The Impact of Investor Sentiment on Conditional Volatility in the Tel Aviv Stock Exchange [i]

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JEL: G11, G41

Key words: Sentiment; Bond market; Stock market; Behavioral finance.

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[i] We are thankful to Shmuel Hauser, the Ono Academic College, and Bizportal.co.il for granting us the opportunity to access and explore their unique sentiment indexes. Financial aid by the Ono Research Fund is thankfully acknowledged. Should any errors remain in the text, they are due to the authors.

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Abstract

We study how changes in investor sentiment affect the conditional volatility of the returns of stocks and bonds traded in Tel Aviv Stock Exchange (TASE). We model the conditional volatility of these returns as a function of changes in market sentiment proxies, developed by Bizportal and ONO academic college, based on trading activity measures of the Israeli equity and debt markets. We find that changes in sentiment affect to a different, and in some cases in opposite manner, stocks' and bonds' conditional volatilities and that these effects are subject to market states. These results suggest that changes in sentiment proxies reflect important information about changes in investors' market risk expectations, that may explain future variations in stocks and bonds market returns.

We innovate in two aspects; first, we are the first to use bond returns from a limit-order book rather than OTC bond markets. Second, given the former, we are the first to measure retail investors' sentiment, who are highly active in the limit-order market, while the few existing bond sentiment papers measure institutional investors' sentiment, who are less prone to behavioral biases.

These sentiment proxies are based on several trading activity measures of the Israeli equity and debt markets

1. Introduction

Behavioral finance argues that investors may trade on economically irrelevant signals, known as "noise", therefore asset price anomalies might be an outcome of changes in investors' sentiment (Shleifer and Summers, 1990; Brown and Cliff, 2004). An extensive body of literature beginning with Kyle (1985), Black (1986), De Long, Shleifer, Summers and Waldman (1990) and others show that noise traders making irrational investment decisions might affect stock returns.[1]

Existing studies are primarily concerned with the impact of investor sentiment on the pricing of stocks, while only a few papers are interested in the effect on bond pricing. The few exceptions are Nayak (2010) and Spyrou (2013), who show that bond yield spreads co-vary with sentiment in a way similar to stocks, i.e., underpriced during pessimistic periods and overpriced when optimism reigns. In a more recent paper, Bethke, Gehde-Trapp and Kempf (2017) show that investors in corporate bonds exhibit flight-to-quality when sentiment is low. Nayak (2010) and Bethke et al. (2017) use TRACE over-the-counter (OTC) data and Spyrou (2013) uses European bond market data, where most trade is conducted OTC.

Our manuscript contributes to the study of sentiment in both stock and bond markets, where the latter uses a unique dataset. Specifically, our study of sentiment in corporate bonds appears to be the first conducted in a continuous order-driven bond market, rather than OTC. While retail investors are virtually absent in OTC markets and are not the price makers in these platforms, retail investors are highly active in the Israeli limit order book bond market. Therefore, our study measures sentiment among small investors, who are more likely to trade on noise than large, institutional investors.

Specifically, we use six market sentiment proxies, three for the stock market and three for the bond market. All are partially based on the following familiar proxies.[2] First, Brown and Cliff (2004) propose, among others, the ratio of the new highs to new lows (HI/LO), designed to capture

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[1] Barber and Odean (2008) and Karlsson, Loewenstein and Seppi (2009) show that individual sentiment traders tend to buy more aggressively than sell attention-grabbing stocks (i.e., stocks in the news, stocks with extreme one day returns, etc.), hence having a much greater effect on stock prices during high sentiment periods. Yu and Yuan (2011) show that a low tradeoff between stock market expected returns and risk during high sentiment periods is explained by higher participation rate of sentiment-driven traders.

[2] The sentiment proxies we use were suggested by Prof. Shmuel Hauser of Ono Academic College and Ben Gurion University and computed and published by the financial website Bizportal.co.il.

the relative strength of the market. Second, Dennis and Mayhew (2002) and Brown and Cliff (2004), suggest using trading activity measures in derivatives, such as the Put-Call Ratio (PCR), proxying for expected beliefs of price drops vs. price increases. Whaley (2000) propose the Volatility Index (VIX), which many consider as a "fear index" by measuring the implied volatility of S&P100 stock index options.[3]

An important and sensitive measure of both, the stock and bond market sentiment, is the state of the market, whether it is stable or in a crisis. Investors' sentiment appears to be highly relevant in times of financial distress. Several empirical studies, including Longstaff (2004), Chen, Lesmond and Wei (2007), Acharya, Amihud and Bharath (2013), Næs, Skjeltorp and Ødegaard (2011), Dick-Nielsen, Feldhütter and Lando (2012), Friewald, Jankowitsch and Subrahmanyam (2012) and others highlight the flight-to-quality effect during financial crises. In such episodes, investors abandon low graded bonds in favor of investment grade bonds. Other papers, including Pastor and Stambaugh (2003), Longstaff (2004), and Acharya and Pedersen (2005) also document flight-to-liquidity in stocks and bonds following a financial crisis, in which investors shift their holdings to the most liquid assets available.

