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The European tango between market risk and credit risk: A non-linear approach

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ABSTRACT

Financial markets are closely connected, with credit and market risks dynamically influencing each other, particularly during extreme events. While their interdependence is well-documented in the literature, the direction and intensity of information flow remain uncertain. Using transfer entropy on European credit and stock volatility indices, we quantify this flow and its dynamics during the most recent extreme events. Our findings reveal a shifting dominance, with the credit market leading during extreme uncertainty, challenging the conventional view of risk market leadership. These patterns underscore the need to monitor the credit market as a potential early warning sign of financial instability.

1. Introduction

Financial markets are deeply interconnected, with each influencing the other dynamically, especially during crises. The volatility feedback loop hypothesis suggests that credit and risk markets are interconnected, with shocks in one market leading to increased volatility in the other (Foglia et al., 2024). For example, the correlation between credit risk, measured by credit default swap (CDS) spreads, and market risk, measured by the T-bill-Eurodollar (TED) spread, increased significantly during the financial crisis, indicating heightened interconnectedness and risk spillovers during turbulent periods (Wu and McMillan, 2013). The study of systemic risk in CDS indices shows that systemic risk indicators change significantly during crises, suggesting that credit risk can propagate through the financial system, affecting several sectors differently (Choe et al., 2020).

The dynamic relationship between credit risk (iTraxx) in Europe and equity volatility (VSTOXX) undergoes significant changes during financial crises. In market turmoil periods, CDS spreads become highly sensitive to stock market volatility, contrasting with normal conditions, which are more influenced by stock returns (Alexander and Kaeck, 2008). Moreover, lead–lag patterns have been identified in this relationship. Stock market return movements often anticipate CDS spread fluctuations in crisis periods, but this relationship can shift in post-crisis phases, leading to a bidirectional relationship (Breitenfellner and Wagner, 2012).

The relationship between iTraxx and VSTOXX appears to be contingent on the severity of the crisis. For instance, the relationship exhibits a breakdown during global crises, such as the Global Financial Crisis. This situation has the effect of undermining cross-hedging strategies that rely on its stability. Conversely, this relationship tends to persist despite market turbulence during more localized crises, such as the European sovereign debt crisis (Da Fonseca and Gottschalk, 2014).

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The concept of information flow and its impact on market dynamics is crucial. For instance, political developments can significantly influence CDS spreads, indicating that external shocks can permeate through the financial system and affect credit risk (Wisniewski and Lambe, 2015). The relationship between credit and risk markets changes significantly during different phases of the financial cycle. During pre-crisis periods, the information flow between them is relatively stable. In contrast, extreme events trigger a surge in risk spillovers, suggesting that market participants react more strongly to changes in credit risk, which in turn affects market risk. This heightened interaction can serve as an early warning signal for financial instability (Dimpfl and Peter, 2013; Lim et al., 2017). In post-crisis periods, information flow may decrease but remain higher than in the pre-crisis period, reflecting persistent uncertainty and adjustments in financial markets (Caserini and Pagnottoni, 2022; Dimpfl and Peter, 2013).

Transfer entropy (TE) is a powerful approach for analyzing these relationships. It has been applied in several financial contexts to measure the strength and direction of information flow between financial markets, and it is well-suited for capturing non-linear dynamics and asymmetric information transmission effects (Caserini and Pagnottoni, 2022; Dimpfl and Peter, 2013; Schreiber, 2000). Despite its advantages, few studies have applied TE to evaluate the dynamics between European credit and risk markets from a non-parametric perspective, free from linearity, normality, and homoscedasticity assumptions. Additionally, the analysis of the relationship between European credit and risk markets during critical periods, such as the COVID-19 pandemic and the Russia–Ukraine war, remains largely unexplored. These events represent moments of heightened financial uncertainty and potential crises, making their study crucial for understanding the dynamics of risk transmission in extreme conditions.

Although several recent studies (after 2019) have applied TE to analyze relationships in financial markets [e.g., Caserini and Pagnottoni (2022), Korbel et al. (2019), Lim et al. (2017) and Yue et al. (2020), among others], only Caserini and Pagnottoni (2022) analyzed the dynamics of financial contagion between the CDS and sovereign bond markets in the European context, finding that bond markets were more prominent in pricing sovereign credit risk, especially during crisis periods.

Considering the referred, this paper has two major main goals: (i) to analyze and quantify the bi-directional information flows between the iTraxx Europe Main 3-Month Volatility (iTraxx3M) and STOXX 50 Volatility EUR (VSTOXX) indices; (ii) to evaluate the evolution of the relationship between both credit and risk markets, especially in extreme situations.

