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Stock Market Synchronization and Stock Volatility: The Case of an Emerging Market

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Abstract

The purpose of this paper is to study the effect of stock market synchronization on the volatility of its component assets. For this objective, we calculate the stock market's synchronization using the Minimum Spanning Tree Length (MSTL) network analysis method. Then, we implement forecasting tests in and out the sample to assess the forecasting power on the stock market's synchronization to predict the individual stock realized volatility. Additionally, we test a VAR and a forecast error variance decomposition analysis to study Granger causality's presence on volatility. Our results show that synchronization within a market exists and changes over time. Our main results show that an increase in synchronization causes an increase in financial assets' realized volatility in the following month. Our results made it possible to study financial markets' synchronization and take a systemic risk approach to improve investment management. Our main idea was that the stock markets' synchronization positively correlates with financial assets' volatility. The greater the synchronization, the greater the volatility in the following period. This study offers a new approach to study the stock market volatility.
JEL Classification: G15, G17, G18.

Keywords: Stock market synchronization, stock volatility, Minimum Spanning Tree, Forecasting, Financial Network Analysis.

Sincronización del mercado de valores y volatilidad de los activos: El caso de un mercado emergente

Resumen

El propósito de este trabajo es estudiar el efecto de la sincronización bursátil sobre la volatilidad de sus activos componentes. Para este objetivo, calculamos la sincronización del mercado de valores utilizando el método de análisis de red de longitud mínima del árbol de expansión (MSTL). Luego, implementamos pruebas de pronóstico dentro y fuera de la muestra para evaluar el poder de pronóstico en la sincronización del mercado de valores para predecir la volatilidad realizada por las acciones individuales. Además, probamos un VAR y un análisis de descomposición de varianza de error de pronóstico para estudiar la presencia de causalidad de Granger en la volatilidad. Nuestros resultados muestran que la sincronización dentro de un mercado existe y cambia con el tiempo. Nuestros principales resultados muestran que un aumento en la sincronización provoca un aumento en la volatilidad realizada de los activos financieros en el mes siguiente. Nuestros resultados permitieron estudiar la sincronización de los mercados financieros y adoptar un enfoque de riesgo sistémico para mejorar la gestión de las inversiones. Nuestra idea principal era que la sincronización de los mercados de valores se correlaciona positivamente con la volatilidad de los activos financieros. Cuanto mayor sea la sincronización, mayor será la volatilidad en el período siguiente. Este estudio ofrece un nuevo enfoque para estudiar la volatilidad del mercado de valores.
Clasificación JEL: G15, G17, G18.

Palabras clave: Sincronización del mercado de valores, volatilidad de las acciones, árbol de expansión mínimo, pronóstico, análisis de redes financieras.

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1. Introduction

In recent financial crises, including the one caused by COVID19, the prices of financial assets fell significantly and volatility increased compared to regular periods. However, beyond the obvious, a hidden and risky phenomenon occurred in financial markets for the risk management of investment funds and the markets' financial stability. We refer specifically to the phenomenon of the synchronization of the returns of financial assets, which is a generalized increase in the correlation between pairs of assets (Martens & Poon, 2001), decreasing the possibilities of diversification of international portfolios (Ansotegui & Esteban, 2002) and increasing the risk of contagion that occurs when assets influence each other within the financial market in a context of synchronization.

The first effect of a high stock market's synchronization is a reduction in diversification benefits as a consequence of a high correlation. The investor requires more assets to maintain diversification and even resort to other markets' assets, increasing transaction costs. Diversification is a central component in investment risk management because it is necessary to distribute the money among several investment assets; however, the market's systematic risk related to the correlation between the market's assets limits diversification. In this way, if the correlation between assets increases, systematic risk will increase. Consequently, diversification will be more limited, forcing investors to add more assets to their portfolios, consider assets of a different class or geographical area, increase transaction costs, and negatively impact profitability.

Another consequence is a highly synchronized market is the prelude to higher realized volatility. This phenomenon means that the more synchronized the international market is, the more likely an increase in the stock indices' volatility. Assets' synchronization also affects market volatility. Magner, Lavin, Valle & Hardy (2020) show that the global network of correlations in international financial markets has predictive power on stock indices' volatility. In such a case, an increase in the synchronization of assets - increased correlations between the indices' returns - is a predictor of increased market volatility in North America and Europe and Latin America and Asia. although the latter to a lesser extent.

The financial literature studies the dynamic correlation of assets such as co-movements (López-García, Sánchez-Granero, Trinidad-Segovia, Puertas & Nieves, 2020) (Jach, 2017), systematic risk (Antonakakis, Chatziantoniou & Filis, 2013) (Kang, Maitra, Dash & Brooks, 2019), and cointegration (Ansotegui & Esteban, 2002) (Yang, Chen, Niu & Li, 2014). The network analysis methodology, in specific Minimum spanning tree (MST), contributes which a systemic and complex vision of the phenomenon of correlation between asset returns, and at the same time represented by a time series, valid for the financial stability regulator and for the portfolio manager who needs to manage a significant fraction of the risk of their investments through diversification.

Several theories allow us to explain the existence of synchronization in the markets. The law of the only price (Isard, 1977) (Haskel & Wolf, 2001) explains that the stock market is synchronized because the financial asset with similar risk, characteristics (such as maturity in fixed income), and market regulation will have the same return rate. Like this theory, the international CAPM (Engel, 2008) indicates domestic and international factors explain the assets' return. From a cointegration's point of view, the price of financial assets correlates because they all belong to a market that is closely followed by attentive investors who, through the publicly available information, will make decisions to buy or sell by making prices are adjusted to the economic value of the asset (Ansotegui & Esteban, 2002) (Yang, Chen, Niu & Li, 2014).

However, little research studies the effects of the stock market's synchronization. The contribution of this paper is to review the Granger Causality between the synchronization of equity assets and the volatility realized, contributing to two bodies of literature. First, this paper is related to the literature on the network-based analysis of financial markets, which has increased exponentially since the 2008 subprime crisis (Gai, Haldane & Kapadia, 2011) (Havlin, Kenett, Ben-Jacob, Bunde, Cohen, Hermann & Solomon, 2012). In specific, we use empirical correlations to calculate the Minimum Spanning Tree Length (MSTL) to represent the optimal path distance to travel the entire stock network (Eryiğit, & Eryiğit, 2009) (Zhao, Li, & Cai, 2016). This approach proves to be very efficient to adequately represent a complex system's behavior given its high dimensionality, such as equity markets.

Second, we use the MSTL to forecast the stock's volatility realized. This methodology identifies clusters within markets and observes the interrelation phenomenon over time (Bonanno, Lillo, & Mantegna, 2001), but little research uses this measure to forecast relevant characteristics for investors. Our research is related to the forecasting literature (Clark & McCracken, 2001) (Wang, 2019), particularly interested in detecting Granger causality between observable and measurable variables to construct systems help improve economic and financial forecasts. For this, the paper implements in-sample and out-of-sample testing methodologies, complemented with VAR tests.

We chose the Chilean stock market as a good study laboratory because it is a small market with high liquidity problems, where the systemic factors that affect asset returns are more limited compared to global research. Most of the investigations have studied the correlation networks between assets with global data sets using indices. This approach helps understand the aggregate phenomenon, but the indices' portfolio nature means that the variations in their returns are less than that of an asset. This behavior is also extrapolated to the index's correlation to another index, underestimating correlation and underlying volatility in the market. Second, because this market is small, synchronization is more severe due to less diversity of assets. Third, because liquidity problems narrow the range of possibilities even further, making timing even more critical. Fourth, there are no schedule problems, which can substantially affect the estimated correlations since when working with closing prices, there are differences in schedules and exchange rates.

For our objective, we use daily returns of 26 shares of the Chilean stock market between the period of November 2006 to April 2020, and we calculate the Chilean stock market synchronization (MSTL) and implement in-sample and out-of-sample tests to measure the stock market synchronization's predictive capacity in the assets' volatility. Finally, following Yang & Zhou (2017) we create an VAR and Error Variance Decomposition Analysis to study the Granger Causality between stock market synchronization (MSTL) and asset volatility.

The main results indicate that the MSTL follows a homogeneous normal distribution, obeying the stationarity expressed by Banerjee, Doran & Peterson (2007) and Perron, (1988) without persistence, varying periodically according to economic cycles, with an average value equivalent to one-third of its maximum expansion and decreasing to one fifth during a crisis. When evaluating the predictive power of synchronization, we validated Granger Causality in 15 assets following an estimate according to Newey & West (1987) and Newey & West (1994) within the sample, while outside the sample, we found significance of the ENCNEW test (Clark & McCracken, 2001) for 17 assets through recursive windows (p/r=0.4, 1 and 2). Additionally, through VAR tests (Pfaff, 2008) we find that the volatility of assets depends on the delayed timing of the market and not the other way around. These results are reinforced with a Forecast Error Variance Decomposition Analysis (Diebold & Yılmaz, 2014), where it is found that a not insignificant proportion of the realized variance of assets is explained by market timing.