Based on the above-mentioned measures of sentiment, we use six measures that were adapted to the local market given data availability, and in particular the continuous trade in the bond market. While we elaborate on each of our six sentiment proxies in the text, we note here that they are made of two groups, one for stocks and the second for bonds. The three stock market sentiment proxies involve relative strength as a proxy for time-series momentum, ratio of put to call options, and a local volatility index, similar to VIX. The three bond market sentiment proxies measure time-series momentum, a stability index based on daily bond return volatility, and a default risk measure. In order to control for the varying effect of sentiment in times of crises, we split the sample into three subperiods, before, during and after the financial crisis of 2008-9.

[3] Other sentiment proxies are the dividend premium (DIV) (Baker and Wurgler, 2004), measured as the difference between the average market-to-book value ratios of dividend payers and nonpayers; the close-end-fund discount (CEF) (Lee, Shleifer and Thaler, 1991; Neal and Wheatly, 1998), measured as the difference between the net asset value of funds who issued a fixed number of shares and their respective market price; and Initial Public Offering (IPO) measures like the first-day-return and IPO-Volume (Ljungqvist, Nanda and Singh, 2006; Cornelli, Goldreich and Ljungqvist, 2006), which involve investors' sentiment in the pricing of stock IPO. Baker and Stein (2004), Baker and Wurgler (2004, 2007), and Kaniel, Saar and Titman (2007) use liquidity indicators, like the market volume (VOL) and Turnover Ratio (TURN), in order to proxy for investors' sentiment.

Sentiment may affect a number of economic measures, in stock and bond pricing. We follow the strand of the literature that examines the effect of sentiment on the conditional volatility of returns. Thus far, the literature related sentiment to conditional volatility of stock returns only, thus we add to the literature by testing sentiment effects on bonds' conditional volatility of returns as well. Lee, Jiang and Indro (2002) show that changes in investor sentiment are inversely related to the conditional volatility of U.S. stock market indexes (Dow Jones Industrial Averages (DJIA), S&P500 and NASDAQ). They report that when investors become bullish conditional volatility declines, and vice versa. Verma and Verma (2007) use an EGARCH model in order to study the asymmetric effects of market sentiment over the conditional volatility of major U.S. stock market indexes. They show greater effect of irrational bullish than bearish investors on the volatility of U.S. stock index returns, suggesting that investor sentiment is critical in modeling market volatility. Nevertheless, while the effect of investor sentiment on the volatility of stock markets is well documented, little is known about this effect on the conditional volatility in the bonds market.

We apply an EGARCH (1,1) model to estimate the influence of the change among different investor sentiment proxies in order to explore the markets' sensitivity to changes in sentiment. Our main empirical finding is that sentiment affects differently the bond and the stock markets and is conditional on the state of the market. We show that under normal market conditions, when sentiment is estimated to be relatively high, changes in momentum-based indicators largely explain changes in the conditional volatility of the bond and stock index returns, while they hardly explain the variability of these indexes in times of financial turmoil. Conditional on very low sentiment, i.e. during the financial crisis of 2008, we show that the change in volatility-based sentiment proxies has a larger effect on the conditional volatility of the Tel-Bond-20 returns than in times of normal market conditions, while this pattern is reversed in the TA-35 stock index returns. These results imply that our market sentiment proxies may highlight a potential future change in the bonds and stock market volatilities, and hence may be informative for traders.

The rest of the paper is organized as follows: Section 2 presents the data, Section 3 elaborates on the methodology we implemented, Section 4 presents the results separately for stocks and bonds, and Section 5 summarizes and concludes the paper.

2. Data

Our data on investor sentiment in the TASE is drawn from two sources. First, we use TASE equity and debt market indices as published in the TASE website. To quantify investor sentiment on the Israeli equity and debt markets, we use two major indices of assets prices in these markets. For the equity market, we use the TA-35 index, which is a value-weighted index of the 35 largest market capitalizations companies listed on TASE. For the debt market, we use the Tel-Bond-20 index. It consists of the 20 corporate bonds with the highest market capitalization of issues among all the bonds traded in the local debt market. All are fixed-interest and linked to the Consumer Price Index. Bond trading in TASE is continuous limit order driven and electronic, similar to the way stocks are traded in developed stock exchanges worldwide. This aspect improves the corporate and government bonds liquidity and allows significant retail investors participation (Abudy and Wohl, 2017). As a result, our study appears to be the first to measure a wide range of investor types and their sentiment in the bond market, unlike the dealer-based bond trading in most exchanges where the predominant investor type is large institutions.

Second, we use the Bizportal's market sentiment indicators,[4] developed with Prof. Shmuel Hauser from the Ono Academic College, as proxies for investor sentiment in TASE. These sentiment proxies are based on several trading activity measures of the Israeli equity and debt markets. For the equity market, these indicators are: 1) Stock Market Momentum Index (SMMI), calculated as the ratio between the last 5-days moving average of TA-35 index and its moving average in the last year. 2) Stock Market Sentiment Index (SMSI), based on Put-Call-Ratio of options written on the underlying TA-35 index. 3) Stock Volatility Index (SVIX), based on daily observations of implied volatilities of at-the-money put and call options of TA-35 index.

