MACROECONOMIC DETERMINANTS OF MERGER AND ACQUISITION WAVES IN EMERGING MARKETS (BRICS)

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ABSTRACT

Mergers and acquisitions (M&As) are characterized by waves that alternate between prolonged periods of relative stability and short phases marked by sharp increases in transaction volume, often driven by the cyclical dynamics of capital markets and overall economic conditions. This study aims to identify and analyze how macroeconomic and market variables relate to the formation of M&A wave patterns in the context of BRICS member countries. Quarterly data covering the period from 2004-Q2 to 2021-Q3 are analyzed using a Markov-Switching model, with exchange rates, lending interest rates, stock market indices, and gross domestic product included as explanatory variables The sample comprises 63,943 M&A transactions across the five BRICS countries. The results indicate that M&A activity exhibits a wave-like pattern and that macroeconomic variables explain these dynamics when the analysis is conducted at the country level, thereby confirming the validity and effectiveness of the Markov-Switching model, as well as the adequacy of the proxies used to capture wave dynamics. However, this finding does not hold when M&A activity is examined in an aggregated sectoral form. Moreover, in the high-activity regime, the variance of the series is higher, and during the COVID-19 pandemic, aggregate M&A activity across the BRICS countries reached a minimum level not observed since 2005. This study contributes to the literature by addressing the relative scarcity of research on M&A waves through the adoption of an innovative methodological approach (Markov-Switching) and a broader analytical focus on emerging BRICS economies.

Keywords: Merger and Acquisition Waves. Markov-Switching Model. Macroeconomic Variables. Multivariate Analysis.

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DETERMINANTES MACROECONÔMICOS DE ONDAS DE FUSÕES E AQUISIÇÕES EM MERCADOS EMERGENTES (BRICS)

RESUMO

A atividade de fusões e aquisições (F&As) é caracterizada pela ocorrência em ondas que alternam entre longos períodos de normalidade e curtos momentos de abrupta elevação da quantidade de operações, ocasionados muitas vezes pela ciclicidade do mercado de capitais e pelo desempenho da economia. Este estudo visa identificar e analisar como as variáveis macroeconômicas e de mercado se relacionam com o padrão de ondas de F&As no contexto de países membros do BRICS. Foram utilizados dados trimestrais correspondentes ao período de 2004-2T até 2021-3T, em um modelo *Markov-Switching* que teve como variáveis explicativas câmbio, taxa de juros de empréstimos, índice do mercado de ações e produto interno bruto. A amostra analisada foi composta de 63.943 processos de F&As dos cinco países do BRICS. Constatou-se que as F&As analisadas apresentaram padrão de ondas e que as variáveis macroeconômicas conseguem explicá-las, quando se considera a análise por país, confirmando, assim, a validade e eficácia do modelo *Markov-Switching*, bem como das *proxies* utilizadas na previsão de ondas dessa atividade. No entanto, esse resultado não foi observado para a análise das F&As agregadas setorialmente. Ademais, no estado de alta, a variância da série é maior e, durante a pandemia de COVID-19, a quantidade de F&As no agregado dos BRICS atingiu um patamar mínimo que não era observado desde 2005. Este estudo contribui para preencher parte da lacuna na literatura no que se refere à escassez de pesquisas sobre o tema (F&As), ao inovar na abordagem metodológica (*Markorv-Switching*), além de adotar um contexto ampliado de análise (BRICS).

Palavras-Chave: Ondas de Fusões e Aquisições. Modelo *Markov-Switching*. Variáveis Macroeconômicas. Análise Multivariada.

1. INTRODUCTION

The economic and financial literature – particularly research conducted outside the United States and the United Kingdom – remains relatively underdeveloped with respect to the analysis of the determinants of merger and acquisition (M&A) activity occurring in waves. Previous studies have confirmed the existence of such wave patterns (Town, 1992; Rhodes-Kropf & Viswanathan, 2004; Gorton, Kahl & Rosen, 2009; Duchin & Schmidt, 2013), often concentrated within specific economic sectors (Andrade, Mitchell & Stafford, 2001), with extended periods of low M&A activity followed by comparatively brief episodes of heightened activity (Bianchi & Chiarella, 2019). Despite these findings, the underlying drivers of this pattern remain insufficiently understood, as the literature still lacks robust empirical evidence to fully explain these dynamics (Fonseca & Almeida, 2023).

The cyclical behavior of M&A activity appears to be driven by macroeconomic forces (Szücs, 2016), reflecting efforts toward more efficient asset reallocation (Xu, 2017), with empirical evidence showing peaks and troughs closely associated with stock market performance (Baker et al., 2012). Although short-term feedback effects may be present, Kalra et al. (2013) identify signs of long-term stabilization, suggesting efficiency in the M&A markets examined. Therefore, whether motivated by diversification strategies, managerial synergies (Katz et al., 1997), or corporate restructuring through improved resource allocation (Camargos & Coutinho, 2008), macroeconomic conditions generally function as key factors influencing the decision to pursue an M&A transaction (Kim et al., 2019) or, alternatively, to abandon it (Kumar et al., 2023).

In international literature, studies such as Lambrecht (2004) and Triantafyllopoulos and Mpourletidis (2014) link M&A waves to alternating phases of the business cycle. These authors emphasize that periods of strong capital market performance are frequently associated with overly optimistic expectations regarding M&A outcomes, often disregarding the complexity and inherent challenges of this corporate strategy (Coutinho & Camargos, 2008), which may ultimately result in shareholder value destruction (Harford, 2005; Gugler et al., 2012).

Within the scope of this study, major disruptions in the global macroeconomic environment (namely the Global Financial Crisis and the COVID-19 pandemic) clearly affected the volume of M&A transactions during the period analyzed. In Brazil, the political and economic crisis between 2014 and 2017 likewise constituted a significant factor influencing M&A activity.

Identifying the onset of a new M&A wave can represent a strategic advantage for investors and firms seeking to capitalize on emerging investment and business opportunities. From an empirical perspective, however, this task is challenging due to the inherent difficulty of modeling M&A activity. In this context, nonlinear analytical frameworks – such as Markov-Switching (M-S) models – may be more appropriate than linear alternatives (Duong, 2013). This is because such a model is capable of handling data series that exhibit non-stationary variance, abrupt changes between one state and another, and, in addition, allows for the joint estimation of two (or more) conditions that alternate with one another, governed by a transition probability criterion. As such, it offers methodological advantages over Logit models, which have also been applied in the analysis of M&A activity (Fonseca & Almeida, 2023).

