

Data-driven modeling of global financial linkages : Structural break analysis using computational intelligence

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Abstract

This paper applies a set of econometric tools to examine cross-border associations among major emerging equity markets. Since the COVID-19 outbreak disrupted stock markets (SkMs) across the globe, the study relies on structural break methods to assess how

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international linkages among the selected markets shifted around this shock. The empirical strategy combines the Chow breakpoint test, the Chow forecast test, the cointegration procedure developed by author and the Granger Causality (GC) test. The full sample is split into two sub-periods, Pre-COVID (June 1st, 2011 – March 10th, 2020) and COVID (March 11th, 2020 – July 31st, 2021). The results point to a robust long-run cointegrating relationship among the selected markets before the pandemic, one that is no longer detectable once the pandemic period is considered separately. These findings may be of practical value to investors, investment firms, and portfolio managers weighing diversification across these markets.

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1. Introduction

COVID-19 ranks among the most contagious pandemics on record, and its consequences have touched the daily lives of billions of people around the world. The outbreak was first traced to Wuhan, in China's Hubei province, in December 2019, and the WHO declared it a global pandemic on 11 March 2020 [1]. Governments across the world responded with nationwide lockdowns to slow transmission, measures that reshaped ordinary life for entire populations. The contagious nature of the virus also forced a shutdown of business activity, manufacturing, travel, stock markets (SkMs), and much of everyday economic life. The International Monetary Fund, in its 2020 "Global Economic Outlook" report, projected that global GDP would contract by roughly 3% [2]. Against this backdrop, the present study examines the cross-market linkages among a set of leading emerging economies, namely India, Korea, Taiwan, Brazil, and China, during the pandemic period, using the classification of the MSCI - EMI.

Growing globalization and advances in technology have, over time, drawn India's SkMs closer to the developed markets, bringing benefits such as reduced risk through diversification and more efficient allocation of capital [3]. This diversification benefit takes on added importance during a crisis, since correlations between markets can shift sharply once a shock, such as COVID-19 hits. Understanding how these linkages behave during such a period is therefore central to judging whether cross-border diversification still pays off.

2. Review of literature

Early research conducted before the 1970s generally found weak or negligible correlations across national stock markets, as shown by Grubel [4] and Levy and Sarnat [5]. More recent work tells a different story: Goldstein and Mussa [6] point to growing interconnection between national SkMs over recent decades. Emerging markets show meaningful integration too, even though that process has lagged behind developed economies. A series of crisis episodes appear to have tightened the links between major markets, prompting a wave of studies on international linkages. Arshanapalli and Doukas [7], for example, applied a cointegration-based framework with an error-correction mechanism to examine links among major developed markets before and after 1987, finding that several markets became significantly more responsive to movements in the US market after October 1987.

Kurihara and Nezu [8] documented a strong cointegrating link between Japanese and US stock prices. Shachmurove [9], in turn, found that other markets exert a meaningful influence on Brazil's and Russia's SkMs, while Indian and Chinese SkMs are comparatively less affected. Wong, Agarwal, and Du [10] later reported integration between selected developed markets and Indian SkMs over the long run, with Granger causality results pointing to a strong influence running from the US and Japan toward Indian SkMs, a relationship that does not hold in reverse.

Singh and Kishor [11] combined tri-variate autoregression, a spillover index, and TGARCH modelling to test linkages between the Indian market and other major exchanges, concluding that no long-run cointegration links Nifty and other stock indices, even though a one-directional causal link runs from Japan, the UK, and the US toward Indian SkMs. In a comparable suggestion, Kaundal and Sharma [12] proposed that investors diversify their portfolios by owning stock in the SKMs of the ASEAN member countries, such as Japan, Singapore, Hong Kong, and Taiwan, as the Indian SkM is weakly integrated with these markets.

Empirical findings from Rajwani and Mukherjee [3] revealed that the Indian financial markets are not integrated with those of a number of other Asian markets. Singh and Kaur [13] conducted a study analyzing the interaction of the US markets with those of China and India across a long time period following the time of events of the subprime mortgage crisis of 2008. They showed that a one-way causality can be traced from the US market to the markets of China, India, and other markets. Specifically, at the time of crisis, there was a cause-and-effect relationship from the

Chinese market to the Indian one, in addition to the existence of significant spillovers from the US market to the Indian market and vice versa in the period of crisis. Singh and Singh [14] analyzed both short-term and long-term correlations of the US market with the BRIC countries' markets during the periods before, during, and after the financial crisis, noting that the choice of markets in question was determined mainly by the nature of these countries' growth.

