Research Report

Lead-Lag Relationships in Market Microstructure

THIS STUDY EXPLORES HIGH-FREQUENCY CROSS-ASSET LEAD-LAG RELATIONSHIPS FOR VARIOUS MARKET MICROSTRUCTURE DIMENSIONS. UTILIZING DATA FROM STOCKS, FUTURES, AND EXCHANGE TRADED PRODUCTS, THE FINDINGS UNCOVER SIGNIFICANT LEAD-LAG PATTERNS, PARTICULARLY AMONG FUNDAMENTALLY RELATED INSTRUMENTS. OUR RESULTS DEMONSTRATE THAT KNOWLEDGE ABOUT LEAD-LAG RELATIONSHIPS CAN BE LEVERAGED FOR FORECASTING SHORT-TERM CHANGES IN FINANCIAL MARKETS.

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Introduction

In financial markets, lead-lag effects refer to situations where some financial instruments provide indications of future price, liquidity, or volatility developments in other instruments. These effects arise due to unequal information dissemination across markets.

The emergence of algorithmic and high-frequency trading (HFT) has led to a significant shift in information dynamics within financial markets. In this fast-paced environment, order book activities, such as order submissions or cancellations, rather than trades have become the central source of information (Brogaard et al., 2019). High-frequency traders (HFTs) utilize real-time market data and can react within less than a millisecond to changes in the order book. Their actions are often driven by patterns within the order book dynamics, rather than relying on fundamental information. These pattern-based trading activities of HFTs have led to increased co-movements in returns and liquidity, driven by the rapid dissemination of information and correlated HFT strategies (Melcaniece et al., 2019).

This transformation in the trading behavior raises the question of whether lead-lag relationships are more related to market microstructure information, such as order book activities, rather than to changes in fundamental information (Huth and Abergel, 2014). Understanding these changing relationships entails both opportunities and risks for various market participants. Changes in lead-lag relations may expose institutional investors and market makers to the risk of unknown interdependencies within their portfolios. However, these changes can also present opportunities for HFTs.

Data and Methodology

To investigate the existence of pattern-driven lead-lag relationships in financial markets, we analyze non-contemporaneous correlations across a broad spectrum of assets and market microstructure dimensions like prices, liquidity, or volatility. Thereby, we follow a data-driven approach by examining all potential lead-lag relationships and do not rely on any underlying assumptions such as the fundamental relationship between two instruments, e.g., derivatives and their underlying. To conduct the analysis, we use trade and order book data with nanosecond precision from Deutsche Börse's A7 Analytics Platform, encompassing 19 heavily traded financial instruments, such as the EURO STOXX 50 Future (FESX), the Bund-Future, or the Xetra-Gold exchange-traded commodity. Our sample period spans six months, from January 2021 to June 2021. To quantify and assess lead-lag relationships, we utilize the estimator introduced by Hayashi and Yoshida (2005). This so-called HY-estimator estimates the correlation between two irregularly spaced time series (X and Y) with different lengths. The HY-estimator is calculated for a discrete grid of leads and lags. In our analysis, this grid covers leads and lags from a few microseconds up to one minute. The resulting HY-curve then consists of the estimated correlation coefficients ($\hat{\rho}$) for each predefined lead or lag ℓ.

In Figure 1, we show the HY-curve for representative instruments pairs from different asset classes. For example, the black-dotted HY-curve shows the estimated correlation coefficients for the midpoints of the DAX Future (FDAX) and the transaction prices of the DAX exchange-traded

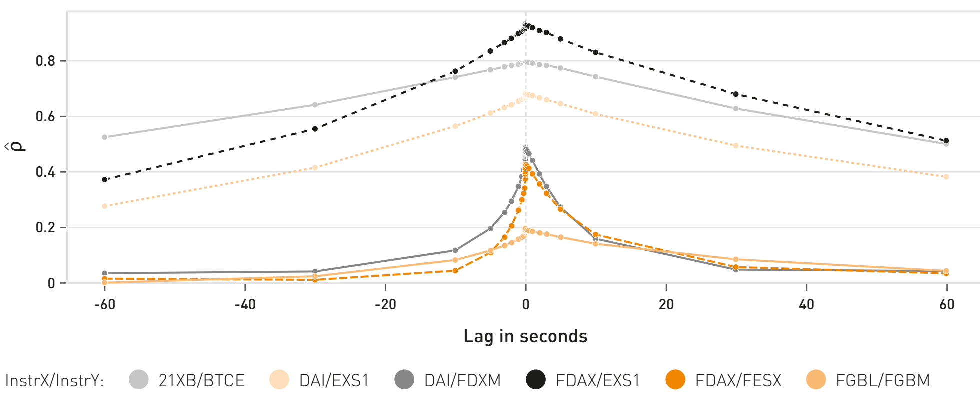


Figure 1: HY-Curves for X: Midpoint and Y: Transaction Price for Selected Instruments