The economic and financial literature contains a substantial body of research focused on developed economies, particularly the United States and the United Kingdom (Achim, 2015). In contrast, empirical studies addressing emerging markets – such as the BRICS countries (Brazil, Russia, India, China, and South Africa) – remain relatively scarce. In this context, the limited number of studies addressing these five major global economies further underscores the relevance of this research, as they play a vital role in M&A activity both as acquirers and as targets (Iqbal et al., 2018).

Moreover, M&A activity in BRICS countries exhibits structural characteristics that differ from those observed in developed economies (Opoku-Mensah et al., 2019), including a stronger presence of informal institutions (Da Silva et al., 2019) and greater government involvement (Kinateder et al., 2017). These markets are also characterized by more aggressive M&A strategies (Sun et al., 2012) and lower levels of competition in domestic markets (Tahir & Tahir, 2019). At the same time, they offer an attractive business environment for investors, as M&A transactions in these contexts tend to generate higher short-term returns (Kinateder et al., 2017).

Recent structural transformations within the BRICS economies further underscore their relevance. China began transitioning toward a more market-oriented economic system in the 1980s (Hitt & Xu, 2016). In 1991, the *dissolution of the Soviet Union* (Johnson & Kovzik, 2016) coincided with the *liberalization of the Indian economy* (Balakrishnan, 2011). In Brazil, the implementation of the *Real Plan* in 1994 successfully curbed hyperinflation, restoring monetary stability and international credibility. In South Africa, *the end of apartheid* led to the removal of longstanding economic sanctions (Kilambo, 2023).

In line with Figueiredo and Camargos (2024), this study seeks to identify and analyze how macroeconomic and market variables explain the behavior of M&A waves, extending the analysis beyond Brazil to include other emerging BRICS economies, using a Markov-Switching modeling framework.

Examining the relationship between macroeconomic and market variables and M&A wave dynamics in emerging markets such as the BRICS – where empirical research remains limited despite their significance in global economic activity and investor return expectations – contributes to advancing the understanding of this complex and impactful corporate strategy.

Accordingly, this study helps address gaps in the literature on M&A waves, introduces a nonlinear methodological approach through the application of Markov-Switching models, and broadens the empirical scope by focusing on the BRICS economies.

Following this introduction, Section 2 presents the theoretical framework, Section 3 describes the methodology employed, Section 4 reports and discusses the empirical results, and Section 5 concludes the paper.

2. LITERATURE REVIEW

2.1 WAVES OF MERGERS AND ACQUISITIONS

The economic and financial literature largely converges on the view that mergers and acquisitions (M&As) occur in waves (Town, 1992; Gorton, Kahl & Rosen, 2009). In this context, Martynova (2008) identifies three major M&A waves in the United States: the wave of the 1890s (originating in the formation of trusts), the wave of the 1920s (dominated by oligopolistic structures), and the wave of the 1960s (characterized by rapid conglomerate mergers). In addition, the study points to a substantial increase in the value of M&A transactions during the 1980s. Park and Gould (2017), in turn, argue that the defining feature of the fourth wave (which took place in the 1980s) was the widespread belief among owners that “greed is good”; that the fifth wave, occurring between 1993 and 2000, was primarily driven by deregulation processes; and that the sixth wave (2003–2008), according to McCarthy et al. (2016), was effectively the first global wave, as it was no longer centered exclusively on the United States and the United Kingdom and was also marked by the notable success of transactions involving Chinese firms.

With specific regard to the sixth wave – examined in this study – McCarthy et al. (2016) further argue that, unlike earlier waves, it was not driven by developments in the American or British markets, as it unfolded simultaneously across multiple regions worldwide. This period was characterized by increased Asian participation relative to the preceding wave, as well as by distinct features differentiating Western and Eastern M&A transactions. Moreover, this wave, which emerged alongside the financial recovery following the crises of the early 2000s, also came to an end in response to financial market conditions, particularly in the aftermath of the 2008 crisis. Indeed, this evidence reinforces the close relationship between M&A wave dynamics and the broader macroeconomic environment. Finally, another relevant inference drawn from these authors' findings concerns the role of global economic integration, which, as noted by Szücs (2016), intensifies competitive pressures underlying M&A activity and underscores the significant role of financial markets in shaping these dynamics.

Similarly, building on the premise that the global economy experienced a major macroeconomic disruption due to the COVID-19 pandemic, Kooli and Lock Son (2021) argue that a new global wave of M&As is currently underway, particularly in light of developments observed in the final quarter of 2020 and the marked increase in transaction volumes in 2021. Supporting this perspective, a significant rise in the number of M&A deals can indeed be observed, making it plausible to argue that this represents a seventh wave of M&As, also exhibiting global characteristics (Friedlander & Hunt, 2021; Financier, 2021). In this wave, more than half of all transactions occurred in the Americas, compared to approximately 22% in the Asia-Pacific region (McKinsey, 2022).

2.2 M&A Waves from a Neoclassical Perspective

In the presence of shocks inherent to economic activity and the resulting instability of the business environment, merger and acquisition (M&A) activity plays a key role in market stabilization (Rodrigues, 2014) by enabling new organizational arrangements and the restructuring of industrial sectors (Chaudhuri, 2014).

Beyond the general consensus that M&A activity occurs in waves, the financial literature – grounded in neoclassical theory – identifies several stylized facts associated with this phenomenon: (1) M&A waves are linked to overly optimistic business valuations (Goel & Thakor, 2010; Gugler et al., 2012); (2) they are closely related to developments in capital markets (Goel & Thakor, 2010; Gugler et al., 2012; Uddin & Boateng, 2011); (3) they exhibit cyclical dynamics accompanied by persistent asset mispricing (Duchin & Schmidt, 2013; Rhodes-Kropf, Robinson, & Viswanathan, 2005); and (4) they are characterized by a greater reliance on equity as a form of payment (Rhodes-Kropf & Viswanathan, 2004; Shleifer & Vishny, 2003).

The drivers of M&A activity during wave periods differ from those operating outside such phases (Thanos et al., 2020), whether due to macroeconomic conditions, firm-level strategies, or individual managerial decisions. Some firms benefit from engaging in M&A activity during waves – particularly those with limited access to external financing – while others derive greater benefits by operating outside these periods (Becher et al., 2020). More specifically, the theoretical framework underpinning this interpretation is neoclassical in nature, viewing M&A waves as the outcome of external shocks and adopting an exogenous perspective of the firm (Camargos & Coutinho, 2008). This approach places particular emphasis on regulatory (Garcia & Azevedo, 2019), economic, and technological factors, as also highlighted by Harford (2005) and Mitchell and Mulherin (1996).