Azman-Saini et al. [15] studied co-movements across the ASEAN-5 economies and found that the Singapore market is largely insulated from all markets in the group except Indonesia. Ibrahim [16] similarly reported that ASEAN SkM respond only weakly to shifts in the SkM market. Majid et al. [17] likewise found evidence of cointegration among the ASEAN markets covered in their study.

Diamandis [18] used Multivariate Cointegration Analysis (MCA) to uncover a long-term connection among the SkMs studied, noting that the four Latin American markets share durable common features with the US SkM. Using a combination of a Granger-causality-based unit-root test and vector autoregression with variance decomposition, Sharma and Bodla [19] showed that the National Stock Exchange (NSE) exerts a causal influence on the Karachi and Sri Lanka exchanges, with no influence flowing back the other way. Srinivasan, Kalaivani, and Devakumar [20], applying multivariate cointegration together with Granger causality and FEVD analysis, likewise found long-run co-movement among the major SkM they studied. Verma and Rani [21] looked at both short- and long-run relationships across emerging SkM, identifying one-way causal links between the Indian and South Korean SkM and between the Brazilian and Indian SkM. Arora and Kaur [22] and Aggarwal and Raja [23] separately explored the diversification potential offered by the BRICS nations; Arora and Kaur [22] found no long-run cointegration among these markets, attributing this to country-specific price fluctuations, whereas Aggarwal and Raja [23] reported a long history of cointegration among the BRIC economies.

As noted earlier, the containment measures governments adopted to slow COVID-19 transmission took a heavy toll on everyday life. Tourism, manufacturing, services, and other SkM-dependent industries all felt the impact. Against this backdrop, several researchers have examined how COVID-19 affected financial markets. Liu et al. [24], Štifanić et al. [25], and Zhang, Hu, and Ji [26] each applied an event-study methodology and found that the SkM in affected countries fell sharply once the outbreak began.

Asian SkM, in particular, recorded worse abnormal returns than markets elsewhere. Zhang, Hu, and Ji [26], for their part, studied how the pandemic affected financial markets worldwide, concluding that COVID-19 raised the overall risk facing these markets and that a given stock index's reaction was tied to how severely the pandemic struck that region. They argue that policymakers need appropriate measures in place to cushion the financial losses investors face during crises of this kind.

According to Wang et al. [27], it was discovered that there is a correlation between the COVID-19 pandemic and the Electronic Arts Inc. stock price index, while the latter was found to be inversely related to the oil price index. He et al. [2] took a broader sectoral view, examining how COVID-19 affected manufacturing, mining, healthcare, transportation, and other sectors, and found sizeable negative effects on electricity, mining, transportation, and environmental sectors, while information technology, healthcare, and education proved comparatively resilient. Tang and Aruga [28], finally, found that the 2008 Global Financial Crisis had a marked effect on the link between China and global fossil fuel markets, an effect that did not reappear during the COVID-19 pandemic.

3. Research Gaps

Even though plentiful studies look at how the international stock market integrates during times of crisis, there appears to be little evidence that highlights specifically how linkages operated in the emerging markets during the COVID-19 pandemic period. What is more, COVID-19 literature focuses more on short-term market behavior but pays less attention to structural breaks and longer-term co-movements. Also, very few studies have compared and analyzed the performances of emerging markets in the pre-COVID and COVID periods, especially when speaking about closely monitoring India's integration with major emerging markets within the same econometric framework.

4. Objectives

1. To identify structural breaks between select SkMs during the COVID pandemic.
2. To examine the relationship between select SkMs.

