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Drivers of Flows-Performance Sensitivity in Mutual Funds[1]

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Abstract

This paper examines the relationship between mutual fund performance and fund flows in Israel. Israel has a unique setting: Bonds are traded on a limit order book exchange, resulting in high liquidity. Using proprietary daily fund level data, I find a convex performance-flows relationship, meaning investors are more sensitive to good performance than to bad performance, in all three market segments of actively managed funds: government bonds, corporate bonds, and equity. This indicates that the first mover's advantage documented in US corporate bond mutual funds as a source of market fragility, which drives a concave performance-flows relationship, does not exist in Israel, and perhaps more generally in exchanges with a limit order book. I find that flows to passive funds are at minimum 40% less sensitive to performance in comparison to active funds, indicating that passive investments might have a moderating effect at times of financial stress, as flows to them are less procyclical than to active funds.

JEL Codes: G01, G18, G20, G23.
Keywords: Financial fragility, liquidity, bond funds, mutual fund flows, passive investment, index tracking funds.

הגורמים המשפיעים על רגישות זרימות ההון לביצועי קרנות הנאמנות

נעם בן זאב

תקציר

מחקר זה בוחן את הקשר בין ביצועי קרנות הנאמנות לבין הגיוסים והפדיונות בהן. באמצעות שימוש בנתונים יומיים, אני מוצא שמשקיעים רגישים יותר לביצועים חיוביים של הקרנות שבהן הם משקיעים מאשר לביצועים שליליים שלהן. ממצא זה תקף לקרנות שמתמחות בכל אפיקי ההשקעה המקומיים: מניות, אג״ח חברות ואג״ח ממשלתיות. בקרנות שמתמחות באג״ח חברות מדובר בתוצאה ייחודית, שכן ידוע ממחקרים קודמים בתחום זה, שבארה״ב מתקיים קשר הפוך – ומשקיעים רגישים יותר לביצועים שליליים. ההבדלים בין ישראל לארה״ב מוסברים במבנה שוק שונה, כאשר בישראל אג״ח חברות נסחרות בבורסה. אני מוצא שהגיוסים והפדיונות בקרנות הפסיביות (כלומר מחקות מדד) נמוך במחצית, לערך, מאשר בקרנות נאמנות אקטיביות (כלומר מנוהלות) מקבילות. משמעות הדבר היא שקרנות מחקות מהוות גורם ממתן בתקופות משבר, שכן המשקיעים בהן נוטים לפדות פחות כספים בתגובה לביצועי השוק – כפי שאכן קרה במשבר הקורונה.

1. Introduction

The growth of corporate bond funds introduces the risk of fire sales at times of financial stress. I build on the work of Goldstein, Jiang, and Ng (2017) that finds a concave pattern in the sensitivity of flows to performance in corporate bond funds, meaning that investors in those funds are more sensitive to poor fund performance than to good performance, attributing this finding to the illiquidity of the US corporate bond market, and on the work of Abudi and Wohl (2018) that shows the Israeli corporate bond market is much more liquid than the US one. This paper uses proprietary daily fund-level data to explore the drivers of fund flows, and more specifically the relation between fund performance and future flows. I find evidence of a convex flows-performance relation in local corporate bond funds and discuss its implications for financial stability: The convex shape is a sign of lower market fragility. I then compare the sensitivity of flows to performance between actively managed (hereinafter, "active") and index tracking (hereinafter, "passive") mutual funds. My main contribution is finding that while flows to passive funds are sensitive to returns, they are at minimum 40% less sensitive than their active counterparts in the same investment category. This implies that passive funds are a moderating factor at times of financial stress, as outflows from them are not as procyclical as active funds. I test this directly using the COVID-19 crisis as an event of market stress.

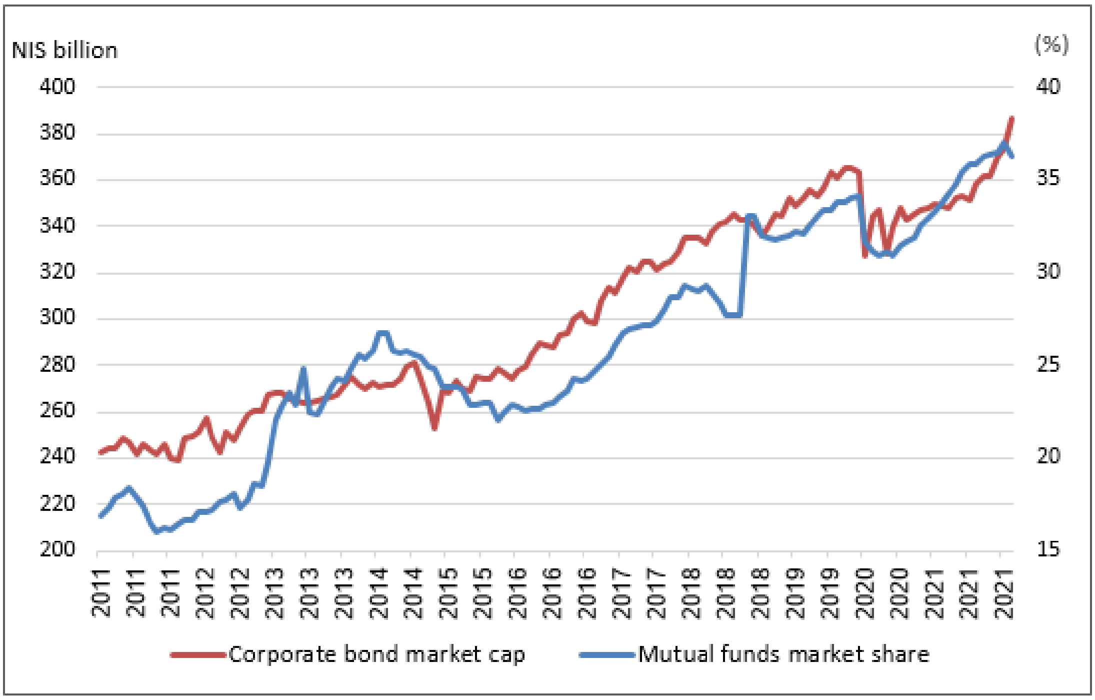
This paper relates to three branches of the literature: First, the literature discussing patterns of flows-performance relations in active mutual funds, to which I contribute by strengthening the hypothesis made by Goldstein et al. (2017) that the convex pattern found in the US is driven by the liquidity mismatch of US corporate bond funds, by demonstrating that this pattern is convex in a different setting with a highly liquid corporate bond market. The Israeli market has a liquid and lively bond market, and they are traded on an exchange. This makes it possible to test the flows-performance relations in a different setting, in which there is high corporate bond liquidity, using the Israeli market as a counterfactual to the US illiquid market. Second, I show that while there is some return chasing in passive funds, as documented in the literature, there is a much lower sensitivity of flows to returns in passive funds compared to their active counterparts. I quantify the difference in sensitivities to performance and contribute to the literature that compares active and passive mutual funds. Lastly, I contribute to domestic policymakers by documenting the Israeli mutual fund industry and capital markets in general, adding to the local knowledge of the underlying mechanisms behind fund flows and their implications for financial stability.

The corporate bond market in Israel is unique in the sense that it is traded on an exchange, as opposed to OTC in the US and the majority of the world. The Israeli mutual fund industry has been growing at a rapid pace, from NIS 137 billion in assets under management in the beginning of 2011 to NIS 348 billion at the end of 2021—a 154% increase over 11 years. The number of mutual funds has nearly doubled during that time, from 906 to 1,771. The corporate bond market has developed quickly, growing almost 60% from NIS 243 billion in 2011 to NIS 386 billion in 2021. As Figure 1 shows, corporate bond funds have grown with it, holding a growing share of the bond market. Hence, the importance of mutual funds to financial stability has increased, and calls for research on the drivers of fund flows and the potential sources of fragility stemming from them.

