

SERIAL ACQUIRERS AND LONG-TERM STOCK PRICE REACTIONS

BY

ANEL MALIKOVA

THESIS

Submitted in partial fulfillment of the requirements
for the degree of Master of Science in Finance
in the Graduate School of Business
Nazarbayev University, 2024

Astana, Kazakhstan

Advisor: Dr. Tom Vinaimont

Introduction

Mergers and acquisitions are determining events in a company's lifecycle, profoundly affecting its operations and overall activities. These transitions provide companies with opportunities to grow faster than firms relying on organic expansion. Among these, serial acquirers - those firms that engage in multiple acquisitions over time - offer a valuable lens to study corporate growth and value creation through repeated transactions. However, serial acquisitions for a long time period and their effect on serial acquirer's stock performance remains the topic of financial debate.

A takeover is a type of M&A where one company gains control over another company (a target firm), resulting in the target company ceasing to exist and function as a standalone entity. The company that is being acquired is the target company, or the target. The company acquiring the target is called the acquiring company. The acquisition often involves public or private companies, adding complexity to how these acquisitions are evaluated in financial markets. Despite the huge amount of money spent on acquisitions and the academic studies investigating acquirer performance surrounding the announcement date, the long-term impact of serial acquisitions on stock prices remains poorly understood.

To evaluate the effect of acquisitions on stock performance, researchers commonly use event study methodologies, with Cumulative Abnormal Returns (CARs) as a standard measure to evaluate whether the acquisition generates value for shareholders (Barber& Lyon, 2017). CARs are calculated as the sum of the abnormal returns over a long event window.

In this thesis work, I am studying the long-term impact of serial acquisitions on the stock price, by firstly using an event dummy regression and then incorporating a modified Almon-lag approach proposed by Doan and Sercu (2020). This thesis seeks to address the following questions:

1. Do serial acquisitions have a measurable long-term impact on the stock price of the acquirer or not?
2. Can consistent patterns or hidden trends in the stock price behavior of serial acquirers be identified?

My primary contribution to this topic lies in applying event study methodologies to an extensive dataset of UK and European companies, spanning the period from January 2000 to August 2024. By extending the analysis to long-term event windows and a broader range of companies, this thesis aims to uncover insightful patterns in the stock price behavior of serial acquirers.

The paper is organized further as follows: section 2 reviews the related literature on serial acquirers; Section 3 describes the dataset and provides descriptive statistics; Section 4 outlines the methodology and the model used in the study; Section 5 presents the empirical results; Section 6 concludes with key findings and implications for future research.

Related Literature

In merger and acquisition research, the selection of event windows— time periods over which stock price reactions are measured—is crucial for accurately representing the market's response to acquisition announcements. Short-term event windows focus on immediate market reactions, whereas long-term windows evaluate the lasting effects of acquisitions.

Usually short-term windows span a few days surrounding the M&A announcement date. A common approach is to examine a window that includes 1) the day before, the day of, and the day after the announcement, 2) three days before, and three days after the announcement and the time period between these days. Mostly the short-term window is used due to the assumptions that the market's initial reaction is unbiasedly captured by this type of window. However, Oler, Harrison, and Allen (2007) argue that the initial market response may be biased and incomplete due to the difficulties to interpret the revealed information about takeover. Thus, results from short-term windows may not fully capture the effect of the event.

Nevertheless, short-term event studies have been the dominant method for assessing the impact of takeovers. The reason for choosing a short window is that, first, price adjustments should occur quickly in efficient markets, and secondly, longer term cumulative abnormal returns (CARs) become too volatile to provide meaningful analysis. According to the review of Renneboog and Vansteenkiste

