Specifically, we find that affected funds with high exposure to Argentina significantly reduced their holdings of EM sovereign bonds and increased cash holding in the post-shock period compared to the pre-shock. We find that these results were primarily driven by *Speculative* funds with portfolios overweighted with low-credit and illiquid EM government bonds. The flows of funds by ultimate investors do not exhibit pronounced patterns for the full sample of funds, with marginally significant flows in the expected direction for both affected and unaffected *Speculative* funds. Collectively, our evidence illustrates that fund managers of exposed funds may choose to make discretionary sales of assets beyond what is necessary solely by redemptions, while managers of non-exposed funds view this unforeseen shock as an opportunity to purchase other sovereign EM bonds. For both groups of funds, cash reserves serve as an important vehicle for portfolio rebalancing.

Drawing from these results, we delve into the financial stability ramifications of cross-fund investments and sales. Our empirical setting randomly assigns funds to affected and unaffected groups according to their pre-determined Argentinian debt exposure and allows us to operationalize a well-known "flow pressure" metric introduced by Coval and Stafford (2007). We modify this metric by replacing the original high-low outflow affected-unaffected status of a fund with a high-low exposure status. Similarly, to Falato, Hortaçsu, Li, and Shin (2020) for each sovereign bond b held by a given fund i, we compute the modified Coval-Stafford pressure metric based on the exposure status of funds other than i. Our modified metric examines alterations in the holdings of specific bonds by mutual funds with high and low exposure to Argentina during the Argentinian elections shock. This allows us to investigate the fire-sale pressure at each bond b level. Furthermore, we aggregate this bond-specific exposure pressure as a weighted sum of each fund i's sovereign bond holdings. The obtained metric quantifies the degree to which fund i is susceptible to exposure-induced bond sales or purchases initiated by "peer" funds that share emerging market sovereign bonds in their portfolios. Our modified Coval-Stafford pressure metric relies on the theoretical contributions of Greenwood, Landier, and Thesmar (2015) and Fricke and Fricke (2021) who show that banks and fund managers have fixed leverage targets and liquidate assets according to their original portfolio weights. They show both theoretically and empirically that the impacted banks/funds may respond to the initial fire-sale of one asset by selling additional assets to fortify their balance sheets.[3]

Our empirical analysis reveals that EM sovereign government bonds with heightened exposure to the risk of cross-fund liquidation exhibited poorer performance in the aftermath of the Argentinian elections. This suggests that the cross-fund dimension may also be pertinent at the level of individual bonds. If we include the buying pressure exerted by non-exposed funds and calculate the net selling pressure, we find a significant negative effect of net selling pressure on bond prices for a sub-sample of investment-grade bonds. This finding suggests that non-exposed funds were net buyers of investment-grade EM bonds that experienced a decrease in prices during the Argentinian elections shock.

Finally, by exploiting the quasi-natural experiment setting, we present evidence of spillover effects from exposed global funds on the performance of peer funds operating in the same bond market and sharing similar bond holdings. We estimate that for the full sample of funds, a one-standard-deviation increase in exposure-induced EM bond sales by peer funds will decrease the returns of a given fund by 1.1 percentage point in the post-shock period. The net selling pressure metric, which considers buys by non-exposed funds, is also positive and statistically significant for the subsample of *Speculative* funds but has a negative impact on fund returns in a subsampple of *Investment* funds that are overweight in the less risky liquid bonds. This sub-sample analysis of funds specializing in speculative versus investment-grade EM sovereign bonds reveals that the result obtained for the full sample is driven by funds that are outweighted with speculative-grade EM sovereign bonds.

[3]In a related setting Sydow *et al.* (2024) empirically show how default shocks propagate through the network of the Euro zone banks and mutual funds.

Our study contributes to several strands of literature on open-ended mutual funds. First, we connect to an expanding body of literature that investigates the structural vulnerabilities within the fund sector arising from shared asset holdings, particularly in the context of fire sale externalities. Notably, studies such as Coval and Stafford (2007), Ben-Rephael, Kandel, and Wohl (2011), as well as Lou (2012), reveal instances of fire sales by open-ended investment funds in equity markets.

Most importantly, we add to studies that examine peer selling pressure among funds which is initiated with portfolio rebalancing by a group of funds and which propagates through the network of all fund's cross-holdings (e.g., Antón and Polk, 2014; Falato, Hortaçsu, Li, and Shin, 2020; Fricke and Wilke, 2023).

Our results demonstrate that significant declines in the portfolio value of funds lead to substantial second-round losses through peer selling pressure by funds which negatively affects other funds' returns. This peer selling pressure generates a contagion effect that may extend across seemingly unrelated assets and institutions. Fire sales of this nature have been examined in the extensive theoretical literature and are widely acknowledged as significant contributors to systemic risk in contemporary financial markets. For instance, Jotikasthira, Lundblad, and Ramadorai (2012) identify contagion resulting from investment funds domiciled in advanced economies liquidating their holdings of emerging markets equities. Manconi, Massa, and Yasuda (2012) investigated contagion from the securitized bond market to the corporate bond market in August 2007, stemming from the portfolio rebalancing of mutual funds. Dannhauser and Hoseinzade (2021) show that bond ETFs amplify the effects of negative fundamental shocks by creating flow-induced pressure on underlying bonds during periods of market turmoil.

The remainder of the paper is organized as follows. Section 2 provides the institutional background on global bond funds and the Argentinian primary presidential election shock. Section 3 describes the data and variables construction. Section 4 presents our empirical strategy and the main empirical results. Section 5 concludes.

2 Institutional Background

2.1 The Argentinian Primary Presidential Elections Shock

Following the election of pro-market candidate Mauricio Macri as president of Argentina in November 2015, which culminated in the resolution of previous debt litigations, Argentina marked its triumphant return to the global capital markets after being cut off for 15 years.[4]

On March 22, 2016, Fitch Ratings upgraded Argentina's long-term local currency issuer default rating from Restricted Default (RD) to 'B' with a Stable Outlook and stated that this action "reflected the improved consistency and sustainability of Argentina's policy framework, reduced external vulnerability, and the expected easing of fiscal financing constraints".[5] The first issuance of sovereign bonds in April 2016 generated \$16.5 billion for the Argentinian government, witnessing an oversubscription of four times, with total bids from international investors reaching \$68.6 billion. As highlighted Reuters, the sentiment among international bond fund managers during this period was described as a "grab-fest," indicative of a pervasive inclination toward pursuing higher yields by investors.[6]

However, the political landscape in Argentina experienced an unexpected shift in August 2019 when President Mauricio Macri suffered a substantial defeat in a primary vote, foreshadowing a likely loss in the subsequent October presidential election. Most commentators predicted that the business-friendly president who lifted currency controls and promoted liberalization policies would win the primary elections.[7]

Zhou *et al.* (2021) report that the top five Argentinian election pollsters: Real-Time Data, Management and Fit, Opinaia, Isonomia, Giacobbe and Elypsis made wrong predictions for the primary presidential elections of 2019. In particular, one of the most trusted pollsters, Elypsis, predicted that the pro-market candidate Macri would win by one percentage point. Zhou *et al.* (2021) summarize the pre-election expectations as follows: "This virtual tie predicted by the pollsters was

[4]See Sturzenegger and Zettelmeyer (2006); Engelen and Lambsdor (2009) for the details of Argentinian default, its resolution and impact on the global financial markets.

[5]`https://www.fitchratings.com/research/sovereigns/fitch-rates-argentina-2019-2021-2026-2046-global-bonds-b-21-04-2016`

[6]`https://www.reuters.com/article/us-argentina-bonds-bids-idUSKCN0XG2W0`

[7]`https://www.bloomberg.com/news/articles/2019-08-11/argentines-vote-in-primary-elections-seen-as-referendum-on-macri`

largely considered to be a win for the incumbent candidate Macri, since he was supposed to gain all the votes of the supporters of the third party in the subsequent presidential election and, eventually, win the election in a runoff".

Moreover, it was widely documented in the financial press that pollsters held several telephone conferences with foreign investors before the primaries telling them:

> "Macri wins by one point: 38 to 37%."

Based on these predictions, the Argentinian stock market rose in the days preceding the election. After Macri lost primaries by 16 points the stock market plunged by 30 percent, which was the second-biggest one-day stock market slump since 1950 internationally. On the same day, the Argentinian Peso depreciated by 15 percent against the US dollar demonstrating that the miscalculation of elections outcome by investors may dearly cost them and significantly impact financial markets. Figure 1 illustrates the dynamics of the Argentinian Stock Market Merval Index and the exchange rate of the Peso (ARS) against the US dollar.

According to the CNBC report the next day post primaries shock was described as follows:[8]

> "Speaking from Buenos Aires on Monday morning, Jimena Blanco, head of Americas research at risk consultancy Verisk Maplecroft, told CNBC that nobody — not even the most optimistic Fernandez supporters — expected to wake up to this result.
>
> "There is a total shock on both sides," Blanco said, emphasizing that almost all polls had predicted a much closer race between the two leading candidates."

In the wake of this political turmoil, sovereign Argentinian bonds experienced a sharp decline of around 30 percent, as detailed in Table A.1 in the Appendix. This market turbulence reflected the unexpected nature of the election outcome, contrary to prevailing predictions.

In May 2020 Argentina defaulted on its debts for the second time since 2001 when it failed to pay around $500 million in interest on its already delayed bond debt. This event marked the ninth time in its history that Argentina has defaulted on its debts, after the most recent episode

[8] https://www.cnbc.com/2019/08/12/argentina-election-macri-suffers-setback-as-analysts-warn-of-peso-depreciation.html

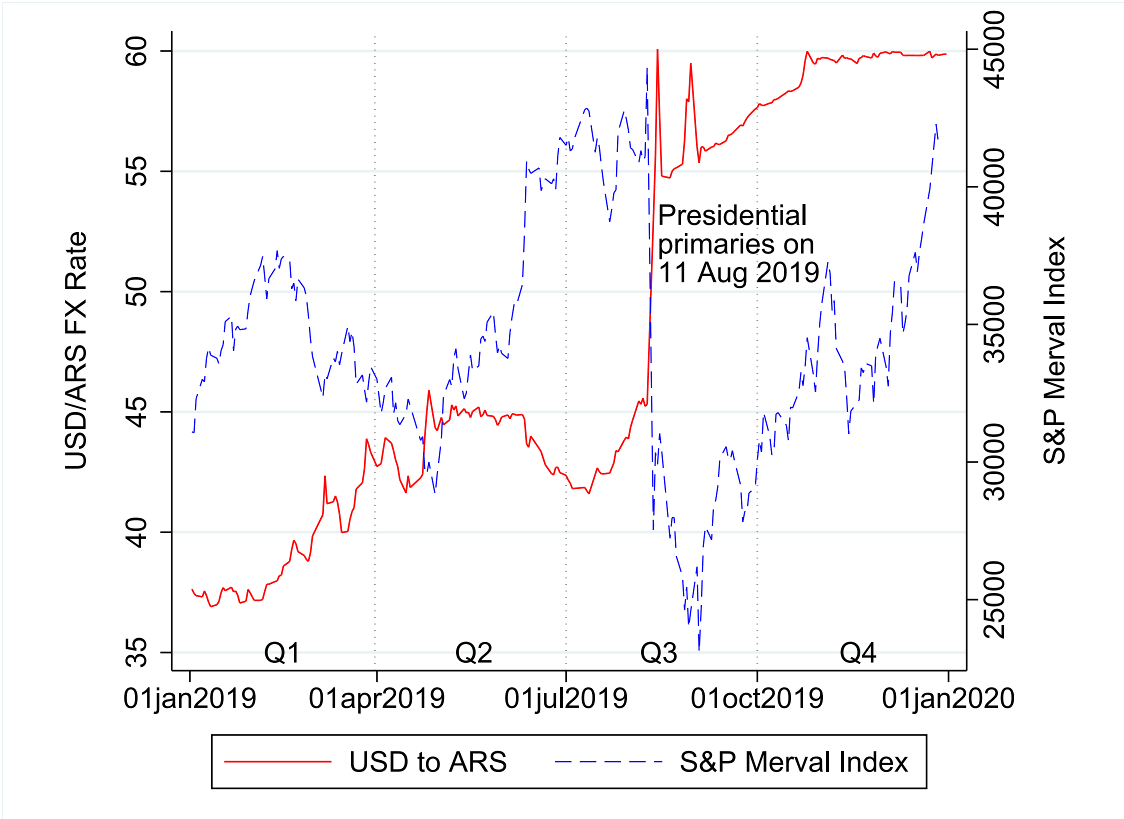


Figure 1: **Argentinian stock market index and Peso exchange rate dynamics**
The figure plots the daily dynamics of the Argentinian S&P Merval stock market index (dashed blue line) and the dynamics of the Argentinian peso exchange rate versus US dollar (solid red line).

in 2001, when it owed \$100 billion.[9] After several rounds of negotiation Argentina successfully reached a debt restructuring agreement with its creditors August 2020 on 99 % of the eligible bonds (approximately \$64.8 billion). As reported by Bloomberg, the agreement provided creditors with 55 cents per dollar and was deemed favorable to creditors.[10]

The unexpected outcome of the Argentinian primary elections and the abrupt overnight revaluation of Argentinian financial assets by investors indicate the presence of the quasi-natural experiment event. This allows us to overcome the endogeneity concerns by employing the difference-in-differences research design in line with the studies that investigate the financial performance of firms affiliated with the politicians after close elections or sudden deaths of politicians (e.g., Akey (2015), Brogaard, Denes, and Duchin (2020)).

[9] https://www.wsj.com/articles/argentina-moves-closer-to-sovereign-debt-default-amid-coronavirus-crisis-11590160035

[10] https://www.bloombergquint.com/business/she-is-blackrock-s-new-star-after-sealing-argentina-s-debt-deal

2.2 Global Bond Funds

According to IMF and BIS, the assets managed by regulated investment funds in the global capital markets have experienced substantial growth since the Global Financial Crisis. Within this category, a specific type of multi-sector bond fund has emerged as a significant source of capital for the bond markets in emerging economies. These open-ended mutual funds are typically active (non-benchmarked), have a broad mandate, and invest cross-jurisdictionally both in advanced and emerging market bonds. Funds that share one or more of these features are occasionally referred to in the literature as global, international, multi-country, cross-over, or broad mandate funds (Cortes and Sanfilippo, 2020; Hui, 2019). Much like commercial banks, open-ended mutual bond funds engage in liquidity transformation. These funds acquire positions in relatively illiquid bonds, financing these holdings by issuing shares to investors with the option to redeem them daily. Goldstein, Jiang, and Ng (2017) explore funds specializing in corporate bonds and demonstrate that in the face of adverse shocks, the liquidity mismatch in mutual funds can create a scenario where a first-mover advantage in redemption decisions among investors triggers a run-like behavior.

Our sample includes 869 global open-ended mutual funds that are domiciled in 26 countries with 32.3% being incorporated in Luxembourg and 26.7% in the US followed by Ireland (8.2%), Canada (6.3%), Argentina (6.2%), Italy (5.5%), UK (4.4%) (see Table A.4 in the Appendix). These global funds invest in sovereign bonds of 95 emerging market economies.[11] The summary statistics reported in the data section shows that the mean *Sovereign government bond share* constitutes 40 per cent of our sample fund's portfolio.