Our conclusions indicate that stock market synchronization increases (decreases) in peak (stable) periods in the economy, causing an increase (decrease) in asset volatility. This phenomenon enables us to anticipate portfolio management in terms of diversification effectiveness and generating preventive alerts of increased risk.

The paper is organized as follows. Section 2 discusses the literature. Section 3 presents a detail of the methodology and the data used. In section 4, we present the results. Finally, we conclude in section 5.

2. Literature review

2.1 Financial network and stock market synchronization

The methodologies to study the inter-market and intra-market interconnectedness study the co-movement between the returns of the assets, caused by the behavior of the investor (Barberis & Thaler, 2005) (Green & Hwang, 2009) and macroeconomic factors (Cohen & Frazzini, 2008). Among the most prominent methodologies are the unit roots and cointegration test, autoregression vector models, correlation-based test (Forbes, & Rigobon, 2002), causality test (Billio, Caporin, Frattarolo & Pelizzon, 2021), GARCH models multivariate (Engle, 2002), and variance decomposition models (Diebold & Yilmaz, 2009).

Due to their internationalization and increase in investment alternatives, the increasing complexity of financial markets has motivated the development of methodologies that study correlations and volatilities and incorporate complexity while presenting the phenomenon in a parsimonious way. Onnela, Chakraborti, Kaski, & Kertesz (2003) argue that the minimal spanning tree length (MSTL) simply the market's complexity setting clusters between world stock markets (Eryiği & Eryiğit, 2009), correlations between markets and clusters (Gao & Mei, 2019), and identifying between centrality and peripheral markets (Zhao, Li & Cai, 2016).

Additionally, MSTL increases during the financial crisis, turning it into an efficient crisis indicator. In other words, in crises, MSTL contracts due to high asset correlation (Wang Xie & Stanley, 2018) which leads to the costs per position in an investment increasing, making diversification difficult (Coelho, Gilmore, Lucey Richmond & Hutzler, 2007).

Finally, MSTL is very efficient in demonstrating the phenomenon of market synchronization, significant for financial stability and investors' diversification strategies. New literature has shown that this correlation is not constant over time and varies significantly from one period to another (Magner, Lavin, Valle & Hardy, 2020). This phenomenon is known as stock market synchronization, and it represents the sum of the correlations between the assets that make up a market.

2.2. Volatility forecasting

McAleer, & Medeiros (2008) study models that forecast the assets' volatility to find optimal investment strategies and anticipate market movements, reducing economic losses from crisis. However, volatility is not directly observable despite being in a latent state (Andersen, Bollerslev & Meddahi, 2005) (Koopman, Jungbacker & Hol, 2005), using the realized volatility as a real volatility proxy that is consistent estimates of the true (latent) integrated volatility, becoming a benchmark practical.

The volatility is essential to asset pricing, derivatives, portfolio selection, risk management, and hedge (Wang, 2019). Therefore, its forecast becomes essential for decision-making in destabilizing scenarios for the system, increasing risk (Magner, Lavin, Valle & Hardy, 2020). In a standard scenario, the lower price fluctuation causes greater control in risk management; however, peak moments generate great uncertainty that is quickly transferred to prices, being able to obtain a better forecast probability for periods after these. "Jumps" (stochastic processes that have discrete movements, with random arrivals and many continuous movements) (Clement & Liao, 2017).

Other methodologies include the VIX as an essential risk indicator; a large VIX affects the international market more significantly instead of the smaller original VIX, finding an improvement in the forecast for the first case and demonstrating that it impacts significantly in the volatility of a step forward (Wang, 2019). Additionally, under structural ruptures, linear combination methods outperform non-linear methods when improving risk prediction using different window sizes. Even with all the discoveries and models used, volatility is still a complicated indicator to forecast.

3. Data and Methodology

This research uses daily closing prices of the following 26 shares currently belonging to the S&P Ipsa stock market index (see Table 2) these assets present the highest liquidity and the entire sample in the financial market for the period under study. We obtained our database from the Thomson Reuters Datastream platform from November 2006 to April 2020 with 3,358 days in 162 months.

3.1 Returns and realized variance

We use daily closing price p to estimate the daily logarithmic return $R_{i,t}$ of day t for asset i where, $R_{i,t} = ln\,(P_{i,t})\; - ln(P_{i,t-1})$. As Andersen, Bollerslev, Diebold, & Ebens (2001) we obtain the realized volatility for each stock through the daily return of the asset:

$$RV_{i,T} = \sum_{i=1}^{C_T} R_{i,t,T}^2 \tag{1}$$

RV is the realized volatility, and R represents the logarithmic return of asset i on day t of month t for days C_T of the respective month T.

3.2 Minimum spanning tree length (MSTL)

The Minimum spanning tree is based on the correlation of the assets' daily returns under study (Mantegna, 1999). In this research, we use the Pearson correlation in time-variable series (Benesty et al., 2009), where i,j quantifies the correlation relationship between assets' return on edge i and j, , when i and j are stocks, representing a Pearson correlation matrix NxN (where N represents the number of stocks). Finally, we convert the correlation in distances (d) (equation 2) for each edge of assets i,j evaluated in the month T.

$$d_{i,j}^{T} = \sqrt{2(1-\rho_{i,j}^{T})} \tag{2}$$

The distance (d), in this way, means the continuous quantitative relationship between the edge i,j, , when i and j are stocks, with limit values between $0 \leq d_{i,j} \leq 2$. With these distances, we calculate an adjacency matrix weighted network of N(N-1)/2 elements used quantitatively as distance, where, in case of representing a higher correlation, the distance tends to 0. In contrast, when representing a lower correlation, the distance tends to 2.

From the adjacency matrix, we extract the smallest distance of each edge i,j (Prim, 1957), when i and j are stocks, and estimate the MST representing the minimum distance for the connection between all network assets (Mantegna, 1999). Finally, we quantify the euclidean distance between each edge i,j and obtain the MSTL (equation 3) for 162 monthly (T).

$$MSTL(T) = \frac{1}{N-1} \sum d_{i,j}^{T} \in T^{t} d_{i,j}^{T} \tag{3}$$

The minimum distance's length between all the assets studied is represented as a weighted euclidean variable of the network for each month, where the length is reflected numerically between $0 \leq MSTL(T) \leq 2*(N-1)$. The distance length MSTL tends to its Minimum when the individual distance tends to zero, while when the individual distance tends to 2, the MSTL tends to its maximum so that both demonstrative variables present a negative correlation. Onnela, Chakraborti, Kaski, & Kertesz (2003) argue that the minimum spanning tree length (MSTL) is simply the complexity of the market that establishes groupings between world stock markets (Eryiğit, & Eryiğit, 2009), correlations between markets and groupings (Gao & Mei, 2019). What makes it a complete indicator compared to others that do not measure the relationship between assets.

The MSTL and realized volatility series of assets used in the estimates follow the stationarity expressed by Banerjee, Doran & Peterson (2007) and Perron (1988) without persistence, varying periodically in the function of economic cycles.

3.3 Forecast test

Autoregressive models have commonly explained asset volatility (Corsi, 2009). For this research, we add information from the systemic network as an explanatory variable of each shares' volatility by representing the monthly MSTL, each residual of the models complies with assumptions of normality, homoscedasticity and no auto-correlation.

To explain the monthly realized volatility of the shares and subsequently evaluate the influence of the explanatory variable under study (MSTL), we use an AR (p) model within the sample that includes 6 temporary lags of the asset volatility plus a lag temporary of MSTL (table 1, panel a). In the sample, we estimate with all the observations, having as main objective to validate our alternative hypothesis H1: $\beta_i \neq 0$ the existence of Granger causality (Granger, 1969) in the explanatory variable (MSTL) included in our models

Out of sample, we estimate through recursive windows considering a p / r = 0.4, p / r = 1, p / r = 2, obtaining results through the ENCNEW test (Clark & McCracken, 2001), for this, we generate a Benchmark model (table 1, panel c) and compare the core model for each stock (table 1, panel b). For each of the 26 companies, the null hypothesis H1: $\beta_i \neq 0$, will be validated if the MSTL generates a decrease in the forecast error when incorporated into the benchmark model, validating the effectiveness of the inclusion of our variable. For the estimation, we used a HAC standard error methodology for stationary covariance processes in time series, correcting the deviations of homoscedasticity and autocorrelation of errors produced by the long-term variance (Newey, & West, 1987) (Newey, & West, 1994).