This paper contributes to the literature by employing TE to dynamically assess the bidirectional information flow between European credit and risk markets, especially under stress periods. By capturing bidirectional information flows, this assessment allows the identification of how extreme events shape the interaction between these key risk dimensions. Additionally, while focusing on the European market, this study contributes to a better understanding of its unique characteristics and offers a framework applicable to other markets.

The remainder of the letter is structured as follows: Section 2 presents the data and methods, Section 3 presents and discusses the results, and Section 4 presents the conclusions.

2. Data and methods

2.1. Data

The study uses daily closing prices of the iTraxx3M and VSTOXX indices from January 31, 2015, to February 13, 2025, comprising a total of 2523 observations, obtained from https://www.spglobal.com/spdji/en/index-family/fixed-income/corporates/#indices and https://www.investing.com, respectively (accessed February 14, 2025). The primary index quantifies corporate credit risk within the European market by employing CDSs from 125 companies. The second index quantifies short-term expected volatility in European equity markets by analyzing options from 50 large eurozone companies. The combination of these indices aims to provide a comprehensive perspective on the key financial risks in Europe.

2.2. Methods

The Granger causality test is a widely used approach to evaluate directional predictability between time series, primarily designed to detect linear relationships. In contrast, TE offers several methodological advantages for analyzing financial contagion, as it does not rely on assumptions of linearity or stationarity. This makes it particularly well-suited for complex and dynamic systems like financial markets (Caserini and Pagnottoni, 2022; Dimpfl and Peter, 2013, 2014, 2019; Wang et al., 2020). TE captures both linear and nonlinear dependencies, identifies the direction and intensity of information flow, and helps identifying between driving and responding forces within financial markets (Caserini and Pagnottoni, 2022; Dima et al., 2014; Dimpfl and Peter, 2014, 2019; Sipahi and Porfiri, 2020). Additionally, it is less sensitive to noise and irregular events, making it a reliable tool for analyzing volatile financial data. TE can also detect sudden shifts in information dynamics, serving as an early warning indicator for financial crises (Lim et al., 2017; Toriumi and Komura, 2018). These features are particularly relevant in the context of recent high-volatility periods, such as the COVID-19 pandemic and the Russia–Ukraine war, which were characterized by nonlinear dynamics and abrupt regime shifts in market behavior (Caserini and Pagnottoni, 2022; Hung et al., 2022). Moreover, TE adapts dynamically to evolving market structures, making it effective for detecting contagion effects and changing lead–lag relationships in turbulent environments (Akgüller et al., 2025; Hung et al., 2022). Its main limitations include the computational intensity required for high-frequency or long time series data (Wang et al., 2020) and potential constraints when applied to small samples (Caserini and Pagnottoni, 2022; Shorten et al., 2021). However, these limitations do not affect the sample used in this letter.

Thus, TE not only complements traditional linear methods by providing a more nuanced understanding of nonlinear interactions, but it can also uncover alternative relationships that may challenge existing findings and offering new perspectives on market dynamics (Dimpfl and Peter, 2019; Harré, 2015; Nichols et al., 2005; Shorten et al., 2021; Sipahi and Porfiri, 2020). These features make it a robust tool for analyzing financial risk transmission, particularly under extreme conditions.

Given the nonlinear and potentially asymmetric nature of financial market interactions, particularly during periods of turbulence, and in line with the study's main goals, this analysis applies the TE framework proposed by Schreiber (2000) to the log returns series. This approach allows for quantifying the bi-directional information flows between indices and assessing how the relationship between risk and credit markets evolves during periods of financial turbulence.

Eq. (1) defines the TE under the assumption of a Markovian process of k and l orders for Y and X, respectively.

$$TE_{Y\to X}(k,l) = \sum_{x,y} p\left(x_{t+1}, x_t^{(k)}, y_t^{(l)}\right) loglog \frac{p\left(x_t^{(k)}, y_t^{(l)}\right)}{p\left(x_t^{(k)}\right)} \tag{1}$$

To identify which of the paired variables influences the other, the NET TE, defined in Eq. (2), was considered:

$$NET\ TE_{YX} = TE_{Y\to X} - TE_{X\to Y} \tag{2}$$

The dominant direction of the information flow could be positive (from Y to X, if $TE_{Y\to X}(k, l) > TE_{X\to Y}(k, l)$), negative (from X to Y, if $TE_{Y\to X}(k, l) < TE_{X\to Y}(k, l)$) or equal to zero (the same dominance of information flow in both directions if $TE_{Y\to X}(k, l) = TE_{X\to Y}(k, l)$).

To dynamically analyze the information flow and evaluate how extraordinary events (such as the COVID-19 pandemic and the Russia–Ukraine war) can affect the bidirectional relationship between the analyzed markets, the TE and NET TE were estimated using a sliding window (SW) of 500 observations. This window size provides enough data points for accurate TE estimation while effectively capturing temporal dynamics, striking a balance between statistical reliability and sensitivity to evolving dynamics, consistent with previous studies employing TE in financial contexts. All the TE estimates were made using the R package RTransferEntropy.

