The printed media's impact on fund flows by class

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Abstract

This study investigates how tone of daily print media affects the aggregate flows to and from different classes of mutual funds (government bonds, corporate bonds, stocks, and money market instruments). Using a proprietary data set, we find that tone of print media has a significant positive (negative) impact on the mean returns of net flows (conditional variances), except for the safer money market instrument funds that appear as a mirror image to other, riskier fund classes. These effects are primarily driven by outflows from these funds caused by extremely negative tone especially in non-business newspapers. Using daily fund flows allows us to observe 'flight to liquidity', as money flows from high-risk funds such as corporate bonds and stocks to safer funds, such as money market instruments when tone is negative. We are also able to observe 'risk taking' and 'risk attenuation' as money flows between high-risk funds and moderate risk funds, such as government bonds, partially in response to changes in media tone.

1 Introduction

This study examines the influence of tone of print media on highly specialized (non-general) mutual fund flows.[1] For people who are generally not among the group of professional investors, general rather than business newspapers are the main, if not the only, channel for transmitting economic information (Peress (2014)). Since the media are not unbiased reporters of the news, newspapers not only report the news, but also influence the decisions of the individual investors by emphasizing or downplaying relevant economic events. Thus, tone of print media reporting influences investors (Shiller (2005); Tetlock (2011); Solomon et al. (2014)), which in turn affects financial markets, and so on. As such, exploring the flows to and from mutual fund classes is of importance to investors and stability supervisors alike. The former's focus is momentum or return-chase trading while the latter are mainly interested in herd behavior of novice investors, sometimes referred to as 'dumb money' (see Akbas et al. (2015); Jiang and Verardo (2018)). An unsettled empirical question, though, is what are the driving forces of fund flows? Three main hypotheses describe the relationships between flows and returns (see Ben-Rephael et al. (2011)). (1) Feedback trading: Investors react to lag returns, with positive (negative) returns leading to positive (negative) flows. This hypothesis is adaptive rather rational in nature. (2) Temporary price pressure: If the demand for investments is inelastic to some extent, a large flow into (out of) equity funds will push market prices up (down), and this will be reversed in subsequent periods. Consequently, lagged positive flows should predict negative returns, and vice versa. (3) Information: Good (bad) news regarding market prices leads to positive (negative) returns and to flows into (out of) the respective funds. This hypothesis is rational in nature, thus, assuming efficient markets, no persistent relations between past and future flows/returns are expected.

[1] We focus on funds in which most assets conform to the fund's specialization. For instance, in the government bonds class we select funds without any stocks or options. This is in order to obtain more robust results. For further details see Section 3.

Some studies examine the direct influence of print media on capital markets (for example, Tetlock (2015); Ferguson et al. (2015); Frank and Sanati (2018)). Others (Sirri and Tufano (1998) Berk and Green (2004); Cao et al. (2008); Rakowski and Wang (2009); Ben-Rephael et al. (2012); Barber et al. (2016); Goldstein et al. (2017); Franzoni and Schmalz (2017)) explore the performance-flow relations of mutual funds, and sometimes their role as mediators, with regard to financial anomalies (see the survey in Nigam et al. (2018)). Yet, few investigate the influence of print media on performance-flow relations (Solomon et al. (2014)). To the best of our knowledge, we are the first to investigate the print media's influence on aggregated fund flows to various classes (see Jank (2012) on the relations between net flows to mutual funds and market indices). This study tries to fill the gap by examining the influence of tone, derived from daily print media, on the mean returns and on the conditional variances (risk) of aggregated daily flows to/from specialized funds between January 1, 2011 and March 31, 2019, in Israel. Using a proprietary data set, we examine the following specialized mutual fund classes: government bonds (hereafter 'GOV'), corporate bonds (hereafter 'CORP'), stocks (hereafter 'STOCK'), money market instruments (hereafter 'CASH'), and all funds including general funds (hereafter 'TOT').

In contrast with the relevant literature (see for instance, Peress (2014)), and implementing tone assessment of Saadon and Schreiber (2019), we examine the extent of an article's impact by the newspaper in which it is published (large circulation versus small), its location in the newspaper (first page in a weekend supplement compared with an inside page on a weekday), and its size (number of square inches). Then, the relevant newspaper articles are translated into equivalent monetary terms as if they had been commercial advertisements, assuming that advertisements are price sensitive (see Appendix A and Saadon and Schreiber (2019) for more details on the calculation of tone). The translation of tone into equivalent monetary value is justified both theoretically and empirically, compared to the practice in which the number of positive less the number of negative articles or words is considered. We use tone of print media as a measure of investors' sentiment or mood, even though newspapers almost never provide new information that should affect the financial markets in real time. This is because newspapers in Israel are printed at night (general newspapers: Yediot Aharonot, Ma'ariv, Israel Hayom) or in the evening (business newspapers: Globes, TheMarker, Calcalist) before the markets' open. In contrast with the newspapers, the Internet is currently the main channel conveying new information to the public. However, appearances in the print media also represent appearances in the electronic media, so that the use of print media data is similar in essence to the use of electronic media, though at a lag.

The print media is expected to influence naive ("nonprofessional") investors in two ways: (1) creating pessimism, optimism, fear, or euphoria as they react to stale information (Tetlock (2011)); and (2) making information on the financial markets accessible to those who have not been exposed to it through other media outlets (Peress (2014)). For instance, a wide-ranging article in a widely distributed newspaper may create a reverberation that may influence media and public discourse, leading to a "herd mentality" of selling on the part of naive investors, which will in turn lead to follow-up articles, and in some cases to actions on the part of the government and regulators entrusted with the supervision of financial markets.

This study is closely related to Solomon et al. (2014), who investigate the influence of printed media on a fund's holdings; to Gabaix and Koijen (2020) who introduced the Inelastic Market Hypothesis; to Jank (2012) and Cao et al. (2008) who explore the dynamic relationships between aggregate flows and market indices, and to Ben-Rephael et al. (2011) who examined the relationships in Israel. However, most studies are conducted using US data, especially equity funds. Thus, they are not necessarily representative of other countries (see Ferreira et al. (2012)), and their sample's frequency is at least monthly. In addition, they do not model the influence of media tone on the conditional mean and volatility of fund flows, particularly by class.

Our contribution is threefold. First, we examine the print media's influence on both daily mean and conditional volatility returns for four highly specialized fund classes, rather than equity or sometimes bond funds as is common in the literature. Secondly, using a proprietary data set, which includes all funds in a small open economy such as Israel, we investigate the influence of tone (equivalent monetary value) derived from various newspaper types, particularly business and general newspapers, on fund flows. Third, using aggregate inflows and outflows, we distinguish between a movement from poor performance funds to successful ones within an asset class and movements between two different fund classes. The former might reflect a market efficiency mechanism (return chasing), while the latter might point to a change in investors' revealed preferences. Moreover, Gabaix and Koijen (2020) show both theoretically and empirically that the former barely influences the entire stock market prices with a multiplier of approximately 1 while the latter substantially affects prices (a multiplier of 5). We distinguish between movements within asset classes and movements between them using both univariate models (GARCH/Quantile regressions) and comprehensive multivariate ones: Engle and Kroner (2004)'s VAR-GARCH with external regressors and a BEKK representation. The latter also enables us to examine spillover effects such as the impact of past shocks to fund flows on the current covariances between inflows and outflows.

We find that conditional means (variances) of a fund's net flows are positively (negatively) influenced by the print media tone except for money market funds that are perceived as 'flight to liquidity' funds (see Ben-Rephael (2017); Franzoni and Schmalz (2017)). This is corroborated by the results of quantile regressions, in which tone effects are larger (in absolute values) in the distribution extremes, especially on the far left side of the net flows distribution. Moreover, since tone is defined in this paper as positive tone minus negative tone (see Appendix A), we find through the quantile regressions that negative tones are more influential than positive tones, namely the former are larger (in absolute values) and more robust than the latter.

We also find that tone that is derived from general (non-business) newspapers has a greater impact on net fund flows than respective tones from business newspapers, especially on the far left of the distribution of fund flows. By regressing each fund's inflows on all fund outflows in lag and each fund's outflows on all fund inflows in lag, we find in a system of bivariate VAR-GARCH with diagonal BEKK representation the followings:

(1) Selling risky funds in high-risk classes (CORP and STOCK) yesterday is followed by buying funds in a low-risk class (CASH) today (flight to liquidity),

(2) Selling funds in a moderate-risk class (GOV) yesterday is followed by buying funds in high-risk classes (CORP and STOCK) today (risk taking), and

(3) Buying funds in a moderate-risk class (GOV) yesterday is followed by selling funds in high-risk classes (CORP and STOCK) today (risk attenuation)

Finally, we find that lagged inflow or outflow shocks negatively influence the current conditional covariance between inflows and outflows.

The rest of the study is structured as follows: Section 2 presents the hypotheses and the statistical models that are implemented in this study; Section 3 describes the local environment and the data; Section 4 discusses the results of univariate regressions; Section 5 discusses the results of bi-variate VAR-GARCH-BEKK regressions; Section 6 conducts robustness checks, and Section 7 concludes.

2 Hypotheses and main statistical models

2.1 Testable hypotheses

Following Rakowski and Wang (2009); Akbas et al. (2015); Blocher (2016); Goldstein et al. (2017); Saadon and Schreiber (2019), we conjecture some testable hypotheses, as follows:

H1: Net flows to funds in high risk classes (CORP and STOCK) are positively influenced by tone while net flows to the safer class (CASH) are negatively influenced by tone because the CASH class is a mirror image of other risky classes. This hypothesis assumes that investors increase (decrease) their risk appetite following positive (negative) media tones. As GOV is in between risky and safe classes, the influence of tone on net flows to GOV can be either positive or negative.

H2: As tone = positive tone - negative tone (see Appendix A), positive tones (hereafter 'POS') behave like tone while negative tones (hereafter 'NEG') behave contrary to with greater intensity to tone, in affecting net flows to the various fund classes (except CASH). Although, the positive (negative) relations between POS (NEG) and tone are algebraic tautology, we test it statistically as significant relations between tone and net flows can be the result of either positive relations between POS and net flows, or NEG and net flows, or both. Yet, we expect more robust relations between NEG and net flows due the asymmetric influence of tone on stock markets as reported in the literature (see Saadon and Schreiber (2019)).

H3: The conditional variance of net fund flows to all risky fund classes are negatively influenced by tone while net flows to the safe fund class (CASH) are positively influenced by tone. This conjecture assumes risk averse investors who prefer high returns but dislike risks. As a result, positive tone might presumably point on more volatile future returns, which in turn negatively affect risk averse investor's net flows (all other things being equal particularly, expected means). In contrast, the CASH class which is a safer fund class, is a mirror image to the other risky classes in both basic parameters: the mean and the variance.

H4: The impact of tone is greater in the extremes of the flows distribution, particularly on the left side of the distribution i.e., tone's influence is asymmetrical particularly left skewed. We check for non-linearity of investors' risk aversion (see Tversky and Kahneman (1992)) by implementing the quantile regressions.

H5: The tone's impact is greater when it is derived from general (non business) newspapers. This hypothesis is based on the evidence (Peress (2014)) that naive investors make decisions to buy and sell funds based on newspaper reports. Even though Peress did not distinguish between general and business newspapers, we conjecture that most naive investors do not read business newspapers, and are influenced mainly by general newspapers.

H6: The effect of the various tones weakens with the time horizon and without outliers. This conjecture is in line with the literature (see for instance Ben-Rephael et al. (2011)) and H4, respectively.

As fund flows and market indexes are daily and at least the latter are characterized by clustering and co-movements over time, the above hypotheses are examined using, *inter alia*, the GARCH models for the univariate dependent variables (net flows) and the bivariate VAR-GARCH-BEKK model for fund inflows and outflows as dependent variables.

2.2 Main statistical models

Our main statistical (benchmark) model for the univariate regressions is EGARCH(1,1) in which the conditional Mean and Variance equations are as follows:

$$\begin{aligned}
&Mean^f: NET_t = \mu + ROR_{t-1} + NET_{t-1} + BM_{t-1} + ALL_{t-1} + OVIX_t \\
&\quad + Sunday + TONE_t + \epsilon_t \qquad (1) \\
&Variance^f: log(\sigma_t^2) = \omega + \alpha|\frac{\epsilon_{t-1}}{\sigma_{t-1}}| + \beta log(\sigma_{t-1}^2) + \gamma\frac{\epsilon_{t-1}}{\sigma_{t-1}} + TONE_t
\end{aligned}$$

where, NET_t is the aggregate net flows to a fund class (f) at date t. Fund class, f, is categorized as: Government bonds (GOV), corporate bonds (CORP), equity (STOCK), money market instruments (CASH), and total flows to all funds including general funds (TOT). The latter is also estimated as a dependent variable in order to uncover whether tone has an impact on financial markets as a whole rather than on specialized funds only. Each mean equation (except the intercept - μ) consists of a self fund's rate of return in a lag in percent, ROR_{t-1}, where $ROR_t = \frac{MV_t - NET_t}{MV_{t-1}} - 1$ and where MV_t is the aggregated market value of the funds included in class f at time t, NET_{t-1} is the net flows to a self fund class in an one day lag, ALL_{t-1} is the net flows to all funds in specialized classes in a lag, and BM_{t-1} is the return on a benchmark investment in a lag. Particularly, BM for GOV and CORP is the daily rate of return on government and corporate bond indexes, respectively, BM for equity (STOCK) is the rate of return on TA125 stock index, and BM for money market funds (CASH) is daily changes in the 3 month makam (similar to the treasury bills) yield. The BM for TOT is the simple mean of BM of all particular BMs.[2] OVIX reflects the changes in the Israeli overnight VIX (OVIX, from today's open to yesterday's close). This in order to control for shocks that occurred after the newspapers printing time. BM and OVIX control for the objective actual economic developments, so that tone is the net influence of the (subjective) print media given the market's actual performance. Sunday is a dummy for Sundays, in which trading volumes are thinner, and TONE is our main examined variable, which is published before market opening. In the variance equation, the only external regressor is tone (TONE) such that a negative and significant coefficient means that increasing tone is followed by decreasing volatility (H3).

The second statistical model assesses two contemporaneous variables in a bivariate VAR-GARCH(1,1)-BEKK. We examine two models with the same dependent variables but with different independent variables as follows:

(I) Inflows versus outflows and tone:

$$\begin{aligned} Mean_{in} : IN_t^f = \mu_{in} + IN_{t-1}^f + OUT_{t-1}^f + ROR_{in,t-1}^f + ALL_{in,t-1} + \\ OVIX_{in,t} + Sunday_{in} + TONE_{in,t} + \epsilon_{in,t} \\ Mean_{out} : OUT_t^f = \mu_{out} + OUT_{t-1}^f + IN_{t-1}^f + ROR_{out,t-1}^f + ALL_{out,t-1} + \\ OVIX_{out,t} + Sunday_{out} + TONE_{out,t} + \epsilon_{out,t} \end{aligned} \tag{2}$$

Where, subscripts 'in' and 'out' represent inflows and outflows to/from a fund class and superscript f represents the class ($f \in$ (GOV, CORP, STOCK, CASH). All other terms are the same as in the univariate EGARCH(1,1) equation above (see eqn. (1)).

[2] We examine also a contemporaneous BM_t in the robustness checks section.

(II) Movements between classes:

$$
\begin{aligned}
Mean_{in}^{f}: IN_t &= \mu_{in} + IN_{t-1} + \sum_{f=1}^{4} OUT_{t-1} + ROR_{t-1} + ALL_{in,t-1} + \\
&\quad OVIX_{in,t} + Sunday_{in} + TONE_{in,t} + \epsilon_{in,t} \\
Mean_{out}^{f}: OUT_t &= \mu_{out} + OUT_{t-1} + \sum_{f=1}^{4} IN_{t-1} + ROR_{out,t-1} + ALL_{out,t-1} + \\
&\quad OVIX_{out,t} + Sunday_{out} + TONE_{out,t} + \epsilon_{out,t}
\end{aligned}
\tag{3}
$$

Where, subscripts 'in' and 'out' represent inflows and outflows to/from a fund class ($f \in$ GOV, CORP, STOCK, CASH). All other terms are the same as in eqn. (2).

