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Does trading mechanism shape cross-market integration? Evidence from stocks and corporate bonds on the Tel Aviv Stock Exchange

Elroi Hadad
Department of Industrial Engineering and Management, Shamoon College of Engineering, Beer-Sheva, Israel

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Abstract

Purpose – This study investigates the influence of trading mechanisms on cross-market integration between stocks and corporate bonds on the Tel Aviv Stock Exchange (TASE) during the COVID-19 crisis. Unlike the worldwide practice of trading corporate bonds on an over-the-counter (*OTC*) market, TASE uses a limit-order-book (LOB) for both stocks and bonds, potentially creating unique volatility dynamics through direct information spillover. We analyze the volatility dynamics and spillover effects between TASE's stock and corporate bond markets.

Design/methodology/approach – We employ an exponential general autoregressive conditional heteroskedastic (EGARCH)(1,1) model to assess the impact of stock market fear, measured by implied volatility, on Tel-Bond 20 Index returns and volatility. A bivariate diagonal Baba-Engle-Kraft-Kroner (BEKK) model is also applied to capture time-series integration and cross-volatility spillovers between the TA-35 Index (stocks) and the Tel-Bond 20 Index (corporate bonds), especially during financial stress.

Findings – The EGARCH model reveals a significant contagion effect, with increased stock market fear lowering corporate bond returns and increasing bond volatility. It also indicates a leverage effect, where negative shocks disproportionately amplify bond volatility. Diagonal BEKK results confirm strong cross-market volatility persistence, especially during crises, highlighting substantial financial contagion between stocks and bonds in TASE. While TASE's market design improves the overall market quality, these findings underscore the LOB trading mechanism in facilitating financial contagion and systemic risk.

Practical implications – The LOB trading in TASE facilitates direct information flow, intensifying volatility spillover and cross-market integration, with the degree of integration fluctuating based on market conditions. Investors and managers should consider alternative hedging strategies during volatile periods, as stock market sentiment significantly impacts bond stability. Regulators should assess how trading mechanisms affect market integration and risk, especially during periods of distress.

Originality/value – This study offers new insights into how trading mechanisms influence cross-market dynamics, contributing to the literature on market design and financial contagion.

Keywords Corporate bonds, Stocks, Cross-market integration, Trading mechanism, Conditional volatility

Paper type Research paper

1. Introduction

Firms use capital markets to finance their business activity via the issuance of equity or corporate debt. Since both equity and corporate bonds are claims on the same asset, their

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expected returns should be associated with rational pricing in liquid and frictionless markets. In a perfectly liquid and rational market, equity and corporate bonds should have linked expected returns, as they both represent claims on the same asset, as noted by Merton (1974). However, this cross-market linkage might be altered in times of crisis and generally change over time, resulting from changes in macroeconomic conditions or investor sentiment (Campbell *et al.*, 2020).

If equity and corporate bond markets exhibit integration, risk premia in one market should influence the other, and the relative magnitude of return premia for stocks should align with those of contingent bond returns premia (Choi and Kim, 2018). Financial literature supports this view of integration, indicating that stock-bond correlations can vary between positive and negative values, reflecting shifts in the risk-return tradeoff over time.

The risk-return tradeoff between stocks and corporate bonds, as noted by Choi and Kim (2018), is less documented and often examined in isolation within either equity or debt markets, primarily in the USA. This gap is surprising given the significant increase in debt financing and increased corporate bond trading volume, especially post-financial crisis (Abraham *et al.*, 2021; Bai *et al.*, 2019; Graham *et al.*, 2015). Gebhardt *et al.* (2005) suggest that spillover effects may arise when investors in one market (e.g. corporate bonds) underreact to information from another market (e.g. stocks). Examining the co-movements of price volatility between stock and corporate bond markets is crucial, as corporate bond returns volatility is not just driven by different risk characteristics (i.e. downside risk, credit risk and liquidity risk) but can also be affected by informational frictions, leading to volatility spillover effects.

Recent studies highlight positive intertemporal relationships between stock and corporate bond markets, including momentum spillover from the USA stocks to bonds (Choi and Kim, 2018; Downing *et al.*, 2009; Gebhardt *et al.*, 2005; Gurun *et al.*, 2016; Haesen *et al.*, 2017; Hong *et al.*, 2012) and cross-sectional evidence between the USA stocks and corporate bonds of the same firms (Anginer and Yildizhan, 2018; van Zundert and Driessen, 2022). Choi and Kim (2018) further highlight that integration between the USA equities and corporate bonds weakens with noisier investor demand, underscoring the role of information asymmetry and investor behavior. Notably, van Zundert and Driessen (2022) find stronger cross-sectional correlations between the USA equities and non-investment-grade bonds than with investment-grade bonds, suggesting a different risk-return tradeoff and potential mispricing. Similarly, Bali *et al.* (2021) observed mispricing between the USA stocks and corporate bonds, with economic uncertainty premia varying according to heterogeneous risk-aversion levels in these markets. They attribute these differences to clientele behavior, noting that institutional investors dominate the USA corporate bond market, while retail investors are more active in equity markets (Bajo *et al.*, 2013).

Retail and institutional investors differ significantly in information efficiency, with institutional investors possessing greater resources and skills for processing market data (Boulatov *et al.*, 2013; Hendershott *et al.*, 2015). Institutional investors tend to gather firm-specific information and closely monitor management activities (Bajo *et al.*, 2013), exhibiting different risk preferences and investment strategies compared with retail investors (Boulatov *et al.*, 2013; Hendershott *et al.*, 2015). Given that momentum spillover often stems from initial underreaction to information (Barberis *et al.*, 1998; Hong and Stein, 1999; Wu *et al.*, 2023), this heterogeneity in information processing can drive spillovers across equity and corporate bond markets, influencing cross-asset price dynamics.

Motivated by recent evidence on the time-series relationship between stocks and corporate bonds and the potential impact of clientele behavior on asset dynamics, we hypothesize that financial integration between stocks and corporate bonds is more pronounced in corporate bond markets with high retail investor activity. Retail investors, often less informed and more susceptible to psychological biases and sentiment (Barber and Odean, 2008; Kaniel *et al.*, 2008; Kumar and Lee, 2006), may impact market dynamics significantly. This aspect of financial interconnectedness aligns with extensive literature on financial contagion, where markets exhibit heightened co-movements following a shock in one of these markets (Patel *et al.*, 2022). Our study investigates the specific dynamics of interconnectedness between equity and corporate bond markets during and after the COVID-19 pandemic, highlighting how these markets respond to external shocks and the potential influence of high retail trading activity on market dynamics.