For the debt market, the following indicators are used: 1) Bonds Market Momentum Index (BMMI), calculated as the ratio between the 5 days moving average of Tel-Bond-20 index and its moving average in the preceding year. 2) Bond Market Stability Index (BMSI), calculated as the volatility of daily returns of the Tel-Bond-20 index. 3) Default Risk Index (DRI), is the ratio of the market value of all bonds with respective yield-to-maturity above 8% to the market value of all traded bonds.

Our sample consists of daily values of the TA-35 and Tel-Bond-20 indexes, along with their respective market sentiment indicators. The sample period starts in January/2000 until March/2019. The dataset begins on the date the TA-35 and Tel-Bond-20 indexes were launched by the

[4] The data of the investor sentiment proxies may be found at https://www.bizportal.co.il/publictrustindices. Most of the data items are available starting on January 2000, while some from January 2007. All series end on 3/2019.

exchange.[5] Finally, we conduct our regression and EGARCH (1,1) analyses on simple daily returns data, computed from adjusted TA-35 and Tel-Bond-20 index levels.[6] In the next sections we show the regression and the EGARCH (1,1) fitting model methodology we used for quantifying the investors sentiment effect in TASE.

3. Methodology

Our main purpose in this research is to investigate investor sentiment effects on the volatility of major indices in the Israeli stock and bond markets. We investigate whether one of them outperforms any of the others or adds an additional dimension of investor sentiment. We apply an EGARCH model on TA-35 and Tel-Bond-20 index in order to explore the asymmetric effect of the sentiment indicators on the indexes' conditional volatilities.

Our point of departure is using a random-walk model aimed to determine the extent by which past returns explain variability in daily returns of TA-35 and Tel-Bond-20 indexes. This test is consistent with the weak-form market efficiency hypothesis whereby past returns of the *k*-type index capture all relevant economic information that affects the index values. Specifically, we apply a time series regression of the form

$$R_{k,t} = \beta_0 + \beta_1 R_{k,t-1} + \varepsilon_{k,t}, \tag{1}$$

where $R_{k,t}$ is the daily return of the *k*-type index (*k*=[TA-35; Tel-Bond-20]), *t* represents time and $\varepsilon_{k,t}$ is the error term of (1).

Next, we model the unexplained portion of the daily variations in the *k*-type index, which results in other non-fundamental factors, e.g., investor sentiment and time-series momentum, although there is a debate in the literature whether time-series momentum stems from behavioral trades.[7] We model the squared residuals of the *k*-type regression by using the proposed investor sentiment proxy in the following regression,

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[5] It should be noted that the data for SMSI indicator has some missing data while the available data for the Tel-Bond-20 returns and its respective market sentiment proxies starts from October 2, 2008.

[6] We used continuously compounded returns yet found no noticeable differences.

[7] There is an ongoing debate in the literature whether time-series momentum stems from behavioral or rational trading patterns by different investor types. For example, Daniel, Hirshleifer and Subrahmanyam (1998), Barberis, Shleifer and Vishny (1998) and others advocate for behavioral effects, like representativeness and conservatism or overconfidence and self-attribution while Kedar-Levy (2013) shows that these trading patterns may be rational, and Moskowitz, Ooi and Pedersen (2012) show that time-series momentum is not related to sentiment.

$$\left(R_{k,t} - \hat{R}_{k,t}\right)^2 = \beta_0 + \beta_1 SENT_{k,i,t} + \varepsilon_{k,t}, \tag{2}$$

where $\hat{R}_{k,t}$ is the fitted value of the *k*-type regression in equation (1), $SENT_{k,i,t}$ is the *i*-type investor sentiment proxy related to the *k*-type index, and $\varepsilon_{k,t}$ is the residual of (2). Hence, for each *k*-type index, we run separate regressions of the squared deviations obtained from equation (1) and the respective *i*-type investor sentiment proxy, namely *i*={SMMI, SMSI, SVIX} for the TA-35 index *i*={BMMI, BMSI, DRI} for the Tel-Bond-20 index.

The null hypothesis for the *i*-type investor sentiment proxy is *H0*: $\beta_i = 0$, and rejection of the null will indicate that the investor sentiment proxy explains variations in the *k*-type market index. Further, in order to answer which of the *i*-type investor sentiment indices better explains variations in market, we shall compare the adjusted R^2 results from equation (2).

Additionally, we study the effect that the sentiment proxies have over the conditional volatility of the daily returns in both indexes. Following Verma and Verma (2007) we suggest employing an EGARCH model (Nelson, 1991) over the daily returns of the TA-35 and Tel-Bond-20 indexes in order to explore the asymmetric effect of investor sentiment on the conditional volatility of the indexes. In that sense, EGARCH models can identify whether a negative shock leads to subsequent conditional variance that differs from a positive shock. Moreover, the EGARCH model specifies the conditional variance in logarithmic form; hence there in no need to impose estimation constraints in order to avoid negative variance estimation, which is one of the primary motivations for using the EGARCH model (Bollerslev, Chou and Kroner, 1992).