(2019), acquirers often underperform in comparison to non-acquirers, and it is especially notable in public firms due to overestimated synergies, integration complexities, and initial market misjudgments based on heuristics and biases. Among the 151 studies reviewed by them, 62 focus solely on short-term returns, only 23 examine long-term returns, and 66 analyze both short- and long-term wealth effects. Renneboog and Vansteenkiste's review (2019) includes serial acquirers from 1999 to 2018. In my literature review I went through the issues of the 3 top journals in the finance area published in the *Journal of Financial Economics*, *Journal of Finance*, and *Review of Financial Studies*. To examine the recent trend in event studies, I found that out of 22 event studies that examine the performance of serial acquirers, 68% of them focused on short-window event studies, making these more prevalent than long-window studies (7 on long-term performance, 15 on short-term performance). In Table 1, I summarize many of the recent studies of abnormal stock return performance following the event study type and the research approaches used in each of the studies, drawing on papers published in the *Journal of Financial Economics*, *Journal of Finance*, and *Review of Financial Studies*.

Table 1. Summary of Recent Studies on Abnormal Stock Return Performance

Author(s)	Event Study Type	Research Approach
Kepler, J.D., Naiker, V., Stewart., C. (2023)	Short-window	Market Adjusted, OLS model, difference-in-differences specification
Hsu, P., Li, K., Tsou, C. (2023)	Short-window	1) Univariate Portfolio Sorting 2) Fama-MacBeth Regressions and Double Sorting on Size
Abongeh A. Tunyi (2021)	Short-window	OLS and recursive approach
Bonaime, A. and Wang, Y. (2024)	Short window	DID regression (before and after the merger)
Minh Phuong Doan, Piet Sercu (2021)	Intermediate window	Hybrid Model (Splines + Almon Lags)
Hossain et al (2021)	Short-window	Deal-level regression and OLS regression

This trend sheds a light on a research gap in understanding the sustained wealth effects of mergers and acquisitions over extended periods. The wealth effects of mergers and acquisitions have been analyzed by recent studies. For evaluating the impact of M&As on acquisition targets, event study methods are predominantly used and continue to be the preferred approach.

Regardless of deal characteristics, acquirers have realized significant gains from acquisitions over the past three decades (1988–2017), yet these gains are not captured in short-run event studies due to market anticipation prior to the bid (Tunyi, 2021). This emphasizes the importance of long-term event studies in providing a more comprehensive understanding of the economic consequences of M&A transactions. Additionally, their study questions the reliability of event study

methodology, since there are limitations of such methods to quantify the impact of M&As on acquirers. They addressed the bias of understating the wealth gains for acquirers by implementing a two-step approach—first, evaluating market anticipation of M&A events, and second, analyzing returns to less anticipated deals. The study highlights that acquirers earn higher abnormal returns when their mergers are less anticipated by the market, achieving cumulative abnormal returns of 5.4% to 7.5% around bid announcements for unanticipated deals and shows that market anticipation of subsequent deals partially accounts for leading to lower returns in higher-order acquisitions (Tunyi, 2021).

Prior recent literature suggests that serial acquirers tend to underperform compared to single acquirers. The study of Hossain et al (2021) on serial acquirers in Australia, covering 2696 acquisitions between 2000 and 2016, reveals that serial acquirers consistently experience lower abnormal returns after acquisition announcements, even after controlling for firm and deal characteristics, as well as industry and year fixed effects. This finding contrasts with the more favorable performance of single acquirers in the same market. The literature also highlights that serial acquirers tend to take on riskier acquisitions, which is often interlinked with managerial overconfidence (Hossain et al, 2021).

This research paper and the focus on within-window CAR patterns over the intermediate horizon was inspired by Doan and Sercu's (2021) study of the returns

pattern that follows takeover announcements by two leading serial acquirers, AB Inbev SA and Heineken. Their method confirms the presence of a drop-and-recovery pattern, but the amplitude of the pattern shows no link with deal size. In examining within-window CAR patterns over an intermediate horizon, they draw on a hybrid parameterization approach similar to the one used in Doan and Sercu's (2021) study. Given the size of the event window, they apply a modified Almon (1965) lag model, enhanced by a smooth-pasted tail from splines. This approach incorporates two key parameters: a shape parameter that characterizes the post-event return pattern as either monotonic or whip-shaped, and a scaler that defines the sign and magnitude of the event. Together, these parameters can categorize after event returns into nine types, including a drop-and-recovery pattern identified by Doan and Sercu (2021). They focus on serial acquirers closely because the data provided by serial acquisitions allows for a deeper understanding of firm-related heterogeneity and within-window patterns can be studied firm-by-firm. In this thesis, I adopt the methodology proposed and applied in their studies, extending its application from a single serial acquirer to a broader dataset encompassing a larger universe of firms, specifically those in the UK and Europe.