With respect to regulatory shocks and their influence on M&A activity, Andrade, Mitchell, and Stafford (2001) identify three major M&A waves in the United States – during the 1960s, 1980s, and 1990s – linking these movements to clusters of transactions triggered by industry-specific shocks, primarily associated with deregulation processes.

In addition to shocks directly related to competition policy and overseen by regulatory agencies, there are also shocks associated with financing policies (Popli & Sinha, 2014). This latter category includes changes in access to financing sources, which, depending on the institutional context, may lead to a higher proportion of cash-financed transactions and, consequently, lower acquisition premiums (Sonenshine, 2020). In general, greater access to financing tends to stimulate M&A activity; however, empirical evidence also shows that some firms experience value destruction despite facing no financing constraints (Becher et al., 2020). Also noteworthy is the contribution of Garcia and Azevedo (2019), who adopt a regulatory perspective to examine the impact of M&As on market competition and the role of regulatory authorities in shaping firms' M&A decisions.

The economic shock hypothesis can be traced back to Golbe and White (1988), who document increasing M&A activity in the mid-1950s, followed by stabilization and a subsequent peak in the late 1960s. Similar findings are reported by Mitchell and Mulherin (1996) in their analysis of the M&A wave of the 1980s. Overall, neoclassical theory conceptualizes economic agents as reactive, emphasizing their responses to external shocks – economic, regulatory, and technological in nature.

2.3 Empirical Literature on M&A Waves

The economic and financial literature contains a substantial body of empirical research examining M&A waves and their relationship with macroeconomic variables. However, with respect to the application of Markov-Switching (M-S) models to the analysis of M&A activity, as employed in this study, the number of empirical contributions remains limited. Town (1992), using data from 1895 to 1989 for the United States and the United Kingdom, compared M-S models with Autoregressive Integrated Moving Average (ARIMA) models and found stronger empirical support for the former. Using a similar methodological approach and dataset, Linn and Zhu (1997) likewise validated the existence of M&A waves, rejecting the hypothesis that M&A activity follows a *random walk*.

Resende (1999) examined the applicability of the M-S model to M&A behavior in the United Kingdom at the sectoral level, confirming its suitability for capturing regime changes in activity patterns. Chen and Lin (2008) also reported superior performance of the M-S model in a panel data study covering the period from 1990 to 2005, based on a sample of 26 countries belonging to the Organisation for Economic Co-operation and Development (OECD).

Using U.S. data from 1973 to 2003, Gärtner and Halbheer (2009) questioned the existence of an M&A wave during the 1980s. Applying an M-S model, the authors found that the wave effectively began only in 1995 and that the boom period was characterized by higher volatility in M&A activity and strong regime persistence.

Employing quarterly U.S. data from 1983 to 2016, Bianchi and Chiarella (2019) estimated a Poisson distribution embedded within an M-S framework with time-varying transition probabilities. Their results indicate that M&A wave dynamics are sector-specific, with each sector exhibiting distinct patterns of momentum and persistence.

The primary objective of these empirical studies has been to assess whether the M-S model is appropriate for modeling M&A activity. In a related line of research, M-S models have also been used to investigate the relationship between M&A activity and macroeconomic and market variables, as illustrated by Resende (2008).

Based on this review of the literature, the following hypotheses are tested:

H_1: M&A activity occurs in waves when analyzed at the country level;

H_2: Macroeconomic variables explain M&A activity when analyzed at the country level;

H_3: M&A activity occurs in waves when analyzed across different economic sectors;

H_4: Macroeconomic variables explain M&A activity when analyzed across different economic sectors.

From an analytical perspective, hypotheses **H_1** and **H_3** address the existence of wave patterns, whereas hypotheses **H_2** and **H_4** focus on explaining these patterns through macroeconomic variables. This structure enables direct comparison with the findings of Kim et al. (2019), who show that changes in macroeconomic conditions significantly affect the frequency of M&A transactions in the United States.

It is also important to distinguish between the first set of hypotheses (**H_1** and **H_2**) and the second (**H_3** and **H_4**). While the former relates to the *temporal* concentration of M&A activity, the latter addresses its concentration across sectors. This distinction allows for comparison with the conclusions of Bianchi and Chiarella (2019), who argue that M&A wave patterns are fundamentally sector-specific and vary substantially in terms of both timing and persistence within the United States.

3 METHODS

This study is descriptive and quantitative in nature and employs quarterly data, reflecting availability constraints associated with some of the selected variables.

The dependent variable is the number of M&A transactions rather than their value, as transaction amounts are not disclosed for all deals. The explanatory variables considered are as follows:

- Exchange Rate (U.S. dollar and IMF Special Drawing Rights – SDR): a depreciation of the domestic currency is expected to make the acquisition of local firms by foreign companies more attractive; therefore, a positive relationship is anticipated.

- Interest Rate (INT): the average loan interest rate calculated by the International Monetary Fund (IMF). Higher interest rates restrict access to financing, leading to an expected negative relationship.

- Stock Market (MKT): given that mispriced equity may be used as a means of payment in M&A transactions, a positive relationship is expected.

- Economic Performance (GDP): higher GDP levels may be interpreted as a proxy for greater aggregate national wealth; consequently, a positive relationship is expected.

Table 1 summarizes these variables, highlighting their respective proxies and data sources.

Table 1
Macroeconomic Variables and Expected Sign

Variable	Proxy	Expected Coefficient Sign	Operational Source
Exchange Rate	USD and SDR	+	Nakamura (2002), Wang (2009), Vissa and Thenmozhi (2022).
Interest Rate	Loan Rate	-	Di Giovanni (2005), Wang (2009), Duong (2013), Fonseca and Almeida (2023).
Stock Market	IBOVESPA; SZSE; NSEI; MOEX; JTOPI	+	Di Giovanni (2005), Wang (2009), Resende (2008), Duong (2013), Kim et al. (2019), Fonseca and Almeida (2023).
Economic Performance	GDP	+	Nakamura (2002), Di Giovanni (2005), Wang (2009), Resende (2008), Cortés et al., (2017), Kim et al. (2019), Hussain and Loureiro (2022), Maung (2022).

Source: prepared by the authors (2023).