5. Research Methodology

Data

Table 1
Top Five Major Emerging Markets used for examining the
International Linkages

Country	SkM	Period (Daily)		Number of Observations
		From	To	
India	National Stock Exchange (NSE)	June 1st 2011	June 30th 2021	2656
China	Shanghai Stock Exchange (SSE)	June 1st 2011	June 30th 2021	2656
Korea	Korean Stock Price Index (KOSPI)	June 1st 2011	June 30th 2021	2656
Taiwan	Taiwan Weighted Index (TWII)	June 1st 2011	June 30th 2021	2656
Brazil	Brazil SkM (BOVESPA)	June 1st 2011	June 30th 2021	2656

Source: MSCI Emerging Market Index - 2021

Table 1 indicates the exchanges selected for an analysis of the relations between India and other emerging economies of the world. As per the report called the “MSCI Emerging Market Index, 2021”, amongst the economies under study, China has shown the fastest growth, followed by Korea, Taiwan, India, and Brazil, which makes it necessary to analyze India’s relations with the leading economies in the world. The sample consists of a decade’s worth of daily information between 1 June, 2011, and 30 July, 2021, and the market data of all five exchanges has been collected from the Bloomberg database.

The study utilized GC and Johansen co-integration tests to ascertain the connections between Indian SkM and other prominent emerging markets. The ADF test is used to determine the stationarity of SkMs, while Chow break and Chow forecast tests are utilized to investigate any structural gaps present in the data.

6. Results and Discussion

Table 2 presents the descriptive statistics of the selected markets. The skewness and kurtosis results show a lack of normality of any of the represented series, which is confirmed by the Jarque-Bera test that rejects

the null hypothesis of the normality in every case owing to the p-value below the 5% level. Overall, there is a total of 2293 daily observations that took place in the time interval prior to the onset of the COVID-19 outbreak.

Table 2
Descriptive Statistics

	Statistics	LBOVESPA (Log of Brazil Stock Exchange Index)	LKOSPI (Log of Korea Compos- ite Stock Price Index)	LNSE (Log of National Stock Ex- change Index)	LSSE (Log of Shang- hai Stock Exchange Index)	LTWII (Log of Taiwan Weight- ed Index)
Pre- COVID	Mean	4.801	3.314	3.898	3.437	3.96
	Median	4.768	3.305	3.913	3.455	3.959
	Maximum	5.077	3.415	4.092	3.713	4.69
	Minimum	4.574	3.218	3.657	3.29	3.822
	Stdev.	0.111	0.036	0.121	0.084	0.065
	Skewness	0.736	0.828	-0.196	0.184	1.221
	Kurtosis	2.638	3.175	1.773	2.588	13.974
	Jarque-Bera	219.743	265.063	158.664	29.201	12075.5
	Probability	0	0	0	0	0
	Obs.	2293	2293	2293	2293	2293
During -COVID	Mean	5.021	3.409	4.094	3.518	4.139
	Med.	5.028	3.406	4.109	3.529	4.137
	Maximum	5.117	3.519	4.202	3.568	4.256
	Minimum	4.803	3.164	3.881	3.425	3.939
	Stdev.	0.071	0.089	0.085	0.036	0.08
	Skewness	-0.816	-0.44	-0.457	-0.964	-0.285
	Kurtosis	2.9	2.089	1.992	2.66	1.988
	Jarque-Bera	40.397	24.296	27.982	58.02	20.433
	Prob.	0	0	0	0	0
	Obs	363	363	363	363	363

Source: Authors' calculations

Checking the stationarity of the series is essential when working with SkM time-series data. This study applies the ADF test in three specifications — intercept only, trend and intercept, and neither at both the level and the first difference, across two windows: the pre-COVID period (1 Junest 2011 to 10 Marchth 2020) and the COVID period (11 Marchth 2020 to 31 Julyst 2021). Table 3 reports the ADF results for the NSE, SSE, KOSPI, TWII, and BOVESPA. At level, none of the series can be shown to be stationary. However, all five series turn stationary across all three specifications, with the null now rejected at 1%. The one exception is the Taiwan index (TWII), which is stationary in the trend-and-intercept form even at level, but only in the pre-COVID window. This points to the sample variables being integrated of order one prior to the pandemic. Looking at the COVID window, it was the National Stock Exchange (NSE) that turned out to be stationary at level in the trend-and-intercept specification. Taken together, these results confirm that the sample series are integrated of order one, $I(1)$.