Table 1. Forecasting models

Panel A - In the sample core model
(1) $RV_{i,T} = c + \beta_i * MSTL_{T-1} + Y_{i,1} * RV_{i,T-1} + Y_{i,2} * RV_{i,T-2} + Y_{i,3} * RV_{i,T-3} + Y_{i,4} * RV_{i,T-4} +$ (2) $Y_{i,5} * RV_{i,T-5} + Y_{i,6} * RV_{i,T-6} + \varepsilon_T$
Panel B - out-of-sample core mode
(3) $RV_{i,T} = c + \beta_i * MSTL_{T-1} + Y_{i,1} * RV_{i,T-1} + Y_{i,2} * RV_{i,T-2} + Y_{i,3} * RV_{i,T-3} +$ (4) $Y_{i,4} * RV_{i,T-4} + Y_{i,5} * RV_{i,T-5} + Y_{i,6} * RV_{i,T-6} + \varepsilon_T$
Panel C - out-of-sample Benchmark model
(5) $RV_{i,T} = c + Y_{i,1} * RV_{i,T-1} + Y_{i,2} * RV_{i,T-2} + Y_{i,3} * RV_{i,T-3} + Y_{i,4} * RV_{i,T-4} + Y_{i,5} * RV_{i,T-5} +$ (6) $Y_{i,6} * RV_{i,T-6} + \varepsilon_T$
Panel D VAR models
(7) $RV_{i,T} = c + Y_{i,1} * RV_{i,T-1} + Y_{i,2} * RV_{i,T-2} + \beta_{i,1} *. MSTL_{T-1} + \beta_{i,2} * MSTL_{T-2} \quad + \varepsilon_T$ (8) $MSTL_T = c + Y_{i,1} * RV_{i,T-1} + Y_{i,2} * RV_{i,T-2} + \beta_{i,1} * MSTL_{T-1} + \beta_{i,2} * MSTL_{T-2} \quad + \varepsilon_t$

This table presents the forecast models. {\rm RV}_{i,T} represents the monthly volatility of asset i in month T, and MSTL represents the logarithmic variation of the minimum distance from the network in its respective month T.

Source: Authors' elaboration.

3.4 VAR and Forecasting Error Variance Decomposition

We performed a VAR to test the causal relationship between two stationary variables. This method has proven to be especially useful to describe the dynamic behavior of economic, financial time series, and forecast evaluations.

We estimate a VAR model of simultaneous equations using two lags of the MSTL and the volatility realized for each share (See Table 1, Panel D), complying with the assumptions of normality, homoscedasticity and no auto-correlation for the residuals. The main purpose of this estimation is to validate our alternative and independent hypotheses of the existence of Granger causality in the explanatory variable (MSTL) with both lags included in our models with estimation by ordinary least squares.

Additionally, we generate an impulse in the MSTL to measure this shock's intensity in the realized volatility of assets and in the network itself. In case these impulses can explain future volatility spills, we interpret them as significant drivers. In this way, decomposing the variance of the forecast error (Diebold, & Yılmaz, 2014), we measure how much the innovation contributes to the variance of the total forecast error from H months ahead for each realized volatility for the quarters of the coming year (H = 1, H = 3, H = 6, H = 9, H = 12) since the shock occurred.

Where $AS_{t,H}$ represents the sum of variance percentages of the forecast error from H months ahead, using data from month t. AS shows the impulse response and $a^2_{h,(i,MSTL)}$ represents the contribution to the variance of the error to forecast assets i due to changes in MSTL.

4. Results

This section presents descriptive statistics of the Chilean stock market's synchronization phenomenon and historical statistics of each asset included in the study. Then, we present the results of the in-sample and out-of-sample tests to study the predictive power of the MSTL on the volatility of equity assets. Then, we report an VAR model to evaluate the Granger causality between the volatility of equity assets and the estimated MSTL synchronization index. Finally, we report the results of the forecasting error variance decomposition analysis.

4.1 Synchronization stock market in Chile

Table 2 reports the results of descriptive statistics and unit root test calculated for each of the equity assets, including information for the total study period and the MSTL synchronization index during different sub-periods of the sample.

The results show that energy companies (Copec, Enelam, Colbún, and ECL), banking (Bsantander, Chile, BCI), and retail (Cencosud, Falabella, and Ripley) present less centrality, reducing their probability of failure in high times and its similarity in behavior with other assets. This phenomenon translates into an opportunity for diversification optimization (Peralta & Zareei, 2016). On the contrary, assets in the beverage sector (Conchatoro and Andinab), and other companies as

Security, Aguasa, IAM, and Vapores, present a greater centrality, being the primary source and receiver of information transfer in the market (Sensoy, Nguyen, Rostom & Hacihasanoglu, 2019).

When observing the MSTL synchronization, skewness tends to approach zero in the pre-crisis and crisis periods, implying the network's Gaussian distribution (Coelho, Gilmore, Lucey, Richmond & Hutzler, 2007). Also, the average value of the network during these periods tends to decrease concerning the post-crisis period and the total period, which indicates that the correlation between assets increases, implying that the market synchronization also does the same. On the other hand, there is an increase in the data's standard deviation since the uncertainty and economic events during these periods cause unexpected returns on assets.

In the post-crisis period, we observe that assets tend to increase their distance compared to the pre-crisis and crisis periods, showing less market synchronization and decreased data deviation with values closer to those reflected in the entire network.

Table 2. Descriptive statistics and unit root test for synchronization Chilean stock market and assets volatility

	mean	sd	median	min	max	range	skew	kurtosis	Unit root test	centrality
CAP	1.50E-02	2.44E-02	8.41E-03	1.04E-03	2.11E-01	2.10E-01	5.74E+00	3.94E+01	-1.03E+01***	2.08E+01
SQMB	1.14E-02	1.74E-02	6.19E-03	6.83E-04	1.35E-01	1.34E-01	4.70E+00	2.69E+01	-7.58E+00***	2.14E+01
CENCOSUD	7.09E-03	1.09E-02	4.91E-03	4.22E-04	9.90E-02	9.86E-02	6.48E+00	4.85E+01	-1.10E+01***	2.04E+01
COPEC	5.27E-03	6.29E-03	3.46E-03	5.38E-04	5.67E-02	5.62E-02	4.76E+00	3.05E+01	-7.83E+00***	2.00E+01
FALABELLA	5.80E-03	1.00E-02	3.69E-03	4.45E-04	1.09E-01	1.09E-01	7.45E+00	6.89E+01	-1.06E+01***	2.04E+01
VAPORES	1.59E-02	4.92E-02	6.68E-03	1.14E-03	5.68E-01	5.67E-01	9.31E+00	9.73E+01	-1.25E+01***	2.20E+01
CMPC	6.17E-03	6.93E-03	4.28E-03	1.05E-03	7.26E-02	7.16E-02	6.06E+00	5.13E+01	-8.90E+00***	2.04E+01
RIPLEY	8.27E-03	1.27E-02	4.42E-03	1.73E-04	9.91E-02	9.89E-02	4.43E+00	2.42E+01	-1.00E+01***	2.13E+01
ENELAM	5.23E-03	9.65E-03	2.97E-03	6.91E-04	9.83E-02	9.76E-02	6.82E+00	5.60E+01	-9.23E+00***	2.05E+01
BSANTANDER	5.46E-03	9.49E-03	3.13E-03	7.55E-04	9.26E-02	9.18E-02	6.66E+00	5.25E+01	-9.28E+00***	2.05E+01
SALFACORP	9.76E-03	1.16E-02	6.46E-03	9.00E-04	8.40E-02	8.31E-02	3.77E+00	1.68E+01	-8.49E+00***	2.17E+01
BCI	4.89E-03	5.89E-03	3.44E-03	4.94E-04	5.59E-02	5.54E-02	5.36E+00	3.84E+01	-9.29E+00***	2.07E+01
ENTEL	5.01E-03	6.44E-03	3.28E-03	3.98E-04	5.82E-02	5.78E-02	5.04E+00	3.26E+01	-6.15E+00***	2.08E+01
CHILE	4.02E-03	8.77E-03	2.09E-03	2.80E-04	8.32E-02	8.29E-02	7.12E+00	5.62E+01	-1.05E+01***	2.06E+01
PARAUCO	6.34E-03	1.20E-02	4.25E-03	4.83E-04	1.41E-01	1.41E-01	8.92E+00	9.42E+01	-1.10E+01***	2.17E+01
COLBUN	4.64E-03	6.78E-03	3.13E-03	4.57E-04	7.61E-02	7.57E-02	7.71E+00	7.49E+01	-1.03E+01***	2.10E+01
SONDA	5.54E-03	7.72E-03	3.49E-03	6.78E-04	7.10E-02	7.03E-02	5.16E+00	3.42E+01	-9.49E+00***	2.13E+01
ECL	6.41E-03	1.12E-02	3.84E-03	6.20E-04	1.20E-01	1.19E-01	7.13E+00	6.47E+01	-1.04E+01***	2.16E+01
AESGENER	5.42E-03	7.03E-03	3.36E-03	5.47E-04	6.36E-02	6.30E-02	4.97E+00	3.21E+01	-7.33E+00***	2.12E+01
ANDINAB	5.73E-03	7.94E-03	3.78E-03	4.79E-04	8.45E-02	8.40E-02	6.73E+00	5.90E+01	-9.51E+00***	2.16E+01
ITAUCORP	5.50E-03	1.29E-02	3.06E-03	2.87E-04	1.58E-01	1.58E-01	1.04E+01	1.19E+02	-1.13E+01***	2.13E+01
CCU	4.79E-03	4.85E-03	3.48E-03	8.80E-04	4.32E-02	4.23E-02	4.51E+00	2.78E+01	-7.16E+00***	2.15E+01
CONCHATORO	4.87E-03	4.92E-03	3.54E-03	4.10E-04	3.29E-02	3.25E-02	3.06E+00	1.12E+01	-9.32E+00***	2.20E+01