Much has been written about the dangers of fire sales in mutual funds, and the potential implications for financial stability and the real economy (see, for example, Shleifer and Vishny 1992 and 2011, Coval and Stafford 2007), especially in corporate bond funds, by both academics and policymakers (such as the Financial Stability Board, the Bank for International Settlements, and central banks). The risk of fire sales in bond funds is greater than in other mutual funds, because of the liquidity mismatch between the daily liquidity that mutual funds are obligated to provide for investors, and the low liquidity of the underlying assets—US corporate bonds (see, for example, Jiang, Li, Sun and Wang 2022). More recently, we have seen this mechanism in action during the COVID-19 crisis. Hadad, Moreira and Muir (2021) discuss the disruption of debt markets during that time, and show that outflows from bond funds were a major driver of price dislocations. Mutual funds had to sell assets in order to obtain cash to transfer to investors redeeming their money. The excessive supply of bonds offered by funds at a rapid pace caused prices to drop and yields to rise, impacting the real economy via corporations' cost of capital. Ma, Xiao, and Zeng (2022) quantify this effect, and find that an astonishing one-third of the increase in government bond yields and a quarter of the increase in corporate bond yields during the COVID-19 crisis was caused by sales pressure in debt mutual funds. Falato, Goldstein, and Hortacsu (2021) discuss the outflows in corporate bond funds during the COVID-19 crisis and the fire sale risk, and examine the Federal Reserve's measures to backstop transmission to the real economy. Debt funds were shown to have experienced large sales pressure during the pandemic, causing a rise in yield in the Israeli market as well.[1]

Figure 1

The size of the corporate bond market and the share of it held by mutual funds



In the context of the Israeli mutual fund market, Ben-Rephael, Kandel, and Wohl (2011) look at daily aggregate fund flows in the Israeli equity market and find evidence of "temporary price pressure": They document that flows drive market returns in the immediate horizon, and that half of that price change is reversed within 10 days. Abudi, Barel, and Wohl (2016) examine active fund performance between the years 2003 and 2008 and show that they underperform, net of fees. Two more recent papers address fund flows in the local market: Mugerman, Steinberg and Wiener (2022) study a change in local regulation regarding fund names and find that salience of risk information affects fund flows. Arbaa, Varon and Benzion (2017) explore the flows into equity funds in Israel, and find that investors are more sensitive to recent performance as opposed to the long-horizon performance of the fund, and that the sensitivity of flows to performance is larger with advertised funds. I relate to these papers by further

[1] See Bank of Israel Financial Stability Reports for the first half of 2020 and 2021.

examining the drivers of fund flows in the Israeli mutual fund industry, and its sensitivity to fund performance.

Goldstein, Jiang and Ng (2017) discuss the sources of market fragility caused by corporate bond mutual funds, and explore the flow patterns in and out of these funds. They find that the sensitivity of flows to performance in corporate bond funds is concave, meaning the flows are more sensitive to negative performance than to positive performance. This novel finding is contrasted by the stylized fact that in the case of equity mutual funds there is a convex sensitivity of flows to performance, meaning performance is more sensitive to positive performance than to negative performance, a result that has been well established in the mutual fund literature over the past 30 years.[2] The authors explain this result as driven by first-mover advantage, in a framework of strategic complementarities, as in the model presented in Chen, Goldstein and Jiang (2010). In short, according to their model, when an investor redeems money from a mutual fund, the fund needs to sell assets it holds in order to rebuild its stock of cash. The sale of the asset might cause price pressure, lowering the valuation of that asset, thus imposing a negative externality on the rest of the holders of the said asset (including indirect holding, via mutual funds that hold it). The more illiquid the asset is, the higher the price impact of the sale, and the larger the negative externality. This means that there is a first mover advantage—by redeeming money from a fund, an investor lowers its value—and it is therefore optimal for other investors to try to redeem their money from the fund first, before the value goes down. This mechanism can explain a fire sale in mutual funds that hold illiquid assets, such as US corporate bonds.

The model presented in Chen et al. (2010) and the results in Goldstein et al. (2017) regarding concavity in flows to performance sensitivity make it clear that bond mutual funds are a source of market fragility, arising from the liquidity mismatch between the high mutual fund liquidity offers investors and the low liquidity of the assets held by the funds—US corporate bonds.

Abudi and Wohl (2018) show that liquidity in the Israeli bond market is much higher than in the US one—"We find it (the Israeli bond market) to be a lively market with many transactions per bond-day, very little off-exchange trading and low spreads".

[2] See, for example, Ippolito (1992), Brown, Harlow and Starks (1996), Chavelier and Ellison (1997), Sirri and Tufano (1998), Lynch and Musto (2003), Huang, Wei and Yan (2007), and more recently Goldstein, Jiang and Ng (2017).

They go on to quantify the difference in market liquidity between the two countries, and show that the average half-quoted spread is 0.077% in Israel, as opposed to 0.439% in the US, as shown in Harris (2015). The authors attribute the difference in liquidity to the different market structure, with Israel having an exchange for bonds.

Based on the model of Chen et al. (2010) and the results of Goldstein et al. (2017) and Abudi & Wohl (2018), I hypothesize that the sensitivity of flows to performance in Israeli corporate bond mutual funds is convex (higher sensitivity to good performance), contrary to the US market's concave shape (higher sensitivity to poor performance). I expect to find a convex shape because the Israeli bond funds do not suffer from liquidity mismatch as their US equivalents do. I closely follow the methodology of Goldstein et al. (2017) and implement it on data from the Israeli market. Using both a semiparametric approach and a fully parametric fixed effect panel regression, I find a convex relation between performance and flows. This gives rise to the conclusion that the different market structure—having an exchange for bonds—causes higher liquidity and mitigates a source of market fragility that is present in the US. I further validate this finding by employing different tests using various measures of fund performance, including different "alphas" from different models, as well as simpler measures such as fund returns and relative performance within fund-category.

So far, I have only discussed actively managed mutual funds, meaning non-index tracking. I extend the research by applying a similar methodology to test the difference in sensitivity of flows to performance between active and passive funds. I find that flows in passive funds are far less sensitive to performance than their active counterparts.

Passive investment has risen quickly throughout the world in the past decade. Israel is no different, with passive funds growing from 2.5% (in terms of size) of mutual funds that invest domestically at the beginning of 2011, to 62% at the end of 2021.

The rise in passive investment has raised questions about the impacts of passive investment on financial stability. Baruch and Zhang (2022) show that the growth of passive investment diminishes stock price efficiency and increases asset prices co-movement. However, Coles, Heath and Ringgenberg (2022) find that passive investment does not undermine price efficiency in equilibrium. Ben-David, Franzoni and Moussawi (2017, 2018) find that stocks with higher ETF ownership display significantly higher volatility, and that ETFs change the correlation structure of returns, thus increasing the undiversifiable market risk. Da and Shive (2017) find evidence of the connection between ETF activity and return comovement. Jhunjhunwala and Sethi (2022) document this in emerging markets, showing that this is a global phenomenon. I relate to this literature by focusing on a different aspect of financial stability regarding passive investment, namely the flows-performance relations.

In the context of fund flows, the literature suggests that investors in active funds seek "alpha", meaning the fund managers' ability to outperform the market in terms of return and risk. In the seminal work of Berk and Green (2004), investors frequently monitor the performance of the mutual funds they hold, and move their money from fund to fund in search of better alpha. In contrast, passive investors (i.e., people who invest in passive funds) are not trying to outperform the market, and are therefore not expected to monitor fund performance as closely, or to react to performance by inflows or outflows. They simply wish to track market returns. However, this does not mean passive investors are indifferent to market returns. Clifford, Fulkerson and Jordan (2014) find that ETF (exchange-traded fund, a type of passive fund) investors chase returns, and explain this by naïve extrapolation, meaning investors tend to assume that the returns of the near past are good predictors of near future returns, what Frazzini and Lamont (2008) call "dumb money". This was previously found in open-end passive funds as well, by Elton, Gruber and Busse (2004) and Kim (2019). Surveys done by Choi and Robertson (2020) and previously by Greenwood and Shleifer (2014) provide more direct evidence that households believe that return extrapolation is a good way to predict market returns. Ben-David, Lee, Rossi and Song (2022) also document return chasing in both active and passive funds.

I hypothesize that while passive investors are sensitive to fund performance, they are much less sensitive than active investors. I find a positive and significant impact of fund returns on subsequent fund flows in both active and passive funds. However, the magnitudes of this effect are very different between the two groups: The sensitivity of flows to returns in passive corporate bond funds is found to be 44% lower than the active bond funds, with similar differences in equity funds (40%) and government bond funds (61%). This is the paper's main contribution to the literature, as to the best of my knowledge I am the first to quantify these differences in sensitivity of flows to performance between active and passive funds. These results indicate that passive funds are moderating factors in times of stress, as the outflows from them are less procyclical than from active funds. I demonstrate this by using data from the COVID-19 crisis in March 2020, showing that controlling for all else, passive investors redeemed less money from the funds than the active investors during the crisis.

I further examine the difference between the sensitivity of flows to performance between active and passive funds by comparing the returns of passive funds to the systemic part only of active fund returns. This comparison nets out the part of the fund return that could be attributed to manager skill (alpha) and takes into account only the part of the return that stems from the market. I find qualitatively identical results, with a 43% difference in sensitivity of flows to performance between active and passive corporate bond funds, 59% in equity funds and 49% in government funds.

The remainder of this paper is organized as follows: Section 2 describes the data and variable construction and provides summary statistics. Section 3 presents the empirical methodology. Section 4 shows the main results, Section 5 provides robustness tests, and Section 6 concludes.