Figure 2 plots the 2019 monthly dynamics of the average bond price returns of three groups of bonds. A solid red line plots the return dynamics of the Argentinian M-bonds in our sample. A dotted light grey line plots the average return dynamics of all investment-grade (from A to BBB credit ratings) EM sovereign bonds held by our sample funds. A dashed dark grey line plots the average return dynamics of below investment-grade (below BBB) EM sovereign bonds held by our sample funds.

[11]See Table A.5 in the Appendix for the distribution of sample funds across countries of domicile and distribution of sovereign bond issuances across the borrowing countries.

As visible from the plot and right-hand side axis the Argentinian bonds experienced a catastrophic negative return of about 50 percent between July and August 2019 right after the primary presidential elections, in the following months, the returns stabilized and showed a slight rebound. On the contrary, the returns of other emerging market bonds indicated on the left-hand side axis did not drop in August right after the Argentinian elections but steeply declined in September-October by about 0.9 percent for speculative-grade EM bonds and by about 0.4 percent for investment-grade EM bonds. This preliminary graphical evidence suggests that following the losses on Argentinian bonds the affected global mutual funds started rebalancing their portfolios which put a selling pressure on other EM bonds. We demonstrate that this was indeed the case in the following sections of our paper.

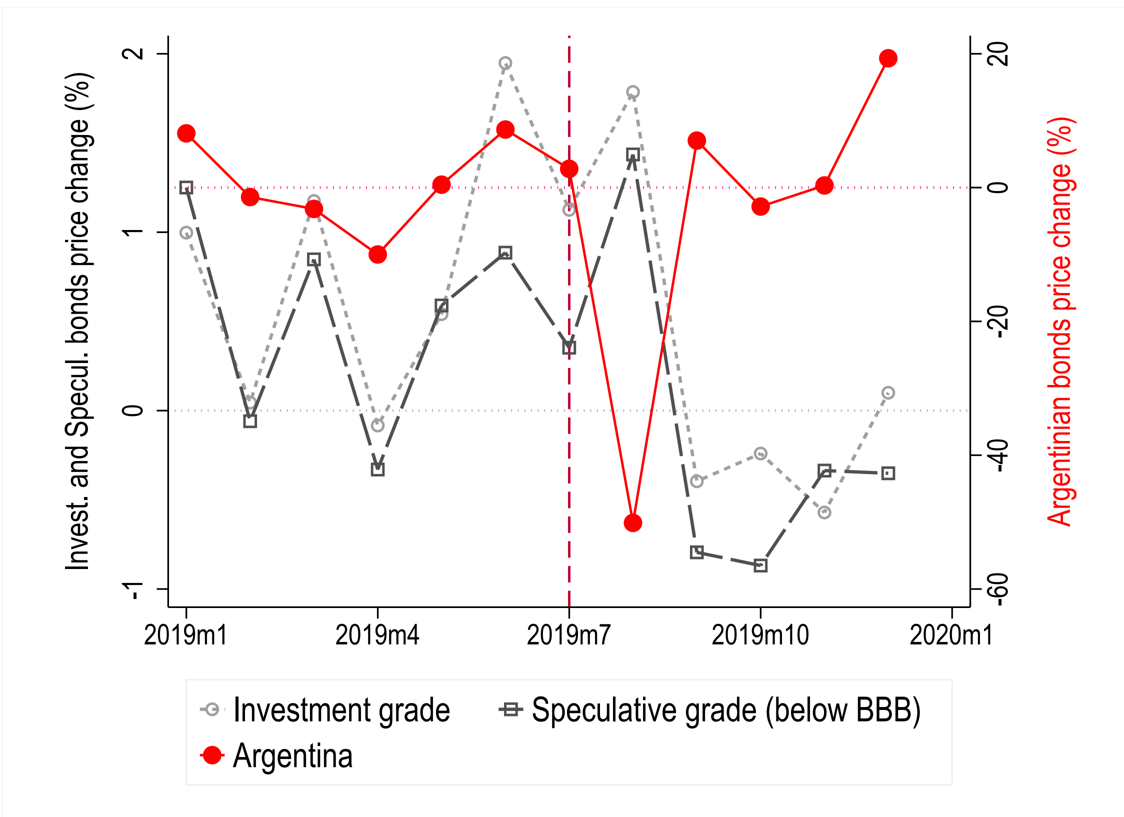


Figure 2: **Dynamics of bond returns**

The figure plots the 2019 monthly dynamics of the average bond price returns of three groups of bonds. A solid red line plots the return dynamics of the Argentinian M-bonds. A dotted light grey line plots the return dynamics of investment-grade (from A to BBB credit rating) EM sovereign bonds. A dashed dark grey line plots the return dynamics of below investment-grade (below BBB) EM sovereign bonds.

3 Data and Variables Description

In this section we describe the data sources and sample characteristics, explain how the key variables are constructed, report summary statistics of the variables and provide graphical illustration of the two-mode network of funds and bonds.

Our sample consists of international open-ended bond mutual funds from January 2019 - December 2019. We have collected our data set from Bloomberg which provides monthly portfolio positions of each fund in nominal and market value terms. Change in the fund's position in nominal terms reflects the change in the number of bonds held by the fund, while change in the market value also captures the price dynamics of bonds.

First, we identified all Argentinian sovereign bonds issued in 2016-2018 under the New York Law in US dollar and Euro (M-bonds). Table A.1 in the Appendix lists all these bonds and their characteristics. Next, we collected the monthly data on all global open-ended funds that held these bonds as well as portfolio holdings of all other EM sovereign bonds and fund-specific variables.

3.1 Fund's Exposure to Argentinian Election Shock

Our empirical strategy exploits the cross-sectional variation across funds in *ex ante* exposure to a collapse of Argentinian bond prices in the post-election period.

$$Argentinian\ Bond\ Share_i = \frac{ArgVal_i}{TotSovVal_i}, \tag{1}$$

where $ArgVal_i$ is fund's i total dollar value of Argentinian M-bonds holdings and $TotSovVal_i$ is the fund's i dollar value of total EM sovereign bond holdings which include bonds of other countries with credit ratings below AA.[12]

Because fund's portfolio reallocation as the election shock unfolds may be related to unobserved changes in its investment opportunities, we purge our specifications of this variation by using only the fund's exposure to Argentina measured one month prior to the presidential primary elections, specifically at the end of June 2019. Given the Argentinian bonds' overnight loss of 30 percent,

[12] Bloomberg classifies bonds into three major categories: *Treasuries* which includes sovereign bonds with prime ratings above AA, *Sovereigns* which includes sovereign bonds with below prime ratings AA and *Corporates* which includes bonds issued by the private sector.

after the primary elections, this variable captures the share of sovereign bond holdings lost by the fund i after the shock.

By taking the pre-elections Argentinian exposure we quasi-randomly assign affected and unaffected status across funds. In the next step, we create two indicator variables based on the position of fund i in the distribution of funds' exposure to the Argentinian shock.

$$I(Exposed)_i = \begin{cases} 1, & \text{if } Argentinian\ Bond\ Share_i \geq Percentile(80th), \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

$$I(NonExposed)_i = \begin{cases} 1, & \text{if } Argentinian\ Bond\ Share_i \leq Percentile(20th), \\ 0, & \text{otherwise.} \end{cases} \tag{3}$$

Funds with high share of Argentinian bonds fall into the affected group while funds with low share fall into the unaffected group. The difference between EM sovereign bond portfolio re-balancing of affected and unaffected groups provides an estimate of the causal impact of the Argentinian election shock.

3.2 Modified Coval-Stafford Fire-sales Measures

Substantial evidence consistently indicates that fire sales by funds have enduring effects on asset prices. Coval and Stafford (2007) introduced a popular "flow pressure" metric where fire-sales of individual securities are caused by funds with excess (in)outflows initiated by funds' investors. In other words, shocks to funds' liabilities lead to re-balancing of assets which generates cumulative selling or buying pressure on affected securities.

We can introduce innovation into Coval and Stafford (2007) approach by replacing the source of selling/buying pressure with funds' exposure to significant losses caused by overnight revaluation of the Argentinain debt. Building on the theoretical contributions of Greenwood, Landier, and Thesmar (2015) and Fricke and Fricke (2021) who show that banks and fund managers have fixed leverage targets and liquidate assets according to their original portfolio weights, we can identify the impact of cumulative sell/buy pressure on other EM sovereign bonds from funds with high/low exposure to Argentina.

We define Argentinian loss induced buys and sells for a given bond b in time period t as follows:

$$Sell\ Pressure_{b,t} = Exposed\ Induced\ Sales_{b,t} =$$
$$= \frac{\sum_{j}^{N}[max(0, -\Delta Holdings_{j,b,t}|Arg.\ Bond\ Share_j \geq Percentile(80th)]}{Amount\ Outstanding_b} \quad (4)$$

where $Arg.\ Bond\ Share_j > Percentile(80th)$ corresponds to an indicator variable $I(Exposed)_j$ taking value one which means that a fund j belongs to N funds with pre-shock high exposure to Argentina. $-\Delta Holdings_{j,b,t}$ is the quantity of bond b sold by the affected fund j in month t.

Similarly, for funds with low pre-shock exposure to Argentina we follow the logic of Coval and Stafford (2007) and define:

$$Buy\ Pressure_{b,t} = NonExposed\ Induced\ Buys_{b,t} =$$
$$= \frac{\sum_{j}^{K}[max(0, \Delta Holdings_{j,b,t}|Arg.\ Bond\ Share_j \leq Percentile(20th)]}{Amount\ Outstanding_b} \quad (5)$$

where $Fund\ Exposure_j < Percentile(20th)$ corresponds to an indicator variable $I(NonExposed)_j$ taking value one which means that a fund that j belongs to K funds with low exposure to Argentina. $\Delta Holdings_{j,b,t}$ is the quantity of bond b purchased by the fund j belonging to an unaffected group.

Wardlaw (2020) underscores that the utilization of scaling pressure proxies based on dollar volume, calculated as the product of concurrent price and share volume, establishes a mechanical relationship. In our approach, these proxies are adjusted by the *Amount outstanding*, which corresponds to the number of bonds outstanding multiplied by their face value. This adjustment using the amount outstanding eliminates any inherent mechanical effects.

As can be seen from Table 2, in the month before elections, the Argentinian bonds, on average, constituted 21 per cent of the EM sovereign bonds portfolio of *exposed* funds and 0.5 per cent of *non-exposed* funds. Considering that in the month after the elections, Argentinian bonds lost half of their market value, we can infer that the average *exposed* fund lost about 10 per cent of its EM sovereign bonds portfolio, while *non-exposed* funds experienced minimal losses. Morris, Shim, and Shin (2017) demonstrate that funds facing significant losses strategically sell their other assets in order to dissuade investor redemptions and increase the pool of liquid assets available for potential sales to meet future redemption requests. Conversely, the unaffected group of *non-exposed* funds can be on a buy side of bonds that *exposed* funds were forced to sell.

Variables (4) and (5) measure the cumulative change in holdings of a given asset b caused by funds with extreme exposure to Argentina. The net effect is the linear combination of these cumulative portfolio rebalancings:

$$Net\ Sell\ Pressure_{b,t} = Buy\ Pressure_{b,t} - Sell\ Pressure_{b,t} \tag{6}$$

Given the exogenous nature of the event that assigned *exposed* and *non-exposed* status to the sample funds our modified Coval-Stafford metric captures the net effect of portfolio rebalancing of funds with extreme exposure to an unanticipated election shock on other EM sovereign bonds in their portfolio. This allows us to study the impact of this modified selling pressure metric on bond returns in the natural experiment setting.

3.3 Fire-sales and Peer Pressure on Mutual Funds

The work in this section is inspired by Falato *et al.* (2021), where the authors find that mutual funds affect each other through fire-sale pressure of commonly held assets.

For each mutual fund i, we aggregate pressure induced on each bond b as a weighted average of the fund's i holdings of sovereign EM government bonds. To avoid mechanical correlation in the analysis, we follow Falato *et al.* (2021) and exclude the selling pressure of the fund itself in a given bond b from the calculation of *Peer (Net) Sell Pressure.* This allows us to isolate the fire-sale pressure from other funds.

$$Peer\ Sell\ Pressure_{i,t} = \sum_{b=1}^{B} Sell\ Pressure_{b,t}^{i \neq j} * w_{i,b,t-1} \tag{7}$$

$$Peer\ Net\ Sell\ Pressure_{i,t} = \sum_{b=1}^{B} Net\ Sell\ Pressure_{b,t}^{i \neq j} * w_{i,b,t-1} \tag{8}$$

where $Sell\ Pressure_{b,t}^{i \neq j}$ and $Net\ Sell\ Pressure_{b,t}^{i \neq j}$ are calculated by formulas (4) and (6) excluding own fund's i change in bonds holdings.

$w_{i,b,t-1}$ is share of bond b in fund's i holdings of sovereign EM government bonds in period *t-1*. *The Peer (Net) Sell Pressure*$_{i,t}$ will take high values if a given fund i has a high share of bonds with high $Sell\ (Net)\ Pressure_{b,t}^{i \neq j}$ induced by other funds' exposure to Argentina.

3.4 Fund Returns, Flows and Holdings Growth

Our variables of interest at the fund level are the fund's monthly return, flow, individual bond holdings, and liquidity position. Firstly, we searched for all Argentinian sovereign bonds issued in the 2016-2018 period, known as the 'Macri bonds,' listed in Table A.1 in the Appendix. Subsequently, we identified all open-ended mutual funds that held these bonds during our sample period of 2019. There were 865 such funds from 212 distinct fund families listed in Table A.2.

We take monthly fund return series from Bloomberg. The literature calculates the implied fund's flow generated by the ultimate investors according to the formula (e.g., Goldstein *et al.* (2017)):

$$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1 + R_{i,t})}{TNA_{i,t-1}}, \tag{9}$$

where $TNA_{i,t}$ is the total net asset value of a fund and $R_{i,t}$ is the fund's monthly return.

For capturing the fund's liquidity dynamics we take the monthly change in the cash holding normalized by the fund's size.

$$Cash\ growth_{i,t} = \frac{Cash_{i,t} - Cash_{i,t-1}}{TNA_{i,t-1}}, \tag{10}$$

We are interested in the impact of the fund's exposure to the Argentinian election shock and the subsequent portfolio rebalancing on returns of individual bonds. We focus only on sovereign EM government bonds issued by countries with below prime credit ratings. Our sample funds held 1,715 such bonds from 95 countries. Table A.5 list all these countries along with the number of bonds issued by each country and country's credit ratings. The growth of individual bond holdings is defined:

$$Bond\ holdings\ growth_{i,b,t} = \frac{Holdings_{i,b,t} - Holdings_{i,b,t-1}}{TNA_{i,t-1}}, \tag{11}$$

All variables are defined in Table 1 with summary statistics provided in Table 2. As a standard practice, all continuous variables have been winsorized at the 1% and 99% levels to reduce the impact of outliers.

