The Impact of Deal Frequency and Acquisition Blocks on Bidder Performance

An Analysis of European Deals

Abstract: This study investigates the performance of serial acquirers, with a particular focus on how differences in acquisition strategies influence announcement returns. It integrates Morillon's (2021) bidder classification: *loners*, *occasional*, *joggers*, *sprinters*, and *marathoners*. We analysed the frequency of deals and whether these deals are clustered in blocks. The sample is unique as it focuses on the European market rather than the US market. It includes 928 acquirers which in total undertook 3,961 acquisitions in twelve countries and forty-one industries across 20 years, from 2000 to 2019. We conducted an event study that measured performance through cumulative abnormal returns. Contrary to US studies by Morillon (2021) and Macias et al. (2023), our findings indicate that the most frequent and continuous bidders in Europe are not immune to declining announcement returns. We also found that acquirers which do three or more deals quickly after each other are likely to face declining results. This is not the case for more selective acquirer which undertake two acquisitions in a block. Further, we examined the influence of growth, overvaluation, payment method, and cash position on deal performance. Our findings contribute to the literature on M&A by distinguishing types of bidders instead of investigating the performance of serial acquirers in general. Additionally, it investigates factors such as acquisitiveness and bidder characteristics. For practice, it offers insights, highlighting the importance of careful planning and resource allocation.

Keywords: Acquisition Blocks, Bidder Classification, Bidder Returns, Deal Frequency, Serial Acquirers

Lund University | Department of Business Administration
BUSN79 | Degree project in Accounting and Finance
Group 14
May 2024

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Word count: 11,087 (without appendix and tables)

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1. Introduction

Despite the extensive finance research investigating M&A, the factors determining deals' success are poorly understood (Renneboog & Vansteenkiste, 2019). There is also no consensus as to whether deals add value for acquirers. Research illustrated that after the financial crisis, M&A deals were no longer value-destroying as abnormal returns turned positive (Alexandridis et al., 2017). Moreover, Bain & Company noted that frequent acquirers outperformed single acquirers by 130% from 2012 to 2022 (Harding et al., 2024, April 8). These findings contrast with a larger body of research that suggests that M&A is generally deteriorating value (Renneboog & Vansteenkiste, 2019). Rehm et al. (2012) provide another perspective, stating that the deal strategy of acquirers influences announcement returns. For instance, large deals involve more risks and returns are relatively low. In fact, firms are generally better at handling multiple smaller deals rather than one or few large deals (Harding et al., 2024, April 8).

Although one in every five acquirers is a serial acquirer, the literature on the performance is scare (Karolyi et al., 2015). According to Renneboog & Vansteenkiste (2019), returns gradually decline with subsequent deals. Hence, it could be insightful to study M&A strategies and distinguish between bidders. An initial step was undertaken by Macias et al. (2016) who clustered acquirers into several distinct types. The study showed that given this classification, the acquirers' declining return phenomenon is not homogeneous for the US sample. The most frequent serial acquirers do not earn declining returns as they continue acquiring, while less frequent acquirers do. This could be explained by the reducation of integration costs in an acquistion series compared to a single or few acquisitions (Zhang, 2021). So, among the serial acquirers there is a set of companies that continuously keep acquiring. Additionally, there are bidders that buy in waves, which is one of the most unsolved questions in finance due to its complexity (Brealey et al., 2023).

Considering the findings of Alexandris et al. (2017) that announcement returns do not apply for the most frequent acquirers, makes it relevant to investigate the role of the bidder characteristics. We fill this gap by testing whether firm characteristics of different types of acquirers affect the performance and take the bidder classification from Macias, et al. (2016) as a starting point. The main research question is formulated as follows: *'How does serial acquirers' buying strategy, in terms of deal frequency and acquisitions blocks, affect the performance?'*. Deal frequency concerns the total amount of deals of one acquirer within a certain time. Blocks are transactions that happen within 365 days from one another are therefore clustered in the same acquisition block. We extend our question by also shedding light on additional factors that could explain the deal performance. According to Renneboog and Vansteenkiste (2019), overarching topics include bidder's and target's acquisitiveness, managerial quality and relatedness. Similarly, Macias et al. (2023) suggest that future research could investigate acquirer classification further by integrating other acquirer characteristics, CEO-related events, and industry dynamics. Based on an extensive literature study we integrate the following factors: growth, overvaluation, payment method and cash position. In this way, we include industry and acquirer characteristics to enlarge the understanding of bidding returns. This leads to the second research question: '*What is the role of the factors* growth, *overvaluation, payment method and cash position in serial acquirer deal performance?'*

Our paper contributes to the M&A literature by studying the performance of the most frequent and continuous acquirers, indicating whether they have superior integration skills. Furthermore, our study adds value by further investigating returns within acquisition blocks. It is unique as we analysed Continental European firms rather than US companies. Our study employs a data set of 3,961 deals undertaken by 928 unique acquirers, with announcement dates from 2000 to 2019. We used the Capital IQ and MSCI database to obtain data for European bidders and targets. In the next section, we provide background information about M&A performance in general and afterwards shift focus to serial acquirer performance.

2. Literature review

2.1 M&A performance

Mergers and acquisitions are assumed to contribute to growth of companies on top of their organic growth. Deals could enhance value by consolidation and providing access to new customers and products. The performance of M&A has been extensively studied and the results are ambiguous between a value-adding or destructive nature of deals. It can be concluded that M&A performance is negative to at best slightly positive in both in the short and the long run. The next two paragraphs give background information about M&A performance in general for short and long-term studies. As there is evidence that the deal frequency affects the performance of the deals (Mulherin et al., 2017), we will then introduce serial acquirers.

2.2 Short-term studies

The initial, and largest, flow of literature measured short-term performance by focusing on the deal announcement effect (Renneboog & Vansteenkiste, 2019). By observing a short event window, which is usually not more than 10 days, the stock reaction is triggered by the announcement and is not very sensitive to long-term trends and structural industry changes (Nain & Wang, 2018). This entails that stock price changes reflect the market assessment about the value of the deal. Benefiting from a stronger bargaining positions, targets generally have a stronger announcement effect than bidders (Renneboog & Vansteenkiste, 2019). Hence, targets capture most of synergy value at the cost of acquirers. In fact, the bidder returns are negative or close to zero and decreased threefold from 1992 to 2009 (Netter et al., 2011). Likewise, Martynova and Renneboog (2011) demonstrated a 0.53% abnormal return for bidders in Europe and the UK in the 1990s. Another study reported a loss of 1.6 cents per dollar around the deal announcement from 1980 until 2001 (Moeller et al., 2005). These findings illustrate the results in the field as the vast majority of research on takeover announcements demonstrate zero or negative returns (Renneboog & Vansteenkiste, 2019). In fact, a meta-analysis examined 33 empirical studies and found that merely 47.6% of deals have positive announcement returns (Meckl & Röhrle, 2016). Interestingly, after 2009 abnormal returns became positive with an average return of 1.05% (Alexandridis et al., 2017). It is suggested that this is the result of improvements in corporate governance following the financial crisis. It is noteworthy that in this study the majority of deals adds value (54%), which is a strong improvement compared to 39% in the 1990s. The results confirm an earlier study of Cai et al. (2011) which concluded that bidding is on average creating more value for the bidder's shareholders. Moreover, a study to returns in Central and Eastern European countries found that acquiring companies obtain positive returns (Zaremba & Płotnicki, 2016).

For bidders, the ownership of the target is also relevant for deal success. The literature stream showcases negative announcement returns for acquirers of public targets (Mulherin et al., 2017). That is because information about these companies is widely available. As there is less information available about private targets, they are less liquid compared to public targets. As a result, bidders reap the liquidity discount when they acquire these companies (Fuller et al., 2002; Hazelkorn et al., 2004). These conclusions are mitigated, however, by Cai et al. (2011) who reported positive announcement effects also for acquiring public companies.

2.3 Long-term studies

Another set of studies looked at the stock reaction in the long run. In this case the event window is enlarged up to several years. A technical complexity of this approach is that it is difficult to ascribe an event, such as an announcement, to the stock reaction as there are more events and trends influencing the stock price. Fama (1998) suggests, however, that in the long-term the stock market is efficient and under- and overreactions will balance out each other. This efficiency argument is debated and adjustments to the methodology could be required to cope with temporary misvaluations (Loughran & Ritter, 2000). Attempts to adapt the method result in a view in which stock prices tend to decline, meaning that synergies are commonly overestimated (Andrade et al., 2001). In settings with a longer timeframe, the returns are often significantly negative for bidders (Renneboog & Vansteenkiste, 2019), or they at least do not significantly differ from zero (Bessembinder & Zhang, 2013). King et al. (2004) found empirical evidence that on average the abnormal returns start declining 22 days after the announcement. Thereby, the researchers conclude that the return moves towards zero or becomes negative. A widely accepted clarification for this negative performance is that the market initially overestimates the synergies, but gradually adjusts as more information becomes available (Renneboog & Vansteenkiste, 2019).

2.4 Defining serial acquirers

Opposite to one-time or single acquirers, there are serial acquirers. These are sometimes also referred to as frequent or multiple acquirers. Serial acquirers form a significant part of all bidders involved in acquisitions. In the US, for example, serial acquirers accounted for approximately 75% of all acquisitions (Macias et al., 2023). Therefore, it is relevant to understand the motives of these bidders. The finance literature, however, is developing and struggled in defining the concept (Renneboog & Vansteenkiste, 2019). That is because there is debate as to how many deals should be undertaken to be considered a serial acquirer. An initial study in the field by Fuller, et al. (2002) took five acquisitions within three years as the threshold to become a serial acquirer. A later study from Karolyi, et al. (2015) followed this definition. Nevertheless, there are other studies which use different approaches, such as more than two acquisition over a three or five year period (Billett & Qian, 2008). In the current study we follow the dominant literature steam and take the threshold of five acquisitions to define serial acquirers. This is also consistent with the study of Morillon (2020), which forms the foundation of the classification we use in our analysis. The threshold of five deals has the counterintuitive implication that companies with two until four acquisitions in the sample period are also considered 'single acquirers'. It is more logical, however, when one considers that these acquisitions happen only *occasional*ly during the sample period, so there can be years in between the deals.

If firms are doing multiple bids, it is expected that returns for later deals are lower than for the initial acquisitions (Fuller et al., 2002). That is because less anticipated announcements earn higher returns (Cai et al., 2011). If the market is surprised by the bid, the stock reaction is stronger. Thus, the later bids fail to surprise the market. To consider the bidding strategies of bidders, the next paragraph elaborates on bidding classifications.

2.5 Classifying acquirers

A complicating factor for serial acquirers is that companies usually acquire in 'blocks'. That means that they acquire multiple companies within a specific timeframe and remain inactive for a period thereafter. Most studies look at the number of deals rather than the acquiring waves (Morillon, 2021). Consequently, acquisition patterns are neglected within these studies. Macias, et al. (2016) aimed to overcome this by looking beyond the number of acquisitions. The study also incorporated the number of acquisitions blocks and the intensity of these blocks. The latter can be understood as the number of deals within a block. A cluster analysis by Macias et al. (2016) led to a classification of bidders based on their acquisition patterns and was refined by Morillon (2021). Rehm et al. (2012) provide an alternative classification, which incorporates the number of deals and the deal size. However, the sample consisted of the world's top1000 companies and they were not empirically tested. The studies of Macias et al. (2016) and Morillon (2021), on the other hand, checked if different benchmarks for the bidder types would influence their results. The classification compiles: *loners, occasional acquirers, sprinters, and marathoners*. *Loners* are companies which are involved in one acquisition during the sample period. Interestingly, *occasional* acquirers are also considered to be single acquirers in the literature. This type of bidder is involved in two until four deals during the sample period. As sample periods could range from about 10 to 37 years (Fuller et al., 2002; Macias et al., 2023; Morillon, 2021), these companies undertake on average less than one acquisition per year. The literature defines companies differently when they are involved in more than five acquisitions during the sample period. These companies are referred to as multiple or serial acquirers. Macias et al. (2016) distinguished between the *sprinter* and the *marathoner*. The unique aspect of *sprinters* is that they are buying in waves. This could be for strategic reasons, but they could also take advantage of market sentiment. The sample should include at least one block with three or more deals. *Marathoners*, on the other hand, continuously acquire targets and have a focus on the long term. They have more than 20 deals during the total period. An extension was provided by Morillon (2021) who added the *jogger*, which is a more selective bidder compared to the *sprinter*. This type acquirers in smaller chunks and never has more than two deals in one block.

Thus, the scale ranges from single to the most frequent acquirers (see Table 1).

Table 1. Bidder classification

Type	*Description*	*Requirements*
Single acquirers		
Loner	Single acquirers	1 acquisition in total period
Occasional acquirer	Few deals	2-4 acquisitions in total period
Serial acquirers		
Jogger	Active, but selective bidders that do not buy in chunks	≥ 5 deals in total period and ≤ 2 deals per block
Sprinter	Bidders that acquire quickly and in chunks	≥ 5 deals in total period and ≥ 3 deals in at least one block
Marathoner	Firms that continuously acquire other companies	≥ 20 deals in total period

3. Hypotheses development

3.1 Superior performance of marathoners

When companies increase their acquisitiveness the short and long-term performance declines (Renneboog & Vansteenkiste, 2019). That means that with each additional acquisition, the impact on the stock price diminishes. The effect is stronger when the investors are from countries with poor corporate governance or when investor protection is weak (Boubakri et al., 2012; Karolyi et al., 2015). By examining serial acquirer performance, Karolyi et al. (2015) and Boubakri et al. (2012) found that announcement returns are significantly lower after the fifth acquisition because the market anticipates the deals. Morillon (2021) and Macias et al. (2023) provide nuances to the idea that serial acquirers face declining performance. The authors suggest that the most frequent acquirers are not subject to deteriorating performance, while less frequent bidders are. There is actually a set of serial acquirers that persistently perform above average and generate value by doing deals (Golubov et al., 2015). That could justify the ongoing acquisitions by large companies. As a matter of fact, the world's largest companies are continuously acquiring and integrating new targets, indicating that they might have developed superior skills for M&A (Rehm et al., 2012, January 1). A study from Bain & Company found that frequent acquirers understand that several small acquisitions are less risky than one big deal (Harding et al., 2024, April 8). Furthermore, they combine M&A strategy with solid integration planning. The results imply that this category of companies is immune to declining returns following bid announcements.

Hypothesis 1: *Marathoners are exempt from declining returns as they are undertaking more deals*.

3.2 Performance within acquisition blocks

The performance outlooks, which are in general pointing towards decreasing performance, naturally bring forwards the question of why companies would initiate acquisition waves. Zhang et al. (2021) provide the argument that serial acquirers outperform single acquirers as their acquisitiveness results in lower integration costs. That is because they can carry out a strategic integration plan and take advantage of learning and scope. They also propose that, with an increasing number of acquisitions in a block, there is a point where the acquirer lacks resources for the integration process, so it becomes problematic and expensive. This results in disappointing performance of the latest deals, which marks the point where an acquisition series ends. It is logical that these companies tempered their acquisition style (Macias et al., 2023). After a wave of deals they wait until new seemingly profitable opportunities arise rather than following a continuous M&A strategy. For this kind of block acquirers, Morillon (2021) provides additional insights by stating that performance decline is not linearly with each acquisition. Rather, they found that decline occurs within blocks. This effect is the strongest for companies which buy several companies shortly after each other. This finding corroborates the integration costs argument of Zhang et al. (2021). Thus, as further acquisitions cannot count on positive announcement returns, it is not rational to pursue an acquisition strategy for these firms. In sum, when companies acquire in blocks, the performance is likely to worsen by every deal during the wave.