We use daily returns of the TA-35 and Tel-Bond-20 index as dependent variables in the following EGARCH(1,1) model,

$$r_{k,t} = \mu_k + \varepsilon_{k,t}, \tag{3}$$

where $r_{k,t}$ is the return of the *k*-type index, μ is a constant term relevant for index *k*, and $\varepsilon_{k,t}$ is the relevant error term. The logarithmic conditional variance of the market index is modeled by

$$log\left(\sigma_{k,t}^2\right) = \omega + \alpha\left[\frac{\left|\varepsilon_{k,t-1}\right|}{\sigma_{k,t-1}} - \frac{\sqrt{2}}{\pi}\right] + \beta\left(\frac{\varepsilon_{k,t-1}}{\sigma_{k,t-1}}\right) + \gamma log\left(\sigma_{k,t-1}^2\right) + \delta_i \Delta SENT_{k,i,t} \tag{4}$$

where $\sigma_{k,t}^2$ is the conditional variance of the returns of the *k*-type market index, $\varepsilon_{k,t-1}$ is the first-order autoregressive lag from (3), $\Delta SENT_{k,i,t}$ is the change in the *i*-type investor sentiment proxy related to the *k*-type index from *t* to *t-1*, and $\omega, \alpha, \beta, \gamma, \delta_i$ are parameters to be estimated. ω is a constant and α represents the symmetric effect of the general autoregressive model. The β

coefficient captures the asymmetric effect, or the "leverage effect" of innovations on the volatility of the *k*-type market index returns. Therefore, if $\beta < 0$, negative innovations (i.e., bad economic news) generate higher volatility than positive innovations. γ measures persistence in the conditional volatility irrespective of market shocks, i.e., when γ is relatively large, the conditional market variance takes a long time to fade out.

We are interested in exploring how changes in investor sentiment proxies affect the conditional volatility of the stock and bond market returns, and thus our main interest is the δ_i coefficient, which captures the impact of a change in the *i*-type investor sentiment proxy on the conditional variance of the *k*-type market index returns. The null hypothesis is $H_0\colon \delta = 0$, while rejecting the null indicates that the change in the *i*-type sentiment measure affects the conditional volatility of the *k*-type market index returns. See Lee *et al*. (2002) and Verma and Verma (2007).

In light of the strong evidence of flight-to-quality and flight-to-liquidity in U.S. capital markets during the subprime crisis of 2008-2009 (Dick-Nielsen et al., 2012; Friewald et al., 2012), it would be reasonable to assume that investor sentiment effects might be substantially different during the financial crisis, as opposed to more stable periods. Thus, we are interested in quantifying the investor sentiment effect on the conditional volatility in periods before, during and after the global financial crisis. Following Dick-Nielsen et al. (2012) we define three sub-periods of interest: (1) the period before the financial crisis (January 2000 – August 2009); (2) the financial crisis period (September 2008 – June 2009); and (3) after the financial crisis (July 2009 – March 2019).

Assuming that behavioral explanations drive, at least partially, time-series momentum, these indicators would have a positive correlation with investor sentiment (i.e., a positive momentum proxy for high investor sentiment). Thus, in times when market conditions are normal, we expect the coefficient of the change in SMMI and BMMI to be positive, indicating that higher momentum is followed by an increase in the volatility of the market returns. On the other hand, during the financial crisis, when capital constraints become binding and investor sentiment is low, we expect the coefficient of the change in SMMI and BMMI to be negative, due to the adverse effect of the change in investor sentiment on the conditional volatility. In a similar manner, since the PCR and VIX indicators are widely viewed as bearish indicators (Brown and Cliff, 2004), and hence with a negative correlation with sentiment, we expect the δ coefficient of the change in PCR, SVIX, and BMSI to be positive, with a much higher magnitude during the financial crisis. The scale of the δ coefficient will be compared between the investor sentiment proxies and between the sub-periods in order to understand which of the sentiment indicators has the largest effect on the conditional volatility in TASE.

4. Results

In the following sections we show sentiment effects through regressions and EGARCH (1,1) fitting model estimation for both the stock and bond markets in TASE.

4.1. Stock market sentiment

4.1.1. Regressions

Daily returns of TA-35 are used in the regression analysis in order to explore the effect of each market sentiment indicator on the stocks market daily return variations. Table 1 summarizes the two-stage regression results for the TA-35 index and its respective investor sentiment proxies: SMMI, SMSI and SVIX.

Consistent with the weak-form efficient market hypothesis, we find in Panel A that $R_{\mathrm{TA-35},t-1}$ is not significant, and the adjusted R-squared of the estimation of equation (1) is low (0.03). This means that variations in the TA-35 index cannot be explained by the index on the previous day. The squared residuals from the estimation of equation (1) may capture the variations in the market due to non-economic factors, e.g., investors' sentiment. We use the squared residuals in order to quantify the effect of the investor sentiment proxies on the market volatility.