Table 3
Stationarity Test

Periods	Levels	Var.	Results	
			Test Stat.(Critical Value)	p-value
Pre-COVID	Level	LNSE	-1.033(-3.343)	0.74
			-3.140(-3.962)	0.09
			1.288(-2.565)	0.95
		LSSE	-1.566(-3.433)	0.49
			-2.066(-3.962)	0.56
			0.103(-2.565)	0.71
		LKOSPI	-2.571(-3.433)	0.09
			-3.306(-3.962)	0.06
			-0.231(2.565)	0.6
		LBOVESPA	-0.922(-3.433)	0.78
			-2.309(-3.962)	0.42
			-0.529(-2.565)	0.83
		LTWII	-2.588(-3.433)	0.09
			-6.942(-3.962)	0.00*
			0.258(-2.565)	0.76

Contd...

	1st difference	LNSE	-43.533(-3.433)	0.00*
			-43.525(-3.962)	0.00*
			-43.505(-2.565)	0.00*
		LSSE	-45.287(-3.433)	0.00*
			-45.278(-3.962)	0.00*
			-45.296(-2.565)	0.00*
		LKOSPI	-45.491(-3.433)	0.00*
			-45.481(-3.962)	0.00*
			-45.500(-2.565)	0.00*
		LBOVESPA	-48.068(-3.433)	0.00*
			-48.079(-3.962)	0.00*
			-48.073(-2.565)	0.00*
		LTWII	-23.005(-3.433)	0.00*
			-23.004(-3.962)	0.00*
			-23.008(-2.565)	0.00*
During COVID	Level	LNSE	-0.603(-3.448)	0.86
			-3.780(-3.983)	0.01*
			1.262(-2.571)	0.94
		LSSE	-1.513(-3.448)	0.52
			-1.835(-3.983)	0.68
			-0.658(-2.571)	0.85
		LKOSPI	-1.036(-3.448)	0.74
			-2.264(-3.983)	0.45
			1.775(-2.571)	0.98
		LBOVESPA	-1.776(-3.448)	0.39
			-1.913(-3.983)	0.64
			1.800(-2.571)	0.98
		LTWII	-0.685(-3.448)	0.84
			-2.920(-3.983)	0.15
			1.940(-2.571)	0.98

Contd...

	1st difference	LNSE	-21.948(-3.448)	0.00*
			-21.912(-3.983)	0.00*
			-21.817(-2.571)	0.00*
		LSSE	-18.026(-3.448)	0.00*
			-18.029(-3.983)	0.00*
			-18.024(-2.571)	0.00*
		LKOSPI	-20.782(-3.448)	0.00*
			-20.780(-3.983)	0.00*
			-20.577(-2.571)	0.00*
		LBOVESPA	-30.314(-3.448)	0.00*
			-30.330(-3.983)	0.00*
			-30.164(-2.571)	0.00*
		LTWII	-19.222(-3.448)	0.00*
			-19.200(-3.983)	0.00*
			-19.004(-2.571)	0.00*

Note: *Reject null.

Parameter Stability Test for Determining Structural Breaks

Parameter stability tests are run next on the five markets to detect any structural break tied to the COVID-19 shock. The table below reports both the Chow breakpoint and Chow forecast tests; the first statistic is F-based, while the other two rest on chi-square formulations. Because the WHO declared COVID-19 a pandemic on 11 March 2020, that date is used as the breakpoint.

Table 4
Structural Break Analysis

Chow Test	Value	Prob.
(Fisher's Statistical Test Statistic) F-statistic	22.629	0.000*
Log likelihood ratio	111.209	0.000*
Wald Statistic	113.143	0.000*
Chow Forecast test	<i>Value</i>	<i>Prob.</i>
F-statistic	2.743	0.000*
Likelihood ratio	957.118	0.000*

Note: *Reject null

Table 4 points to a structural discontinuity: the hypothesis that model parameters stay constant across the two sub-periods is rejected at the 5% level. The Chow forecast test then corroborates this result. With the p-value falling below 5%, the no-structural-break null is again rejected, so both the Chow and Chow forecast tests point to a meaningful structural shift brought on by the COVID-19 pandemic.