3.5 Two-mode Network: Funds and Bonds Before the Shock

Figures B.1 and Figures B.2 in the Appendix plot the bipartite graphs representing two-mode networks consisting of two sets of units: affected funds j and sovereign EM bonds b they held. The lines of the graph connect only nodes representing funds (green circles) with nodes representing bonds (red triangles). The pictures shows the extent of cross-holding of bonds by the sample funds. The size of the node for a bond b, marked by the red color and caption with the bond's country of issuance, is proportional to the summation of the total sales by affected funds j in a given period $\sum_j^N [-\Delta Holdings_{j,b,t} | Arg.\ Bond\ Share_j \geq Percentile(80th)]$. The size of the node for fund j, marked by the green color, is proportional to the quantity of all bonds sold by the fund. Figures B.1 and Figures B.2illustrate the *pre-shock* period (May-July 2019) and the *post-shock* period (August-October 2019) respectively. Both graphs illustrates only top 10 per cent of the affected funds and bonds that represent at least 25 per cent of fund's total sales in a given period.

The visual examination of the bipartite graphs covering the pre- and post-shock periods suggests that in the post-shock period, the sizes of nodes are larger, which corresponds to a higher volume of bond fire-sales. Moreover, it appears that in the post-shock period, the affected funds liquidated positions in a wider array of bonds, indicating a portfolio rebalancing as graph became visibly more bushy after the shock.

Table 1: **Variables definitions**

This table shows variable definitions and sources for all variables used in the empirical analysis. We have obtained all the data from Bloomberg. Own calculations are based on the Bloomberg data.

Variable	Definition	Source
A. Fund level variables		
Fund return (%)	The monthly total fund's return	Bloomberg
Flow (%)	Growth of total net assets adjusted for monthly return	Own calc.
Peer Sell Pressure	Is a weighted sum of peers' *Sell Pressure* in each bond, with weights calculated based on the bond weight in a sovereign portfolio of a given fund. Defined in (7)	Own calc.
Peer Net Sell Pressure	Is a weighted sum of peers' *Net Sell Pressure* in each bond, with weights calculated based on the bond weight in a sovereign portfolio of a given fund. Defined in (8)	Own calc.
Fund size (in USD millions)	Total amount of money invested in the fund, including cash and securities	Bloomberg
Sovereign EM government bonds share	Share of fund's sovereign EM government bond holdings (below prime) in total fund's holdings	Bloomberg
Cash growth (%)	Monthly change of cash normalized by fund size.	Own calc.
Argentinian bonds share	Share of Argentinian bond holdings in total fund's EM sovereign bond holdings before the Argentinian elections	Bloomberg
I(Exposed) (0,1)	Indicator variable takes value one if a fund belongs to the top percentile (20%) of *Argentinian bonds share* in a month before elections	Own calc.
I(NonExposed) (0,1)	Indicator variable takes value one if a fund belongs to the bottom percentile (20%) of *Argentinian bonds share* in a month before elections	Own calc.
Investment grade bond share	Share of sovereign bond holdings with A and BBB credit ratings in total fund's sovereign bond holdings	Bloomberg
B. Bond level variables		
Bond price change (%)	Bond's monthly price growth	Bloomberg
Sell Pressure	The sum of the value of "forced" fund sales in period t of each bond b by funds with *Exposed to Argentina* equals one status relative to the outstanding value of a bond. Defined in (4)	Own calc.
Net Sell Pressure	The sum of the value of fund purchases in period t of each bond b by funds with *Non-Exposed to Argentina* equals one status minus *Sell Pressure* in a given bond relative to the outstanding value of a bond. Defined in (6)	Own calc.
Share of bonds with X rating	Share of sovereign bonds with a credit rating X in the total number of sovereign bonds that are held by all sample funds	Bloomberg
C. Fund-Bond level variables		
Bond holdings growth (%)	Monthly change in the quantity of bond b in fund's i portfolio relative to fund's size	Own calc.

Table 2: **Summary statistics**

This table shows summary statistics for all variables used in the empirical analysis. Sample period: January 2019 - December 2019. Units of observation in Panel A: fund-month. Units of observation in Panel B: bond-month. Units of observation in Panel C: fund-bond-month. Table 1 provides a detailed description of the variables used in the study.

	Mean	St. Dev	Min	p50	Max	N
A. Fund level						
Fund return$_{i,t}$ (%)	2.207	3.273	-16.206	1.928	23.723	10,110
Flow$_{i,t}$	0.005	0.151	-0.489	-0.019	0.902	10,110
Peer Sell Pressure$_{i,t}$	-0.002	0.010	-0.064	0.000	0.000	10,110
Peer Net Sell Pressure$_{i,t}$	-0.001	0.009	-0.058	0.000	0.008	10,110
Fund size$_{i,t}$ ($ Mln.)	1,571	5,535	2.000	308	135,438	10,110
Sovereign govt. bonds share$_{i,t}$	0.401	0.248	0.051	0.360	0.972	10,110
Cash share$_{i,t}$	0.054	0.115	-0.114	0.028	1.000	8,165
Cash share growth$_{i,t}$	0.001	0.049	-0.298	0.000	0.356	8,034
Investment grade bond share$_{i,t}$	0.485	0.284	0.000	0.490	1.000	10,110
Arg. bonds share$_i$ (All funds)	0.057	0.098	0.000	0.020	0.719	10,110
Arg. bonds share$_i$ (Exposed funds)	0.208	0.141	0.077	0.161	0.719	1,960
Arg. bonds share$_i$ (Non-Exposed funds)	0.004	0.002	0.001	0.004	0.007	2,046
B. Bond level						
Bond price change$_{b,t}$ (%)	0.4507	2.5776	-20.7571	0.1833	12.1663	19,501
Sell Pressure$_{b,t}$	-0.0001	0.0001	-0.0005	0.0000	0.0000	19,501
Net Sell Pressure$_{b,t}$	0.0048	0.0545	-0.4426	0.0000	0.2935	19,501
Share of bonds with A rating$_{b,t}$	0.1878	0.3906	0.0000	0.0000	1.0000	19,501
Share of bonds with BBB rating$_{b,t}$	0.4359	0.4959	0.0000	0.0000	1.0000	19,501
Share of bonds with BB rating$_{b,t}$	0.1812	0.3852	0.0000	0.0000	1.0000	19,501
Share of bonds with B rating$_{b,t}$	0.1386	0.3455	0.0000	0.0000	1.0000	19,501
Share of bonds below B rating$_{b,t}$	0.0565	0.2309	0.0000	0.0000	1.0000	19,501
C. Fund-Bond level						
Negative Bond holdings growth$_{i,b,t}$	-0.019	0.057	-0.249	-0.001	0.000	77,119
Positive Bond holdings growth$_{i,b,t}$	0.020	0.058	0.001	0.001	0.240	72,007

4 Results

This section describes the methodology and results of our empirical study. The first subsection investigates the relationship between fund's i exposure to the Argentinian election shock and the dynamics of its investor flows and portfolio composition. The second subsection examines the relationship between bond returns and modified Coval-Stafford measure of sell pressure. In the third subsection, we employ the fund-level Falato *et al.* (2021) peer sell pressure variables to explore the impact of other peer funds' sales on fund's i returns.

4.1 Fund's Exposure and Portfolio Rebalancing

Shek, Shim, and Shin (2018) decompose the changes in the mutual fund holdings of assets into the part due to investor flows and the part due to discretionary trading by the fund managers. In this subsection, we evaluate how a fund's exposure to the election shock affects post-shock investor flows, changes in the liquidity position and bond holdings.

Our specification belongs to a difference-in-differences research design, where funds are either first affected at time t_0 before the election shock or never affected. In our case, at time t_0, funds are either exposed to Argentina based on the definition of variable (2) or not exposed based on the definition in (3).

Specifically, we estimate the following specification which allows the examination of the parallel trends in the pre-shock period:

$$Y_{i,t} = \delta_i + \tau_t + \sum_{t \in Pre} \beta_t \cdot I(Exposed\ status)_i \times \tau_t + \sum_{t \in Post} \beta_t \cdot I(Exposed\ status)_i \times \tau_t + \varepsilon_{i,t} \tag{12}$$

where the dependent variables $Y_{i,t}$ are either fund's i flows (9), growth of the cash position (10) or growth of bond holdings (11), δ_i are fund fixed effects, τ_t denotes the full set of time fixed effects.

We separately run regression (12) with the indicator variable of fund's i exposure status to Argentina being *high*: $I(Exposed\ status)_i = I(Exposed)_i$, and regressions with the indicator variable capturing fund's i *low* exposure to Argentina: $I(Exposed\ status)_i = I(NonExposed)_i$.

In these regressions, the key variables of interest are $I(Exposed)_i \times \tau_t$ or $I(NonExposed)_i \times \tau_t$, which correspond to the interaction between *high* or *low* fund i's pre-election exposure to Argentina with month fixed effects. The stand-alone time-invariant $I(Exposed)_i$ and $I(NonExposed)_i$ indicator variables are subsumed by the fund fixed effects.

The month-specific coefficients of interest are $\{\beta_t\}_{t \in Pre}$ and $\{\beta_t\}_{t \in Post}$, where *Pre* refers to the months before the Argentinian presidential primary elections [January 2019-June 2019] and *Post* refers to the month after the elections [August 2019-December 2019], which together allow us to examine both pre-trends and post-shock differential effects. Under our hypothesis that the Argentinian election shock was "econometrically exogenous," we expect the coefficients$\{\beta_t\}_{t \in Pre}$ not to be significantly different from zero. If the shock and subsequent losses were indeed impactful, $\{\beta_t\}_{t \in Post}$ should be significantly different from zero. The month before the Argentinian presidential elections (July 2019) serves as the reference period. The standard errors are clustered at the fund level.

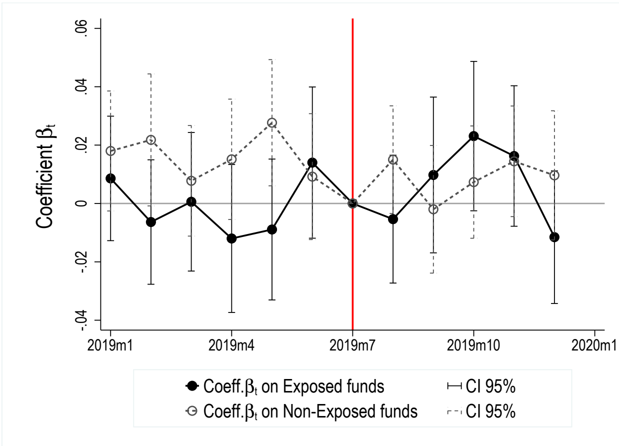
Figure 3 plots the estimated coefficients of the model (12), along with their 95% confidence intervals, on the full sample of funds. In all panels, the black solid line illustrates the regression coefficients β_t on the $I(Exposed)_i \times \tau_t$ interaction term; while the dotted grey line illustrates the coefficients β_t on the $I(NonExposed)_i \times \tau_t$ interaction term of another regression. The red vertical line indicates the election month, which serves as the reference period.

Panel (A) plots the estimated coefficients on fund flows in columns (1) and (4) of Table 3. As can be seen from the coefficient plot, the fund's exposure status had no significant impact on the fund flows from ultimate investors after the Argentinian election shock. This suggests that investors of exposed funds did not exhibit the "bank-run" type of behavior on funds that incurred substantial losses due to high Argentinian exposure.

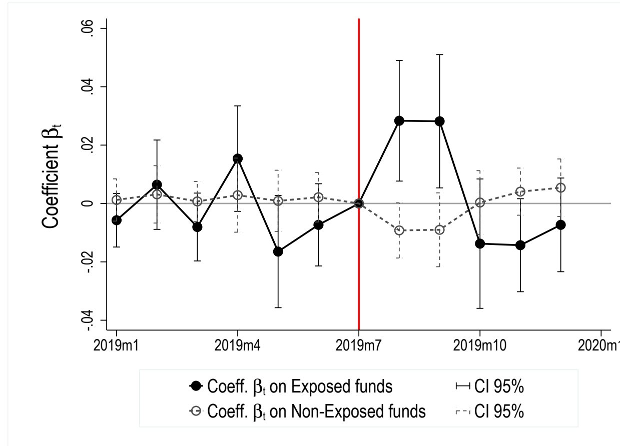
Panel (B) plots the estimated coefficients on fund's change in the cash position columns (1) and (4) of Table 4. In the pre-election months, the exposure status of the fund essentially had no effect on changes in its liquidity position. The coefficients on interaction terms in the post-election period are significant for affected funds with high exposure to Argentina, indicating that relative to the pre-election month, these funds exhibited a growth of cash of 3 per cent in two post-shock months.

Panel (C) plots the estimated coefficients on fund's change in the bond holdings columns (1)

A: Impact of fund's Exposure$_i^k$ on Flows



B: Impact of fund's Exposure$_i^k$ on Cash growth



C: Impact of fund's Exposure$_i^k$ on bond ΔHoldings

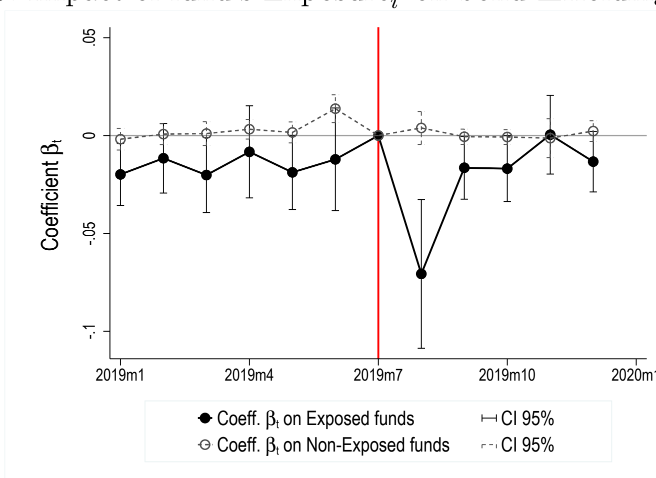


Figure 3: **Coefficients plot: Effect of fund's exposure on funds' change in bond holdings, flows and cash growth**

This picture plots the dynamics of β_t coefficients with their 95% confidence intervals for the following model:

$$Y_{i,t} = \delta_i + \tau_t + \sum_{t \in Pre} \beta_t \cdot I(Exposed\ status)_i \times \tau_t + \sum_{t \in Post} \beta_t \cdot I(Exposed\ status)_i \times \tau_t + \varepsilon_{i,t}$$

where δ_i are fund fixed effects, τ_t denotes the full set of time fixed effects. Figure A illustrates coefficients reported in columns (1) and (4) of Table 3. Figure B illustrates coefficients reported in columns (1) and (4) of Table 4 where $Y_{i,t}$ are $Flow_{i,t}$ and $\Delta\text{Cash}_{i,t}/\text{TNA}_{i,t}$ respectively. Figure C illustrates coefficients reported in columns (1) and (4) of Table 5 where $Y_{i,b,t}$ is a positive or negative change in the fund's sovereign bond holdings $\Delta Holdings_{i,b,t}/\text{TNA}_{i,t}$. $I(Exposed\ status)_i$ is the indicator variable capuruing the funds's pre-determined exposure to Argentina as defined in formulas (2) and (3). The black solid line illustrates the coefficients β_t on $I(Exposed)_i \times \tau_t$ interaction term; while the dotted grey line illustrates the coefficients β_t on $I(NonExposed)_i \times \tau_t$ interaction term. The month before the Argentinian presidential elections (2019m7) is the reference period. $Pre \in 2019m1 - 2019m6$ and $Post \in 2019m8 - 2019m12$ Standard errors are clustered at the fund's level.

and (4) of Table 5. It is important to emphasize that we exclude Argentinian bond holdings in this exercise and consider only all other sovereign EM government bonds holdings of our sample funds. The modified Coval-Stafford selling pressure formulas (4) and (5) measure the cumulative change in all affected funds' holdings on individual bonds. Here, we aim to test whether *high* or *low* exposure to Argentina induces fire sales or purchases of other EM bonds at the fund level by affected and unaffected funds. Because we normalize the monthly change in the quantity of individual bond holdings by the fund's size, the coefficients can be interpreted as measuring the dollar value of the change in holdings in response to the fund's (un)affected status in the post-shock months. We follow the logic of the original Coval-Stafford formula and use positive change in the bond's b position for unaffected funds and negative changes for affected funds.