To examine financial market integration within a high retail trading environment, we focus on volatility connectedness between stocks and bonds on the Tel Aviv Stock Exchange (TASE), where retail trading is prevalent across both markets (Abudy and Shust, 2023; Abudy and Wohl, 2018; Gur-Gershgoren *et al.*, 2020; Hadad and Kedar-Levy, 2024). TASE's setup allows stocks and bonds to trade on the same limit-order book (LOB), which facilitates direct information flow and reduces information heterogeneity between institutional and retail investors. In contrast, corporate bonds in the USA are traded over-the-counter (*OTC*), limiting retail investors' participation due to low transparency and high transaction costs (Edwards *et al.*, 2007). Abudy and Wohl (2018) document that the Israeli corporate bond market exhibits higher liquidity and narrower spreads than the USA *OTC* bond market, suggesting a stronger interdependence and information flow between stock and corporate bond markets and making TASE an ideal context for studying cross-market integration.

Our primary objective is to analyze co-movements from stocks and corporate bonds, to understand connectedness amid heightened uncertainty periods and to explore potential volatility dynamics driven by information spillover. To capture spillover, we utilize a univariate EGARCH model (Nelson, 1991) to Tel-Bond 20 index returns (representing the bond market) and assess the impact of a change in the stock market "fear gauge" – proxied by the implied volatility of Tel Aviv-35 (TA-35) Index returns (representing the stock market) – on its returns and volatility. Additionally, we employed a bivariate diagonal Baba-Engle-Kraft-Kroner (BEKK) model (Engle, 2002) on the returns of the TA-35 and Tel-Bond 20 indices to capture return co-movement and illustrate market integration. Recognizing that bond mispricing intensifies during crises (Batten *et al.*, 2018), we examined volatility dynamics throughout the COVID-19 crisis and other periods of financial distress from 2017 to 2022.

Our findings reveal that market returns demonstrate volatility clustering, particularly during financial distress periods, including the COVID-19 pandemic, political uncertainty and inflation concerns. We identify a strong contagion effect from stocks to bonds: as stock market fear rises, corporate bond returns fall and volatility escalates, indicating heightened risk premiums. The diagonal BEKK model confirms robust interdependencies, with major news events amplifying conditional volatility and correlations between stocks and bonds. These results suggest that stock and corporate bond markets in TASE are economically integrated, with their co-movement highly sensitive to informational frictions.

We innovate in two aspects. First, our findings highlight the critical role of investor behavior during financial turmoil, such as the COVID-19 pandemic, inflation fears and political uncertainty, in shaping corporate bond dynamics. Investor reactions to new information and heightened risk perceptions significantly influence market integration, reinforcing cross-asset dynamics between stocks and corporate bonds (Baele *et al.*, 2020; Ponrajah and Ning, 2023). Secondly, while prior studies in *OTC* bond markets associate market integration with shifts between contagion and flight-to-safety behavior (Baur and Lucey, 2009; Ponrajah and Ning, 2023), our findings from TASE reveal a strong contagion effect, which intensifies during heightened periods. We attribute these differences to variations in clientele behavior and market structure, whereby TASE's unique LOB system is characterized by high retail trading activity and transparency (Abudy *et al.*, 2024; Hadad and Kedar-Levy, 2024), in contrast to institutional investor dominance in *OTC* markets (Bajo *et al.*, 2013). Retail investors, being more prone to sentiment-driven behavior (Baker and Stein, 2004; Baker and Wurgler, 2007), amplify price volatility and contagion effects, as sentiment spreads quickly across asset classes. While TASE's market design enhances the overall market quality (Abudy and Shust, 2023; Abudy *et al.*, 2024), our findings suggest that these same features make the market highly responsive to systemic shocks, emphasizing the dual-edged impact of trading infrastructure on market quality.

Our study has important implications for investors, managers and regulators. First, our results suggest that investors should consider the price dynamics between markets, especially during financial turmoil, to make informed investment decisions. Secondly, our results highlight the need for diversification and risk management, as corporate bonds are not only driven by differences in risk characteristics but also affected by informational frictions. Thirdly, the role of TASE's unique trading mechanism in shaping market integration between stocks and bonds underscores the importance of understanding the impact of trading mechanisms on market dynamics for regulators to ensure market stability.

The rest of the paper is structured as follows: Section 2 provides a literature review describing the theoretical and empirical evidence of market integration between stocks and bonds and the potential impact of investor sentiment on corporate bond returns; Section 3 describes the data and variables; Section 4 details the methodology; Section 6 presents empirical results and Section 6 concludes.

2. Literature review

Equity and corporate bonds are theoretically linked by shared economic fundamentals, as both represent claims on a firm's underlying assets (Merton, 1974). This relationship suggests that risk premiums across equity and corporate bonds should be correlated, given their mutual dependence on firm-specific fundamentals (Gebhardt *et al.*, 2005). However, empirical evidence reveals significant deviations, particularly during periods of economic crises, macroeconomic shifts or changes in investor sentiment, highlighting the dynamic and evolving nature of cross-market integration (Campbell *et al.*, 2020; Choi and Kim, 2018).

Historical evidence from the USA markets provides further insights into these dynamics. Studies indicate a strong correlation between stock and bond returns, suggesting that equities often lead bonds in reflecting new information (Chordia *et al.*, 2017; Haesen *et al.*, 2017). For instance, Huang *et al.* (2015) find that a decline in stock liquidity negatively affects the USA bond yield spreads, with stronger effects observed after the financial crisis. Similarly, Chung *et al.* (2019) highlight the impact of idiosyncratic stock volatility on bond returns via concurrent stock price movements. Choi and Kim (2018) emphasize that the integration between stocks and corporate bonds fluctuates with investor sentiment, indicating that sentiment plays a significant role in driving spillovers between these markets. Radi *et al.* (2024) further explored behavioral influences, showing that herding and anti-herding behaviors in stock and corporate bond markets substantially shape stock-bond return correlations.

