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THE RELATIONSHIP BETWEEN OPTIMISM AND MERGER AND ACQUISITION WAVES: EVIDENCE FROM THE BRAZILIAN MARKET

Relação entre otimismo e ondas de fusão e aquisição: evidências do mercado brasileiro

La relación entre optimismo y ondas de fusión y adquisición: evidencias del mercado brasileño

Rodrigo Raposo da Fonseca[1] | rodrigo_fonseca4@hotmail.com | ORCID: 0000-0002-0357-6852
Vinicio de Souza e Almeida[2] | vinicio@ccsa.ufrn.br | ORCID: 0000-0002-1092-0332

[1]Universidade Federal do Rio Grande do Norte, Programa de Pós-Graduação em Administração, Natal, RN, Brazil
[2]Universidade Federal do Rio Grande do Norte, Departamento de Administração, Natal, RN, Brazil

ABSTRACT

Why mergers and acquisitions occur in waves is still a subject little explored in the financial literature, especially in the context of markets outside the USA and UK. Therefore, this study investigates whether agents' optimism could lead to an M&A wave, using Brazilian data from 2007 to 2017 of transactions and the Business Confidence Index, which measures the optimism of the entrepreneurs about the current and future economic scenario. We used Harford's (2005) definition for an M&A wave. Using a Logit binary response model, the study pointed out that optimism increases the probability of an M&A wave. Ibovespa was the variable that had the greater effect on the probabilities of an M&A wave. The results were significant for different lags.

Keywords: mergers and acquisitions waves, mergers and acquisitions, optimism, agent confidence, logit.

RESUMO

O motivo das fusões e aquisições (F&As) acontecerem em ondas é ainda um tema pouco explorado na literatura financeira, especialmente no contexto de mercados fora dos EUA e Reino Unido. Diante disso, este trabalho investiga se o otimismo dos agentes econômicos pode levar a uma onda de F&As, utilizando dados brasileiros entre 2007 e 2017 sobre as transações e o Índice de Confiança do Empresário, que mede o otimismo dos empresários com a situação atual e futura da economia. Foi utilizada a definição de onda de F&As como em Harford (2005). A partir de um modelo de resposta binária logit, os resultados apontam que o otimismo aumenta a probabilidade de ocorrência de uma onda de F&As. O Ibovespa foi a variável que apresentou maior efeito nas probabilidades de ocorrência de uma onda de F&As. Os resultados foram significantes para diferentes lags.

Palavras-chave: *ondas de fusão e aquisição, fusão e aquisição, otimismo, confiança dos agentes, logit.*

RESUMEN

La razón por la que las fusiones y adquisiciones suceden en oleadas sigue siendo un tema poco explorado en la literatura financiera, especialmente en el contexto de los mercados fuera de los Estados Unidos y el Reino Unido. Ante esto, el presente trabajo investiga si el optimismo de los agentes económicos puede conducir a una ola de fusiones y adquisiciones, utilizando datos brasileños entre 2007 y 2017 sobre transacciones y el Índice de Confianza del Emprendedor, que mide el optimismo de los emprendedores con la situación actual y futuro de la economía. La definición de ola de fusiones y adquisiciones se utilizó como en Harford (2005). Basado en un modelo de respuesta binaria Logit, el trabajo señaló que el optimismo aumenta la probabilidad de que ocurra una ola de fusiones y adquisiciones. El Ibovespa fue la variable que tuvo mayor efecto sobre la probabilidad de que ocurra una ola de fusiones y adquisiciones. Los resultados fueron significativos para diferentes rezagos.

Palabras clave: *olas de fusiones y adquisiciones, fusiones y adquisiciones, optimismo, confianza del agente, logit.*

INTRODUCTION

According to the literature on finance, it is a stylized fact that mergers and acquisitions (M&A) occur in waves (Duchin & Schmidt, 2013; Gärtner & Halbheer, 2009; Gorton, Kahl, & Rosen, 2009; Gugler, Mueller, Weichselbaumer, & Yurtoglu, 2012; Lambrecht, 2004; Rhodes-Kropf & Viswanathan, 2004; Town, 1992). However, although researchers have been aware of this phenomenon for some time (Mitchell & Mulherin, 1996), there are still doubts about its motivations.

Some authors relate this cyclical pattern of M&A transactions to economic cycles, increasing in times of high economics and periods of high valuations in the capital market (Harford, 2005; Lambrecht, 2004; Triantafyllopoulos & Mpourletidis, 2014). These periods of optimism in the market affect managers' decisions, leading them to overestimate the likelihood of making successful decisions. This phenomenon explains why operations are concentrated in certain periods and why these operations become, on average, a factor that destroys shareholder value (Gugler, Mueller, Weichselbaumer, & Yurtoglu, 2012; Harford, 2005; Nofsinger, 2005).

Research on M&A waves is still scarce compared to other topics (Rao-Nicholson, Salaber, & Cao, 2016), especially outside the US and UK markets. This study did not find any research on the M&A waves for the Brazilian market.

Therefore, this research seeks to contribute to the literature on M&A waves by, first, investigating whether the agents' optimism influences M&A waves. In this case, the study adopts the Business Confidence Index (BCI), a metric built by directly asking the entrepreneurs about their perception of the current and future economic environment. Second, this research addresses M&A waves in an emerging market, offering a study in a context with little data on the issue. The findings may subsidize future research and should increase understanding of the motivation around M&A waves.

WAVES OF MERGERS AND ACQUISITIONS

Neoclassical theory

Neoclassical theory indicates that waves of mergers and acquisitions (M&A) reallocate assets for more efficient use (Xu, 2017). According to the theory, shocks in the industry (Harford, 2005) cause destabilization in the existing market structure, and M&A emerges to stabilize it (Rodrigues, 2014). These shocks can come from deregulation, technological innovation, and industry consolidation, among other reasons. However, Harford (2005) points out that the market must have sufficient liquidity to accommodate this reallocation of assets.