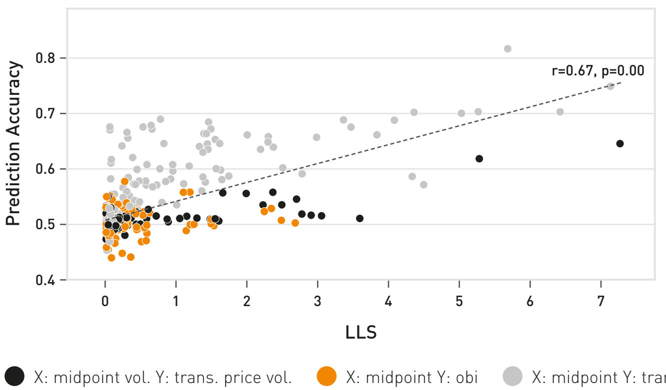
fund (EXS1) with a maximum correlation of more than 0.8 for lags between +/- 10 seconds.

Results

Our results uncover significant cross-asset lead-lag relationships among various microstructure measures. In order to assess the magnitude of the detected lead-lag relationships, we introduce a novel measure called lead-lag-strength (LLS) that takes the skewness of the HY-curve and the overall correlation into account. Measuring lead-lag relationships with the LLS, we find the strongest relationships between transaction prices and midpoints, the order book imbalance (OBI) and midpoints, and between transaction prices and midpoint volatility. In particular, our results imply that changes in the OBI and the transaction price in a given asset provide information about future changes in the midpoint of another asset, which can also be seen from Figure 1 where almost all HY-curves are skewed to the right. These lead-lag patterns vary among instruments, but predominantly exist among financial instruments that are fundamentally related, such as those with common underlying components (e.g., the FDAX and FESX) or those exposed to the same risk factors (e.g., long-term and medium-term bond futures).

Instrument-wise, we find the strongest lead-lag relationship between FESX's transaction prices leading FDAX's midpoints (see also the dark orange-dotted curve in Figure 1). On average, the reaction of the FDAX takes less than a microsecond, highlighting the speed of information transmission in modern financial markets. In addition, we provide evidence that the detected lead-lag effects are persistent over time and do not depend on the current level of liquidity or volatility. Regarding the determinants of a lead-lag relationship, our results show that instruments with higher liquidity and trading activity tend to lead other instruments in almost all microstructure measures examined.

Lastly, our results reveal the predictive power of the identified lead-lag relationships using the LLS. We evaluate this predictive power by utilizing the leading (in terms of the LLS) time series to predict the direction of the next change in the lagging time series. The prediction accuracy for each instrument combination within the selected measure combinations of this LLS-based prediction approach is displayed as a dot in Figure 2. Furthermore, the LLS value itself is shown for each instrument combination along with descriptive statistics for the LLS-based prediction approach and a naïve benchmark. Given the binary balanced distribution, Figure 2 highlights that the simple prediction setup significantly outperforms the naïve benchmark for instrument pairs that exhibit a higher LLS value. Overall, the LLS emerges as a valuable indicator for identifying lead-lag relationships and can, e.g., be used to develop statistical arbitrage trading strategies in HFT.



	LLS-Prediction	Benchmark
count	674.000	674.000
mean	0.518	0.505
std	0.045	0.024
min	0.438	0.470
25%	0.497	0.493
50%	0.504	0.501
75%	0.517	0.511
90%	0.570	0.535
95%	0.636	0.545
max	0.816	0.601

Figure 2: Relationship between Average Prediction Accuracy (based on LLS) and the LLS

Conclusion

The speed of information dissemination and the increasing pattern-driven trading behavior raise the question whether lead-lag relationships are more related to market microstructure information, such as limit order book activities, rather than to changes in the (fundamental) price of an asset. To tackle this question, this study examines cross-asset lead-lag relationships between different microstructure dimensions using data from Xetra and Eurex. We find high-frequency lead-lag effects for price, OBI, and volatility measures among fundamentally related instruments. Our findings indicate that short-term lead-lag effects in the HFT environment still embed fundamental information, albeit at an accelerated pace and derived from the most granular pieces of information, such as a single order submission. These results help market operators and regulators to anticipate and assess potential contagion effects and threats to market efficiency and stability. Additionally, our findings can enhance the development of protective mechanisms that consider various microstructure measures and operate across different instruments. Professional investors can leverage the identified lead-lag relationships using the LLS to predict changes in lagging assets.

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