Hypothesis 2: *Returns within blocks (for joggers and sprinters) are likely to decline.*

3.3 Influence of acquirer growth rate

3.3.1 Industry is characterised by growth

The announcement returns after a bid are influenced by factors such as the internal growth (Renneboog & Vansteenkiste, 2019). Interestingly, a study to the world’s 1000 largest companies’ deals illustrated that deals in fast-growing sectors underperformed relative to deals in mature industries (Rehm et al., 2012, January 1). This is in line with the statement that M&A success for acquirers varies based on the industry (Kiymaz & Baker, 2008). Because growth is an important characteristic of industries, it seems intuitively logical that sector growth influences announcement returns. In the study of Rehm et al (2012) a sector was considered to be fast-growing when the annual growth was above 7%. In contrast, deals in fast-growing industries have a stronger disrupting effect on the acquirer. The deal motives are often related to product extension and innovation. Other than for stable markets the integration risk can be more prudent in rapidly growing markets. This could be problematic as an higher ex ante estimated integration risk leads to lower abnormal returns (Hoberg & Phillips, 2018). This can be overcome when the bidder is doing extensive due diligence and developed integration capabilities (Harding et al., 2024, April 8).

3.3.2 Impact of acquirer growth

The most frequent acquirers are assumed to have developed better capabilities and run a more planned M&A strategy (Rehm et al., 2012, January 1). If these companies have high growth rates, they are in a strong position to identify low-growth targets and improve these companies (Liu & Tu, 2023). This study by Liu and Tu (2023) examined market reactions at bid announcements for different levels of earnings growth and found that fast-growing acquirers have significantly better returns. It further suggested a U-shaped pattern for the relationship between earnings growth and announcement returns. This indicates that market reactions are strongly positive for bidders with earnings decline or those with significant growth. The reaction is positive for bidders with earnings decline as the deal gives potential for improvement. However, in the long term, these returns become negative as the speculated synergy often fails to materialise. This is not the case for the returns for companies with high initial earnings growth as they have ongoing growth. (Liu & Tu, 2023). The companies with a moderate earnings growth face the lowest returns. This can be computed in the through of the U-shape. The approach of Lui and Tu (2023) is different from the study of Rehm et al. (2012) as the former used acquirer earnings growth and the latter industry growth. Yet, there is little research to the effect of the growth of individual companies on returns. The current study aims to enhance this by testing the effect of acquirer growth on performance. As growth demands availability of resources we assume that integration capabilities are even more important for fast-growing firms. As we proposed that *marathoners* have developed these to a greater extent than *joggers* and *sprinters*, we expect *marathoners* to outperform these types.

Hypothesis 3a: *High-growth joggers and sprinters generally face declining returns, while marathoners with high growth have stable or positive returns.*

3.4 The exacerbating effect of overvaluation

Industries characterised by fast growth are known for relatively high valuations. There could even be overvaluation when the market is too optimistic. This entails that a company is overvalued when the stock price exceeds the underlying value. Companies acquiring in markets with high valuations, are less likely to capture abnormal returns (Rehm et al., 2012, January 1). Yet, there are still deals in highly valued markets. A possible explanation for this is that prior successes put pressure on the management to keep acquiring to create an illusion of growth (Jensen, 2005). This effect is strengthened by high market valuations because bidders want to take advantage of their stock value by acquiring undervalued targets (Van Bekkum et al., 2011). In this situation they aim to use the momentum if they expect their own value to decrease in the future. Hence, the overvaluation creates time pressure for the management to make deals. Another argument is that firms are willing to pay more if their own growth prospects are expected to deteriorate, while the target offers higher growth potential (Ismail, 2011). In this way, the company hopes to improve its outlook. It could be that investors are critical towards these deals because the acquisitiveness signals low confidence in the bidder's organic growth. Ismail (2011) also found that expected synergies have no relationship with the premium paid by the bidder. Therefore, investors cannot rely on the synergy analysis to accurately estimate the value. This leaves room for managers to be overoptimistic and make investors more reluctant towards deals. As overvaluation comes together with uncertainty about market developments, we expect it to impact the relationship between growth and performance negatively. Studying this matter is important to extend the knowledge about the role of overvaluation in M&A activities (Van Bekkum et al., 2011). Moreover, it could provide insights in historical stock market booms, such as the 'dot-com bubble'.

Hypothesis 3b: *Overvaluation exacerbates the value destruction of fast-growing serial acquirers.*

3.5 Overvaluation and equity deals

Studies to the 'misvaluation hypothesis' found evidence for the negative announcement returns when stocks were used to buy targets (Martynova & Renneboog, 2011). According to this hypothesis bidders acquire with their own stock in good times and use stock in times their own equity is undervalued (Shleifer & Vishny). The idea behind this is that an equity deal could signal that management considers its own shares to be overvalued (Hazelkorn et al., 2004; Myers & Majluf, 1984). Consequently, by acquiring an undervalued target the management can replace its own overvalued equity. As such, shareholder value can be created because overvalued equity is allocated to buy other assets at an effective discount (Savor & Lu, 2009; Vagenas-Nanos, 2020). Following the announcement, rational investors adjust the bidder's stock price because they notice that the management might find its own shares overvalued. Cash acquisitions, on the other hand, signal undervaluation of the company's own equity and the sufficient availability of profitable projects. The markets tend to reward these acquisitions with positive announcement returns.

Contrary to the misvaluation hypothesis stock-for-stock deals no longer impose negative market reactions (Alexandridis et al., 2017; Cai et al., 2011). Hence, there could be additional reasons which explain to success of stock deals. One plausible explanation is that serial acquirers adjust the payment method for each specific deal (Macias et al., 2012). In this way, the bidders can incorporate factors such as market conditions. For instance, they increase acquisitiveness and equity deals when they are overvalued (Macias et al., 2012). That is because growth opportunities result in higher stock valuations and these make cash payments unpopular (Yang et al., 2019). The target overvaluation does not play a role in this matter (Macias et al., 2012). This strategic bidding is unique to serial acquirer as single bidders generally stick to cash payments. The market initially reacts positively to stock deals which triggers companies to increase acquisition speed to take further advantage of the overvaluation (Macias, Raghavendra, et al., 2016). Eventually, the market corrects overvaluation and deals returns turn negative. Therefore, we expect that within blocks the initial equity deals are more successful than the later equity deals. The market initially reacts positive to stock deals which triggers companies to increase acquisition speed to take further advantage of the overvaluation (Macias, Raghavendra, et al., 2016). Eventually, the market corrects overvaluation and deals returns turn negative. Therefore, we expect that within blocks the initial equity deals are more successful than the later equity deals.

Hypothesis 4: *Announcement returns are positive when serial acquirers are overvalued and finance deals with stock payments, but later stock deals in a block reap negative returns.*

3.6 Impact of cash position of performance

While the payment method may reflect future growth opportunities, the cash position is informative to assess a firm's direct expansion possibilities. An illustrative situation for this is when a firm is financially constrained. In this scenario, the management probably fails to execute the strategy and do the required investments. However, when such a constrained company gets acquired by a liquid firm, the cash holdings improve and its investments become more stable (Erel et al., 2015). A strong cash position of the bidder gives it a strong position to look out for targets. The bidder could either benefit from improving their target's financial situation or from synergies. Companies with higher cash holdings tend to undertake more deals as they can rely more on internal financing (Isil et al., 2017). This is especially true in poor macroeconomic conditions. That is because financing costs are higher in these times and with cash holdings firms are less reliant on financers. In fact, by using internal funds they do not have to reject profitable opportunities and they can move on with the most promising deals. The downside of the strong liquidity is that in good economic times there might be too many funds to invest, which makes firms less selective, resulting in overinvestment. In conclusion, with higher cash holdings companies can be more acquisitive which leads to worse returns in good economic times than in bad economic times. On average, these effects balance each other out, but the study of Isil et al. (2017) found evidence for slightly decreasing announcement returns. Shifting from financing theories to the agency perspective, it can be stated that cash-rich firms are more likely to pursue acquisitions than firms with weaker cash positions. This is in because the cash flow hypothesis from Jensen (1986) suggests that shareholders prefer to limit excess cash. A way to switch cash for other assets is to buy other companies. Cash-rich companies are involved in more acquisitions than their counterparts (Yang et al., 2019). In the end, this destroys value as the majority of studies indicates negative or insignificant announcement returns for M&A. In sum, different perspectives suggest that strong cash positions negatively affect announcement returns. Therefore, we expect that liquidity is inversely related to announcement returns for all serial acquirers.

Hypothesis 5: *Serial acquirers with strong cash positions are more likely to have declining announcement returns.*

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4. Data collection, description, and sample

The sample came from two different sources: Capital IQ and the MSCI index. We used the latter database to collect the market data around the M&A transaction announcement and for the estimation window, while Capital IQ provided us with all the information regarding the acquirers: details about the deal, historical financial data, and stock returns.

The sample was initially comprised of 9,728 observations with 1,876 unique acquirers, spanning from 01/01/2000 to 31/12/2019 from the European market. This means that both the bidders and targets are European companies. In line with the previous literature (Agrawal et al., 1992; Fuller et al., 2002), we set six restrictions: (1) deals are closed, (2) the target status is either public or private, (3) the acquirer owns a majority stake of the target firm after the transaction, and (4) the security type is common equity. With the introduction of restriction (3), the number of observations decreased to 7,380; and with the introduction of restriction (4), the number of observations was equal to 5,785 with 1,495 unique acquirers. Moreover, we further shrank our sample given the availability of data; if acquirers did not have available stock data for the estimation window, their transactions were excluded (5). With the introduction of restriction (5), the number of observations was 4,471 with 1,074 unique acquirers. Lastly, following Macias et al. (2023), we excluded acquirers that belong to the finance industry (6) (Fama-French 48 industry classification, codes from 44 to 47). Therefore, the final sample is comprised of 3,961 observations for 928 unique acquirers.

In Table 2 panel A, we present a breakdown of the sample by acquirer categories, as defined in Table 1. Column two illustrates the number and the percentage of unique acquirers per category. Serial acquirers represent 29.16% of the sample; however, as shown in column seven, they are responsible for 67.07% of the total transactions in the sample. Most of the acquirers in the European market are single acquirers; these findings are comparable to the ones presented by Morillon (2021) about the American market for the period 1979-2016, although his sample was about ten times larger.

In Table 2 panel B, it is possible to observe a breakdown of the acquirers' distribution by category across location. The European market analyzed is comprised of 19 countries: however, in only 12 countries did transactions occur. Most of the acquirers are from Germany, France, and Italy, which in total account for 63.67% of the sample.

In Table 2 panel C, it is possible to observe a breakdown of the acquirers' distribution by category across industries. Following Macias, Raghavendra, et al. (2016) example, we employ the Fama-French industry categorization, which groups the SIC codes in 48 industries. The largest industry present in the sample is *Business services* (16.56%), while the other industries are represented similarly.

Table 2, Panel A.

This table describes the distribution of the acquirer types and their acquisition across the sample. Moreover, it highlights the following variables per acquirer within their type: number of acquisitions, number of blocks, and block intensity. Lastly, it presents an overview of said variables for the grouping of serial acquirers and for the total sample.

Category	No. of acquirers (%)	Variable	Min	Mean	Max	No. of acquisitions (%)
(1) *Loner*	305	No. of acquisitions	1	1	1	305
	(32.87)	No. of blocks	1	1	1	(7.70)
		Block intensity	1	1	1	
(2) *Occasional*	341	No. of acquisitions	2	2.944	4	926
	(36.75)	No. of blocks	1	2.367	4	(13.38)
		Block intensity	1	1.421	4	
(3) *Jogger*	194	No. of acquisitions	5	8.641	19	1149
	(20.91)	No. of blocks	2	5.092	9	(29.10)
		Block intensity	1	1.393	2	
(4) *Sprinter*	71	No. of acquisitions	5	11.399	19	1112
	(7.65)	No. of blocks	1	4.331	9	(28.27)
		Block intensity	3	5.279	17	
(5) *Marathoner*	17	No. of acquisitions	20	29.115	41	469
	(1.83)	No. of blocks	2	5.866	8	(11.84)
		Block intensity	1	11.546	34	
Total serial	282	No. of acquisitions	5	13.282	41	2730
(3+4+5)	(30.39)	No. of blocks	1	4.915	9	(68.92)
		Block intensity	1	4.72	34	
Total	928	No. of acquisitions	1	9.458	41	3961
(1+2+3+4+5)	(100)	No. of blocks	1	3.950	9	(100)
		Block intensity	1	3.496	34	

Panel B.
This table illustrates the distribution of the acquirer types across the locations of our sample. The first row has *frequencies,* and the second row has *row percentages.*

	Austria	Belgium	Cyprus	France	Germany	Greece	Ireland	Italy	Luxembourg	Netherlands	Portugal	Spain
Loner	7	19	5	92	79	27	12	52	8	21	12	26
	1.94	5.28	1.39	25.56	21.94	7.50	3.33	14.44	2.22	5.83	3.33	7.22
Occasional	20	22	5	96	114	19	13	48	6	22	7	38
	4.88	5.37	1.22	23.41	27.80	4.63	3.17	11.71	1.46	5.37	1.71	9.27
Jogger	8	13	0	69	51	5	9	29	3	15	2	19
	3.59	5.83	0.00	30.94	22.87	2.24	4.04	13.00	1.35	6.73	0.90	8.52
Sprinter	2	4	0	28	15	1	1	10	0	4	2	10
	2.60	5.19	0.00	36.36	19.48	1.30	1.30	12.99	0.00	5.19	2.60	12.99
Marathoner	0	2	0	4	5	0	2	0	1	3	0	0
	0.00	11.76	0.00	23.53	29.41	0.00	11.76	0.00	5.88	17.65	0.00	0.00
Total	37	60	10	289	264	52	37	139	18	65	23	93
	3.40	5.52	0.92	26.59	24.29	4.78	3.40	12.79	1.66	5.98	2.12	8.56

Panel C.
This table illustrates the distribution of the acquirer types across the industries of our sample. The first row has *frequencies,* and the second row has *row percentages.*

	Agriculture	Food products	Candy & Soda	Beer & Liquor	Recreation	Amusement	Books	Consumer goods	Apparel	Healthcare	Medical equipment	Pharma
Loner	1	8	0	6	3	11	7	6	9	4	7	20
	1.22	9.76	0.00	7.32	3.66	13.41	8.54	7.32	10.98	4.88	8.54	24.39
Occasional	2	10	1	3	0	6	4	10	5	3	3	16
	3.17	15.87	1.59	4.76	0.00	9.52	6.35	15.87	7.94	4.76	4.76	25.40
Jogger	0	5	0	5	0	5	2	3	3	0	4	6
	0.00	15.15	0.00	15.15	0.00	15.15	6.06	9.09	9.09	0.00	12.12	18.18
Sprinter	0	1	0	0	0	0	1	2	0	3	1	0
	0.00	12.50	0.00	0.00	0.00	0.00	12.50	25.00	0.00	37.50	12.50	0.00
Marathoner	0	0	0	0	0	0	1	0	1	0	0	0
	0.00	0.00	0.00	0.00	0.00	0.00	50.00	0.00	50.00	0.00	0.00	0.00
Total	3	24	1	14	3	22	15	21	18	10	15	42
	0.28	2.21	0.09	1.29	0.28	2.02	1.38	1.93	1.66	0.92	1.38	3.86