IAM	3.92E-03	7.15E-03	2.19E-03	2.01E-04	7.24E-02	7.22E-02	6.54E+00	5.33E+01	-1.07E+01***	2.22E+01
SECURITY	4.78E-03	5.92E-03	3.02E-03	2.32E-04	4.07E-02	4.05E-02	3.53E+00	1.55E+01	-1.01E+01***	2.28E+01
AGUASA	3.56E-03	8.45E-03	1.84E-03	1.92E-04	9.77E-02	9.75E-02	8.97E+00	9.36E+01	-1.11E+01***	2.22E+01
MSTL	1.58E+01	1.98E+00	1.63E+01	9.31E+00	1.85E+01	9.24E+00	-1.26E+00	1.23E+00	-8.22E+00***	
Pre crisis	1.51E+01	2.33E+00	1.53E+01	1.04E+01	1.85E+01	8.10E+00	-4.41E-01	-9.10E-01		
Crisis	1.47E+01	2.33E+00	1.52E+01	1.03E+01	1.73E+01	6.97E+00	-6.40E-01	-1.06E+00		
Post crisis	1.55E+01	2.01E+00	1.63E+01	9.31E+00	1.79E+01	8.55E+00	-1.35E+00	1.32E+00		

This table reports the summary statistic of monthly stock returns from November 2006 to April 2020. In the MSTL row we report the statistics of Minimum Spanning Tree Length and in the Unit Root Test row we report the stationarity of the series with * p <10%, ** p <5%, *** p <1%. Additionally, we present three periods: Pre crisis (between November 2006 and September 2008); Crisis (between October 2008 and March 2009); Post crisis (between April 2008 and April 2020).

Source: Authors' elaboration.

4.2 In-Sample Analysis

Table 3 reports the models reported in Table 1, panel A. We consider monthly frequencies and use HAC standard errors according to Newey & West (1987) and Newey, & West (1994). The results show that the MSTL coefficients are negative and statistically significant for 15 of the 26 actions studied, demonstrating a greater than 50% predictive power. This result means that an expansion (contraction) in the asset correlation network predicts a decrease (increase) in volatility realized in the following month by more than 50% of the market. This negative lagged coefficient is consistent with the research of Magner, Lavin Valle & Hardy (2020), which found a negative and lagged relationship between the variation of the MSTL and PMFGL and the realized volatility of 11 stock market indices worldwide.

The assets whose realized volatility has a statistical significance with the delayed synchronization of the market belong to the retail industries (Cencosud, Falabella, Ripley), energy (Copec, Enelam, Colbun, ECL), banking sector (BSantander, Chile, BCI), beverage (Concha y Toro, AndinaB), utilities (IAM), tech-companies (Sonda), and real estate (Salfacorp). Industrial sectors, telecommunications, other financial services, and raw materials extraction did not present a statistical relationship with the lagged synchronization index.

Regarding the retail industry, table 3 shows that the realized volatility of the Cencosud stock (beta = -1.30.E-03; p = 1.09.E-02), Falabella (beta = -1.19.E-03; p = 3.11.E-02), and Ripley (beta = -1.44.E-03; p = 2.00.E-04) turned out to be statistically significant, increasing when the MSTL of the network decreased in the previous month. In other words, an increase in synchronization is a preview of an increase in realized volatility of companies in the Retail sector.

Respect to the energy industry, table 3 shows that the realized volatility of the stock is inversely related to the synchronization of the stock market lagged in one month. Thus, Copec (beta = -6.26.E-04; p = 5.94.E-02), Enelam (beta = -6.37.E-04; p = 5.85.E-02), Colbun (beta = -7.53.E -04; p = 1.37.E-02), and ECL (beta = -1.06.E-03; p = 6.62.E-02) show an increase in their volatility realized after a decrease in the MSTL of the network of assets.

Stocks' realized volatility in the banking sector also showed a negative and statistically significant relationship with the lagging MSTL of the network. Within this group, in table 3 we see that Banco Santander (beta = -9.65.E-04; p = 1.31.E-02), Banco Chile (beta = -1.04.E-03; p = 4.37.E-02), and BCI (beta = -7.67.E-04; p = 7.90.E-03) turned out to be statistically significant, increasing when the MSTL of the network decreased in the previous month. The only exception was the realized volatility of ItauCorp (beta = -5.62.E-04; p = 1.82.E-01) and Security (beta = -6.27.E-04; p = 1.14.E-01) which did not showed a statistically significant relationship with market timing.

Other companies show a negative and statistically significant relationship between their realized volatility and the lagged MSTL of the market. Table 3 shows that such companies are from the drinking sector: Concha y Toro (beta = -8.36.E-04; p = 3.52.E-02) and AndinaB (beta = -4.89.E-04; p = 9.28.E- 02); utilities sector: IAM (beta = -5.89.E-04; p = 8.30.E-02); Sonda technology sector (beta = -1.33.E-03; p = 5.20.E-03), and Salfacorp construction sector (beta = -2.40.E-03; p = 1.05.E-02).

Additionally, we note features derived from the in-the-sample model. First, we note a strong autocorrelation in the realized volatility of the stocks studied. Table 3 shows that we noticed 25 out of a total of 26 companies present a positive and statistically significant constant and positive statistical significance in any of the 6 lags of realized volatility.