Recent studies further reveal time-varying correlations between stocks and bonds, which oscillate between negative and positive, depending on market conditions. Negative dependence arises when bonds, seen as safe-haven assets, attract investors during periods of heightened risk (Baele *et al.*, 2020; Opitz and Szimayer, 2018). This flight-to-safety behavior prompts reallocations from bonds to stocks during market upturns and back to bonds during downturns (Aslanidis *et al.*, 2020; Ponrajah and Ning, 2023). Rising interest rates also reinforce this negative dynamic by increasing bond returns while reducing equity returns (Ponrajah and Ning, 2023). Empirical studies confirm this negative co-movement during crises (Aslanidis *et al.*, 2020; Baele *et al.*, 2020; Connolly *et al.*, 2005), attributing them to flight-to-quality, where investors seek higher-quality bonds or flight-to-liquidity, where investors prioritize more liquid assets (Acharya *et al.*, 2013; Acharya and Pedersen, 2005; Chen *et al.*, 2007; Dick-Nielsen *et al.*, 2012; Friewald *et al.*, 2012; Longstaff, 2004; Næs *et al.*, 2011; Pástor and Stambaugh, 2003; Tachibana, 2020). These dynamics, as noted by Baur and Lucey (2009), contribute to financial stability by mitigating investor losses during turbulent periods.

Conversely, positive dependence often signals financial contagion, emerging after economic shocks when investors adjust positions across both markets to manage heightened risks (Katsiampa *et al.*, 2022). This contagion typically stems from systemic economic risks or significant macroeconomic changes that simultaneously impact stocks and bonds (Bernanke and Kuttner, 2005; Boyd *et al*., 2005; Yang *et al*., 2009). Although extensive research has documented contagion within stock markets (Forbes and Rigobon, 2002a; Morana and Beltratti, 2008; Nguyen *et al*., 2022) and bond markets (Cronin *et al*., 2016; Forbes and Rigobon, 2002b; Leschinski and Bertram, 2017; Li *et al*., 2022), studies specifically addressing stock-bond contagion remain limited (Baur and Lucey, 2009; Choi and Kim, 2018). Recent studies suggest that stock-bond integration alternates between contagion during downturns and flight-to-quality during crises, underscoring the sensitivity of cross-asset dynamics to market stress (Baele *et al*., 2020; Baur and Lucey, 2009; Cappiello *et al*., 2006; Ponrajah and Ning, 2023). However, these findings predominantly focus on government bonds, leaving corporate bond dynamics underexplored.

Other research highlights the role of sentiment and irrational behavior in bond markets. For example, Piazzesi (2005) shows that Federal Open Market Committee announcements significantly affect bond market volatility, suggesting underreaction among bond investors. Nayak (2010) and Bethke *et al*. (2017) identify sentiment-driven co-movements in bond yield spreads and flight-to-quality during periods of low sentiment, while Lu *et al*. (2010) demonstrate that information uncertainty and asymmetry are priced into the USA corporate bond yield spreads. International studies further corroborate these trends, finding that sentiment-driven behavior influences corporate bond returns across various markets (Goldstein and Namin, 2023; Lithin *et al*., 2023; Mukherjee, 2019; Rath, 2023). However, these studies predominantly focus on *OTC* corporate bond markets dominated by institutional investors rather than retail-sized participants (Bajo *et al*., 2013; Edwards *et al*., 2007) who are more susceptible to sentiment-driven behavior (Brown and Cliff, 2004).

In the Israeli context, several studies document the significant role of retail investors in enhancing market liquidity and efficiency and in contributing to market quality (Abudy and Shust, 2023; Abudy and Wohl, 2018; Abudy *et al*., 2024). Hadad and Kedar-Levy (2024) further highlight the positive impact of retail activity on corporate bond returns and volatility. While these studies suggest that sentiment plays a role in shaping bond returns, they do not explore the information spillover between equity and corporate bond markets. Compared to *OTC* markets, where institutional investors dominate, the prevalence of retail investors in the TASE could amplify such spillovers, as retail participants are more prone to sentiment-driven behavior (Baker and Wurgler, 2006, 2007).

We utilize unique data from TASE to investigate these dynamics, examining the impact of retail investor activity and centralized trading infrastructure on stock-bond interactions during periods of heightened uncertainty. Details on the data and variables are provided in Section 3.

3. Data and variables

Our dataset includes daily closing prices of the TA-35 Index and the Tel-Bond 20 Index. The TA 35 Index consists of 35 companies with the highest market capitalization, which collectively account for 55% of the trading volume (TASE, 2021) and hence represent the equity market. The Tel-Bond 20 Index consists of 20 corporate bonds with the highest market capitalization, which capture most of the trading volume (Abudy and Wohl, 2018) and hence represent the debt market. Daily observations of the TA-35 Index and Tel-Bond 20 Index are publicly available at https://www.tase.co.il/en, which is the official TASE website.

To account for time-varying volatility and cross-market correlations across a range of financial scenarios, we have chosen a sample period spanning from June 5, 2017, to June 26, 2022. This timeframe covers the periods before, during and after the exceptional market turbulence triggered by the COVID-19 crisis, providing a comprehensive view of market reactions during different phases of the crisis. Additionally, it encompasses the volatility observed during the inflation concerns of 2022 and the period marked by political uncertainty and early election speculation in 2018.

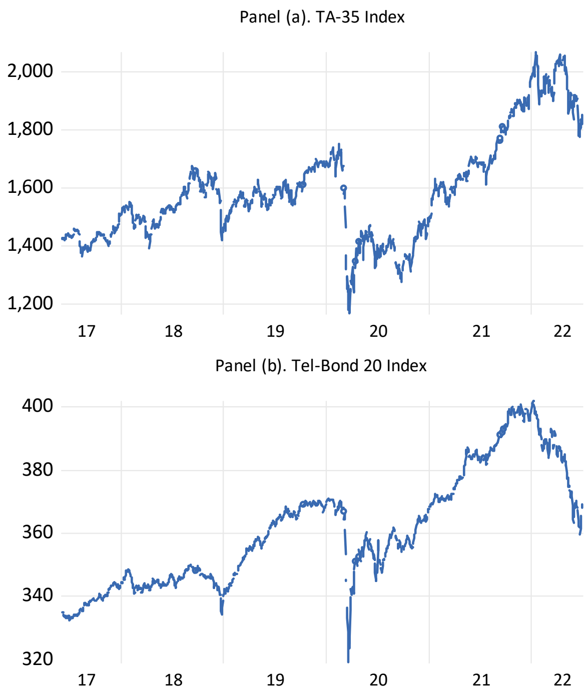
Daily returns are defined as follows:

$$R_t = ln(P_t) - ln(P_{t-1}), \tag{1}$$

Where R_t is the logarithmic price change and P_t is the daily closing price of the Tel-Bond 20 Index and the TA-35 Index and at time t.