Continues

	Chemicals	Plastic products	Textiles	Construction materials	Construction	Steel	Fabricated products	Machinery	Electrical	Cars	Aircraft	Ship building
Loner	7	2	3	10	9	5	1	14	7	7	2	4
	9.86	2.82	4.23	14.08	12.68	7.04	1.41	19.72	9.86	9.86	2.82	5.63
Occasional	7	9	3	7	15	10	1	23	5	9	2	1

	7.61	9.78	3.26	7.61	16.30	10.87	1.09	25.00	5.43	9.78	2.17	1.09
Jogger	9	2	0	6	4	3	0	10	4	4	1	1
	20.45	4.55	0.00	13.64	9.09	6.82	0.00	22.73	9.09	9.09	2.27	2.27
Sprinter	0	1	0	2	8	0	0	4	2	3	1	0
	0.00	4.76	0.00	9.52	38.10	0.00	0.00	19.05	9.52	14.29	4.76	0.00
Marathoner	0	0	0	2	1	1	0	0	0	0	0	0
	0.00	0.00	0.00	50.00	25.00	25.00	0.00	0.00	0.00	0.00	0.00	0.00
Total	23	14	6	27	37	19	2	51	18	23	6	6
	2.12	1.9	0.55	2.48	3.4	1.75	0.18	4.69	1.66	2.12	0.55	0.55

Continues

	Defense	Mining	Oil	Utilities	Communication	Personal services	Business services	Computers	Electronics	Lab equipment	Business supplies
Loner	1	5	6	13	9	3	49	9	15	4	4
	0.85	4.24	5.08	11.02	7.63	2.54	41.53	7.63	12.71	3.39	3.39
Occasional	1	0	5	10	14	3	65	7	13	6	8
	0.76	0.00	3.79	7.58	10.61	2.27	49.24	5.30	9.85	4.55	6.06
Jogger	1	1	3	10	12	0	39	7	4	1	2
	1.25	1.25	3.75	12.50	15.00	0.00	48.75	8.75	5.00	1.25	2.50
Sprinter	0	0	2	5	2	2	18	3	2	2	0
	0.00	0.00	5.56	13.89	5.56	5.56	50.00	8.33	5.56	5.56	0.00
Marathoner	0	0	0	0	1	0	9	0	0	0	0
	0.00	0.00	0.00	0.00	10.00	0.00	90.00	0.00	0.00	0.00	0.00
Total	3	6	16	38	38	8	180	26	34	13	14
	0.28	0.55	1.47	3.50	3.50	0.74	16.56	2.39	3.13	1.2	1.29

Continues

	Shipping container	Transportation	Wholesale	Retail	Hospitality	Other
Loner	2	11	4	14	3	7
	2.25	12.36	4.49	15.73	3.37	7.87
Occasional	3	9	14	17	8	6
	2.44	7.32	11.38	13.82	6.50	4.88
Jogger	0	5	12	10	5	6
	0.00	7.58	18.18	15.15	7.58	9.09
Sprinter	0	1	1	1	0	2
	0.00	8.33	8.33	8.33	0.00	16.67
Marathoner	0	0	0	0	0	1
	0.00	0.00	0.00	0.00	0.00	100.00
Total	5	26	31	42	16	22
	0.46	2.39	2.85	3.86	1.47	2.02

4.1 Main explanatory variables

The dissertation is focused on the short-term performance of serial acquirers, following the announcement of an acquisition. Particularly, we studied the performance following the first acquisition and the performance following the fifth and higher acquisition (Fuller et al., 2002). We investigated a double effect. Firstly, how the deal's performance varied based on its position in the acquirer's history. Macias et al. (2023) and Morillon (2021) find that deal returns decrease the longer a firm is engaged in acquisitions, thus we are interested in exploring this phenomenon for the European M&A market. Secondly, we investigated the effect that acquiring in quick succession (blocks) has on performance.

To expand on possible reasons for fluctuating performance, we introduced *growth* as a main explanatory variable, which was defined as sales at the time *t* minus sales at the time *t-1*, all divided by sales at the time *t*, where *t* is the year in which the transaction happened (Morillon, 2021).

An additional explanatory variable is *overvaluation,* which was calculated by dividing the natural logarithm of the book value of common equity of the acquirer at the announcement date from the natural logarithm of the market capitalization of the acquirer one day prior to the announcement date *(Fu et al., 2013)*.

Furthermore, we created four dummy variables to describe the payment method used in the transaction. *All cash* is equal to 1 when the acquirer used only cash in the transaction, and 0 when it did not. *All stock* is equal to 1 when the acquirer used only their own stock in the transaction, and 0 when it did not. *Combination* is equal to 1 when the acquirer used a combination of cash and stock in the transaction, and 0 when it did not. *Undisclosed* is equal to 1 when the acquirer's payment method was not reported, and 0 when it was (Macias et al., 2023).

Moreover, variable *cash liquidity* represented the total value of cash and cash equivalents scaled by the total value of assets, to consider the size of the acquirer.

Lastly, the variable relative position (RP*)* was calculated according to equation (1). Its value is comprised between 0 and 1, 0 being the first acquisition and 1 the last acquisition, independently of blocks. A positive coefficient of RP will signal increasing returns occur linearly over time; the more a firm acquires, the better the returns (Morillon, 2021).

Equation (1): $RP_{i,t} = \left(\frac{Days\ since\ first\ acquisition_{i,t}}{Length\ acquisition\ history_{i}}\right)$

Consequently, the variable relative position within a block (RPWB) was calculated following a similar method to RP but focusing just within the block instead of the entire acquisition history.

$$\textit{Equation (2)}: RPWB_{i,t} = \left(\frac{Days\ since\ first\ acquisition\ in\ block_{i,t}}{Block\ length_i}\right)$$

This variable captures a vital aspect of blocks, as a negative coefficients means that declining returns happen within a block of acquisition, independently of the acquirer's performance over time. In other words, RPWB only captures the effect of acquiring in quick succession, and not of the overall performance. A negative coefficient signals that clumped acquisitions are value destroying, regardless of the acquirer's performance in their acquisition history (Morillon, 2021).

With the inclusion of RP and RPWB, we aim to further expand and substantiate the performance analysis of serial acquirers. Being able to capture the effects around the relative position of the transaction in the acquirer's history and in their blocks of acquisitions, will allow us to shed further light on the serial acquirer's phenomenon.

4.2 Control variables definition

Following previous literature, we divided control variables in acquirer-level control variables and deal-level control variables. Acquirer-level control variables are the natural logarithm of assets to account for size, the ratio of long-term debt to assets (leverage), the ratio of EBITDA to assets (ROA), and the ration of CAPEX to assets. All the acquirer-level control variables are measured at t-1 (Morillon, 2021). Deal-level control variables are target's company type (private or public company), the relative size of the acquirer (deal size divided by total assets), dummy variable to mark if the acquirer and the target belong to the same industry, dummy variable equal to 1 if the deal was friendly, dummy variable equal to 1 if it was an unsolicited offer, and a final dummy variable equal to 1 if the deal was domestic (both the acquirer and the target are from the same country).

Furthermore, we employed industry controls following the 48 Fama-French industry classification (Macias, Rau, et al., 2016), a dummy variable equal to 1 when the announcement date is between 1997 and 2001 to account for the dot.com bubble, and a dummy variable equal to 1 when the announcement date is between 2007 and 2008 to account for the global financial crisis.

4.3 Summary statistics

In Table 3 panel A, we present the summary statistics for all the variables. The first half of the table describes the deal-level variables, while the second half describes the firm-level variables. We observe that 95.8% of the targets are private companies, further highlighting the difficulties of obtaining information to study. Moreover, in the sample 0.01% of offers were hostile but 95.1% of the total were unsolicited. Regarding the payment method, a large part of the deals used an undisclosed one (46.4%), closely followed by all cash option (42.4%). Only a small portion of the deals used all stock (4.8%) or a combination of cash and stock (4.1%). European acquirers, over the window of observation, have largely preferred to use cash over their own stock. Most of the acquisitions happened within national borders (64.1%), but only 26.4% of all deals were within the same industry, indicating that European acquirers largely operate in multiple industries.

Regarding the firm-level variables, it is possible to observe that the mean and the median value of leverage is in the range between 0.8% and 17.2%, indicating that European acquirers are lowly levered. Moreover, acquirers are holding on a large portion of cash and cash equivalents (13.5% of their total assets, on average). One could argue that liquidity is a high priority among players in the European M&A market, and it will be interesting to analyse if this factor holds any influence on acquisitions' performance. Moreover, acquirers in the sample are largely overvalued with an average of 2.482 equity-to-book value. Only the bottom 25% of the sample is close to a 1:1 ratio or below. Lastly, we can observe that cumulative abnormal returns (CAR) for the sample are positive for both event windows. More details regarding the takeover announcement returns will be presented in the later sections.

In panel B, we present the breakdown of the summary statistics by acquirer category. The payment method all cash is distributed similarly between acquirer categories, except for *marathoners,* which use cash only 34.1% of the times. Unfortunately, the most common payment method for *marathoners* is undisclosed (64%). Single acquirers make use of stock payment more frequently than serial acquirers; *loners* utilise stock in 8.3% of their deals, *occasional* acquirers in 7.1% of theirs, compared to 4.8% of the entire sample. Domestic transactions are the majority of the deals (around 70%) for all acquirers, except for *marathoners* (42% on average). An interesting variable is relative deal size; it gradually decreases as acquirers become more frequent. *Loners* average deal size is 11.7%, while for *joggers* is only 5% and for *marathoners* is a mere 1.1%. This may indicate that serial acquirers tend to acquire more companies for smaller sums, while single acquirers are more interested in pursuing a defining deal that shapes the future of their company.

Regarding firm-level variables, it is possible to observe that *growth* is, on average, positive with strong values (from 15.4 % to 17.2%) for serial acquirers. It is difficult to derive meaning from these observations. It may be because of low growth that single acquirers are engaging in an acquisition; a transformative and relatively large deal could lead to a restructuring of the firm. On the other hand, growing firms could be interested in capitalizing on their outstanding prospects and engage in a series of acquisitions. There are many explanations and theories, but it is difficult to state which one fits the sample without more information on the individual acquirers. *Marathoners* are more overvalued than any other category. Lastly, cumulative abnormal returns are highest for *loners* and lowest for *marathoners*. However, there is very high variability in the sample, which will likely negatively impact the statistical significance of the regressions' results.

Tabel 3, Panel A.
This table illustrates the summary statistics for all variables in the full sample. The first column lists the name of the variable; they are grouped into three sections: deal-level variables, firm-level variables, macroenvironment variables, and CARs. The second column shows the number of observations; the third column shows the mean; the fourth column shows the standard deviation; the fifth column shows the bottom 25% of the sample; the sixth column shows the median; the last column shows the top 25% of the sample.

	N	Mean	SD	p25	Median	p75
Deal – level variables						
Private target	3961	.969	0.173	1	1	1
All cash	3961	.041	0.199	0	0	0
All stock	3961	.416	0.493	0	0	1
Combination	3961	.039	0.193	0	0	0
Undisclosed	3961	.481	0.500	0	0	1
Hostile	3961	.001	0.032	0	0	0
Unsolicited	3961	.955	0.207	1	1	1
Domestic	3961	.62	0.485	0	1	1
Same industry	3961	.262	0.440	0	0	1
Deal size	3961	.052	0.182	0	0	.014
Firm – level variables						
Log assets	3961	6.98	2.391	5.208	6.994	8.81
Leverage	3961	.152	0.131	.042	.131	.23
Growth	3961	.074	0.406	.011	.083	.167
ROA	3961	.105	0.078	.069	.104	.144
Cash liquidity	3759	.75	0.763	.277	.754	1.209
Overvaluation	3961	.135	0.124	.052	.096	.176
CAPEX	3961	-.041	0.037	-.054	-.032	-.015
Macroenvironment - variables						
Dot.com bubble	3961	.052	0.222	0	0	0
Financial crisis	3961	.141	0.348	0	0	0
CAR (-1;1)	3961	1.046	7.521	-1.145	.481	2.676
CAR (-2;2)	3961	1.608	13.223	-1.708	.741	3.959

Tabel 3, Panel B.

This table illustrates the summary statistics for all variables in the sample across the five acquirer's types. The first column lists the name of the variable; they are grouped into three sections: deal-level variables, firm-level variables, macroenvironment variables, and CARs. Afterwards, there are five groups of columns of; each group shows the summary statistics of the mean and the standard deviation for an acquirer type.

	Loner		*Occasional*		*Jogger*		*Sprinter*		*Marathoner*	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Deal – level variables										
Private target	.925	.264	.959	.198	.974	.16	.976	.154	.991	.092
All cash	.449	.498	.419	.494	.432	.496	.418	.493	.341	.475
All stock	.085	.28	.062	.24	.038	.192	.029	.167	.009	.092
Combination	.069	.254	.058	.234	.037	.188	.03	.17	.009	.092
Undisclosed	.351	.478	.421	.494	.471	.499	.512	.5	.64	.481
Hostile	0	0	0	0	.002	.042	.001	.03	.002	.046
Unsolicited	.941	.236	.941	.236	.947	.224	.968	.177	.985	.121
Domestic	.751	.433	.675	.469	.626	.484	.616	.487	.42	.494
Same industry	.269	.444	.246	.431	.271	.444	.246	.431	.305	.461
Deal size	.117	.28	.081	.228	.053	.182	.026	.12	.011	.058
Firm – level variables										
Log assets	5.385	2.259	5.817	2.264	7.363	2.278	7.543	2.287	8.041	1.789
Leverage	.14	.154	.131	.137	.157	.125	.161	.12	.172	.141
Growth	.023	.661	.075	.605	.063	.189	.089	.342	.096	.14
ROA	.076	.109	.093	.094	.109	.071	.106	.06	.135	.059
Cash liquidity	.18	.162	.159	.148	.122	.111	.125	.106	.114	.096
Overvaluation	.664	.929	.562	.855	.739	.695	.774	.697	1.121	.624
CAPEX	-.048	.049	-.04	.04	-.041	.036	-.042	.037	-.034	.02
Macroenvironment – variables										
Dot.com bubble	.043	.202	.054	.226	.07	.256	.04	.195	.038	.192
Financial crisis	.121	.327	.126	.332	.116	.32	.178	.383	.158	.365
					1.05	9.653				
CAR (-1;1)	1.773	6.617	.995	8.805	1.597	18.853	1.033	4.679	.695	3.989
CAR (-2;2)	2.472	8.868	1.684	14.246	.974	.16	1.493	7.169	1.199	5.725

5. Methodology

Short-term performance for M&A deals is commonly investigated by implementing an event study. Cumulative abnormal returns are the most common method to evaluate the acquirers' performance relative to the market. Since we investigate multiple countries within the Euro-zone, we needed a market index that could capture the effects of all the countries in question. The MSCI EMU perfectly fits to our needs (Martynova & Renneboog, 2011); it "captures large and mid-cap representation across the 10 Developed Markets countries in the EMU", which is comprised of the following countries: Austria, Belgium, Finland, France, Germany, Ireland, Italy, the Netherlands, Portugal, and Spain (MSCI, 2024). These countries represent about 93% of our sample firms.