Table 3. Forecast realized volatility stocks with MSTL

	C	MSTL (-1)	RV (-1)	RV (-2)	RV (-3)	RV (-4)	RV (-5)	RV (-6)	R^2	Prob Wald
CAP	1.64E-02	-4.67E-04	**1.57E-01****	1.57E-01	1.26E-01	8.13E-02	8.38E-03	-1.01E-01	9.00E-02	2.09E-03
	(1.15E-02)	(6.84E-04)	(7.85E-02)	(1.39E-01)	(8.83E-02)	(1.50E-01)	(6.71E-02)	(7.56E-02)		
SQMB	-4.59E-05	2.47E-04	**4.35E-01****	3.21E-02	6.17E-02	2.48E-01	-6.71E-02	-1.97E-02	2.98E-01	2.18E-04
	(8.50E-03)	(4.74E-04)	(1.82E-01)	(1.78E-01)	(1.96E-01)	(2.47E-01)	(1.52E-01)	(5.89E-02)		
CENCOSUD	**2.61E-02*****	**-1.30E-03****	-6.76E-03	-3.13E-02	6.52E-02	1.24E-01	4.83E-02	3.84E-02	7.14E-02	3.01E-04
	(8.63E-03)	(5.05E-04)	(7.30E-02)	(5.26E-02)	(9.82E-02)	(1.95E-01)	(5.02E-02)	(4.17E-02)		
COPEC	**1.20E-02****	**-6.26E-04***	**3.01E-01*****	4.65E-02	-6.28E-02	4.36E-01	-1.76E-01	8.79E-02	3.03E-01	0.00E+00
	(5.69E-03)	(3.30E-04)	(8.49E-02)	(7.86E-02)	(1.73E-01)	(3.90E-01)	(1.09E-01)	(5.94E-02)		
FALABELLA	**2.12E-02****	**-1.19E-03****	-1.70E-02	-7.74E-02	1.47E-01	5.74E-01	7.87E-02	-3.15E-02	2.13E-01	0.00E+00
	(9.06E-03)	(5.47E-04)	(1.11E-01)	(8.43E-02)	(1.46E-01)	(5.80E-01)	(1.03E-01)	(1.72E-01)		
VAPORES	**3.58E-02***	-1.29E-03	-5.47E-03	-2.93E-02	**-2.56E-02***	-1.94E-02	8.21E-03	1.01E-01	1.40E-02	3.00E-01
	(2.02E-02)	(1.32E-03)	(1.91E-02)	(2.47E-02)	(1.51E-02)	(1.22E-02)	(2.50E-02)	(1.42E-01)		
CMPC	**9.81E-03***	-4.35E-04	**2.20E-01****	1.36E-01	-6.89E-02	2.40E-01	7.65E-02	-4.78E-02	1.66E-01	7.40E-05
	(5.56E-03)	(3.29E-04)	(9.76E-02)	(1.07E-01)	(1.54E-01)	(2.82E-01)	(1.52E-01)	(9.36E-02)		
RIPLEY	**2.84E-02*****	**-1.44E-03*****	1.13E-01	2.14E-02	-1.56E-02	2.04E-01	2.67E-02	-1.41E-02	1.26E-01	1.42E-03
	(6.56E-03)	(3.81E-04)	(7.22E-02)	(5.81E-02)	(4.57E-02)	(1.29E-01)	(6.14E-02)	(4.53E-02)		
ENELAM	**1.38E-02****	**-6.37E-04***	**2.14E-01*****	-2.36E-02	7.34E-02	3.41E-02	2.07E-02	-1.76E-02	8.43E-02	5.00E-06
	(5.91E-03)	(3.34E-04)	(4.94E-02)	(5.25E-02)	(9.56E-02)	(3.26E-02)	(4.08E-02)	(5.49E-02)		
BSANTANDER	**1.81E-02*****	**-9.65E-04****	**1.55E-01***	5.40E-02	1.92E-01	1.62E-01	6.08E-02	-1.11E-01	1.73E-01	0.00E+00
	(6.57E-03)	(3.84E-04)	(8.11E-02)	(1.12E-01)	(2.36E-01)	(2.70E-01)	(6.82E-02)	(9.25E-02)		
SALFACORP	**4.63E-02*****	**-2.40E-03****	1.24E-01	-3.61E-02	**-1.10E-01***	1.93E-01	-1.30E-04	-2.67E-02	2.64E-01	0.00E+00
	(1.64E-02)	(9.28E-04)	(1.74E-01)	(7.63E-02)	(5.90E-02)	(1.85E-01)	(7.68E-02)	(4.71E-02)		
BCI	**1.49E-02*****	**-7.67E-04*****	**1.11E-01***	-1.99E-02	1.07E-01	3.14E-01	2.89E-02	-8.40E-02	1.97E-01	0.00E+00
	(4.83E-03)	(2.85E-04)	(6.69E-02)	(8.26E-02)	(1.08E-01)	(3.90E-01)	(1.06E-01)	(1.13E-01)		
ENTEL	2.47E-03	-1.41E-04	**4.19E-01*****	-3.63E-02	1.78E-01	4.27E-01	1.03E-01	-3.56E-02	3.87E-01	0.00E+00
	(5.01E-03)	(2.79E-04)	(8.43E-02)	(6.81E-02)	(1.28E-01)	(4.19E-01)	(9.66E-02)	(8.11E-02)		
CHILE	**1.90E-02****	**-1.04E-03****	4.75E-02	3.59E-02	1.20E-01	2.71E-01	-3.26E-03	-7.35E-02	1.29E-01	0.00E+00
	(8.83E-03)	(5.12E-04)	(8.26E-02)	(8.05E-02)	(7.64E-02)	(3.15E-01)	(6.16E-02)	(5.62E-02)		
PARAUCO	1.04E-02	-4.63E-04	**8.81E-02***	8.71E-03	-9.98E-03	6.36E-01	-1.51E-02	-1.14E-01	1.12E-01	1.00E-06
	(9.17E-03)	(5.29E-04)	(5.10E-02)	(8.29E-02)	(1.44E-01)	(6.70E-01)	(1.45E-01)	(1.46E-01)		
COLBUN	**1.34E-02*****	**-7.53E-04****	2.40E-02	1.58E-01	4.88E-02	3.09E-01	3.49E-01	-1.35E-01	1.67E-01	0.00E+00
	(4.48E-03)	(3.02E-04)	(9.17E-02)	(1.60E-01)	(8.19E-02)	(2.63E-01)	(2.25E-01)	(9.34E-02)		
SONDA	**2.51E-02*****	**-1.33E-03*****	7.95E-02	**-1.06E-01****	-6.23E-02	3.67E-01	7.89E-03	-1.97E-02	2.08E-01	7.00E-06
	(8.18E-03)	(4.69E-04)	(1.13E-01)	(5.19E-02)	(7.64E-02)	(3.85E-01)	(7.81E-02)	(4.98E-02)		
ECL	**1.93E-02****	**-1.06E-03***	6.50E-02	-9.26E-03	4.64E-02	5.51E-01	8.76E-02	-7.69E-02	1.97E-01	0.00E+00
	(9.57E-03)	(5.73E-04)	(6.58E-02)	(5.12E-02)	(1.33E-01)	(5.20E-01)	(1.00E-01)	(1.15E-01)		

AESGENER	3.90E-03	-1.26E-04	5.12E-01**	-2.86E-01*	3.62E-01***	5.88E-02	2.35E-01*	-1.99E-01	3.06E-01	2.90E-05
	(6.50E-03)	(3.74E-04)	(2.01E-01)	(1.64E-01)	(1.38E-01)	(2.00E-01)	(1.38E-01)	(1.38E-01)		
ANDINAB	1.13E-02**	-4.89E-04*	2.07E-01**	-1.44E-02	-6.45E-02	3.40E-01	2.81E-02	-9.03E-02	1.20E-01	1.37E-03
	(5.09E-03)	(2.89E-04)	(8.21E-02)	(5.48E-02)	(1.47E-01)	(3.15E-01)	(1.28E-01)	(6.86E-02)		
ITAUCORP	1.03E-02	-5.62E-04	7.70E-02*	-1.46E-02	-2.07E-01	1.39E+00	1.43E-03	-3.65E-01	2.32E-01	1.16E-03
	(7.72E-03)	(4.19E-04)	(4.60E-02)	(1.40E-01)	(2.56E-01)	(1.20E+00)	(1.19E-01)	(3.27E-01)		
CCU	5.78E-03	-2.37E-04	3.56E-01**	9.31E-02	2.64E-01**	-6.40E-02	1.05E-01	-1.50E-01	2.58E-01	0.00E+00
	(3.66E-03)	(2.18E-04)	(1.42E-01)	(1.24E-01)	(1.17E-01)	(1.36E-01)	(9.69E-02)	(1.29E-01)		
CONCHATORO	1.64E-02**	-8.36E-04**	5.97E-02	7.21E-02	-5.95E-02	2.40E-01	1.82E-01**	-1.43E-01	2.57E-01	1.80E-05
	(7.12E-03)	(3.94E-04)	(1.36E-01)	(7.68E-02)	(5.43E-02)	(2.00E-01)	(9.09E-02)	(9.40E-02)		
IAM	1.11E-02*	-5.89E-04*	7.10E-02	-6.59E-02	-4.71E-02	5.91E-01	5.75E-02	1.07E-02	2.02E-01	1.00E-06
	(5.87E-03)	(3.37E-04)	(5.46E-02)	(4.18E-02)	(1.31E-01)	(5.36E-01)	(6.64E-02)	(5.37E-02)		
SECURITY	1.27E-02*	-6.27E-04	1.04E-01	1.61E-02	8.70E-02	2.58E-01	-1.19E-01**	9.55E-02	1.63E-01	0.00E+00
	(6.87E-03)	(3.94E-04)	(1.15E-01)	(7.63E-02)	(1.73E-01)	(2.69E-01)	(4.68E-02)	(9.18E-02)		
AGUASA	3.82E-03	-2.46E-04	4.77E-02	2.40E-01	9.51E-03	8.85E-01	1.08E-01	-3.17E-02	2.17E-01	0.00E+00
	(6.18E-03)	(3.15E-04)	(7.05E-02)	(2.20E-01)	(1.48E-01)	(8.14E-01)	(1.56E-01)	(7.61E-02)		

This table presents the in-sample analysis with monthly data and core specification from Table 1, Panel A. In all models we included, yet not show, an AR(6) that stands for lag monthly of the dependent variable (we only show the first three lags). *p < 10%, **p < 5%, ***p < 1%.

Source: Authors' elaboration.

4.3 Out-of-Sample

Tables 4 show the ENCNEW test results (Clark & McCracken, 2001) in out-of-sample exercise for all stocks. The results of table 4 correspond to the statistical difference between the core model reported in table 1 panel B versus the benchmark models presented in Table 1 panel C when the proportion of the sample to make the forecast corresponds to a 40%, 50%, and 67% (P / R = 0.4, P / R = 1, and P / R = 2, respectively)

In Table 4, we use an AR (6) model described in Table 1, denoting an autoregressive process of order 6 for the realized volatility of each stock included in the study. For the case, P / R: 0.4, 17 of the 26 stocks studied presented a statistically significant difference. We interpret these results as the core model (See Table 1, panel B) has better predictive capacity than the benchmark model (See table 1, panel C). Of the 17 actions that present statistical significance, 14 reject the null hypothesis with a probability of less than 1%. In contrast, the remaining 3 companies reject the hypothesis with a probability of less than 5%.

When performing the out-of-sample tests, increasing the estimation window to 50% (P / R: 1), 13 companies reject the null hypothesis with a probability less than 10% (See table 4 column 3); while the same test with an estimation window of 67% (P / R: 2) indicates that 5 companies reject the null hypothesis with a probability less than 10%.

The industries that showed the best forecasting performance between the lagged MSTL and the stock's realized volatility are retail, banking, energy, beverage, technology, and utilities, consistent with the results obtained in the out-of-sample tests.