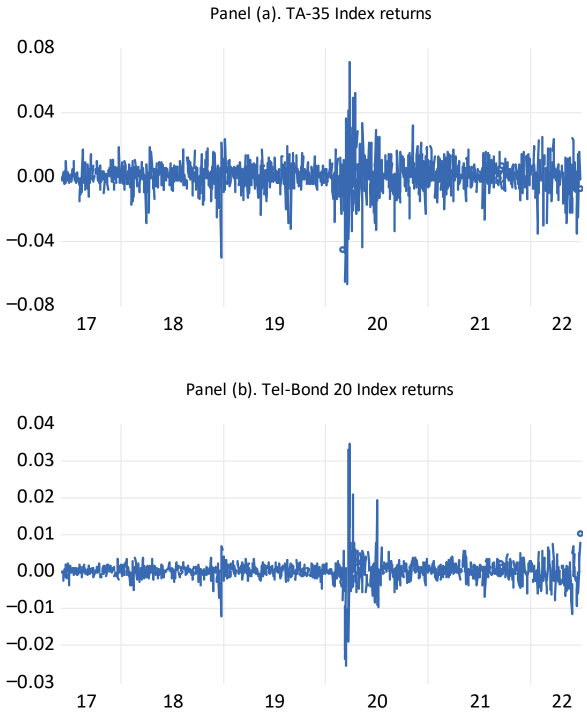
Figure 1 illustrates the price trends of the TA-35 Index and Tel-Bond 20 Index, showing a general upward movement from June 2017 to March 2020, except for a dip in late 2018. Both indexes dropped sharply during the COVID-19 crisis in March 2020 but rebounded similarly from April 2020. They declined again in Q2 2022, reflecting inflation concerns. These patterns suggest that the TA-35 Index and Tel-Bond 20 Index could be correlated. Both Pearson correlation (0.792) and Spearman rank-order correlation (0.768) are highly significant, indicating the existence of covariation between the stock and bond markets and suggesting common behavior in the price trends for both stocks and bonds.

Figure 2 shows the price trends of the TA-35 Index and Tel-Bond 20 Index returns. The figure depicts a common trend, with both indexes exhibiting similar spikes in returns and volatility over time. Specifically, Figure 2 shows that both indexes experienced significant spikes in returns volatility during the COVID-19 crisis period, suggesting that the pandemic had a significant impact on both indexes and underscores the interdependence between the two indexes in times of crisis. The figure also depicts a common volatility trend in returns in December 2018, in line with the rise in the political uncertainty and speculation about early elections (resulting from the resignation of key government officials), which have been observed to influence the TA-35 Index. Further, another volatility trend is observed in January 2022, in line with the rise in fear in the markets resulting from fear of inflation. These results suggest for possible interconnectedness between the two indexes and a potential spillover



Source(s): Author’s own work

Figure 1. Daily closing prices of TA-35 and Tel-Bond 20 Indexes



Source(s): Author's own work

Figure 2. Daily returns of TA-35 and Tel-Bond 20 Indexes

effect between the equity and debt markets. These results suggest that a bivariate GARCH can be employed in order to study the co-movement between the stock and bond markets.

Table 1 shows summary statistics, unit root tests and heteroscedasticity tests for TA- 35 Index and Tel-Bond 20 Index returns for the entire sample. Results in Panel (a) show positive average returns for both indexes, suggesting a bullish trend in stock and bond markets. The returns of the TA 35 Index exhibit a negative skewness, while the Tel-Bond 20 Index returns show a positive skewness, implying that the stock market is more likely to observe outlying negative returns. Considering the volatility, as expected, the TA 35 Index returns exhibit a much larger standard deviation and lower kurtosis than Tel-Bond 20 Index returns, suggesting that corporate bond returns are more concentrated about the mean; however, the kurtosis values of both index returns are higher than three, indicating that the returns distribution could be fat-tailed. Jarque–Bera results confirm the departure from normality, while the conditional heteroscedasticity test suggests the existence of the autoregressive conditional heteroskedasticity (ARCH) effect in both index returns, implying volatility clustering in returns.

Panel (b) results show the Augmented Dickey–Fuller (ADF) test (Dickey and Fuller, 1981) and Phillips–Perron (PP) test (Perron, 1988) for the daily returns of the TA-35 index and Tel-Bond 20 index. Results show that both ADF and PP values are highly significant, suggesting stationarity in TA-35 and Tel-Bond Index returns and stationarity in price levels. These results suggest that GARCH modeling is suitable to model the conditional variances and covariance of the index returns.

Lastly, we consider the volatility of the TA-35 index to quantify how changes in investors' fear in the stock market influence the returns and conditional volatility of the Tel-Bond 20 index. Following Hadad and Kedar-Levy (2024), we use the implied volatility in TASE

Table 1. Summary statistics and unit root tests for TA-35 and Tel-Bond returns

	Rs	*Rb*
Panel (a): summary statistics		
Mean	0.000251	8.29E−05
Median	0.000587	0.000229
Maximum	0.070995	0.034540
Minimum	−0.066993	−0.025511
Std. Dev	0.010548	0.003134
Skewness	−0.610842	0.789193
Kurtosis	10.07618	36.45240
Jarque–Bera	2672.776***	58133.91***
ARCH(1)	0.3255***	0.249***
Observations	1,244	1,244
Panel (b): unit root tests		
ADF	−35.5854***	−15.5341***
PP	−35.737***	−28.1269***

Note(s): Rs: TA-35 returns; Rb: Tel-Bond 20 returns; sample range: 5 June 2017–26 June 2022. Significance: ***1%; **5% and *10%
Source(s): Author's own work

(VIXTA) indicator to capture stock market volatility, which measures the implied volatility of TA-35 index options. Similar to the widely used VIX indicator for S&P100 (Piñeiro-Chousa *et al.*, 2017; Whaley, 2000), the VIXTA captures the fear in the stock market, allowing us to analyze the impact of the change in stock market volatility on corporate bond returns volatility to enhance our understanding about the volatility dynamics in TASE. Daily observations of VIXTA are from the Bizportal website (https://www.bizportal.co.il/publictrustindices). We calculate the variation of the VIXTA indicator as the change in at time *t*, namely

$$\Delta VIXTA_t = VIXTA_t - VIXTA_{t-1}. \tag{2}$$

4. Methodology

To study financial market dynamics among stocks and corporate bonds in the TASE and potential volatility dynamics and spillovers from stocks to corporate bonds, we examine potential volatility dynamics and spillovers from stocks to corporate bonds by modeling the impact of changes in VIXTA, a measure capturing market fear (Baker and Wurgler, 2007; Hadad and Kedar-Levy, 2024; Whaley, 2000), on bond returns and volatility. This step is crucial, as a significant impact of changes in VIXTA on corporate bond returns may reveal risk-return dynamics between equity and bond markets, suggesting that stock market fluctuations influence risk perceptions in TASE's bond market. To capture the volatility patterns of corporate bond returns, we employ univariate GARCH models, which are well suited for handling the volatility clustering commonly observed in financial time series as well as the fat-tailed distribution of asset returns.