Johansen Co-integration Test Results

Stationarity tests confirm the series are integrated of the same order. Thus, JC test can be applied to examine the long-run relationship among the selected SkMs. Table 5 reports these results for the pre-COVID and

Table 5
Johansen Co-integration Test Results

Period	Null hypothesis	Eigen Value	Trace test		Max eigenvalue test	
			Statistics	p-value	Statistics	p-value
Pre-COVID (1st June 2011 – 10th March 2020)	r = 0 (None)	0.0662	184.467 (69.818)	0.000*	156.805 (33.876)	0.000*
	r ≤ 1 (at most 1)	0.006	27.661 (27.661)	0.828	13.792 (27.584)	0.836
	r ≤ 2 (at most 2)	0.0045	13.869 (13.869)	0.847	10.288 (21.131)	0.717
	r ≤ 3 (at most 3)	0.0012	3.581 (3.581)	0.934	2.666 (14.264)	0.966
	r ≤ 4(at most 4)	0.0004	0.914 (0.914)	0.338	0.914 (3.841)	0.338
During COVID (11th March 2020 – 31st July 2021)	r = 0 (None)	0.073	68.412 (69.818)	0.064	27.345 (33.876)	0.245
	r ≤ 1 (at most 1)	0.057	41.067 (47.856)	0.186	21.219 (27.584)	0.263
	r ≤ 2 (at most 2)	0.025	19.848 (29.797)	0.433	9.227 (21.131)	0.813
	r ≤ 3 (at most 3)	0.021	10.620 (15.494)	0.235	7.890 (14.264)	0.389
	r ≤ 4(at most 4)	0.007	2.730 (3.841)	0.098	2.730 (3.841)	0.098

Note: The hypothesized number of cointegrating equations is denoted by the symbol r. Parentheses are used to indicate the p-values. The critical values of Statistics are 15.495 (r=0) and Statistics 14.265 (r=0).

Source: Authors' calculations

during COVID, with the lag length chosen via the AIC, which selects a lag of 2. In the pre-COVID window, the NSE and the other four markets are found to be cointegrated in the long term, since the no-cointegration null is rejected at the 5% level.

During the COVID-19 pandemic, the trace test statistic reveals the existence of one cointegrating vector prior to the outbreak, while there is no such cointegrating vector during the pandemic. In contrast, the maximum eigenvalue statistic provided inconclusive results. When both tests yield contradictory results, the trace test statistic performs better and provides more reliable results. The implication of one cointegrating vector is that any deviation in the short term among these variables has a tendency to revert back towards equilibrium by itself, thus ensuring the short-run correction even before the onset of the COVID-19 pandemic.

VEC Granger Causality Results

Given that the pre-COVID Johansen results confirm a long-standing link among these markets, the VEC GC Wald test is used next to pin down the direction of short-run cause and effect (Table 6). Since Granger-type tests are sensitive to lag choice [29], the AIC criterion is again used to select the lag order, which comes out to 3 in this case. At the 5% level, Table 6 shows a one-way causal path running from NSE to both BOVESPA and SSE, and from KOSPI to both NSE and BOVESPA, while KOSPI and SSE are linked bidirectionally. SSE is found to cause BOVESPA in one direction only, and Taiwan is found to cause both Brazil and Korea.

Table 6
VEC Granger causality (During COVID)

Model	Dependent Variable	Independent Variable	Chi-square	Prob.
1	RNSE	RBOVESPA (Returns of Brazil Stock Exchange Index), RKOSPI (Returns of Korea Composite Stock Price Index), RSSE (Returns of Shanghai Stock Exchange Index), RTWII (Returns of Taiwan Weighted Index)	76.338	0.00*
2	RBOVESPA	RNSE (Returns of National Stock Exchange Index) , RKOSPI, RSSE, RTWII	5.987	0.64

Contd...

3	RKOSPI	RNSE, RBOVESPA, RSSE, RTWII	183.668	0.00*
4	RSSE	RNSE, RBOVESPA, RKOSPI, RTWII	33.833	0.00*
5	RTWII	RNSE, RBOVESPA, RKOSPI, RSSE	56.441	0.00*

Note: *Reject null.