Panel B of Table 1 shows the estimation results of equation (2) for each investor sentiment proxy related to TA-35 index. The results show high statistical significance for SMMI and SVIX (prob.<0.01), with respective adjusted R-squares of 0.028 and 0.137, meaning that these two investor sentiment proxies explain daily market volatility. As expected, the coefficient of SMMI is negative (-0.053), implying that when the SMMI is positive and increasing, i.e. in times of a positive investor sentiment in TASE, the variability of the TA-35 index returns declines. For the SVIX coefficient, we show a positive relation between the SVIX and squared residuals, implying that the variability of the TA-35 index increases when the SVIX increases, which is to be expected because the SVIX measures the volatility level in the market. The SMSI indicator, which is based on the ratio of the volume of put relative to call options, is not significant in the OLS regression test, and henceforth cannot explain variability in the TA-35 index. These results are consistent with the findings of Brown and Cliff (2004).

Table 1: Two stage regression results of TA-35 index volatility and its respective investor sentiment proxies

We test for potential effects of the investor sentiment proxies on TA-35 index volatility by using OLS regression of the squared residuals obtained from equation (1) against each investor sentiment proxy. This table shows the regression results of the TA-35 daily returns against the lagged daily returns in Panel A, and summarizes regressions results for each regression test in Panel B. For each regression, the table shows the number of observations (after adjustments), the regression coefficient, the standard error and the respective *t*-statistics and adjusted R^2. The data are the daily TA-35 index simple returns and the sample period is January 19, 2000 – March 18, 2019.

Panel A: Regression estimation results of the form $R_{TA35,t} = \beta_0 + \beta_1 R_{TA-35,t-1} + \varepsilon_{k,t}$,

Variable	Coefficient	Std. Error	t-Statistic	Prob.	Observations	Model adjusted R^2
Intercept	0.03	0.017	1.730	0.083	N=4,703	0.030
$R_{TA-35,t-1}$	0.02	0.015	1.400	0.162		

Panel B: Regressions estimation results of the form:

$$\left(R_{TA35,t} - \hat{R}_{TA35,t}\right)^2 = \beta_0 + \beta_1 SENT_{TA-35,i,t} + \varepsilon_{TA-35,t}$$

Intercept	1.566	0.053	29.759	0.000	N=4,703	0.028
SMMI	-0.053	0.004	-11.652	0.000		
Intercept	0.674	0.400	1.686	0.092	N=2,275	0.000
SMSI	0.113	0.387	0.292	0.770		
Intercept	-1.424	0.113	-12.606	0.000	N=4,703	0.137
SVIX	0.178	0.006	27.286	0.000		

4.1.2. EGARCH (1,1) Results

Following Uygur and Taş (2014), we model the conditional volatility of TA-35 market index returns as a function of the change of investor sentiment proxies. This allows us to explore whether a change in a given i-type investor sentiment proxy is related to a change in the conditional variance of the stock market, and how this effect differs between the three sample subperiods (before, during and after the financial crisis of 2008). Table 2 summarizes the results of the EGARCH model on the TA-35 daily returns as a function of the change in SMMI and SVIX.[8] The table reports the coefficients of $\omega, \alpha, \beta, \gamma, \delta$ and the respective standard errors of the EGARCH (1,1) model, estimated for the three different subperiods.

The EGARCH coefficients show positive and highly significant α values in periods before and after the subprime crisis, but an insignificant α coefficient during the subprime crisis. These results are indicative of ARCH effect in times of relatively stable market, in which current volatility of TASE returns is highly sensitive to prior period market events. In times of financial distress there is no ARCH effect. The results also show a negative and highly significant γ coefficient in the period before the subprime crisis, indicating persistency of the conditional volatility during this period. However, persistency in the conditional volatility was not found be significant during and after the subprime crisis.

As expected, the results show negative and statistically significant β coefficient in periods before (prob.<0.1) and after (prob.<0.05) the subprime crisis, and insignificant β during the subprime crisis. This finding is suggestive for a leverage effect only in times of normal market conditions. This implies that during normal market conditions there is a negative autocorrelation between past returns and future volatility, meaning that bad news or negative sentiment in the stocks market have higher impact on the conditional variance of TA-35 index returns than a positive sentiment. This outcome is similar to the findings reported by Lee et al. (2002) and Verma and Verma (2007), who show a greater effect of bearish than bullish investors on the conditional volatility of the stock market return. In contrary, we found that in times of financial distress, when market conditions are binding and asset prices drop dramatically, the leverage effect fades out.

Estimated coefficients of $\Delta SMMI$ show statistical significance during and after the subprime crisis (prob.<0.05) but not beforehand, possibly due to the technology crash of the year 2000. There is a negative coefficient for $\Delta SMMI$ of -0.44 in the period after the subprime crisis, suggesting an adverse effect of *SMMI* on the conditional volatility of the local stock market's returns. I.e., a negative shock in *SMMI*, which implies a negative investor sentiment and a bearish change in market returns, leads to an increase in the conditional volatility of the market, as evident in Lee et al. (2002). This implies that during normal market conditions the market momentum

[8] Note that the effect of the change in SMSI cannot be modeled in EGARCH, which requires a continues data sample.

indicator may serve as a good proxy for investor sentiment in TASE, since it has a large effect on the conditional volatility of the market returns. We also observe adverse effect of $\Delta SMMI$ and the conditional volatility of TA-35 returns during the subprime crisis, with a negative $\Delta SMMI$ coefficient of -0.77 (prob.<0.1). This result implies that in times of financial distress, a negative change in market momentum has a larger effect on the conditional volatility of stock returns than in times of normal market conditions. This result may be explained by the flight-to-liquidity effect in times of financial distress, where highly illiquid stocks tend to have greater volatility of returns, as documented by Acharya and Pedersen (2005).