Data and descriptive statistics

Data

The sample of this study builds on the intersections of two datasets: M&A data and daily total returns for each acquirer company from LSEG the former Eikon Refinitiv Datastream. The sample period is bounded between January 2000 and August 2024. The dataset consists of two parts for the UK and Europe separately, as different currencies (pounds and euros) are used in these regions, thus avoiding exchange rate bias. Further when downloading the data I add some further constraints, for the UK data the acquiring companies should be publicly listed companies on the London Stock Exchange. For the European data I select only acquiring companies that are listed on Milan Stock Exchange, Luxembourg Stock Exchange, Frankfurt Stock Exchange, EuroNext Stock Exchange, Madrid Stock Exchange. The cleaning and merging process yields a final sample of 169 UK unique serial acquirers who make 5961 acquisitions and 105 European unique serial acquirers who make 4171 acquisitions between 2000 and 2024. I define serial acquirers as companies that have completed more than 20 acquisitions over the entire period.

All returns are downloaded as daily data, and compounded to weekly data. (Eq. 1)

$$R_{\text{weekly}} = \prod_{i=1}^n (1 + R_{\text{daily},i}) - 1 \quad (1)$$

Where R_{weekly} is the total return for the week.

$R_{\text{daily},i}$ is the daily return for day i within the week.

The use of weekly data is preferred due to the challenges associated with daily returns, particularly the issue of non-synchronicity in trading times. The three factors of Fama and French are taken from the Kenneth French site. Filtering extreme returns was implemented as a preprocessing step to mitigate the impact of outliers and to improve the model fit.

Takeovers are widely recognized as a cyclical phenomenon, with periods of elevated activity often referred to as "takeover waves." These waves are influenced by economic, legal, and market conditions and are well-documented in the literature (Hill & McDonnell, 2016).

The cyclical nature of takeovers is evident in my figures 1 and 2, where distinct peaks in M&A activity can be observed, corresponding to economic booms and

favorable market conditions. Figure 1 depicts the number of acquisitions per day in the UK and Europe between 2000 and 2024. Figure 2 presents the graphical representation of the value of deals per year in the UK and Europe, with a high of \$195bn in 2000 for the UK, and 292bn euro for European countries in 2015.

Fig. 1. Two decades of M&A activity.

The figure presents the # of UK M&A deals (on the right) and European M&A deals (on the left) announced between January 2000 and August 2024.