Given the clustering and distributional characteristics of Tel-Bond 20 Index returns, we tested several asymmetric GARCH models, including EGARCH (Nelson, 1991), Threshold GARCH (TGARCH) (Zakoian, 1994) and Glosten-Jagannathan-Runkle GARCH (GJR-GARCH) (Glosten *et al.*, 1993), which capture asymmetrical effects in which negative shocks can lead to greater volatility than positive shocks of similar magnitude. Following Hadad and Kedar-Levy (2024), we found EGARCH(1,1) to provide the best fit, with the lowest Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC) values among models tested. Model diagnostics confirmed its suitability, with an insignificant autoregressive conditional heteroskedasticity lagrange multiplier

(ARCH-LM) Q-statistics test indicating no serial correlation or heteroscedasticity in residuals. Furthermore, EGARCH effectively models asymmetric volatility due to its logarithmic form, which avoids restrictive coefficient constraints, thus enhancing volatility modeling accuracy (Hadad and Kedar-Levy, 2024; Piñeiro-Chousa *et al.*, 2017).

The EGARCH(1,1) model allows us to assess the influence of changes in stock market fear gauge (change in VIXTA) on bond returns and volatility. The mean equation is specified as follows:

$$Rb_t = \mu + \theta \Delta VIXTA_t + \varepsilon_t, \tag{3}$$

where Rb_t represents the daily return of the Tel-Bond 20 Index, μ is the mean return, θ is the coefficient of the change in VIXTA, capturing its direct effect on bond returns and ε_t is the error term. We expect θ to be negative, indicating that an increase in VIXTA, reflecting a rise in investors' fear, may reduce Tel-Bond 20 Index returns.

The variance equation of the EGARCH(1,1) model is given by

$$log(h_t) = \omega + \alpha \left[\frac{|\varepsilon_{t-1}|}{h_{t-1}} \right] + \beta \left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right) + \gamma log\left(h^2_{t-1}\right) + \delta \Delta VIXTA_t, \tag{4}$$

where h_t is the conditional variance of the residuals of the Tel-Bond 20 Index returns; ω is a constant term; α captures the symmetric response of volatility to shocks, representing the EGARCH(1,1) effect; β captures the leverage effect, showing the differential impact of negative versus positive shocks; γ measures the persistence of volatility, indicating how long volatility shocks remain impactful, and δ is the coefficient for the change in VIXTA, quantifying the effect of changes in stock market fear on the volatility of corporate bond returns. A positive and significant δ may indicate higher anticipated volatility of the Tel-Bond 20 Index returns as a result of increased market fear.

To capture the dynamic, time-varying conditional covariance between the TA-35 Index and Tel-Bond 20 Index returns, we employ multivariate GARCH models capable of modeling time-varying correlations between asset classes. These models are well suited for capturing the interactions between stock and bond markets, allowing us to estimate conditional variances and covariances that evolve over time based on past shocks and variances. This approach provides insights into market spillovers, risk transmission and investor behavior under varying economic conditions.

Among various multivariate GARCH models available, options include the constant conditional correlation (CCC) model (Bollerslev, 1990), the dynamic conditional correlation (DCC) model (Engle, 2002) and the BEKK model (Engle and Kroner, 1995). For instance, Khalid and Ahmad (2023) employed the *DCC* model to analyze stock-bond co-movements within the ASEAN-5 market, investigating how financial integration and development influence these co-movements. However, while the CCC and *DCC* models assume a simpler structure, the BEKK model provides a more dynamic setup by allowing each asset's conditional variances and covariances to depend on its own past values as well as on those of the other asset (Fengler *et al.*, 2017). This feature renders BEKK particularly well suited for examining spillover effects and the causal impact of past volatility between financial asset classes (Allen and McAleer, 2018; Chang and McAleer, 2017; Katsiampa *et al.*, 2022).

Despite its strengths, the full BEKK model has limitations. Studies by Allen and McAleer (2018) and McAleer (2019) critique its extensive parameterization, which can lead to estimation instability and hinder model efficiency, particularly under the Quasi-Maximum Likelihood Estimation (QMLE) framework. Additionally, the full BEKK model often lacks the regularity conditions necessary for QMLE, potentially resulting in biased parameter estimates. To address these issues, we employ the diagonal BEKK model, a reduced form of the full BEKK model, which imposes zero restrictions on the off-diagonal elements in the estimated **A** and **B** matrices. This restriction significantly lowers the number of parameters, improving estimation stability and efficiency while retaining the core dynamics of time-varying volatilities and covariances (Allen and McAleer, 2018; Engle and Kroner, 1995; Katsiampa *et al.*, 2022; McAleer, 2019), making it a preferred choice for modeling stock-bond co-movements.

We employ the diagonal BEKK model to capture the time-varying conditional covariance between TA-35 Index and Tel-Bond 20 Index returns in our sample. The mean equation of our bivariate Diagonal BEKK model is given by

$$\mathbf{R_t} = \mathbf{c} + \boldsymbol{\varepsilon}_\mathbf{t}, \tag{5}$$

where $\mathbf{R_t}$ is a 2×1 vector of daily returns for the TA-35 Index and Tel-Bond 20 Index; $\mathbf{c}$ is a 2×1 vector of constants representing the average returns for each index and $\varepsilon_\mathbf{t}$ is the 2×1 vector of residuals, capturing deviations from the mean and modeled by the diagonal BEKK structure in the variance-covariance matrix $\mathbf{H_t}$, given as a function of the information set $\boldsymbol{\Omega}_{\mathbf{t-1}}$.