The first step in an event study is to select the event windows and the estimation window. We selected two event windows: a 3-days window, CAR (-1;1), and a 5-days window, CAR (-2;2) (Macias et al., 2023). In the smaller window, we will be able to capture the announcement's effects with little to no 'noise'. Given the window's size, it is highly unlikely that other events will influence the returns of the acquirer or the market. However, a small window has the drawback of being too narrow; therefore, the market may not have enough time to react to the announcement in a meaningful way. This is the reason that induced us to introduce a slightly broader event window, the 5-days window. We compute the market model's returns over a 240 days starting 300 days before the announcement date (Martynova & Renneboog, 2011).

To estimate expected returns, it is common to use the market model. This model runs a separate regression for each company using the data within the estimation window and saves the intercepts (α_i) and the coefficients (β_i) of the independent variable. Then, it uses these saved regression equations to predict normal performance during the event windows. The model is as follows *(Equation 3)*:

$$R_{i,t} = \alpha_i + \beta_i R_{m,t} + \varepsilon_{i,t}$$

Where $R_{i,t}$ represents the stock returns *i* at a day *t*, whilst $R_{m,t}$ represents the market returns *m* at a day *t*. The last step in the calculation of CAR is to compute the abnormal return (AR) by subtracting from the stock returns of the event window the expected returns computed from the market model. Lastly, we summed the AR to obtain the CAR for both the event windows.

5.1 Models

As explained before, we are interested in measuring the short-term performance of M&A deals, by employing an event study approach using cumulative abnormal returns (CAR). To test the first hypothesis, we use the following base model (*Model 1*):

$$CAR_{i,t} = \beta_0 + \beta_1 First_{i,t} + \beta_2 Post\ 5^{th}{}_{i,t} + \gamma_1 Firm - level\ controls_{i,t-1} + \gamma_2 Deal \\ - level\ controls_{i,t} + \gamma_2 Macroenvironment_{i,t} + \delta_{i,t} + \varepsilon_{i,t}$$

Where *CAR* is the cumulative abnormal returns over a 3-day window around the announcement date, *First* is an indicator equal to one when the deal is the first one in the acquirer's acquisition history, and *Post* 5^{th} is an indicator equal to one when the deal is the fifth one or greater. We expect the coefficient β_1 to be always positive, while we predict the coefficient β_1 to be negative for the regression on the full sample, and to be negative for the *Joggers* and the *Sprinters,* but to be positive for the *Marathoners* for the regressions by acquirer type.

Firm-level controls is a vector of accounting control variables commonly used in the literature, such as the natural logarithm of book assets (Moeller et al., 2004), the ratio of long-term debt to assets (Bruner, 1988), ROA (Owen & Yawson, 2010), and the ratio of capital expenditures to assets (Macias et al., 2023). All the firm-level controls are measure at *t-1* (Morillon, 2021). *Deal-level controls* is a vector of variables capturing the effects of the ownership status of the target (Fuller et al., 2002), the method of payment (Martin, 1996), the relative deal size (Macias et al., 2023), whether the deal is hostile (Franks & Mayer, 1996), or domestic (Erel et al., 2012), or if it is a diversified deal (Macias, Rau, et al., 2016), or if the offer was unsolicited. We also employ a *Macroenvironment* vector of variables capturing the effects of the global financial crisis of 2007 and 2008 and the dot.com bubble crisis of 1997-2001 (Macias, Rau, et al., 2016). Lastly, we included in the model the industry and year fixed effects ($\delta_{i,t}$) to control for the unobserved effects over time and the idiosyncratic error term ($\varepsilon_{i,t}$)., or if it is a diversified deal (Macias, Rau, et al., 2016), or if the offer was unsolicited. We also employ a *Macroenvironment* vector of variables capturing the effects of the global financial crisis of 2007 and 2008 and the dot.com bubble crisis of 1997-2001 (Macias, Rau, et al., 2016). Lastly, we included in the model the industry and year fixed effects ($\delta_{i,t}$) to control for the unobserved effects over time and the idiosyncratic error term ($\varepsilon_{i,t}$).

For the second hypothesis, we will use the following model (*Model 2)*:

$$CAR_{i,t} = \beta_0 + \beta_1 RP_{i,t} + \beta_2 RPWB_{i,t} + \gamma_1 Firm - level\ controls_{i,t-1} + \gamma_2 Deal - level\ controls_{i,t} + \gamma_2 Macroenvironment_{i,t} + \delta_{i,t} + \varepsilon_{i,t}$$

Where RP and RPWB are the timeliness variables defined in equation (1) and (2). We expect both these variables' coefficient to be negative for the full sample. Furthermore, we predict that the coefficients β_1 is negative for the *Joggers* and the *Sprinters,* but positive for the *Marathoners,* and β_2 is negative for all acquirer types.

For the hypothesis 3a, we will use the following model (*Model 3a)*:

$$CAR_{i,t} = \beta_0 + \beta_1 First_{i,t} + \beta_2 Post\ 5^{th}{}_{i,t-1} + \beta_3 Growth_{i,t-1} + \beta_4 Growth^2{}_{i,t-1} + \gamma_1 Firm - level\ controls_{i,t-1} + \gamma_2 Deal - level\ controls_{i,t} + \gamma_2 Macroenvironment_{i,t} + \delta_{i,t} + \varepsilon_{i,t}$$

Where g*rowth* is a main explanatory variable as defined earlier. Liu and Tu (2023) suggest that growth has a U-shape, therefore we introduced the quadratic term, which we expect to have a positive coefficient. For growing companies, we expect returns to be positive or stable for the *Marathoners*, while we expect declining returns for the *Joggers* and the *Sprinters*.

For the hypothesis 3b, we will use the following model (*Model 3b)*:

$$CAR_{i,t} = \beta_0 + \beta_1 First_{i,t} + \beta_2 Post\ 5^{th}{}_{i,t} + \beta_3 Growth_{i,t-1} + \beta_4 Growth^2{}_{i,t-1} + \beta_5 Overvaluation_{i,t-1} + \beta_6 Growth_{i,t-1} * Overavaluation_{i,t-1} + \gamma_1 Firm - level\ controls_{i,t-1} + \gamma_2 Deal - level\ controls_{i,t} + \gamma_2 Macroenvironment_{i,t} + \delta_{i,t} + \varepsilon_{i,t}$$

In this model, we introduce the variable *overvaluation,* as defined earlier, and its interaction with the variable *growth*. Our expectation is that overvaluation of the acquirer will exacerbate the value destruction brought about by the growth. Therefore, fast growing acquirers that are overvalued will generate lower returns than just growing firms.

For the fourth hypothesis, we will use the following model (*Model 4)*:

$$CAR_{i,t} = \beta_0 + \beta_1 RP_{i,t} + \beta_2 RPWB_{i,t} + \beta_3 Overvaluation_{i,t-1} + \beta_4 All\ stock_{i,t} + \beta_5 Overavaluation_{i,t-1} * All\ stock_{i,t} + \gamma_1 Firm - level\ controls_{i,t-1} + \gamma_2 Deal - level\ controls_{i,t} + \gamma_2 Macroenvironment_{i,t} + \delta_{i,t} + \varepsilon_{i,t}$$

In this model, we introduce the interaction between the variable *overvaluation* and *all stock*. We would normally expect to see positive returns when an overvalued acquirer uses its stock as a payment method. However, given that stock as a payment method was used only 5.8% in the sample, we expect the coefficients to be insignificant. Moreover, we would have normally expected to see β_1 negative for the *Joggers* and the *Sprinters,* but positive for the *Marathoners,* and β_2 negative for all acquirer types.

For the fifth hypothesis, we will use the following model (*Model 5)*:

$$CAR_{i,t} = \beta_0 + \beta_1 First_{i,t} + \beta_2 Post\ 5^{th}{}_{i,t} + \beta_3 Cash\ liquidity_{i,t-1} + \gamma_1 Firm - level\ controls_{i,t-1} + \gamma_2 Deal - level\ controls_{i,t} + \gamma_2 Macroenvironment_{i,t} + \delta_{i,t} + \varepsilon_{i,t}$$

In this model, we introduce the variable *cash liquidity*, as defined earlier. We expect β_2 to be negative, as with a stronger cash position returns would decline.

6. Results

We begin our analysis by verifying how serial acquirers' buying strategy affects their performance in the full sample. In Table 4 panel A, we present the regression results for the entire sample given a 3-days event window. The results for the base model described in *Model 1*, which investigates the takeover announcement returns for serial acquirers, are shown in column 1. The main explanatory variable *First*'s coefficient β_1 is positive and equal to 0.046, which can be interpreted as increase in cumulative abnormal returns of 0.046% if the deal is of the first order. This difference seems to be negligible. The *Post 5^th^*'s coefficient β_2 is positive and equal to 0.062, a result small in magnitude which indicates that, for the full sample, CAR (-1,1) are almost equal to zero. However, there is no statistical significance to support our findings. The limited size of the sample, especially if compared to Morillon (2021), could be a reason for the statistical insignificance. A consequence of a small sample size that may have hindered the validity of the results is the relative high value of the standard deviation, which indicates high variability. A large confidence interval may lead to insignificant p-values.

Most of the control variables present results coherent to the previous literature. Bidder's CARs are lower when their size increases, and when the deal is paid in stock. Bidder's CARs are higher when the deal is paid in cash or in a cash/stock combination, and when the deal is hostile (Fu et al., 2013; Fuller et al., 2002). On the other hand, there are contradicting results; contrary to the literature presented thus far, bidder's CARs tend to be lower when the target is private, and when the transaction is domestic. Lastly, the magnitude of the variables' coefficients are comparable with the ones from the studies of Morillon (2021), Macias et al. (2023), and (Martynova & Renneboog, 2011).

The results for Model 2, which investigates how deals relative position in the acquirers' history or within blocks of acquisitions affect takeover announcement returns, are presented in the second column. RP is not statistically significant, and its positive coefficient has a value of 0.370. The economical interpretation is that the bidder's CAR increase by 0.370 basis point from the first acquisition to the last of the acquirer's acquisition history. This result goes against the literature's findings, such as that decreasing returns are the norm for serial acquirers. However, our result is in favour of the learning hypothesis which suggests that serial acquirers learn how to improve their acquisition strategy by engaging in multiple transactions (Zhang, 2021). RPWB is also not statistically significant, and it has a negative coefficient of -0.165. The economical interpretation is that transactions that happen within a block face declining return. On a first glance, it may appear that RP and RPWB have contradicting results, but that is not the case. The results suggest that later acquisition perform better, but they also suggest that their returns are declining if these deals are within the same block (less than 365 days apart). Therefore, serial acquirers that acquire in blocks, such as the *sprinters* and *marathoners*, will suffer from greater declining returns compared to serial acquirers that do not acquire in block, such as the *joggers*.

The results for Model 3a, which investigates how growth affects the takeover announcement returns for serial acquirers, are shown in the third column. The main explanatory variables *First* and *Post 5th* behave similarly to Model 1. The variable growth and growth square have positive coefficients but are not statistically significant. Their values are of 0.560 and 0.032, respectively, and by computing the mean of the sample equal to 0.074, the effect on the CAR (-1;1) is of 0.041. Solving for the turning point, we obtain a result equal to -8.75. There are no firms out of 928 that have a growth value equal or lesser than -8.75, meaning that the quadratic term is not relevant. Thus, its inclusion is not value adding and it would be better to implement a linear relationship between CAR (-1;1) and growth.

The results for Model 3b are displayed in column 4. Model 3b focuses on the interactions between the growth phenomena and the acquirer's overvaluation in terms of acquisitions performance. Like for Model 1 and 3a, there is no statistical significance for the variables First and Post 5th. However, the coefficient β_1 is negative, indicating that the first acquisition of the acquirer's history is worse performing than the later ones. None of the other main explanatory variables are statistically significant. However, we can still try to interpret their coefficients, even if we do not have support for these results. For the quadratic term, the turning point is equal to 4.470. As it was for Model 3a, including the quadratic term hold little meaning, since there are no firms with a growth value equal or greater to the turning point. The overvaluation term has a negative coefficient, while the interaction term has a positive one. To grasp the effect of these coefficients, we plug in the means for growth (0.074) and for overvaluation (0.75). For the average firm in the sample, the combined effects of growth and overvaluation leads to a decrease in CARs of 0.407%. This effect is in line with our prediction.

Model 4 is showcased in the fifth column. This model investigates the relationship between the relative position, the relative position within the block and whether overvaluation combined with the payment method of all stock has a negative effect on performance. The variable RP behaves very similarly to Model 2, and its magnitude is about the same. The variable RPWB has a positive sign, but a much smaller magnitude; thus, acquisitions within block experience an increase in returns by 0.025%, an amount close to zero. The payment method all stock is not statistically significant, and it has a negative coefficient of -0.072. Overvaluation is also not statistically significant, and it has a negative coefficient of -0.452. Their interaction is statistically insignificant, and it has a negative coefficient of -0.424. By plugging in the mean of the sample for overvaluation (0.75) and by considering a scenario where the payment method was all stock (1), the effect on performance is -0.729. Therefore, even highly overvalued acquirers would witness a decline on performance if they used only their stock as a payment method.

Model 5 is presented in sixth column. This model investigates the effects on acquirers' cash position relative to their announcement returns. Both main explanatory variables First and Post 5th are not statistically significant, and their coefficients are both positive as it is for Model 1 and 3a. Cash liquidity is positive, indicating acquirers with larger cash positions tend to have higher takeover announcement returns. By plugging in the mean for cash liquidity, we can observe that the average firm would have an increase in CAR equal to 0.167%.

Lastly, in the seventh column, we present a regression with all the main explanatory variables to provide a reference to how all the variables interact with one another.

Table 5 describes the regressions for the 3-days window by acquirer type. The table is divided into six panels, each dedicated to one hypothesis. Thus, panel A presents the regression results regarding the first hypothesis. We excluded the *loner* type, as the main explanatory variables are always equal to zero. The variable First presents negative coefficients for each acquirers' type, except for the *joggers*. As it was for the full sample, Post 5th is not statistically significant and its coefficient is negative, even for the *marathoners*. We predicted that *marathoners* do not suffer from the declining returns phenomenon, however, for this sample, the coefficient is equal to -0.993.

Panel B describes the regression results regarding Model 2. The *loner* type was not included in the regression as RP and RPWB would always be equal to zero. The results are consistent with the full sample, as both main explanatory variables behave in the same manner. The effects are not statistically significant for the *occasional*, the *jogger*, and the *marathoner* typology. However, RPWB is weakly significant for the *sprinters*. *Sprinters*' mean block intensity is slightly over five acquisitions per block and the mean number of unique blocks is about four (as, by definition, they may only have a maximum of 19 acquisitions in their history). Thus, the average *sprinter* would have better takeover announcement returns for the first acquisition per block by 0.417 (RP's coefficient), but within the blocks the returns would decline by 0.614 (RPWB's coefficient). Therefore, if we assumed that the average *sprinter* made 11 transactions, only three of them had positive returns (keep in mind that in Panel A of Table 6, the First's coefficient is -0.481), while the remaining eight deals would suffer from declining returns as they are part of a block.