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Table 4. Forecast realized volatility stocks with MSTL

	Pi = 2	Pi = 1	Pi = 0.4
CAP	-0.53	-0.35	-0.8
SQMB	0.18	-0.03	-0.79
CENCOSUD	1.1	1.85**	2.47***
COPEC	0.67	0.72	1.13**
FALABELLA	0.77	1.07*	1.21**
VAPORES	-1.2	-0.49	2.09**
CMPC	-0.14	-0.22	-0.39
RIPLEY	3.24**	4.35***	5.81***
ENELAM	1.44*	1.24*	3.99***
BSANTANDER	0.89	1.36*	3.15***
SALFACORP	4.14***	6.85***	0.14***
BCI	1.18	1.85**	2.92***
ENTEL	-0.02	-0.13	-0.68
CHILE	1.09	1.18*	3.57***
PARAUCO	-0.36	-0.41	-0.69
COLBUN	0.73	1.10*	2.11***
SONDA	3.89**	4.73***	4.41***
ECL	1.21	1.53*	2.22***
AESGENER	-0.27	-0.12	-0.33
ANDINAB	-0.07	-1.48	0.36
ITAUCORP	0.85	0.37	2.17***
CCU	0.71	0.8	3.32***
CONCHATORO	3.29**	4.38***	5.42***
IAM	0.69	0.98*	1.40**
SECURITY	0.51	0.4	-0.56
AGUASA	0.14	0.1	-0.11

This table presents the out-of-sample analysis with monthly data to torecasting realized volatility stocks with MSTL. (P/R = 0.4). 10%, 5%, and 1% critical values are 0.685, 1.079, and 2.098, respectively, when there is only one excess parameter. (P/R = 1). 10%, 5%, and 1% critical values are 0.984, 1.584, and 3.209, respectively, when there is only one excess parameter. (P/R = 2). 10%, 5%, and 1% critical values are 1.280, 2.085, and 4.134, respectively, when there is only one excess parameter. P represents the number of one-step-ahead forecasts, R the sample size of the first estimation window. All models are evaluated with AR(6) presents in Table 1, Panels B and C. *p < 10%, **p < 5%, ***p < 1%.

Source: Authors' elaboration

4.4 VAR and Forecast Error Variance Decomposition Analysis

Tables 5 and 6 show the VAR (2) results using the MSTL and the realized volatility of each asset. We selected the AR (2) using the methodology for selecting the appropriate delay (Pfaff, 2008). This analysis aims to study Granger Causality; the results show partial causality in one direction for 10 of the 26 companies studied. This result means that the lagged MSTL presents a statistical significance on the stock's realized volatility for the following period (See table 5). Additionally, we do not observe causality in the opposite direction. In other words, the lagged realized volatility of financial assets is not related to the timing of the market in the next period.

Table 5. VAR results for realized volatility stocks models

	C	RV	RV	MSTL	MSTL	R^2
		(-1)	(-2)	(-1)	(-2)	
CAP	-6.52E-03	**1.77E-01****	**2.22E-01****	-9.40E-05	1.10E-03	1.87E-01
	(1.85E-02)	(8.37E-02)	(1.06E-01)	(1.09E-03)	(1.09E-03)	
SQMB	-1.15E-02	**4.61E-01*****	1.50E-01	5.80E-04	4.47E-04	1.88E-01
	(1.26E-02)	(9.09E-02)	(1.04E-01)	(7.13E-04)	(7.16E-04)	
CENCOSUD	1.42E-02	4.13E-02	7.45E-02	**-1.05E-03***	5.48E-04	1.89E-01
	(1.09E-02)	(9.47E-02)	(1.27E-01)	(5.58E-04)	(5.69E-04)	
COPEC	3.46E-04	**3.28E-01*****	**2.94E-01****	**-5.29E-04***	**6.43E-04****	2.02E-01
	(6.43E-03)	(9.64E-02)	(1.33E-01)	(2.98E-04)	(3.15E-04)	
FALABELLA	9.04E-03	1.09E-01	2.11E-01	**-8.77E-04***	5.66E-04	1.88E-01
	(1.08E-02)	(9.36E-02)	(1.81E-01)	(5.02E-04)	(5.59E-04)	
VAPORES	1.16E-02	-3.40E-03	-2.43E-02	-1.51E-03	1.81E-03	1.86E-01
	(3.84E-02)	(8.01E-02)	(8.42E-02)	(2.18E-03)	(2.22E-03)	
CMPC	2.40E-03	**2.84E-01*****	2.44E-01	-5.13E-05	9.49E-05	1.93E-01
	(7.49E-03)	(9.62E-02)	(1.63E-01)	(3.43E-04)	(3.67E-04)	
RIPLEY	**2.12E-02***	1.36E-01	5.80E-02	**-1.38E-03****	4.63E-04	1.97E-01
	(1.12E-02)	(8.71E-02)	(9.72E-02)	(5.85E-04)	(5.92E-04)	
ENELAM	6.83E-03	**2.40E-01*****	1.98E-02	-3.76E-04	1.93E-04	1.86E-01
	(8.03E-03)	(8.67E-02)	(1.38E-01)	(4.45E-04)	(4.50E-04)	
BSANTANDER	6.89E-03	**2.13E-01****	2.50E-01*	-6.91E-04	4.51E-04	2.02E-01
	(8.28E-03)	(9.23E-02)	(1.35E-01)	(4.52E-04)	(4.65E-04)	
SALFACORP	**2.66E-02****	**1.68E-01***	5.69E-02	**-2.55E-03*****	**1.35E-03****	1.85E-01
	(1.13E-02)	(9.03E-02)	(9.09E-02)	(5.12E-04)	(5.41E-04)	
BCI	6.63E-03	**2.01E-01****	1.57E-01	**-5.40E-04***	3.24E-04	1.90E-01
	(5.94E-03)	(9.63E-02)	(1.36E-01)	(2.94E-04)	(3.09E-04)	
ENTEL	-6.38E-03	**5.68E-01*****	2.09E-01	1.04E-04	3.87E-04	1.85E-01
	(5.94E-03)	(9.78E-02)	(1.45E-01)	(2.96E-04)	(3.14E-04)	
CHILE	7.63E-03	1.04E-01	1.59E-01	**-9.57E-04****	6.65E-04	7.71E-02
	(7.82E-03)	(8.81E-02)	(1.25E-01)	(4.14E-04)	(4.23E-04)	
PARAUCO	6.57E-03	1.08E-01	1.26E-01	-3.52E-04	2.54E-04	1.86E-01
	(1.18E-02)	(8.94E-02)	(2.08E-01)	(5.89E-04)	(6.29E-04)	
COLBUN	3.50E-03	1.30E-01	**3.69E-01****	-4.08E-04	3.47E-04	1.86E-01

	(6.75E-03)	(9.08E-02)	(1.80E-01)	(3.29E-04)	(3.59E-04)	
SONDA	**1.58E-02****	1.37E-01	-5.85E-02	**-9.84E-04*****	3.07E-04	1.85E-01
	(7.91E-03)	(9.37E-02)	(1.29E-01)	(3.78E-04)	(3.91E-04)	
ECL	1.14E-02	**1.56E-01***	1.44E-01	-7.01E-04	2.65E-04	1.86E-01
	(1.05E-02)	(8.94E-02)	(1.56E-01)	(5.33E-04)	(5.56E-04)	
AESGENER	2.31E-03	**5.64E-01*****	-1.72E-01	2.66E-04	-2.03E-04	1.90E-01
	(5.91E-03)	(9.31E-02)	(1.24E-01)	(3.16E-04)	(3.21E-04)	
ANDINAB	6.17E-03	**2.51E-01*****	4.40E-03	-1.61E-04	4.32E-05	1.95E-01
	(6.93E-03)	(9.16E-02)	(1.50E-01)	(3.85E-04)	(3.96E-04)	
ITAUCORP	4.43E-03	8.88E-02	2.32E-01	-2.76E-04	2.49E-04	1.96E-01
	(1.17E-02)	(8.89E-02)	(2.76E-01)	(6.13E-04)	(6.74E-04)	
CCU	-1.04E-03	**4.00E-01*****	**2.88E-01****	-1.22E-04	2.94E-04	1.91E-01
	(4.53E-03)	(9.54E-02)	(1.28E-01)	(2.28E-04)	(2.34E-04)	
CONCHATORO	**1.05E-02****	1.29E-01	**1.88E-01****	**-8.71E-04*****	**4.20E-04***	1.83E-01
	(4.79E-03)	(9.01E-02)	(9.49E-02)	(2.19E-04)	(2.25E-04)	
IAM	7.78E-03	1.12E-01	-2.50E-02	-5.32E-04	2.66E-04	1.85E-01
	(6.58E-03)	(9.02E-02)	(1.40E-01)	(3.50E-04)	(3.60E-04)	
SECURITY	**9.69E-03***	1.45E-01	7.52E-02	**-5.25E-04***	1.50E-04	1.86E-01
	(5.78E-03)	(9.37E-02)	(1.04E-01)	(2.93E-04)	(2.94E-04)	
AGUASA	-2.01E-03	1.10E-01	**4.03E-01****	-2.87E-04	5.41E-04	1.83E-01
	(7.22E-03)	(8.57E-02)	(1.86E-01)	(3.94E-04)	(4.07E-04)	

This table report the VAR analysis with monthly data and core specification from Table 1, Panel D, Row (8). *p < 10%, **p < 5%, ***p < 1%.
Source: Authors' elaboration.