Source: Authors' calculations

GC Test

With no cointegration detected among these markets during the COVID-19 period, the short-run causal relationships among the five markets are instead assessed using the VAR form of the GC test (Table 7). This test, too, is sensitive to lag length [29], [30], so the lag order is again chosen via AIC, which selects 2 as the optimal lag structure. At the 5% level, Table 7 shows that RKOSPI Granger-causes RNSE (the corresponding null is rejected), but not the reverse (RNSE does not Granger-cause RKOSPI, as that null cannot be rejected at 5%). India and Brazil display a two-way causal relationship, both nulls being rejected at 5%. Taiwan is found to cause India, Korea, and China in one direction, while RBOVESPA and RKOSPI show a reciprocal relationship, as do RTWII and RBOVESPA. Korea and China are linked in one direction only, with the null that RKOSPI does not Granger-cause RSSE rejected at the 5% level.

Table 7
GC Test Results (During COVID)

Null Hypothesis	Observations	F-Statistic	Prob.
"RKOSPI does not Granger Cause RNSE"	361	15.895	0.000*
"RNSE does not Granger Cause RKOSPI"		0.419	0.658
"RBOVESPA does not Granger Cause RNSE"	361	13.983	0.000*
"RNSE does not Granger Cause RBOVESPA"		3.647	0.027*
"RTWII does not Granger Cause RNSE"	361	10.301	0.000*
"RNSE does not Granger Cause RTWII"		1.615	0.203
"RSSE does not Granger Cause RNSE"	361	0.953	0.387
"RNSE does not Granger Cause RSSE"		1.990	0.138

Contd...

"RBOVESPA does not Granger Cause RKOSPI"	361	11.854	0.000*
"RKOSPI does not Granger Cause RBOVESPA"		12.889	0.000*
"RTWII does not Granger Cause RKOSPI"	361	3.899	0.021*
"RKOSPI does not Granger Cause RTWII"		0.856	0.426
"RSSE does not Granger Cause RKOSPI"	361	0.230	0.794
"RKOSPI does not Granger Cause RSSE"		5.92375	0.0029*
"RTWII does not Granger Cause RBOVESPA"	361	6.393	0.0019*
"RBOVESPA does not Granger Cause RTWII"		14.722	0.000*
"RSSE does not Granger Cause RBOVESPA"	361	0.632	0.532
"RBOVESPA does not Granger Cause RSSE"		0.455	0.635
"RSSE does not Granger Cause RTWII."	361	0.466	0.628
"RTWII does not Granger Cause RSSE."		5.238	0.0057*

Note: *Reject null.

7. Conclusion

This study draws on established econometric methods to examine the cross-border links among the selected SkMs using daily data drawn from official exchange sources over a decade, June 2011 to July 2021, split into pre-COVID and COVID sub-periods. The stationarity tests were run at level and first difference across all three specifications. The results confirm that all five series are integrated of order one, $I(1)$, in both sub-periods. The structural break analysis confirms that the data was divided into two sub-parts, i.e., pre- and during-COVID periods. The Johansen cointegration test is then used to assess the long-run relationship among the five markets in each sub-period, revealing one cointegrating equation before the pandemic but none once the pandemic period is considered on its own.

Short-run causality between the markets is assessed with the GC test in each sub-period. Because the markets are cointegrated before the pandemic, the VEC-based Wald form of the test is used for that window, and it points to one-way causality from NSE to both BOVESPA and SSE, from KOSPI to both NSE and BOVESPA, a two-way link between KOSPI and SSE, a one-way link from SSE to BOVESPA, and one-way causality running from Taiwan to both Brazil and Korea. Since no significant cointegration is found for the COVID period, the standard VAR form of

the GC test is applied instead, and it identifies a one-way running from RKOSPI to RNSE. Moreover, a two-way causal relationship was also found between Brazil and India.

One-way causality also runs from Taiwan toward India, Korea, and China, while RBOVESPA and RKOSPI, along with RTWII and RBOVESPA, are related bidirectionally, and Korea and China share a one-way causal link. These findings suggest a few natural extensions: a longer sample period, additional structural-break windows to better understand how sentiment-sensitive industries connect across borders [29], and complementary techniques such as the Nonlinear Autoregressive Distributed Lag (NARDL) model for a deeper look at the degree of cointegration between these markets.

8. Limitations of the study

The study is limited to **five emerging markets**. Relying on **linear econometric methods** may miss nonlinear dynamics during extreme events, and the analysis is limited to **a single structural breakpoint** while leaving out relevant macroeconomic and policy variables, which may influence market interlinkages.

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