Among the findings supporting this theory, Andrade, Mitchell, and Stafford (2001) analyzed M&A in the 1990s, seeking to prove that they occur in clusters within a given industry, responding to deregulation. The study showed that M&A occurred predominantly within a specific industry, different from the dynamic observed in the 1970s. Another finding was that such negotiations in the 1990s were conducted primarily through stock transactions, which also conform to behavioral theory. Despite the increase in M&A conducted through deals between organizations within a specific industry, they were less than half of the transactions.

Although M&A is vital to structuring industries (Chaudhuri, 2014), the neoclassical theory can explain only some of the M&A waves (Gugler, Mueller, & Weichselbaumer, 2012). Also, M&A may be a way to respond to deregulation but the theory cannot explain conglomerate-type mergers, where a company in one sector buys another in a different sector, or the above-normal use of stocks to finance such transactions during waves.

Despite different attempts to explain the motivations behind the M&A waves, there are some consensual aspects in the literature. M&A waves have coincided with strong advances in the capital markets (Goel & Thakor, 2010; Gugler, Mueller, & Weichselbaumer, 2012; Gugler, Mueller, Weichselbaumer, & Yurtoglu, 2012; Haleblian, McNamara, Kolev, & Dykes, 2012; Uddin & Boateng, 2011); there is a cyclic pattern of waves and a more significant number of asset valuation errors (Duchin & Schmidt, 2013; Goel & Thakor, 2010; Rhodes-Kropf, Robinson, & Viswanathan, 2005); and it is possible to observe a greater use of shares in M&A transactions (Rhodes-Kropf et al., 2005; Rhodes-Kropf & Viswanathan, 2004; Shleifer & Vishny, 2003). In addition, some authors have observed the connection between waves and the agents' optimism, influencing how they value assets (Goel & Thakor, 2010; Gugler, Mueller, & Weichselbaumer, 2012; Gugler, Mueller, Weichselbaumer, & Yurtoglu, 2012).

Behavioral theory

The behavioral theory gathers studies that point out pricing errors as the cause of M&A waves. Unlike neoclassical theory, behavioral theory relaxes the assumption of efficient markets (Gugler, Mueller, & Weichselbaumer, 2012). Shleifer and Vishny (2003), noting that each wave in history was recorded by its characteristics, propose a unique model where the market is inefficient when pricing assets, while managers rationally take advantage of moments of asset overvaluation. One of this model's advantages is explaining why transactions involving shares are preferred during M&A waves and why a greater appreciation of shares precedes these periods.

Rhodes-Kropf and Viswanathan (2004) hypothesized that market overvaluation could lead to a wave. They developed a model that, unlike Shleifer and Vishny's (2003) model, assumes that agents are rational and make decisions rationally ex-ante due to periods of overvaluation in the market. This increases the likelihood of a wrong assessment. M&A decisions are shown to be incorrect ex-post. The model assumes that the managers of both buyers and targets know that their assets are not correctly valued. However, they cannot pinpoint exactly how wrong the assessment is. Therefore, they make wrong decisions thinking they are maximizing the company's value.

Rhodes-Kropf et al. (2005) investigated the relationship between periods of high market-to-book (M/B) ratios and M&A waves and found that these periods usually coincide, especially when stock papers finance the transactions. The authors challenge the neoclassical theory, pointing out that, within an industry, even if there is a shock that explains the wave, the buyer's and the target's behavior is explained by the valuation errors. The authors' ideas have great implications for neoclassical theory since the attitude of buyers and targets can be explained by behavioral factors, despite the shocks leading to a wave

Reinforcing the aspect of asset pricing uncertainties and errors, the work of Duchin and Schmidt (2013) used the Garch model and data from 1980 to 2009. They showed that M&A wave periods are characterized by greater uncertainty and lower uncertainty quality analysts' assessment, pointing to an approximately 4.4% higher volatility and a normalized dispersion of forecasts around 20% higher.

THE HARFORD METRIC

The first challenge when discussing M&A waves is identifying how they are formed. The literature shows attempts to define and classify M&A waves, from simple procedures such as observing the number of M&A and news about these events year by year (Duchin & Schmidt, 2013) to more sophisticated methods using econometric models. However, defining and classifying M&A waves is not an easy task (Gärtner & Halbheer, 2009).

Harford (2005) developed one of the most used metrics to define an M&A wave. The author investigated 120 months and used the 24 months – following Mitchell and Mulherin (1996) – with the highest number of M&A as the total period of a wave. The method consists of a thousand simulations with a probability of 1/120 of an operation happening in a given month. Then, the total amount of transactions in each accumulated period of 24 months is observed in the real data collected and compared to the fifth percentile of the highest activity of the simulation data. If the actual empirical data exceeds the simulation values, the period is defined as an M&A wave.

Haleblian et al. (2012) used the method to investigate the characteristics of the first wave entrants. Duchin and Schmidt (2013) adopted it when investigating analysts' uncertainty and quality during and off waves, whereas Rhodes-Kropf et al. (2005) used the metric to test their asset valuation errors model. Xu (2017) adopted a simpler model to define the wave but used Harford's (2005) metric as a robustness measure.

OPTIMISM AND MARKET

Asset pricing is a challenging activity in the market. It is even more challenging in an M&A process where the buyer must price the target company's market value and the value obtained from the two companies' synergy. Managers are subject to valuation errors, be they market, industry, or firm valuation errors (Rhodes-Kropf & Viswanathan, 2004). Such errors can be decisive for the success or failure of the transaction.