Another interesting result is the strong causality verified in the stock market synchronization phenomenon. Table 6 shows that the first lag of the MSTL is statistically significantly related to the MSTL of the following period. The persistence in the MSTL time series, which we interpret as the synchronization of the stock market causing a significant part of the synchronization of the same market in the following period.

Table 6. VAR results for MSTL models

Company	**C**	**RV**	**RV**	**MSTL**	**MSTL**	**R^2**
		(-1)	**(-2)**	**(-1)**	**(-2)**	
CAP	**8.79E+00*****	7.61E+00	7.23E+00	**4.25E-01*****	1.46E-03	1.82E-01
	(1.41E+00)	(6.36E+00)	(8.03E+00)	(8.27E-02)	(8.25E-02)	
SQMB	**9.62E+00*****	-8.60E+00	5.08E+00	**3.77E-01*****	1.38E-02	1.68E-01
	(1.52E+00)	(1.10E+01)	(1.26E+01)	(8.60E-02)	(8.64E-02)	
CENCOSUD	**8.26E+00*****	9.63E+00	1.39E+01	**4.35E-01*****	2.91E-02	1.69E-01
	(1.84E+00)	(1.60E+01)	(2.13E+01)	(9.41E-02)	(9.59E-02)	
COPEC	**9.60E+00*****	-1.28E+01	8.49E+00	**3.82E-01*****	8.63E-03	1.66E-01
	(2.11E+00)	(3.16E+01)	(4.35E+01)	(9.77E-02)	(1.03E-01)	
FALABELLA	**9.27E+00*****	8.70E+00	-8.83E+00	**4.29E-01*****	-1.93E-02	1.67E-01
	(2.00E+00)	(1.74E+01)	(3.37E+01)	(9.34E-02)	(1.04E-01)	
VAPORES	**9.27E+00*****	6.19E-01	1.07E+00	**4.08E-01*****	9.99E-04	1.66E-01

	(1.41E+00)	(2.94E+00)	(3.09E+00)	(7.97E-02)	(8.13E-02)	
CMPC	**1.02E+01*** **	-2.49E+01	3.37E+00	**3.53E-01*** **	6.76E-03	1.70E-01
	(2.09E+00)	(2.69E+01)	(4.55E+01)	(9.57E-02)	(1.02E-01)	
RIPLEY	**8.66E+00*** **	6.90E+00	7.56E+00	**4.23E-01*** **	1.87E-02	1.68E-01
	(1.65E+00)	(1.29E+01)	(1.43E+01)	(8.64E-02)	(8.74E-02)	
ENELAM	**8.49E+00*** **	1.64E+01	1.82E+01	**4.35E-01*** **	1.43E-02	1.73E-01
	(1.55E+00)	(1.67E+01)	(2.66E+01)	(8.57E-02)	(8.66E-02)	
BSANTANDER	**8.27E+00*** **	1.59E+01	1.32E+01	**4.41E-01*** **	2.39E-02	1.72E-01
	(1.68E+00)	(1.87E+01)	(2.74E+01)	(9.14E-02)	(9.41E-02)	
SALFACORP	**8.48E+00*** **	6.30E+00	7.18E+00	**4.23E-01*** **	2.96E-02	1.67E-01
	(2.01E+00)	(1.61E+01)	(1.62E+01)	(9.13E-02)	(9.64E-02)	
BCI	**8.40E+00*** **	2.06E+01	1.10E+01	**4.40E-01*** **	1.54E-02	1.68E-01
	(1.94E+00)	(3.14E+01)	(4.42E+01)	(9.58E-02)	(1.01E-01)	
ENTEL	**9.05E+00*** **	-9.50E+00	2.27E+01	**3.90E-01*** **	3.06E-02	1.66E-01
	(1.97E+00)	(3.24E+01)	(4.82E+01)	(9.82E-02)	(1.04E-01)	
CHILE	**8.90E+00*** **	1.71E+01	-6.84E+00	**4.42E-01*** **	-1.06E-02	1.70E-01
	(1.67E+00)	(1.88E+01)	(2.67E+01)	(8.81E-02)	(9.01E-02)	
PARAUCO	**9.03E+00*** **	6.62E+00	1.86E+00	**4.25E-01*** **	-3.14E-03	1.66E-01
	(1.78E+00)	(1.35E+01)	(3.14E+01)	(8.90E-02)	(9.51E-02)	
COLBUN	**7.96E+00*** **	1.07E+01	4.77E+01	**4.25E-01*** **	5.23E-02	1.72E-01
	(1.87E+00)	(2.51E+01)	(4.97E+01)	(9.08E-02)	(9.92E-02)	
SONDA	**7.36E+00*** **	1.10E+01	4.99E+01	**4.30E-01*** **	8.21E-02	1.79E-01
	(1.93E+00)	(2.29E+01)	(3.16E+01)	(9.24E-02)	(9.57E-02)	
ECL	**9.20E+00*** **	5.21E+00	-2.33E+00	**4.19E-01*** **	-5.71E-03	1.66E-01
	(1.76E+00)	(1.49E+01)	(2.61E+01)	(8.91E-02)	(9.30E-02)	
AESGENER	**8.69E+00*** **	-4.24E+01	**6.99E+01***	**3.45E-01*** **	9.38E-02	1.88E-01
	(1.70E+00)	(2.68E+01)	(3.57E+01)	(9.09E-02)	(9.23E-02)	
ANDINAB	**7.87E+00*** **	1.60E+01	4.53E+01	**4.29E-01*** **	5.02E-02	1.81E-01
	(1.62E+00)	(2.14E+01)	(3.50E+01)	(8.97E-02)	(9.23E-02)	
ITAUCORP	**8.29E+00*** **	6.78E+00	3.58E+01	**4.23E-01*** **	3.74E-02	1.73E-01
	(1.65E+00)	(1.25E+01)	(3.89E+01)	(8.63E-02)	(9.49E-02)	
CCU	**8.51E+00*** **	5.34E-02	3.95E+01	**4.07E-01*** **	4.05E-02	1.68E-01
	(1.91E+00)	(4.03E+01)	(5.39E+01)	(9.61E-02)	(9.89E-02)	
CONCHATORO	**1.02E+01*** **	-1.41E+01	-1.92E+01	**3.86E-01*** **	-2.58E-02	1.67E-01
	(1.95E+00)	(3.66E+01)	(3.85E+01)	(8.88E-02)	(9.13E-02)	
IAM	**7.81E+00*** **	2.10E+01	4.54E+01	**4.38E-01*** **	4.96E-02	1.79E-01
	(1.68E+00)	(2.30E+01)	(3.57E+01)	(8.93E-02)	(9.19E-02)	
SECURITY	**9.11E+00*** **	7.74E+00	5.43E-01	**4.18E-01*** **	1.61E-04	1.65E-01
	(1.84E+00)	(2.98E+01)	(3.30E+01)	(9.33E-02)	(9.36E-02)	
AGUASA	**8.84E+00*** **	1.18E+01	1.45E+01	**4.27E-01*** **	5.75E-03	1.68E-01
	(1.58E+00)	(1.87E+01)	(4.06E+01)	(8.62E-02)	(8.90E-02)	

VAR analysis with monthly data and core specification from Table 1, Panel D, Row (9). *p < 10%, **p < 5%, ***p < 1%.

Source: Authors' elaboration.

Finally, we organize an orthogonalized disturbance that contributes to the mean squared error (MSE) in the H-periods-ahead forecasts (See table 7). Our objective is to study the percentage contribution to each asset's realized volatility (Table 7) and the MSTL market synchronization (table 8). The results show that the most significant proportion of each asset's variance is caused by the lagged realized volatility of the asset, and to a lesser extent, by the market synchronization (table 7).

Regarding market timing, Table 8 shows that the lag explains the vast majority of the variance in market timing and that the realized volatility of each asset explains a minimal (almost negligible) portion.