2. Data Description and Variable Construction

2.1 Data

I utilize the unique setting of the exchange for bonds present in Israel. This makes it possible to observe daily market returns on corporate and government bonds, as well as equity prices. I use two proprietary databases, combine them, and add publicly available information as follows:

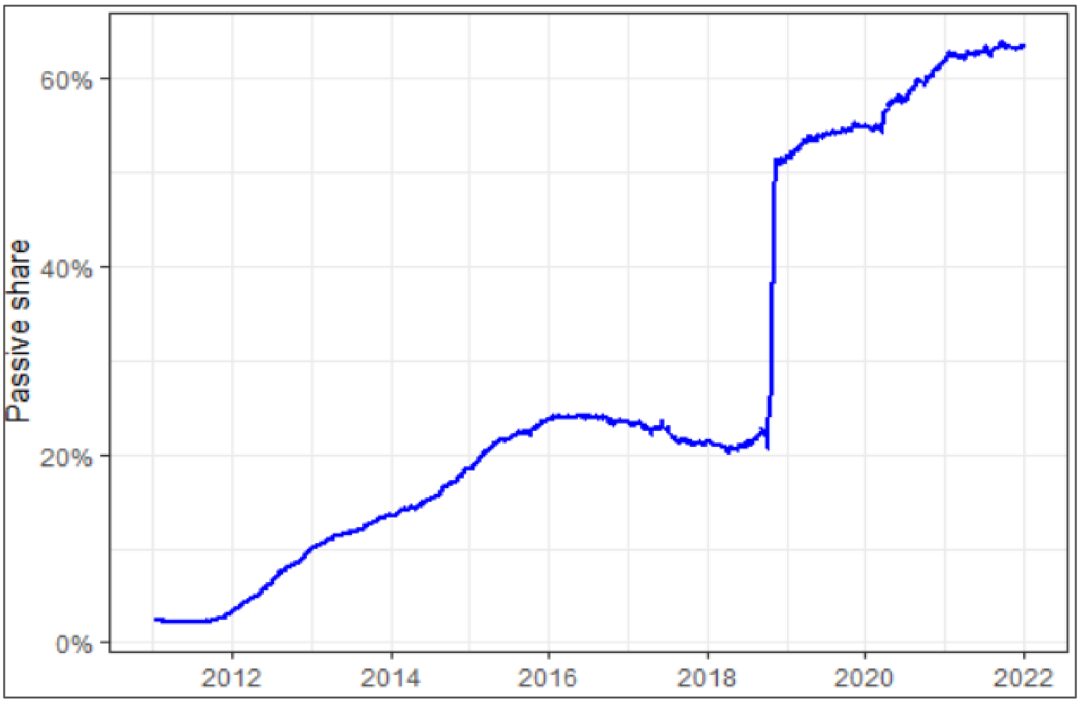
a) Fund data from the Tel Aviv Stock Exchange (TASE): A rich dataset, containing granular daily data at the individual fund level, which includes fund ID, investment category (e.g., domestic equity, foreign government bonds, etc.), and daily fund level data on flows, market value (when applicable, i.e., ETFs), net asset value, and fund price. While existing literature in the US deals with monthly data, and estimates fund flows by using public return data, this setting makes it possible to directly observe fund flows at a higher frequency.

b) A dataset purchased from "Praedicta Ltd.", which includes monthly fund level data, with detailed information on different types of fees and loads, and a passive/active classification (i.e., whether or not the fund tracks an index).

In addition, I use supplementary TASE and Bank of Israel (BOI) data, such as index returns and risk-free rates.

In 2018, a regulatory reform was carried out by the Israel Securities Authority (the local equivalent of the Security and Exchange Commission), ending the use of ETNs—a prominent index tracking vehicle that is not a mutual fund. This leads to a structural break in the data. Prior to the reform, ETNs were the prominent way to track an index in Israel, growing from NIS 58 billion in 2011 to NIS 112 billion in 2021. Figure 2 presents the growth of passive funds' share over time.

Figure 2
The share of passive funds out of all mutual funds that invest domestically, in terms of AUM (assets under management), smoothed by a moving average over a 5-day rolling window. The structural break at the end of 2018 is the result of a regulatory reform, switching from ETNs to ETFs



2.2 Variable construction

The main explanatory variable is the funds' alpha, the risk-adjusted excess return. I obtain alpha estimates by running a regression of the funds' excess returns on the market returns, based on CAPM. Following Goldstein et al. (2017) I use a two-factor model for the estimation of alpha in corporate and government bond funds, as follows:

$$(1)\quad r_i = alpha_i + \beta_1 r_m + \beta_2 r_b + u_i$$

Where r_i is the fund's excess return, r_m is the equity market excess return, and r_b is the bond market excess return. For risk-free rates I use the local equivalent of the literature-standard 3-month T-bills ("makam", issued by the BOI).[3] This equation is estimated separately for each market segment (equity, corporate bonds, and government bonds) in a rolling one-year window, which includes 245 daily observations.

I use two additional measures of fund performance: Annual return, and a variable called "Relative", which is the difference between the fund's return and the mean return of all funds in that investment category: $Relative_{ijt} = r_{ijt} - E(r_{jt})$

Where i indicates a specific fund, j is an investment category (e.g., corporate bonds, equity, and government bonds) and t represents a certain date. The returns are calculated each day, year on year.

The dependent variable in the main equations of this paper is flows, defined as the net flow to the fund as a percentage of its size: $Flows_{i,t} = 100 * \frac{Net\ flows_{i,t}}{Market\ value_{i,t-1}}$

I classified different kinds of fund fees and charges of the fund into two variables: Fees is what the investor pays the fund continuously throughout the life of the investment, and is the sum of the fund's manager fee and fund's trustee fee. Loads is what the investor pays as a one-time fee when making a transaction, known in Israel as creation/redemption loads (i.e., front/rear loads) and an addition load.

For the purpose of consistency with the literature, I take logs of the fund's age in years and of the fund's size in millions of NIS. For the calculation of age, I use two dates: The fund initiation date, and a "last investment policy change date" (LIPCD), where the fund made a fundamental change in its investment policy/category. If applicable, I treat that as the new fund initiation date:

$$Age_{it} = t - max\{Initiaion\ Date_i\ , \qquad LIPCD_i\}$$

I construct a variable called "systemic return", which captures the systemic component of the fund's return. It is calculated as follows: for active funds, it is the difference between the fund's return and the alpha component. $Systemic\ Return_{i,t} =$

[3] In unreported robustness checks, I use different kinds of risk free rates: One-month "makam" and the BOI rate, and find my results to be qualitatively the same, and almost identical quantitatively.

$r_{i,t} - alpha_{i,t}$. For passive funds, it is simply the return of the fund, as alpha is set to be zero.

2.3 Sample Construction and Summary Statistics

The empirical work in this paper can be divided into two segments. First, I closely follow Goldstein et al. (2017) and apply the estimations to Israeli data. For this purpose, I filter for active funds only (i.e., non-index-tracking funds), and filter out extreme observations at the 1^{st} and 99^{th} percentile, as is customary in the literature. My sample spans the years 2011-2021. As I use a full year's data to estimate alpha, the estimations are carried out on a 10-year sample from 2012 to 2021. My full sample is made up of 3,488 unique funds, out of which I focus on 1,249 funds that invest strictly in the domestic market. The active funds' mean alpha is 0.001, with a standard deviation of 0.024. Table 1 presents descriptive statistics of the different variables, broken down by investment policy. Figure 3 presents the distribution of alphas across the active funds in the sample by market segment. As expected, the alphas are centered on zero, with wider tails in riskier assets (equity) and narrower tails in safer assets (government bonds). This stems from the fact that the alpha is measured in terms of annual returns, and it is therefore more likely to be larger (in absolute terms) when the returns are more volatile.

Second, I extend my work by comparing the elasticity of flows with respect to fund performance in active and passive mutual funds. The sample in this section is different in two aspects: Contrary to the first empirical part, I use both passive and active funds. The sample is from the years 2019-2021, due to a reform of passive investment vehicles in the Israeli market. Until the end of 2018, ETNs were prevalent and were the main vehicle through which an investor could track an index. As of 2019, ETNs were cancelled, and therefore the majority of passive investments are included in my data from that year onwards. For robustness, I estimate these equations separately on the full sample of 2011 to 2021 and the results remain qualitatively the same.