This task is particularly complicated in times of optimism in the market. In general, in periods of prosperity, stock prices and P/Es (Price/Earnings) are driven to unsustainable levels (Gugler, Mueller, Weichselbaumer, & Yurtoglu, 2012). Thus, it is not surprising that M&A waves are followed by a market crash (Rhodes-Kropf & Viswanathan, 2004).

Studying the implications of CEO trust for M&A operations, Malmendier and Tate (2008) found that overconfident managers carry out more M&A when they have more internal resources.

Roll (1986) was one of the first authors to propose a theory explaining CEO decision-making in M&A transactions. Using the Hubris hypothesis, the author justified that managers believe the market is wrongly pricing the asset, overestimating their ability to value and manage resources.

In this sense, Rhodes-Kropf and Viswanathan (2004) proposed a model where agents are rational, seeking to maximize shareholder value. However, in periods of overvalued markets, the chances of valuation errors increase, which can lead to M&A waves. This model opposes or extends that of Morck, Shleifer, and Vishny (1990), where the CEO's benefits can interfere in decisions to the detriment of the shareholder's interests. However, this model would not explain why M&A occurs in waves.

A whole segment of studies has shown that CEOs' optimism and excessive confidence are, theoretically and empirically, essential factors in explaining their decisions (Campbell, Gallmeyer, Johnson, Rutherford, & Stanley, 2011). The manager's personal belief that the company is over or under-valued seems to drive a large part of decision-making (Malmendier & Tate, 2015). This behavior is in line with studies in Psychology that indicate that individuals overestimate their abilities (Dessí & Zhao, 2018).

METHODOLOGY

Data

This work used data from all M&A transactions in Brazil between November 2007 and October 2017, a period of 120 months, following Harford (2005). The first sample comprised 3,269 transactions, considering only those where the target was a Brazilian company. Transaction data were obtained from the Bloomberg platform. The definition of sectors also followed the platform's metrics, with the difference that the construction sector was removed from the financial sector to compose a single sector, considering the characteristics of the Brazilian market.

The research used the transaction data and other economic variables, as shown in Exhibit 1. In addition to the Bloomberg platform, data was also collected from the Central Bank of Brazil website. The confidence index adopted was the Business Confidence Index (BCI), produced by the Fundação Getulio Vargas (FGV), which seeks to capture the perception of business people concerning the current and future situation of the economy. It ranges from 0 to 200, and the higher the index, the better the perception of economic agents; if the result is above 100, we can define the situation as optimistic; below that, pessimistic.

Exhibit 1. Variables and description

Variable	Description	Previous studies
Wave	Dummy – 1 if the transaction occurred during an M&A wave	
BCI	Business Confidence Index	
BCI - 1	BCI – lag of 1 period	
BCI - 2	BCI – lag of 2 periods	
BCI - 3	BCI – lag of 3 periods	
BCI - 6	BCI – lag of 6 periods	
BCI - 12	BCI – lag of 12 periods	
Spread	Spread applied on the firms' credit operations (excluding the subsidized ones)	Harford (2005); Gugler, Mueller, Weichselbaumer, and Yurtoglu (2012)
Consultant	Dummy – 1 if the transaction counted on a financial consultant	Bao and Edmans (2011); Hermansson and Song (2016)
Stock	Dummy – 1 if the transaction was totally or partially financed with stocks	Rhodes-Kropf and Viswanathan (2004); Shleifer and Vishny (2003)
Cross-border	Dummy – 1 if cross-border transaction	Chandhuri (2014); Xu (2017)
LogTA	Logarithm of total assets	Rhodes-Kropf et al. (2005)
PB	Price-to-book at the end of the previous year	Rhodes-Kropf and Viswanathan (2004); Rhodes-Kropf et al. (2005); Goel and Thankor (2010); Haleblian et al. (2012)
EBITDA	EBITDA in the previous year	
Leverage	Leverage in the previous year	Rhodes-Kropf et al. (2005)
TOBQ	Tobin's Q in the previous year	Jovanovic and Rousseau (2002)
LogIBOV	Logarithm IBOV	Shleifer and Vishny (2003); Harford (2005); Goel and Thankor (2010); Gugler, Mueller, Weichselbaumer, and Yurtoglu (2012)
Basic materials	Dummy – 1 if in the basic materials sector	
Communications	Dummy – 1 if in the communications sector	
Consumer, cyclical	Dummy – 1 if in the consumer sector – cyclical	
Consumer, non-cyclical	Dummy – 1 if in the consumer sector – non cyclical	
Diversified	Dummy – 1 if in diversified sectors	
Energy	Dummy – 1 if in the energy sector	
Financial	Dummy – 1 if in the financial sector	
Real estate	Dummy – 1 if in the construction sector	
Industrial	Dummy – 1 if in the industrial sector	
Technology	Dummy – 1 if in the technology sector	
Utilities	Dummy – 1 if in the utilities sector	

Source: Elaborated by the authors.

Note: Previous studies are not indicated in the case of independent and control variables used in specific industries.

Model

We used a logit binary response model – Equation 1 – where y = 1 means that transaction k was performed during an M&A wave, given the control variables x. The y=0 means that the transaction did not take place in an M&A wave.

$$P(y = 1|x) = G(\beta 0 + \beta BCI + \beta control) \quad (1)$$

Where,

β0 is the intercept

βBCI is the independent variable BCI

βcontrol are the control variables

RESULTS

Data treatment

Data were collected from 3,269 M&A targeting Brazilian companies. All transactions were considered to identify the M&A wave, but some were excluded from the analysis due to a lack of data. Table 1 shows the data filtering process, through which the proportion of operations that occurred inside and outside the M&A wave remained stable, avoiding bias.