As visible from the coefficient plot in Panel (C), there is a pronounced and statistically significant fire-sale effect of sovereign EM government bonds by high exposure funds in the post-election months. At the same time, the unaffected group of low-exposure funds did not significantly increase positions in other EM bonds.

To explore the variation in the relationships among funds with different levels of credit risk in their sovereign EM bond portfolios, we split our sample into two subsamples based on whether the funds belongs to a group with $\textit{Investment grade bond share}_i \geq \textit{Median}$ or not. We reestimate regression (12) on each of these subsamples for all dependent variables $Y_{i,t}$ and the fund's treatment statuses.

The estimation results for all subsamples are reported in Tables 3 - 5. Panels A in each table display the estimation results of specification (12) with $I(Exposed)_i \times \tau_t$ interaction terms. Panels B display results for the specification with $I(NonExposed)_i \times \tau_t$ interaction terms. More specifically, columns (2) and (5) report results for the subsample of *Speculative* funds with $\textit{Investment grade bond share}_i < \textit{Median}$ in their portfolio. Columns (3) and (6) report results for the sub-sample of *Investment* funds with $\textit{Investment grade bond share}_i \geq \textit{Median}$ in their portfolio.

The estimates of β_t for flows of funds with high exposure (Panel A of Table 3) demonstrate that in the first post-election month, *Speculative* funds, which are overweight in bonds with credit ratings below BBB, exhibited an outflow of 2.7%, while *Investment* funds, which are overweight in bonds with credit ratings BBB and A, exhibited an inflow of 3.5%. Column (5) of the same table for August 2019 reveals that *Speculative* funds with low exposure enjoyed an inflow of 3%. These results suggest that the ultimate investors of international open-ended mutual funds were aware of the funds' portfolio composition in terms of their credit risk and exposure to Argentina and, following the shock, withdrew money from the exposed and risky funds and added money either to non-exposed risky or exposed but overall safer funds. The effect was transitory, as the coefficient estimates in the further post-election months are largely insignificant.

The estimates of β_t for changes in the cash position of *Speculative* funds with high exposure (Panel A of Table 4) display a pronounced pattern in the post-election months. As one can see from column (2) of the table, the exposed *Speculative* funds in the two months after the elections (August and September) saw an increase in the cash position by 3.5%, which significantly reversed in the subsequent months (October-December). Taken together with the outflow of funds from this group of funds right after the elections, as found in Table 3, the increase in cash can only be explained by the shift from illiquid bonds to liquid cash by fund managers.

The estimation results reported in column (2) of Table 5 show that fund managers of exposed *Speculative* funds were engaged in a fire sale of other other sovereign EM government bonds, as their holdings significantly dropped in the post-election period relative to the pre-election reference month. We find no evidence that non-exposed *Speculative* or funds that we classify as *Investment* were engaged in a fire sale in the months after the Argentinian election shock.

Altogether, the empirical results of this subsection resonate with Shek, Shim, and Shin (2018), who find that portfolios of open-ended mutual funds reflect both the fund flows from ultimate investors and discretionary trading by the fund managers, and that discretionary sales by fund managers reinforce the bond sales. Our subsample analysis reveals that this effect is largely driven by *Speculative* funds that are overweight in riskier and less liquid bonds. This evidence corroborates with Jiang, Li, and Wang (2020) and Morris, Shim, and Shin (2017), who identify the dynamic liquidity management by the mutual fund's managers, who tend to scale down their illiquid assets in crisis periods and expand the pool of liquid assets to preserve portfolio liquidity and fulfill future redemption requests.

Table 3: **Fund's exposure and fund's flows**

This table presents the estimates of difference-in-differences regressions across funds that held Argentinian bonds during the Argentinian presidential elections. The dependent variable in Panels A and B is the fund's monthly $Flow_{i,t}$. The indicator variable $I(Exp.)_i$ captures the fund's pre-election *Exposure* to Argentinian debt as defined in equation (2). These are affected funds. The indicator variable $I(NonExp.)_i$ is defined in equation (3) and captures unaffected group of funds. Columns (1) and (4) display results for the full sample of funds. Columns (2) and (5) report results for the sub-sample of *Speculative* funds with *Investment grade bond* $share_i$ < *Median* in their portfolio. Columns (3) and (6) report results for the sub-sample of *Investment* funds with *Investment grade bond* $share_i \geq$ *Median* in their portfolio. The reported coefficients β_t on the interaction term of specification (1) capture the differential response of funds to a shock in a given month conditional on the fund's pre-determined affected or unaffected status. All estimated coefficients are measured relative to the pre-event month July 2019. To account for serial correlation of errors the standard errors are clustered at the fund level. Significance levels are * 10%, ** 5%, *** 1%.

Dependent variable :	$Flow_{i,t}$				$Flow_{i,t}$		
	All	Specul.	Invest.		All	Specul.	Invest.
Panel A. Exposed	(1)	(2)	(3)	**Panel B. Non-Exposed**	(4)	(5)	(6)
$I(Exp.)_i \times Jan$ 2019	0.009	-0.001	0.019	$I(NonExp.)_i \times Jan$ 2019	0.018*	0.040**	0.011
	(0.011)	(0.015)	(0.015)		(0.010)	(0.020)	(0.012)
$I(Exp.)_i \times Feb$ 2019	-0.006	-0.016	0.007	$I(NonExp.)_i \times Feb$ 2019	0.022*	0.025	0.022
	(0.011)	(0.014)	(0.017)		(0.012)	(0.022)	(0.014)
$I(Exp.)_i \times Mar$ 2019	0.001	0.002	-0.001	$I(NonExp.)_i \times Mar$ 2019	0.008	0.014	0.004
	(0.012)	(0.017)	(0.017)		(0.010)	(0.017)	(0.012)
$I(Exp.)_i \times Apr$ 2019	-0.012	-0.025	0.008	$I(NonExp.)_i \times Apr$ 2019	0.015	0.026	0.009
	(0.013)	(0.018)	(0.018)		(0.011)	(0.019)	(0.013)
$I(Exp.)_i \times May$ 2019	-0.009	-0.013	0.001	$I(NonExp.)_i \times May$ 2019	0.028**	0.023	0.029**
	(0.012)	(0.016)	(0.019)		(0.011)	(0.020)	(0.014)
$I(Exp.)_i \times Jun$ 2019	0.014	0.019	-0.003	$I(NonExp.)_i \times Jun$ 2019	0.009	0.013	0.015
	(0.013)	(0.018)	(0.019)		(0.011)	(0.019)	(0.014)
$I(Exp.)_i \times$ **Aug 2019**	-0.005	-0.027*	0.035**	$I(NonExp.)_i \times$ **Aug 2019**	0.016*	0.030*	0.004
	(0.011)	(0.014)	(0.016)		(0.009)	(0.016)	(0.012)
$I(Exp.)_i \times$ **Sep 2019**	0.010	0.017	-0.012	$I(NonExp.)_i \times$ **Sep 2019**	-0.002	-0.005	0.007
	(0.014)	(0.020)	(0.015)		(0.011)	(0.021)	(0.013)
$I(Exp.)_i \times$ **Oct 2019**	0.023*	0.032*	0.000	$I(NonExp.)_i \times$ **Oct 2019**	0.007	0.003	0.017
	(0.013)	(0.017)	(0.019)		(0.010)	(0.017)	(0.012)
$I(Exp.)_i \times$ **Nov 2019**	0.016	0.014	0.014	$I(NonExp.)_i \times$ **Nov 2019**	0.014	0.022	0.015
	(0.012)	(0.017)	(0.017)		(0.010)	(0.017)	(0.012)
$I(Exp.)_i \times$ **Dec 2019**	-0.012	-0.018	-0.011	$I(NonExp.)_i \times$ **Dec 2019**	0.010	0.017	0.012
	(0.012)	(0.016)	(0.016)		(0.011)	(0.020)	(0.014)
Fund FE (i)	YES	YES	YES	Fund FE (i)	YES	YES	YES
Month FE (t)	YES	YES	YES	Month FE (t)	YES	YES	YES
Adj. R-squared	0.109	0.127	0.097	Adj. R-squared	0.109	0.123	0.097
N. funds	847	415	432	N. funds	847	415	432
Observations	10,110	4,954	5,176	Observations	10,110	4,954	5,176

Table 4: **Fund's exposure and growth of cash holdings**

This table presents the estimates of difference-in-differences regressions across funds that held Argentinian bonds during the Argentinian presidential elections. The dependent variable in Panels A and B is the fund's monthly growth of cash $\Delta\text{Cash}_{i,t}/\text{TNA}_{i,t}$. The indicator variable $I(Exp.)_i$ captures the fund's pre-election *Exposure* to Argentinian debt as defined in equation (2). These are affected funds. The indicator variable $I(NonExp.)_i$ is defined in equation (3) and captures unaffected group of funds. Columns (1) and (4) display results for the full sample of funds. Columns (2) and (5) report results for the sub-sample of *Speculative* funds with *Investment grade bond share*$_i$ < *Median* in their portfolio. Columns (3) and (6) report results for the sub-sample of *Investment* funds with *Investment grade bond share*$_i \geq$ *Median* in their portfolio. The reported coefficients β_t on the interaction term of specification (1) capture the differential response of funds to a shock in a given month conditional on the fund's pre-determined affected or unaffected status. All estimated coefficients are measured relative to the pre-event month July 2019. To account for serial correlation of errors the standard errors are clustered at the fund level. Significance levels are * 10%, ** 5%, *** 1%.

Dependent variable :	$\Delta\text{Cash}_{i,t}/\text{TNA}_{i,t}$				$\Delta\text{Cash}_{i,t}/\text{TNA}_{i,t}$		
	All	Specul.	Invest.		All	Specul.	Invest.
Panel A. Exposed	(1)	(2)	(3)	**Panel B. Non-Exposed**	(4)	(5)	(6)
$I(Exp.)_i \times Jan$ 2019	-0.006	-0.011*	0.004	$I(NonExp.)_i \times Jan$ 2019	0.001	-0.004	0.003
	(0.005)	(0.006)	(0.006)		(0.004)	(0.005)	(0.005)
$I(Exp.)_i \times Feb$ 2019	0.006	0.004	0.009	$I(NonExp.)_i \times Feb$ 2019	0.003	-0.004	0.007
	(0.008)	(0.011)	(0.010)		(0.005)	(0.005)	(0.007)
$I(Exp.)_i \times Mar$ 2019	-0.008	-0.014*	-0.001	$I(NonExp.)_i \times Mar$ 2019	0.001	-0.003	0.004
	(0.006)	(0.008)	(0.007)		(0.004)	(0.005)	(0.004)
$I(Exp.)_i \times Apr$ 2019	0.015*	0.024*	-0.004	$I(NonExp.)_i \times Apr$ 2019	0.003	-0.008	0.012
	(0.009)	(0.013)	(0.010)		(0.007)	(0.007)	(0.009)
$I(Exp.)_i \times May$ 2019	-0.016*	-0.033**	0.011	$I(NonExp.)_i \times May$ 2019	0.001	0.001	0.001
	(0.010)	(0.014)	(0.009)		(0.005)	(0.006)	(0.007)
$I(Exp.)_i \times Jun$ 2019	-0.007	-0.010	-0.002	$I(NonExp.)_i \times Jun$ 2019	0.002	0.003	0.002
	(0.007)	(0.010)	(0.007)		(0.004)	(0.006)	(0.005)
$I(Exp.)_i \times$ **Aug 2019**	0.028***	0.035**	0.004	$I(NonExp.)_i \times$ **Aug 2019**	-0.009*	-0.019***	0.002
	(0.012)	(0.016)	(0.006)		(0.005)	(0.007)	(0.006)
$I(Exp.)_i \times$ **Sep 2019**	0.028**	0.035**	0.002	$I(NonExp.)_i \times$ **Sep 2019**	-0.010	-0.028***	0.006
	(0.012)	(0.016)	(0.006)		(0.006)	(0.008)	(0.008)
$I(Exp.)_i \times$ **Oct 2019**	-0.014	-0.031**	0.020	$I(NonExp.)_i \times$ **Oct 2019**	0.001	0.002	-0.003
	(0.011)	(0.015)	(0.015)		(0.006)	(0.006)	(0.008)
$I(Exp.)_i \times$ **Nov 2019**	-0.014*	-0.022**	0.002	$I(NonExp.)_i \times$ **Nov 2019**	0.004	0.006	0.001
	(0.008)	(0.012)	(0.007)		(0.004)	(0.006)	(0.005)
$I(Exp.)_i \times$ **Dec 2019**	-0.007	-0.022**	0.017*	$I(NonExp.)_i \times$ **Dec 2019**	0.005	0.007	0.006
	(0.008)	(0.011)	(0.010)		(0.005)	(0.006)	(0.007)
Fund FE (i)	YES	YES	YES	Fund FE (i)	YES	YES	YES
Month FE (t)	YES	YES	YES	Month FE (t)	YES	YES	YES
Adj. R-squared	0.041	0.013	0.068	Adj. R-squared	0.055	0.41	0.070
N. funds	720	350	370	N. funds	720	350	370
Observations	8,027	3,915	4,112	Observations	8,027	3,915	4,112

Table 5: **Fund's exposure and change in bond holdings**

This table presents the estimates of difference-in-differences regressions across funds that held Argentinian bonds during the Argentinian presidential elections. All sovereign bonds with credit ratings ranging from A to C are used (Argentinian bonds are excluded). The dependent variable in Panel A is a monthly negative change in each sovereign bond position. The indicator variable $I(Exp.)_i$ captures the fund's pre-election *Exposure* to Argentinian debt as defined in equation (2). These are affected funds. The dependent variable in Panel B is a positive change in each sovereign bond position. The indicator variable $I(NonExp.)_i$ is defined in equation (3) and captures unaffected group of funds. Columns (1) and (4) display results for the full sample of funds. Columns (2) and (5) report results for the sub-sample of *Speculative* funds with $\textit{Investment grade bond share}_i < \textit{Median}$ in their portfolio. Columns (3) and (6) report results for the sub-sample of *Investment* funds with $\textit{Investment grade bond share}_i \geq \textit{Median}$ in their portfolio. The reported coefficients β_t on the interaction term of specification (1) capture the differential response of funds to a shock in a given month conditional on the fund's pre-determined affected or unaffected status. All estimated coefficients are measured relative to the pre-event month July 2019. To account for serial correlation of errors the standard errors are clustered at the fund level. Significance levels are * 10%, ** 5%, *** 1%.