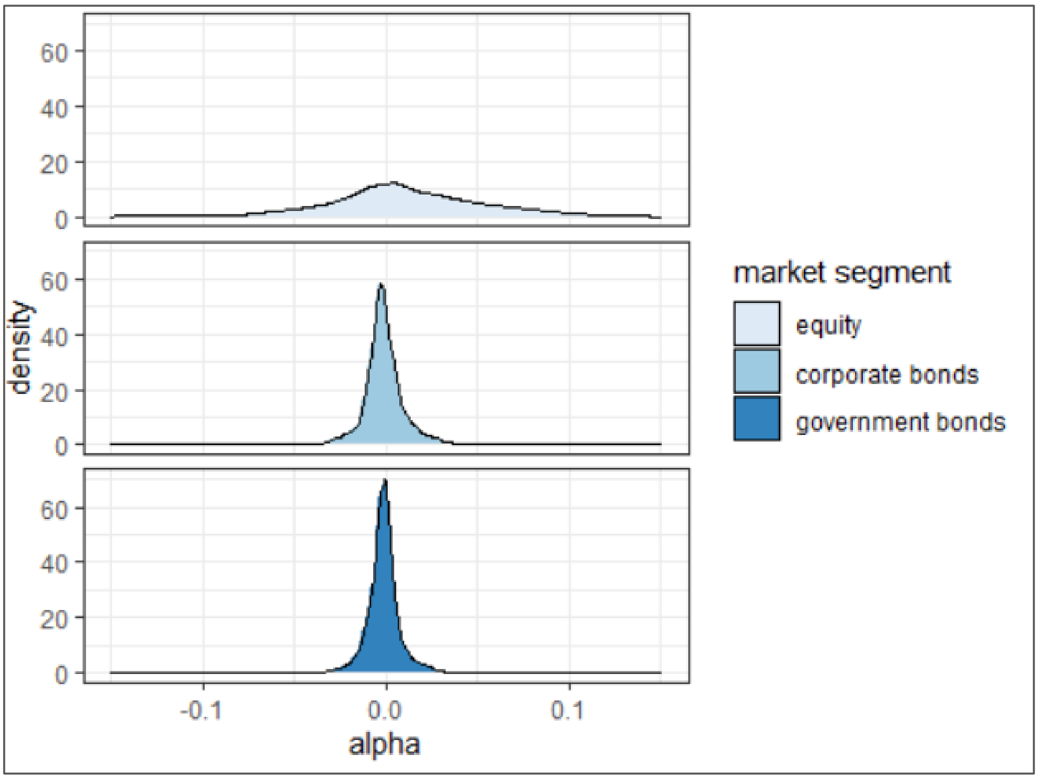
In each part, I estimate the equations separately on three local market segments: Equity, corporate bonds, and government bonds.

Table 1: Summary statistics

	Corporate bonds		Equity		Government bonds	
	Active	**Passive**	**Active**	**Passive**	**Active**	**Passive**
Number of unique funds	284	238	179	136	293	119
Mean flows (%)	0.02	0.06	0.04	0.09	0.03	0.02
Flows standard deviation (%)	0.63	0.52	0.80	0.70	0.60	0.47
Mean annual return (%)	3.44	3.06	8.27	12.53	1.97	1.95
Return standard deviation (%)	4.77	4.55	16.75	20.33	2.56	3.07
Mean alpha (%)	-0.0015	-	0.0098	-	-0.0013	-
Alpha standard deviation (%)	0.0109	-	0.0430	-	0.0085	-
Mean age (years)	7.25	5.60	8.11	5.88	7.49	7.06
Mean size (NIS million)	188.57	190.68	92.84	249.51	238.18	147.34

Figure 3

Fund alpha density by market segment.



3. Empirical Methodology

Following the methodology of Robinson (1988), implemented in Chevalier et al. (1997) and Goldstein et al. (2017), I use a semi-parametric approach to check for the functional form.

$$(2) \quad Flows_{i,t} = f(Alpha_{i,t-1\to t-246}) + \gamma X_{i,t} + u_{i,t}$$

Where $flows_{\mathrm{i,t}}$ is the net flow into fund i at time t as a percent of its size, and $\mathrm{alpha}_{\mathrm{t-1\to t-246}}$ is the first lag of the fund's 1-year alpha calculated in equation 1. *X* is a vector of controls that includes log-size, log-age, fees, loads and the first lag of flows. I estimate this equation separately for equity and for corporate bonds.

Since these semiparametric estimations have little statistical power, I estimate the pattern of flows in response to alpha in a fully parametric fixed effect panel regression (equation 3). I closely follow Goldstein et al. (2017), with several adjustments to the Israeli market and to the rich dataset I have obtained (date fixed effects instead of month FE, etc.).

$$(3)\ Flows_{it} = \alpha + \beta_1 alpha_{i,t-1\to t-246} + \beta_2 alpha_{i,t-1\to t-246} I + \beta_3 I + \gamma X_{i,t} + u_{i,t}$$

Where $\mathrm{flows}_{\mathrm{it}}$ is the net flow into fund i at time t as a percent of its size, α is the constant, and $\mathrm{alpha}_{\mathrm{t-1\to t-246}}$ is the first lag of the fund's 1-year alpha calculated in equation 1. *I* is a dummy variable that is equal to 1 if the alpha is negative. *X* is a vector of controls that includes log-size, log-age, fees, loads and the first lag of flows; u_{it} is the error term. The regression also includes date fixed effects. Standard errors are clustered at the fund level, to allow for intertemporal serial correlation. I estimate this equation separately for equity, corporate bonds, and government bonds.

The two variables of interest are the funds' alpha and the interaction between the alpha and a dummy variable indicating whether the alpha is negative or not. For positive alpha, the dummy variable equals zero, and therefore the flows-performance elasticity is represented solely by the alpha coefficient (β_1). For negative alpha, it is the sum of both the alpha and the interaction term coefficients ($\beta_1 + \beta_2$). Thus, a positive (negative) sign on the coefficient of the interaction term (β_2) indicates a concave (convex) relationship—in absolute terms, the investors are more (less) responsive to negative alphas than to positive alphas.

Next, I expand the exploration of flows-performance relations to include passive funds. Passive, or index-tracking funds, are used by investors to closely follow an index of their choice, without any aim to outperform the index. That is, an investor measures the performance of the passive fund by how small the tracking error is, not by alpha. For this reason, I cannot use alpha as a benchmark for fund performance, and instead use fund returns. Equation 4 describes the estimation method for comparing active and passive funds.

$$(4)\ \mathrm{Flows_{it}} = \alpha + \beta_1 \mathrm{r}_{i,t-1\to t-246} + \beta_2 \mathrm{P} \times \mathrm{r}_{i,t-1\to t-246} + \beta_3 \mathrm{P} + \gamma \mathrm{X}_{i,t} + \mathrm{u}_{i,t}$$

Where $Flows_{it}$ is the net flow into fund i at time t as a percent of its size, α is the constant, and $r_{t-1\to t-246}$ is the first lag of the fund's annual return. *P* is a dummy variable that is equal to 1 if the fund is index-tracking. *X* is a vector of controls that includes log-size, log-age, fees, loads and the first lag of flows; $\mathrm{u_{it}}$ is the error term. The regression also includes date fixed effects. Standard errors are clustered at the fund level, to allow for intertemporal serial correlation. I estimate this equation separately for equity, corporate bonds, and government bonds.

The two variables of interest are the fund's return, r_i, and the interaction between the return and the dummy variable indicating if it is negative. For positive returns, the dummy variable equals zero, and therefore the flows-performance elasticity is represented solely by the return coefficient (β_1). For negative returns, it is the sum of both the return and the interaction term coefficients ($\beta_1 + \beta_2$). Thus, a positive (negative) sign on the coefficient of the interaction term (β_2) would mean that passive investors are more (less) sensitive to fund performance.

In addition to estimating this equation on the full sample, I also estimate it on data from the peak of the COVID-19 crisis in the financial markets, March 2020. In this case, the variable of interest is the dummy variable P, indicating whether or not the fund is passive (i.e., index tracking). One month might be too short a period to identify marginal sensitivities, but if this variable, estimated coefficient β_3, is positive (negative)—it will inform us that all else equal, passive investors drew out less (more) money from the funds. It is important to keep in mind that the dependent variable is net flows, so less outflows are shown as more net flows.

The return of an active fund can be divided into two components: The alpha, which contains information about the fund manager's skill (Berk and Green, 2004), and a systemic component, determined by the fund's beta, market returns, and the risk-free rate (see equation 1). Both components may drive fund flows. In passive funds, alpha is set to zero, and there is only the systemic component. In order to make sure I am not capturing the information channel represented by alpha, I run an additional regression using only the systemic component of the fund returns (equation 5).

$$(5) \quad \mathrm{Flows}_{\mathrm{it}} = \alpha + \beta_1 \mathrm{sys}_{\mathrm{i}_{t-1\rightarrow t-246}} + \beta_2 \mathrm{P} \times \mathrm{sys}_{\mathrm{i}_{t-1\rightarrow t-246}} + \beta_3 \mathrm{P} + \gamma \mathrm{X}_{\mathrm{i,t}} + \mathrm{u}_{\mathrm{i,t}}$$

Where $flows_{it}$ is the net flow into fund i at time t as a percent of its size, α is the constant, and $sys_{t-1\rightarrow t-246}$ is the first lag of the fund's annual return systemic component. *P* is a dummy variable that is equal to 1 if the fund is index-tracking. *X* is a vector of controls that includes log-size, log-age, fees, loads and the first lag of flows; u_{it} is the error term. The regression also includes date fixed effects. Standard errors are clustered at the fund level, to allow for intertemporal serial correlation. I estimate this equation separately for equity, corporate bonds, and government bonds.

4. Main Results

I find a convex relation between flows and performance in all segments of active mutual funds. The result in the equity market is consistent with a large body of literature, and is the same as documented by Ippolito (1992), Brown et al. (1996), Chevalier and Ellison (1997), Sirri and Tufano (1998), Lynch and Musto (2003), Huang et al. (2007) and Goldstein et al. (2017). However, in contrast to the latter's results on corporate bond funds, I find the same convex shape as in equity.