These four variables were selected because they are: (1) available for all countries analyzed; (2) clearly defined, with broadly accepted calculation methods; and (3) accessible through national or international institutions.

3.1 Data Collection

Data on M&A activity were obtained from the Refinitiv platform, using the same filtering criteria adopted by Bianchi and Chiarella (2019), which restrict the sample to acquisitions in which the acquiring firm initially held less than 50% of the target's shares and, following the transaction, obtained ownership exceeding 50%.

All transactions in which either the acquiring or the acquired firm was headquartered in one of the BRICS countries (excluding Hong Kong and Macau) were included. Both disclosed and undisclosed transaction values were considered. For country-level analyses, both acquiring firms and targets were included, whereas for sector-level analyses, only acquiring firms were considered.

Data for the explanatory variables (Exchange Rate, Loan Interest Rate, and GDP) were collected from the International Monetary Fund (IMF) website. Stock market indices for each country (Brazil: IBOVESPA; China: SZSE; India: NSEI; Russia: MOEX; South Africa: JTOPI) were obtained from Investing.com.

The initial cut-off date for the explanatory variables was 2004-Q2, corresponding to the earliest availability of quarterly GDP data for India. The upper bound of the sample period is constrained by the availability of Russian GDP data, which extend only through Q3 2021 due to the effects of the conflict in Ukraine. Consequently, the period of complete data overlap across all countries spans from Q2 2004 to Q3 2021.

3.2. Markov-Switching Model

At the outset, it is important to note that although M&A activity typically occurs in waves, it cannot be adequately represented as a single-regime linear time series with clearly defined peaks and troughs. Rather, it is characterized by abrupt shifts between periods of *high* and *low* activity. For modeling this typical M&A behavior, in addition to nonlinearity, another inherent characteristic is that the previously mentioned discrete variation occurs repeatedly, moving back and forth between regimes of high and low activity.

An influential approach to addressing this modeling challenge was introduced by Hamilton (1989), building on the work of Goldfeld and Quandt (1973), and later became known as the Markov-Switching (M-S) model. This approach was originally supported by empirical applications modeling recurrent cycles of positive and negative growth in U.S. gross national product in the post–World War II period.

In a basic M-S framework with two possible regimes, the probability of transitioning from one regime to another between periods *t* and *t + 1* depends solely on the regime prevailing at period *t* (Goldfeld & Quandt, 1973; Hamilton, 1989). This property defines a Markov process, in which the current state of a variable contains all the information required to infer its future evolution. Accordingly, in a scenario with only two *regimes*, the following transition probabilities apply:

$$\begin{aligned} &Prob\ [\mathrm{S}_{t+1} = 1 \mid \mathrm{S}_t = 1] = p \\ &Prob\ [\mathrm{S}_{t+1} = 2 \mid \mathrm{S}_t = 1] = 1 - p \\ &Prob\ [\mathrm{S}_{t+1} = 2 \mid \mathrm{S}_t = 2] = q \\ &Prob\ [\mathrm{S}_{t+1} = 1 \mid \mathrm{S}_t = 2] = 1 - q \end{aligned} \tag{1}$$

The structure shown in equation (1) is assumed to remain constant throughout the entire period. However, it is also possible to adopt a time-varying specification, as demonstrated by Ding (2012).

In the context of M&As, it is most common to work with only two possible states; nevertheless, when a Markov-Switching (M-S) framework is applied, it is possible to consider multiple states. That said, the notation adopted for the states is not "0" and "1," but rather "1" and "2," precisely to emphasize that the M-S framework extends beyond a strictly binary set of possibilities. For example, one could theoretically introduce a third state ("3"), in which case one would expect to obtain filtered results corresponding to a high state, a low state, and potentially an intermediate state.

Consider the generic models, in which θ denotes an arbitrary set of parameters, while e represents the error term:

$$y_t = \begin{cases} y_{t_h} = \theta_1 + e_h & se\ S_t = alta \\ y_{t_l} = \theta_2 + e_l & se\ S_t = baixa \end{cases} \tag{2}$$

To estimate these parameters, Θ = {p, q, θ_1, θ_2}, given that the state variable S_t is not directly observable, maximum likelihood estimation is employed using the Maximum Likelihood (ML) algorithm, which was formally introduced by Dempster et al. (1977). For a more detailed discussion of the operational implementation of this class of models, see Perlin (2015); for greater formalization and additional details, see Hamilton (1989; 1990; 1994). These studies respectively present the fixed-variance model, followed by the introduction of the ML algorithm allowing the variance to alternate jointly with the mean, and finally a more comprehensive formulation with greater scope for formalization. In summary, this process can be viewed as analogous to an *iterative optimization procedure*, in which the values of each parameter in the set Θ to maximize the log-likelihood function.

In a more simplified form, adapted from Perlin (2015), consider:

$$y_t = \mu_{s_t} + e_{s_t} \tag{3}$$

Still assuming only two possible states, the error term is assumed to be normally distributed with zero mean and standard deviation σ_{s_t}. Let us also assume that $f(y_t|S_t = j, \Theta)$ represents the likelihood function associated with the corresponding state S_t. Thus, the log-likelihood function of the model as a whole is given by:

$$\ln L = \sum_{t=1}^{T} ln \sum_{j=1}^{2} (f(y_t|S_t = j, \Theta)\, \Pr(S_t = j|\psi_t)) \tag{4}$$

An arbitrary assumption is made regarding the initial-state probabilities, such as assigning a value of 0.5 to each state. Incorporating these probabilities yields a dataset denoted as ψ_{t-1}, which allows the computation of transition probabilities for the subsequent period (t=1):

$$\Pr\,(S_t = j|\psi_{t-1}) = p_{j,i}(\Pr(S_{t-1} = i|\psi_{t-1})) \tag{5}$$

Next, the updated probabilities are estimated by incorporating the new information available at the current time *t*:

$$\Pr(S_t = j|\psi_t) = \frac{f(y_t|S_t = j, \psi_{t-1}) \Pr(S_t = j|\psi_{t-1})}{\sum_{j=1}^{2} f(y_t|S_t = j, \psi_{t-1}) \Pr(S_t = j|\psi_{t-1})} \quad (6)$$

From this point onward, by repeatedly applying equations (5) and (6) until the entire available time horizon has been covered, *filtered probabilities* are obtained for each point in time evaluated. Finally, using these *filtered probabilities*, equation (4) can be maximized by varying the parameter set $\Theta = \{\mu, \sigma\}$.