Table 7. Forecast Error Variance Decomposition Results

	Panel A Impulse in RV_i Response in RV_i					**Panel B Impulse in MSTL Response RV_i**				
	H									
	1	**3**	**6**	**9**	**12**	**1**	**3**	**6**	**9**	**12**
CAP	0,8874	0,8925	0,8936	0,8937	0,8937	0,1126	0,1075	0,1064	0,1063	0,1063
SQMB	0,8271	0,8543	0,8619	0,8626	0,8627	0,1729	0,1457	0,1381	0,1374	0,1373
CENCOSUD	0,6840	0,6586	0,6586	0,6586	0,6586	0,3160	0,3414	0,3414	0,3414	0,3414
COPEC	0,6276	0,5978	0,6093	0,6117	0,6121	0,3724	0,4022	0,3907	0,3883	0,3879
FALABELLA	0,7048	0,6778	0,6776	0,6776	0,6776	0,2952	0,3222	0,3224	0,3224	0,3224
VAPORES	0,9696	0,9645	0,9641	0,9641	0,9641	0,0304	0,0355	0,0359	0,0359	0,0359
CMPC	0,6701	0,6709	0,6727	0,6729	0,6729	0,3299	0,3291	0,3273	0,3271	0,3271
RIPLEY	0,8254	0,7729	0,7722	0,7722	0,7722	0,1746	0,2271	0,2278	0,2278	0,2278
ENELAM	0,8333	0,8177	0,8176	0,8176	0,8176	0,1667	0,1823	0,1824	0,1824	0,1824
BSANTANDER	0,7279	0,6966	0,6953	0,6954	0,6954	0,2721	0,3034	0,3047	0,3046	0,3046
SALFACORP	0,7333	0,5736	0,5735	0,5735	0,5735	0,2668	0,4264	0,4265	0,4265	0,4265
BCI	0,6633	0,6208	0,6202	0,6202	0,6202	0,3367	0,3792	0,3798	0,3798	0,3798
ENTEL	0,6355	0,6776	0,7163	0,7282	0,7322	0,3645	0,3224	0,2837	0,2718	0,2678
CHILE	0,7853	0,7437	0,7439	0,7439	0,7439	0,2147	0,2563	0,2561	0,2561	0,2561
PARAUCO	0,7786	0,7733	0,7734	0,7734	0,7734	0,2214	0,2267	0,2266	0,2266	0,2266
COLBUN	0,7216	0,7119	0,7124	0,7128	0,7129	0,2784	0,2881	0,2876	0,2872	0,2871
SONDA	0,7189	0,6586	0,6596	0,6596	0,6596	0,2811	0,3414	0,3404	0,3404	0,3404
ECL	0,7632	0,7380	0,7369	0,7369	0,7369	0,2368	0,2620	0,2631	0,2631	0,2631
AESGENER	0,7344	0,7571	0,7571	0,7571	0,7571	0,2656	0,2429	0,2429	0,2429	0,2429
ANDINAB	0,7606	0,7523	0,7522	0,7522	0,7522	0,2394	0,2477	0,2478	0,2478	0,2478
ITAUCORP	0,8225	0,8213	0,8215	0,8216	0,8216	0,1775	0,1787	0,1785	0,1784	0,1784
CCU	0,6440	0,6487	0,6662	0,6712	0,6724	0,3560	0,3513	0,3338	0,3288	0,3276
CONCHATORO	0,8143	0,7039	0,7012	0,7012	0,7012	0,1857	0,2961	0,2988	0,2988	0,2988
IAM	0,7625	0,7383	0,7383	0,7383	0,7383	0,2375	0,2617	0,2617	0,2617	0,2617
SECURITY	0,7075	0,6680	0,6669	0,6669	0,6669	0,2925	0,3320	0,3331	0,3331	0,3331
AGUASA	0,8177	0,8266	0,8314	0,8325	0,8326	0,1823	0,1734	0,1686	0,1675	0,1674

This table reports the results of forecast error variance decomposition (percentage points), among realized volatility (RV) for each asset i, and MSTL. The variance decomposition is based on the Cholesky ordering stock's realized volatility and MSTL.
Source: Authors' elaboration.

Table 8. Forecast Error Variance Decomposition Results

	Impulse in RV_i Response in MSTL					Impulse in MSTL Response MSTL				
	Month H									
	1	3	6	9	12	1	3	6	9	12
CAP	0	0,0253	0,0398	0,0411	0,0412	1	0,9747	0,9602	0,9589	0,9588
SQMB	0	0,0037	0,0039	0,0039	0,0039	1	0,9963	0,9961	0,9961	0,9961
CENCOSUD	0	0,0088	0,0113	0,0113	0,0113	1	0,9912	0,9887	0,9887	0,9887
COPEC	0	0,0008	0,0008	0,0008	0,0008	1	0,9992	0,9992	0,9992	0,9992
FALABELLA	0	0,0016	0,0017	0,0017	0,0017	1	0,9984	0,9983	0,9983	0,9983
VAPORES	0	0,0013	0,0015	0,0015	0,0015	1	0,9987	0,9985	0,9985	0,9985
CMPC	0	0,0056	0,0071	0,0072	0,0072	1	0,9944	0,9929	0,9928	0,9928
RIPLEY	0	0,0056	0,0074	0,0074	0,0074	1	0,9944	0,9926	0,9926	0,9926
ENELAM	0	0,0210	0,0294	0,0295	0,0295	1	0,9790	0,9706	0,9705	0,9705
BSANTANDER	0	0,0120	0,0209	0,0218	0,0219	1	0,9880	0,9791	0,9782	0,9781
SALFACORP	0	0,0031	0,0042	0,0042	0,0042	1	0,9969	0,9959	0,9958	0,9958
BCI	0	0,0053	0,0077	0,0078	0,0078	1	0,9947	0,9923	0,9922	0,9922
ENTEL	0	0,0013	0,0037	0,0048	0,0052	1	0,9987	0,9963	0,9952	0,9948
CHILE	0	0,0043	0,0044	0,0044	0,0044	1	0,9957	0,9956	0,9956	0,9956
PARAUCO	0	0,0021	0,0025	0,0025	0,0025	1	0,9979	0,9975	0,9975	0,9975
COLBUN	0	0,0235	0,0455	0,0500	0,0506	1	0,9765	0,9545	0,9500	0,9495
SONDA	0	0,0321	0,0436	0,0437	0,0437	1	0,9679	0,9564	0,9563	0,9563
ECL	0	0,0006	0,0006	0,0006	0,0006	1	0,9994	0,9994	0,9994	0,9994
AESGENER	0	0,0202	0,0379	0,0382	0,0382	1	0,9798	0,9621	0,9618	0,9618
ANDINAB	0	0,0391	0,0606	0,0611	0,0612	1	0,9609	0,9394	0,9389	0,9388
ITAUCORP	0	0,0533	0,0826	0,0850	0,0851	1	0,9467	0,9174	0,9150	0,9149
CCU	0	0,0047	0,0129	0,0157	0,0165	1	0,9953	0,9871	0,9843	0,9835
CONCHATORO	0	0,0037	0,0052	0,0053	0,0053	1	0,9963	0,9948	0,9947	0,9947
IAM	0	0,0354	0,0462	0,0464	0,0464	1	0,9646	0,9538	0,9536	0,9536
SECURITY	0	0,0005	0,0006	0,0006	0,0006	1	0,9995	0,9994	0,9994	0,9994
AGUASA	0	0,0082	0,0154	0,0168	0,0170	1	0,9918	0,9846	0,9832	0,9830

This table reports the results of forecast error variance decomposition (percentage points), among realized volatility (RV) for each asset i, and MSTL. The variance decomposition is based on the Cholesky ordering stock's realized volatility and MSTL.

Source: Authors' elaboration.

5. Conclusions

The financial and economic crises have shown that synchronization is relevant because it increases at times of stock market falls, reducing the effects of diversification protection, increasing the cost of investment management, and putting the market in a high-risk position contagious.

Synchronization within a stock market is an important phenomenon to consider when managing investments. High synchronization increases diversification costs and the portfolio's exposure to systemic risks and economic shocks. This phenomenon may be more important when the stock markets are small, little varied in the number of traded assets, low liquidity, high transaction costs, all descriptive characteristics of equity markets in emerging countries.

In this research, we estimate the network of correlations within a stock market and calculate the Minimum Spanning Tree Length (MSTL) to represent how expanded or contracted the market is in each month. The higher (lower) MSTL, the more extended (contracted), then the market is less (more) in sync. Subsequently, we organize in-sample and out-of-sample tests to evaluate the predictive power of the MSTL to predict realized volatility of each asset; and a VAR and forecasting error variance decomposition to study the Granger causality between the MSTL and the realized volatilities. of assets

We contribute to the literature by extending a bridge between network analysis, forecasting, and investment management methodologies, taking a more systemic perspective to better plan and manage portfolio diversification and risk.

Our results indicate that the synchronization of financial assets has a significant effect on the realized volatility of financial assets, opening the possibility of developing new tools that allow managing portfolio diversification and building early warnings of increased risk levels.

Some sectors are more sensitive to variations in the markets' synchronization. High beta sectors such as retail, financial, and technology and sectors with high leverage such as beverage, construction, energy, and utilities present a greater sensitivity to variations in the MSTL with a lag.

The implications for portfolio managers are to consider asset synchronization for their investment decisions, especially those related to diversification. Additionally, the paper raises the possibility of monitoring the financial markets' synchronization as a critical piece of information to forecast periods of greater volatility.

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