As a robustness test, the analysis was also performed considering SW of 250 and 750 observations (results available upon request), with similar qualitative results.

3. Results and discussion

The descriptive statistics (Table 1) reveal that both indices display (i) near zero but negative mean returns, which were higher for VSTOXX but with a higher standard deviation, (ii) positive kurtosis (> 4.3), meaning fat-tailed distributions, and (iii) positive skewness (> 0.80), suggesting that while most returns may be negative or close to zero, there is a higher probability of large positive returns. The results of the Augmented Dickey–Fuller (ADF) and Kolmogorov–Smirnov (K–S) tests allowed us to reject the null hypothesis at the 1 % significance level (***), in both, meaning that the return series do not have a unit root, and the returns are not normally distributed. Further supporting the use of TE is its ability to handle non-stationary, non-Gaussian, and non-linear time series data without needing a predefined model.

Fig. 1 depicts the evolution of TE and NET TE between both indices, considering an SW of 500 observations.

The information flow between both indices varies over time, reflecting different periods of dominance and suggesting periods of greater and lesser independence between the stock and credit risk markets. The NET TE indicates that its pattern changes during crises and high-volatility periods, such as the COVID-19 pandemic or the Russia–Ukraine war, reflecting financial market tensions.

Between 2017 and 2018, corporate credit risk was a stronger influencer of stock market volatility than vice versa, possibly due to an increased perception of credit risk in Europe, influenced by Brexit negotiations and changes in monetary policy expectations.

In early 2018, information flow increased in both directions, but was more pronounced from the stock market to the credit market. After a prolonged period of stability, in February 2018, global financial markets experienced a correction due to rising inflation and interest rate expectations in the US, which escalated trade tensions between the US and its main partners and contributed to the eurozone economic slowdown. Political uncertainties in Europe and investor risk aversion intensified volatility in stock markets. This pattern continued until the first quarter of 2019, reflecting persistent macroeconomic uncertainty and the strong link between stock market risk and credit spreads.

In the early days of the pandemic, there was a notable increase in the transmission of information between the iTraxx3M and VSTOXX markets. This surge was particularly pronounced from iTraxx3M to VSTOXX, signifying that credit market volatility significantly influenced stock market behavior. The overall information exchange transitioned from negative to positive, indicating that the VSTOXX market received more information from iTraxx3M. This result suggests that during the uncertainty at the start of the pandemic, the credit market had a stronger impact on the stock market than the reverse case, which does not align with Caserini and

Table 1
Descriptive statistics.

	iTraxx3M	VSTOXX
Mean	−0.00021	−0.00016
Standard deviation	0.05187	0.07219
Kurtosis	5.70118	4.31668
Skewness	0.90848	0.80181
K–S	0.060***	0.070***
ADF	−14.2240***	−15.8397***

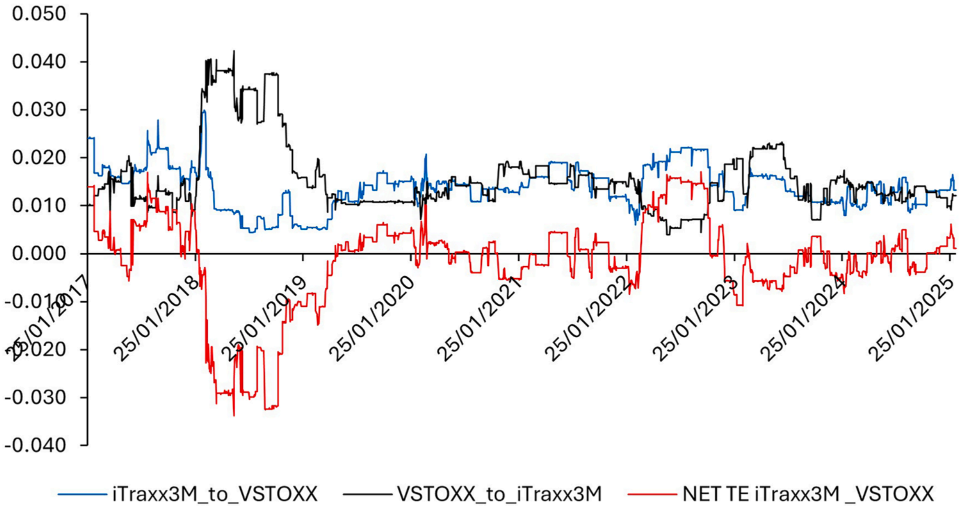

Fig. 1. Time evolution of the TE and NET TE between both indices returns.
Notes: (i) the blue line represents the time evolution of TE from iTraxx3M to VSTOXX; (ii) the black line represents the time evolution of TE from VSTOXX to iTraxx3M; (iii) the red line represents the time evolution of the NET TE when it assumes positive values, it means that the dominant direction of the information flow is from iTraxx3M to VSTOXX. Conversely, when it assumes negative values, it means that the dominant direction of the information flow is from VSTOXX to iTraxx3M.