Thus, in conclusion, the Markov-Switching approach may be defined as a methodology for operationalizing functions in a context of S objective scenarios that are conditionally and probabilistically transitory.

3.3 MSwM – Linear Regressions With Macroeconomic Variables

The model employed was estimated using the algorithm implemented in the MSwM package for R, developed by Sanchez-Espigares and Lopez-Moreno (2021), in which the specified input function corresponds to a linear regression model, expressed as follows:

$$\begin{aligned} \mathrm{E} = y_{n_s} - \beta_{0_{t_{0_s}}} + \beta_{1_{t_{1_s}}} * US_{t_1} + \beta_{2_{t_{2_s}}} * SDR_{t_2} + \beta_{3_{t_{3_s}}} * MktIndex_{t_3} + \beta_{4_{t_{4_s}}} \\ * INT_{t_4} + \beta_{5_{t_{5_s}}} * GDP_{t_5} \end{aligned} \quad (7)$$

Given the selected explanatory variables, Equation (7) represents the linear regression specification embedded within the Markov-Switching (M-S) framework. Accordingly, the corresponding β parameters are estimated separately for each of the two regimes considered. The subscript *t* denotes the lag order, with each lag indexed individually to allow for combinations of different lag lengths across variables. The regime-specific subscripts s indicate that each coefficient corresponds to one of the S possible alternating states within the M-S structure.

In essence, the model fits a regression line that best approximates the full dataset. Therefore, within the M-S framework, this can be interpreted as the presence of two distinct regression lines, each characterized by its own intercept and slope parameters.

To facilitate comparison and interpretation of the estimated coefficients, all variables were standardized by subtracting their respective means and dividing by their standard deviations. For objective model selection and comparison across specifications, the Akaike Information Criterion (AIC) was employed, following the approach adopted by Fonseca and Almeida (2023), to identify the most appropriate M-S specification.

3.4 Stationarity Test

A statistical test that fails to reject the presence of a unit root, indicating an integrated process, implies that the series is non-stationary. In turn, this suggests that non-stationarity may account for the poor fit observed in previously estimated models. When the presence of a unit root is detected, the series must be transformed by applying the immediately subsequent order of differencing.

To assess the stationarity properties of the variables, the Augmented Dickey–Fuller (ADF) test was applied. Under this test, the null hypothesis states that the series contains a unit root and is therefore non-stationary. Lag length selection was based on the Akaike Information Criterion (AIC), beginning with a specification without lags and subsequently estimating the model with one lag. If the information criterion increased, the more parsimonious specification was retained; otherwise, the procedure continued with additional lags until the optimal specification was identified.

Applying this procedure, it was found that first-order differencing was sufficient to render all explanatory variables stationary at the 99% significance level according to the ADF test. Accordingly, when incorporating these variables into the model, the first difference of each standardized index (expressed in points) was used. Table 2 reports the descriptive statistics for each variable prior to standardization.

4 RESULTS

4.1 Descriptive Statistics

Table 2 presents descriptive statistics for the variables analyzed. The total number of M&A transactions examined was 63,943. With the exception of Russia, peak M&A activity was approximately twice the average number of quarterly transactions, whereas in Russia the peak was roughly three times the average.

Table 2
Description of Data in the Period (2004-Q2 to 2021-Q3)

	Brazil	**Russia**	**India**	**China**	**South Africa**
Number of M&As	8,014	15,126	9,632	27,846	3,325
Average quarterly M&As	114	216	138	432	48
Maximum M&As per quarter	228	648	197	861	86
Average GDP (USD bn)	454.27	392.08	459.56	2,175.57	91.12
Average loan rate	41.88%	10.54%	10.51%	5.39%	10.22%
Stock market volatility	23,931.11	753.03	3,532.04	3,503.02	13,807.81
SDR volatility	1.43	23.77	13.86	1.08	4.37
USD volatility	1.22	18.84	12.30	0.64	3.61

Source: prepared by the authors (2023).

Referring again to Table 2, loan interest rates are similar across Russia, India, and South Africa, while China exhibits the lowest rates and Brazil the highest. With respect to exchange rate volatility, parity with the Chinese currency displays the lowest variation, whereas Russia exhibits the highest volatility.

Figure 1 illustrates the quarterly number of M&A transactions by BRICS country.

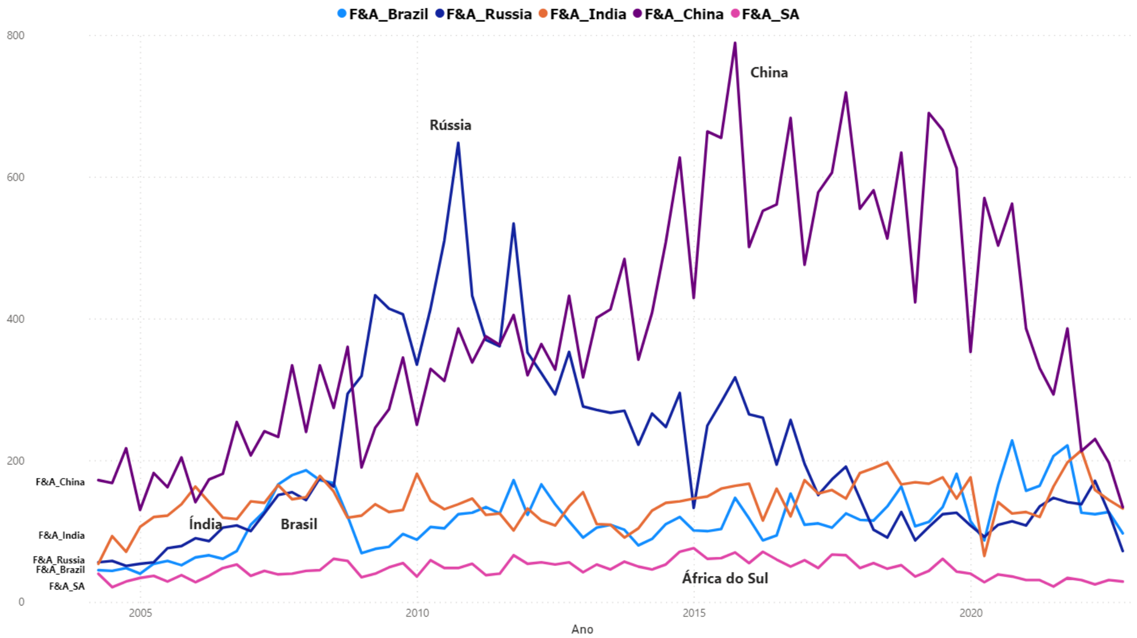


Figure 1 - Number of M&A transactions per quarter
Source: prepared by the authors using data from the survey (2023).