Table 1. Data filtering process

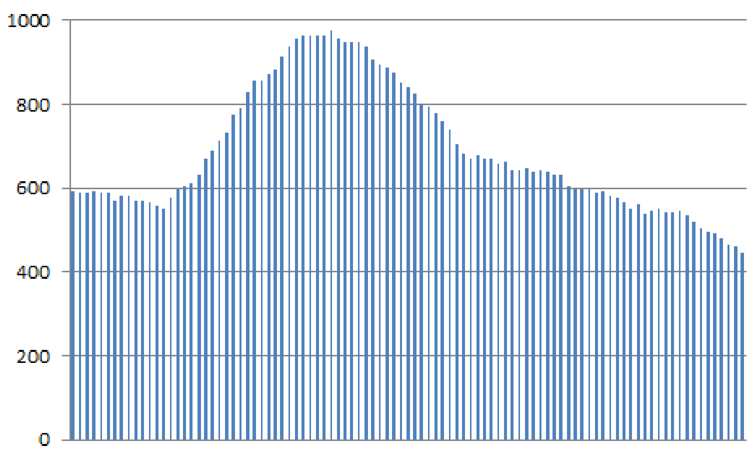
Filter	Number of transactions	Transactions that occurred during M&A waves
All data	3,269	29.89%
Type of payment	2,060	30.00%
Total asset	1,370	29.64%
Price-to-book	1,169	30.37%
EBITDA	1,055	29.57%
Leverage	1,042	29.85%
Tobin's Q	1,033	29.62%

Source: Elaborated by the authors.

Building the M&A wave

The second stage of the study was the analysis of the existence of M&A waves following Harford's (2005) method. The simulations indicated 804 M&A transactions as the number of transactions to define a 24-moths period as an M&A wave. Figure 1 shows the frequency distribution, using actual data, of the total number of M&A for each 24-month period.

Figure 1. M&A transactions accumulated in each period of 24 months between November 2007 and October 2017



Source: Elaborated by the authors.

The period of more intense activity within the 24-month period runs from the end of 2009 to the end of 2013. During this period, the accumulated activity was over 804 transactions, totaling 48 months, representing about 40% of the total period, accumulating more than 50% of transactions. This number is lower than that observed by Mitchell and Mulherin (1996), who found that a quarter of the time accumulates 50% of operations. However, the peak of activity occurs between December 2010 and November 2012, concentrating 30% of M&A. Every transaction that occurred within this interval has the variable WAVE =1.

Descriptive statistics

Table 2 shows the mean, standard deviation, and the number of observations of the model variables. About 30% of the observations take place during a wave. Average confidence is around 100 points across all lags. Within the sectors, most of the operations are from companies in the non-cyclical consumer sector, composed of food and fish production and processing companies.

Table 2. Descriptive statistics

Variables	Mean	Standard-deviation	Obs
Wave	0.30	0.46	1,033
BCI	100.20	12.92	1,033
BCI - 1	100.54	12.74	1,033
BCI - 2	100.75	12.67	1,033
BCI - 3	100.99	12.77	1,033
BCI - 6	101.11	12.98	1,033
BCI - 12	101.72	12.60	1,033
Spread	0.14	0.02	1,033
Consultant	0.25	0.44	1,033
Stock	0.12	0.32	1,033
Cross-border	0.51	0.50	1,033
LogTA	3.72	0.94	1,033
PB	10.64	139.75	1,033
EBITDA	4,029.80	11,343.05	1,033
Leverage	3.90	10.03	1,033
TOBQ	3.16	34.57	1,033
LogIBOV	4.75	0.07	1,033
Basic materials	0.12	0.32	1,033
Communications	0.06	0.24	1,033
Consumer, cyclical	0.08	0.27	1,033
Consumer, non-cyclical	0.27	0.44	1,033
Diversified	0.01	0.11	1,033
Energy	0.06	0.23	1,033
Financial	0.04	0.21	1,033
Real estate	0.12	0.32	1,033
Industrial	0.10	0.31	1,033
Technology	0.06	0.24	1,033
Utilities	0.07	0.26	1,033

Source: Elaborated by the authors.

Note: The dummy indicates if the transaction occurred during the M&A wave; BCI represents the business confidence index, BCI-1 to BCI-12 indicates the confidence index considering lags of 1, 2, 3, 6, and 12 periods. The others are control variables for the characteristics of the transactions and the buyer's sector/industry.

Table 3 shows the descriptive statistics of the transactions inside and outside the wave and the variation between them.

Table 3. Descriptive statistics and difference between operations during M&A waves and off M&A waves

Variables	Wave		Off wave		Δ	Δ%
	Mean	Standard-deviation	Mean	Standard-deviation		
BCI	106.21	3.15	97.68	14.54	8.53	8.74%
BCI - 1	106.62	3.34	97.99	14.29	8.63	8.81%
BCI - 2	106.98	3.47	98.13	14.14	8.86	9.03%
BCI - 3	107.39	3.54	98.30	14.21	9.09	9.25%
BCI - 6	108.68	3.49	97.92	14.14	10.76	10.99%
BCI - 12	111.04	2.68	97.80	13.06	13.25	13.55%
Spread	0.15	0.01	0.14	0.02	0.01	6.41%
Consultant	0.26	0.44	0.25	0.43	0.01	2.56%
Stock	0.11	0.44	0.12	0.33	-0.02	-12.89%
Cross-border	0.47	0.50	0.53	0.50	-0.06	-10.52%
LogTA	3.65	0.90	3.75	0.96	-0.10	-2.77%
PB	3.48	11.76	13.65	166.36	-10.17	-74.50%
EBITDA	3,172.46	9,846.06	4,390.67	11,904.93	-1,218.21	-27.75%
Leverage	2.95	6.10	4.31	11.26	-1.36	-31.50%
TOBQ	1.84	1.49	3.72	41.20	-1.88	-50.59%
LogIBOV	4.82	0.03	4.72	0.07	0.09	2.01%
Basic materials	0.11	0.31	0.12	0.33	-0.01	-9.24%
Communications	0.03	0.18	0.08	0.26	-0.04	-56.80%
Consumer, cyclical	0.07	0.25	0.08	0.27	-0.01	-15.44%
Consumer, non-cyclical	0.28	0.45	0.26	0.44	0.02	8.79%
Diversified	0.00	0.06	0.02	0.12	-0.01	-78.40%
Energy	0.08	0.26	0.05	0.22	0.02	47.69%
Financial	0.03	0.16	0.05	0.22	-0.03	-49.98%
Real estate	0.15	0.36	0.10	0.31	0.05	46.93%
Industrial	0.13	0.34	0.09	0.29	0.04	45.39%
Technology	0.04	0.20	0.07	0.26	-0.03	-39.44%
Utilities	0.07	0.25	0.07	0.26	-0.01	-7.61%
Observations	306		727			