Figures 4a and 4b illustrate the results of the semiparametric estimation (equation 2), showing a convex relation between flows and alphas in corporate bond funds as well as in equity funds, suggesting that in both types of fund the investors are more sensitive to positive performance than to negative performance.

Table 2 shows the results of the panel data fixed-effect estimation (equation 3). I find a convex flows-performance pattern in all three market segments, as captured by the negative coefficient on the interaction term. For example, in corporate bonds, when alpha is positive, the sensitivity of flows to performance (as measured by alpha) is 7.04, meaning an increase of 1 percentage point in alpha will cause an increase of 7 percentage points in flows to the fund. If, however, the alpha is negative, then the sensitivity is much weaker: $7.04 - 3.92 = 3.12$, meaning there is no symmetry in investors' reaction to underperformance and outperformance: a negative alpha of 1 percentage point will cause an outflow of 3.12 percentage points—a 55.7% decrease in the sensitivity of flows to performance. Similarly, the flows-performance sensitivity in equity and government bond funds is 91.4%, and 57.8% lower in the case that the fund's alpha is negative. The strong result in equity funds is consistent with the shape of the semi-parametric estimation, where the pattern seems flat around zero and negative alphas, and rises quickly as the alpha increases in the positive area. There is a large difference in the sensitivity of flows to alpha across market segments, in the order that we would expect: it is much harder to achieve a 1% alpha (in terms of annual returns) in government bonds than in equity funds, where returns and volatility are much higher. Therefore, we would expect the market to reward it with heavier flows. Indeed, we see that the sensitivity is highest in government bonds, then corporate bonds, and then equity. However, this comparison in terms of return doesn't have much meaning, as different market segments are expected to have different returns. We should instead focus on a relative comparison of the sensitivity to positive and negative alphas within each segment. The rest of the coefficients are in the direction that is consistent with previous empirical work and with theory: all else equal, higher fees and loads reduce the flows into the fund. Older and larger funds experience less flows than newer funds, and there is strong persistence in flows, as captured by the lag of flows. The economic and statistical significance for the main explanatory variables of interest, the alpha and the interaction term, are the largest among all covariates.

Figure 4a

Flows-performance sensitivity in active corporate bond funds, as estimated by equation 2. Dashed lines represent 95% confidence intervals

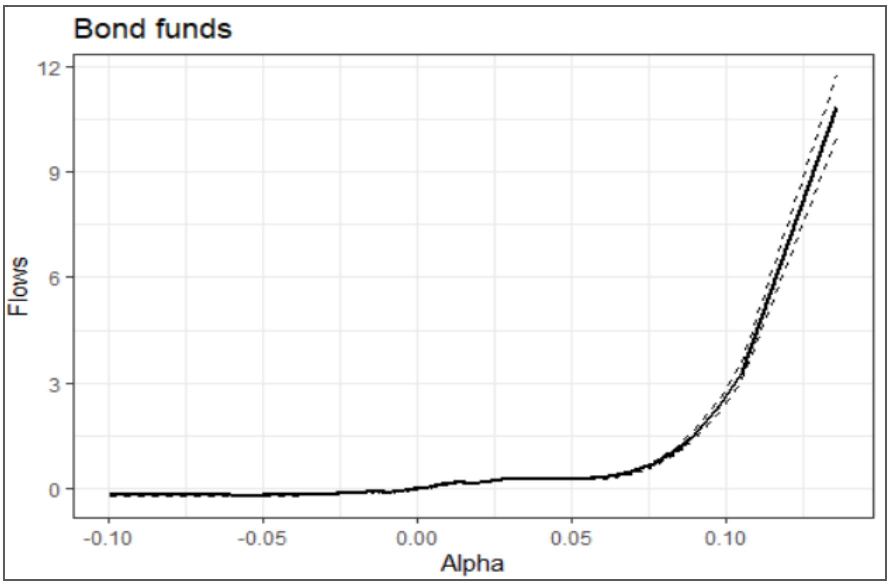


Figure 4b

Flows-performance sensitivity in active equity funds, as estimated by equation 2. Dashed lines represent 95% confidence intervals

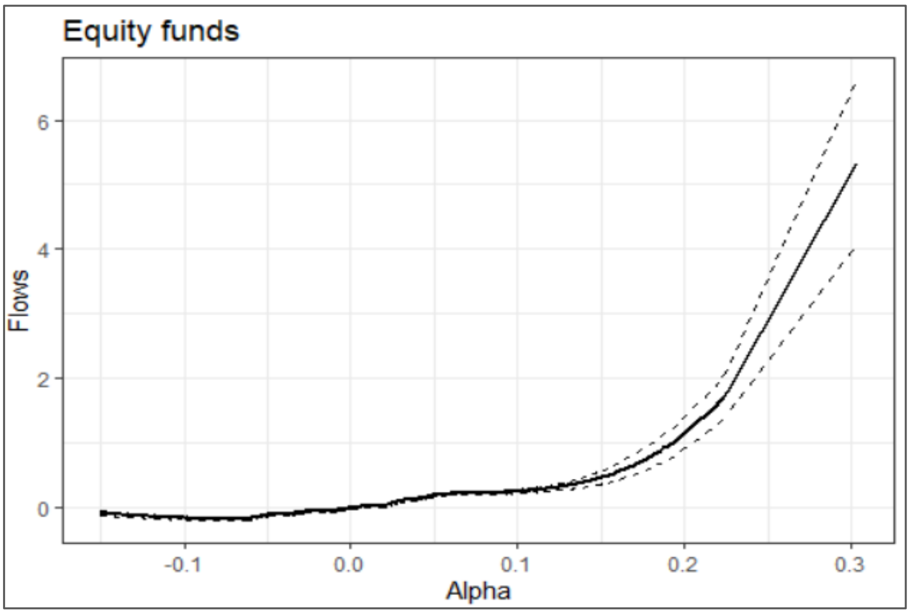


Table 2: Equation 3 Estimation Results

This table presents flow-performance relations, in active corporate bond funds, equity funds, and government bond funds, in the years 2012-2021. The table shows the asymmetry between investor sensitivity to good and bad performance. *Percent flows* $(Flows_{it})$ is the net flow into fund i at time t as a percent of its size, Alpha is the first lag of the fund's 1-year alpha calculated in equation 1. I is a dummy variable that is equal to 1 if the alpha is negative. The regression also includes date fixed effects. Standard errors are clustered at the fund level, to allow for intertemporal serial correlation.

Dependent variable:	Percent flows		
Fund type:	corporate bonds	equity	government bonds
Alpha	7.039***	4.657***	15.217***
	(1.095)	(0.559)	(2.118)
Alpha*I	-3.920***	-4.363***	-8.808***
	(1.39)	(0.588)	(2.655)
I	-0.102***	-0.028	-0.092***
	(0.013)	(0.018)	(0.014)
Log Market Value	-0.009*	-0.018***	-0.027***
	(0.005)	(0.007)	(0.006)
Lag Percent Flows	0.164***	0.079***	0.266***
	(0.017)	(0.011)	(0.028)
Log Age	-0.017**	-0.014**	-0.002
	(0.008)	(0.006)	(0.01)
Fees	-0.088***	-0.059***	-0.146***
	(0.015)	(0.017)	(0.033)
Loads	-0.051**	0.034	-0.035***
	(0.021)	(0.047)	(0.013)
Observations	246,762	153,331	256,192
R^2	0.182	0.117	0.283
Adjusted R^2	0.174	0.102	0.276
Note: * P<0.1, ** P< 0.05, *** P < 0.01			

Table 3 shows the results of estimating equation 4, in which I compare between the flows-performance sensitivities in passive and active funds. I find that flows in passive funds are substantially less responsive to returns in all three market segments, as captured by the negative coefficient on the interaction term. For example, in corporate bonds, the sensitivity of flows to performance (as measured by annual return) is 0.032. For passive funds, that sensitivity is $0.032 - 0.014 = 0.018$, meaning a decrease of 43.75% in the sensitivity of flows to performance in passive funds. Similarly, the flows-performance sensitivity in equity funds and in government bond funds is 40% and 61.1% lower for passive funds. As before, the direction of control variable estimates are as expected: Size, age, fees and loads have a negative effect on flows, and there is strong persistence in flows.

Table 4 shows the results of estimating equation 5, in which I use only the systemic component of the fund's return as a measure of performance. The results are almost identical to those presented in Table 3: Flows-performance sensitivity in passive funds is 43.33% lower in corporate bond funds, 40% lower in equity funds, and 59.4% lower in government bond funds.