The variance-covariance matrix of our Diagonal BEKK model is expressed as follows:

$$\mathbf{H_t} = \mathbf{M^T M} + \mathbf{A^T}\boldsymbol{\varepsilon}_{\mathbf{t-1}}\mathbf{A} + \mathbf{B^T H_{t-1} B}, \tag{6}$$

where $\mathbf{M}$, $\mathbf{A}$ and $\mathbf{B}$ are 2×2 parameter matrices, with $\mathbf{A}$ and $\mathbf{B}$ structured as diagonal elements. This setup ensures positive definiteness, meaning that the conditional covariance remains valid over time. The bivariate case for our diagonal BEKK can be written as follows:

$$\boldsymbol{H_t} = \begin{bmatrix} h_{11,t} & h_{12,t} \\ h_{12,t} & h_{22,t} \end{bmatrix} = \boldsymbol{M^T M} + \begin{bmatrix} a_{11,t} & 0 \\ 0 & a_{22,t} \end{bmatrix}^T \begin{bmatrix} \varepsilon^2_{1,t-1} \\ \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon^2_{2,t-1} \end{bmatrix} \begin{bmatrix} a_{11,t} & 0 \\ 0 & a_{22,t} \end{bmatrix}$$

$$+ \begin{bmatrix} b_{11,t} & 0 \\ 0 & b_{22,t} \end{bmatrix}^T \begin{bmatrix} h_{11,t-1} & 0 \\ 0 & h_{22,t-1} \end{bmatrix} \begin{bmatrix} b_{11,t} & 0 \\ 0 & b_{22,t} \end{bmatrix}$$

which results in a system of equations

$$\begin{aligned} h_{11,t} &= m^2_{11} + a^2_{11}\varepsilon^2_{1,t-1} + b^2_{11}h_{11,t-1} \\ h_{22,t} &= m^2_{22} + a^2_{22}\varepsilon^2_{2,t-1} + b^2_{22}h_{22,t-1} \quad , \\ h_{12,t} &= m_{11}m_{22} + a_{11}a_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + b_{11}b_{22}h_{12,t-1} \end{aligned} \tag{7}$$

where $h_{11,t}$ is the conditional variance of the TA-35 Index indexes, $h_{22,t}$ is the conditional variance of the Tel-Bond 20 Index and $h_{12,t}$ is their conditional covariance.

Following McAleer (2019), we apply the quasy maximum likelihood estimate (QMLE) method under multivariate normal and student's t-distributions using the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm, which yields consistent and asymptotically normal parameter estimates. To select the best-fit model, we use the AIC and SIC criteria.

Finally, to study the co-movement between stocks and corporate bond indexes, we model the dynamic correlation between TA-35 Index and Tel-Bond 20 Index over our sample. The dynamic correlation is given by

$$r_t = \frac{h_{12,t}}{\sqrt{h_{11,t} \cdot h_{22,t}}} \tag{8}$$

Following Baur and Lucey (2009), we focus on shifts in correlation levels, which align with conventional definitions of contagion and are closely related to the concept of flight-to-quality behavior. Specifically, we define financial contagion as a positive stock-bond correlation that significantly increases in a crisis period compared to a normal period. Conversely, a positive pre-crisis correlation level accompanied by a negative change in correlation during crisis periods would suggest flight-to-quality behavior, indicated by declining stock prices and increasing bond returns.

5. Results

5.1 EGARCH(1,1) estimation results

Table 2 presents the estimation results of our EGARCH(1,1) model. As expected, the θ coefficient is negative and highly significant, indicating a strong negative relationship between changes in stock market fear and corporate bond returns. This suggests that when VIXTA increases – signaling heightened fear and bearish sentiment in the stock market – corporate bond returns tend to decrease. This negative reaction reflects a contagion effect between stocks and bonds, where increasing market fear in the stock market reduces the attractiveness of corporate bonds, leading investors to shift away from them due to perceived rising risk. This shift highlights the influence of stock market sentiment on bond returns within TASE, ultimately affecting corporate bond yields and potentially raising financing costs for companies reliant on bond issuance.

The positive and highly significant coefficient for $\Delta VIXTA$ in the variance equation further implies that increases in market fear not only reduce bond returns but also elevate bond market volatility. Fear-driven increases in VIXTA amplify volatility in corporate bonds, suggesting that heightened volatility could reflect contagion effects between stocks and corporate bonds. This behavior can drive down corporate bond prices in the short term, as retail investors, who form a substantial proportion of participants in TASE (Abudy and Shust, 2023; Abudy and Wohl, 2018), may respond to fear with selling pressure in response to stock market distress. This heightened volatility is likely to prompt investors to demand higher risk premiums, resulting in higher corporate bond yields and increasing financing costs for companies.

Additionally, in line with Hadad and Kedar-Levy (2024), we observe a highly significant and negative β coefficient, indicating a leverage effect in Tel-Bond 20. This asymmetry suggests that negative economic shocks disproportionately increase bond market volatility,

Table 2. Estimation results for EGARCH(1,1) model

Variable	Coefficient	Std. Error
Mean equation: $Rb_t = \mu + \theta\Delta VIXTA_t + \varepsilon_t$		
C	0.000180***	4.34E−05
$\Delta VIXTA$	−0.000426***	0.000107
Variance equation: $log(h_t) = \omega + \alpha\left[\frac{\lvert\varepsilon_{t-1}\rvert}{h_{t-1}}\right] + \beta\left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right) + \gamma log(h^2_{t-1}) + \delta\Delta VIXTA_t$		
ω	−0.485080***	0.066962
α	0.227581***	0.021206
β	−0.052826***	0.013829
γ	0.975320***	0.004814
$\Delta VIXTA$	0.087034***	0.015642
R-squared	0.021999	
Adjusted *R*-squared	0.021212	
Akaike info criterion	−9.682689	
Schwarz criterion	−9.653845	
Hannan–Quinn criterion	−9.671843	

Note(s): Rb: Tel-Bond 20 returns; Significance: ***1%; **5% and *10%. Obs.: 1,244
Source(s): Author's own work

signaling heightened sensitivity in bond markets during adverse conditions. Such a response may reflect investor concerns over corporate bond stability in downturns, underscoring the importance of risk management during periods of market stress. The positive and significant α and γ coefficients in the variance equation imply high volatility persistence in the Tel-Bond 20 Index, meaning that volatility shocks have prolonged impacts, which can further affect bond market stability.

Overall, these results suggest that in TASE, shifts in stock market fear significantly impact bond market dynamics, highlighting potential spillover from stocks to bonds. This outcome can be explained by changes in investment decisions of retail-size investors, who are more sensitive to market fear (Baker and Wurgler, 2006, 2007). We further study the broader interconnectedness and interdependencies between stock and bond market volatilities using the Diagonal BEKK model.

5.2 Diagonal BEKK estimation results

Table 3 shows the estimation results of the diagonal BEKK model coefficients under both multivariate normal and student's t-distributions. The student's t-distribution specification provides a better fit, as indicated by a higher log-likelihood and lower AIC, Schwarz and Hannan–Quinn criteria, suggesting this specification captures the data's heavy tails effectively. The significance of the coefficient estimates highlights strong volatility persistence and cross-volatility dynamics between TA-35 and Tel-Bond 20 Index returns, underscoring the potential for spillover effects noted in the EGARCH model.