Source: Elaborated by the authors.

Off-wave transactions, in general, occur in periods of lower trust. The results for the variables spread and stock are different from what is predicted in the current literature – although the difference is not accentuated (Harford, 2005; Rhodes-Kropf & Viswanathan, 2004). Furthermore, price-to-book (PB) behaves differently than expected (Haleblian et al., 2012; Shleifer & Vishny, 2003). Tobin's Q is also smaller during waves, contrary to the literature (Jovanovic & Rousseau, 2002).

Analysis of results

The first stage of data analysis was the estimation of the models. Table 4 shows the estimation result for all models. Models I to VI represent the contemporary BCI, the BCI with one lag, two, three, six, and 12, respectively. The models were tested to capture the impact of the optimism effect over time. The model with robust standard errors was used as the logit model must assume heteroscedasticity (Gujarati & Porter, 2011; Wooldridge, 2006),

Table 4. Results of the estimated models:

Wave	I	II	III	IV	V	VI
Intercept	-209.30***	-204.80***	-201.84***	-199.35***	-192.55***	-165.66***
	(16.50)	(16.28)	(15.84)	(15.51)	(16.05)	(17.43)
BCI	0.12***	0.10***	0.09***	0.07***	0.07***	0.18***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)
Spread	35.25***	34.33***	30.93***	28.89***	24.02***	17.96***
	(6.175)	(6.16)	(5.99)	(5.87)	(5.55)	(6.23)
Consultant	0.18	0.09	0.04	0.00	0.03	-0.14
	(0.27)	(0.27)	(0.27)	(0.27)	(0.26)	(0.26)
Stock	-0.70*	-0.60*	-0.56	-0.60*	-0.78**	-0.74**
	(0.37)	(0.36)	(0.36)	(0.35)	(0.35)	(0.35)
Cross-border	0.21	0.21	0.18	0.16	0.19	0.27
	(0.24)	(0.24)	(0.23)	(0.23)	(0.23)	(0.23)
LogAT	-0.04	-0.04	-0.05	-0.06	-0.08	0.05
	(0.17)	(0.16)	(0.16)	(0.15)	(0.15)	(0.15)
Price-to-book	-0.01	-0.01	-0.01	0.00	0.00	-0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
EBITDA	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Leverage	-0.02	-0.02	-0.02	-0.02	-0.02	-0.01
	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)

Continue

Table 4. Results of the estimated models: Concludes

Wave	I	II	III	IV	V	VI
TOBQ	-0.06	-0.09	-0.10***	-0.10*	-0.09*	-0.07
	(0.05)	(0.06)	(0.06)	(0.06)	(0.05)	(0.05)
LogIBOV	40.11***	39.44***	39.24***	39.10***	37.94***	29.82***
	(3.42)	(3.38)	(3.30)	(3.26)	(3.46)	(3.71)
Basic Materials	-0.30	-0.01	0.20	0.29	0.23	0.52
	(0.48)	(0.47)	(0.47)	(0.48)	(0.46)	(0.45)
Communications	-0.53	-0.17	0.10	0.12	-0.13	-0.18
	(0.48)	(0.50)	(0.53)	(0.53)	(0.52)	(0.54)
Consumer, Cyclical	-0.13	0.15	0.32	0.37	0.27	0.60
	(0.49)	(0.48)	(0.49)	(0.50)	(0.49)	(0.50)
Consumer, Non-cyclical	0.03	0.33	0.49	0.55	0.43	0.69*
	(0.38)	(0.37)	(0.39)	(0.41)	(0.39)	(0.40)
Diversified	-2.76**	-2.41**	-2.13**	-1.99*	-1.97*	-2.28**
	(1.19)	(1.13)	(1.07)	(1.03)	(1.07)	(1.07)
Energy	0.57	0.96	1.20**	1.24**	1.11*	1.62***
	(0.66)	(0.65)	(0.64)	(0.63)	(0.60)	(0.56)
Financial	-0.71	-0.43	-0.23	-0.14	-0.21	0.15
	(0.69)	(0.66)	(0.67)	(0.66)	(0.62)	(0.61)
Real Estate	0.52	0.78*	0.96**	1.01**	0.84*	1.19**
	(0.47)	(0.47)	(0.48)	(0.48)	(0.46)	(0.47)
Industrial	0.34	0.61	0.80	0.87*	0.73	1.12**
	(0.47)	(0.47)	(0.49)	(0.49)	(0.47)	(0.48)
Technology	0.15	0.45	0.63	0.67	0.53	0.85
	(0.61)	(0.59)	(0.60)	(0.61)	(0.62)	(0.68)
Obs.	1,033	1,033	1,033	1,033	1,033	1,033
Pseudo R2	0.57	0.55	0.54	0.53	0.51	0.53
AIC	588,906	604,691	621,632	636,382	653,474	630,259
BIC	697,591	713,376	730,317	745,067	762,159	738,944
Wald test	280.19***	276.62***	286.71***	297.52***	324.25***	245.41***

*10% significance, **5% significance, and ***1% significance

Source: Elaborated by the authors.