Table 2: EGARCH (1,1) model results

We test the effect of the change in investor sentiment proxies on the conditional volatility of TASE market returns based on the EGARCH (1,1), with mean and variance equations according to equations (3) and (4) respectively. The table reports estimation coefficients and standard errors (in parenthesis), the model's adjusted R^2, AIC and Schwarz criterion of the EGARCH (1,1) model, estimated for the three sample subperiods. The data are the daily TA-35 index simple returns and the sample periods vary by sample.

Panel A: Estimation results of the mean equation: $r_t = \mu + \varepsilon_t$,

Variable	Before Crisis	Subprime Crisis	After Crisis
Intercept	0.067 (0.0226)***	.0960 (0.1563)	0.0556 (0.0132)***

Panel B: Estimation results of the variance equation:

$$\log(\sigma^2_{TA35,t}) = \omega + \alpha\left[\frac{|\varepsilon_{TA35,t-1}|}{\sigma_{TA35,t-1}} - \frac{\sqrt{2}}{\pi}\right] + \beta\left(\frac{\varepsilon_{TA35,t-1}}{\sigma_{TA35,t-1}}\right) + \gamma\log(\sigma^2_{TA35,t-1}) + \delta_i \Delta SENT_{TA35,i,t}$$

Variable	Before Crisis	Subprime Crisis	After Crisis
ω	0.4164 (0.0646)***	1.990 (0.4773)***	-0.7283 (0.0595)***
α	0.1759 (0.0425)***	-0.1362 (0.2232)	0.4509 (0.0487)***
β	-0.0555 (0.0295)*	-0.1482 (0.1438)	-0.0823 (0.0334)**
γ	-0.2603 (0.0435)***	-0.2536 (0.2351)	0.0506 (0.0438)
$\Delta SMMI$	-0.1501 (0.1232)	-0.7703 (0.4682)*	-0.4443 (0.1843)**
$\Delta SVIX$	0.8803 (0.0431)***	0.4743 (0.1322)***	1.3248 (0.0717)***
Adjusted R-squared	-0.0003	-0.0035	-0.0009
Akaike Info Criterion	3.2618	4.4157	2.3391
Schwarz Criterion	3.2813	4.5593	2.3582
Time Period	01/20/2000 – 08/31/2009	09/01/2008 – 05/31/2009	06/01/2009 – 03/18/2019
Number of Observations	2,362	177	2,407

*, **, and *** indicate significance at the 10%, 5% and 1% level respectively

As expected, the $\Delta SVIX$ has a positive and highly significant coefficient in all three subperiods, suggesting that there is a large positive effect of the change in *SVIX* on the conditional volatility of TA-35 index return. This means that an increase in the *SVIX* sentiment indicator, pointing at a rise in future market risk's expectations and a lower investor sentiment, significantly increases the conditional variance of TASE index returns. Since an increase in *SVIX* is largely attributed to higher fear and stress in the market, and subsequently to a lower investors' sentiment, this result is also consistent with the negative effects of sentiments on volatility reported by Verma and Verma (2007). Our results further show large differences in the $\Delta SVIX$ coefficient between the three subperiods. We observe a coefficient of 0.47 during the subprime crisis, while we observe a coefficient of 0.88 and 1.32 before and after the subprime crisis, respectively. These values suggest that during normal periods, a temporary hike in volatility between *t* and *t-1* has a much greater effect on the conditional volatility of TA-35 returns than in times of financial distress.

4.2. Bond market sentiment

4.2.1. Regressions

Table 3 summarizes the two-stage regression results of the Tel-Bond-20 index with its respective investor sentiment proxies: BMMI, BSI and DRI. The results in Panel A show that the majority of the variation in the Tel-Bond-20 index returns are explained by the previous return of the index, as evident by the highly significant value of $R_{Tel-Bond\ 20,t-1}$ (prob. <0.01) in the estimation of equation (1).

Table 3 also shows estimation results of equation (2) for all investor sentiment proxies related to Tel-Bond-20 index. We find that all three investor sentiment proxies are highly significant (Prob. <0.01), while the BMSI has a greater explanatory power than the BMMI and DRI indexes (with respective adjusted R-squared of 0.123, 0.012 and 0.055). As expected, the results show a negative estimated coefficient for BMMI indicator (-0.036) and a positive estimated coefficient for BMSI (0.089), implying that a positive momentum of investor sentiment in the bonds market, which is reflected by a higher BMMI and a lower BMSI, significantly lowers the variability of the Tel-Bond-20 index. For the DRI index, a measure of the risk of default in the bonds market, the estimation results show a positive coefficient of 0.010, implying that when the DRI index increases, the variability of the Tel-Bond-20 index increases, and hence the DRI index is closely related to the variability of the Tel-Bond-20 market returns.