Panel C shows the regressions for Model 3a. First is not statistically significant for all types, while Post 5th is only statistically significant for *joggers*. Growth is not statistically significant for serial acquirers, but it is for the *occasional* type. For the *jogger* type, the growth variables present a U-shape, as predicted by Liu and Tu (2023), but the turning point is for a growth value of 4.382, which is not present in our sample. Thus, once more, the quadratic term for growth lacks economic significance.

Panel D shows the regressions results for Model 3b. The coefficients for growth, growth squared, overvaluation, and the interaction term have a statistical significance ranging from 10% to 1% confidence for the *jogger* category. By plugging the means of the *jogger* category for the main explanatory variables, we compute that, for the average *jogger* firm, the total effect on CAR (-1;1) is -2.619. Thus, overvaluation exacerbates the value destruction for fast-growing serial acquirers, although we find weak empirical support only for the *jogger* type.

Panel E shows the regressions results for Model 4. The variables RP and RPWB are not significant except for RPWB for *sprinters*. Overvaluation is only statistically significant for *marathoners*. We will focus on the *sprinter*s since the main explanatory variables for timeliness are only statistically significant for this type. Overvaluation has a positive coefficient of 0.165, all stock has a negative coefficient of 3.750, and the interaction term has a positive coefficient of 0.563. By plugging in the means and assuming that the deal was funded with all stock, we obtain an effect on CAR (-1;1) of -3.187. Thus, an overvalued acquirer that pays in stock tends to see a reduction in takeover announcement returns by 3.187%.

Lastly, panel F shows the regressions results for Model 5. We do not find statistical significance for the variable cash liquidity. However, by looking at cash liquidity's coefficients across the acquirer's types, we can observe that the predicted negative sign is present for all serial acquirers except for *sprinters*, that have a large positive coefficient. On the other hand, *marathoners* have a large negative coefficient, indicating that holding on to large sums of cash is counterproductive for the most frequent and continuous acquirer. Given the lack of statistical significance, we are wary of making strong assumptions.

Table 4
This table summarizes the regression results for the entire sample given the 3-days window, CAR (-1;1). Each column displays the results for each hypothesis, starting with hypothesis (1) in the first column to hypothesis (5) in the last column.

Variables	(1) Model 1	(2) Model 2	(3) Model 3a	(4) Model 3b	(5) Model 4	(6) Model 5
First	0.046		0.062	-0.086		0.020
	(0.408)		(0.387)	(0.408)		(0.413)
Post 5th	0.062		0.068	0.093		0.075
	(0.216)		(0.214)	(0.219)		(0.218)
RP		0.370			0.388	
		(0.444)			(0.463)	
RPWB		-0.165			0.025	
		(0.284)			(0.271)	
Growth			0.560	-0.903		
			(1.327)	(3.192)		
Growth squared			0.032	0.101		
			(0.094)	(0.062)		
Overvaluation				-0.608	-0.452	
				(0.672)	(0.638)	
Growth x overvaluation				2.064		
				(2.625)		
Overvaluation x stock					-0.424	
					(0.801)	
Cash liquidity						1.237
						(1.200)
Leverage	0.588	0.625	0.553	1.975	2.147	0.842
	(1.385)	(1.389)	(1.358)	(1.454)	(1.424)	(1.434)
Log assets	-0.150*	-0.153*	-0.141*	-0.225***	-0.240***	-0.141*
	(0.083)	(0.089)	(0.083)	(0.084)	(0.091)	(0.085)
ROA	-0.628	-0.602	-0.676	-1.557	-0.939	-0.614
	(4.400)	(4.435)	(4.368)	(4.357)	(3.589)	(4.398)
CAPEX	2.407	2.281	2.296	3.696	3.648	2.167
	(2.897)	(2.882)	(2.907)	(3.156)	(2.977)	(2.944)
Private status	-0.359	-0.364	-0.371	-0.348	-0.553	-0.366
	(0.650)	(0.651)	(0.652)	(0.770)	(0.692)	(0.651)
All cash	0.449	0.452	0.501	1.106	0.863	0.487
	(1.036)	(1.040)	(1.008)	(1.089)	(1.083)	(1.038)
All stock	-0.442	-0.465	-0.410	-0.018	-0.072	-0.392
	(1.123)	(1.134)	(1.132)	(1.173)	(1.250)	(1.131)
Combination	1.767*	1.760*	1.800*	2.350**	2.096*	1.808*
	(1.009)	(1.014)	(1.002)	(1.132)	(1.105)	(1.013)
Undisclosed	0.566	0.567	0.616	1.406	1.143	0.600
	(1.101)	(1.105)	(1.063)	(1.170)	(1.146)	(1.106)
Deal size	2.665***	2.680***	2.665***	4.222***	3.870***	2.637***
	(0.867)	(0.863)	(0.865)	(1.195)	(1.009)	(0.864)
Hostile	2.207	2.281	2.118	2.175	2.159	2.232
	(2.344)	(2.325)	(2.334)	(2.180)	(2.201)	(2.345)
Domestic	-0.096	-0.097	-0.086	-0.167	-0.157	-0.092
	(0.235)	(0.234)	(0.222)	(0.191)	(0.198)	(0.234)
Same industry	0.000	-0.004	0.000	0.017	-0.002	-0.006
	(0.255)	(0.257)	(0.255)	(0.250)	(0.255)	(0.254)
Unsolicited	-0.121	-0.113	-0.129	-0.123	-0.117	-0.119
	(0.403)	(0.396)	(0.403)	(0.435)	(0.419)	(0.402)
Dot.com bubble	-1.141	-1.266	-1.184*	-0.686	-0.299	-1.129
	(0.709)	(0.864)	(0.698)	(1.172)	(1.192)	(0.710)
Financial crisis	-0.028	-0.226	-0.053	-1.179*	-1.159*	-0.019
	(0.481)	(0.651)	(0.479)	(0.606)	(0.600)	(0.481)
_cons	-1.586	-1.214	-1.785	-0.789	-0.885	1.077
	(3.943)	(3.945)	(3.972)	(1.738)	(1.772)	(2.223)
Observations	3961	3961	3961	3759	3759	3961
R-squared	0.028	0.028	0.029	0.045	0.035	0.029
Standard errors	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered
Method	FE	FE	FE	FE	FE	FE

*Standard errors are in parentheses: *** p<.01, ** p<.05, * p<.1*

Table 5, Panel A

This table summarizes the regression results for Model (1) by serial acquirer type given the 3-days window, CAR (-1;1). Each column displays the results for each serial acquirer type.

Variables	(1) *Occasional*	(2) *Jogger*	(3) *Sprinter*	(4) *Marathoner*
First	-0.506	1.112	-0.481	-2.911
	(0.707)	(1.132)	(0.703)	(2.247)
Post 5th		-0.724*	-0.028	-0.993
		(0.401)	(0.294)	(0.855)
Leverage	4.190	-2.940	-1.049	-1.214
	(4.206)	(2.463)	(3.348)	(2.017)
Log assets	-0.194	-0.146	-0.155	-0.128
	(0.220)	(0.089)	(0.193)	(0.182)
ROA	5.190	-14.198	4.676	-0.886
	(5.155)	(14.084)	(4.921)	(5.598)
CAPEX	6.958	-6.267	4.051	-18.722
	(5.921)	(6.331)	(5.643)	(11.426)
Private status	-0.140	-0.102	0.049	3.059
	(1.383)	(1.283)	(1.083)	(2.398)
All cash	-0.228	2.119*	-2.299	-6.402
	(1.906)	(1.247)	(3.174)	(4.309)
All stock	-0.679	-0.601	-3.293	-10.206**
	(2.192)	(1.715)	(2.996)	(4.593)
Combination	1.631	2.784*	-1.746	-4.655
	(1.678)	(1.585)	(3.177)	(4.137)
Undisclosed	0.066	2.984*	-3.080	-6.491
	(2.123)	(1.575)	(3.256)	(4.506)
Deal size	2.859	4.278***	3.706*	-5.534
	(1.815)	(1.571)	(1.907)	(5.970)
Hostile		5.030	0.821	2.609
		(4.729)	(0.935)	(2.881)
Domestic	-0.528	0.104	-0.211	0.102
	(0.559)	(0.421)	(0.336)	(0.571)
Same industry	0.796	-0.726	0.544	-0.305
	(0.831)	(0.559)	(0.370)	(0.429)
Unsolicited	0.240	-0.095	-1.007	0.431
	(0.939)	(0.619)	(0.813)	(2.697)
Dot.com bubble	-2.228	-3.421**	0.703	
	(1.352)	(1.577)	(1.805)	
Financial crisis	-2.917*	-2.583**	-0.085	-1.490
	(1.618)	(1.258)	(1.184)	(2.511)
_cons	4.394	-0.680	25.481***	6.705
	(3.134)	(1.931)	(2.835)	(6.216)
Observations	926	1149	1112	469
R-squared	0.074	0.046	0.169	0.119
Standard errors	Clustered	Clustered	Clustered	Clustered
Method	FE	FE	FE	FE

*Standard errors are in parentheses: *** p<.01, ** p<.05, * p<.1*

Table 5, Panel B

This table summarizes the regression results for Model (2) by acquirer type given the 3-days window, CAR (-1;1). Each column displays the results for each acquirer type.

Variables	(1) *Occasional*	(2) *Jogger*	(3) *Sprinter*	(4) *Marathoner*
RP	1.123	0.273	0.417	0.075
	(0.831)	(0.962)	(0.709)	(2.557)
RPWB	0.805	-0.663	-0.614*	-0.286
	(1.063)	(0.506)	(0.355)	(0.697)
Leverage	4.239	-3.084	-1.100	-1.244
	(4.201)	(2.517)	(3.392)	(2.136)
Log assets	-0.198	-0.186**	-0.141	-0.139
	(0.221)	(0.094)	(0.194)	(0.180)
ROA	5.598	-13.749	4.590	-0.833
	(5.134)	(13.996)	(4.985)	(5.413)
CAPEX	7.108	-6.821	3.880	-20.952
	(5.938)	(6.294)	(5.605)	(12.272)
Private status	-0.063	-0.141	-0.017	2.990
	(1.371)	(1.262)	(1.080)	(2.383)
All cash	-0.238	2.205*	-2.296	-7.099
	(1.894)	(1.266)	(3.137)	(4.123)
All stock	-0.650	-0.527	-3.408	-10.394**
	(2.176)	(1.691)	(3.046)	(4.588)
Combination	1.706	2.689*	-1.746	-5.324
	(1.682)	(1.588)	(3.138)	(3.807)
Undisclosed	0.045	3.086*	-3.088	-7.076
	(2.112)	(1.616)	(3.218)	(4.317)
Deal size	2.889	4.355***	3.708*	-6.584
	(1.787)	(1.593)	(1.882)	(5.685)
Hostile		5.428	1.171	2.754
		(4.607)	(0.982)	(2.937)
Domestic	-0.495	0.157	-0.220	0.134
	(0.561)	(0.430)	(0.336)	(0.551)
Same industry	0.802	-0.723	0.551	-0.413
	(0.841)	(0.572)	(0.370)	(0.429)
Unsolicited	0.319	-0.055	-0.979	0.165
	(0.931)	(0.614)	(0.800)	(2.732)
Dot.com bubble	-2.395*	-6.151	0.489	-0.550
	(1.365)	(6.370)	(1.667)	(3.646)
Financial crisis	-3.293**	-6.411	-0.127	-1.707
	(1.653)	(6.421)	(1.139)	(2.495)
_cons	3.393	3.238	4.177*	7.160
	(2.835)	(6.992)	(2.498)	(5.953)
Observations	926	1149	1112	469
R-squared	0.078	0.045	0.171	0.106
Standard errors	Clustered	Clustered	Clustered	Clustered
Method	FE	FE	FE	FE

*Standard errors are in parentheses: *** p<.01, ** p<.05, * p<.1*

Table 5, Panel C
This table summarizes the regression results for Model (3a) by acquirer type given the 3-days window, CAR (-1;1). Each column displays the results for each acquirer type.

Variables	(1) *Occasional*	(2) *Jogger*	(3) *Sprinter*	(4) *Marathoner*
First	-0.606	0.943	-0.468	-2.656
	(0.717)	(0.938)	(0.691)	(2.155)
Post 5th		-0.762*	-0.007	-1.036
		(0.409)	(0.295)	(0.828)
Growth	5.686**	-5.977	1.074	2.721
	(2.628)	(7.588)	(1.119)	(2.187)
Growth squared	0.354**	0.682	0.131	-2.929
	(0.164)	(2.360)	(0.403)	(2.114)
Leverage	4.028	-2.749	-1.161	-1.184
	(4.244)	(2.231)	(3.402)	(2.037)
Log assets	-0.093	-0.182	-0.119	-0.123
	(0.225)	(0.111)	(0.209)	(0.173)
ROA	5.992	-11.928	5.257	-1.086
	(5.386)	(11.488)	(5.057)	(4.953)
CAPEX	9.921	-2.399	3.774	-13.766
	(6.303)	(7.368)	(5.249)	(12.891)
Private status	-0.239	-0.130	-0.011	3.170
	(1.426)	(1.286)	(1.111)	(2.390)
All cash	0.102	1.746	-2.127	-6.641
	(1.811)	(1.251)	(3.170)	(4.356)
All stock	-0.737	-1.020	-3.142	-10.378**
	(2.163)	(1.971)	(2.974)	(4.590)
Combination	2.077	2.403	-1.648	-5.219
	(1.598)	(1.702)	(3.178)	(4.189)
Undisclosed	0.365	2.651*	-2.906	-6.801
	(2.079)	(1.421)	(3.254)	(4.570)
Deal size	2.452	4.620**	3.698*	-6.189
	(1.743)	(1.942)	(1.904)	(6.164)
Hostile		4.855	0.664	2.182
		(5.105)	(0.953)	(3.080)
Domestic	-0.576	0.158	-0.175	0.112
	(0.553)	(0.473)	(0.337)	(0.557)
Same industry	0.941	-0.749	0.541	-0.374
	(0.843)	(0.585)	(0.368)	(0.431)
Unsolicited	-0.191	-0.100	-1.001	0.400
	(1.068)	(0.631)	(0.788)	(2.667)
Dot.com bubble	-2.280	-2.552*	0.566	
	(1.427)	(1.341)	(1.756)	
Financial crisis	-2.843*	-1.684	-0.099	-1.294
	(1.646)	(1.439)	(1.206)	(2.547)
_cons	3.953	0.069	24.920***	6.769
	(3.048)	(2.345)	(2.884)	(6.058)
Observations	926	1149	1112	469
R-squared	0.096	0.061	0.172	0.132
Standard errors	Clustered	Clustered	Clustered	Clustered
Method	FE	FE	FE	FE

*Standard errors are in parentheses: *** p<.01, ** p<.05, * p<.1*

Table 5, Panel D
This table summarizes the regression results for Model (3b) by acquirer type given the 3-days window, CAR (-1;1). Each column displays the results for each acquirer type.