Dependent variable :	$-\Delta Holding_{i,b,t}/\text{TNA}_{i,t}$				$\Delta Holding_{i,b,t}/\text{TNA}_{i,t}$		
	All	Specul.	Invest.		All	Specul.	Invest.
Panel A. Exposed	(1)	(2)	(3)	**Panel B. Non-Exposed**	(4)	(5)	(6)
$I(Exp.)_i \times Jan$ 2019	-0.020**	-0.037**	-0.003	$I(NonExp.)_i \times Jan$ 2019	-0.002	-0.005	-0.001
	(0.008)	(0.016)	(0.005)		(0.003)	(0.003)	(0.005)
$I(Exp.)_i \times Feb$ 2019	-0.012	-0.065	-0.014	$I(NonExp.)_i \times Feb$ 2019	0.001	-0.001	0.003
	(0.009)	(0.015)	(0.010)		(0.003)	(0.004)	(0.005)
$I(Exp.)_i \times Mar$ 2019	-0.020**	-0.030**	-0.003	$I(NonExp.)_i \times Mar$ 2019	0.001	-0.001	0.002
	(0.010)	(0.015)	(0.006)		(0.003)	(0.003)	(0.007)
$I(Exp.)_i \times Apr$ 2019	-0.008	-0.007	-0.014	$I(NonExp.)_i \times Apr$ 2019	0.003	-0.003	0.011***
	(0.012)	(0.016)	(0.014)		(0.003)	(0.004)	(0.004)
$I(Exp.)_i \times May$ 2019	-0.019*	-0.040*	0.001	$I(NonExp.)_i \times May$ 2019	0.002	-0.008**	0.008
	(0.010)	(0.021)	(0.006)		(0.003)	(0.004)	(0.005)
$I(Exp.)_i \times Jun$ 2019	-0.012	-0.020	-0.003	$I(NonExp.)_i \times Jun$ 2019	0.014***	0.006	0.022***
	(0.013)	(0.020)	(0.007)		(0.004)	(0.005)	(0.005)
$I(Exp.)_i \times$ **Aug 2019**	-0.071***	-0.098***	-0.021	$I(NonExp.)_i \times$ **Aug 2019**	0.004	-0.005	0.013*
	(0.019)	(0.026)	(0.017)		(0.004)	(0.004)	(0.007)
$I(Exp.)_i \times$ **Sep 2019**	-0.016**	-0.026**	-0.004	$I(NonExp.)_i \times$ **Sep 2019**	-0.001	-0.002	0.004
	(0.008)	(0.013)	(0.009)		(0.002)	(0.003)	(0.003)
$I(Exp.)_i \times$ **Oct 2019**	-0.017**	-0.024*	-0.004	$I(NonExp.)_i \times$ **Oct 2019**	-0.001	-0.001	-0.001
	(0.009)	(0.014)	(0.005)		(0.002)	(0.003)	(0.003)
$I(Exp.)_i \times$ **Nov 2019**	0.001	-0.009	0.013*	$I(NonExp.)_i \times$ **Nov 2019**	-0.001	-0.004	0.001
	(0.010)	(0.018)	(0.007)		(0.005)	(0.008)	(0.006)
$I(Exp.)_i \times$ **Dec 2019**	-0.013*	-0.021*	0.001	$I(NonExp.)_i \times$ **Dec 2019**	0.002	0.001	0.004
	(0.008)	(0.012)	(0.005)		(0.003)	(0.005)	(0.004)
Fund FE (i)	YES	YES	YES	Fund FE (i)	YES	YES	YES
Month FE (t)	YES	YES	YES	Month FE (t)	YES	YES	YES
Adj. R-squared	0.215	0.303	0.149	Adj. R-squared	0.237	0.296	0.185
N. funds	865	411	454	N. funds	756	357	399
Observations	77,082	41,326	35,756	Observations	71,990	39,460	32,530

4.2 Bond Level Selling Pressure Effects

In this subsection, we examine whether the rebalancing of portfolios by funds with high and low exposure to Argentinian debt can exert fire-sale pressure on sovereign EM government bond prices. In our analysis, we use all sovereign bonds with credit ratings ranging from A to C that were held by our sample funds. Because we are interested in the spillover effects on other bonds, we exclude the Argentinian bonds, which were the source of staggering portfolio losses.

Figure C.1 illustrates the scatter plots of the raw data of the bond price changes against the sell pressure metrics, along with the fitted regression lines for the subsamples of speculative grade ($<$ BBB) and investment grade ($\geq$ BBB) bonds. This preliminary evidence suggest that in the pre-election period, the relationship between bond prices and sell pressure metrics was essentially flat. In the post-election period, one can observe a significant rotation in the regression line for the *Sell pressure* metrics, indicating a positive relationship between changes in bond prices and cumulative fire sales of these bonds induced by affected funds with high Argentinian exposure.

The examination of Panel (D) of Figure C.1 reveals a significant rotation of the regression line for the *Investment* grade bonds subsample, indicating a negative relationship between changes in bond prices and $Net\ Sell\ Pressure_{b,t}$ metrics, which includes purchases by the unaffected funds with low exposure to Argentina. This preliminary evidence suggests that unaffected funds were net buyers of investment grade bonds with negative returns in the post-election period.

We estimate an OLS regression of the change in bond prices as a function of the *(Net) Selling Pressure* and the interaction between these measures of pressure and an indicator of the pre- or post-election period. We employ the specification where a single "Post Shock" indicator is included for all periods posterior to the occurrence of the shock in affected groups:

$$B_{b,t} = \delta_b + Post\ shock_t + \beta_1 \cdot (Net)\ Sell\ Pressure_{b,t} + \beta_2 \cdot (Net)\ Sell\ Pressure_{b,t} \times Post\ shock_t + \varepsilon_{b,t} \tag{13}$$

where $B_{b,t}$ is a monthly price change in percent of each sovereign bond b. δ_b is a bond fixed effect. $Post\ shock_t$ denotes the indicator variable that takes value one if the observation belongs to three months (August 2019 - October 2019) after the Argentinian primary residential elections and zero if it belongs to three months (May 2019 - July 2019) before the election shock.

Sell Pressure$_{b,t}$ is the sum of the value of "forced" fund sales in period t of each bond b by funds with high exposure status relative to the outstanding value of a bond. *Net Sell Pressure*$_{b,t}$ is the sum of the value of fund purchases in period t of each bond b by funds with low exposure status minus *Sell Pressure*$_{b,t}$ in a given bond relative to the outstanding value of a bond. The affected or unaffected status of a fund is defined in formulas (2) and (3) based on the top and bottom percentiles of the distribution of the fund's *Argentinian bond shares*$_i$ in its portfolio before presidential elections. To aid interpretation, we standardize *Sell Pressure*$_{b,t}$ and *Net Sell Pressure*$_{b,t}$ by their means and standard deviations. The standard errors are clustered at the bond level.

The main coefficient of interest, β_2, captures whether the relation between (Net) $Sell\ Pressure_{b,t}$ and bond price changes is more or less pronounced in the post-election period relative to the pre-election shock period. Our identification strategy relies on a quasi-random assignment of high and low exposure status to funds due to the unanticipated Argentinian presidential election outcome. As was demonstrated in the previous subsection, high exposure *(affected)* funds exhibited fire-sale type behavior in the post-election period that was not present in the pre-election period. Since the (Net) $Sell\ Pressure_{b,t}$ is shock-based in the post-election period, the possible endogeneity concerns regarding the relationship between bond price dynamics and the sell pressure metrics are greatly reduced.

Table 6 provides the estimation results. Columns (1) and (2) display results for the full sample of bonds. Columns (3) and (4) report results for the sub-sample of bonds with a speculative credit rating (< BBB). Columns (5) and (6) report results for the sub-sample of bonds with investment-grade credit rating (BBB and A).

The coefficient on the $Post\ shock_t$ indicator variable in all columns indicates that in the post-election period, the average return of sovereign EM bonds was negative at 85 basis points (b.p.). Based on the coefficient estimate on (Net) $Sell\ Pressure_{b,t}$ we see that in the pre-shock period, both *Sell pressure* metrics were statistically insignificant, supporting the notion that bond prices were unaffected by sales or purchases by high and low exposure funds prior to the shock. The statistically significant coefficient on $Sell\ Pressure_{b,t}$ for $Investment$ grade bonds subsample reported in column

(5) of Table 6 is economically small (8 b.p).

The main coefficient of interest on $Sell\ Pressure_{b,t} \times Post\ shock_t$ shows that in the post-election period, bond prices significantly respond to sell pressure by funds with high losses due to high exposure to Argentina across all subsamples. For example, for *Speculative* grade bonds as visible from column (3), a one-standard-deviation increase in *Sell pressure* produces a 25 b.p. movement in bond returns. Following the interpretation of Falato *et al.* (2021), we can conclude that sales by mutual funds that are experiencing staggering portfolio losses tend to harm bond valuations.

The graphical evidence in Figure C.1 displays a negative relationship between changes in the bond prices and $Net\ Sell\ Pressure_{b,t}$ metrics for the *Investment*-grade bonds subsample. The formal regression results reported in column (6) of Table 6 confirm this result. The inclusion of purchases by the unaffected group of funds with low exposure to Argentina into the *Net sell pressure* metrics reveals that this funds use the post-shock negative price dynamics in the *Investment*-grade EM sovereign bonds as a buying opportunity.

The results of this subsection support the hypothesis that portfolio rebalancing by affected and unaffected groups of funds, caused by substantial portfolio losses on Argentinian bonds, had a distorting impact on prices of other sovereign EM bonds. In the post shock period, affected funds exert a significant sell pressure on all sample bonds, with the most pronounced effect on the low-rated *Speculative* bonds. An interesting and new finding shows that unaffected funds use the Argentinian presidential election shock, which caused losses to affected funds, as a buying opportunity to invest in *Investment*-grade bonds that experienced depressed prices in the post-shock environment.

4.3 Fund Level Peer Pressure Effects

Having established that the sell pressure by funds exposed to substantial portfolio losses has a significant impact on bond prices, let us now consider whether there is a spillover effect from the depressed bonds prices to funds' returns. Previous studies have demonstrated the phenomenon of cross-fund contagion through cross-fund holdings during bond market stress initiated by extreme outflows from the affected funds (Falato, Hortaçsu, Li, and Shin, 2020 and Fricke and Wilke, 2023).

Figure C.2 illustrates the scatter plots of the raw data of the fund returns against the peer

Table 6: **Impact of (net) sell pressure on bond prices**

This table reports the estimation results of following regression:

$$B_{b,t} = \delta_b + Post\ shock_t + \beta_1 \cdot (Net)\ Sell\ Pressure_{b,t} + \beta_2 \cdot (Net)\ Sell\ Pressure_{b,t} \times Post\ shock_t + \varepsilon_{b,t}$$

where $B_{b,t}$ is a price change in percent of each sovereign bond. All sovereign bonds with credit ratings ranging from A to C are used (Argentinian bonds are excluded). *Post-shock* denotes the indicator variable that takes value one if the observation belongs to three months after Argentinian presidential elections 2019m8-2019m10 and zero if it belongs to three months 2019m5-2019m7 before the event. $Sell\ Pressure_{b,t}$ is the sum of the value of "forced" fund sales in period t of each bond b by funds with *affected* status relative to the outstanding value of a bond. $Net\ Sell\ Pressure_{b,t}$ is the sum of the value of fund purchases in period t of each bond b by funds with *unaffected* status minus $Sell\ Pressure_{b,t}$ in a given bond relative to the outstanding value of a bond. The affected and unaffected status of a fund is defined based on the top and bottom percentiles of the distribution of fund's $Argentinian\ bond\ shares_i$ in the portfolio before presidential elections respectively. To aid interpretation, we standardize $Sell\ Pressure_{b,t}$ and $Net\ Sell\ Pressure_{b,t}$ by their mean and standard deviations. Columns (1) and (2) display results for the full sample of bonds. Columns (3) and (4) report results for the sub-sample of bonds with a speculative credit rating (< BBB). Columns (5) and (6) report results for the sub-sample of bonds with investment-grade credit rating. The Standard errors are clustered at the bond level. Significance levels are * 10%, ** 5%, *** 1%.

Dependent variable :	*Bond price change (%)$_{b,t}$*					
	All rated bonds		Speculative grade bonds (< BBB)		Investment grade bonds (BBB and A)	
	(1)	(2)	(3)	(4)	(5)	(6)
Post shock	-0.857***	-0.853***	-0.848***	-0.843***	-0.868***	-0.861***
	(0.047)	(0.048)	(0.112)	(0.112)	(0.036)	(0.036)
Sell Pressure$_{b,t}$	-0.031		-0.165*		0.079***	
	(0.042)		(0.085)		(0.027)	
Sell Pressure$_{b,t}$ × Post shock	0.161***		0.249**		0.121***	
	(0.050)		(0.096)		(0.046)	
Net Sell Pressure$_{b,t}$		0.006		0.014		0.005
		(0.036)		(0.077)		(0.025)
Net Sell Pressure$_{b,t}$ × Post shock		-0.117**		-0.095		-0.195***
		(0.049)		(0.088)		(0.067)
Bond FE (b)	YES	YES	YES	YES	YES	YES
Adj. R-squared	0.179	0.179	0.197	0.196	0.117	0.116
N. Bonds	1,715	1,715	649	649	1,066	1,066
Observations	9,757	9,757	3,667	3,667	6,090	6,090

sell pressure metrics, along with the fitted regression lines for the subsamples of *Speculative* and *Investment* funds. The graphs for the *Speculative* funds in Panels (A) and (C) suggest that in the post-election period, the relationship between fund returns and peer sell pressure metrics significantly changes relative to the pre-election period. In the post election period, one can observe a significant rotation in the regression lines for the *Peer Sell Pressure* and *Peer Net Sell Pressure* metrics, indicating a positive relationship between fund returns and cumulative fire-sales of affected bonds in the cross-holding of *Speculative* funds.

The graphs illustrating the *Investment* funds in Panels (B) suggest that the relationship between fund returns and the *Peer Sell Pressure* was essentially flat in both periods. The only scatter plot that does not fit the pattern is displayed in Panel (D) of Figure C.2 for *Peer Net Sell Pressure* of *Investment* funds - a positive relationship with fund returns in the pre-election period changes to a flat one.