Figure 1 reveals distinct wave patterns, with a pronounced peak in India, followed by Brazil, Russia, and finally China, where the wave extends over a longer duration.

An Augmented Dickey–Fuller (ADF) unit root test was performed, indicating that first-order differencing was sufficient to achieve stationarity. For all variables, the null hypothesis of a unit root was rejected at the 99% significance level.

4.2 M&A Waves in Each Country

The results are presented below, together with the conclusions regarding hypothesis **H₁**, as summarized in Table 3.

Table 3
Results for **H₁** Based on Conditional Means, Standard Deviations, Persistence, and R^2

	Brazil	Russia	India	China	South Africa
Number of M&As	7,877	14,961	9,414	29,684	3,235
Mean	149 | 97	329 | 117	163 | 127	665 | 364	56 | 47
Standard deviation	23 | 17	47 | 65	25 | 21	154 | 48	17 | 6
Mean (High | Low) – 1	54%	159%	28%	83%	19%
Persistence | R^2	84% | 0.64 – 89% | 0.34	97% | 0.24 – 97% | 0.59	90% | 0.59 – 90% | 0.56	95% | 0.85 – 98% | 0.27	82% | 0.66 – 81% | 0.74
H1	Not rejected	Not rejected	Not rejected	Not rejected	Rejected

Source: prepared by the authors (2023).

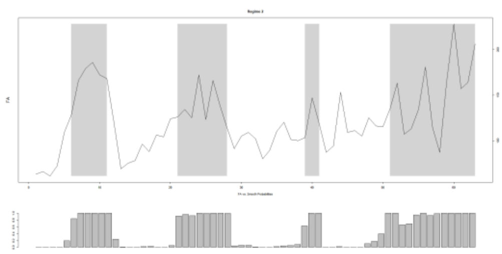
With respect to volatility, in addition to varying across regimes – as also documented by Gärtner and Halbheer (2009) and Duong (2013) – it is generally higher during expansionary phases (Table 3). Russia constitutes an exception, exhibiting lower volatility during the boom regime.

Regarding regime duration, the expected length of a state, $(p \,/\, (1-p))$, indicates that the average expansionary phase across the five countries lasts approximately 14 quarters, whereas contractionary phases persist for about 20 quarters, in line with the findings of Duong (2013).

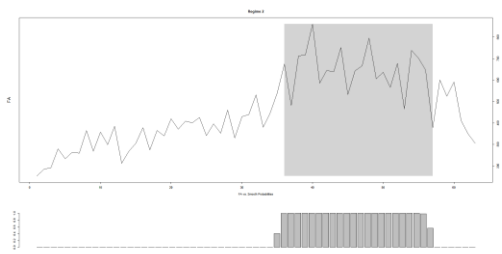
Figure 2 presents the best-performing specification for each market analyzed. The five-digit sequence corresponds to the lag structure of the variables, always ordered as follows: USD, SDR, GDP, INT, and MKT.

Kim et al. (2019) report that macroeconomic effects on M&A activity typically emerge between one and four quarters after wave formation. By contrast, the results of this study indicate that the most frequent lag values are “0” and “4”. The strong presence of contemporaneous effects (lag “0”) contrasts with the conclusions of Kim et al. (2019), who argue that short-term macroeconomic fluctuations do not significantly drive M&A concentration, with long-term trends playing a more prominent role. The evidence presented here suggests that short- and long-term dynamics are both relevant.

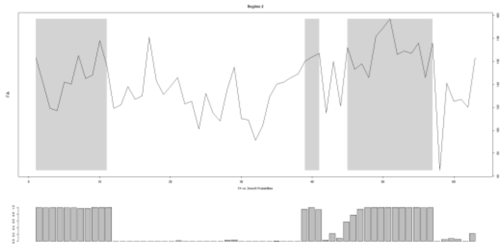
Brazil: 2 0 4 2 1, AIC = 602.98



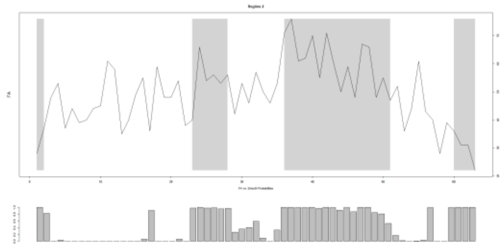
China: 4 4 0 4 2, AIC = 751.19



India: 1 1 0 0 4, AIC = 560.11



South Africa: 1 1 1 4 0, AIC = 471.31



Russia: 0 3 0 0 4, AIC = 561.89

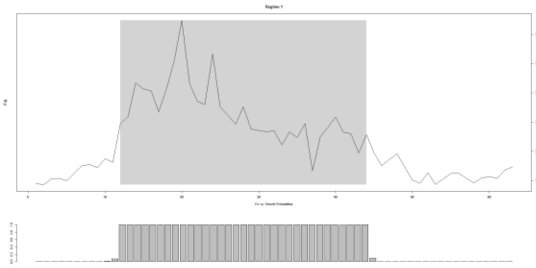


Figure 2 - Best-Performing MSwM Specifications
Source: prepared by the authors using data from the survey (2023).

As observed in developed economies examined by Town (1992) and Resende (1999), the BRICS countries exhibit strong regime persistence, exceeding 80% in all cases analyzed.

Consistent with neoclassical theory, these results support the presence of external shocks affecting most of the M&A series in the markets studied. Finally, hypothesis $\mathbf{H_1}$ – that M&A activity occurs in waves – is rejected only for South Africa, with weak evidence of non-rejection observed in the case of India.

4.3 M&A Waves and Macroeconomic Variables in Each Country

In Table 4, the first coefficient sign (from left to right) corresponds to the expansionary (bull) regime, while asterisks indicate levels of statistical significance. The column "B0" refers to the intercept of the linear regression.