Table 3: Two stage regression results of Tel-Bond-20 index volatility and its sentiment proxies

We test for potential effect of the investor sentiment proxies on Tel-Bond-20 index volatility by using OLS regression of the squared residuals obtained from equation (1) against each investor sentiment proxy. This table shows the regression results of the Tel-Bond-20 daily returns against the lagged daily returns (Panel A), and summarizes regressions results for each regression test in Panel B. For each regression, the table shows the number of observations (after adjustments), the regression coefficient, the standard error and the respective t-statistics and adjusted R^2. The data are the daily Tel-Bond-20 index simple returns and the sample period is October 2, 2008 – March 18, 2019.

Panel A: Model estimation results:

$$R_{Tel-Bond\ 20,t} = \beta_0 + \beta_1 R_{Tel-Bond\ 20,t-1} + \varepsilon_{k,t},$$

Variable	Coefficient	Std. Error	*t*-Statistic	Prob.	Number of Observations	Model adjusted R^2
Intercept	0.016	0.007	2.340	0.019	N=2,969	0.036
$R_{Tel\text{-}Bond\text{-}20,t-1}$	0.191	0.018	10.607	0.000		

Panel B: Regressions estimation results:

$$\left(R_{Tel-Bond\ 20,t} - \hat{R}_{Tel-Bond\ 20,t}\right)^2 = \beta_0 + \beta_1 SENT_{Tel-Bond\ 20,i,t} + \varepsilon_{k,t}$$

Intercept	0.225	0.023	9.574	0.000	N=2,722	0.012
BMMI	-0.036	0.006	-5.882	0.000		
Intercept	-0.236	0.025	-9.513	0.000	N=2,969	0.123
BMSI	0.089	0.004	20.476	0.000		
Intercept	0.0003	0.006	0.048	0.962	N=1,854	0.056
DRI	0.010	0.001	10.496	0.000		

4.2.2. EGARCH (1,1) Results

We study the effect of a change in bonds market's investor sentiment proxies on the conditional variance of the Tel-Bond-20 index returns. Table 4 summarizes the results of the EGARCH model on the Tel-Bond-20 daily returns as a function of the change in BMMI and

BMSI.[9] The table summarizes the estimated coefficients of $\omega, \alpha, \beta, \gamma, \delta$ and the respective standard errors of the EGARCH (1,1) model, estimated for the three different subperiods.

Table 4 shows a positive and highly significant α (prob.<0.01) for all estimated subperiods, suggesting that the volatility of Tel-Bonds 20's returns is highly sensitive to market events.

Table 4: EGARCH (1,1) model results

We test the impact of a change in sentiment proxies have on the conditional volatility of Tel-Bond-20 returns with an EGARCH (1,1) model, as specified in equations (3) and (4). The table shows estimation coefficients and standard errors, and the model's adjusted R^2, AIC and Schwarz criterion. The data are the daily Tel-Bond-20 index simple returns and the sample period is January 19, 2000 – March 18, 2019.

Panel A: Estimation results of the mean equation:

$$r_t = \mu + \varepsilon_t,$$

Variable	Before Crisis	Subprime Crisis	After Crisis
Intercept	0.085 (0.0175)***	-0.030 (0.0576)	0.022 (0.0034)***

Panel B: Estimation results of the variance equation:

$$\log(\sigma^2_{TA35,t}) = \omega + \alpha \left[\frac{|\varepsilon_{TA35,t-1}|}{\sigma_{TA35,t-1}} - \frac{\sqrt{2}}{\pi} \right] + \beta \left(\frac{\varepsilon_{TA35,t-1}}{\sigma_{TA35,t-1}} \right) + \gamma \log(\sigma^2_{TA35,t-1}) + \delta_i \Delta SENT_{TA35,i,t}$$

Variable	Before Crisis	Subprime Crisis	After Crisis
ω	-0.8406 (0.1039)***	-0.7873 (0.2723)***	-0.1638 (0.0273)***
α	0.9049 (0.1543)***	0.6105 (0.2465)***	0.1445 (0.0251)***
β	-0.1281 (0.0887)	-0.0287 (0.1296)	-0.0611 (0.0132)***
γ	0.8184 (0.0390)***	0.0922 (0.1520)	0.9841 (0.0040)***
$\delta \Delta BMMI$	0.1896 (0.3261)	-0.8076 (0.6280)	0.2532 (0.0826)***
$\delta \Delta BMSI$	0.3778 (0.0864)***	0.7957 (0.1675)***	0.2563 (0.0631)***
Adjusted R-squared	-0.0033	-0.0005	-0.0005
Akaike Info Criterion	1.6347	2.6151	-0.4017
Schwarz Criterion	1.7178	2.7586	-0.3824
Time Period	02/11/2008 – 08/31/2009	09/01/2008 – 05/31/2009	06/01/2009 – 03/18/2019
Number of Observations	379	177	2,407

*, ** and *** indicate significance at the 10%, 5% and 1% level respectively

[9] Note that the effect of the change in DRI cannot be modeled in EGARCH, which requires a continues data sample.