Variables	(1) *Occasional*	(2) *Jogger*	(3) *Sprinter*	(4) *Marathoner*
First	-0.696	1.395	-0.029	-2.779
	(0.655)	(1.003)	(0.554)	(2.285)
Post 5th		-0.744	0.079	-0.929
		(0.529)	(0.304)	(0.851)
Growth	10.258	-27.901*	1.837	4.157
	(6.252)	(14.246)	(1.640)	(5.051)
Growth squared	0.282**	4.667*	0.360	-2.048
	(0.134)	(2.520)	(0.587)	(6.447)
Overvaluation	0.640	-3.409*	0.221	-1.786**
	(0.980)	(1.899)	(0.275)	(0.812)
Growth x Overvaluation	-5.442	35.203**	-0.960	-1.174
	(6.133)	(16.857)	(1.399)	(3.350)
Leverage	6.734	-1.098	2.258	0.851
	(5.276)	(2.188)	(1.811)	(2.253)
Log assets	-0.246	-0.056	-0.366***	-0.087
	(0.282)	(0.130)	(0.120)	(0.205)
ROA	3.316	-7.326	0.499	12.590
	(6.070)	(7.527)	(3.019)	(7.498)
CAPEX	11.090	-7.041	6.464	-15.581
	(7.671)	(6.652)	(4.389)	(15.189)
Private status	-0.987	5.173	-0.525	2.515
	(1.742)	(3.492)	(1.075)	(2.622)
All cash	0.238	1.416	-2.126	-0.642
	(2.082)	(1.511)	(3.216)	(2.965)
All stock	-0.291	-3.759	-3.408	-4.473
	(2.383)	(3.260)	(3.330)	(4.458)
Combination	2.261	4.338*	-2.139	
	(1.847)	(2.409)	(3.415)	
Undisclosed	0.888	2.187	-2.822	-0.897
	(2.248)	(1.449)	(3.226)	(3.100)
Deal size	2.847	4.266	4.331*	-5.961
	(2.058)	(3.509)	(2.342)	(6.885)
Hostile		6.967	0.764	0.304
		(5.777)	(0.936)	(3.833)
Domestic	-0.268	-0.341	-0.316	-0.085
	(0.593)	(0.429)	(0.296)	(0.606)
Same industry	1.556	-0.350	0.284	-0.345
	(0.991)	(0.523)	(0.365)	(0.427)
Unsolicited	0.118	-0.717	-1.196	0.323
	(1.012)	(0.938)	(0.759)	(2.706)
Dot.com bubble	-1.454	-4.488*	-0.731	
	(2.604)	(2.689)	(1.884)	
Financial crisis	0.555	-0.110	-0.888	-4.005
	(2.228)	(1.607)	(0.843)	(2.974)
_cons	-2.304	-2.701	25.081***	2.026
	(4.937)	(3.087)	(3.609)	(5.384)
Observations	860	1092	1068	459
R-squared	0.126	0.452	0.198	0.157
Standard errors	Clustered	Clustered	Clustered	Clustered
Method	FE	FE	FE	FE

*Standard errors are in parentheses: *** p<.01, ** p<.05, * p<.1*

Table 5, Panel E

This table summarizes the regression results for Model (4) by acquirer type given the 3-days window, CAR (-1;1). Each column displays the results for each acquirer type.

Variables	(1) *Occasional*	(2) *Jogger*	(3) *Sprinter*	(4) *Marathoner*
RP	0.918	0.449	0.049	0.963
	(0.836)	(1.204)	(0.621)	(2.155)
RPWB	1.455	-0.574	-0.631*	-0.224
	(1.088)	(0.479)	(0.356)	(0.731)
Overvaluation	0.313	-2.022	0.165	-1.733*
	(0.609)	(2.386)	(0.272)	(0.853)
All stock	0.040	-0.077	-3.750	
	(2.400)	(2.641)	(3.599)	
Overvaluation x stock	-0.980	1.043	0.563	85.072
	(1.218)	(2.553)	(1.772)	(72.212)
Leverage	7.191	-2.217	2.268	0.768
	(5.263)	(2.137)	(1.743)	(2.250)
Log assets	-0.358	-0.207*	-0.376***	-0.074
	(0.293)	(0.114)	(0.113)	(0.199)
ROA	1.610	-8.986	-0.333	11.061
	(5.830)	(9.721)	(3.220)	(7.894)
CAPEX	5.791	-2.640	6.011	-21.076
	(5.850)	(7.428)	(4.991)	(13.236)
Private status	-0.723	-0.175	-0.427	2.422
	(1.588)	(1.412)	(1.080)	(2.518)
All cash	0.253	2.719**	-2.317	101.061
	(2.061)	(1.164)	(3.204)	(82.631)
Combination	2.128	3.757**	-2.190	101.849
	(1.893)	(1.536)	(3.395)	(81.353)
Undisclosed	0.754	3.804**	-3.033	101.175
	(2.268)	(1.490)	(3.213)	(82.914)
Deal size	3.999**	6.773***	4.178*	1.098
	(1.940)	(2.569)	(2.394)	(10.397)
Hostile		5.779	1.312	1.030
		(4.958)	(0.953)	(3.281)
Domestic	-0.400	0.105	-0.388	0.028
	(0.574)	(0.388)	(0.290)	(0.601)
Same industry	1.179	-0.686	0.305	-0.370
	(0.892)	(0.491)	(0.363)	(0.397)
Unsolicited	0.082	-0.159	-1.114	0.076
	(1.012)	(0.679)	(0.779)	(2.777)
Dot.com bubble	-0.064	-0.273	-2.322	
	(2.723)	(2.408)	(2.138)	
Financial crisis	0.984	0.390	-2.247*	-4.084
	(2.362)	(1.061)	(1.352)	(3.032)
_cons	-2.621	1.574	27.190***	-100.012
	(4.394)	(2.856)	(4.301)	(82.120)
Observations	860	1092	1068	459
R-squared	0.090	0.069	0.196	0.130
Standard errors	Clustered	Clustered	Clustered	Clustered
Method	FE	FE	FE	FE

*Standard errors are in parentheses: *** p<.01, ** p<.05, * p<.1*

Table 5, Panel F
This table summarizes the regression results for Model (5) by acquirer type given the 3-days window, CAR (-1;1). Each column displays the results for each acquirer type.

Variables	(1) *Occasional*	(2) *Jogger*	(3) *Sprinter*	(4) *Marathoner*
First	-0.519	1.125	-0.417	-2.872
	(0.729)	(1.141)	(0.695)	(2.172)
Post 5th		-0.731*	-0.038	-1.023
		(0.404)	(0.293)	(0.862)
Cash liquidity	0.602	-0.860	3.798	-2.310
	(2.645)	(2.042)	(2.316)	(3.588)
Leverage	4.344	-3.073	-0.452	-1.510
	(4.419)	(2.514)	(3.327)	(1.958)
Log assets	-0.187	-0.154*	-0.123	-0.020
	(0.226)	(0.092)	(0.192)	(0.229)
ROA	5.176	-14.268	4.579	-0.642
	(5.121)	(14.128)	(4.939)	(5.646)
CAPEX	6.920	-5.933	2.433	-18.214
	(5.964)	(6.514)	(5.733)	(11.860)
Private status	-0.143	-0.103	0.032	2.950
	(1.381)	(1.282)	(1.081)	(2.407)
All cash	-0.202	2.099*	-2.269	-6.498
	(1.907)	(1.248)	(3.183)	(4.308)
All stock	-0.650	-0.616	-3.188	-10.374**
	(2.224)	(1.722)	(3.003)	(4.675)
Combination	1.665	2.768*	-1.613	-4.866
	(1.680)	(1.589)	(3.203)	(4.158)
Undisclosed	0.086	2.968*	-3.047	-6.610
	(2.140)	(1.568)	(3.266)	(4.503)
Deal size	2.857	4.304***	3.636*	-5.661
	(1.812)	(1.583)	(1.896)	(5.929)
Hostile		5.004	0.507	2.374
		(4.718)	(1.027)	(2.721)
Domestic	-0.526	0.100	-0.233	0.083
	(0.557)	(0.418)	(0.335)	(0.602)
Same industry	0.806	-0.718	0.532	-0.313
	(0.832)	(0.557)	(0.364)	(0.430)
Unsolicited	0.245	-0.096	-0.967	0.420
	(0.931)	(0.618)	(0.818)	(2.641)
Dot.com bubble	-2.218	-3.425**	0.519	
	(1.357)	(1.577)	(1.691)	
Financial crisis	-2.915*	-2.603**	-0.139	-1.547
	(1.614)	(1.257)	(1.173)	(2.566)
_cons	4.299	-0.485	24.632***	6.086
	(3.118)	(2.039)	(2.844)	(6.305)
Observations	926	1149	1112	469
R-squared	0.074	0.046	0.174	0.120
Standard errors	Clustered	Clustered	Clustered	Clustered
Method	FE	FE	FE	FE

*Standard errors are in parentheses: *** p<.01, ** p<.05, * p<.1*

7. Robustness check

To test for robustness, we introduced a 5-days window, CAR (-2;2); the results are presented in Appendix C, we present the regression table for the six hypotheses on the full sample. The results are extremely similar to the ones for the 3-days window. The statistical significance across the two event windows is consistent, and there are minor differences in the coefficients' magnitudes. Furthermore, by analysing the sample across multiple subsample such as acquirer's categories, we were able to point out inconsistencies between acquirer's types and to further highlight the robustness of our results. Appendix D contains the results of this analysis: the regressions by acquirer type for the 5-days window. The table is divided into 6 panels, each dedicated to one hypothesis. The results from the 3-days window are similar to the ones for the 5-days window, therefore we restrain from presenting them in detail. We invite the readers to analyse them at their pleasure. Lastly, by including three sets of control variables (firm-level, deal-level, and macroenvironment control variables) in all of the regressions, we aimed at accounting for omitted or confounding factors. Out of the control variables, log assets, deal size, and combination are statistically significant for the full sample. The first one is able to capture the effect of the acquirer's size; the second one explains how the relative size of the deal affects performance, while the last one captures the effects of the payment method cash combined with stock. To understand the remaining control variables, please refer to paragraph 4.2.

8. Discussion

The aim of this study is to investigate the performance of serial acquirers. It particularly embraces the idea that differences in bidder acquisition strategy could lead to different performance. Therefore, the bidder classification of Morillon (2021) is incorporated in the analysis, which distinguished between*: loners, occasional bidders, joggers, sprinters, and marathoners* (see Table 1). The division in different types allows us to study whether potential M&A performance determinants are important to certain bidder categories. From a theoretical perspective, the most relevant study objects are the most frequent and continuous acquirers and the bidders which buy in blocks. The former can be classified as *marathoners* and the latter as *joggers* and *sprinters*. Initial studies from Morillon (2021) and Macias et al. (2023) found evidence for the hypothesis that *marathoners* are immune to performance decline while making many deals. Moreover, they conclude that *joggers* and *sprinters* face declining returns during their acquisition blocks. The current study aims to contribute to the literature by testing if these results hold in the European context as the other studies focused on the US market. In includes a total of 3,961 deals undertaken by 928 unique acquirers and addresses the main research question: *'How does serial acquirers' buying strategy, in terms of deal frequency and acquisitions blocks, affect the performance?'*

Based on this question, it is hypothesised that the *marathoners* are not facing declining returns (hypothesis 1) and that returns within blocks are likely to decline (hypothesis 2). There was no support for the first hypothesis, thus *marathoners*, the most frequent and continuous acquirers, are not immune to declining announcement returns. So, the result for our European sample contrast with Morillon (2021) and Macias et al. (2023) who found extraordinary performance for *marathoners* in the US market. Therefore, the results do not underscore the expected superior integration skills of these companies. Rather, it seems that *marathoners* do not have a special position and follow the general pattern for serial acquirer which entails that later integrations become more problematic and expensive (Zhang, 2021) and reap negative announcement returns (Boubakri et al., 2012; Karolyi et al., 2015). Analysing the full sample illustrates that announcement returns are near zero acquisitions when one does not take waves into consideration. However, our study finds support for the second hypothesis for the *sprinters* category, indicating that for these bidders' returns decline during acquisition blocks and thus acquiring in blocks is a value destroying strategy. The study cannot find empirical evidence to support this relationship for *joggers*. The M&A strategy could be a reason for the difference between *joggers* and *sprinters*; *sprinters* are more active, while *joggers* do not execute more than two deals per block (see Table 1). As planning and due diligence are key success factors for deals (Harding et al., 2024, April 8), we argue that the selective strategy of *joggers* allows them to use more resources in the process. *Sprinters*, on the other hand, do a flurry of bids over a short period of time, which is associated with value destruction and empire building (Morillon, 2021).

After looking at acquisition strategies, we expand our study by investigating the effects of various factors. We connect this with the second research question: *'What is the role of the factors growth, overvaluation, payment method and cash position in serial acquirer deal performance?'* Regarding the role of growth, we can conclude that growth is not significantly influencing the performance of serial acquirers. Thus, there is no evidence for the expected U-shape, which implies that low and high growth acquirers are most successful. An explanation for the absence of the expected relationship could be that investors are reluctant towards low-growth investments and afraid of overpayment for high-growth companies. Then, a stable, medium-growth company is also a reasonable investment. An alternative is that fast-growing companies often have high organic growth. Proceeding with growth through acquisitions could result in inadequate funds for organic growth and, therefore, high opportunity costs. In this way, acquisitiveness of fast-growing companies could signal a lack of opportunities. Our results provide significant support, however, for the *occasional* acquirers. That means that *occasional* acquirers have better performance when their growth is high.

We also expected that growth relates to overvaluation. In hypothesis 3b, we anticipated that overvaluation would exacerbate the value destruction of fast-growing serial acquirers. Our findings support this expectation specifically for *jogger* firms, where the interaction between growth and overvaluation is statistically significant, indicating that overvaluation significantly worsens the negative impact of growth on returns. For other types of acquirers, such as *sprinters* and *marathoners*, overvaluation does not necessarily worsen value destruction, highlighting a unique vulnerability in *jogger* firms to overvaluation during acquisition announcements.

For the fourth hypothesis, we investigated if the payment method is relevant for certain bidders. Although this is extensively studied for M&A in general, little is known about how the bidder type affects this relationship. Our study aimed to contribute meaningfully to the debate as to whether stock deals add value (e.g. Alexandridis et al., 2017; Martynova & Renneboog, 2011). We found that overvalued *sprinters* which acquire with stock face 3.187% lower announcement returns. Thus, in line with our hypothesis, we argue that *sprinters* take advantage of their stock value by doing equity deals, but with every deal the overvaluation decreases, and less value is created.

Regarding our last hypothesis, we did not find significant support for the impact of cash liquidity on performance. Despite the lack of significance, results indicate that holding cash is not improving performance, except for *sprinters*. Liquidity management is important for *sprinters* as they are acquisitive during specific blocks. This requires sufficient funds and by maintaining strong cash positions, these companies demonstrate liquidity is guaranteed.