Note: The model's coefficients are at the top. The standard errors are in brackets. The models I to IV correspond to the variable BCI contemporaneous and lags 1, 2, 3, 6, and 12, respectively. The variable of interest was significant in all lags. The control variables spread and logIBOV were also significant.

The results shown in Table 4 indicate that the independent variable BCI is significant and positive in all models. The finding is in line with the work of Gugler, Mueller, Weichselbaumer, and Yurtoglu (2012), who argue that optimism can lead to an M&A wave. For the authors, optimism leads managers to misvalue assets, i.e., based on the perspective of management theory, managers take advantage of this moment of euphoria and anticipate that the market will respond positively to M&A announcements. Thus, this research adopts P/E and spread as a proxy for optimism. From the agents' perception, it is possible to isolate the manager's perception concerning the current market and its future, especially in the Brazilian market, characterized by a smaller and more concentrated capital market.

The spread was significant in all models. Unlike what Harford (2005) points out, an increase in the spread is associated with a greater probability of an M&A wave. This phenomenon may occur because the Brazilian market has a large share of credit subsidized by the National Development Bank (BNDES). The spread included in the model excludes this type of credit operation. At the same time, periods of optimism are related to bull markets (Goel & Thakor, 2010), leading to periods of high-interest rates. As a result, the cost of credit may increase, and this phenomenon could be observed due to idiosyncrasies typical of the Brazilian market. Some studies use spread to measure optimism (e.g., Gugler, Mueller, Weichselbaumer, & Yurtoglu, 2012), but due to the aforementioned phenomenon, it might not be a good choice of proxy in the case of Brazil.

The stock variable proved to be significant in almost all models. It was only not significant at lag 2. The data show a negative impact, contrary to the international literature (Gugler, Mueller, Weichselbaumer, & Yurtoglu, 2012; Rhodes-Kropf & Viswanathan, 2004), although some studies point out that not all waves primarily use this form of payment (Andrade et al., 2001; Shleifer & Vishny, 2003). The fact that the Brazilian capital market is still small, composed of few companies, accessible only to larger firms, may explain the behavior of the variable in Table 2, which shows that only 12% of the transactions involved stocks, confirming the hypothesis.

Tobin's Q was significant and negative at lags 2, 3, and 6 (Table 3). Tobin's Q is high in the sample's off-wave period, contrary to the hypothesis raised by the M&A theory (Jovanovic & Rousseau, 2002). Perhaps companies with higher investment efficiency – Tobin's Q around 1 – are more likely to make acquisitions. The IBOV variable was significant, presenting a positive impact and pointing out that a larger market increases the probability of an M&A wave. This finding is in line with several empirical studies (Haleblian et al., 2012; Harford, 2005; Goel & Thakor, 2010; Rhodes-Kropf & Viswanathan, 2004; Shleifer & Vishny, 2003).

Looking at Pseudo R2 and the Akaike (AIC) and Bayesian Schwarz (BIC) information criteria, Model I is the best fit. Pseudo R2 demonstrated that this model has more predictive power than the others. Furthermore, when selecting models based on the likelihood ratio, both AIC and BIC suggest adopting Model I, which has a lower value for each criterion.

Although the lag of the variables is discussed, the BCI captures not only perceptions about the future but also the present. Thus, it is interesting that the only model that improves its fit is the model with 12 lags. Furthermore, the Wald test was significant in all models, indicating that the combination of variables is significant in explaining the probability of wave occurrence. Continuing the analysis of the models, Table 5 shows the predictive capacity of each one.

Table 5. Model's predictive power

	I	II	III	IV	V	VI
Total hit rate (%)	89.74%	88.87%	87.51%	86.83%	85.87%	88.00%
Positive hit rate (%)	84.01%	81.73%	78.46%	77.07%	75.16%	79.17%
Negative hit rate (%)	92.02%	91.80%	91.41%	91.10%	90.63%	91.82%

Source: Elaborated by the authors.

Note: Model I was the strongest model, where BCI is not lagged.

Model I had the highest prediction capacity, with an overall hit rate close to 90%, remaining above 80% even for positive hits where the dummy wave was equal to 1 (fewer observations). The predictive power of the models decreases when advancing the lag, especially the positive hits.

One of the disadvantages of logit concerning linear models is that the interpretation of its coefficients is not direct. Table 6 shows that the average marginal effect can be calculated for a precise understanding.

Table 6. Average marginal effect of the model's variables

Variables	I	II	III	IV	V	VI
BCI	0.008***	0.007***	0.006***	0.005***	0.005***	0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Spread	2.349***	2.311***	2.128***	2.053***	1.696***	0.826**
	(0.013)	(0.602)	(0.568)	(0.544)	(0.482)	(0.402)
Consultant	0.013	0.006	0.003	0.000	0.002	-0.006
	(0.020)	(0.019)	(0.019)	(0.019)	(0.019)	(0.011)
Stock	-0.038**	-0.034*	-0.033*	-0.035**	-0.043***	-0.027**
	(0.016)	(0.017)	(0.018)	(0.017)	(0.016)	(0.011)
Cross-border	0.014	0.014	0.012	0.011	0.014	0.012
	(0.016)	(0.016)	(0.016)	(0.017)	(0.017)	(0.011)
LogAT	-0.003	-0.003	-0.004	-0.005	-0.006	0.002
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.007)
PB	-0.001	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
EBITDA	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Leverage	-0.001	-0.001	-0.001	-0.001	-0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
TOBQ	-0.004	-0.006	-0.007*	-0.007*	-0.007*	-0.003
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)
LogIBOV	2.673***	2.655***	2.699***	2.778***	2.679***	1.371***
	(0.347)	(0.354)	(0.353)	(0.348)	(0.328)	(0.265)

*10% significance, **5% significance, and ***1% significance

Source: Elaborated by the authors.