As expected, in the period after the subprime crisis, the table reports a negative and statistically significant β coefficient (prob.<0.01), an indication of a leverage effect and a negative correlation between past returns and future volatility of the Tel-Bond-20 index returns. Hence, in normal times, a negative shock in the bonds market has greater impact on the conditional variance of Tel-Bond-20 returns than a positive shock has. This finding is similar to the findings reported by Nayak (2010), who shows that sentiment-driven mispricing and systematic reversal trends in the bonds market are very similar to those for the stocks market. Nonetheless, in the periods before and during the subprime crisis, our results show an insignificant β coefficient, suggesting that there is no leverage effect in the bonds market in times of financial distress. This outcome may be explained by the flight-to-quality effect before and during the subprime crisis, in which many investors toss their holdings in corporate bonds towards higher quality bonds, predominantly government bonds. Thus, negative shocks, while significantly outnumber positive shocks, exhibit an insignificant leverage effect.

Our results show differences in the γ coefficients between subperiods, which capture the persistency of the conditional volatility irrespective to the market shocks. As expected, the γ coefficient is found to be positive and highly significant in the periods before and after the subprime crisis, implying that during these periods, shocks to the conditional variance of Tel-Bond-20 will be highly persistent, i.e. a large noisy signal (positive or negative) will lead future variance to be high. In contrary, during the subprime crisis, persistency of the conditional variance fades out, implying that a temporary shock cannot affect future variance of bond market returns.

Regarding the coefficients of changes of investor sentiment proxies (δ), $\Delta BMMI$ has a positive and highly significant coefficient of 0.2532 in the normal period following the subprime crisis, which implies a positive effect on the conditional volatility of Tel-Bond-20 index returns. In the period before and during the subprime crisis, the $\Delta BMMI$ coefficient is not significant. These results suggest that during a normal period, where market conditions are normal and the overall sentiment is positive, a decrease in BMMI, which implies a decline in momentum, is associated with a decline in the conditional volatility. While the coefficient during the financial crisis is negative, and thus suggestive of a contrary effect (when sentiment is low, a decrease in BMMI increases conditional volatility), this coefficient is not significant, possibly due to much noise.

Concerning the BMSI index, our results show a positive and highly statistically significant $\Delta BMSI$ coefficient in all periods, implying that a positive change in BMSI increases the conditional volatility of the Tel-Bond-20 index returns. Hence, an increase in the BMSI, which reflects a higher market risk's expectations and a decrease in sentiment, is significantly related to an increase in the conditional variance of Tel-Bond-20 index returns. As expected, the coefficient of $\Delta BMSI$ during the subprime is much higher than the estimated coefficients found before and after the subprime crisis (0.79, 0.37 and 0.25 respectively).

In summary, our results show that the momentum-based indicators can explain return volatility in the Israeli stocks and bonds market returns. For the stocks market, we show that a positive change in momentum (i.e., positive change in SMMI) also increases the conditional volatility of TA-35 returns, while a positive change in BMMI reduces the conditional volatility of Tel-Bond-20 index's returns. Yet, we find that the change in momentum affects the conditional volatility of Tel-Bond-20 index only in times of normal market conditions. For the volatility-based indicators, we find that a change in these indicators also increases the conditional volatility of returns in both the TA-35 and Tel-Bond-20 indexes and in all subperiods, however they differ in magnitude. We find that in times of normal market conditions, a positive change in the implied volatility-based $SVIX$ indicator typically has a larger effect on the conditional volatility of the stock market returns than in times of financial distress. In contrary, we observe a lower effect of $\Delta BMSI$ on the conditional volatility of the Tel-Bond-20 index returns during the periods before and after the subprime.

5. Conclusions

An extensive body of literature shows that noise traders may affect financial asset prices. Because rational investors should not trade on noise, behavioral trades due to sentiment may help explain those trades. We use several proxies of market sentiment indicators in order to study the effect that noise traders may have on the conditional volatility of the stock and bond markets' index returns in TASE. Our test of bond market sentiment appears to be the first to measure retail investors' sentiment, as they are highly active in the Israeli limit order book market, as opposed to OTC bond trading in most of developed exchanges. Additionally, given our unique dataset of retail investors in corporate bonds, our paper is the first to explore retail investors' sentiment, rather than institutional investors' sentiment on conditional volatility.

Using an EGARCH model on the TA-35 and Tel-Bond-20 index returns, we show that a change in market sentiment proxy, which reflects a change in risk expectations and investor sentiment, largely explain movements in the conditional volatility of both the stock and bond market returns. More specifically, our results show that momentum-based indicators and volatility-based indicators are closely related to bond and stock market return volatility in TASE. We also find that the index that captures risk of default in the bond market explains the volatility of the corporate bond index.

Given the low sentiment that was measured during the financial crisis of 2008, we find that the change in volatility-based sentiment proxies has a larger effect on conditional volatility of corporate bond index returns than in times of normal market conditions, while this pattern is reversed in the stock index returns.

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