9. Practical contributions

Our study was designed to investigate how differences in bidder types and their characteristics could influence announcement returns. This fills a gap in the literature, but it could also help managers and M&A advisors to understand why certain strategies work, while others fail. Although not significant, our results indicate that that returns improve with each deal, except for when companies execute more than two deals per year.

We investigated all bidder types separately and found different performance for *sprinters* and *joggers*. Both types buy in blocks, but the block intensity is higher for *sprinters*, meaning that *sprinters* acquire more within a block. In our study, *sprinters* executed three or more deals in a block, while a *jogger* is more selective and does not exceed two per block. We found that *sprinters* face declining performance within blocks, which our results did not support for *joggers*. Therefore, in our sample *joggers* seem to have a better acquisition strategy during blocks. As integration skills and due diligence are crucial for success (Harding et al., 2024, April 8), we propose that *joggers* have more resources for this process.

Our results also suggest that *sprinters* use equity deals to benefit from overvaluation, but when they are undertaking more deals, announcement returns decline. So, during blocks the benefit from overvaluation is exploited at first but deteriorates. This is in line with the assumption that the market corrects the stock price. As a last point we bring forward that holding cash improves announcement returns for *sprinters*. We conclude that that companies doing waves of acquisitions should carefully plan their deals. Our study also looked at the most frequent and continuous acquirers and could not find evidence for the idea that these outperform less frequent acquirers like in the US market. Therefore, companies in Europe should not count on superior integration skills.

10. Limitations and future research directions

The most crucial limitation that the study presents is the low variability of the sample size. As discussed in paragraph four, the relatively small sample size played a role in the lack of statistical significance in our results. Perhaps, using a different database may yield a larger sample size. Moreover, our study included 12 countries, thus increasing the 'noise' around the data. Previous research, such as Martynova and Renneboog (2011), took large steps to account for these disturbances in data, for instance, reviewing the entire sample against news announcements from three different news agencies in eleven languages. However, due to the nature of the dissertation, we could have not included these measures in our study. The inclusion of such corrective measures may have improved the overall quality of the work. Lastly, an important difference between studies in the EU and the US is the availability of data. The large differences and integration issues within the EU are a common predicament that transcend the field of finance. The sample could be expanded by including the UK market, which is insightful as the Anglo-Saxon governance system and affect bidder performance (Mateev & Andonov, 2018).

As our study indicates that *joggers* outperform *sprinters* during waves, the performance within blocks could be a fruitful area for future research. We propose that *joggers* have better planning skills and more resources available for implementation that *sprinters*. Future research could integrate these aspects into the study to performance. It could particularly focus on 'block acquirers' and test for a larger sample. Additionally, a contribution to the literature would be to take a long-term perspective to investigate if these patterns hold over a longer time (Renneboog & Vansteenkiste, 2019).

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Appendix

Appendix A
This appendix includes a detailed list of all the variables included in this dissertation.

Variables	Definition
Private target	Dummy variable equal to 1 if the target firm is help privately, equal to 0 otherwise.
All cash	Dummy variable equal to 1 if the payment method is cash, equal to 0 otherwise.
All stock	Dummy variable equal to 1 if the payment method is stock, equal to 0 otherwise.
Combination	Dummy variable equal to 1 if the payment method is a combination of cash and stock, equal to 0 otherwise.
Undisclosed	Dummy variable equal to 1 if the payment method is undisclosed, equal to 0 otherwise.
Hostile	Dummy variable equal to 1 if the takeover is hostile, equal to 0 otherwise.
Unsolicited	Dummy variable equal to 1 if the deal is unsolicited, equal to 0 otherwise.
Domestic	Dummy variable equal to 1 if the acquirer and the target are from the same country, equal to 0 otherwise.
Same industry	Dummy variable equal to 1 if the acquirer and the target belong to the same industry according to the 48 industry classification of Fama and French, equal to 0 otherwise.
Log assets	Natural logarithm of the book value of total assets
Deal size	Deal size divided by the book value of total assets
Leverage	Total debt divided by the book value of total assets
Growth	Sales at the time t minus sales at the time $t-1$, all divided by sales at the time t, where t is the year in which the transaction happens.
ROA	EBITDA divided by the book value of total assets
Cash liquidity	Book value of cash and cash equivalents divided by the book value of total assets
Overvaluation	Natural logarithm of the book value of common equity of the acquirer at the announcement date divided from the natural logarithm of the market capitalization of the acquirer one day prior to the announcement date.
CAPEX	Deal size divided by the book value of total assets
Dot.com bubble	Indicator variable equal to 1 if announcement year is between 1997 and 200, equal to 0 otherwise.
Financial crisis	Indicator variable equal to 1 if announcement year is between 2007 and 2008, equal to 0 otherwise.
CAR (-1;1)	Short term cumulative abnormal returns during a 3-day window centred at the announcement date of the current acquisition.
CAR (-2;2)	Short term cumulative abnormal returns during a 5-day window centred at the announcement date of the current acquisition.
First	Indicator variable equal to 1 if the transaction is the first one for the acquirer, equal to 0 otherwise.
Post 5th	Indicator variable equal to 1 if the transaction is of the fifth or higher order for the acquirer, equal to 0 otherwise.

Appendix B
This is the correlation table for the sample.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Deal – level variables										
(1) Private target	1.000									
(2) All cash	0.011	1.000								
(3) All stock	-0.147	-0.175	1.000							
(4) Combination	-0.115	-0.170	-0.042	1.000						
(5) Undisclosed	0.122	-0.812	-0.200	-0.194	1.000					
(6) Hostile	-0.040	0.022	-0.007	-0.006	-0.031	1.000				
(7) Unsolicited	0.032	-0.071	0.026	-0.026	0.064	-0.032	1.000			
(8) Domestic	-0.052	-0.011	0.089	0.031	-0.047	0.025	0.004	1.000		
(9) Same industry	-0.020	0.063	0.030	0.026	-0.090	0.017	-0.027	-0.001	1.000	
(10) Deal size	-0.148	0.060	0.247	0.179	-0.272	0.048	-0.050	0.049	0.095	1.000
Firm – level variables										
(11) Log assets	0.032	0.033	-0.108	-0.129	0.090	0.032	-0.051	-0.185	0.011	-0.146
(12) Leverage	-0.004	0.015	0.006	-0.037	0.000	-0.006	0.005	-0.054	-0.007	-0.040
(13) Growth	0.010	-0.017	0.005	0.024	0.014	0.010	0.027	0.000	0.014	0.001
(14) ROA	0.015	0.047	-0.148	-0.037	0.054	0.017	0.015	-0.085	0.049	-0.043
(15) Cash liquidity	-0.004	-0.023	0.025	0.039	-0.027	-0.005	0.010	0.040	0.019	0.087
(16) Overvaluation	0.010	-0.037	-0.029	0.031	0.040	-0.002	0.070	-0.116	0.046	0.085
(17) CAPEX	0.008	-0.045	0.022	0.000	0.026	0.002	0.014	-0.005	0.049	-0.010
Macroenvironment - variables										
Dot.com bubble	-0.011	-0.029	0.049	0.029	0.002	-0.007	0.051	-0.023	-0.013	0.053
Financial crisis	0.022	0.038	-0.040	-0.018	-0.005	-0.013	0.035	0.001	0.011	-0.001
(18) CAR (-1;1)	-0.018	-0.003	-0.004	0.052	-0.018	0.012	-0.001	0.004	0.009	0.072
(19) CAR (-2;2)	-0.007	-0.006	-0.009	0.043	-0.006	0.012	-0.003	0.012	0.011	0.047

	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
Firm – level variables											
(11) Log assets	1.000										
(12) Leverage	0.315	1.000									
(13) Growth	-0.064	-0.001	1.000								
(14) ROA	0.210	0.039	0.038	1.000							
(15) Cash liquidity	-0.300	-0.309	0.005	-0.085	1.000						
(16) Overvaluation	0.022	0.041	0.073	0.343	0.142	1.000					
(17) CAPEX	-0.092	-0.156	0.012	-0.149	0.142	0.017	1.000				
Macroenvironment - variables											
Dot.com bubble	-0.002	0.001	0.050	0.040	-0.021	0.078	-0.086	1.000			
Financial crisis	-0.004	-0.035	0.041	0.043	-0.060	0.027	-0.083	-0.095	1.000		
(18) CAR (-1;1)	-0.070	-0.023	0.019	-0.015	0.043	-0.023	0.018	-0.021	-0.032	1.000	
(19) CAR (-2;2)	-0.070	-0.020	0.008	-0.026	0.039	-0.035	0.020	-0.021	-0.027	0.956	1.000

Appendix C

This table summarizes the regression results for the entire sample given the 5-days window, CAR (-2;2). Each column displays the results for each hypothesis, starting with hypothesis (1) in the first column to hypothesis (5) in the last column.

Variables	(1) Model 1	(2) Model 2	(3) Model 3a	(4) Model 3b	(5) Model 4	(6) Model 5
First	0.274		0.278	0.121		0.236
	(0.722)		(0.676)	(0.728)		(0.729)
Post 5th	-0.019		-0.018	0.044		-0.000
	(0.338)		(0.332)	(0.340)		(0.339)
RP		0.695			0.745	
		(0.697)			(0.731)	
RPWB		-0.380			-0.110	
		(0.487)			(0.454)	
Growth			0.105	-2.894		
			(2.595)	(6.503)		
Growth squared			0.003	0.151		
			(0.183)	(0.112)		
Overvaluation				-1.210	-0.928	
				(1.371)	(1.299)	
Growth x overvaluation				4.343		
				(5.374)		
Overvaluation x stock					-0.793	
					(1.341)	
Cash liquidity						1.800
						(1.820)
Leverage	1.359	1.452	1.350	3.677	4.019	1.729
	(2.399)	(2.405)	(2.333)	(2.617)	(2.538)	(2.460)
Log assets	-0.253*	-0.277*	-0.251*	-0.387***	-0.427***	-0.240
	(0.143)	(0.154)	(0.140)	(0.147)	(0.160)	(0.146)
ROA	-3.256	-3.228	-3.276	-4.875	-3.567	-3.236
	(8.569)	(8.644)	(8.483)	(8.298)	(6.691)	(8.567)
CAPEX	5.166	4.791	5.142	7.839	7.411	4.817
	(4.522)	(4.483)	(4.579)	(5.370)	(4.845)	(4.611)
Private status	-0.102	-0.123	-0.104	0.221	-0.257	-0.113
	(0.912)	(0.915)	(0.918)	(1.225)	(1.003)	(0.913)
All cash	1.377	1.372	1.378	2.081	1.665	1.433
	(1.386)	(1.392)	(1.317)	(1.487)	(1.444)	(1.386)
All stock	-0.344	-0.402	-0.346	0.252	0.145	-0.273
	(1.474)	(1.487)	(1.520)	(1.596)	(1.696)	(1.483)
Combination	3.353**	3.326**	3.350**	3.950**	3.476**	3.414**
	(1.352)	(1.358)	(1.335)	(1.615)	(1.515)	(1.353)
Undisclosed	1.732	1.714	1.734	2.748	2.284	1.782
	(1.550)	(1.553)	(1.442)	(1.719)	(1.626)	(1.553)
Deal size	2.992**	3.061**	2.993**	5.487***	4.835***	2.952**
	(1.194)	(1.187)	(1.194)	(1.933)	(1.438)	(1.194)
Hostile	4.451	4.623	4.434	4.588	4.438	4.488
	(3.666)	(3.599)	(3.692)	(3.430)	(3.348)	(3.677)
Domestic	0.097	0.099	0.098	-0.082	-0.045	0.103
	(0.398)	(0.396)	(0.367)	(0.299)	(0.315)	(0.398)
Same industry	0.144	0.138	0.144	0.134	0.099	0.136
	(0.415)	(0.421)	(0.418)	(0.406)	(0.415)	(0.416)
Unsolicited	-0.312	-0.316	-0.314	-0.399	-0.395	-0.309
	(0.673)	(0.657)	(0.675)	(0.751)	(0.709)	(0.672)
Dot.com bubble	-1.835*	-2.101*	-1.843*	-0.542	0.242	-1.817*
	(0.961)	(1.230)	(0.946)	(1.777)	(1.851)	(0.965)
Financial crisis	0.531	0.001	0.526	-1.869*	-1.968**	0.544
	(0.728)	(1.003)	(0.733)	(0.997)	(0.961)	(0.730)
_cons	2.487	3.630	2.459	0.530	0.613	-0.745
	(3.389)	(3.391)	(3.541)	(2.614)	(2.721)	(2.481)
Observations	3961	3961	3961	3759	3759	3961
R-squared	0.024	0.024	0.024	0.043	0.030	0.024
Standard errors	Clustered	Clustered	Clustered	Clustered	Clustered	Clustered
Method	FE	FE	FE	FE	FE	FE

*Standard errors are in parentheses: *** p<.01, ** p<.05, * p<.1*

Appendix D, Panel A
This table summarizes the regression results for Model (1) by serial acquirer type given the 5-days window, CAR (-2;2). Each column displays the results for each serial acquirer type.

Variables	(1) *Occasional*	(2) *Jogger*	(3) *Sprinter*	(4) *Marathoner*
First	-0.531	2.206	-0.372	-2.367
	(1.090)	(2.255)	(1.146)	(2.805)
Post 5th		-0.859	-0.252	-1.429
		(0.594)	(0.429)	(1.001)
Leverage	7.986	-5.162	-0.531	-2.381
	(7.500)	(4.717)	(5.123)	(3.108)
Log assets	-0.379	-0.310**	-0.273	-0.183
	(0.385)	(0.148)	(0.322)	(0.263)
ROA	8.522	-27.895	7.169	-4.675
	(8.050)	(29.012)	(7.918)	(8.559)
CAPEX	13.344	-3.906	6.193	-34.603**
	(9.284)	(10.419)	(9.743)	(14.959)
Private status	0.632	0.189	0.706	6.304*
	(2.103)	(2.067)	(1.733)	(3.004)
All cash	0.723	2.938	-2.161	-7.326
	(2.753)	(1.797)	(3.299)	(5.864)
All stock	-0.025	-2.235	-3.133	-12.445*
	(3.147)	(2.519)	(3.213)	(6.355)
Combination	3.373	3.324	-1.189	-3.960
	(2.490)	(2.199)	(3.319)	(6.045)
Undisclosed	1.989	4.613*	-3.493	-7.746
	(3.208)	(2.668)	(3.439)	(5.975)
Deal size	3.021	5.949**	4.973**	-5.338
	(2.666)	(2.500)	(2.519)	(7.835)
Hostile		9.430	0.741	6.578*
		(7.789)	(1.583)	(3.153)
Domestic	-0.386	0.315	-0.084	0.563
	(0.821)	(0.796)	(0.502)	(0.883)
Same industry	2.126	-1.158	0.562	-0.202
	(1.416)	(1.028)	(0.550)	(0.619)
Unsolicited	-0.414	-0.279	-1.586	1.151
	(1.557)	(1.123)	(1.528)	(2.711)
Dot.com bubble	-2.509	-5.410**	-0.038	
	(1.680)	(2.579)	(2.514)	
Financial crisis	-4.226*	-5.078**	0.076	-2.076
	(2.369)	(2.189)	(1.805)	(3.264)
_cons	2.627	-0.826	39.548***	5.128
	(4.706)	(3.105)	(3.564)	(8.078)
Observations	926	1149	1112	469
R-squared	0.068	0.045	0.171	0.122
Standard errors	Clustered	Clustered	Clustered	Clustered
Method	FE	FE	FE	FE

*Standard errors are in parentheses: *** p<.01, ** p<.05, * p<.1*

Appendix D, Panel B

This table summarizes the regression results for Model (2) by acquirer type given the 5-days window, CAR (-2;2). Each column displays the results for each acquirer type.