Note: Although significant, the effect of the increase of one BCI unit slightly increases the probability of an M&A wave. On the other hand, the variable spread presents a more considerable increase, even though it is necessary to consider that the increase of one unit means an increase of 100% spread.

The effect of an extra unit on the BCI increases the probability of the wave happening by about 1%. The effect decreases as the lag increases and rises only in the last lag (Model VI). All models were significant. The spread was also significant in all models. An increase of one unit in this variable corresponds to an effect of 100% – for example, a 0.01 unit increase in the variable means a 2.35% increase in probability.

The use of stocks to finance the transaction decreases the probability of a wave happening by about 3.8%. The variable that most affects the probability of an M&A wave occurring is the IBOV. A 1% increase in the index increases the probability of a wave occurring by 2.67%.

CONCLUSION

This study investigated the relationship between the optimism of economic agents and M&A waves considering transactions involving Brazilian companies. This relationship is a promising research topic in the field, explored only by a limited number of researchers usually focused on developed markets (USA and UK mainly).

The study measured optimism using the Business Confidence Index (BCI), an index of market perception of the current and future situation of the economy (FGV, 2017?). The research findings are in line with studies that included optimism in the model (Goel & Thakor, 2010; Gugler, Mueller, & Weichselbaumer, 2012; Gugler, Mueller, Weichselbaumer, & Yurtoglu, 2012) but using a measure of perception. The study observed a positive and significant relationship between optimism and the probability of M&A waves. In addition, when lagging the variable that measures optimism by up to 12 periods, the positive and significant result remained despite the decrease in the effect over time.

The variables spread and IBOV, which measure the bank spread for corporate credit operations and variations in the Ibovespa index, respectively, had the most significant effect on the probabilities of an M&A wave. The spread had a negative effect, contrary to the current literature (Gugler, Mueller, Weichselbaumer, & Yurtoglu, 2012; Harford, 2005), which may have occurred since the data collected did not include subsidized credit operations – a phenomenon that needs further investigation. The market index maintains a positive relationship with the probability of a wave, as found by several other studies in other markets (Goel & Thakor, 2010; Gugler, Mueller, Weichselbaumer, & Yurtoglu, 2012; Harford, 2005; Rhodes-Kropf & Viswanathan, 2004; Xu, 2017).

The literature on M&A usually focuses on the North American market (Mager & Meyer-Fackler, 2017), especially in the case of M&A waves. This study is an effort to develop the literature on the subject considering emerging markets, conducting an empirical survey on the agents' perception of the economic environment and the likelihood of an M&A wave. Identifying an M&A wave to avoid transactions motivated by the agents' euphoria may be of interest to market agents since M&A tends to be value-destroying. Thus, it would be possible to improve the governance mechanisms for M&A transactions during these periods.

The limitations of this study include data scarcity, a problem that may be faced in other emerging markets, and the fact that the literature does not have a consolidated metric to define the M&A wave. This research intends to build literature on M&A waves for the Brazilian market and other less developed markets using different metrics, databases, and methodologies.

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REFERENCES

Andrade, G., Mitchell, M., & Stafford, E. (2001). New evidence and perspectives on mergers. *Journal of Economic Perspectives*, *24*(7), 2286-2315. doi: 10.1093/rfs/hhr014

Bao, J., Edmans, A. (2011). Do investment banks matter for M&A returns? *The Review of Financial Studies*, *15*(2), 103-120. doi: 10.1257/jep.15.2.103

Campbell, T. C., Gallmeyer, M., Johnson, S. A., Rutherford, J., & Stanley, B. W. (2011). CEO optimism and forced turnover. *Journal of Financial Economics*, *101*(3), 695-712. doi: 10.1016/j.jfineco.2011.03.004

Chaudhuri, A. R. (2014). Cross-border mergers and market segmentation. *The Journal of Industrial Economics*, *62*(2), 229-257. doi: 10.1111/joie.12047

Dessí, R., & Zhao, X. (2018). Overconfidence, stability and investments. *Journal of Economic Behavior & Organization*, *145*, 474-494. doi: 10.1016/j.jebo.2017.11.030

Duchin, R., & Schmidt, B. (2013). Riding the merger wave: Uncertainty, reduced monitoring, and bad acquisitions. *Journal of Financial Economics*, *107*(1), 69-88. doi: 10.1016/j.jfineco.2012.07.003

Fundação Getulio Vargas. [2017]. *Nota metodológica: Atualização de classificação setorial para CNAE 2.0 e revisão metodológica das sondagens empresariais do* IBRE/FGV. Retrieved from https://portalibre.fgv.br/sites/default/files/2020-03/nota-metodol_gica_portal-ibre_cnae-2-0.pdf

Gärtner, D. L., & Halbheer, D. (2009). Are there waves in merger activity after all? *International Journal of Industrial Organization*, *27*(6), 708-718. doi: 10.1016/j.ijindorg.2009.03.003

Goel, A. M., & Thakor, A. V. (2010). Do envious CEOs cause merger waves? *The Review of Financial Studies*, 23(2), 487-517. doi: 10.1093/rfs/hhp088

Gort, M. (1969). An economic disturbance theory of mergers. *The Quarterly Journal of Economics*, 83(4), 624-642. doi: 10.2307/1885453

Gorton, G., Kahl, M., & Rosen, R. J. (2009). Eat or be eaten: A theory of mergers and firm size. *The Journal of Finance*, *64*(3), 1291-1344. doi: 10.1111/j.1540-6261.2009.01465.x

Gugler, K., Mueller, D. C., & Weichselbaumer, M. (2012). The determinants of merger waves: An international perspective. *International Journal of Industrial Organization*, *30*(1), 1-15.doi: 10.1016/j.ijindorg.2011.04.006

Gugler, K., Mueller, D. C., Weichselbaumer, M., & Yurtoglu, B. B. (2012). Market optimism and merger waves. *Managerial and Decision Economics*, 33(3), 159-175. doi: 10.1002/mde.2542

Gujarati, D. N., & Porter, D. C. (2011). *Econometria básica*-5. Porto Alegre, RS: Amgh Editora.