We estimate an OLS regression of the montly fund returns as a function of the *Peer (Net) Selling Pressure* and the interaction between this measure of peer pressure and an indicator of the pre- or post-election period. We employ the specification where a single "Post shock" indicator is included for all periods posterior to the occurrence of the shock:

$$R_{i,t} = \delta_i + Post\ shock_t + \beta_1 \cdot Peer\ (Net)\ Sell\ Pressure_{i,t} + \\ + \beta_2 \cdot Peer\ (Net)\ Sell\ Pressure_{i,t} \times Post\ shock_t + \varepsilon_{i,t} \quad (14)$$

where $R_{i,t}$ is a monthly fund return in percent. *Post shock* denotes the indicator variable that takes value one if the observation belongs to three months after Argentinian presidential elections August 2019 - October 2019 and zero if it belongs to three months before the event, May 2019 - July 2019. $Peer\ Sell\ Pressure_{i,t}$ is a weighted sum of peers' $Sell\ Pressure_{b,t}$ in each bond, with weights calculated based on the bond weight in a sovereign portfolio of a given fund. $Peer\ Net\ Sell\ Pressure_{i,t}$ is a weighted sum of peers' $Net\ Sell\ Pressure_{b,t}$ in each bond, with weights calculated based on the bond weight in a sovereign portfolio of a given fund. The peer pressure metrics capture how sensitive a given fund's portfolio is to the fire sales of other funds initially induced by exposure to Argentina.

To aid interpretation, we standardize *Peer Sell Pressure*$_{i,t}$ and *Peer Net Sell Pressure*$_{i,t}$ by their means and standard deviations. The standard errors are clustered at the bond level.

The *Peer (Net) Sell Pressure*$_{i,t}$ have a shift-share structure at the fund level in the spirit of Bartik (1991). The share component is the pre-election fund's exposure to bonds affected by fire-sales, $w_{i,b,t-1}$ in formulas (7) and (8), while the shift component is the bond's sell pressure *Sell Pressure*$_{b,t}$ caused by losses of funds with high exposure to Argentina. Goldsmith-Pinkham, Sorkin, and Swift (2020) study identification assumptions needed for a Bartik instrument derived from exogeneity of shares. Our case corresponds to the quasi-random assignment of bond-level shocks to funds that allows for endogeneity between a fund's shares of bonds and fund returns (Borusyak, Hull, and Jaravel (2022)). The *Peer (Net) Sell Pressure*$_{i,t}$ metrics maintain the Bartik shift-share structure where the shift works through the exogenous quasi-random assignment of affected and unaffected funds around the election shock.

We present the results in Table 7. Columns (1) and (2) display estimates for the full sample of funds. Columns (3) and (4) report results for the sub-sample of funds with a higher share of speculative credit-rated bonds in their portfolio (*Investment grade bond share*$_i$ $<$ *Median*). Columns (5) and (6) report results for the sub-sample of funds with a higher share of investment credit-rated bonds in their portfolio (*Investment grade bond share*$_i$ $\geq$ *Median*).

The coefficients on the *Post shock*$_t$ in the first two columns for all funds indicate that in the post-election period, the average return of our sample funds was negative at 85 basis points (b.p.), corresponding to the negative average return on all sample bonds reported in Table 6. The sub-sample analysis shows that the *Speculative* funds exhibited a negative return of 150 b.p. in the post-election period, while the *Investment* funds had a negative return of 20 b.p.

Let us examine the peer pressure effects for the *Speculative* funds subsample. Based on the coefficient estimates on *Peer Sell Pressure*$_{b,t}$ and *Peer Net Sell Pressure*$_{b,t}$ we observe that both *Peer sell pressure* metrics had a negative impact on fund returns before the shock. The main coefficients of interest, β_2, capture the differential impact of *Peer (Net) Sell Pressure*$_{i,t}$ on fund returns in the post-election period. As seen in columns (3) and (4), these coefficients are highly statistically and economically significant. A one-standard-deviation increase in *Peer Sell Pressure* and *Peer Net Sell Pressure* results in respective movements of 140 and 130 b.p. in *Speculative* funds'

Table 7: **Impact of Peer Sell Pressure on fund performance**

This table reports the estimation results of the following regression:

$$R_{i,t} = \delta_i + Post\ shock_t + \beta_1 \cdot Peer\ (Net)\ Sell\ Pressure_{i,t} + \\ + \beta_2 \cdot Peer\ (Net)\ Sell\ Pressure_{i,t} \times Post\ shock_t + \varepsilon_{i,t}$$

where $R_{i,t}$ is a monthly fund return. *Post-shock* denotes the indicator variable that takes value one if the observation belongs to three months after Argentinian presidential elections 2019m8-2019m10 and zero if it belongs to three months 2019m5-2019m7 before the event. *Peer Sell Pressure*$_{i,t}$ is a weighted sum of peers' *Sell Pressure*$_{b,t}$ in each bond, with weights calculated based on the bond weight in a sovereign portfolio of a given fund. *Peer Net Sell Pressure*$_{i,t}$ is a weighted sum of peers' *Net Sell Pressure*$_{b,t}$ in each bond, with weights calculated based on the bond weight in a sovereign portfolio of a given fund. To aid interpretation, we standardize *Peer Sell Pressure*$_{i,t}$ and *Peer Net Sell Pressure*$_{i,t}$ by their mean and standard deviations. Columns (1) and (2) display results for the full sample of funds. Columns (3) and (4) report results for the sub-sample of *Speculative* funds with *Investment grade bond share*$_i$ < *Median* in their portfolio. Columns (5) and (6) report results for the sub-sample of *Investment* funds with *Investment grade bond share*$_i$ ≥ *Median* in their portfolio. The Standard errors are clustered at the bond level. Significance levels are * 10%, ** 5%, *** 1%.

Dependent variable :	*Monthly fund return (%)*$_{b,t}$					
	All funds		Speculative funds		Investment funds	
	(1)	(2)	(3)	(4)	(5)	(6)
Post shock	-0.838***	-0.861***	-1.459***	-1.481***	-0.233***	-0.202***
	(0.069)	(0.071)	(0.127)	(0.128)	(0.052)	(0.060)
Peer Sell Pressure$_{i,t}$	-0.690***		-0.855***		0.012	
	(0.233)		(0.321)		(0.299)	
Peer Sell Pressure$_{i,t}$ × Post shock	1.091***		1.396***		-0.075	
	(0.154)		(0.211)		(0.318)	
Peer Net Sell Press.$_{i,t}$		-0.656***		-0.865**		0.163*
		(0.242)		(0.341)		(0.090)
Peer Net Sell Press.$_{i,t}$ × Post shock		0.976***		1.285***		-0.298**
		(0.150)		(0.206)		(0.116)
Fund FE (i)	YES	YES	YES	YES	YES	YES
Adj. R-squared	0.419	0.412	0.428	0.424	0.412	0.420
N. funds	852	852	420	420	432	432
Observations	5,112	5,112	2,520	2,520	2,592	2,592

returns. Consistent with the findings of Fricke and Wilke (2023), cross-fund liquidations from peer funds adversely affect fund performance.

Turing to the estimation results for the *Investment* funds subsample, we observe that the impact of $Peer\ Sell\ Pressure_{b,t}$ on fund returns, as reported in column (5), was insignificant in both the pre- and post-election periods. This can be explained by the lower exposure to Argentina in this subset of funds. The negative and significant coefficient on the $Peer\ Net\ Sell\ Pressure_{i,t} \times Post\ shock_t$ term in column (6) can be attributed to the bottom shopping strategy pursued by unaffected *Investment* funds in the post-election period. The bond level results reported in Table 6 in the previous subsection revealed that depressed investment grade bonds enjoyed buying by unaffected funds with low exposure to Argentina. The fund-level results in this subsection corroborate the bond level evidence and illustrate that this buying activity was carried out by funds with a share of investment-grade bonds above the median.

Overall, these results suggest that the sales and purchases of bonds by peer funds have a significant statistical and economic impact on fund returns in the periods of portfolio rebalancing prompted by portfolio losses. Therefore, the spillover effect of cross-fund liquidations and potential contagion through the network of cross-holdings deserves additional attention from fund managers and the regulators.

5 Conclusion

Our study explores the repercussions of an exogenous shock on global funds investing in emerging market sovereign government bonds, with a particular focus on the network of interconnections among these funds. Leveraging the fortuitous events surrounding the Argentinian primary presidential elections in August 2019, our difference-in-difference research design provides insights into the mechanisms of portfolio rebalancing, selling pressure propagation, and the potential spillover effects on peer funds within the same bond market.

Our empirical analysis reveals that the initial portfolio losses incurred by exposed funds lead to discretionary sales of other EM sovereign bonds and cash hoarding by fund managers. Notably, these strategic moves aim to discourage redemptions and expand the pool of liquid assets for potential sales to fulfill future redemption requests, aligning with the findings of Morris, Shim, and Shin (2017). Our study also indicates that non-exposed more liquid *Investment* funds view the shock as a buying opportunity, resulting in a nuanced landscape of portfolio rebalancing strategies.

Our examination of the modified Coval-Stafford pressure metric highlights the significance of exposure-induced bond sales or purchases by "peer" funds. The metric, grounded in the theoretical and empirical framework of Greenwood, Landier, and Thesmar, 2015; Falato, Hortaçsu, Li, and Shin, 2020; Fricke and Fricke, 2021), captures the susceptibility of funds to exposure-induced asset sales/purchases initiated by peers, providing a quantitative measure of the potential impact on bond returns. This sets our study apart from research that focuses on information-driven and redemption-induced sales/purchases of assets.

Our findings contribute to the broader literature on open-ended mutual funds, offering insights into the structural vulnerabilities, peer selling pressure dynamics, and contagion effects arising from unexpected shocks and subsequent portfolio rebalancing. The study underscores the importance of the network interconnections among funds operating in the same market for a comprehensive understanding of financial stability considerations. This may help regulators and market participants in anticipating and mitigating potential systemic risks.

References

[1] Akey, Pat (2015) ”Valuing Changes in Political Networks: Evidence from Campaign Contributions to Close Congressional Elections,” The Review of Financial Studies, Vol. 28, pp. 3188–3223.

[2] Antón, Miguel and Christopher Polk (2014) ”Connected stocks,” Journal of Finance 69, pp. 1099–127.

[3] Becker, Bo and Victoria Ivashina. (2015) ”Reaching for yield in the bond market,” The Journal of Finance, Vol. 70, pp. 1863-1902.

[4] Ben-Rephael, Azi, Shmuel Kandel, and Avi Wohl (2011) ”The Price Pressure of Aggregate Mutual Fund Flows,” The Journal of Financial and Quantitative Analysis 46, pp. 585-603.

[5] Borusyak, K., Hull, P., and Jaravel, X, (2022). “Quasi-Experimental Shift-Share Research Designs,” The Review of Economic Studies, 89(1), 181–213.

[6] Brogaard, Jonathan, Matthew Denes and Ran Duchin (2020) ”Political Influence and the Renegotiation of Government Contracts”, The Review of Financial Studies (forthcoming)

[7] Chen, Qi, Itay Goldstein, and Wei Jiang. (2010) ”Payoff complementarities and financial fragility: evidence from mutual fund outflows,” Journal of Financial Economics Vol. 97, pp. 239-262.

[8] Choi, Jaewon and Mathias Kronlund (2018) ”Reaching for Yield in Corporate Bond Mutual Funds,” The Review of Financial Studies, Vol. 31, pp. 1930–1965.

[9] Cortes, Fabian and Luca Sanfilipp (2020) ”Do Multi-Sector Bond Funds Pose Risks to Emerging Markets?” IMF Working Paper 20/152.

[10] Coval, Joshua and Erik Stafford (2007) “Asset fire sales (and purchases) in equity markets,” Journal of Financial Economics, Vol. 86, pp. 479-512.

[11] Dannhauser, Caitlin and Saeid Hoseinzade (2022) ”The Unintended Consequences of Corporate Bond ETFs: Evidence from the Taper Tantrum”, The Review of Financial Studies 35, pp. 51–90.

[12] Engelen, Christian and Johann G. Lambsdor (2009) ”Hares and Stags in Argentinean Debt Restructuring,” Journal of International Economics, Vol. 78, pp. 141-148.

[13] Falato, Antonio, Ali Hortaçsu, Dan Li and Chaehee Shin (2021) ”Fire-Sale Spillovers in Debt Markets,” Journal of Finance 76, pp. 3055-3102.

[14] Fricke Christoph and Daniel Fricke (2021) ”Vulnerable asset management? The case of mutual funds,” Journal of Financial Stability, Vol. 52, pp. 1-21.

[15] Fricke, Daniel and Hannes Wilke (2023) ”Connected funds,” The Review of Financial Studies 36(11), pp. 4546–4587.

[16] Goldsmith-Pinkham, P., Sorkin, I., and Swift, H., (2020). “Bartik Instruments: What, When, Why, and How,” American Economic Review, 110(8), 2586-2624.

[17] Goldstein Itay, Hao Jiang and David Ng (2017) ”Investor flows and fragility in corporate bond funds,” Journal of Financial Economics, Vol. 126, pp. 592-613.

[18] Greenwood, R., A. Landier, and D. Thesmar. (2015) "Vulnerable banks," Journal of Financial Economics 115, pp. 471–85.

[19] Hui, Cho-Hoi (2018) "Emerging market bond funds: flow-performance relationship and long-term institutional investor," BIS Paper 102.

[20] Jiang Hao, Dan Li and Ashley Wang (2020) "Dynamic Liquidity Management by Corporate Bond Mutual Funds," Journal of Financial and Quantitative Analysis pp. 1-31.

[21] Jiang Hao, Yi Li, Zheng Sun and Ashley Wang (2022) "Does Mutual Fund Illiquidity Introduce Fragility into Asset Prices? Evidence from the Corporate Bond Market," Journal of Financial Economics, Vol. 143, pp. 277-302.

[22] Jotikasthira, C., C. Lundblad, and T. Ramadorai (2012) "Asset fire sales and purchases and the international transmission of funding shocks," Journal of Finance 67, pp. 2015–50.

[23] Lou, Dong (2012) "A Flow-Based Explanation for Return Predictability," Review of Financial Studies 25, pp. 3457–3489.

[24] Manconi, A., M. Massa, and A. Yasuda. (2012) "The role of institutional investors in propagating the crisis of 2007–2008," Journal of Financial Economics 104, pp. 491–518.

[25] Morris, Stephen, Ilhyock Shim, and Hyun Song Shin (2017). "Redemption risk and cash hoarding by asset managers," Journal of Monetary Economics 89, pp. 71–87.

[26] Shek, Jimmy, Ilhyock Shim, and Hyun Shin (2018) "Investor Redemptions and Fund Manager Sales of Emerging Market Bonds: How Are They Related?," Review of Finance 22, pp. 207–241.

[27] Sturzenegger, Federico and Jeromin Zettelmeyer (2006) Debt Defaults and Lessons from a Decade of Crises: Cambridge, *MIT Press*.

[28] Sydow, Matthias, Aurore Schilte, Giovanni Covi, Marija Deipenbrock, Leonardo Del Vecchio, Pawel Fiedor, Gábor Fukker, Max Gehrend, Régis Gourdel, Alberto Grassi, Björn Hilberg, Michiel Kaijser, Georgios Kaoudis, Luca Mingarelli, Mattia Montagna, Thibaut Piquard, Dilyara Salakhova, and Natalia Tente (2024) "Shock amplification in an interconnected financial system of banks and investment funds," Journal of Financial Stability, 101234.