For the conditional variance equations of the two systems above, denote the residual vector as $\epsilon_t = (\epsilon_{1,t}, \epsilon_{2,t})$, where subscripts 1 and 2 refer to the first and the second mean equations of the two VAR-GARCH-BEKK systems (e.g., 1 refers to subscript 'in' and 2 to subscript 'out', in eqn. (3)). We assume that ϵ_t is bivariate and normally distributed with $\epsilon_t | I_{t-1} \sim (0, H_t)$ where I_{t-1} reflects the information set at t-1. We implement the diagonal BEKK representation, proposed by Baba et al. (1990), as follows:

$$
H_t = C_0' C_0 + A_{11}' \begin{bmatrix} \epsilon_{1,t-1}^2 & \epsilon_{2,t-1}\epsilon_{1,t-1} \\ \epsilon_{1,t-1}\epsilon_{2,t-1} & \epsilon_{2,t-1}^2 \end{bmatrix} A_{11} + B_{11}' H_{t-1} B_{11} \tag{4}
$$

where, $A_{11} = \begin{bmatrix} a_{11} & 0 \\ 0 & a_{22} \end{bmatrix}$ and $B_{11} = \begin{bmatrix} b_{11} & 0 \\ 0 & b_{22} \end{bmatrix}$ are diagonals and C_0' is restricted to be upper triangular. In Baba et al. (1990) a property of the BEKK model is that conditional covariance matrices like H_t above are positive definite by construction as the constant term is decomposed into a product of two triangular matrices. Accordingly, the number of estimated parameters in the conditional variance equation is 7 (3 for the upper triangular term - $C_0' C_0$, 2 for A_{11} and another 2 for B_{11}). Together with the two mean equations we end up with a maximum of 31 parameters (including an AR term in both Mean equations), which is a reasonable compromise between flexibility (many parameters and consequently a curse of dimensionality) and feasibility (few parameters). The conditional density function for statistical models 2-4, provided that θ is a vector of unknown parameters to estimate and Y_t are our 2 x 1 vectors of variables in models (2-4):

$$f(Y_t|I_{t-1};\theta) = (2\pi)^{-1}|H_t|^{-\frac{1}{2}}exp(-\frac{\epsilon_t' H_t^{-1}\epsilon_t}{2}) \tag{5}$$

Thus, the multivariate quasi-maximum-likelihood estimates can be obtained by maximizing the function:

$$L = -\frac{1}{2}NTlog(2\pi) - \frac{1}{2}\sum_{t=1}^{T}(log|H_t| + \epsilon_t' H_t^{-1}\epsilon_t) \tag{6}$$

where, N is the number of equations ($N = 2$ in our case) and T is the number of observations ($T = 2021$ daily observations). The standard errors are calculated by the quasi-maximum likelihood method of Huber-White; a robust method to the underlying residuals distribution. It is well known that the diagonal BEKK is preferred to the Full BEKK in which off diagonal figures are not assumed to be 0, like in matrices A_{11} and B_{11} (see Chang and McAleer (2018)). Moreover, Chang and McAleer (2018) assess the effect of a shock in asset j at t-1 on the subsequent co-volatility between j and another asset, i, at time t. This co-volatility spillover effect is defined as:

$$\frac{\partial H_{ij,t}}{\partial \epsilon_{j,t-1}} = a_{ii} \times a_{jj} \times \epsilon_{i,t-1}, \qquad i \neq j \tag{7}$$

As $a_{ii} > 0$ for all i, a test of the co-volatility spillover effect is given as a test of the null hypothesis: $H_0 : a_{ii} \times a_{jj} = 0$.

If H_0 is rejected against the alternative hypothesis, $H_1 : a_{ii} \times a_{jj} \neq 0$, one can argue that there is a spillover from the returns shock of asset j at t-1 to the co-volatility between assets i and j at t that depends only on the returns shock of asset i at t-1. As spillovers might vary over time, we base our estimates on the average return shocks of the entire sample period (see more details in Chang and McAleer (2018)).

3 The environment and Data

In March 2019 there were 2099 mutual funds in Israel (including 596 ETFs); Of those we focus on specialized funds that are categorized in four classes:

- 202 government bond funds without stocks or other risky assets (GOV) out of 245 government bond funds that are included in this class by the Israeli Securities Authority (ISA).
- 29 high risk corporate bond funds (CORP) out of 307 corporate bond funds. We include in this class funds with exclamation mark (!) that represent high risk characteristics.
- 205 local equity funds including options (STOCK) out of 760 equity funds.
- 36 money market funds without options or other risky assets (CASH) out of 62 money market funds.
- 1,503 all funds excluding ETFs (TOT)

The sample period extends from January 1 2011 to March 31 2019 (2,021 trading days). Despite the 'minimum holdings' guidelines, that set a lower threshold to specialized fund holdings[3], our sample contains more specialized funds than the Israeli Securities Authority (ISA) definitions. This in order to get stronger relations between tone and net flows to specific class types. Indeed, implementing the various procedures on the common wider definitions yield less robust results since the class types are not specialized as our choice. Almost all mutual fund investors are retail however, some funds are held by wealthy families (as an alternative to portfolio management) or directly by portfolio managers. Also, the funds are not used for tax benefited retirement investments. Finally, by categorizing our selected specialized funds into four classes we end up with three types of risk: High risk (CORP and STOCK), Moderate risk (GOV) and Low risk/safe class (CASH). The time line of fund flows is as follows:

i) An investor transmits an order (to buy or sell mutual fund units) to the bank. It can be

[3] Most specialized fund classes are obliged by the law to hold a minimum of class assets and face various limitations. For example, the wide government and corporate fund classes (including our subset GOV and CORP classes) must hold at least 75 percent of their assets in bonds, CASH must hold money market assets with average duration of maximum 90 days, and STOCK must hold at least 50 percent equities.

by phone, by fax, electronically, or in person.

ii) Orders for the same day can be transmitted from 8:00 to 15:30–16:00 (depending on the fund's prospectus), as the Tel Aviv Stock Exchange (TASE) trading day ends at 17:30 local time. This allows funds sufficient time to adjust their positions according to the daily flows (for a detailed description see Ben-Rephael et al. (2011)). Yet, according to previous articles (Cao et al. (2008); Tetlock (2015); Ferguson et al. (2015); Ben-Rephael et al. (2011), among others) and local experts, the contemporaneous impact of fund flows on financial market indexes (both means and variances) is neglected, either because a particular fund is usually a price taker or because in most cases today's orders are effective only tomorrow (we test this point in the robustness checks section).

iii) The bank transfers the orders electronically to the TASE.

iv) The TASE transmits its flows to each fund family (there are about 40 fund families that manage 1,503 funds) every 10–15 minutes. It should be emphasized that flow transmissions are not related to the trading at the TASE.

v) At the end of a trading day, each fund calculates and transmits its Net Asset Value, which is its Market Value (NAV/MV) to the TASE for clearing.

The local mutual fund industry differs from that of the US in at least three aspects (other than the size, of course): (1) Stocks account for a much higher share of TOT fund flows in the US than in the local industry, (2) Movements from one class to another in the US are common while in Israel (naive) investors 'park' their money on the sidelines, temporarily. Thus, it is uneasy to uncover the movements between classes[4], (3) Local banks serve as gatekeepers such that there are few truly independent investors. This phenomenon that may increase herd behavior, however, is similar to the situation in the US in which investors rely on the Morningstar recommendations when they buy or sell mutual funds (see Ben-David et

[4] Ideally we could take into consideration cash reserves of investors in their bank accounts however, there are no such data on a daily basis in Israel and investors are anonymous. We focus on extremely specialized fund classes in order, *inter alias*, to uncover movements from one class to another (changes in investors revealed preferences) versus the common examination in the literature that is movements within a fund class (return chasing).

al. (2019)).

Table I presents summary statistics of the main variables included in this study.

[Enter Table I here]

Panels A–C present Net, In, and Out aggregated reported daily flows (not an estimation as other studies do) to the four classes in millions of Shekels. It is quite clear that Net flows are small compared to both In and Out flows. However, on some days, Net flows can be very large especially for the CASH class. This evidence might point to the CASH funds as a 'flight to liquidity' class (which will be discussed later). This also explains the relatively high volatility of that class compared to other classes (Std = 154.5 million shekels). During the sample period some of the classes attracted positive net flows (GOV and STOCK) while the safe class (CASH) evidenced negative net flows. The latter can be explained by the low inflation environment which fostered movements to risky fund classes. Notice also the large and profound positive net flows to the mutual industry (21.8 million shekels) compared to the respective net flows to our extremely specialized funds. This means that most investors' flows are headed to general domestic funds or funds that invest in international assets. Panels D–E show the daily rates of return on the fund class's holdings and on the class's benchmark, while Panel F presents the various definitions of tone. Notice that tone which is derived from business/economical newspapers (TONE.ECON) is positive and larger than the common tone (TONE). Consequently, tone derived from general (non business) newspapers (TONE.GEN) is negative and larger (in absolute values) than the common tone. This evidence, firstly documented in Saadon and Schreiber (2019) for Israel, suggests that the print media's habit of focusing on negative news (asymmetry reporting) is more prominent in general rather than in business newspapers.

In what follows we describe the results of the univariate as well as bivariate regressions. As a first impression, though, we present in figures 1-4 the pairwise contemporaneous correlation coefficients (except for tone which is published before the market opening) between the main variables of each fund class. Each figure contains the correlation coefficient and its significance level (* for 0.1, ** for 0.05, and *** for 0.01), in the upper triangle, the variable's distribution on the diagonal, and a bivariate distribution with a cubic spline approximation (red lines) in the lower triangle.

[Enter Figures 1-4 here]

In all cases there are significant positive correlations between tone and both net flows to all fund classes (NET.TOT) and to NET.GOV, NET.CORP, and NET.STOCK while there is a negative correlation with NET.CASH, as expected by H1.[5] In contrast, the correlation between the rate of return on a self fund class (ROR) and the net flows to NET.GOV is insignificant and for CASH is even negative (see Barber et al. (2016)). Additionally, the correlations between net flows to each fund class and the rate of return on the class's benchmark depends on the class: For CASH (safer class) the correlations are negative while for the three other classes they are positive. Finally, in almost all cases OVIX (the local volatility index – VIX – measured from today's opening back to yesterday's close and controlled for the latest developments that are not embedded in market prices) is a mirror image of tone. Namely, there are negative correlations between OVIX and both net flows to all fund classes (NET.TOT) and to each one of the unsafe fund classes while they are insignificant for CASH. To sum up, all net flows are positively correlated but the CASH class variables draw a mirror image to other classes' variables particularly with regard to tone.

4 Results of univariate regressions

The basic (benchmark) statistical model results of a univariate regression (EGARCH(1,1)) is depicted in the following table.

[Enter Table II here]

[5] Ben-Rephael et al. (2011) found significant correlation coefficient of 0.451 between Net flows to stock funds and the stock index TA-25. This figure is partially comparable to ours 0.2 in Figure 3 as our benchmark is broader (TA-125) index and our sample period is ten years later.

The table contains three parts: Mean equation, conditional variance equation, and goodness of fit measures, for each one of the fund classes separately, including all funds (TOT). The table clearly demonstrates our priors regarding tone impact on fund net flows by class. Particularly, in the mean equation, tone's coefficient is positive and significant for all fund classes except for the CASH class which is negative and significant (hypothesis H1). Scaling back the coefficients of tone in the mean equation yields: 9.6, 1.4, 27, -37, and 96 for GOV, CORP, STOCK, CASH and TOT equations, respectively.[6] The relatively large coefficients of tone in the STOCK and CASH equations might be an anecdotal evidence to movements between risky and safe asset classes, which in turn substantially affects prices (see Gabaix and Koijen (2020)). In the conditional variance equation all tone's coefficients are negative and significant, again except for CASH (hypothesis H3). These two robust results regarding the CASH class might suggest that during the sample period it was the ultimate 'flight to liquidity' class (see Ben-Rephael (2017)). Persistence in self flows (NET_{t-1}) and in returns (positive performance-flows) was found in most classes (see Ben-Rephael et al. (2011); Goldstein et al. (2017)). In addition, OVIX's coefficient, which control for developments after yesterday's market close, is negative except for the CASH class, again. Finally, a leverage effect, in which yesterday's shock asymmetrically influences today's variance, prevails ($\gamma > 0$) for all classes as expected from daily financial data.

Following the positive (negative) influence of tone on the mean (variance) net flows and the definition of tone (TONE = POS - NEG, see Apendix A), it is interesting to identify the responsible factor for that influence as it can be either POS or NEG or both. This identification is done in Table III.

[Enter Table III here]

Notice that the only difference between this table and Table II is the substitute of TONE with POS and NEG. Recall that both POS and NEG, likewise NET are published before the

[6] An LS regression with the same variables yields the following tone's coefficients: 13, 1.1, 12, -100, and 52 for GOV, CORP, STOCK, CASH and TOT equations, respectively.

market open. In the mean equation all NEG's coefficients are negative and mostly significant except in CASH equation in which the coefficient is positive and significant. However, only in GOV and STOCK class equations the POS coefficient is positive and significant. This means that even tough POS and NEG are sometimes insignificant e.g., for TOT, the difference between them (TONE) turn significant in Table II. Additionally, CASH is a mirror image to other classes i.e., its POS coefficient is negatively significant while its NEG coefficient is positively insignificant. Other variables in the mean equation behave similar to those in Table II. In the conditional variance equation, both POS and NEG coefficients are in line with our prior (hypothesis H2) namely, POS negatively co-variate with net flows (good news decrease the conditional variance) while NEG positively influences net flows. Here too CASH behaves differently from other classes regarding NEG.

We further investigate the influence of tone on net flows by class along the net flows' distribution. This investigation is quite relevant since the printed media usually emphasizes extreme events especially negative ones (see Garz (2014)). Therefore, we conjecture (H4) that the coefficients impact is non-linear i.e., is larger (in absolute values) in the extremes and particularly in the far LHS of net flows' distribution (except for the CASH class). In order to examine the non-linearity of TONE coefficients along the net flows' distribution, we implement a quantile regression with all the independent variables as in Table IV.

[Enter Table IV here]

In all classes (except CASH and TOT), the most LHS (τ=0.05) TONE coefficient is positive and significant i.e., more negative tones go hand in hand with more negative net flows. In contrast, CASH displays a mirror image to other classes pointing again to its different role as a 'flight to liquidity' class especially in deteriorating market situations (see for instance Ben-Rephael (2017)). In contrast, the other extreme of the net flows distribution i.e., the most right side (τ=0.95) TONE is mostly negative but insignificant. Interestingly, the TONE coefficient in the CASH equation at τ=0.5 and up is negative and significant which means that positive tones negatively affect net flows to the CASH class. Finally, TOT exhibits neither significant positive nor significant negative relations with tone. These result conforms to our conjecture (H4) that there is an asymmetry in tone impact on funds' net flows and the main impact is on the LHS of the distribution. This results is consistent with a non linear utility function of risk averse investors that proposed by Tversky and Kahneman (1992). As with the EGARCH regression we further re-estimate our model (using the quantile regression) with POS and NEG tones rather than the TONE. By doing so we try to uncover which of tone's components, POS or NEG, is more influential on net flows along the fund flows distribution.

[Enter Table V here]

In all classes the most LHS (τ=0.05 and τ=0.1) NEG is negative and significant (except CASH) while POS is insignificant. This reasonable result might indicate that in a case of extreme negative net flows that is probably the result of markets tumbling, the dominant tone component is the negative tone. In the other distribution's extreme i.e., the most right side (τ=0.9 and up) POS exhibits similar behavior (except CASH) though with smaller coefficients and significance. For example, the NEG coefficient of τ=0.05 for the GOV class is larger in absolute values than the respective POS of τ=0.95 (-0.20** versus 0.13**). This evidence that POS can be significant in the right side of the distribution ($\tau \geq 0.5$) while in the LHS of the distribution NEG are usually significant only in the most negative extremes ($\tau \leq 0.1$) reflects the fact that market indexes and consequently fund net flows tend to move up moderately but moving down more aggressively and sometimes as free fall. Note also that other dependent variables do not show similar patterns as POS and NEG. Though, one notable variable is OVIX which is negative and significant along the LHS of the net flows distribution (except for CASH). This can be explained as OVIX controls for latest developments and since negative news apparently have more impact on fund flows than good news.

We next differentiate between tones that are derived from all newspapers and those that are derived from business (for professional readers) newspapers only. We conjecture that the impact of the latter on net flows will be smaller than the respective impact of the former (hypothesis H5) so that general (non professional) newspapers have more impact than all newspapers. Such an influence on net flows of the non professional readers should be more prominent in the distribution extremes and especially in the left extreme. To the best of our knowledge, such differentiation is novel in the literature. The influence of tones that are derived from business newspapers only on fund net flows are shown in Table VI.[7]

[Enter Table VI here]

In comparison with Table IV, that includes all newspapers, at least two points are worth mentioning. First, the most LHS (τ=0.05) TONE coefficients are insignificant and smaller (in absolute values) than their respective figures in Table IV. Secondly, TONE remains negatively significant along the right hand side of the distribution starting from $\tau \geq 0.2$ for CASH. Other variables in this table have similar coefficients and significance levels as in Table IV and tones in the CASH class exhibit the same opposite behavior (flight to liquidity). These pieces of evidence can be partially explained by different investor types: Naive investors who read general newspapers only (Peress (2014)) are mainly influenced by negative tones while more sophisticate investors who read business newspapers are not affected by newspaper headlines likewise naive investors; sometimes they act as momentum traders and some other times as contrarians. Therefore, the insignificance of tone coefficients in the most LHS of the distribution might indicate heterogeneous behavior of sophisticated investors.