Variables	(1) *Occasional*	(2) *Jogger*	(3) *Sprinter*	(4) *Marathoner*
RP	1.614	0.807	0.799	-2.282
	(1.317)	(1.523)	(1.100)	(3.302)
RPWB	1.270	-0.875	-1.145**	-0.997
	(1.786)	(0.909)	(0.545)	(0.904)
Leverage	8.061	-5.441	-0.523	-2.671
	(7.494)	(4.845)	(5.169)	(3.358)
Log assets	-0.390	-0.379**	-0.262	-0.259
	(0.387)	(0.157)	(0.321)	(0.271)
ROA	9.214	-27.242	6.912	-4.349
	(8.043)	(28.864)	(7.989)	(8.408)
CAPEX	13.463	-4.753	5.947	-36.508**
	(9.329)	(10.301)	(9.591)	(16.749)
Private status	0.785	0.094	0.583	6.172*
	(2.095)	(2.018)	(1.733)	(3.023)
All cash	0.716	3.091*	-2.138	-7.725
	(2.739)	(1.859)	(3.243)	(5.640)
All stock	0.011	-2.108	-3.286	-12.324*
	(3.135)	(2.467)	(3.285)	(6.415)
Combination	3.500	3.172	-1.213	-4.389
	(2.520)	(2.214)	(3.264)	(5.551)
Undisclosed	1.956	4.778*	-3.463	-7.998
	(3.198)	(2.768)	(3.379)	(5.744)
Deal size	3.088	6.035**	5.080**	-6.607
	(2.609)	(2.535)	(2.501)	(7.614)
Hostile		10.291	1.340	7.584**
		(7.601)	(1.677)	(3.106)
Domestic	-0.342	0.389	-0.102	0.556
	(0.827)	(0.820)	(0.504)	(0.871)
Same industry	2.133	-1.163	0.558	-0.346
	(1.437)	(1.057)	(0.552)	(0.600)
Unsolicited	-0.277	-0.227	-1.581	0.774
	(1.541)	(1.114)	(1.496)	(2.724)
Dot.com bubble	-2.750	-12.746	0.914	0.835
	(1.717)	(13.118)	(2.003)	(4.981)
Financial crisis	-4.812**	-14.512	1.051	-0.452
	(2.434)	(13.309)	(1.277)	(2.932)
_cons	1.251	8.908	4.437	5.250
	(4.227)	(14.313)	(3.406)	(7.381)
Observations	926	1149	1112	469
R-squared	0.071	0.044	0.174	0.120
Standard errors	Clustered	Clustered	Clustered	Clustered
Method	FE	FE	FE	FE

*Standard errors are in parentheses: *** p<.01, ** p<.05, * p<.1*

Appendix D, Panel C

This table summarizes the regression results for Model (3a) by acquirer type given the 5-days window, CAR (-2;2). Each column displays the results for each acquirer type.

Variables	(1) *Occasional*	(2) *Jogger*	(3) *Sprinter*	(4) *Marathoner*
First	-0.685	1.807	-0.345	-2.026
	(1.117)	(1.833)	(1.129)	(2.707)
Post 5th		-0.941	-0.212	-1.490
		(0.622)	(0.437)	(0.963)
Growth	7.953*	-14.074	2.132	3.809
	(4.148)	(15.556)	(1.617)	(2.879)
Growth squared	0.509*	0.868	0.270	-3.929
	(0.260)	(4.722)	(0.646)	(2.904)
Leverage	7.799	-4.639	-0.758	-2.349
	(7.551)	(4.161)	(5.191)	(3.148)
Log assets	-0.238	-0.401*	-0.202	-0.175
	(0.388)	(0.204)	(0.345)	(0.252)
ROA	9.722	-22.795	8.336	-4.917
	(8.427)	(23.512)	(8.199)	(7.676)
CAPEX	17.461*	4.551	5.667	-27.702
	(9.884)	(12.912)	(8.821)	(16.345)
Private status	0.494	0.050	0.593	6.460**
	(2.168)	(2.195)	(1.758)	(3.009)
All cash	1.275	2.088	-1.820	-7.664
	(2.644)	(1.829)	(3.306)	(5.869)
All stock	-0.013	-3.177	-2.835	-12.695*
	(3.113)	(3.292)	(3.193)	(6.320)
Combination	4.092*	2.457	-0.996	-4.742
	(2.419)	(2.473)	(3.338)	(6.080)
Undisclosed	2.497	3.871*	-3.149	-8.184
	(3.193)	(2.285)	(3.455)	(5.991)
Deal size	2.477	6.844**	4.954*	-6.266
	(2.573)	(3.361)	(2.523)	(7.948)
Hostile		9.046	0.438	5.964
		(8.641)	(1.622)	(3.502)
Domestic	-0.438	0.444	-0.014	0.577
	(0.817)	(0.915)	(0.504)	(0.871)
Same industry	2.333	-1.214	0.555	-0.298
	(1.441)	(1.087)	(0.547)	(0.621)
Unsolicited	-1.018	-0.295	-1.576	1.108
	(1.754)	(1.170)	(1.476)	(2.666)
Dot.com bubble	-2.588	-3.386	-0.312	
	(1.790)	(2.055)	(2.480)	
Financial crisis	-4.132*	-2.957	0.047	-1.802
	(2.397)	(2.726)	(1.854)	(3.348)
_cons	1.927	1.029	38.433***	5.208
	(4.579)	(4.210)	(3.828)	(7.913)
Observations	926	1149	1112	469
R-squared	0.084	0.064	0.175	0.134
Standard errors	Clustered	Clustered	Clustered	Clustered
Method	FE	FE	FE	FE

*Standard errors are in parentheses: *** p<.01, ** p<.05, * p<.1*

Appendix D, Panel D

This table summarizes the regression results for Model (3b) by acquirer type given the 5-days window, CAR (-2;2). Each column displays the results for each acquirer type.

Variables	(1) *Occasional*	(2) *Jogger*	(3) *Sprinter*	(4) *Marathoner*
First	-0.822	3.039	0.496	-2.092
	(1.031)	(2.050)	(0.867)	(2.850)
Post 5th		-0.839	-0.044	-1.409
		(0.922)	(0.443)	(0.991)
Growth	15.921	-58.169*	3.718*	5.144
	(10.139)	(30.453)	(2.069)	(6.189)
Growth squared	0.387*	8.645*	0.788	-3.514
	(0.198)	(5.214)	(0.773)	(7.443)
Overvaluation	1.082	-7.003*	0.614	-2.202*
	(1.632)	(4.130)	(0.448)	(1.110)
Growth x Overvaluation	-9.412	70.367*	-2.012	-0.519
	(10.004)	(36.418)	(2.126)	(4.034)
Leverage	12.378	-1.759	4.904*	-0.102
	(9.769)	(3.753)	(2.734)	(3.680)
Log assets	-0.507	-0.156	-0.641***	-0.143
	(0.503)	(0.247)	(0.203)	(0.284)
ROA	5.431	-14.224	0.011	11.370
	(9.550)	(16.368)	(4.621)	(11.431)
CAPEX	20.167*	-6.799	11.043	-28.829
	(12.043)	(12.059)	(7.638)	(19.329)
Private status	-0.884	11.207	-0.378	5.728*
	(2.646)	(7.378)	(1.690)	(3.209)
All cash	1.061	0.503	-1.681	-2.015
	(3.081)	(2.989)	(3.263)	(3.091)
All stock	0.452	-9.939	-3.348	-7.855
	(3.416)	(6.778)	(3.549)	(6.077)
Combination	4.081	5.221	-1.691	
	(2.868)	(5.047)	(3.523)	
Undisclosed	2.985	1.859	-2.830	-2.623
	(3.469)	(2.860)	(3.311)	(3.225)
Deal size	2.449	5.614	5.649**	-5.125
	(3.086)	(7.079)	(2.859)	(9.010)
Hostile		13.222	0.668	3.815
		(10.106)	(1.571)	(4.585)
Domestic	0.001	-0.570	-0.256	0.369
	(0.889)	(0.806)	(0.439)	(0.949)
Same industry	3.264*	-0.477	0.143	-0.288
	(1.677)	(0.994)	(0.544)	(0.613)
Unsolicited	-0.550	-1.604	-1.890	0.982
	(1.711)	(1.830)	(1.444)	(2.724)
Dot.com bubble	-1.152	-6.953	-0.812	
	(3.081)	(4.781)	(3.391)	
Financial crisis	2.723	1.267	-1.664	-5.514
	(2.321)	(3.078)	(1.435)	(3.712)
_cons	-3.379	-3.440	39.195***	0.949
	(7.025)	(6.286)	(4.428)	(6.068)
Observations	860	1092	1068	459
R-squared	0.115	0.470	0.210	0.152
Standard errors	Clustered	Clustered	Clustered	Clustered
Method	FE	FE	FE	FE

*Standard errors are in parentheses: *** p<.01, ** p<.05, * p<.1*

Appendix D, Panel E

This table summarizes the regression results for Model (4) by acquirer type given the 5-days window, CAR (-2;2). Each column displays the results for each acquirer type.

Variables	(1) *Occasional*	(2) *Jogger*	(3) *Sprinter*	(4) *Marathoner*
RP	1.393	0.753	0.224	-1.514
	(1.323)	(2.096)	(0.969)	(2.857)
RPWB	2.222	-0.725	-1.189**	-0.898
	(1.879)	(0.824)	(0.533)	(0.915)
Overvaluation	0.446	-4.416	0.521	-1.957*
	(1.014)	(4.942)	(0.416)	(1.040)
All stock	-1.499	2.758	-1.212	65.419
	(1.494)	(5.112)	(2.780)	(121.453)
Overvaluation x stock	13.035	-4.093	4.986*	-0.436
	(9.773)	(3.800)	(2.624)	(3.810)
Leverage	-0.671	-0.422**	-0.664***	-0.218
	(0.527)	(0.207)	(0.187)	(0.283)
Log assets	3.029	-17.763	-1.933	9.637
	(9.103)	(19.841)	(4.857)	(12.062)
ROA	11.812	2.400	9.595	-36.560*
	(9.058)	(14.006)	(8.965)	(17.506)
CAPEX	-0.413	0.517	-0.335	5.547*
	(2.447)	(2.497)	(1.745)	(3.120)
Private status	1.102	3.247*	-1.940	80.769
	(2.972)	(1.948)	(3.220)	(139.297)
All cash	0.853	-3.025	-2.574	
	(3.304)	(5.064)	(4.032)	
Combination	3.908	4.285*	-1.801	83.079
	(2.863)	(2.516)	(3.505)	(137.842)
Undisclosed	2.758	5.195*	-3.098	80.577
	(3.429)	(2.727)	(3.261)	(139.648)
Deal size	4.252	10.495**	5.747*	0.623
	(2.853)	(4.760)	(2.941)	(17.289)
Hostile		10.902	1.624	5.689
		(8.177)	(1.627)	(3.469)
Domestic	-0.238	0.268	-0.384	0.456
	(0.854)	(0.711)	(0.430)	(0.930)
Same industry	2.646*	-1.137	0.162	-0.307
	(1.519)	(0.879)	(0.539)	(0.572)
Unsolicited	-0.628	-0.476	-1.795	0.654
	(1.702)	(1.290)	(1.490)	(2.804)
Dot.com bubble	0.926	1.143	-1.602	
	(3.157)	(3.526)	(3.236)	
Financial crisis	3.225	2.239	-2.436	-5.122
	(2.449)	(1.738)	(1.474)	(3.691)
_cons	-3.577	4.762	41.382***	-80.366
	(5.976)	(5.273)	(4.532)	(139.234)
Observations	860	1092	1068	459
R-squared	0.081	0.070	0.207	0.135
Standard errors	Clustered	Clustered	Clustered	Clustered
Method	FE	FE	FE	FE

*Standard errors are in parentheses: *** p<.01, ** p<.05, * p<.1*

Appendix D, Panel F

This table summarizes the regression results for Model (5) by acquirer type given the 5-days window, CAR (-2;2). Each column displays the results for each acquirer type.

Variables	(1) *Occasional*	(2) *Jogger*	(3) *Sprinter*	(4) *Marathoner*
First	-0.549	2.239	-0.273	-2.377
	(1.132)	(2.276)	(1.127)	(2.772)
Post 5th		-0.879	-0.268	-1.421
		(0.599)	(0.427)	(1.011)
Cash liquidity	0.823	-2.367	5.793	0.574
	(4.146)	(3.470)	(3.580)	(4.994)
Leverage	8.197	-5.528	0.379	-2.307
	(7.817)	(4.864)	(5.057)	(2.966)
Log assets	-0.370	-0.332**	-0.224	-0.210
	(0.394)	(0.155)	(0.320)	(0.293)
ROA	8.503	-28.088	7.021	-4.735
	(7.989)	(29.091)	(7.923)	(8.552)
CAPEX	13.292	-2.984	3.727	-34.729**
	(9.353)	(10.919)	(9.903)	(14.649)
Private status	0.628	0.186	0.680	6.331*
	(2.101)	(2.066)	(1.740)	(3.062)
All cash	0.758	2.882	-2.115	-7.302
	(2.729)	(1.781)	(3.313)	(5.863)
All stock	0.016	-2.277	-2.973	-12.403*
	(3.187)	(2.530)	(3.224)	(6.367)
Combination	3.419	3.281	-0.987	-3.907
	(2.462)	(2.195)	(3.374)	(6.095)
Undisclosed	2.017	4.568*	-3.442	-7.717
	(3.214)	(2.640)	(3.457)	(5.967)
Deal size	3.018	6.019**	4.865*	-5.307
	(2.663)	(2.521)	(2.507)	(7.847)
Hostile		9.357	0.263	6.636**
		(7.757)	(1.713)	(3.000)
Domestic	-0.383	0.304	-0.117	0.568
	(0.819)	(0.790)	(0.497)	(0.908)
Same industry	2.141	-1.137	0.543	-0.200
	(1.415)	(1.022)	(0.543)	(0.617)
Unsolicited	-0.406	-0.282	-1.525	1.154
	(1.543)	(1.123)	(1.540)	(2.721)
Dot.com bubble	-2.495	-5.420**	-0.319	
	(1.679)	(2.580)	(2.412)	
Financial crisis	-4.222*	-5.133**	-0.007	-2.061
	(2.364)	(2.197)	(1.792)	(3.257)
_cons	2.498	-0.290	38.253***	5.282
	(4.611)	(3.256)	(3.592)	(8.089)
Observations	926	1149	1112	469
R-squared	0.068	0.045	0.176	0.122
Standard errors	Clustered	Clustered	Clustered	Clustered
Method	FE	FE	FE	FE

*Standard errors are in parentheses: *** p<.01, ** p<.05, * p<.1*