Haleblian, J., McNamara, G., Kolev, K., & Dykes, B. J. (2012). Exploring firm characteristics that differentiate leaders from followers in industry merger waves: A competitive dynamics perspective. *Strategic Management Journal*, 33(9), 1037-1052. doi: 10.1002/smj.1961

Harford, J. (2005). What drives merger waves? *Journal of Financial Economics*, 77(3), 529-560. doi: 10.1016/j.jfineco.2004.05.004

Hermansson, C., Song, H S. (2016). Financial advisory services meetings and their impact on saving behavior: A difference-in-difference analysis. *Journal of Retailing and Consumer Services*, *30*, 131-139. doi: 10.1016/j.jretconser.2016.01.017

Hsu, K. C., Wright, M., & Zhu, Z. (2017). What motivates merger and acquisition activities in the upstream oil & gas sectors in the US? *Energy Economics*, *65*, 240-250. doi: 10.1016/j.eneco.2017.04.028

Jovanovic, B., & Rousseau, P. L. (2002). The Q-theory of mergers. *American Economic Review*, 92(2), 198-204. doi: 10.1257/000282802320189249

Lambrecht, B. M. (2004). The timing and terms of mergers motivated by economies of scale. *Journal of Financial Economics*, 72(1), 41-62. doi: 10.1016/j.jfineco.2003.09.002

Mager, F., & Meyer-Fackler, M. (2017). Mergers and acquisitions in Germany: 1981–2010. *Global Finance Journal*, *34*, 32-42. doi: 10.1016/j.jfineco.2017.03.004

Malmendier, U., & Tate, G. (2008). Who makes acquisitions? CEO overconfidence and the market's reaction. *Journal of Financial Economics*, *89*(1), 20-43. doi: 10.1016/j.jfineco.2007.07.002

Mitchell, M. L., & Mulherin, J. H. (1996). The impact of industry shocks on takeover and restructuring activity. *Journal of Financial Economics*, *41*(2), 193-229. doi: 10.1016/0304-405X(95)00860-H

Morck, R., Shleifer, A., & Vishny, R. W. (1990). Do managerial objectives drive bad acquisitions? *The Journal of Finance*, *45*(1), 31-48. doi: 10.1111/j.1540-6261.1990.tb05079.x

Nofsinger, J. R. (2005). Social mood and financial economics. *The Journal of Behavioral Finance*, *6*(3), 144-160. doi: 10.1207/s15427579jpfm0603_4

Rao-Nicholson, R., Salaber, J., & Cao, T. H. (2016). Long-term performance of mergers and acquisitions in ASEAN countries. *Research in International Business and Finance*, *36*, 373-387. doi: 10.1016/j.ribaf.2015.09.024

Rhodes-Kropf, M., Robinson, D. T., & Viswanathan, S. (2005). Valuation waves and merger activity: The empirical evidence. *Journal of Financial Economics*, 77(3), 561-603. doi: 10.1016/j.jfineco.2004.06.015

Rhodes-Kropf, M., & Viswanathan, S. (2004). Market valuation and merger waves. *The Journal of Finance*, 59(6), 2685-2718. doi: 10.1111/j.1540-6261.2004.00713.x

Rodrigues, V. (2014). Restructuring and merger waves. *International Journal of Economic Theory*, *10*(4), 355-369. doi: doi.org/10.1111/ijet.12044~

Roll, R. (1986). The hubris hypothesis of corporate takeovers. *Journal of Business*, *59*(2), 197-216. doi: 0021-9398/86/5902-0001

Shleifer, A., & Vishny, R. W. (2003). Stock market driven acquisitions. *Journal of Financial Economics*, *70*(3), 295-311. doi: 0.1016/S0304-405X(03)00211-3

Town, R. J. (1992). Merger waves and the structure of merger and acquisition time-series. *Journal of Applied Econometrics*, 7(S1), S83-S100. doi: 10.1002/jae.3950070507

Triantafyllopoulos, Y., & Mpourletidis, K. (2014). Mergers and acquisitions and economic crisis: A case study approach from a qualitative analysis in Greece. *Procedia-Social and Behavioral Sciences*, *148*, 437-445. doi: 10.1016/j.sbspro.2014.07.063

Uddin, M., & Boateng, A. (2011). Explaining the trends in the UK cross-border mergers & acquisitions: An analysis of macro-economic factors. *International Business Review*, *20*(5), 547-556. doi: 10.1016/j.ibusrev.2010.11.003

Wooldridge, J. M. (2006). *Introdução à econometria: Uma abordagem moderna*. São Paulo, SP: Pioneira Thomson Learning.

Xu, E. Q. (2017). Cross-border merger waves. *Journal of Corporate Finance*, *46*, 207-231. doi: 10.1016/j.jcorpfin.2017.07.004

AUTHOR'S CONTRIBUTION

Rodrigo Raposo da Fonseca: Project Management; Formal Analysis; conceptualization; Data Curation; Writing – First Writing; Writing – Proofreading and Editing; Investigation; Methodology; Software; Supervision; Validation; visualization.

Vinicio de Souza e Almeida: Project Management; Formal Analysis; conceptualization; Writing – First Writing; Writing – Proofreading and Editing; Methodology; Supervision; Validation; visualization.