5 Bivariate VAR-GARCH-BEKK regression results

This section examines the influence of tone on fund flows using equations (2) - (3). These equations estimate the influence of tone in a VAR-GARCH system, in which dependent

[7] For space consideration and since tones that are derived from general newspapers are characterized by more zeros than the respective tones that are derived from business newspapers, we do not exhibit a similar results for general newspapers only. We cope with this issue in the robustness check section.

contemporaneous variables such as inflows and outflows are regressed on tone and other control variables in lag (as in previous regressions). As net flows (NET) = inflows (IN) - outflows (OUT), this assessment can also shed light on the net flows' component (either inflows or outflows or both) that is more influenced by tone. We first examine tone's impact on inflows and outflows to the various funds by class whereas inflows and outflows run in a VAR-GARCH-BEKK system.

[Enter Table VIII here]

It can be seen that the TONE coefficients are often positive and significant (except for GOV) in the In equation and negative and significant (except for CASH) in the OUT equation. Additionally, the size of TONE coefficients in OUT equation is always larger than the respective size in IN equations. This evidence is in line with the asymmetry of tone influence that was found earlier (Table IV) namely, negative tones (NEG) have more impact on outflows (OUT) than (the same level) positive tones (POS) have on inflows (IN). This evidence also reconfirms the notion that markets, and consequently all fund flows, go up moderately (by stairs) but go down much quicker (by elevator). Finally, note that in contrast with previous tables, the coefficients of the independent variables in lag, IN_{t-1} and OUT_{t-1}, are not positive and significant any more. This means that the auto-correlation that was found for net flows (NET_{t-1}) does not prevail in both inflows and outflows equations.
Implementing the partial differentiation of Chang and McAleer (2018) yields the influence of inflows' shocks on the covariance between inflows and outflows changes and vice versa (see eqn. (4)). The diagonal of A matrix is significantly positive ($A_{in,in} > 0, A_{out,out} > 0$ including CASH) and the mean of shocks is negative i.e., $\overline{\epsilon_{t-1}} < 0$. This means that lagged inflows or outflows shocks negatively influence the current covariance between inflows and outflows. In other words, a shock to one series yesterday might reduce the current conditional covariance between them.
The last analysis examines the relations between aggregate inflows versus outflows in each fund class. However, it is important to distinguish between movements within each class

(return chasing) and a movement from one class to another (changes in investors revealed preferences). The former is important to investors while the latter is of interest to financial stability managers. Yet, almost all the literature on mutual fund examines the former whilst surprisingly silent regarding the latter. In order to distinguish between the two types of flows we conduct eqn. (3) in which each fund inflows are regressed on fund outflows of all classes (and some control variables including tone) and each fund outflows are regressed on fund inflows of all classes (and some control variables including tone), in a VAR-GARCH-BEKK system. If one of the other classes outflows' (lagged) coefficient is positive and significant, one can argue that there is a movement from that class to the independent (current) class. In other words, a movement between classes occurs if yesterday's selling in one class is followed by today's buying in another class.[8]

[Enter Table IX here]

In the mean IN equations, one can identify movements from CORP and STOCK to CASH (flight to quality) and movement from GOV to CORP and STOCK (risk taking). In that regard we find at least two patterns: (1) Selling yesterday STOCK and CORP funds is followed by buying CASH funds today (flight to quality from risky classes to the safe class) and (2) Selling yesterday GOV funds is followed by buying today CORP and STOCK funds (risk taking from moderate risk class to high risk classes). In the mean OUT equations we find a reversed/opposite movement from CORP and STOCK classes to GOV i.e., risk attenuation from high risk classes to a moderate risk class.

Figure 5 summarizes the movements between the three types of risk classes based on regression results of eq. (3).

[Enter Figure 5 here]

[8] Our model is based on the reasonable assumption that there is a minimal delay of a day between the selling proceeds and the consequent buying orders as a result of both bank settlement procedures and learning time. Therefore, we do not include a same day movement between two classes i.e., selling a fund in one class and using the proceeds purchasing a fund in another class on the same day.

Regarding the auto-correlation of inflows and outflows in Table (IX), we find negative coefficients as in the previous tables. Implementing the partial differentiation of Chang and McAleer (2018) yields the influence of inflows' lagged shocks on the current covariance between inflows and outflows (see eqn. (4)). The diagonal of A matrix is significantly positive ($A_{in,in} > 0, A_{out,out} > 0$) and all mean shocks are non positive i.e., $\overline{\epsilon_{t-1}} \leq 0$ and mostly close to 0. Compared to Table VIII, lagged inflows or outflows shocks have minor negative influence on the current conditional covariance between inflows and outflows.

6 Robustness checks

In what follows we conduct several robustness checks with regard to the above tables, mainly to tone's definition while keeping the statistical methods usually unchanged. Our benchmark table is Table II in which net flows of each class are regressed on tone and some control variables in EGARCH(1,1) model. First, we check our basic method of tone (see Saadon and Schreiber (2019)) against the common definition in the literature i.e., tone equals the number of positive articles minus number of negative articles.

[Enter Table X here]

In comparison with the benchmark (Table II) it is quite clear that tone coefficients and their significance levels are not the same as those in Table II. In the mean equation, the TONE coefficients of GOV and TOT are insignificant while in the Variance equation, the TONE coefficients of GOV, STOCK, and TOT are insignificant. This means that our basic method of tone yields better results regarding tone impact on net flows. Notice, that Saadon and Schreiber (2019) found differences between these two alternative definitions of tone where the dependent variable was the TA-125 stock market index. Moreover, they showed that our method of tone calculation is preferable to the common definition in the literature.

Secondly, we check the lasting impact of tone on various net flows by converting the sample period from daily frequency to both weekly and monthly frequencies. Since, Solomon et al.

(2014)[9] and Saadon and Schreiber (2019) report on tone's influence on market securities of more than a day it is of interest to uncover whether tone's influence on net flows lasts for a week or a month.

[Enter Table XI here]

Two irrelevant variables are excluded from the regressions: 'OVIX' and 'Sunday' so, a comparison between Table II (our benchmark) and this table is not straightforward. For the weekly frequency, tone's coefficients in the Mean equation are totally different from those in Table II and only TONE coefficient in the TOT equation is positive and significant. Similarly in the Variance equation, only the TONE coefficients of TOT and STOCK are negative and significant likewise in Table II whilst in all other classes they are either positive significant or insignificant. This means that weekly tones do not influence weekly net flows to funds in specialized classes. For the monthly frequency the picture is similar: In the Mean equation TONE coefficients are totally different from those in Table II namely, only TONE coefficients in the STOCK and TOT equations are positive and significant as in Table II. Additionally, in the Variance equation not even one TONE coefficient is negative and significant, as in Table II. Another prominent difference is the coefficient of the lagged net flows (NET_{t-1}) which is close to 1 for the two frequencies. This evidence confirms the well known fact that weekly/monthly net flows to mutual funds are auto regressive while NET_{t-1} in our benchmark table (Table II) that presents results of daily data are less auto correlative.
On the background of tones' incapability to influence net flows at the weekly and monthly frequencies, it is of interest to check whether more TONE lags can affect the current net flows on a daily frequency. This check is done in Table XII.

[Enter Table XII here]

The table contains five daily lags of the TONE (including the pre-opening tone, $TONE_t$). In the mean equations one can see a seesaw teethes pattern of the TONE starting from

[9] They find that the effect of holdings' media coverage on fund flows is driven by the news in the most recent month before holdings' disclosure and that the media effect fades away after two months.

$TONE_t$ which is quite similar to the respective TONE coefficients in Table II (positive and significant except for CASH) and ending with $TONE_{t-4}$ with similar coefficients and significance levels (except for GOV which is insignificant). Thus, the lagged TONE coefficients convey some information regarding net flows but they are indecisive. In contrast, the TONE coefficients in the variance equations are totally different from those in Table II (except $TONE_t$ which is negative and significant). Other variables are usually similar to the respective variables in Table II.

We further check whether adding contemporaneous benchmarks BM_t to our basic equation (Eqn. (1) may change the TONE coefficient. This might be possible if investors are affected by the same day benchmark index returns when they buy or sell mutual funds. Although, most studies on performance-flows test the impact of past performance on current flows we check for this possibility in Table XIII.

[Enter Table XIII here]

The results confirm that TONE coefficients are similar to those in Table II, except for TONE coefficient of CORP in the mean equation, where it is insignificant. On the other hand, all BM_t are positive and significant (except CASH) whereas BM_{t-1} of CORP turn negative and significant.

We next consider the effect of outliers on the previous results. Particularly, it is common in the relevant literature to exclude outliers of 99 and 1 percentiles (see for instance Goldstein et al. (2017)). In order to check the outliers impact we winsorize net flows at the 99 and 1 percentiles and check the results against our benchmark table (Table II).

[Enter Table XIV here]

While in the variance equation almost all the TONE coefficients are similar to the respective coefficients of Table II, the TONE coefficients in the mean equation are quite different and sometimes counter intuitive. For example, TONE coefficients of the TOT class is negative and significant at the 0.1 significance level. These results justifies the inclusion of all observations, especially outliers when examining (non linear) relations between flows and printed media tones, in which extreme events particularly negative ones are emphasized, as has been done in this study.

We further check whether the benchmark results (in Table II) are sensitive to the heterogeneity of newspapers' tone i.e., are for the same tone values different opinions among newspapers regarding financial markets matter?. This is checked in the following table.

[Enter Table XV here]

Generally, tone coefficients are similar to those of the benchmark table though, they are insignificant for GOV in the conditional mean equations and for GOV, CORP, and STOCK in the conditional variance equations. In addition, the coefficient levels are sometimes different from the respective ones in the benchmark table (Table II). For example, the coefficient of tone in the STOCK mean equation equals 0.049^{***} compared to 0.107^{***} in the benchmark table and equals -0.01 compared to -0.062^{***} in the variance equation. As almost all other variables are the same, these differences in tone coefficients can be explained by the different heterogeneity of newspapers attitude concerning the financial markets in which some are very positive while others are almost neutral. Thus, it appears that tone that is derived from all articles is sensitive for heterogeneity among the newspapers at least for GOV, CORP, and STOCK classes.

Finally, we examine the robustness of our benchmark model results (Table II) regarding General newspapers using both LS and TOBIT regressions. The former may show the non scaled coefficients in the various classes, particularly tone coefficients while the latter might reveal biases of the coefficients due to many zeros in the General newspapers data i.e., nothing is published in some days. Notice, however, that only in very few cases tone value was zero as a result of equality between positive and negative tones.

[Enter Table XVI here]

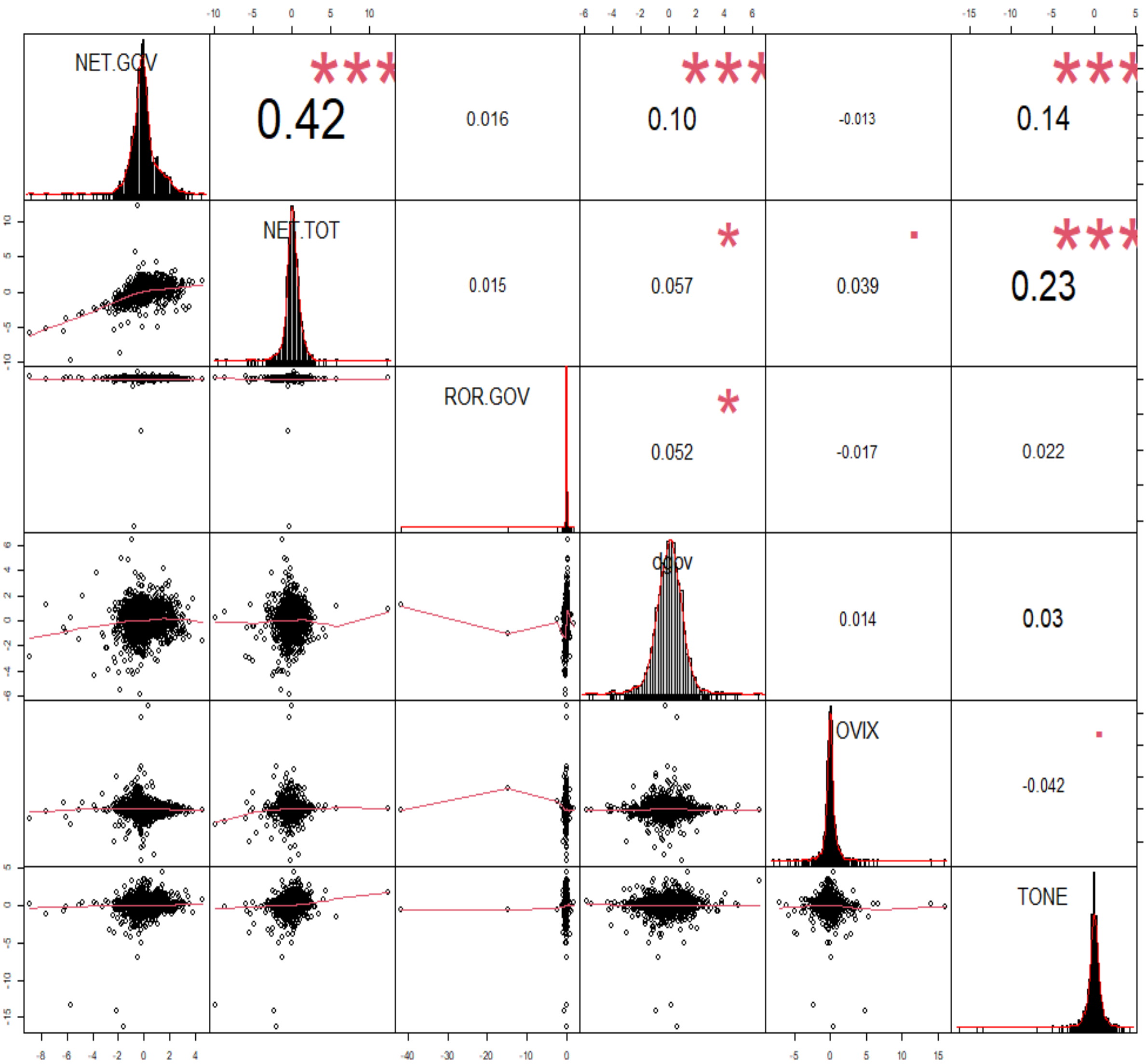
It can be seen that most coefficients are similar to those of our benchmark (Table II) and to those of economic newspapers (Table VI), qualitatively even though the tone here is derived from General newspapers only and data is non scaled. Interestingly, the LS results regarding tone coefficients here are quite similar to the respective results of all newspapers (see FN 6), quantitatively. However, the tone coefficients here might be biased since there are many zeros in General newspapers data (585 out of 2011 observations compared to 103 of tone that is derived from all newspapers). Therefore, the coefficients of the TOBIT regressions appear robust to the possibility of latent variables that contains zeros. Indeed, tone coefficients of TOBIT regressions are much larger (in absolute values) for CASH and TOT while similar to the respective figures in other classes. Moreover, tone coefficients are significant in STOCK and CASH classes which may point on 'flight to liquidity' movement from risky assets such as stocks (STOCK) to safe ones as money market instruments (CASH) and 'take on risk' from CASH to STOCK. These movements are partly the results of tone derived by General newspapers and consumed by novice people which in turn substantially affects market prices (see Gabaix and Koijen (2020)).

7 Summary

This study explores the influence of tone, derived from daily print media (general and business newspapers), on the aggregate flows to/from several highly specialized mutual fund classes. In particular, we examine four fund classes: government bonds, corporate bonds, stocks, and money market instruments for the period 1/1/2011 – 31/3/2019, in Israel. For each fund class, we implement a univariate EGARCH(1,1) model in order to uncover the influence of tone (net, positive, and negative) on net flows, inflows, and outflows of these fund classes. We find that tone of print media has a significant positive (negative) impact on the conditional means (variances) of fund net flows for risky classes (government bonds, corporate bonds, and stocks). In contrast, net flows to the safe fund class i.e., money market instruments, behave like a mirror image to the other three classes. Thus, this can be considered a 'flight to liquidity' class. Using a quantile regression, we also find that tone has a non-linear impact on flows. Such non-linearity is reflected by tone's coefficients, which are significant only for extreme negative net flows and outflows.