Pagnottoni (2022). The abrupt increase in the perception of credit risk due to the economic uncertainties caused by the pandemic may explain this behavior. The market volatility has soared to levels not seen since the global financial crisis, reflecting uncertainty about the economic impact of the pandemic (International Monetary International Monetary, 2020). However, this behavior changed after the first half of 2020, indicating a short-lived impact, with the stock market having a stronger influence on the credit market. The economic policy measures implemented to mitigate the pandemic's effects helped stabilize the financial markets and restore investor confidence, which may account for the short-lived impact.

At the time of the onset of the Russia–Ukraine war in February 2022, a shift in the behavior of TE between market indices was observed, with market risk becoming more influenced by credit risk. This shift may have resulted from the war's impact on European corporate credit risk and stock market volatility, with the former anticipating volatile movements in the stock market. Interestingly, in the final quarter of 2022, market risk began to drive information flow to the European credit market. From 2024 onwards, the relationship between both indices remained dynamic, with frequent oscillations and no fixed dominance pattern. This dynamic environment, influenced by economic and geopolitical uncertainties, underscores the interconnected nature of financial markets, where shocks in one segment can rapidly propagate and impact others, and suggests that both markets are constantly adapting to economic and geopolitical uncertainties. In the post-2022 period, the alternating dominance observed in NET TE suggests the absence of persistent leadership between credit and risk markets, potentially signaling high systemic uncertainty. These fluctuations may reflect rapid shifts in investor sentiment and information processing, particularly in the context of geopolitical and macroeconomic instability. While informative, this pattern may obscure underlying structural breaks that fixed-size windows are unable to capture, a limitation acknowledged in this approach. Future research could address this by employing adaptive windowing techniques or structural break tests to more effectively detect regime changes.

4. Conclusion

Our findings allowed us to conclude that the relationship between credit risk and market risk is dynamic, non-linear, adaptive, and sensitive to economic, financial, and geopolitical shocks. This result highlights the importance of applying approaches such as TE to capture these interactions.

Using an SW approach, the TE and NET TE values allowed us to detect patterns of informational dominance that vary over time, showing that in periods of high uncertainty, such as the COVID-19 pandemic and the Russian invasion of Ukraine, credit risk can lead the transmission of information to market risk. However, this leadership is not fixed; it alternates depending on prevailing economic and geopolitical conditions. Just as in a tango, where leadership shifts in response to rhythm and movement, the dominance in information transmission between credit and equity markets evolves dynamically. While credit risk tends to dominate during financial stress, market risk can regain influence in more stable periods. This scenario reinforces the need for a flexible, context-aware financial risk monitoring and assessment approach.

The above result challenges the traditional view that the stock market anticipates developments in the credit sector. Thus, corporate debt market conditions, as an indicator of credit risk, can predict turbulence in equity markets, particularly during financial and geopolitical uncertainty periods. For instance, during the COVID-19 crisis, the deterioration of credit spreads preceded sharp increases in stock market volatility, highlighting the predictive power of credit risk in forecasting broader market instability. This evidence is particularly relevant for institutional investors and financial regulators, as it reinforces the importance of monitoring credit spreads to anticipate systemic risks. By integrating these insights into risk assessment frameworks, market participants can implement proactive risk management strategies, and policymakers can take timely measures to stabilize financial markets during times of stress. From a policy and investment perspective, the dynamics of TE and NET TE can offer relevant signals for early intervention. Although these measures do not provide absolute thresholds, sudden and persistent shifts in the dominant direction of information flow, particularly between stock and credit markets, may serve as early warning of mounting systemic stress. For example, during the early phase of the COVID-19 pandemic, the observed inversion in NET TE toward credit market leadership indicated that corporate credit conditions were deteriorating faster than reflected by stock markets. If monitored in real time, such patterns could enable regulators to implement targeted liquidity measures or macroprudential interventions and assist investors in adjusting portfolio allocations to mitigate cascading risk effects.

Future research could expand on our findings by comparing TE results with those derived from alternative approaches, such as the Diebold and Yilmaz spillover index, allowing a complementary perspective on risk transmission in financial markets.

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CRediT authorship contribution statement

Dora Almeida: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Paulo Ferreira:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Andreia Dionísio:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors have nothing to declare.

Data availability

The raw data supporting the conclusions of this article will be made available by the authors on request.

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