The conditional variance-covariance equations are given by

$$\begin{aligned} h_{11,t} &= 1.99e^{-06} + 0.0804\varepsilon^2_{1,t-1} + 0.8988h_{11,t-1} \\ h_{22,t} &= 1.7545e^{-07} + 0.15296\varepsilon^2_{2,t-1} + 0.8144h_{22,t-1} \\ h_{12,t} &= 1.70522e^{-07} + 0.11095\varepsilon_{1,t-1}\varepsilon_{2,t-1} + 0.85557h_{12,t-1}. \end{aligned} \tag{6}$$

Table 3. Estimation results from the diagonal BEKK model under normal distribution and student's t-distribution

Model (1) multivariate normal distribution	Coefficient	Std. Error	Model (2) multivariate student's t-distribution Coefficient	Std. Error
Rs	0.000727***	0.000233	0.000777***	0.000206
Rb	0.000220***	4.96E−05	0.000239***	4.42E−05
	Variance equation coefficients			
M(1,1)	2.08E−06***	4.14E−07	1.99E−06***	5.41E−07
M(1,2)	2.34E−07***	5.39E−08	1.71E−07***	6.59E−08
M(2,2)	1.82E−07***	3.11E−08	1.75E−07***	4.07E−08
A1(1,1)	0.296386***	0.015574	0.283690***	0.022250
A1(2,2)	0.417817***	0.018979	0.391110***	0.027008
B1(1,1)	0.944550***	0.005950	0.948058***	0.007589
B1(2,2)	0.892894***	0.009765	0.902446***	0.012494
		t-dist coef	7.11169***	0.997217
	Log likelihood	10278.98	Log likelihood	10333.92
	Avg. log likelihood	4.131423	Avg. log likelihood	4.153503
	Akaike info criterion	−16.51122	Akaike info criterion	−16.59793
	Schwarz criterion	−16.47414	Schwarz criterion	−16.55673
	Hannan–Quinn criterion	−16.49728	Hannan–Quinn criterion	−16.58244

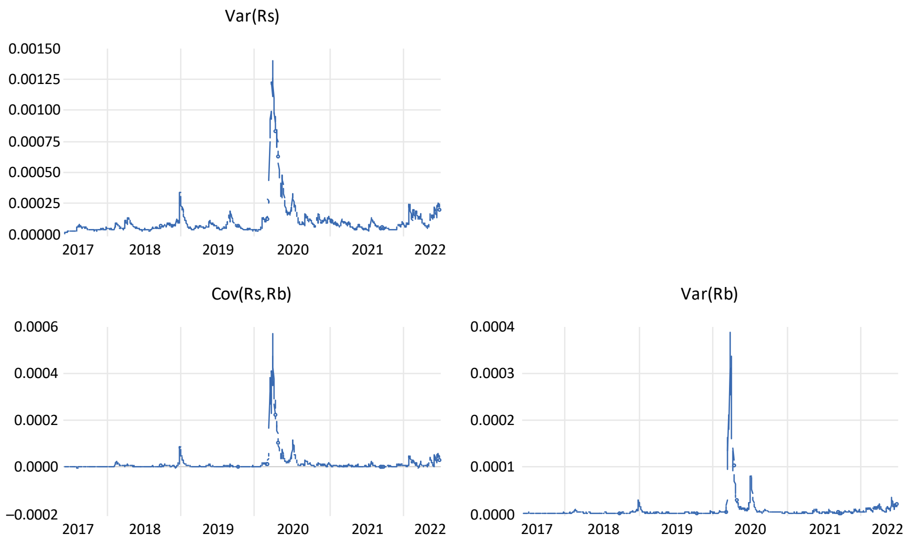
Note(s): Rs: TA-35 returns; Rb: Tel-Bond 20 returns; Significance: ***1%; **5% and *10%. Obs.: 1,244
Source(s): Author's own work

The ARCH coefficient for TA-35 returns (0.0804) is lower than that for Tel-Bond 20 (0.15296), indicating that bond volatility is more sensitive to past shocks. This heightened sensitivity in the bond market may be due to corporate bonds' lower liquidity and infrequent trading compared to stocks, which tend to show stronger volatility clustering. The GARCH coefficients, 0.8988 for TA-35 and 0.8144 for Tel-Bond 20, suggest high persistence in both markets, though stock volatility is more enduring.

Cross-volatility terms indicate spillover effects between the markets. The bond market's ARCH effect (0.1529) dominates its cross-volatility term (0.1109), suggesting that bond volatility is largely driven by market-specific shocks. However, the cross-volatility GARCH coefficient is higher than the own GARCH coefficient (0.8555 and 0.8144, respectively), indicating that bond market persistence is also influenced by stock market conditions and suggesting that corporate bond stability depends somewhat on stock volatility within TASE. This persistent cross-volatility effect emphasizes that bond market stability on TASE may be somewhat contingent on stock market conditions, mirroring the contagion effect noted in the EGARCH model.

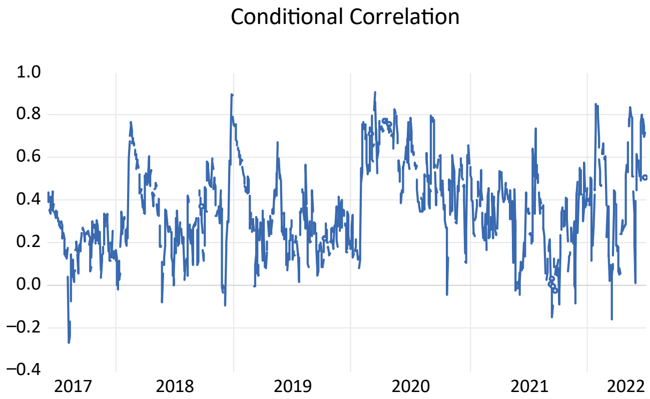
Figures 3 and 4 provide visual support for this relationship. Figure 3 illustrates that while TA-35 exhibits consistently higher volatility than Tel-Bond 20 (which aligns with the typically greater risk and price movement potential in stocks), both indexes display time-varying covariances that increase sharply during crisis periods, such as the COVID-19 pandemic and periods of political instability in December 2018. These covariance spikes indicate a heightened interdependence between stocks and bonds during periods of financial stress, reflecting how market conditions can amplify volatility spillovers and reduce the perceived safety of corporate bonds as a diversification tool.