The results presented in Tables 3 and 4 indicate that at times of market stress, the redemptions from actively managed funds will be much higher than from passive funds. I test this on a focused sub-sample of March 2020, a month of high redemptions in corporate bond mutual funds at the height of the COVID-19 crisis. I re-estimate equation 4 on bond funds in that month (Table 5). The variable of interest is the dummy variable indicating whether or not the fund is passive. A positive coefficient on that variable would mean that passive funds have experienced lower outflows (measured as higher net flows) during the COVID-19 crisis. There are few observations, due to the short time window chosen, but the results are clear that outflows were lower in passive funds, as indicated by the positive coefficient of the “Passive” dummy variable. This result further supports the conclusion that passive funds have a moderating effect on fire sales and therefore contribute to financial stability[4].

[4] For more information about redemptions from passive and active mutual funds during the COVID-19 crisis, see the Bank of Israel Financial Stability Report for the first half of 2021.

Table 3: Equation 4 Estimation Results

This table presents flow-performance relations, in active and passive corporate bond funds, equity funds and government bond funds, in the years 2019-2021. The table shows the asymmetry between investor sensitivity to performance in active and passive funds. *Percent flows* ($Flows_{it}$) is the netflow into fund i at time t as a percent of its size, *Fund Annual Return* is the first lag of the fund's annual return, calculated as the percent change in share price. *Passive* is a dummy variable indicating if the fund is index-tracking. The regression also includes date fixed effects. Standard errors are clustered at the fund level, to allow for intertemporal serial correlation.

Dependent variable:	Percent flows		
Fund type:	corporate bonds	equity	government bonds
fund annual return	0.032***	0.010***	0.072***
	(0.003)	(0.001)	(0.006)
fund annual return X Passive	-0.014***	-0.004***	-0.044***
	(0.002)	(0.001)	(0.005)
Passive	-0.013	-0.005	-0.095**
	(0.025)	(0.039)	(0.041)
log market value	0.003	-0.016***	-0.015**
	(0.005)	(0.005)	(0.007)
lag percent flows	0.094***	0.071***	0.008
	(0.013)	(0.012)	(0.005)
log age	-0.059***	-0.022**	-0.011
	(0.008)	(0.010)	(0.011)
fees	-0.099***	-0.077***	-0.301***
	(0.026)	(0.025)	(0.076)
loads	-0.145***	-0.134	-0.182***
	(0.045)	(0.114)	(0.069)
Observations	161,440	93,309	125,905
R^2	0.094	0.088	0.116
Adjusted R^2	0.089	0.081	0.111
Note: *p<0.1, **p<0.05, ***p<0.01			

Table 4: <u>Equation 5 Estimation Results</u>

This table presents flow-performance relations, in active and passive corporate bond funds, equity funds, and government bond funds, in the years 2019-2021. The table shows the asymmetry between investor sensitivity to performance in active and passive funds. *Percent flows* ($Flows_{it}$)is the net flow into fund i at time t as a percent of its size, *Fund Systemic Annual Return* is the first lag of the fund's annual return, after subtracting the alpha from it. *Passive* is a dummy variable that is equal to 1 if the fund is index-tracking. The regression also includes date fixed effects. Standard errors are clustered at the fund level, to allow for intertemporal serial correlation.

Dependent variable:	Percent flows		
Fund type:	corporate bonds	equity	government bonds
Fund Systemic Annual Return	0.030***	0.010***	0.069***
	(0.003)	(0.001)	(0.006)
Fund Systemic Annual Return × Passive	-0.013***	-0.004***	-0.041***
	(0.002)	(0.001)	(0.005)
Passive	-0.002	-0.006	-0.092**
	(0.025)	(0.042)	(0.047)
Log Market Value	0.007	-0.015***	-0.01
	(0.005)	(0.005)	(0.007)
Lag Percent Flows	0.089***	0.069***	0.007
	(0.013)	(0.011)	(0.004)
Log Age	-0.055***	-0.028***	-0.01
	(0.009)	(0.011)	(0.013)
Fees	-0.089***	-0.077***	-0.306***
	(0.026)	(0.025)	(0.085)
Loads	-0.128***	-0.143	-0.190***
	(0.043)	(0.153)	(0.073)
Observations	156,876	91,463	119,778
R^2	0.088	0.088	0.116
Adjusted R^2	0.084	0.081	0.111
Note: * P<0.1, ** P< 0.05, *** P < 0.01			

Table 5: The COVID-19 Case

Equation 4 Estimation Results, on March 2020 Corporate Bond Fund Data

This table presents flow-performance relations, in active and passive corporate bond funds, equity funds, and government bond funds, in March 2020. The table shows the asymmetry between investor sensitivity to performance in active and passive funds. Percent flows is the net flow into fund i at time t as a percent of its size, Fund Annual Return is the first lag of the fund's annual return, calculated as the percent change in share price. Passive is a dummy variable that is equal to 1 if the fund is index-tracking. Standard errors are clustered at the fund level, to allow for intertemporal serial correlation.

Dependent variable:	Percent flows	
Fund Annual Return	0.003 (0.004)	0.006 (0.007)
Fund Annual Return × Passive	0.0001 (0.006)	0.002 (0.005)
Passive	0.161** (0.075)	0.171** (0.073)
Log Market Value	0.035** (0.018)	0.028* (0.017)
Lag Percent Flows	0.169*** (0.028)	0.107*** (0.025)
Log Age	-0.070* (0.036)	-0.064* (0.034)
Fees	0.16 (0.097)	0.215** (0.094)
Loads	0.158 (0.307)	0.297 (0.305)
Constant	-0.368 (0.128)	
Date fixed effects	No	Yes
Observations	1,628	1,628
R^2	0.158	0.284
Adjusted R^2	0.154	0.274
Note: *p<0.1; >**p<0.05; >***p<0.01		

To summarize this section, my results show three main findings: First, there is a convex flows-performance relation in corporate bond funds. This is an important finding, as concave relations, in which the investors are more sensitive to poor performance (as found by Goldstein el al. 2017 in the US bond market), are associated with market fragility. It is therefore a source of fragility that does not exist in the Israeli market, possibly due to the fact that Israel has a limit order book exchange for bonds, which supports a liquid market.

Second, I find evidence of return chasing in passive funds, consistent with the findings of Clifford et al. (2014) and Ben-David et al. (2022).

Third, I find that return chasing in passive funds is much lower than in active funds. I show that this cannot be explained by information of manager skill, by using the systemic component only of the fund's return. This finding implies that passive funds act as a moderating factor at times of stress, as flows to them are less procyclical than to their active counterparts, reducing the risks of fire sales and spillovers to the real economy. I show that this was indeed the case during the COVID-19 crisis. During March 2020, passive investors have redeemed less money from mutual funds, all else equal, meaning active investors have exacerbated the negative market trends far more than their passive counterparts.

5. Robustness

I subject my results to a battery of robustness tests. For the first part, discussing the convexity of flows-performance in active mutual funds, I show that the results are robust to the choice of performance measure, the time window in which it is measured, and the choice of estimation model. In the second part, showing the reduced flows-performance sensitivity in passive funds, I show that the results are robust to the selection of time samples.

In the previous section, I have shown that the flows-performance relation is convex via semiparametric estimation. An additional way to check for convexity is a piecewise regression. A convex shape means that the higher the alpha, the higher the flows sensitivity. I therefore allow for three different slopes in a linear regression, adding flexibility to the previous regression by allowing flows to be more sensitive to very high alphas and separating them from low positive alphas. I do this in two steps: First, I regress flows on all controls, and alpha on all controls, and save the residuals. Second, I run the flows residuals on the alpha residuals in a piecewise regression with two breaks. Those breaks are different for corporate bond funds and for equity funds, due to the different magnitudes of alpha in each category. The second stage regressions are as follows:

(6a) Bond funds:

$$Flows_{it} = \alpha + \beta_1 alpha_{it} + \beta_2 alpha_{it}\delta_1 + \beta_3(alpha_{it} - 0.07)\delta_2 + u_{i,t}$$

Where $flows_{it}$ is the residual from a regression of flows on all controls, $alpha_{it}$ is the residual from a regression of alpha on all controls, δ_1 and δ_2 are dummy variables that take the value of 1 if alpha is equal to or larger than 0 and 0.07, respectively.

(6b) Equity funds:

$$Flows_{it} = \alpha + \beta_1 alpha_{it} + \beta_2 alpha_{it}\delta_1 + \beta_3(alpha_{it} - 0.17)\delta_2 + u_{i,t}$$

Where $flows_{it}$ is the residual from a regression of flows on all controls, $alpha_{it}$ is the residual from a regression of alpha on all controls, δ_1 and δ_2 are dummy variables that take the value of 1 if alpha is equal to or larger than 0 and 0.17, respectively.

Figures 5a and 5b illustrate the results of the piecewise regression (equation 6), leading to the same conclusion as the semiparametric estimation: Investors are more sensitive to outperformance than to underperformance of the funds.