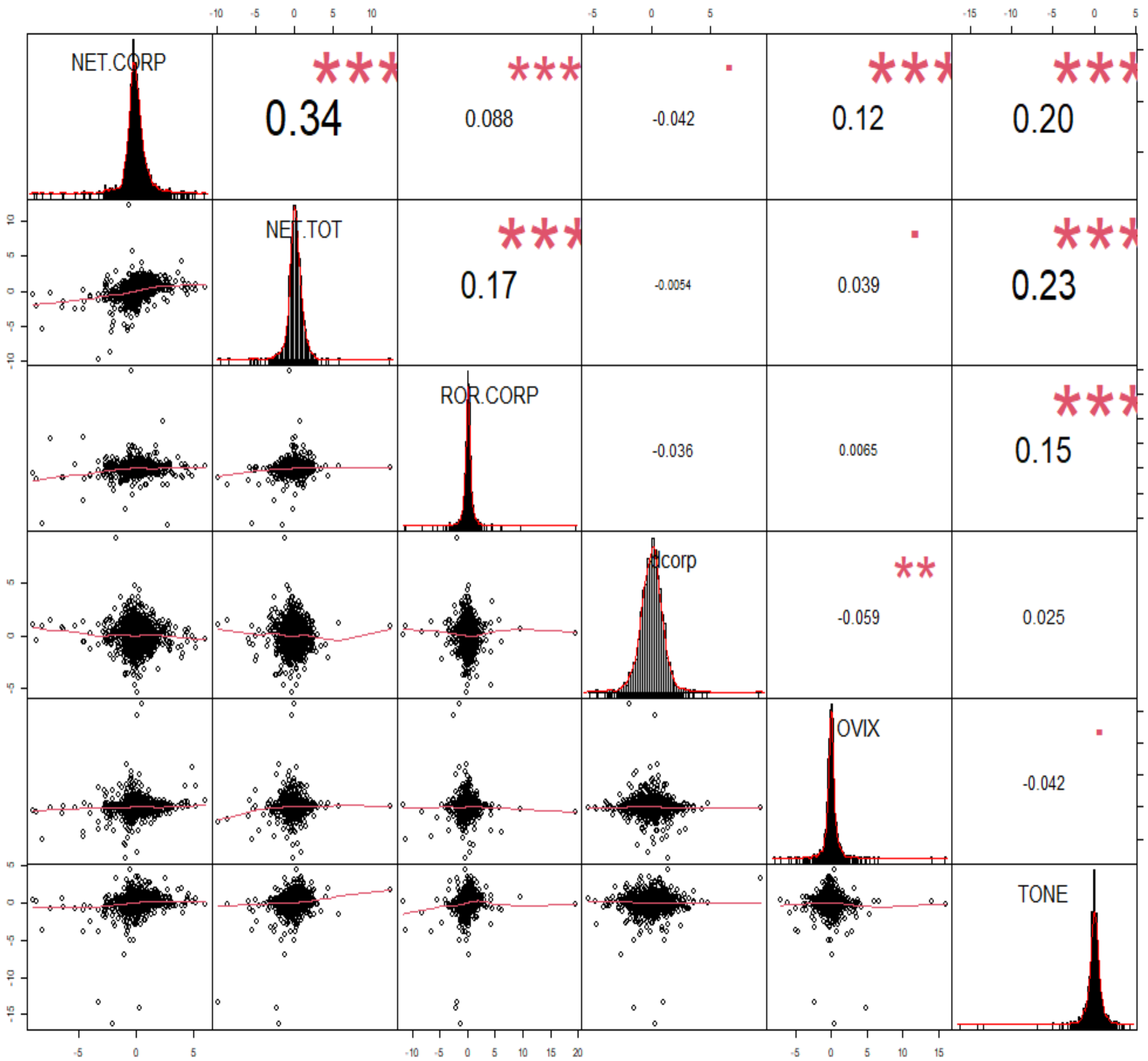
For each fund class, we further implement a bivariate VAR-GARCH model with diagonal BEKK representation to examine the tone's influence on both inflows and outflows in a system. Such an examination enables us to distinguish between movements within each class (return chasing) and movements from one class to another (changes in investors' revealed preferences). The former is important to investors, while the latter is of interest to financial stability supervisors. We find movements from risky funds such as corporate bond and stock classes to the safe class of money market instrument i.e., selling corporate bonds and stocks yesterday is followed by buying money market instruments today (flight to liquidity). Additionally, we find a movement from the government bonds class to corporate bond and stock classes (risk taking) and vice-versa (risk attenuation). The results are robust to various definitions of tone, but sensitive to different frequencies, tone lags, and outliers.

Figure 1: Correlation coefficients of net flows to GOVERNMENT bond funds and other related variables



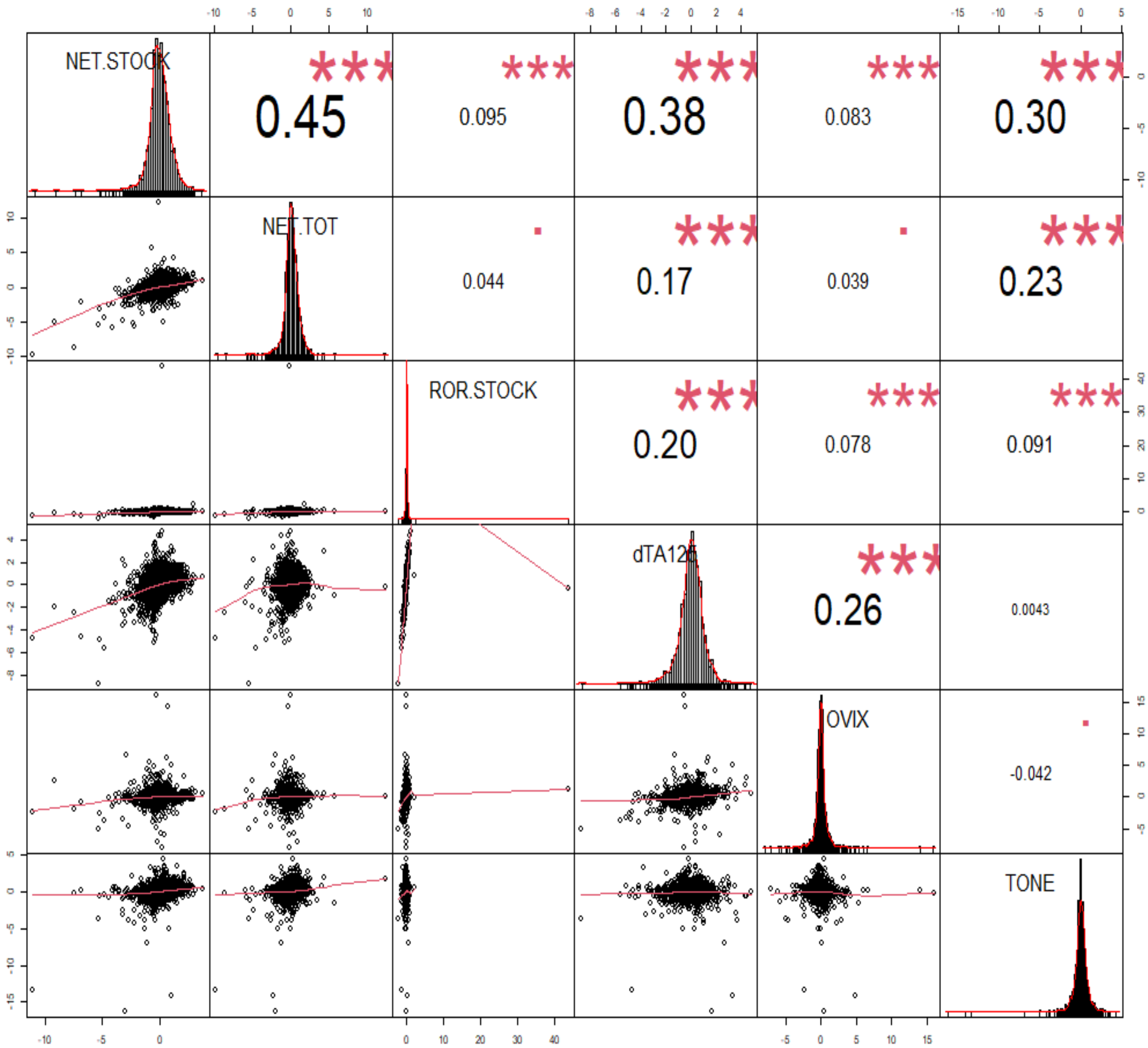
The figure depicts pairwise correlation coefficients between net flow to government bond funds' class, net flows to all funds including non specialized ones (NET.TOT), rate of return on government bond funds (ROR.GOV), changes of governmental bond index (dgov), changes in overnight Israeli VIX (OVIX, from today open to yesterday close), and tone. The lower triangle presents bi-variate distribution for each pair and a cubic spline line (in red). All data are daily for the period 1/2011 - 3/2019 (2021 daily observations). ***, **, and * denote 0.01, 0.05, and 0.1 significance level, respectively.

Figure 2: Correlation coefficients of net flows to CORPORTAE bond funds and other related variables



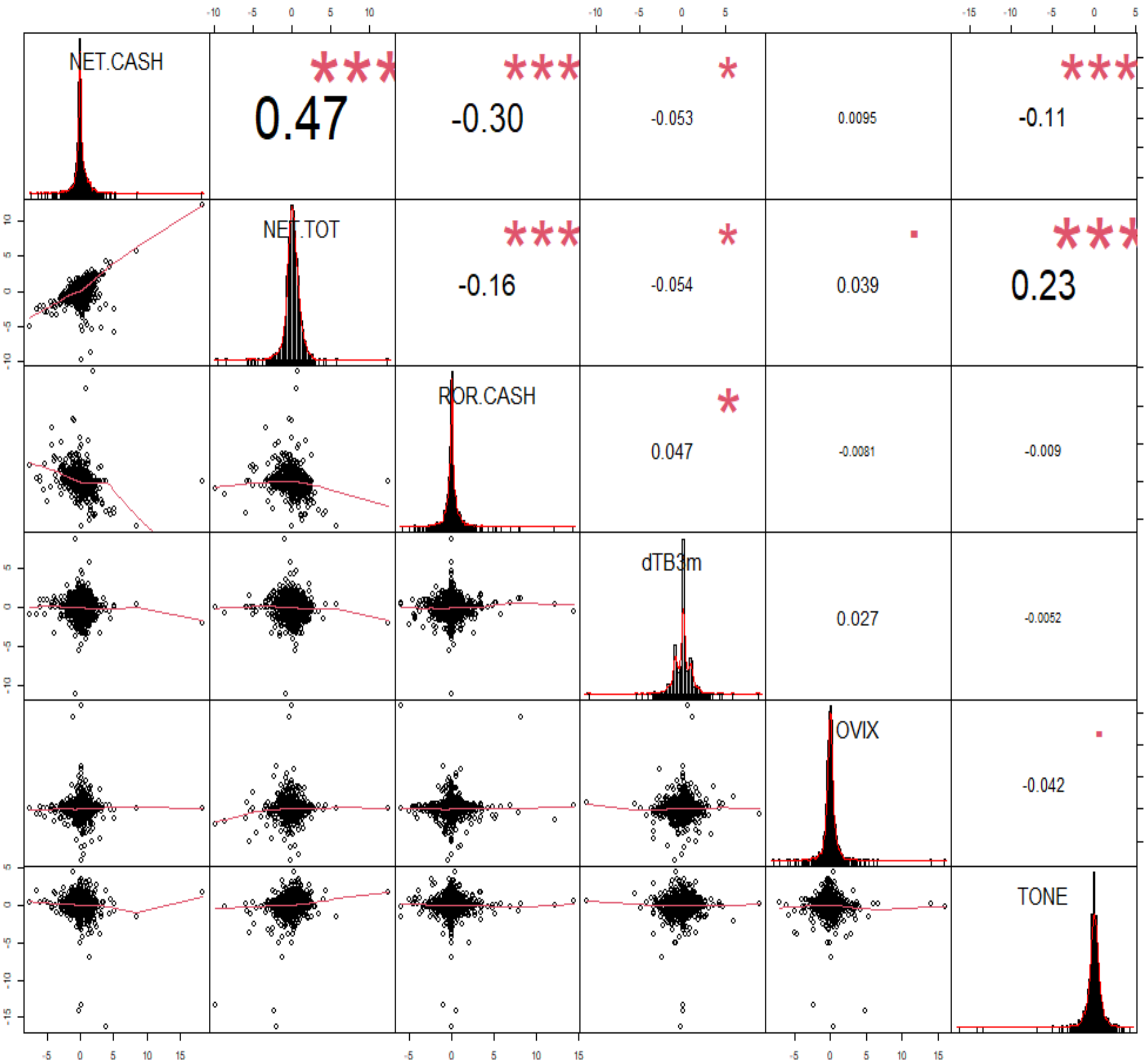
The figure depicts pairwise correlation coefficients between net flow to corporate bond funds' class, net flows to all funds including non specialized ones (NET.TOT), rate of return on corporate bond funds (ROR.CORP), changes of governmental bond index (dgov), changes in overnight Israeli VIX (OVIX, from today open to yesterday close), and tone. The lower triangle presents bi-variate distribution for each pair and a cubic spline line (in red). All data are daily for the period 1/2011 - 3/2019 (2021 daily observations). ***, **, and * denote 0.01, 0.05, and 0.1 significance level, respectively.

Figure 3: Correlation coefficients of net flows to STOCK funds and other related variables



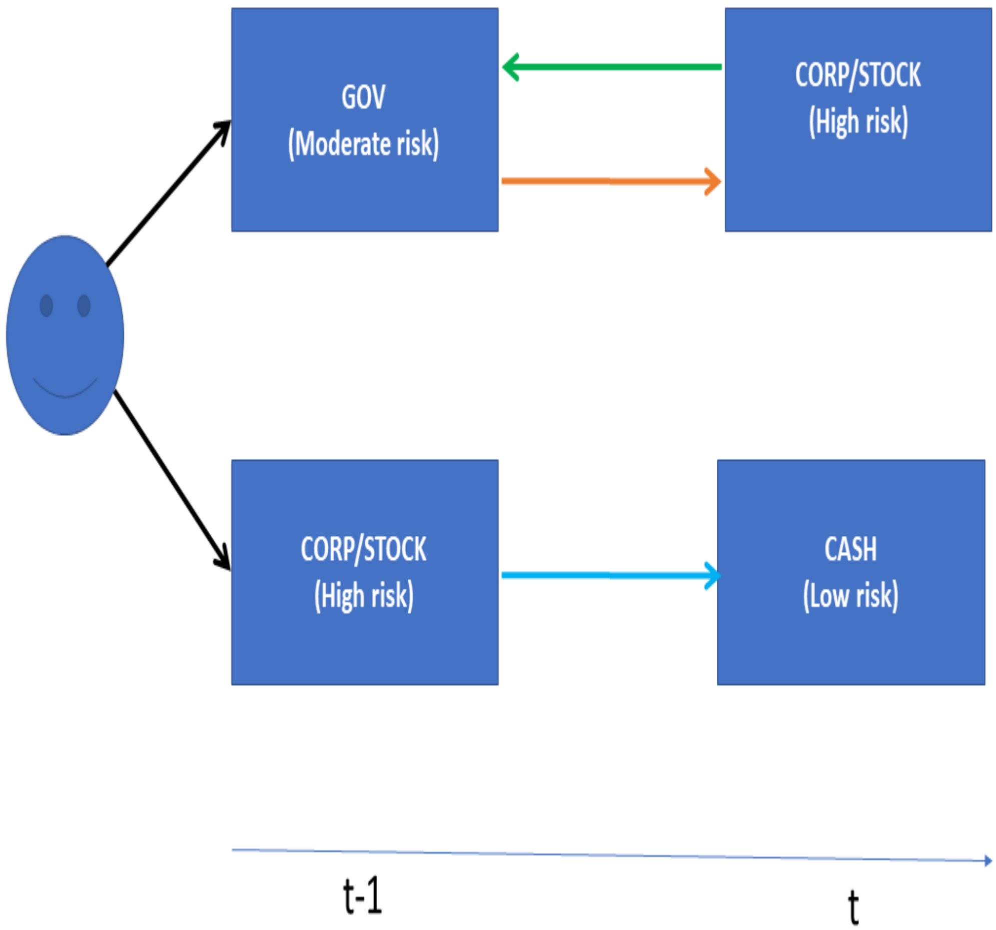
The figure depicts pairwise correlation coefficients between net flow to stock funds' class, net flows to all funds including non specialized ones (NET.TOT), rate of return on stock bond funds (ROR.STOCK), rate of return on the Tel-Aviv 125 stock index (dTA125), changes in overnight Israeli VIX (OVIX, from today open to yesterday close), and tone. The lower triangle presents bi-variate distribution for each pair and a cubic spline line (in red). All data are daily for the period 1/2011 - 3/2019 (2021 daily observations). ***, **, and * denote 0.01, 0.05, and 0.1 significance level, respectively.

Figure 4: Correlation coefficients of net flows to CASH funds and other related variables



The figure depicts pairwise correlation coefficients between net flow to money market (CASH) funds' class, net flows to all funds including non specialized ones (NET.TOT), rate of return on money market funds (ROR.CASH), changes in 3 month Makam (dTB3m, similar to 3 month T-bills), changes in overnight Israeli VIX (OVIX, from today open to yesterday close), and tone. The lower triangle presents bi-variate distribution for each pair and a cubic spline line (in red). All data are daily for the period 1/2011 - 3/2019 (2021 daily observations). ***, **, and * denote 0.01, 0.05, and 0.1 significance level, respectively.