Table 4

Results for $\mathbf{H_2}$: By Country, Macroeconomic Variables Explain M&A Activity

	Number of M&As	Rejected H2	B0	US	SDR	GDP	INT	MKT
Brazil	8,014	No	153*** | 99***	6 | -32***	-53*** | 25***	52*** | 15**	-0 | 24***	-0 | 25***
Russia	15,126	No	327*** | 123***	50* | 20*	-0 | -99***	90* | 24***	-48* | 33***	44*** | -30***
India	9,632	No	163*** | 128***	36*** | 33***	-32*** | -57***	-40*** | 40***	-16*** | 13**	23** | 8
China	27,846	No	647*** | 365***	331*** | -13	-402*** | 106**	200*** | 73***	-9 | -41	17 | -11
South Africa	3,325	No	57*** | 47***	-56*** | 10**	38 | -2	-33*** | +11***	28*** | -8***	18*** | -14***

Note: ***, *, and * denote statistical significance at the 99%, 95%, and 90% levels, respectively.
Source: prepared by the authors (2023).

Consistent with the findings of Resende (2008), Table 4 shows sign changes across regimes; however, no variable exhibits sign alternation across all countries. Such alternation is most prevalent in the INT and MKT variables (five countries), followed by US (four), SDR (three), and GDP (two).

The statistical significance of these coefficients leads to the non-rejection of $\mathbf{H_2}$, indicating that macroeconomic variables explain M&A activity across all national contexts, in line with the evidence reported by Resende (2008) for the United Kingdom.

The positive coefficients associated with the U.S. exchange rate, GDP, and stock market (MKT) variables are consistent with the findings of Kim et al. (2019), Vissa and Thenmozhi (2022), and Fonseca and Almeida (2023). By contrast, the SDR exchange rate and interest rate (INT) variables display a more balanced distribution of positive and negative coefficients, diverging from the predominant patterns documented in the literature.

With respect to coefficient sign alternation, unlike Resende (2008), no empirical context exhibits complete alternation across all explanatory variables. The highest incidence of alternation is observed for interest rate and stock market variables.

Overall, these results support the neoclassical interpretation that economic shocks influence M&A activity across all BRICS countries, consistent with evidence reported by Sonenshine (2020) for other markets.

4.4 M&A Waves in BRICS Sectors

The same procedure applied to **H_1** was repeated for the twelve economic sectors within the BRICS countries. Table 5 summarizes the results for **H_3**.

Table 5
BRICS – **H_3**: By Sector, M&A Activity Occurs in Waves

	Brazil	**Russia**	**India**	**China**	**South Africa**
Products and Services	Not rejected	Rejected	Rejected	Not rejected	Rejected
Consumer Goods	Not rejected	Rejected	Rejected	Not rejected	Rejected
Energy	Not rejected	Not rejected	Rejected	Rejected	Rejected
Entertainment	Not rejected	Rejected	Rejected	Not rejected	Rejected
Financial	Rejected	Not rejected	Rejected	Not rejected	Rejected
Health	Rejected	Rejected	Rejected	Rejected	Rejected
Technology	Rejected	Rejected	Rejected	Rejected	Rejected
Industry	Rejected	Not rejected	Rejected	Not rejected	Rejected
Materials	Not rejected	Rejected	Not rejected	Rejected	Rejected
Real Estate	Not rejected	Not rejected	Not rejected	Rejected	Not rejected
Retail	Rejected	Rejected	Not rejected	Rejected	Rejected
Telecommunications	Not rejected	Rejected	Rejected	Not rejected	Rejected

Source: prepared by the authors (2023).

According to Table 5, **H_3** is not rejected in seven of the twelve sectors in Brazil and in six sectors in China. However, overall, M&A activity in the BRICS countries does not generally occur in sector-specific waves.

Comparing **H_1** and **H_3**, the former is generally not rejected, while the latter is rejected in most cases. This suggests that neoclassical shocks operate more strongly at the country level than at the sectoral level. This finding contrasts with Bianchi and Chiarella (2019), who argue that wave patterns are primarily sector-specific. The results instead indicate that shocks are more diffusely distributed across sectors, implying that geographical factors dominate sectoral ones. This conclusion aligns with the findings of Resende (1999) for the United Kingdom, who shows that sectoral M&A wave patterns exhibit significant joint movement, while the results of the present study indicate that this joint movement arises from common effects affecting all sectors within the same country.

Comparisons with Bianchi and Chiarella (2019) reveal partial convergence, particularly regarding the difficulty of identifying aggregate wave patterns. As in their study, no aggregate waves are detected here, while disaggregated analyses yield mixed evidence in favor of M&A wave behavior.

Across nearly all sectoral contexts, volatility varies by regime and is higher during expansionary phases, consistent with Gärtner and Halbheer (2009) and Duong (2013).

4.5 M&A Waves and Macroeconomic Variables in BRICS Sectors

Based on Table 6, the same analytical framework used to test **H_2** was applied to **H_4**. As this constitutes a secondary analysis, and in the absence of a strict decision rule, **H_4** was not rejected when at least half of the estimated slope coefficients were statistically significant.

Table 6
BRICS – **H_4**: By Sector, Macroeconomic Variables Explain M&A Activity

H4 Rejection	Brazil	Russia	India	China	South Africa
Products and Services	Yes	Yes	Yes	No	No
Consumer Goods	Yes	Yes	No	No	Yes
Energy	No	No	Yes	Yes	No
Entertainment	No	Yes	No	No	Yes
Financial	No	Yes	Yes	Yes	Yes
Health	Yes	No	No	No	No
Technology	Yes	No	No	Yes	No
Industry	Yes	No	No	No	No
Materials	Yes	No	No	No	No
Real Estate	Yes	No	Yes	Yes	Yes
Retail	Yes	No	Yes	Yes	Yes
Telecommunications	No	Yes	Yes	No	No

Source: prepared by the authors (2023).

As shown in Table 6, for most of the countries analyzed, the hypothesis that macroeconomic variables explain M&A activity is not rejected in at least six sectors. Overall, for the BRICS economies, **H_4** is not rejected, indicating that macroeconomic variables explain M&A activity across sectors. This result is consistent with the findings of Resende (2008) for the United Kingdom.

With respect to coefficient sign alternation, the SDR variable exhibits the highest frequency of alternation, appearing in at least one sector in all countries, followed by the stock market variable (MKT), which fails to alternate only in the Russian case. These comparisons consider only sectors in which **H_4** is not rejected and in which the respective macroeconomic variable is statistically significant at the 90% level in both regimes. Overall, the results differ substantially from those reported by Resende (2008), as no sector exhibits sign alternation across all explanatory variables.

4.6 Additional Observations Across Countries

During the period analyzed, two major global macroeconomic disruptions (the 2008 Subprime Financial Crisis and the COVID-19 pandemic) substantially increased systemic risk, affecting both the explanatory variables and the volume of M&A activity. In Brazil, the political and economic crisis between 2014 and 2017 likewise constituted a significant factor influencing M&A activity.