There is strong empirical evidence that CAPM alpha predicts flows better than other performance measures, as shown by Berk and Van Binsbergen (2016) and by Barber, Huang and Odean (2016). Table 6 re-estimates equation 3, and differs from Table 2 by using one-factor (CAPM) alpha instead of two-factor, showing my results are robust to the choice of performance measurement. The sensitivity of flows to performance is again found to be convex across all market segments. The sensitivity to underperformance (negative alpha) is weaker than to outperformance (positive alpha) by 56%, 91%, and 53% in corporate bond funds, equity funds, and government bond funds, respectively. This result is very similar to the reduction of sensitivity in the main specification (table 2).

In unreported estimations[5] I repeat the estimation with alphas calculated at different horizons—two years and six months, instead of the one-year alpha in the main part of the paper. The results remain qualitatively unchanged.

There is a debate in the literature regarding the correct way to assess and measure fund performance in the context of flows. By using alpha I follow the rational framework of Berk and Green (2004). Ben-David et al. (2022) criticize the choice of alpha as a measure of fund performance. They argue that retail investors do not run CAPM regressions to derive alpha, and instead rely on simpler information that is readily available to them. I therefore test my hypothesis using two different measures

[5] All estimation tables and additional robustness tests are available upon request from the author.

of fund performance, which are simple, and are not model based: Simple annual returns, and a relative within-category performance measure, calculated as the difference between the fund's annual return and the mean return of all other funds in the category.

I repeat the estimation presented in table 2 (equation 3), using simple performance measures instead of alpha: Table 7 shows the results of the estimation using fund returns as a proxy for performance, and table 8 shows the same estimation using relative performance—meaning the difference between the fund's return and the mean return of all other funds in the category. The results in both tables are qualitatively the same as in Table 2, with differences in magnitude. Using simple returns shows stronger results than using alphas, with the sensitivity of flows to performance being lower in the case of negative returns by 86% in corporate bond funds, 84% in equity funds, and 69% in government bond funds. When using relative performance, the sensitivity of flows to performance is found to be lower when the fund has a below category-average return. In those cases, the sensitivity is lower by 48% in corporate bond funds, 89% in equity funds, and 88% in government bond funds. The results are economically and statistically significant, no matter how performance is measured.

Figure 5a

Flows-performance sensitivity in active corporate bond funds, as estimated by equation 4a. The grey area represents a 95% confidence interval

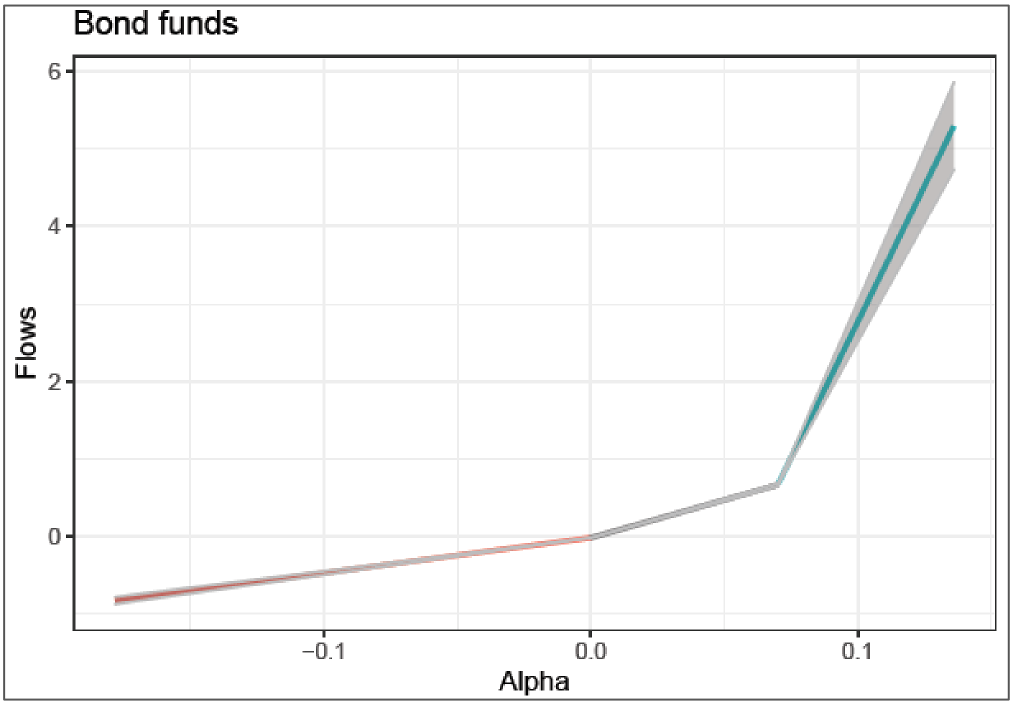


Figure 5b

Flows-performance sensitivity in active equity funds, as estimated by equation 4b. The grey area represents a 95% confidence interval

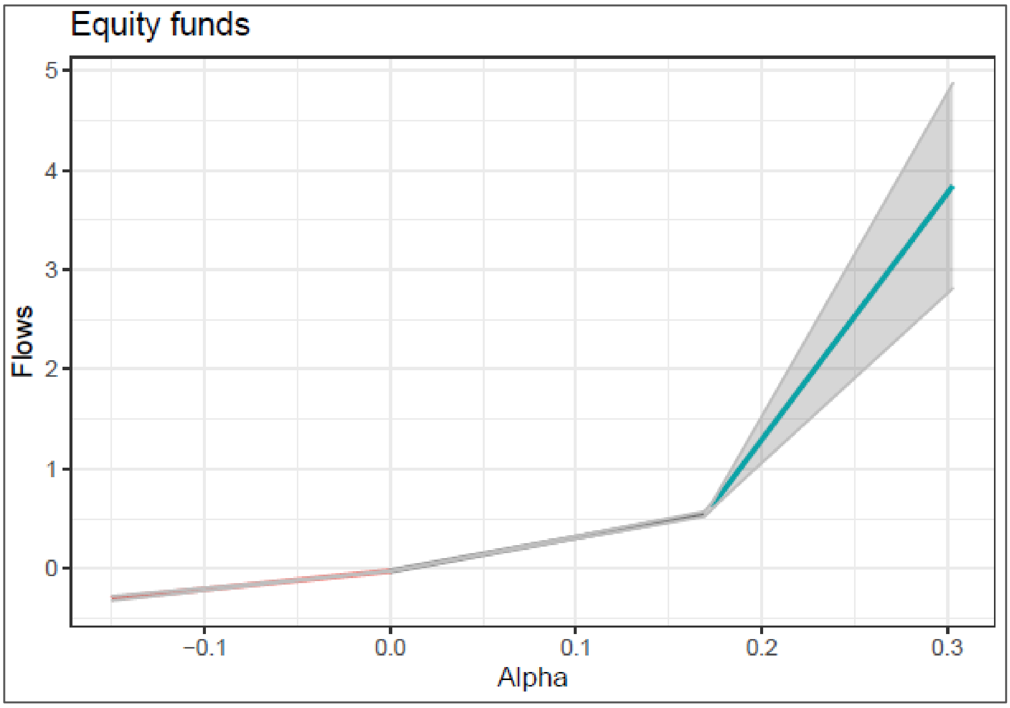


Table 6: <u>Equation 3 estimation results, using alpha from the 1-factor CAPM</u>

This table presents flow-performance relations in active corporate bond funds, equity funds, and government bond funds, in the years 2012-2021. The table shows the asymmetry between investor sensitivity to good and bad performance. Percent Flows is the net flow into fund i at time t as a percent of its size, Alpha is the first lag of the fund's 1-year alpha calculated with CAPM. I is a dummy variable that is equal to 1 if the alpha is negative. The regression also includes date fixed effects. Standard errors are clustered at the fund level, to allow for intertemporal serial correlation.

Dependent variable:	Percent flows		
Fund type:	corporate bonds	equity	government bonds
Alpha	7.084***	4.241***	15.217***
	(1.088)	(0.472)	(2.118)
Alpha×I	-4.015***	-3.875***	-8.808***
	(1.368)	(0.539)	(2.655)
I	-0.104***	-0.022	-0.092***
	(0.013)	(0.019)	(0.014)
Log Market Value	-0.009*	-0.020***	-0.027***
	(0.005)	(0.007)	(0.006)
Lag Percent Flows	0.165***	0.079***	0.266***
	(0.017)	(0.01)	(0.028)
Log Age	-0.008**	-0.015***	-0.002
	(0.01)	(0.006)	(0.01)
Fees	-0.085***	-0.056***	-0.146***
	(0.015)	(0.018)	(0.033)
Loads	-0.042	0.05	-0.035***
	(0.030)	(0.046)	(0.013)
Observations	246,762	153,331	256,192
R^2	0.182	0.117	0.283
Adjusted R^2	0.174	0.103	0.276
Note: * P<0.1, ** P< 0.05, *** P < 0.01			

Table 7: Equation 3 Estimation Results

This table presents flow-performance relations, in active corporate bond funds, equity funds and government bond funds, in the years 2012-2021. The table shows the asymmetry between investor sensitivity to good and bad performance. Performance is measured by simple annual returns. *Percent flows* ($Flows_{it}$)is the net flow into fund i at time t as a percent of its size. *I* is a dummy variable that is equal to 1 if the alpha is negative. The regression also includes date fixed effects. Standard errors are clustered at the fund level, to allow for intertemporal serial correlation.