Figure 5: BiVariate VAR-GARCH(1,1)-BEKK: Movements between classes - summary



The figure draws movements between the four classes. CASH is the lower risk (safe) class, GOV is characterized by moderate risk while CORP and STOCK are the high risk classes. The arrows are determined by the Inflows/Outflows model of BiVariate VAR-GARCH(1,1) with BEKK representaion (see Table IX) in which outflows coefficients are positive and significant in the Inflows equation and inflows coefficients are positive and significant in the Outflows equation.

Table I: **Basic statistics of the main variables**

	Mean	Median	Max	Min	Std	COV
Panel A: Net flows (ILS, million)						
NET.GOV	3.233	0.287	206.548	-396.214	45.060	7.17
NET.CORP	0.024	-0.185	32.361	-48.331	5.387	0.45
NET.STOCK	1.670	1.694	74.448	-215.211	19.578	8.53
NET.CASH	-4.249	-14.232	2815.336	-1164.997	154.539	-2.75
NET.TOT	21.836	21.916	2736.512	-2140.335	220.612	9.90
Panel B: Out flows (ILS, million)						
OUT.GOV	41.705	32.147	443.004	4.882	32.866	126.89
OUT.CORP	4.978	3.990	55.813	0.572	4.110	121.12
OUT.STOCK	33.057	29.552	300.793	4.210	20.820	158.78
OUT.CASH	149.927	115.051	1314.005	8.533	138.390	108.34
OUT.TOT	713.441	659.265	3827.693	123.204	303.009	235.45
Panel C: In flows (ILS, million)						
IN.GOV	44.938	31.903	251.079	3.650	38.114	117.90
IN.CORP	5.002	3.846	37.463	0.123	4.273	117.06
IN.STOCK	34.727	32.172	135.297	1.828	21.876	158.74
IN.CASH	145.678	104.956	3022.805	6.713	158.414	91.96
IN.TOT	735.277	704.189	3246.387	173.638	290.301	253.28
Panel D: Fund performance (ROR, %)						
ROR.GOV	-0.019	0.010	1.919	-45.813	1.097	0.00
ROR.CORP	0.015	0.015	7.719	-4.571	0.395	0.00
ROR.STOCK	0.083	0.044	136.655	-6.528	3.129	3.23
ROR.CASH	0.009	0.007	4.866	-1.991	0.337	0.00
ROR.TOT	0.029	0.016	19.415	-1.556	0.503	0.00
Panel E: BenchMark Return (ROR, %)						
dgov	0.015	0.020	0.917	-0.795	0.139	10.79
dcorp	0.014	0.020	1.394	-0.776	0.149	9.40
dTA125	0.007	0.051	4.092	-7.471	0.856	0.82
dTB3m	-0.001	0.001	0.381	-0.477	0.043	-2.33
dTOT	0.009	0.018	0.967	-1.912	0.216	4.17
Panel F: The tone (ILS, million)						
TONE	0.001	0.004	0.332	-1.234	0.076	1.32
NEG	0.028	0.014	1.234	0.000	0.060	46.67
POS	0.029	0.019	0.334	0.000	0.038	76.32
TONE.ECON	0.020	0.015	0.237	-0.746	0.044	45.45
TONE.GEN	-0.019	-0.009	0.175	-0.704	0.041	-46.34

This table presents basic statistic of the main variables. COV (coefficient Of Variation) is defined as Mean/Std in percent. Out and In are daily flows (in millions of shekels) from and to mutual funds' class, respectively. Net = In - Out is the daily net flows of the fund classes (Government bonds (GOV), corporate bonds (CORP), stocks (STOCK), money markets instruments (CASH), and all funds including non specialized ones but except ETFs (TOT). Performance (ROR) is measured as: $\frac{TNA_t^f - Net_t^f}{TNA_{t-1}^f} - 1$ (in percent) where, TNA_t^f is the aggregate net asset value (NAV, before commissions and fees) of class f at day t where, f $\in (GOV, CORP, STOCK, CASH, TOT)$. Panel E presents statistics on the various fund benchmark returns: 'dgov' and 'dcorp' are daily rate of return (ROR) of the government and corporate indexes, respectively, 'dTA125' is the ROR on the Tel-Aviv 125 stock index, 'dTB3m' is the changes in the 3 month 'Makam' (similar to the T-bills) yield, and 'dTOT' is the simple mean of all other class' benchmarks. In Panel F, TONE = POS - NEG is the equivalent value of positive (POS) - negative (NEG) newspapers article monetary equivalent (in millions of shekels) derived from All newspapers. TONE.ECON and TONE.GEN are tones derived from Business newspapers (Globes, TheMarker, Calcalist), and General newspapers (Yedioth Ahronoth, Ma'ariv, Israel Hayom), respectively. The data sample span the period 1/2011 - 3/2019 (2021 daily observations).

Table II: EGARCH(1,1) regression results: Net flows to mutual funds by class and tone

	GOV	CORP	STOCK	CASH	TOT
Mean equation					
μ	-0.012***	-0.029***	-0.02***	0	0.015***
ROR_{t-1}	0	0.155***	0.009***	0.116***	0.006
NET_{t-1}	0.935***	0.527***	0.709***	0.525***	0.721***
BM_{t-1}	0.047***	-0.003	-0.045***	0.007***	0.058***
ALL_{t-1}	0.002	0.013	-0.019***	0.118***	-0.124***
$OVIX_t$	0.008**	0.111***	0.098***	0.021***	0.112***
$Sunday$	-0.02	-0.008	-0.01	-0.062***	-0.258***
$TONE_t$	0.016***	0.019*	0.108***	-0.018***	0.033**
Variance equation					
ω	-0.083***	0.013***	-0.19***	0.012***	-0.043*
α	-0.059***	0.007	-0.175***	0.067***	0.014
β	0.949***	0.997***	0.695***	0.998***	0.862***
γ	0.439***	0.15***	0.319***	0.09***	0.663***
$TONE_t$	-0.042***	-0.026***	-0.074***	0.017***	-0.068***
Goodness of fit					
AIC	0.454	1.936	2.114	1.576	1.984
BIC	0.493	1.975	2.153	1.615	2.023
Liklihood	-408.863	-1785.525	-1950.858	-1451.522	-1830.158

This table presents results of an EGARCH(1,1) model explaining the various (aggregate) net flows by class at date t (NET_t). The conditional Mean and Variance equations are as follows:
$Mean^f: \quad NET_t = \mu + ROR_{t-1} + NET_{t-1} + BM_{t-1} + ALL_{t-1} + OVIX_t + Sunday + TONE_t + \epsilon_t,$
$Variance^f: \quad log(\sigma_t^2) = \omega + \alpha|\frac{\epsilon_{t-1}}{\sigma_{t-1}}| + \beta log(\sigma_{t-1}^2) + \gamma\frac{\epsilon_{t-1}}{\sigma_{t-1}} + TONE_t$
The fund classes (f) are categorized in this study as: Government bonds (GOV), corporate bonds (CORP), equity (STOCK), and money market instruments (CASH). TOT is the total net flows of all funds including non specialized (general) funds but excluding ETFs (TOT). Each mean equation consists of (except the intercept), a self fund's rate of return (ROR) in an one day lag, net flows to the fund's class in a lag (NET_{t-1}), net flows to all specialized funds in a lag (ALL_{t-1}), return on an one day lag benchmark investment (BM, change rates of government and corporate bond indexes for GOV and CORP, respectively, rate of return on TA125 for STOCK, and changes in 3 month Makam (similar to T-bills) yield for CASH), changes in the Israeli overnight VIX (OVIX, from today open to yesterday close) in order to control for shocks that occurred after the newspapers printing), a dummy for Sundays, in which trading volumes are thinner, and tone (TONE, published before the market opening). In the variance equation the only external regressor is tone (TONE). In the lower panel the following goodness of fit measures are presented: Akaike information criterion (AIC), Bayesian information criterion (BIS), and Log likelihoods. All data are daily and standardized for the period 1/2011 - 3/2019 (2021 daily observations). ***, **, and * denote 0.01, 0.05, and 0.1 significance level, respectively.

Table III: EGARCH(1,1) regression results: Net flows to mutual funds by class with Negative versus Positive tones

	GOV	CORP	STOCK	CASH	TOT
Mean equation					
μ	-0.016***	-0.034	-0.019	0.007*	0.02
ROR_{t-1}	0	0.152	0.009***	0.117***	0.005
NET_{t-1}	0.93***	0.547	0.707***	0.506***	0.743***
BM_{t-1}	0.045***	-0.002	-0.044**	0.008	0.059**
ALL_{t-1}	0.002	0.006	-0.02	0.169***	-0.137***
$OVIX_t$	0.009**	0.102	0.098***	0.023***	0.096***
$Sunday$	-0.014	0.016	-0.009	-0.072***	-0.26***
POS_t	0.012**	0.015	0.059***	-0.019***	0.007
NEG_t	-0.01*	-0.007	-0.078***	0.009	-0.035
Variance equation					
ω	-0.085***	0.015***	-0.183***	0.01***	-0.091***
α	-0.059***	0.016	-0.166***	0.066***	0.01
β	0.948***	0.999***	0.705***	1***	0.809***
γ	0.44***	0.169***	0.326***	0.061***	0.682***
POS_t	-0.005	-0.058***	-0.062**	-0.005	0.06**
NEG_t	0.043***	0.004	0.047**	-0.023***	0.124***
Goodness of fit					
AIC	0.456	1.908	2.116	1.571	1.975
BIC	0.501	1.952	2.16	1.615	2.02
Liklihood	-408.532	-1756.436	-1949.26	-1443.468	-1818.905

This table presents results of an EGARCH(1,1) model explaining the various classes' net flows at date t (NET_t). The conditional Mean and Variance equations are as follows:

$Mean^f: \quad NET_t = \mu + ROR_{t-1} + NET_{t-1} + BM_{t-1} + ALL_{t-1} + OVIX_t + Sunday + POS_t + NEG_t + \epsilon_t,$

$Variance^f: \quad log(\sigma_t^2) = \omega + \alpha|\frac{\epsilon_{t-1}}{\sigma_{t-1}}| + \beta log(\sigma_{t-1}^2) + \gamma\frac{\epsilon_{t-1}}{\sigma_{t-1}} + POS_t + NEG_t$

The fund classes (f) are categorized in this study as: Government bonds (GOV), corporate bonds (CORP), equity (STOCK), money market (CASH), and all funds including non specialized (general) funds but excluding ETFs (TOT). Each mean equation consists of (except the intercept), a self fund's rate of return (ROR) in an one day lag, net flows to the fund's class in lag (NET_{t-1}), net flows to all specialized funds in lag (ALL_{t-1}), return on an one day lag benchmark investment (BM, changes in government and corporate bond indexes for GOV and CORP, respectively, rate of return on TA125 stock index for STOCK, and changes in 3 month Makam yield for CASH), changes in the Israeli overnight VIX (OVIX, from today open to yesterday close) in order to control for shock that occurred after the newspapers printing), a dummy for Sundays, in which trading volumes are thinner, and tone (positive (POS) and negative (NEG) tones, published before the market opening). In the variance equation the only external regressors are positive (POS) and negative (NEG) tones. In the lower panel the following goodness of fit measures are presented: Akaike information criterion (AIC), Bayesian information criterion (BIS), and Log likelihoods. All data are daily and standardized for the period 1/2011 - 3/2019 (2021 daily observations). ***, **, and * denote 0.01, 0.05, and 0.1 significance level, respectively.

Table IV: Quantile regression results: Net flows to funds by class and tone derived from all newspapers

	τ=0.05	τ=0.1	τ=0.2	τ=0.5	τ=0.8	τ=0.9	τ=0.95
Government bonds (GOV)							
Intercept	-0.56^{***}	-0.38^{***}	-0.21^{***}	0	0.18^{***}	0.34^{***}	0.57^{***}
ROR_{t-1}	0.23	0.13	0.09	0	0	0.01	0.02
NET_{t-1}	0.85^{***}	0.84^{***}	0.87^{***}	0.93^{***}	0.95^{***}	0.94^{***}	0.91^{***}
BM_{t-1}	0.12^{***}	0.09^{***}	0.06^{***}	0.05^{***}	0.05^{***}	0.05^{**}	0.08^{**}
ALL_{t-1}	0.02	0.02	0.01	-0.01	-0.01	-0.02	-0.04^{*}
$OVIX_t$	0.03^{*}	0.02	0.01	0.01	0.01	0.02	0.06^{*}
$Sunday$	0.01	0.03	0.01	0.01	0.03	0.07	0.01
$TONE_t$	0.14^{***}	0.08^{***}	0.04^{**}	0.01	-0.01	-0.02	-0.05
Corporate bonds (CORP)							
Intercept	-0.99^{***}	-0.63^{***}	-0.39^{***}	-0.01	0.42^{***}	0.69^{***}	1.07^{***}
ROR_{t-1}	0.22^{***}	0.16^{***}	0.15^{***}	0.12^{***}	0.1^{***}	0.05	0.02
NET_{t-1}	0.56^{***}	0.54^{***}	0.52^{***}	0.58^{***}	0.6^{***}	0.57^{***}	0.57^{***}
BM_{t-1}	0.05	-0.01	-0.01	-0.02	-0.02	0.01	0
ALL_{t-1}	-0.05	-0.03	-0.02	0.01	0.07^{***}	0.1^{***}	0.11^{**}
$OVIX_t$	0.14^{***}	0.12^{***}	0.1^{***}	0.09^{***}	0.07^{***}	0.08^{*}	0.16^{**}
$Sunday$	-0.13	-0.08	-0.04	0	0.01	-0.01	0.03
$TONE_t$	0.18^{***}	0.09^{**}	0.06^{**}	-0.01	-0.04	-0.08	-0.08
Stocks (STOCK)							
Intercept	-1.13^{***}	-0.74^{***}	-0.44^{***}	-0.02	0.48^{***}	0.83^{***}	1.18^{***}
ROR_{t-1}	0.04	0.03	0.02	0.01	0	-0.01	-0.02
NET_{t-1}	0.72^{***}	0.69^{***}	0.64^{***}	0.63^{***}	0.56^{***}	0.55^{***}	0.5^{***}
BM_{t-1}	0.06	0.06	0.03	-0.01	-0.05	-0.01	-0.03
ALL_{t-1}	0.01	0.04	0	-0.01	-0.03	-0.05^{*}	-0.03
$OVIX_t$	0.09	0.13^{**}	0.11^{***}	0.08^{***}	0.12^{***}	0.13^{**}	0.12
$Sunday$	0.14	0.15	0.13^{***}	0.04	-0.07	-0.17^{**}	-0.23^{**}
$TONE_t$	0.25^{*}	0.11	0.07^{*}	0.06^{**}	0.07	0.07	0.09
Money markets (CASH)							
Intercept	-0.95^{***}	-0.59^{***}	-0.31^{***}	-0.02^{**}	0.34^{***}	0.7^{***}	1.24^{***}
ROR_{t-1}	0.14^{***}	0.12^{***}	0.12^{***}	0.13^{***}	0.13^{***}	0.19^{***}	0.18^{***}
NET_{t-1}	1.25^{***}	1.07^{***}	0.89^{***}	0.62^{***}	0.6^{***}	0.58^{***}	0.43^{**}
BM_{t-1}	0.02	0.05	0.02	0	0.05	0.02	0.09^{**}
ALL_{t-1}	-0.79^{***}	-0.6^{***}	-0.39^{***}	-0.04	0	0.03	0.09
$OVIX_t$	-0.09	-0.06^{**}	-0.03	0	0.02	0.04	0
$Sunday$	-0.18	-0.07	-0.07	-0.05^{***}	-0.13^{**}	-0.18^{*}	-0.26^{**}
$TONE_t$	0.03	-0.01	-0.03	-0.03^{**}	-0.11^{***}	-0.12^{***}	-0.1^{*}
All funds (TOT)							
Intercept	-0.98^{***}	-0.65^{***}	-0.37^{***}	0.03^{*}	0.46^{***}	0.75^{***}	1.19^{***}
ROR_{t-1}	0.03	0.02	0.01	0.1	0.15	0.07	0.12
NET_{t-1}	0.94^{***}	0.86^{***}	0.84^{***}	0.74^{***}	0.65^{***}	0.6^{***}	0.54^{***}
BM_{t-1}	0.14	0.05	0.06	0	0	0.03	-0.03
ALL_{t-1}	-0.33^{***}	-0.26^{***}	-0.25^{***}	-0.13^{***}	-0.06	-0.04	-0.12
$OVIX_t$	0.15^{*}	0.11^{**}	0.07^{*}	0.06^{***}	0.08^{***}	0.07	0.02
$Sunday$	-0.42	-0.13	-0.12^{***}	-0.19^{***}	-0.23^{***}	-0.27^{***}	-0.41^{***}
$TONE_t$	0.14	0.09	0	0.01	-0.01	-0.05	0

The table depicts quantile regression results explaining various classes' net flows, along the flows distribution, at date t (NET_t):
$NET_t = \mu + ROR_{t-1} + NET_{t-1} + BM_{t-1} + ALL_{t-1} + OVIX_t + Sunday + TONE_t + \epsilon_t$.
Each equation contains the very same variables as earlier tables (for a description of the variables see Table II for instance). The daily data are standardized for the period 1/2011 - 3/2019 (2021 daily observations). ***, **, and * denote 0.01, 0.05, and 0.1 significance level, respectively.