[29] Wardlaw, Malcolm (2020) "Measuring Mutual Fund Flow Pressure as Shock to Stock Returns," Journal of Finance 75, pp. 3221-3243

[30] Zhou, Zhenkun, Matteo Serafino, Luciano Cohan, Guido Caldarelli and Hernán A. Makse (2021) "Why polls fail to predict elections", The Journal of Big Data 8:137.

Appendix A Summary statistics on funds and bonds

Table A.1: **List of new 'Macri Bonds' held by international bond funds**

This table reports all 'Macri Bonds' issued by Argentina under New York Law in 2016-2018 in US dollars and Euro. The growth of funds' holdings of these bonds is a key dependent variable of our study.

Bond	**ISIN**	**Issue Date**	**Maturity Date**	**Curr.**	**Par**	**Amount (M)**	**% Price change 9-12 Aug. 2019**
ARG 6 7/8 01/26/27	US040114HL72	03/14/2017	01/26/2027	USD	1000	3,749,835	- 28.13
ARG 7 1/2 04/22/26	US040114GX20	03/14/2017	04/22/2026	USD	1000	6,497,345	- 28.85
ARG 7 5/8 04/22/46	US040114GY03	03/14/2017	04/22/2046	USD	1000	2,749,648	- 26.33
ARG 5 5/8 01/26/22	US040114HK99	03/14/2017	01/26/2022	USD	1000	3,249,930	- 27.06
ARG 7 1/8 07/06/36	US040114HG87	03/14/2017	07/06/2036	USD	1000	1,749,800	- 25.43
ARG 5 7/8 01/11/28	US040114HQ69	01/04/2018	01/11/2028	USD	1000	4,250,000	- 26.20
ARG 6 7/8 04/22/21	US040114GW47	03/14/2017	04/22/2021	USD	1000	4,497,440	- 26.75
ARG 6 5/8 07/06/28	US040114HF05	03/14/2017	07/06/2028	USD	1000	999,520	- 26.10
ARG 6 7/8 01/11/48	US040114HR43	01/04/2018	01/11/2048	USD	1000	3,000,000	- 23.95
ARG 4 5/8 01/11/23	US040114HP86	01/04/2018	01/11/2023	USD	1000	1,750,000	- 25.51
ARG 7 1/8 06/28/17	US040114HN39	05/18/2018	06/28/2117	USD	1000	2,602,855	- 24.69
ARG 5 1/4 01/15/28	XS1715303779	11/02/2017	01/15/2028	EUR	1000	1,000,000	- 29.44
ARG 3 3/8 01/15/23	XS1715303340	11/02/2017	01/15/2023	EUR	1000	1,000,000	- 22.19
ARG 6 1/4 11/09/47	XS1715535123	11/02/2017	11/09/2047	EUR	1000	750,000	- 22.70
ARG 3 7/8 01/15/22	XS1503160225	10/05/2016	01/15/2022	EUR	1000	1,250,000	- 25.23
ARG 5 01/15/27	XS1503160498	10/05/2016	01/15/2027	EUR	1000	1,250,000	- 23.97

Table A.2: **Families of funds**

This table shows the distribution of funds by families and countries where funds within families are incorporated.

Fund family	N. fund	N. Countr.	Fund family	N. fund	N. Countr.
Aberdeen Standard Investments	6	3	Cornestone Advosors	1	1
ABN AMRO	6	1	Credit Suisse Asset Management	5	1
AcomeA	1	1	CTBC Investments	1	1
Actinver SOFI SA de CV	1	1	Danske Invest Management	4	2
Aegon Asset Management	2	2	Deal	1	1
AGF Investments	2	1	Deka Vermoegensmanagement	8	2
Aha Asset Management	1	1	Delaware Investments	6	1
Algebris Investments	1	1	Delta Asset Management	7	1
Allaria Ledesma Fondos	1	1	DJE Investment	1	1
AllianceBernstein	10	3	Doubleline Capital	6	1
Allianz Global Investors	9	3	Driehaus Capital Management	1	1
American Beacon Advisors	1	1	DuPont Capital Management	1	1
American Century Investment	6	1	DWS Investment	15	4
Amundi	35	3	Eastspring Investments	2	1
Arca Holding	3	1	Eaton Vance Management	2	1
Ashmore Investment Management	8	3	Emirates NBD Asset Management	1	1
Aston Asset Management	1	1	Envestnet Asset Management	1	1
Aviva Investors	3	1	Epsilon	8	1
AXA	2	2	Ersel Gestion Internationale	1	1
Axis Administradora	2	1	Erste-Sparinvest	1	1
Baillie Gifford Overseas	2	1	Eurizon Capital	27	2
BankInvest Asset Management	2	1	Euromobiliare Asset Management	6	1
Banque de Luxembourg Investments	1	1	Fagus Multimanager	1	1
Barings	3	1	Federated Global Management	1	1
BBVA	3	1	Fidelity Investments	35	4
BCC Risparmio & Previdenza	1	1	Fiera Investments	1	1
BG Fund Management	2	1	First Private Investment	1	1
BICE Inversiones Administradora	1	1	First State Investments	2	1
BlackRock	23	3	Franklin Templeton	5	1
Blackstone Group	1	1	Frost Investment Advisors	1	1
BlueBay Asset Management	3	1	Gainvest	1	1
BMO Asset Management	2	1	Galicia Administradora de Fondos	1	1
BNP Paribas Investment	5	2	Gallery Trust	1	1
BNY Mellon Global Management	8	3	GAM Luxembourg	12	1
Boston Management & Research	1	1	Gerente de Fondos	1	1
Brinker Capital	2	1	Goldman Sachs Asset Management	11	2
C y C Administradora de Fondos	1	1	Great-West Capital Management	1	1
CAIAC Fund Management	1	1	Grupo SS SA SGFCI/Argentina	1	1
Callan	1	1	GuideStone Capital Management	2	1
Candriam Luxembourg	5	1	Guipuzcoano SGIIC	1	1
Canoe Financial	1	1	Hartford Funds Management	6	1
Capital International Management	5	2	Helaba Invest	4	1
Capital Research & Management	3	1	Henderson Management SA	1	1
Carmignac Gestion	3	2	HSBC Investment Funds	4	2
Carne Global Fund Managers	3	1	IFM Independent Fund Management	2	1
CI Investments	1	1	Insight Investment Management	3	1
CIBC Asset Management	2	1	Interfund Advisory	6	1
City National Rochdale	1	1	Invesco Fund Managers	23	4
Clarington Capital Management	1	1	Investec Asset Management	7	2
Columbia Management Investment	4	1	Investis Asset Management	5	1
Consultatio Asset Management	4	1	IPConcept	1	1
Consultinvest Asset Management	8	1	Ivy Investment Management	2	1

Table A.3: **Families of funds (cont.)**

Fund family	N. fund	N. Countr.	Fund family	N. fund	N. Countr.
John Hancock Advisers	5	1	OP-Rahastoyhtio	1	1
JPMorgan Funds	12	4	Payden & Rygel Global	6	2
Jupiter Asset Management	1	1	Pellegrini SFCI/Argentina	1	1
Jyske Invest	7	1	PFA Invest International	3	1
Kairos Investment Management	1	1	PGIM	9	2
KBC Asset Management	1	1	Pictet Asset Management	2	1
La Francaise des Placements	2	2	PIMCO	49	3
Lazard Asset Management	1	1	Pioneer Investment Management	2	1
Lazard Fund Managers	5	2	Pramerica Management	2	1
Legal & General Investment	6	1	Pripal Global Investors	4	2
Legg Mason Global Funds	13	3	Putnam Investment Management	8	3
Lemanik Asset Management	1	1	Quilter Investors	5	1
LGT Capital Partners	2	2	Raiffeisen Kapitalanlage	2	1
LLB Invest	2	1	RBC Global Investment	4	2
Lombard Odier Funds	1	1	RiverNorth Capital Management	1	1
Lord Abbett	8	2	Russell Investment	2	2
LRI Invest	5	1	Sabadell Asset Management	2	1
M&G Investment Management	4	2	Santander Rio Asset Management	5	1
Mackenzie Financialrp	18	1	SBS Asset Management	2	1
Macquarie Investment Management	1	1	Schroder	17	5
Macro Fondos SGFCI	1	1	SEI Investments	7	2
Manulife Investment Management	2	2	Sella SGR	1	1
Mariva Asset Management	2	1	Societe Generale Private Wealth	1	1
Marks & Spencer	1	1	Sparinvest	5	2
Massachusetts Financial Services	4	1	St James's Place Group	1	1
MDO Management	1	1	Standard Investments	4	1
MEAG Munich Ergo	2	1	Stone Harbor Investment Partners	1	1
Mediolanum International Funds	5	1	SunAmerica Asset Management	1	1
MegaINVER	3	1	Swisscanto Asset Management	6	2
Merian Global Investors	1	1	Syd Fund Management	5	1
MFS Investment Management	3	1	T Rowe Price Global Investment	12	3
Mirae Asset Global Investments	1	1	TCW Investment Management	2	1
MML Investment Advisors	2	1	TD Asset Management	5	1
Morgan Stanley Investment	5	2	Teachers Advisors	4	1
Morningstar Investment	1	1	Threadneedle Management	4	2
MultiConcept Fund Management	1	1	Thrivent Asset Management	1	1
MutualFirst Financial	1	1	Touchstone Advisors	1	1
Myria Asset Management	1	1	TFI	1	1
National Bank Investments	1	1	Transamerica Asset Management	2	1
Nationwide Fund Advisors	1	1	UBP Asset Management	1	1
Natixis Advisors	2	1	UBS Fund Management	10	3
Natixis Investment Managers	3	1	Union Investment	14	2
Neuberger Berman Europe	7	2	Universal-Investment	5	1
New Capital Fund Management	1	1	Van Eck Associates	1	1
New York Life Investment	1	1	Vanguard Group	7	2
NN Investment Partners	3	1	Virtus Investment Partners	3	2
Nomura Asset Management	1	1	Vontobel Asset Management	2	1
Nordea Investment Management	3	3	Voya Investments	4	1
Northern Lights Fund Trust	1	1	Warburg Invest	1	1
Northern Trust Investments	1	1	Wellington Management Group	3	2
Nuveen Fund Advisors	2	2	Wells Fargo Bank	1	1
Nykredit Portefolje Administration	3	1	Western Asset Management	2	1
Olive Street Investment Advisers	1	1	Wilmington Funds Management	1	1
Omnis Investments	1	1	Wilshire Associates	1	1

Table A.4: **Countries of funds' incorporation**

This table shows the distribution of our sample funds by countries where they are incorporated.

Country of fund's domicile	Freq.	Percent	Cum.
ARGENTINA	53	6.24	6.24
AUSTRALIA	1	0.12	6.35
AUSTRIA	7	0.81	7.16
CANADA	55	6.35	13.51
CAYMAN ISLANDS	1	0.12	13.63
CHILE	2	0.23	13.86
DENMARK	25	2.89	16.74
FINLAND	2	0.23	16.97
FRANCE	4	0.46	17.44
GERMANY	23	2.66	20.09
GREECE	1	0.12	20.21
HONG KONG	1	0.12	20.32
IRELAND	71	8.2	28.52
ITALY	48	5.54	34.06
JERSEY, C.I.	1	0.12	34.18
LIECHTENSTEIN	4	0.46	34.64
LUXEMBOURG	280	32.33	66.97
MEXICO	1	0.12	67.09
POLAND	1	0.12	67.21
SOUTH KOREA	1	0.12	67.32
SPAIN	3	0.35	67.67
SWITZERLAND	5	0.58	68.24
TAIWAN	5	0.58	68.82
TURKEY	1	0.12	68.94
UNITED KINGDOM	38	4.39	73.33
UNITED STATES	231	26.67	100
Total	865	100	

Table A.5: **Distribution of sovereign government bonds by countries of issuance**

This table shows the distribution of our sample bonds by countries of issuance and countries' 2019 credit rating.

Country	N. bonds	Credit rating	Country	N. bonds	Credit rating
ALBANIA	3	B	LATVIA	10	A
ANGOLA	3	C	LEBANON	26	C
ARGENTINA	16	BB	LITHUANIA	13	A
ARMENIA	4	B	MACEDONIA	5	B
ARUBA	1	BB	MALAYSIA	78	BBB
AZERBAIJAN	3	BB	MALDIVES	1	B
BAHAMAS	3	B	MEXICO	67	BBB
BAHRAIN	14	B	MONGOLIA	4	B
BARBADOS	2	B	MOROCCO	4	BB
BELARUS	3	B	MOZAMBIQUE	1	C
BELIZE	1	B	MONTENEGRO	5	B
BENIN	1	B	NAMIBIA	2	BB
BERMUDA	4	A	NIGERIA	64	B
BOLIVIA	3	B	OMAN	14	BB
BOSNIA-HERZE.	1	B	PAKISTAN	7	B
BRAZIL	50	BB	PANAMA	14	BBB
BULGARIA	6	BBB	PAPUA N.GUINEA	1	B
CAMEROON	1	B	PARAGUAY	6	BB
CAYMAN ISLANDS	13	A	PERU	30	BBB
CHILE	44	A	PHILIPPINES	44	BBB
CHINA	91	A	POLAND	56	A
COLOMBIA	40	BBB	PORTUGAL	22	BBB
CONGO	1	C	ROMANIA	43	BBB
COSTA RICA	22	B	RUSSIA	40	BBB
CROATIA	16	BBB	RWANDA	1	B
CYPRUS	10	BBB	SAUDI ARABIA	13	A
DOMINICAN REPB.	47	BB	SENEGAL	5	B
ECUADOR	1	B	SEYCHELLES	1	BB
EGYPT	56	B	SLOVAKIA	17	A
EL SALVADOR	8	B	SOUTH AFRICA	42	BB
ETHIOPIA	1	C	SPAIN	69	A
GABON	2	B	SRI LANKA	36	C
GEORGIA	1	BB	SURINAME	1	C
GHANA	29	B	Serbia	21	BB
GREECE	37	BB	TAJIKISTAN	1	B
GUATEMALA	7	BB	THAILAND	28	BBB
HONDURAS	3	BB	TRINIDAD AND TO	2	BBB
HUNGARY	29	BBB	TUNISIA	10	B
ICELAND	8	A	TURKEY	64	BB
INDIA	42	BBB	UAE	11	A
INDONESIA	94	BBB	UGANDA	5	B
IRAQ	1	B	UKRAINE	15	B
ITALY	147	BBB	URUGUAY	16	BBB
IVORY COAST	9	BB	UZBEKISTAN	2	BB
JAMAICA	6	B	VENEZUELA	10	C
JORDAN	3	BB	VIETNAM	6	BB
KAZAKHSTAN	6	BBB	ZAMBIA	16	C
KENYA	16	B			