Dependent variable:	Percent flows		
Fund type:	corporate bonds	equity	government bonds
Fund Annual Return	0.043***	0.019***	0.098***
	(0.003)	(0.002)	(0.008)
Fund Annual Return*I	-0.037***	-0.016***	-0.068***
	(0.006)	(0.002)	(0.016)
I	-0.102***	-0.021	-0.047***
	(0.016)	(0.015)	(0.018)
Log Market Value	-0.005	-0.021***	-0.040***
	(0.005)	(0.006)	(0.006)
Lag percent Flows	0.113***	0.083***	0.169***
	(0.035)	(0.009)	(0.031)
Log Age	-0.050***	-0.035***	-0.049***
	(0.008)	(0.008)	(0.010)
Fees	-0.126***	-0.073***	-0.213***
	(0.016)	(0.014)	(0.041)
Loads	-0.119***	-0.096	-0.104***
	(0.027)	(0.060)	(0.022)
Observations	265,868	145,585	282,075
R^2	0.179	0.132	0.267
Adjusted R^2	0.171	0.117	0.260
Note: * P<0.1, ** P< 0.05, *** P < 0.01			

Table 8: Equation 3 Estimation Results

This table presents flow-performance relations, in active corporate bond funds, equity funds and government bond funds, in the years 2012-2021. The table shows the asymmetry between investor sensitivity to good and bad performance. Performance is captured by Relative Return, calculated as the difference between a fund's annual return and the category's mean annual return on that date. *Percent flows* ($Flows_{it}$) is the net-flow into fund i at time t as a percent of its size. I is a dummy variable that is equal to 1 if relative is negative. The regression also includes date fixed effects. Standard errors are clustered at the fund level, to allow for intertemporal serial correlation.

Dependent variable:	Percent flows		
Fund type:	corporate bonds	equity	government bonds
Relative Return	0.042***	0.028***	0.153***
	(0.004)	(0.003)	(0.013)
Relative Return*I	-0.020***	-0.025***	-0.134***
	(0.006)	(0.003)	(0.016)
I	-0.048***	-0.010	-0.045***
	(0.012)	(0.016)	(0.016)
Log Market Value	-0.004	-0.022***	-0.035***
	(0.005)	(0.007)	(0.005)
Lag percent Flows	0.125***	0.093***	0.175***
	(0.038)	(0.010)	(0.032)
Log Age	-0.056***	-0.029***	-0.059***
	(0.008)	(0.008)	(0.009)
Fees	-0.105***	-0.065***	-0.143***
	(0.013)	(0.011)	(0.025)
Loads	-0.094***	-0.079	-0.065***
	(0.029)	(0.049)	(0.019)
Observations	265,868	145,585	282,075
R^2	0.123	0.072	0.244
Adjusted R^2	0.123	0.072	0.244
Note:	* P<0.1, ** P< 0.05, *** P < 0.01		

Table 9 re-estimates equation 4, and differs from table 3 by using daily fund returns instead of annual, checking if the results are robust to the choice of return horizon the investors consider. I find the results are qualitatively the same, but are statistically significant only for equity and government bond funds. Even in the case of corporate bonds, though, there is still a statistically and economically significant negative coefficient on the "Passive" dummy variable, indicating flows are weaker in passive funds, all else equal. I find that at the daily horizon, flows in passive funds are less sensitive to performance in comparison to active funds by 39% in equity funds, 49% in government bond funds, and 22% in corporate bonds funds.

Table 10 re-estimates equation 4, and differs from Table 3 by using the full sample, from the years 2011-2021, checking if my results are robust to the choice of only considering data from after the 2018 passive investment reform that cancelled ETNs. I obtain statistically significant results, indicating the same conclusion that arises from Table 3: Compared to active funds, passive fund flows are much less sensitive to performance. In this estimation, I find that the flow-performance sensitivity is 24% weaker in corporate bond funds, 25% weaker in equity funds, and 46% weaker in government bond funds - showing that the results hold even when accounting for the years prior to the regulatory reform in passive investments.

Table 9: <u>Equation 4 estimation results, using daily returns</u>

This table presents flow-performance relations in active and passive corporate bond funds, equity funds and government bond funds, in the years 2019-2021. The table shows the asymmetry between investor sensitivity to performance in active and passive funds. Percent flows is the net flow into fund i at time t as a percent of its size, Fund Daily Return is the first lag of the fund's daily return, calculated as the percent change in share price. Passive is a dummy variable that is equal to 1 if the fund is index-tracking. The regression also includes date fixed effects. Standard errors are clustered at the fund level, to allow for intertemporal serial correlation.

Dependent variable:	Percent flows		
Fund type:	corporate bonds	equity	government bonds
Lag Fund Daily Return	0.074***	0.099***	0.265***
	(0.018)	(0.018)	(0.03)
Lag Fund Daily Return × Passive	-0.016	-0.039***	-0.130***
	(0.015)	(0.011)	(0.027)
Passive	-0.062**	-0.105**	-0.179***
	(0.028)	(0.045)	(0.048)
Log Market value	0.006	-0.013**	0.002
	(0.005)	(0.005)	(0.007)
Lag Percent Flows	0.101***	0.080***	0.009
	(0.014)	(0.014)	(0.006)
Log Age	-0.060***	-0.025**	-0.02
	(0.009)	(0.011)	(0.012)
Fees	-0.097***	-0.084***	-0.334***
	(0.03)	(0.027)	(0.082)
Loads	-0.166***	-0.103	-0.252***
	(0.062)	(0.107)	(0.078)
Observations	158,940	90,569	123,483
R^2	0.07	0.069	0.048
Adjusted R^2	0.066	0.061	0.042
Note:	* P<0.1, ** P< 0.05, *** P < 0.01		

Table 10: <u>Equation 4 estimation results, using the full sample period: 2011-2021</u>

This table presents flow-performance relations, in active and passive corporate bond funds, equity funds and government bond funds, in the years 2011-2021. The table shows the asymmetry between investor sensitivity to performance in active and passive funds. Percent flows is the net flow into fund i at time t as a percent of its size, Fund Annual Return is the first lag of the fund's annual return, calculated as the percent change in share price. Passive is a dummy variable that is equal to 1 if the fund is index-tracking. The regression also includes date fixed effects. Standard errors are clustered at the fund level, to allow for intertemporal serial correlation.

Dependent variable:	Percent flows		
Fund type:	corporate bonds	equity	government bonds
Fund Annual Return	0.038*** (0.003)	0.012*** (0.001)	0.090*** (0.007)
Fund Annual Return × Passive	-0.009*** (0.002)	-0.003*** (0.001)	-0.041*** (0.006)
Passive	-0.038** (0.016)	-0.011 (0.029)	-0.115*** (0.029)
Log Market Value	-0.013*** (0.004)	-0.020*** (0.004)	-0.040*** (0.005)
Lag Percent Flows	0.120*** (0.024)	0.088*** (0.008)	0.036* (0.019)
Log Age	-0.061*** (0.007)	-0.039*** (0.007)	-0.049*** (0.01)
Fees	-0.134*** (0.014)	-0.082*** (0.013)	-0.279*** (0.046)
Loads	-0.131*** (0.025)	-0.103** (0.041)	-0.137*** (0.028)
Observations	430,281	229,925	359,509
R^2	0.156	0.113	0.171
Adjusted R^2	0.151	0.104	0.165
Note: * P<0.1, ** P< 0.05, *** P < 0.01			

6. Conclusion

The Israeli financial markets have experienced significant growth and development in the past decade, with the corporate bond market and mutual fund industry growing especially fast. Little research has been done on the sources of financial fragility arising from corporate bond funds, and even less for passive corporate bond funds.

I provide evidence that the concave flows-performance pattern, found in the US corporate bond mutual fund industry, does not exist in the Israeli market, and provide an explanation for the difference: The Israeli bond market is liquid, due to its unique market structure – having an exchange for bonds, and investors redeeming their money don't impose large liquidation costs on other investors. Therefore, the payoff complementarities of the US market do not hold in the local context. Instead, I find the well-known convex shape in funds from all market segments. I extend the examination of flow-performance relations to the passive market, and show that passive investors chase returns, but are less sensitive to them than active investors. I demonstrate this by using the COVID-19 crisis as an event of market stress.

The implications of my results for financial stability are that having an exchange for bonds, which in turn causes the bond market to be more liquid, reduces the risk of fire sales, with all the known spillover effects to the real economy. Passive investment acts as a moderating factor in times of market stress, reducing the sales pressure on mutual funds and thus the price pressure on underlying assets.

Additional research is needed to understand the dynamic relations between performance and flows, namely the effect in the opposite direction of this paper: How do flows affect performance of funds and underlying assets? The growth of passive investment also calls for research on the implications of comovement of returns in domestic financial markets.

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