Table V: Quantile regression results: Net flows to funds by class and Negative versus Positive tones derived from all newspapers

	τ=0.05	τ=0.1	τ=0.2	τ=0.5	τ=0.8	τ=0.9	τ=0.95
Government bonds (GOV)							
μ	−0.56***	−0.39***	−0.21***	0	0.18***	0.34***	0.56***
ROR_{t-1}	0.12	0.19	0.09	0	0	0.01	0.01
NET_{t-1}	0.85***	0.84***	0.87***	0.92***	0.95***	0.95***	0.94***
BM_{t-1}	0.13***	0.09***	0.06***	0.05***	0.06***	0.05**	0.06*
ALL_{t-1}	0.02	0.04*	0.02	-0.01	-0.01	-0.02	−0.03*
$OVIX_t$	0.01	0.02	0.02	0.01	0.01	0.01	0.06*
$Sunday$	-0.02	0.01	0	0.01	0.06	0.09**	0.02
POS_t	0	0.01	0.01	0.01*	0.03**	0.04***	0.02
NEG_t	−0.2***	−0.17***	-0.06	0	0.03	0.1*	0.13**
Corporate bonds (CORP)							
μ	−1***	−0.67***	−0.39***	-0.01	0.42***	0.69***	1.07***
ROR_{t-1}	0.2***	0.13***	0.15***	0.12***	0.11***	0.07	0.09*
NET_{t-1}	0.57***	0.55***	0.53***	0.58***	0.61***	0.55***	0.56***
BM_{t-1}	0.05	-0.02	-0.01	-0.02	-0.02	0	0
ALL_{t-1}	-0.06	-0.01	-0.02	0.01	0.07***	0.11***	0.11**
$OVIX_t$	0.14***	0.12***	0.1***	0.09***	0.07***	0.07**	0.17**
$Sunday$	-0.19	-0.11	-0.06	0.01	0.01	0.03	0.1
POS_t	0	0.01	0.01	0	0.04	0.11**	0.12*
NEG_t	−0.44***	−0.3***	−0.09**	0.03	0.11**	0.12**	0.17
Stocks (STOCK)							
μ	−1.14***	−0.74***	−0.44***	-0.02	0.46***	0.83***	1.17***
ROR_{t-1}	0.03	0.03	0.02	0.01	0	-0.01	-0.01
NET_{t-1}	0.73***	0.68***	0.64***	0.62***	0.6***	0.56***	0.54***
BM_{t-1}	0.09	0.05	0.03	0	-0.05	-0.01	-0.12
ALL_{t-1}	0	0.04	0	-0.02	-0.03	-0.01	-0.05
$OVIX_t$	0.08	0.11*	0.11***	0.08***	0.14***	0.15***	0.15**
$Sunday$	0.13	0.12	0.13***	0.03	0.03	−0.13*	-0.11
POS_t	-0.04	0.05	0.03	0.06***	0.12***	0.13***	0.16***
NEG_t	−0.33**	-0.18	-0.06	0	0.05	0.11	0.13
Money markets (CASH)							
μ	−0.95***	−0.59***	−0.31***	−0.02**	0.34***	0.7***	1.21***
ROR_{t-1}	0.15***	0.12***	0.12***	0.13***	0.13***	0.17***	0.17***
NET_{t-1}	1.3***	1.1***	0.89***	0.61***	0.54***	0.53***	0.29*
BM_{t-1}	0.03	0.04	0.02	0	0.04	0.05	0.11***
ALL_{t-1}	−0.84***	−0.6***	−0.38***	-0.03	0.06	0.03	0.25
$OVIX_t$	-0.07	-0.05	-0.03	0	0	0.04	0
$Sunday$	-0.15	-0.08	−0.09**	−0.04**	−0.11**	-0.03	−0.25*
POS_t	-0.08	−0.08**	−0.04**	-0.01	0.03	0.08*	0.03
NEG_t	-0.04	-0.04	0	0.02	0.15***	0.21***	0.24***
All funds (TOT)							
μ	−0.98***	−0.65***	−0.37***	0.03**	0.45***	0.76***	1.13***
ROR_{t-1}	0.03	0.02	0.01	0.1	0.16	0.05	0.24
NET_{t-1}	0.91***	0.86***	0.85***	0.76***	0.64***	0.6***	0.55***
BM_{t-1}	0.12	0.05	0.06	0	0.02	0.04	-0.02
ALL_{t-1}	−0.3***	−0.27***	−0.25***	−0.14***	-0.04	-0.07	-0.07
$OVIX_t$	0.14*	0.11**	0.07**	0.06***	0.08***	0.06	0.02
$Sunday$	−0.42*	-0.14	−0.12***	−0.19***	−0.22***	−0.22**	−0.32**
POS_t	-0.08	0.01	0.01	0.03*	0.04	0.11**	0.11*
NEG_t	−0.33**	-0.13	0	0.04	0.09	0.08	0.11

The table depicts quantile regression results explaining various classes' net flows, along the flows distribution, at date t (NET_t):
$NET_t = \mu + ROR_{t-1} + NET_{t-1} + BM_{t-1} + ALL_{t-1} + OVIX_t + Sunday + POS_t + NEG_t + \epsilon_t$.
Each equation contains the very same variables as previous tables (for a description of the variables see Table III). The daily data are standardized for the period 1/2011 - 3/2019 (2021 daily observations). ***, **, and * denote 0.01, 0.05, and 0.1 significance level, respectively.

Table VI: EGARCH(1,1) regression results: Net flows to mutual funds by class using tone derived from Business newspapers only

	GOV	CORP	STOCK	CASH	TOT
Mean equation					
μ	-0.014	-0.032***	-0.037***	-0.002***	0.024***
ROR_{t-1}	0	0.155***	0.01***	0.116***	0.005
NET_{t-1}	0.931***	0.537***	0.71***	0.544***	0.758***
BM_{t-1}	0.049***	-0.003	-0.03**	0.008***	0.067***
ALL_{t-1}	0.002	0.008	-0.017	0.085***	-0.158***
$OVIX_t$	0.01**	0.105***	0.088***	0.02***	0.115***
$Sunday$	-0.016	0.009	0.014	-0.064***	-0.262***
$TONE_t$	0.011	0.023*	0.091***	-0.018***	-0.003**
Variance equation					
ω	-0.076***	0.012***	-0.177***	0.013***	-0.056**
α	-0.067***	0.014**	-0.169***	0.067***	0.031
β	0.952***	0.996***	0.705***	0.997***	0.846***
γ	0.434***	0.156***	0.33***	0.098***	0.694***
$TONE_t$	-0.014	-0.038***	-0.08***	0.014***	-0.109***
Goodness of fit					
AIC	0.462	1.928	2.117	1.577	1.982
BIC	0.501	1.967	2.155	1.615	2.02
Liklihood	-415.909	-1777.429	-1952.352	-1451.034	-1826.833

This table presents results of an EGARCH(1,1) model explaining the various classes' net flows at date t (NET_t) with tones derived from business (professional) newspapers, only. The conditional Mean and Variance equations are as follows:

$Mean^f: \quad NET_t = \mu + ROR_{t-1} + NET_{t-1} + BM_{t-1} + ALL_{t-1} + VIX_{t-1} + Sunday + TONE_t + \epsilon_t,$

$Variance^f: \quad log(\sigma_t^2) = \omega + \alpha|\frac{\epsilon_{t-1}}{\sigma_{t-1}}| + \beta log(\sigma_{t-1}^2) + \gamma\frac{\epsilon_{t-1}}{\sigma_{t-1}} + TONE_t$

The fund classes (f) are categorized as: Government bonds (CASH). Each mean equation consists of (except the intercept), a self fund's rate of return (ROR) in an one day lag, net flows to the fund's class in a lag (NET_{t-1}), net flows to all specialized funds in a lag (ALL_{t-1}), rate of return on an one day lag benchmark investment (BM, see details in Table II), a dummy for Sundays, in which trading volumes are thinner, and tone (TONE, published before the market opening). In the variance equation the only external regressor is tone (TONE). In the lower panel the following goodness of fit measures are presented: Akaike information criterion (AIC), Bayesian information criterion (BIS), and Log likelihoods. All data are daily and standardized for the period 1/2011 - 3/2019. ***, **, and * denote 0.01, 0.05, and 0.1 significance level, respectively.

Table VII: Quantile regression results: Net flows to funds by class and tone derived from Business newspapers only

	τ=0.05	τ=0.1	τ=0.2	τ=0.5	τ=0.8	τ=0.9	τ=0.95
Government bonds (GOV)							
Intercept	-0.55^{***}	-0.37^{***}	-0.2^{***}	0	0.18^{***}	0.33^{***}	0.55^{***}
ROR_{t-1}	0.3	0.19	0.08	0	0	0.01	0.01
NET_{t-1}	0.86^{***}	0.85^{***}	0.87^{***}	0.92^{***}	0.95^{***}	0.93^{***}	0.91^{***}
BM_{t-1}	0.11^{***}	0.1^{***}	0.06^{***}	0.05^{***}	0.05^{**}	0.05^{***}	0.06
ALL_{t-1}	0.03	0.03	0.02	0	-0.01	-0.02	-0.03
$OVIX_t$	-0.06^{***}	-0.04^{***}	-0.03^{***}	-0.01	-0.02^{**}	-0.02^{**}	-0.04
$Sunday$	0.01	0.02	0	0.01	0.04	0.09	0.03
$TONE_t$	0.05	0.04	0.02	0	0	0	-0.01
Corporate bonds (CORP)							
Intercept	-0.98^{***}	-0.63^{***}	-0.38^{***}	-0.02	0.4^{***}	0.7^{***}	1.01^{***}
ROR_{t-1}	0.21^{***}	0.14^{***}	0.14^{***}	0.12^{***}	0.09^{**}	0.05	0.04
NET_{t-1}	0.58^{***}	0.54^{***}	0.53^{***}	0.59^{***}	0.6^{***}	0.54^{***}	0.53^{***}
BM_{t-1}	-0.07^{***}	-0.03	-0.02	0	0.04	0.06	0.09^{*}
ALL_{t-1}	-0.12^{**}	-0.05	-0.04^{*}	0.01	0.08^{***}	0.1^{***}	0.12^{**}
$OVIX_t$	-0.06	-0.06	-0.07	-0.08^{***}	-0.09^{*}	-0.03	0.01
$Sunday$	-0.2	-0.05	-0.01	0.02	0.02	-0.05	0.01
$TONE_t$	0.06	0.07^{*}	0.03	-0.01	-0.01	-0.05	-0.04
Stocks (STOCK)							
Intercept	-1.11^{***}	-0.75^{***}	-0.45^{***}	-0.02	0.48^{***}	0.83^{***}	1.2^{***}
ROR_{t-1}	0.03	0.03	0.02	0.01	0	-0.01	-0.02
NET_{t-1}	0.73^{***}	0.69^{***}	0.63^{***}	0.63^{***}	0.55^{***}	0.55^{***}	0.51^{***}
BM_{t-1}	0.08	0.07	0.03	-0.02	-0.06	0	-0.08
ALL_{t-1}	0	-0.01	-0.01	-0.02	-0.02	-0.03	-0.03
$OVIX_t$	-0.2^{***}	-0.18^{***}	-0.12^{***}	-0.09^{***}	-0.06	-0.05	-0.05
$Sunday$	0.25	0.16	0.15^{***}	0.04	-0.06	-0.16^{**}	-0.34^{***}
$TONE_t$	0.07	0.03	0.02	0.05^{**}	0.08^{**}	0.06	0.09
Money markets (CASH)							
Intercept	-0.98^{***}	-0.58^{***}	-0.31^{***}	-0.02^{**}	0.34^{***}	0.73^{***}	1.24^{***}
ROR_{t-1}	0.14^{***}	0.11^{***}	0.12^{***}	0.12^{***}	0.14^{***}	0.16^{***}	0.21^{***}
NET_{t-1}	1.18^{***}	1.09^{***}	0.89^{***}	0.63^{***}	0.58^{***}	0.56^{***}	0.46^{***}
BM_{t-1}	0.01	0.02	0.02	0	0.04	0.02	0.08^{**}
ALL_{t-1}	-0.72^{***}	-0.61^{***}	-0.38^{***}	-0.05	0.02	0.02	0.08
$OVIX_t$	-0.06	-0.04	-0.03	0.01	0.03	0.04	-0.01
$Sunday$	-0.15	-0.08	-0.08	-0.05^{***}	-0.14^{**}	-0.18^{*}	-0.25^{**}
$TONE_t$	-0.03	-0.03	-0.04^{**}	-0.03^{**}	-0.08^{***}	-0.11^{***}	-0.09
All funds (TOT)							
Intercept	-0.99^{***}	-0.63^{***}	-0.37^{***}	0.02	0.45^{***}	0.76^{***}	1.19^{***}
ROR_{t-1}	0.03	0.02	0.01	0.11	0.15	0.22	0.1
NET_{t-1}	0.95^{***}	0.88^{***}	0.82^{***}	0.75^{***}	0.65^{***}	0.61^{***}	0.53^{***}
BM_{t-1}	0.13^{*}	0.08	0.05	-0.01	-0.02	-0.02	-0.03
ALL_{t-1}	-0.33^{***}	-0.28^{***}	-0.21^{***}	-0.13^{***}	-0.07	-0.05	-0.11
$OVIX_t$	-0.09	-0.09^{**}	-0.07^{***}	-0.07^{***}	-0.04	-0.06	-0.01
$Sunday$	-0.37	-0.14	-0.13^{***}	-0.17^{***}	-0.23^{***}	-0.28^{***}	-0.4^{***}
$TONE_t$	0.03	0.05	-0.01	0	0.01	-0.02	0.01

The table depicts quantile regression results explaining various classes' net flows, along the flows distribution, at date t (NET_t):
$NET_t = \mu + ROR_{t-1} + NET_{t-1} + BM_{t-1} + ALL_{t-1} + OVIX_t + Sunday + TONE_t + \epsilon_t$.
Each equation contains the very same variables as previous tables (for description of the variables, see Table II). The daily data are standardized for the period 1/2011 - 3/2019 (2021 daily observations). ***, **, and * denote 0.01, 0.05, and 0.1 significance level, respectively.

Table VIII: BiVAR-GARCH(1,1)-BEKK results: Inflow and Outflow to/from funds by class and tone

	GOV	CORP	STOCK	CASH
IN equation				
μ_{in}	0.009	-0.009	-0.005	0.014***
OUT_{t-1}	-0.001	-0.013***	0.005	-0.001***
IN_{t-1}	-0.018	-0.076	-0.098	0
$ROR_{in,t-1}$	0.012	-0.009	-0.029	0.05***
$BM_{in,t-1}$	0.047***	0.005	0.074	-0.013***
ALL_{t-1}	0***	0	0	0***
$Sunday$	0.019	0.113***	0.123***	0.027***
$TONE_{in,t-1}$	0.001	0.035***	0.038**	-0.019***
AR_1	-0.23	-0.302*	-0.247	-0.334***
$Adj.R^2$	0.14	0.25	0.21	0.21
$D.W.$	1.99	2.05	2.17	2.33
OUT equation				
μ_{out}	0.019**	0.015	-0.015*	-0.006
IN_{t-1}	0.001	-0.016***	0.011***	-0.001***
OUT_{t-1}	-0.014***	-0.04**	-0.012	-0.003
$ROR_{out,t-1}$	0.012	-0.006	0.019	-0.039***
$BM_{out,t-1}$	-0.073***	0.016	-0.001	-0.001
ALL_{t-1}	0***	0	0***	0***
$Sunday$	-0.002	0.066**	0.164***	0.072***
$TONE_{out,t-1}$	-0.075***	-0.046***	-0.085***	0
AR_1	-0.164*	-0.391***	-0.322***	-0.264
$Adj.R^2$	-0.01	0.18	0.15	0.23
$D.W.$	1.7	1.94	2.21	2.12
BEKK parameters				
$M_{in,in}$	0.005***	0.013***	0.148***	0.001***
$M_{in,out}$	0.009***	0.016***	0.029***	0
$M_{out,out}$	0.03***	0.065***	0.195***	0.001***
$A_{in,in}$	0.341***	0.385***	0.496***	0.8***
$A_{out,out}$	0.634***	0.739***	1.07***	0.224***
$B_{in,in}$	0.944***	0.929***	0.759***	0.844***
$B_{out,out}$	0.808***	0.766***	0.429***	0.979***
Goodness of fit				
$Likelihood$	-3652	-4260	-4397	-2994
AIC	3.69	4.3	4.44	3.03
SIC	3.77	4.38	4.51	3.11

This table depicts the interrelations between the inflows and outflows of fund classes and tone using an BiVAR-GARCH(1,1) as in equation (2). The dependent variables in the Mean equations are the changes in inflows and outflows. An auto regressive term of one lag was added to the Mean equations. All other variables of the Mean equation are the same as in prior tables except for ALL_{t-1} which is all inflows to specialized funds in the IN equation and all outflows from specialized funds in the OUT equation. For a description of other variables, see Table II). The variance (BEKK) equation includes: an 2*2 coefficient matrix (only 2 are presented as $M_{in,out} = M_{out,in}$), and 2 matrix diagonals of A and B (see explanations in the text). In the lower panel some goodness of fit measures are presented including the Log Likelihood, the Akaike information criterion (AIC), and the Schwarz information criterion. The daily data span the period 1/2011 - 3/2019. ***, **, and * denote 0.01, 0.05, and 0.1 significance level, respectively.