Appendix B Network

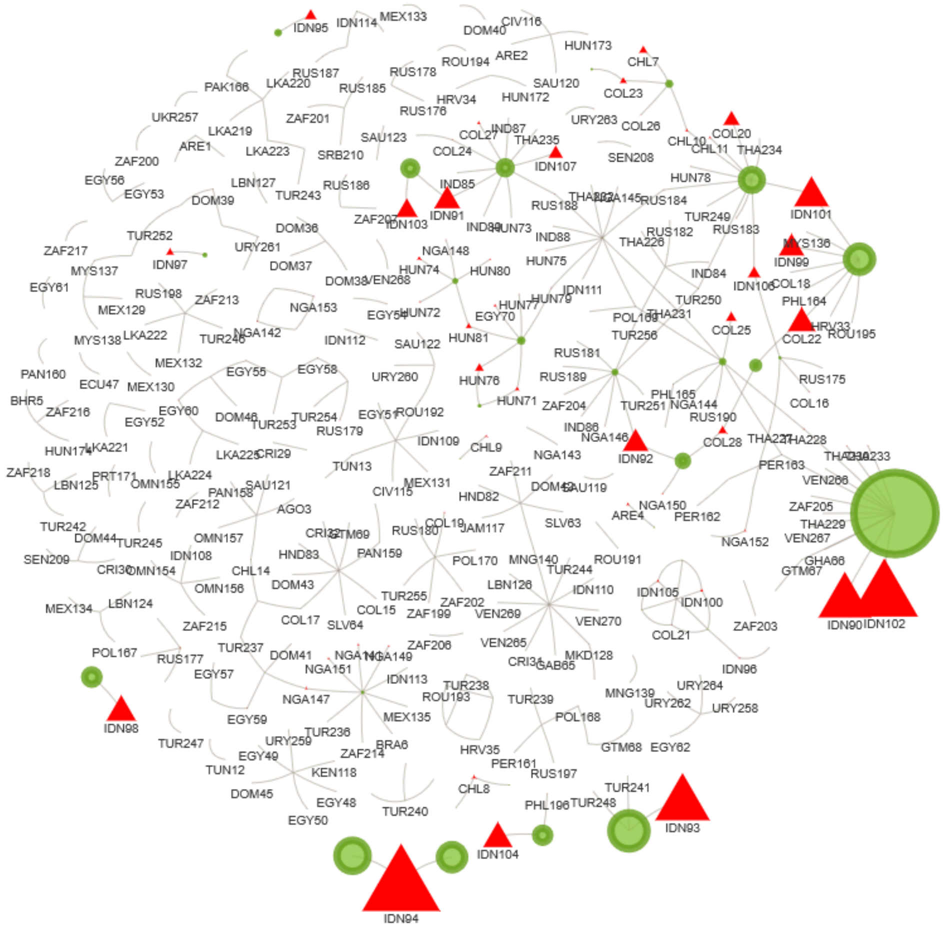


Figure B.1: Two-mode Network: Funds and Bonds Before the Shock

This picture represent the bipartite graph where lines connect only nodes representing funds (green circles) with nodes representing bonds (red triangles). The size of the node for a bond b (marked by the red color and caption with the bond's country of issuance) is proportional to the summation of the total sales by affected funds j in the *pre-shock* period $\sum_j^N[-\Delta Holdings_{j,b,t}|Arg.\ Bond\ Share_j \geq Percentile(80th)]$. The size of the node for fund j (marked by the green color) is proportional to the quantity of all bonds sold by the fund. The *pre-shock* period covers May-July 2019. The graph illustrates only top 10 per cent of the affected funds and bonds that represent at least 25 per cent of fund's total sales in a given period.

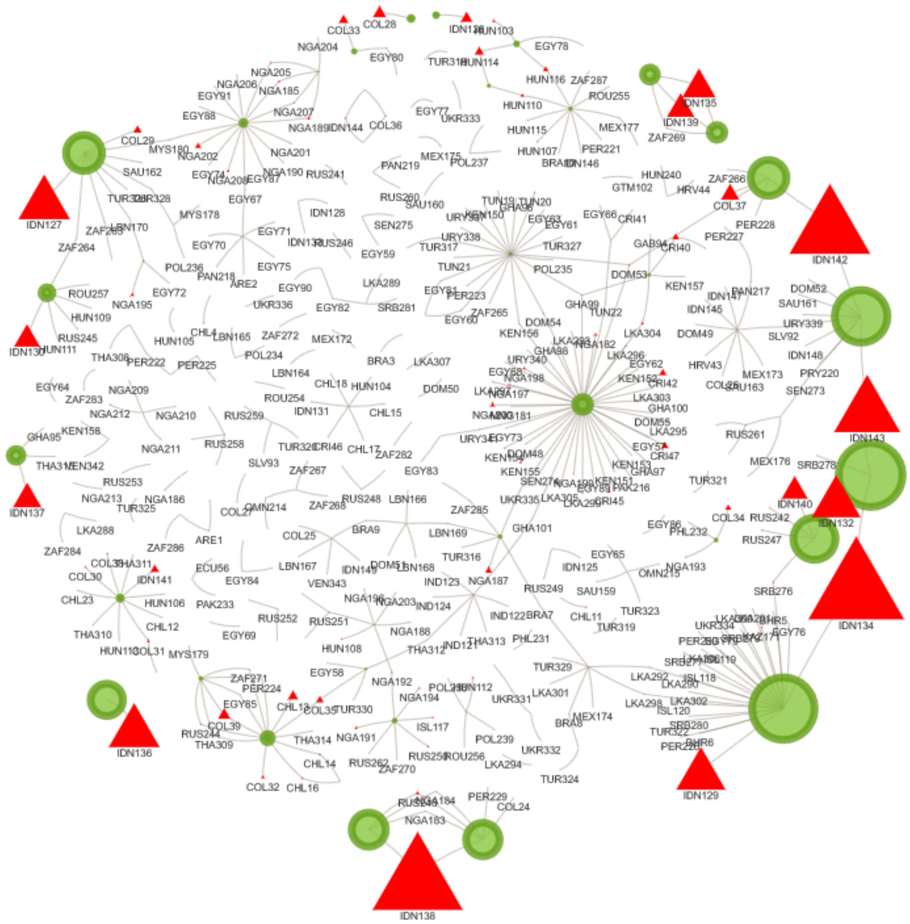
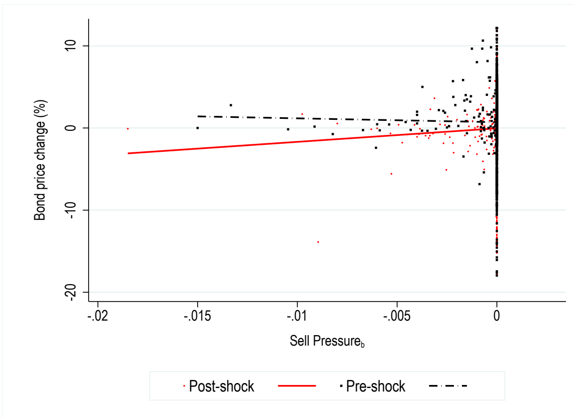


Figure B.2: Two-mode Network: Funds and Bonds After the Shock

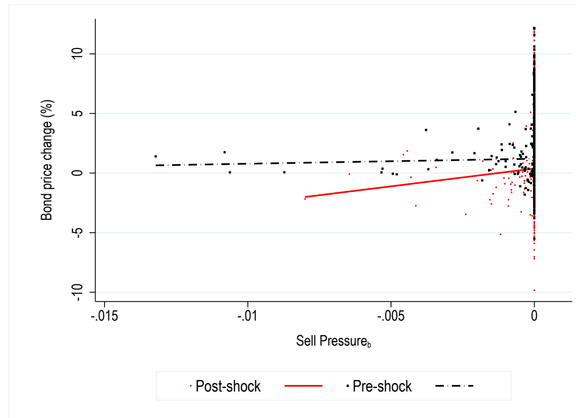
This picture represent the bipartite graph where lines connect only nodes representing funds (green circles) with nodes representing bonds (red triangles). The size of the node for a bond b (marked by the red color and caption with the bond's country of issuance) is proportional to the summation of the total sales by affected funds j in the *post-shock* period $\sum_j^N[-\Delta Holdings_{j,b,t}|Arg.\ Bond\ Share_j \geq Percentile(80th)]$. The size of the node for fund j (marked by the green color) is proportional to the quantity of all bonds sold by the fund. The *post-shock* period covers August-October 2019. The graph illustrates only top 10 per cent of the affected funds and bonds that represent at least 25 per cent of fund's total sales in a given period.

Appendix C Scatter plots

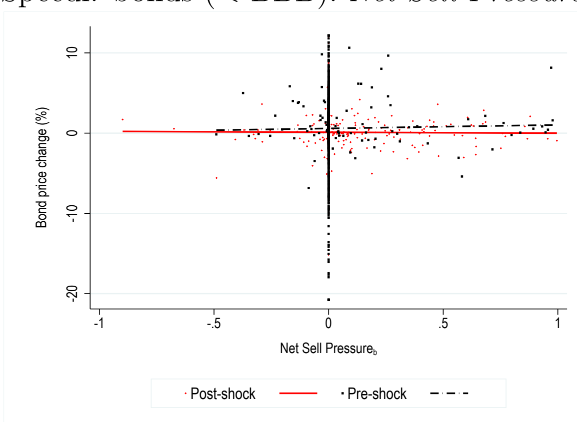
A: Specul. bonds (< BBB): *Sell Pressure*



B: Invest. bonds (≥ BBB): *Sell Pressure*



C: Specul. bonds (< BBB): *Net Sell Pressure*



D: Invest. bonds (≥ BBB): *Net Sell Pressure*

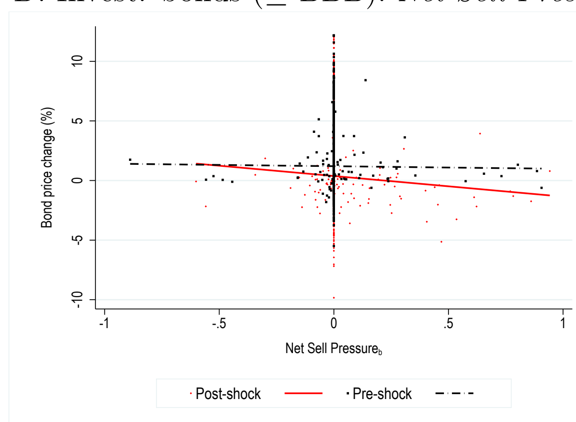


Figure C.1: Scatter plot: Bond's percentage change and *(Net) Sell Pressure*

This picture plots monthly percentage price change of each sample sovereign bond against bond's *(Net) Sell Pressure*. Panels A and C illustrate a sub-sample of bonds with speculative credit ratings (< BBB). Panels B and D illustrate a sub-sample of bonds with investment-grade credit ratings (BBB and A). In all figures observations before the Argentinian elections (Pre-shock) are represented by black dots and the black dashed line represents the fitted linear regression for this sub-sample. Observations after elections (Post-shock) are represented by red dots and the red solid line represents the fitted linear regression for this sub-sample.

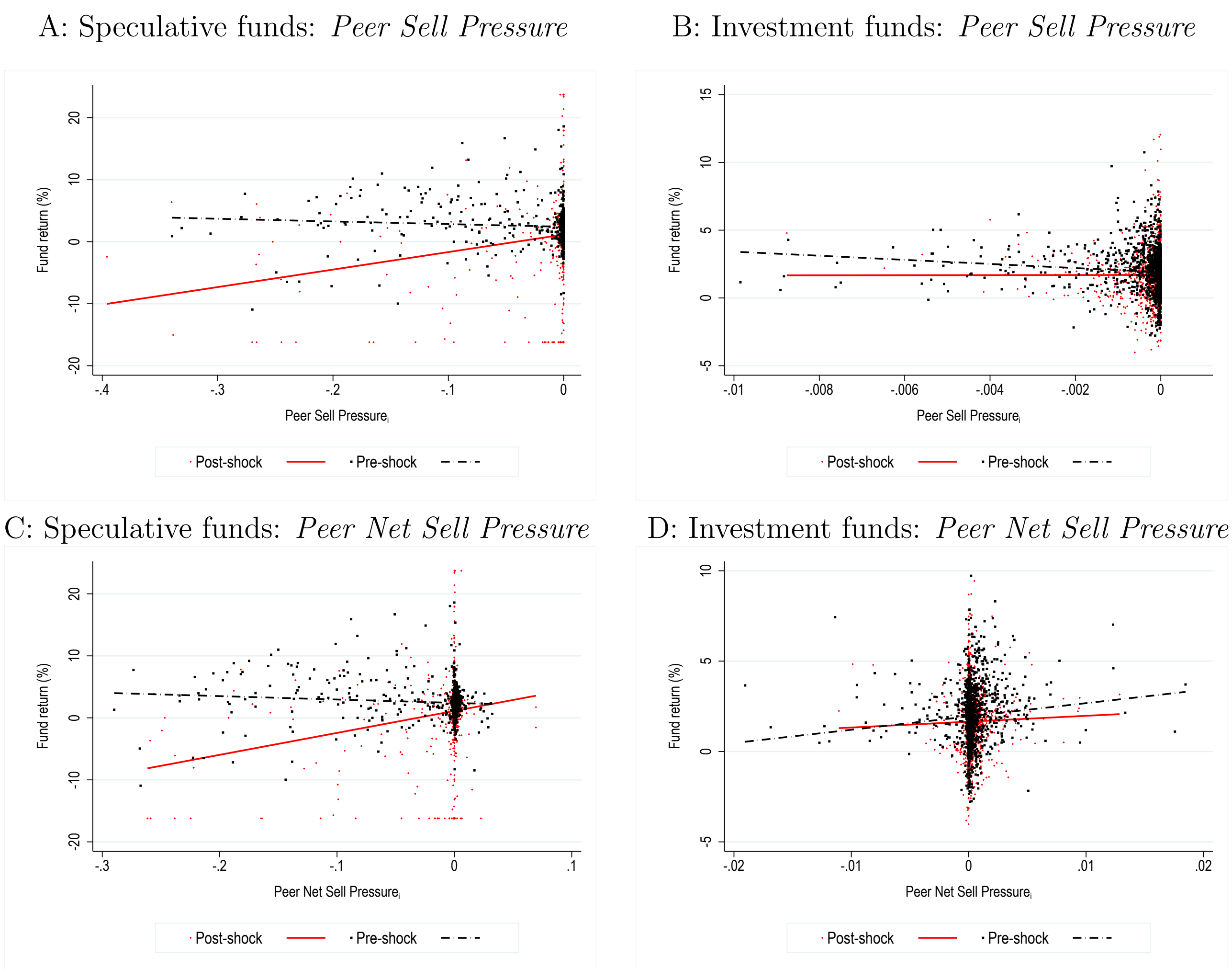


Figure C.2: Scatter plot: Fund's return and *Peer (Net) Sell Pressure*

This picture plots monthly returns of each sample fund against fund's *Peer (Net) Sell Pressure*. Panels A and C illustrate a sub-sample of *Speculative* funds with *Investment grade bond share$_i$ < Median* in their portfolio. Panels B and D illustrate a sub-sample of *Investment* funds with *Investment grade bond share$_i$ ≥ Median* in their portfolio. In all figures observations before the Argentinian elections (Pre-shock) are represented by black dots and the black dashed line represents the fitted linear regression for this sub-sample. Observations after elections (Post-shock) are represented by red dots and the red solid line represents the fitted linear regression for this sub-sample.