Figure 4 further illustrates dynamic conditional correlation patterns, showing that correlations between TA-35 and Tel-Bond 20 generally remain positive (with an average correlation of 0.355) but vary over time, occasionally turning negative. These periods of negative correlation, seen in mid-2017 and early 2022, indicate episodes of flight behavior, where investors shift from stocks to bonds during heightened risk and that bond markets temporarily act as a safe haven amid equity market stress. Such behavior underscores the



Source(s): Author's own work

Figure 3. Conditional variances and covariances: Rs: TA-35 returns and Rb: Tel-Bond 20 returns



Source(s): Author’s own work

Figure 4. Conditional correlation between TA-35 and Tel-Bond 20 Index returns

tendency of retail and institutional investors within TASE to reallocate assets based on perceived market risks. This pattern aligns with Ponrajah and Ning (2023), who observe that stock–bond dependence switches between positive and negative regimes, with contagion during downturns and flight-to-quality in crises, emphasizing the responsiveness of cross-asset dynamics to market stress. However, such instances are infrequent, and the time-varying correlation level remains positive, with a clear positive stock–bond return linkage, implying consistent behavior in stock and bond prices over time.

The figure also shows three major spikes in conditional correlation: (1) December 2018, associated with political instability and early election speculation; (2) March 2020, coinciding with the COVID-19 outbreak and (3) January 2022, linked to inflationary concerns. The recurrence of these spikes during periods of crisis suggests that investor behavior aligns across markets in times of heightened uncertainty, reinforcing the concept of positive contagion within TASE. These findings have important implications, as the observed spikes in conditional correlation during crises suggest that TASE’s stock and bond markets become more interconnected under stress, implying that the benefits of diversification are diminished when markets are under stress, as volatility shocks transmit more readily between asset classes. This contagion-like behavior is consistent with the findings of Baur and Lucey (2009), where increased volatility in one market often leads to heightened volatility in the other. Likewise, Ponrajah and Ning (2023) found that stock–bond correlations tend to become more positive during downturns, highlighting the limitations of diversification in such periods. For investors and portfolio managers, this interdependence suggests that alternative assets or hedging strategies may be necessary during high-correlation periods to mitigate risk when stocks and bonds move in tandem.

The diagonal BEKK findings thus reinforce the EGARCH results, demonstrating that TASE’s stock and bond markets are interconnected not only directly but also through sustained cross-volatility effects. This persistence in volatility spillovers, particularly during crises, suggests that volatility in one market can sustain and influence volatility in the other, creating a contagion channel. These results emphasize the importance of robust risk management strategies, as traditional diversification benefits may diminish in interconnected markets under stress.

In essence, the findings highlight that equity and corporate bond markets are integrated, underscoring the impact of the trading mechanisms, like the LOB system in TASE, on market integration. This implies that market participants and policymakers need to consider the trading infrastructure when evaluating the dynamics between different asset classes and making investment decisions.

6. Conclusions

Existing financial literature highlights the impact of sentiment on stock returns volatility, emphasizing the role of investor behavior in shaping stock market dynamics. Research has also indicated spillover effects between stock and bond markets, suggesting bidirectional influences between price changes in these asset classes. Despite stocks and corporate bonds both representing claims on the same underlying asset (Merton, 1974) and having potential for information spillover, behavioral studies exploring cross-market integration between these two assets remain limited.

This study offers novel insights into the linkage between stocks and corporate bonds in the TASE, a market distinguished by high retail trading activity. Our findings demonstrate a robust return and volatility connectedness between the markets, characterized by time-varying correlation. We document volatility clustering and substantial interdependencies between the markets, particularly during periods of financial turmoil, such as the COVID-19 pandemic, political uncertainty and inflation concerns. Both stocks and corporate bonds show responsiveness to innovations, and the dynamic conditional correlation between the markets is notably strong. Contrary to the flight-to-safety behavior often observed in *OTC* markets during crises (Baele *et al*., 2020; Ponrajah and Ning, 2023), our results point to a positive contagion effect in TASE, where interdependencies between stocks and bonds increase during turbulent times.

These findings underscore significant market integration within TASE, offering valuable insights into the connection between stock and corporate bond markets. However, they also raise concerns for investors, as contagion during crises causes bond prices to fall alongside stocks, undermining diversification benefits when they are most needed. Unlike the stabilizing effect of negative stock-bond dynamics observed in other *OTC* markets (Baur and Lucey, 2009), the contagion observed in TASE exacerbates instability during turbulent periods.

Our results highlight the pivotal role of TASE's exchange-based bond market and its centralized trading mechanism in shaping market integration. The platform's direct information flow facilitates volatility spillovers and amplifies interdependencies between stocks and corporate bonds, particularly during periods of financial stress. This pattern aligns with global evidence of volatility spillovers in markets with high retail trading activity, highlighting the significant influence of retail investors on cross-market dynamics. While Abudy and Shust (2023) emphasize TASE's contribution to market quality through enhanced liquidity, price discovery and stability, our findings reveal a dual-edged nature of this infrastructure. The same features that promote market quality also enable the rapid transmission of shocks, leaving TASE highly susceptible to systemic risk. This duality underscores how transparency and centralized trading can simultaneously foster efficient information flow and exacerbate destabilizing contagion during heightened uncertainty.

Overall, this study reinforces the interconnectedness of stock and bond markets and highlights the critical role of trading mechanisms in shaping cross-market linkages. The findings have broad implications for investors, regulators and market participants. For investors, understanding these linkages is essential for making informed decisions and developing effective risk management strategies, particularly during volatile periods. For regulators, recognizing the dynamics of market integration is essential to maintaining financial stability and designing effective policies for centralized exchanges and *OTC* markets characterized by high retail trading activity.

Despite these insights, our study has certain limitations. While this analysis is robust within TASE's unique LOB trading environment, the findings may not fully generalize to *OTC*s with different trading mechanisms. Furthermore, the study's focus on specific crisis periods – including the COVID-19 pandemic, late 2018 political uncertainty and early 2022 inflation concerns – provides key insights into volatility spillovers during financial stress but limits the applicability of the results to other periods and contexts.

Future research could explore the influence of macroeconomic and monetary conditions and other behavioral factors in driving volatility spillover between stocks and corporate bonds in the TASE and in similar markets. Additionally, exploring the causal patterns between stocks and corporate bonds in TASE and the spillover effect between stocks and corporate bonds in other *OTC* markets will provide valuable insights into cross-market linkages in global markets. Such studies would further contribute to the understanding of the relative advantages and drawbacks of *OTC* markets compared to centralized exchanges.

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Corresponding author
Elroi Hadad can be contacted at: hadadel@sce.ac.il