Table IX: BiVAR-GARCH(1,1)-BEKK: Movements between classes and tone

	GOV	CORP	STOCK	CASH
IN equation				
μ_{in}	-0.01	-0.036***	-0.031***	-0.004
IN_{t-1}	-0.247*	-0.245**	-0.241	-0.239
$GOV_{out,t-1}$	-0.001	0.002***	0.001*	0
$CORP_{out,t-1}$	-0.005**	-0.011***	0.003	0.002**
$STOCK_{out,t-1}$	-0.005**	0.001	0	0.002*
$CASH_{out,t-1}$	0	0	0	0
$ROR_{in,t-1}$	0.012	-0.01	-0.031	-0.007
$BM_{in,t-1}$	0.053***	0.003	0.061**	0.002
$ALL_{in,t-1}$	0***	0**	0	0
$Sunday$	0.004	0.125***	0.07**	0
$TONE_{in,t-1}$	0.005	0.025**	0.025**	-0.004
AR_1	-0.247*	-0.284**	-0.226	-0.251
$Adj.R^2$	0.14	0.25	0.21	0.24
$D.W.$	1.98	2.13	2.25	2.23
OUT equation				
μ_{out}	0	-0.04***	-0.02**	-0.017***
OUT_{t-1}	-0.273**	-0.27**	-0.207	-0.243
$GOV_{in,t-1}$	0	0.003***	0.001**	0
$CORP_{in,t-1}$	-0.002	-0.002	-0.005*	-0.001
$STOCK_{in,t-1}$	-0.004	0.003	-0.001	0
$CASH_{in,t-1}$	0*	0	0	0
$ROR_{out,t-1}$	0.012	0	0.008	-0.015
$BM_{out,t-1}$	-0.053***	-0.004	-0.014	0.008
$ALL_{out,t-1}$	0***	0*	0	0*
$Sunday$	-0.006	0.159***	0.075***	0.031***
$TONE_{out,t-1}$	-0.015*	-0.018**	-0.013	0.002
AR_1	-0.168	-0.24**	-0.21	-0.265
$Adj.R^2$	-0.04	0.2	0.18	0.23
$D.W.$	1.64	2.03	2.22	2.15
BEKK parameters				
$M_{in,in}$	0.007***	0.031***	0.166***	0.002***
$M_{in,out}$	0.007***	0.019***	0.016**	0.001
$M_{out,out}$	0.023***	0.079***	0.152***	0.002***
$A_{in,in}$	0.421***	0.499***	0.652***	0.88***
$A_{out,out}$	0.619***	0.64***	0.766***	0.506***
$B_{in,in}$	0.925***	0.871***	0.733***	0.867***
$B_{out,out}$	0.808***	0.748***	0.566***	0.948***
Goodness of fit				
$Likelihood$	-3193	-3473	-3331	-1819
AIC	3.24	3.52	3.38	1.86
SIC	3.33	3.61	3.47	1.95

This table shows movements between fund classes by regressing fund's Inflows on all Outflows in a lag and fund's Outflows on all Inflows in a lag. The dependent variables in the mean equations are the changes in inflows and outflows whilst other variables are the same as in previous tables (For a description see Table II). The variance (BEKK) equation and goodness of fit measures are similar to Table (VIII). ***, **, and * denote 0.01, 0.05, and 0.1 significance level, respectively.

Table X: EGARCH(1,1) regression results: Net flows to mutual funds by class where TONE equals the **Number** of positive articles minus the **Number** of negative articles

	GOV	CORP	STOCK	CASH	TOT
Mean equation					
μ	-0.014***	-0.053***	-0.047***	-0.026***	0.008
ROR_{t-1}	0	0.115***	0.01***	0.109***	0.002***
NET_{t-1}	0.935***	0.505***	0.744***	0.607***	0.784***
BM_{t-1}	0.045***	-0.002	-0.059***	-0.004	0.053***
ALL_{t-1}	0.002	0.005	-0.018*	0.008	-0.148***
$OVIX_t$	0.006***	0.085***	0.081***	0.021***	0.085***
$Sunday$	-0.001	0.012	0.026**	-0.045***	-0.225***
$TONE_t$	0.007	0.031***	0.089***	-0.011*	0.008
Variance equation					
ω	-0.069***	0.013***	-0.121***	0.019***	-0.042*
α	-0.053***	0.017***	-0.224***	0.056***	0.004
β	0.956***	0.998***	0.787***	0.996***	0.857***
γ	0.428***	0.154***	0.296***	0.154***	0.689***
$TONE_t$	-0.02	-0.049***	0.01	0.026***	-0.026
Goodness of fit					
AIC	0.412	1.885	2.115	1.496	1.965
BIC	0.449	1.921	2.152	1.532	2.002
Liklihood	-398.028	-1866.128	-2095.963	-1478.398	-1946.529

This table presents results of an EGARCH(1,1) model explaining the various (aggregated) net flows by class at date t (NET_t) with tones that are defined as TONE = Number of positive articles - Number of negative articles. All other variables are the same as in Table II.The conditional Mean and Variance equations are as follows:

$Mean^f: \quad NET_t = \mu + ROR_{t-1} + NET_{t-1} + BM_t + BM_{t-1} + ALL_{t-1} + OVIX_t + Sunday + TONE_t + \epsilon_t,$

$Variance^f: \quad log(\sigma_t^2) = \omega + \alpha|\frac{\epsilon_{t-1}}{\sigma_{t-1}}| + \beta log(\sigma_{t-1}^2) + \gamma\frac{\epsilon_{t-1}}{\sigma_{t-1}} + TONE_t$

The fund classes (f) are categorized in this study as: Government bonds (GOV), corporate bonds (CORP), equity (STOCK), and money market instruments (CASH). TOT is the total net flows of all funds including general purpose funds. Each Mean equation consists of (except the intercept), a self fund's rate of return (ROR) in an one day lag, net flows to the fund's class in a lag (NET_{t-1}), net flows to all specialized funds in a lag (ALL_{t-1}), return on an one day lag benchmark investment (BM, change rates of government and corporate bond indexes for GOV and CORP, respectively, rate of return on TA125 for STOCK, and changes in 3 month Makam (similar to treasury bills) yield for CASH), changes in the Israeli overnight VIX (OVIX, from today open to yesterday close) in order to control for shock that occurred after the newspapers printing), a dummy for Sundays, in which trading volumes are thinner, and tone (TONE, published before the market opening). In the variance equation the only external regressor is tone (TONE). In the lower panel the following goodness of fit measures are presented: Akaike information criterion (AIC), Bayesian information criterion (BIS), and Log likelihoods. All data are daily and standardized for the period 1/2011 - 3/2019 (2021 daily observations). ***, **, and * denote 0.01, 0.05, and 0.1 significance level, respectively.

Table XI: EGARCH(1,1) regression results of various frequencies: Net flows to mutual funds by class and tone

	GOV	CORP	STOCK	CASH	TOT
Mean equation - Weekly					
μ	0	-0.013***	-0.017*	0.001	-0.02***
ROR_{t-1}	0.001	-0.01	0.012***	-0.012	0.012
NET_{t-1}	0.988***	0.989***	0.969***	1.017***	0.966***
BM_{t-1}	0.028***	0.047***	0.047*	0.019***	0.07***
ALL_{t-1}	-0.016***	0.013	0.019	-0.002	0.005
$TONE_t$	-0.007	-0.042***	0.01	-0.008**	0.028**
Variance equation - Weekly					
ω	-0.273**	-0.487***	-2.83***	-0.033	-1.5***
α	-0.011	-0.331***	-0.147	0.017	-0.202***
β	0.935***	0.835***	0.114	0.97***	0.542***
γ	0.453***	0.732***	0.513***	0.618***	0.74***
$TONE_t$	-0.097	0.121**	-0.342**	0.111	-0.386***
Goodness of fit - Weekly					
AIC	-2.148	-0.52	-0.374	-1.011	-0.567
BIC	-2.044	-0.416	-0.269	-0.906	-0.462
Liklihood	468.585	121.86	90.659	226.362	131.726
Mean equation - Monthly					
μ	0	0	0.01***	-0.006**	0
ROR_{t-1}	-0.005	0.034	0.014***	-0.098***	-0.001
NET_{t-1}	1.001***	1.004***	0.997***	1.014***	0.991***
BM_{t-1}	0.042***	-0.009	0.052***	-0.038***	0.07***
ALL_{t-1}	-0.001	-0.002	-0.005***	-0.036***	-0.001
$TONE_t$	-0.007	-0.023	0.001***	0.022***	0.005***
Variance equation - Monthly					
ω	-1.143***	-3.488*	-1.153***	-2.6***	-0.659*
α	-0.365***	-0.282	0.425***	0.455***	0.325***
β	0.853***	0.481	0.816***	0.605***	0.903***
γ	0.692***	0.986***	-0.582***	1.386***	0.738***
$TONE_t$	0.713	-0.571	0.462***	1.665***	0.427
Goodness of fit - Monthly					
AIC	-4.661	-3.766	-3.636	-3.424	-3.51
BIC	-4.371	-3.476	-3.346	-3.134	-3.219
Liklihood	239.376	195.532	189.169	178.767	182.971

This table compares results of weekly and monthly EGARCH(1,1) model explaining the various classes' net flows as in Table II. Weekly and monthly data are based on the average daily data in a week/month. The conditional Mean and Variance equations are as follows:
$Mean: \quad NET_t^f = \mu + ROR_{t-1} + NET_{t-1} + BM_{t-1} + ALL_{t-1} + TONE_t + \epsilon_t,$
$Variance: \quad log(\sigma_t^2) = \omega + \alpha|\frac{\epsilon_{t-1}}{\sigma_{t-1}}| + \beta log(\sigma_{t-1}^2) + \gamma\frac{\epsilon_{t-1}}{\sigma_{t-1}} + TONE_t$
The fund classes (f) as well as equation variables and goodness of fit statistics are the same as in Table II. All data are standardized for the period 1/2011 - 3/2019. ***, **, and * denote 0.01, 0.05, and 0.1 significance level, respectively.

Table XII: EGARCH(1,1) regression results: Net flows to mutual funds by class with many lags in tone

	GOV	CORP	STOCK	CASH	TOT
Mean equation					
μ	-0.016***	-0.046***	-0.042***	-0.02***	0.017***
ROR_{t-1}	0.003	0.072***	0.477***	0.12***	0.305***
NET_{t-1}	0.916***	0.534***	0.591***	0.461***	0.581***
BM_{t-1}	0.044***	0.029***	-0.125***	0.011***	-0.014**
ALL_{t-1}	0.001***	0.025***	-0.028***	0.131***	0.009
$OVIX_t$	-0.014***	-0.088***	-0.064***	0.03***	-0.064***
$Sunday$	-0.015	0.04***	0.021	-0.053***	-0.214***
$TONE_t$	0.013***	0.006	0.087***	-0.018***	0.039***
$TONE_{t-1}$	-0.007***	-0.009***	-0.014***	0.002	-0.019***
$TONE_{t-2}$	0.009***	0.024***	0.019***	0.001	0.025***
$TONE_{t-3}$	-0.003	-0.005	0.026***	-0.013***	-0.033***
$TONE_{t-4}$	-0.001	0.025***	0.023***	-0.006**	0.037***
Variance equation					
ω	-0.051**	0.01***	0	0.014***	0.025***
α	-0.012	0.027***	-0.004	0.07***	-0.043***
β	0.966***	0.997***	0.988***	0.997***	0.975***
γ	0.452***	0.136***	0.11***	0.113***	0.361***
$TONE_t$	-0.228***	-0.159***	-0.136***	0.125***	-0.059***
$TONE_{t-1}$	0.07	0.116**	0.036	-0.164***	-0.069
$TONE_{t-2}$	0.152***	-0.012	0.036	0.037	0.092*
$TONE_{t-3}$	-0.013	-0.014	0.03	0.024	0.155***
$TONE_{t-4}$	0.023	0.067**	0.076***	-0.006	-0.104***
Goodness of fit					
AIC	0.45	1.974	2.018	1.73	2.028
BIC	0.524	2.049	2.092	1.804	2.102
Liklihood	-318.636	-1468.751	-1501.545	-1284.387	-1508.964

This table presents results of an EGARCH(1,1) model explaining the various classes' (aggregate) net flows at date t (NET_t) by more than one lag. The conditional Mean and Variance equations are as follows:
$Mean: \quad NET_t = \mu + ROR_{t-1} + NET_{t-1} + BM_{t-1} + ALL_{t-1} + OVIX_t + Sunday + \sum_{i=0}^{4} NET_{t-i} + \epsilon_t,$
$Variance: \quad log(\sigma_t^2) = \omega + \alpha|\frac{\epsilon_{t-1}}{\sigma_{t-1}}| + \beta log(\sigma_{t-1}^2) + \gamma\frac{\epsilon_{t-1}}{\sigma_{t-1}} + \sum_{i=0}^{4} NET_{t-i}$
All variables are the same as in Table II except the additional tone lags. As $TONE_t$ is determined before the market open it is equivalent to NET_{t-1} and ROR_{t-1}. This holds also for $TONE_{t-i}$. All data are daily and standardized for the period 1/2011 - 3/2019 (2021 daily observations). ***, **, and * denote 0.01, 0.05, and 0.1 significance level, respectively.

Table XIII: EGARCH(1,1) regression results with contemporaneous benchmark (BM): Net flows to mutual fund classes and tone

	GOV	CORP	STOCK	CASH	TOT
Mean equation					
μ	-0.012***	-0.042***	-0.025**	-0.001	0.009
ROR_{t-1}	0	0.158***	0.017	0.113***	0.007
NET_{t-1}	0.934***	0.55***	0.719***	0.542***	0.652***
BM_t	0.022***	0.292***	0.322***	-0.012***	0.157***
BM_{t-1}	0.041***	-0.071***	-0.044***	0.002	0.039***
ALL_{t-1}	0.005*	-0.018	-0.011	0.112***	-0.06***
$OVIX_t$	-0.005***	-0.002	-0.001	0.025***	-0.002
$Sunday$	-0.018	-0.044	-0.057***	-0.058***	-0.237***
$TONE_t$	0.019***	0.004	0.078***	-0.017***	0.03***
Variance equation					
ω	-0.086***	0.009***	-0.423***	0.012***	0.009
α	-0.034	0.035***	-0.152***	0.07***	-0.051**
β	0.947***	0.995***	0.517***	0.998***	0.934***
γ	0.45***	0.154***	0.401***	0.088***	0.536***
$TONE_t$	-0.054***	-0.021***	-0.118***	0.017***	-0.022
Goodness of fit					
AIC	0.446	1.788	1.895	1.573	1.949
BIC	0.487	1.83	1.937	1.615	1.991
Liklihood	-398.273	-1640.24	-1738.717	-1441.18	-1788.595

This table presents results of an EGARCH(1,1) model explaining the net flows as in Table II except the addition of BM_t. This additional variable may control for a possible same day net flows. In contrast, we do not consider the influence of net flows on BM_t since our net flows are quite small compared to the benchmark indexes. The conditional Mean and Variance equations are as follows:
$Mean: \quad NET_t^f = \mu + ROR_{t-1} + NET_{t-1} + BM_t + BM_{t-1} + TOTAL_{t-1} + Sunday + TONE_t + \epsilon_t,$
$Variance: \quad log(\sigma_t^2) = \omega + \alpha|\frac{\epsilon_{t-1}}{\sigma_{t-1}}| + \beta log(\sigma_{t-1}^2) + \gamma\frac{\epsilon_{t-1}}{\sigma_{t-1}} + TONE_t$
The fund classes (f) are categorized in this study as: Cash money (CASH), government bonds (GOV), corporate bonds (CORP), equity (STOCK), all funds including general funds (TOT). All data are daily and standardized for the period 1/2011 - 3/2019. ***, **, and * denote 0.01, 0.05, and 0.1 significance level, respectively.