As shown in Table 7, all countries experienced growth in M&A activity prior to the 2008 crisis. During the crisis, activity initially surged and subsequently declined toward its end. In 2009, growth resumed, consistent with the patterns identified by Hussain and Loureiro (2022) in other economies.

Table 7
The 2008 Financial Crisis and M&A Activity

Country	**2008 Financial Crisis / Number of M&As**		
	Before (2005–2006)	During (2007–2008)	After (2009)
Brazil	Slow upward trend.	Formation of a new global peak in M&A activity, reaching up to three times the level observed in 2006.	Decline that ended at a level below 50% of the previous global M&A peak, followed by a slow recovery along an upward trend.
Russia	Slow upward trend.	Still following a slow upward trend, with a momentum gain that nearly doubled the level observed in the previous year.	Sharp gain in momentum, reaching nearly three times the level observed in 2008.
India	On an upward trend, with M&A activity already at a considerably high level.	Small gain in momentum within the upward trend.	Decline of 30% from the level that had been increasing, followed by slow growth.
China	On an upward trend, but with recurring ups and downs.	A 30% momentum gain relative to the highest peak observed in 2006, after which the series continued along a slow upward trend, still marked by recurring ups and downs.	First sharp decline, reaching nearly 50% of the peak observed in 2008, followed by slow growth.
South Africa	In a clearly defined upward trend.	Sharp decline of 25%, followed by slow growth until reaching a new global M&A peak.	Decline of 30% from the global peak, followed by pronounced growth until, in 2009, it reached 90% of the 2008 M&A peak.

Source: prepared by the authors (2023).

According to Table 7, Brazil exhibited the most pronounced peak in M&A activity during the crisis, occurring in 2007, followed by a sustained upward trend before entering a downturn in 2008, unlike the patterns observed in other countries (Hussain & Loureiro, 2022). Unlike Brazil, China was the country least affected by the crisis in its M&A series since it continued to display recurring ups and downs while progressing along a slow upward trajectory. Therefore, it can be stated that, among the BRICS countries, with the exception of China, an upward movement was observed that culminated in a peak in the M&A series. However, there was a lag across countries, beginning first in Brazil and India, followed by South Africa, and finally giving rise to what would culminate in 2010 as the major wave in Russia.

Table 8 compares M&A activity during the COVID-19 pandemic. Unlike what was observed in Table 7, years later the countries were no longer in an upward trend, with only Brazil and India still resisting by not yet following a clear downward movement.

Table 8
The COVID-19 Pandemic and M&A Activity

Country	The COVID-19 Pandemic and M&A Activity		
	Before (2017-2019)	During (2020-2022)	Final (2022)
Brazil	M&A series at a stable level, with frequent fluctuations.	Momentum led to a new historical peak in M&A activity.	Decline, reaching a level below half of that observed in the previous year.
Russia	Downward trend.	Slow upward trend.	Momentum, returning to a level close to that observed in 2017, followed by a decline to a minimum not observed since 2006.
India	Stable series, with limited variation.	Decline, generating a new historical low.	Momentum leading to a new historical peak, followed by a continuous decline
China	Downward trend.	Short decline, with continuation of the downward movement.	Decline reaching a level not observed since the mid-2000s.
South Africa	Downward trend.	Downward trend, reaching a minimum level not observed since 2004.	Brief recovery, followed by a return to a downward trend, reaching a level not observed since 2005.

Source: prepared by the authors (2023).

According to Table 8, during the pandemic period, all countries experienced a decline followed by a continued downward trajectory in M&A activity, with the exception of Russia, which exhibited a brief recovery movement. Brazil and India stand out as the most distinctive cases within the BRICS group, as both reached new historical peaks in the aftermath of the crisis. This behavior is consistent with the global surge in M&A activity observed during the same period (BCG, 2023).

Finally, it should be noted that all countries experienced a decline in M&A activity in 2022, leading the BRICS group as a whole to return to a level of low M&A activity not observed since 2005.

5 CONCLUDING REMARKS

Based on studies that predominantly focus on developed economies, it is well established that M&A activity occurs in waves, characterized by short periods of intense activity followed by prolonged phases of lower activity. It is also widely recognized that this wave-like behavior is closely related to the broader macroeconomic environment.

The objective of this study was to test a more suitable methodological approach for analyzing this relationship within a less explored but increasingly prominent global context (the BRICS economies). This objective was achieved, with empirical evidence supporting both the adequacy of the proposed model and the existence of a relationship between M&A activity and macroeconomic variables. At the country level, the hypotheses that M&A activity occurs in waves and that macroeconomic variables explain this behavior were not rejected. By contrast, when the analysis was conducted at the sectoral level, these hypotheses were generally rejected.

These findings suggest that, from a broader perspective, the shocks emphasized by neoclassical theory are more relevant for explaining wave formation at the country level than at the sectoral level. Accordingly, even among economies at similar stages of development and with comparable sectoral structures, country-specific characteristics limit the generalization of results across nations. At the same time, the observed compensatory patterns suggest that the distinct sources of systemic risk faced by individual BRICS countries may offer diversification benefits when considered collectively.

The study therefore fulfills its objectives by identifying the presence of M&A waves in the markets analyzed and by determining which macroeconomic variables are capable of explaining this wave-like behavior. These results confirm the validity and effectiveness of the Markov-Switching model. In addition, the findings show that during the COVID-19 pandemic, aggregate M&A activity across the BRICS countries reached a minimum level not observed since 2005.

The academic and practical contributions of this research are noteworthy. Given that M&A studies (particularly those addressing wave phenomena) are predominantly concentrated on the United States and the United Kingdom (Mager & Meyer-Fackler, 2017), this work helps address a gap in the literature by expanding the scope of analysis to five major emerging economies. Moreover, the empirical results offer insights relevant to managers and investors, especially in light of existing evidence suggesting that, on average, M&A transactions tend to destroy more value than they create (Harford, 2005; Gugler et al., 2012).

The primary limitation of this study relates to the availability of explanatory variables, which restricts the analysis to the period from 2004-Q2 to 2021-Q3. A further limitation is the exclusion of transaction value measures from the analysis. Future research could explore contagion effects across countries using approaches such as Value at Risk (VaR) or Vector Error Correction (VEC) models, with the aim of identifying short-term dynamic relationships in M&A activity.

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