Table XIV: EGARCH(1,1) regression results without outliers (winsorized at the 1/99 percent): Net flows to mutual fund classes and tone

	GOV	CORP	STOCK	CASH	TOT
Mean equation					
μ	-0.011***	-0.041***	-0.037*	-0.026***	-0.005
ROR_{t-1}	0.001	0.116***	0.011	0.089***	0.01
NET_{t-1}	0.885***	0.468***	0.518***	0.38***	0.592***
BM_{t-1}	0.048***	0.003	0.009	0.014*	0.051***
ALL_{t-1}	-0.001	0	-0.037***	0.064***	-0.158***
$Sunday$	-0.009***	-0.052***	-0.05***	0.022***	-0.041***
$OVIX_t$	-0.017***	-0.02	0.046	-0.058***	-0.186***
$TONE_t$	0	0.007	0.036*	-0.02***	-0.024*
Variance equation					
ω	-0.027	-0.04***	-0.016*	0.001	-0.067**
α	-0.031*	0.018	0.025***	0.026***	0.004
β	0.979***	0.959***	0.976***	0.994***	0.925***
γ	0.293***	0.211***	0.166***	0.092***	0.346***
$TONE_t$	-0.03***	-0.055***	-0.036**	0.009	-0.095***
Goodness of fit					
AIC	0.342	1.59	1.814	1.202	1.687
BIC	0.381	1.63	1.853	1.242	1.727
Liklihood	-296.346	-1424.694	-1630.433	-1075.635	-1515.015

This table presents results of an EGARCH(1,1) model explaining the various classes' net flows as Table II except the fact that all outliers above the percentile 0.99 and below 0.01 of the dependent variable, were removed (40 observations). The conditional Mean and Variance equations are as follows:

$Mean: \quad NET_t^f = \mu + ROR_{t-1} + NET_{t-1} + BM_{t-1} + ALL_{t-1} + Sunday + TONE_t + \epsilon_t,$

$Variance: \quad log(\sigma_t^2) = \omega + \alpha|\frac{\epsilon_{t-1}}{\sigma_{t-1}}| + \beta log(\sigma_{t-1}^2) + \gamma\frac{\epsilon_{t-1}}{\sigma_{t-1}} + TONE_t$

The fund classes (f) are categorized in this study as: Government bonds (GOV), corporate bonds (CORP), equity (STOCK), and money market instruments (CASH). Each mean equation consists of (except the intercept), a self fund's rate of return (ROR) in an one day lag, net flows to the fund's class in a lag (NET_{t-1}), net flows to all specialized funds in a lag (ALL), rate of return on an one day lag benchmark investment (BM), a dummy for Sundays, in which trading volumes are thinner, and tone (published before the market opening). In the variance equation the only external regressor is tone. In the lower panel the following goodness of fit measures are presented: Akaike information criterion (AIC), Bayesian information criterion (BIS), and Log likelihoods. All data are daily and standardized for the period 1/2011 - 3/2019. ***, **, and * denote 0.01, 0.05, and 0.1 significance level, respectively.

Table XV: EGARCH(1,1) regression results: Net flows to mutual fund classes and tone adjusted for newspapers heterogeneity

	GOV	CORP	STOCK	CASH	TOT
Mean equation					
μ	-0.015***	-0.032***	-0.019	-0.007	0.005*
ROR_{t-1}	0.002	0.174***	0.01***	0.115***	0.007
NET_{t-1}	0.933***	0.504***	0.713***	0.531***	0.7***
BM_{t-1}	0.053***	0.006	-0.029*	0.011**	0.063***
ALL_{t-1}	0	0.007*	-0.021	0.095***	-0.127***
$OVIX_t$	0.012***	0.095***	0.116***	0.022**	0.112***
$Sunday$	-0.022***	0.015	-0.008	-0.07***	-0.236***
$TONE.Adj_t$	0.003	0.003	0.049***	-0.021*	0.03***
Variance equation					
ω	-0.068***	0.014***	-0.131***	0.015***	-0.026
α	-0.047**	0.013*	-0.178***	0.071***	-0.002
β	0.955***	0.996***	0.762***	0.998***	0.871***
γ	0.432***	0.169***	0.32***	0.104***	0.658***
$TONE.Adj_t$	-0.012	-0.048***	-0.01	0.012*	-0.064***
Goodness of fit					
AIC	0.503	1.944	2.153	1.63	2.032
BIC	0.543	1.984	2.194	1.67	2.072
Liklihood	-426.55	-1686.693	-1869.739	-1412.221	-1763.862

This table presents results of an EGARCH(1,1) model explaining the various classes' net flows as Table II except the tone which is adjusted for newspapers heterogeneity i.e., $TONE.Adj_t = \frac{TONE_t}{Std(TONE_{it})}$ where, $TONE_{it} = POS_{it} - NEG_{it}$, is the difference in shekels between the monetary value of newspaper i ($i \in$ 1..6) positive tone (POS_{it}) and negative tone (NEG_{it}) in day t, and $TONE_t = \Sigma TONE_{it}$ where i ($i \in 1..6$) is a daily newspaper: Yediot Aharonot, Ma'ariv, Israel Hayom, Globes, TheMarker, Calcalist. Both POS and NEG are the monetary equivalent values of articles had they were advertisements depending on the newspaper circulation, the place within the newspaper and the article size (See Appendix A for more details on TONE calculations). A larger $Std(TONE_{it})$ reflects less homogeneity between newspapers' tone thus, a smaller $TONE.Adj$ and vice versa.
The conditional mean and variance in the EGARCH(1,1) equations are as follows:
$Mean^f: \quad NET_t = \mu + ROR_{t-1} + NET_{t-1} + BM_{t-1} + ALL_{t-1} + Sunday + TONE.Adj_t + \epsilon_t,$
$Variance^f: \quad log(\sigma_t^2) = \omega + \alpha|\frac{\epsilon_{t-1}}{\sigma_{t-1}}| + \beta log(\sigma_{t-1}^2) + \gamma\frac{\epsilon_{t-1}}{\sigma_{t-1}} + TONE.Adj_t$
The fund classes (f) are categorized in this study as: Government bonds (GOV), corporate bonds (CORP), equity (STOCK), and money market instruments (CASH). Each mean equation consists of (except the intercept), a self fund's rate of return (ROR) in an one day lag, net flows to the fund's class in a lag (NET_{t-1}), net flows to all specialized funds in a lag (ALL), rate of return on an one day lag benchmark investment (BM), a dummy for Sundays, in which trading volumes are thinner, and tone (published before the market opening). In the variance equation the only external regressor is tone. In the lower panel the following goodness of fit measures are presented: Akaike information criterion (AIC), Bayesian information criterion (BIS), and Log likelihoods. All data are daily and standardized for the period 1/2011 - 3/2019.
***, **, and * denote 0.01, 0.05, and 0.1 significance level, respectively.

Table XVI: LS versus TOBIT regressions: Benchmark model when tone is derived from General newspapers only

	GOV	CORP	STOCK	CASH	TOT
LS equation					
C	-0.73	-0.03	-0.14	7.65**	13.17***
ROR_{t-1}	32.64	159.15***	9.35	6145.57	1114.36
NET_{t-1}	0.87***	0.54	0.58***	0.83	0.7
BM_{t-1}	33.5	-0.58	0.84*	99.91	80.31***
ALL_{t-1}	0	0	0	-0.38	-0.26
$OVIX_t$	1.48***	0.73	2.45	-0.9	19.64
Sunday	0.28	-0.31	-0.02	-23.12***	-49.45
$TONE_t$	18.81*	1.2	29.9***	-197.35***	28.95
Goodness of fit					
R^2	0.799	0.327	0.402	0.235	0.389
$Adj.R^2$	0.798	0.324	0.4	0.232	0.387
LogLik.	-8218.766	-5389.218	-7631.002	-11737.877	-12172.494
D.W.	2.242	2.13	2.128	2.162	2.175
TOBIT equation					
C	-3.36***	-0.98***	-0.55	-67.19***	-12.28*
ROR_{t-1}	2112.67	232.23	7.82	8086.73	979.7
NET_{t-1}	0.92***	0.74	0.62***	0.55	0.84
BM_{t-1}	13.06***	-0.14	-0.47	108.96	39.45
ALL_{t-1}	0	0	-0.01***	0.02	-0.43
$OVIX_t$	0.19	0.62	1.57	0.05	7.66**
Sunday	1.71	0.02	-0.18	-33.84**	-55.11
$TONE_t$	15.48	2.97	24.81**	-334.51***	137.81
Goodness of fit					
Log(scale)	2.95***	1.41***	2.59***	5.26***	5.16***
LogLik.	-4358	-2968	-4472	-5391	-7222
Wald Stat.	3840	823	828	250	636

The table shows the benchmark model results (EGARCH(1,1), see Table 1) regarding General newspapers using both LS and TOBIT regressions. This in order to reveal any biases due to many zeros in General newspapers data (TOBIT). The TOBIT lower bound is set to 0. The fund classes are categorized as: Government bonds (GOV), corporate bonds (CORP), equity (STOCK), money market instruments (CASH), and all funds including general funds (TOT). Each equation consists of (except the intercept), a self fund's rate of return (ROR) in an one day lag, net flows to the fund's class in a lag, net flows to all specialized funds in a lag (ALL), rate of return on an one day lag benchmark investment (BM), a dummy for Sundays, in which trading volumes are thinner, and tone that is derived from General newspapers only thus, contains relatively many zeros (585 compared to 103 in the common tone that derived from all newspapers). The goodness of fit of the TOBIT measures include Log(scale) which is the log of standard deviation of the latent uncensored normal variable. All data are daily but non scaled as in most earlier tables for the period 1/2011 - 3/2019. For a comparison with the EGARCH(1,1) and LS regression results of non scaled data for tone that is derived from all newspapers see FN (6). ***, **, and * denote 0.01, 0.05, and 0.1 significance level, respectively.

References

Akbas, F., Armstrong, W. J., Sorescu, S., Subrahmanyam, A. (2015). Smart money, dumb money, and capital market anomalies, Journal of Financial Economics, 118(2), 355–382.

Baba, Y., Engle, R. F., Kraft, D. F., and Kroner, K. F. (1990). Multivariate simultaneous generalized ARCH. Manuscript, University of California, San Diego, Department of Economics.

Barber, B. M., Huang, X., and Odean, T. (2016). Which factors matter to investors? Evidence from mutual fund flows. The Review of Financial Studies, 29(10), 2600–2642.

Ben-David, I., Li, J., Rossi, A., Song, Y. (2019). What do mutual fund investors really care about?. Fisher College of Business, Working Paper (2019-03).

Ben-Rephael, A., S. Kandel, and Wohl, A. (2011). The price pressure of aggregate mutual fund flows. Journal of Financial and Quantitative Analysis 46 (02): 585–603.

Ben-Rephael, A., Kandel, S., and Wohl, A. (2012). Measuring investor sentiment with mutual fund flows. Journal of Financial Economics, 104(2), 363–382.

Ben-Rephael, A. (2017). Flight to liquidity, market uncertainty, and the actions of mutual fund investors. Journal of Financial Intermediation, 31, 30–44.

Berk, J. B., and Green, R. C. (2004). Mutual fund flows and performance in rational markets. Journal of political economy, 112(6), 1269–1295.

Blocher, J. (2016). Network externalities in mutual funds, Journal of Financial Markets, 30, 1–26.

Cao, C., Chang, E. C., and Wang, Y. (2008). An empirical analysis of the dynamic relationship between mutual fund flow and market return volatility. Journal of Banking and Finance, 32(10), 2111–2123.

Chang, C. L., McAleer, M., and Wang, Y. A. (2018). Modelling volatility spillovers for bio-ethanol, sugarcane and corn spot and futures prices. Renewable and Sustainable Energy Reviews, 81, 1002–1018.

Engle, R. F., and Kroner, K. F. (1995). Multivariate simultaneous generalized ARCH. Econometric theory, 11(1), 122–150.

Ferguson, N. J., Philip, D., Lam, H., and Guo, J. M. (2015). Media content and stock returns: The predictive power of press. Multinational Finance Journal, 19(1), 1–31.

Ferreira, M. A., Keswani, A., Miguel, A. F., and Ramos, S. B. (2012). The flow-performance relationship around the world. Journal of Banking and Finance, 36(6), 1759–1780.

Frank, M. Z., and Sanati, A. (2018). How does the stock market absorb shocks?. Journal of Financial Economics, 129(1), 136–153.

Franzoni, F., and Schmalz, M. C. (2017). Fund flows and market states. The Review of Financial Studies, 30(8), 2261–2673.

Gabaix, X., and Koijen, R. S. (2020). In Search of the Origins of Financial Fluctuations: The Inelastic Markets Hypothesis. Available at SSRN.

Garz, M. (2014). Good news and bad news: Evidence of media bias in unemployment reports, Public Choice, 161(3-4), 499-–515.

Goldstein, I., Jiang, H., Ng, D. T. (2017). Investor flows and fragility in corporate bond funds, Journal of Financial Economics, 126(3), 592–613.

Jank, S. (2012). Mutual fund flows, expected returns, and the real economy. Journal of Banking and Finance, 36(11), 3060–3070.

Jiang, H., and Verardo, M. (2018). Does herding behavior reveal skill? An analysis of mutual fund performance. The Journal of Finance, 73(5), 2229–2269.

Nigam, R. M., Srivastava, S., and Banwet, D. K. (2018). Behavioral mediators of financial decision making–a state-of-art literature review. Review of Behavioral Finance, 10(1), 2–41.

Pástor, Ľ., Stambaugh, R. F., and Taylor, L. A. (2015). Scale and skill in active management. Journal of Financial Economics, 116(1), 23–45.

Peress, J. (2014). The media and the diffusion of information in financial markets: Evidence from newspaper strikes, The Journal of Finance, Vol. 69, 5, 2007–2043.

Rakowski, D., Wang, X. (2009). The dynamics of short-term mutual fund flows and returns: A time-series and cross-sectional investigation, Journal of Banking and Finance, 33(11), 2102–2109.

Saadon, Y. Schreiber, Ben Z. (2019). The Effect of Print Media Tone on Stock Indexes, Available at SSRN: https://ssrn.com/abstract=3200113 or http://dx.doi.org/10.2139/ssrn.3200113

Sirri, E. R., and Tufano, P. (1998). Costly search and mutual fund flows. The journal of finance, 53(5), 1589–1622.

Shiller, R. J. (2005). Irrational Exuberance, Princeton University Press.

Solomon, D. H., Soltes, E., and Sosyura, D. (2014). Winners in the spotlight: Media coverage of fund holdings as a driver of flows. Journal of Financial Economics, 113(1), 52–73.

Tetlock, P. C. (2015). The role of media in finance. In Handbook of media Economics (Vol. 1, pp. 701–721). North-Holland.

Tetlock, P. C. (2011). All the news that's fit to reprint: Do investors react to stale information?. The Review of Financial Studies, 24(5), 1481-1512.

Tversky, A., Kahneman, D. (1992), Advances in prospect theory: Cumulative representation of uncertainty. Journal of Risk and Uncertainty, 5(4), 297–323.

Wallace, T.D. Hussain, A. (1969). The use of error components models in combining cross section with time series data, Econometrica, 55–72.

Appendix A Tone derivation from local newspapers

We use tone calculations from the "Ifat Media Research" company, which analyzed for us all of the financial markets press coverage in all newspapers in Israel, while measuring the equivalent monetary value of each article. The monetary value is set according to the cost of advertising in the article's location, with this cost used as an indicator of the volume of readers' exposure to the article. Each article published in the print media, that related to the financial markets, was analyzed according to its tone in relation to the financial markets—positive, negative, or neutral—its equivalent monetary value, and the extent of its relevance to the financial markets, at values ranging from 5 percent to 100 percent (100 percent being the maximum relevance). The sample contained only articles with more than 50 percent of their area devoted to the financial markets in general (but not to specific firms or external events), such that the reasonable reader encountering this article "absorbs" tone from it with only a superficial reading. In total, about 17,000 articles were analyzed, from which 4,064 articles were found that dealt with the financial markets (usually markets performance) and answered all the criteria we set in this study (1,770 were defined as having a positive tone, 1,722 as having a negative tone, and 554 as being neutral). The team that analyzed the articles and evaluated their tone represented "the average person". Therefore, the people chosen for making the classification were generally graduates or students in communications tracks, who are not economists, and whose understanding of the financial markets is obtained from reading newspapers.

In order to evaluate tone as reflected by the newspapers (TONE), we calculate the difference in shekels between the monetary value of total positive media and total negative media each day (TONE = POS - NEG). POS and NEG are the monetary equivalent values of positive and negative articles had they were advertisements (depending on the newspaper circulation, the place within the newspaper and the article size). It is worth noting that there were almost no cases in which both negative and positive coverage were found in the same newspaper on the same day. We also categorized tones that derived from the six daily newspapers that are published in Israel into general newspapers(Yediot Aharonot, Ma'ariv, Israel Hayom) and business newspapers(Globes, TheMarker; Calcalist). Based on this categorization we calculated TONE.GEN which is tone that derived from general newspapers only and TONE.ECON representing a tone that derived from business/economic newspapers only.