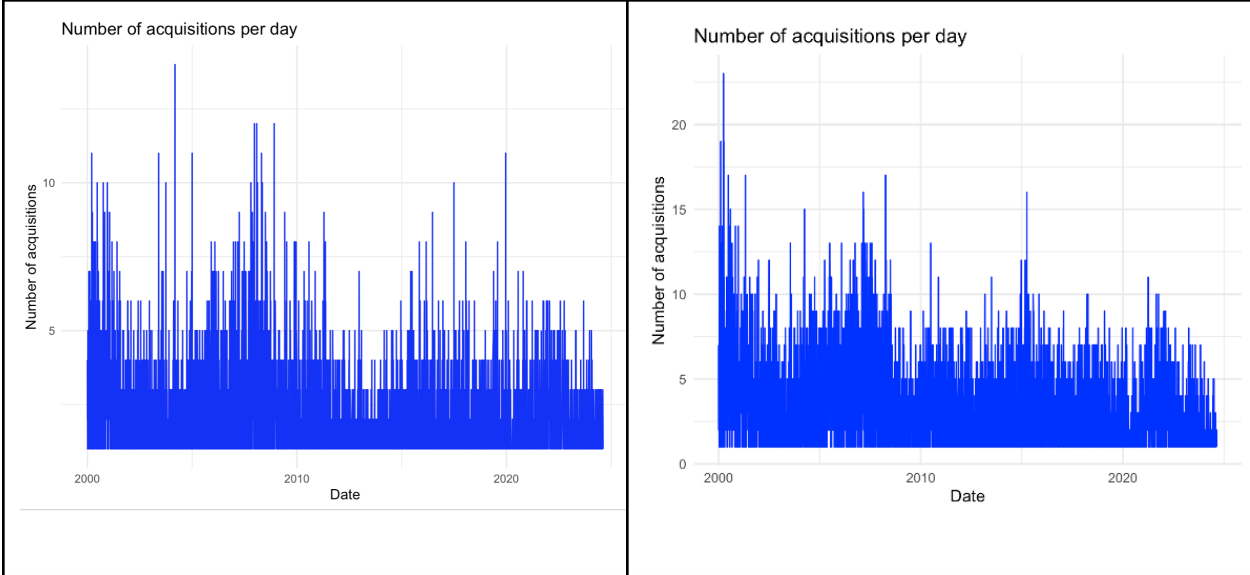
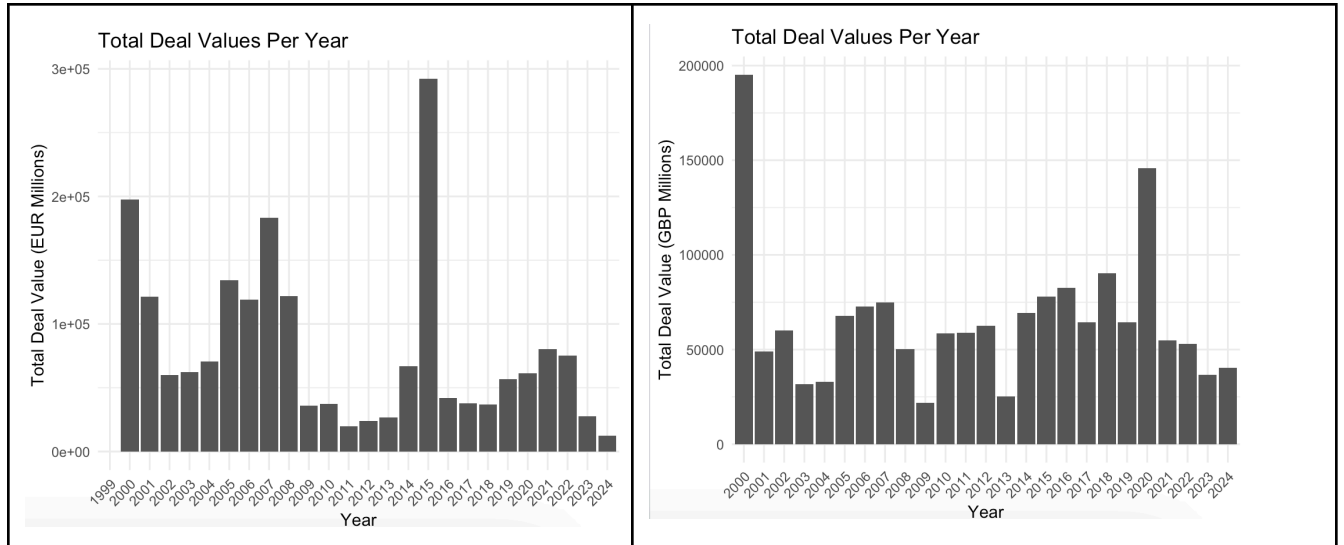


Fig. 2. Two decades of M&A activity.

The figure presents the value of UK M&A deals (on the right) and European M&A deals (on the left) announced between January 2000 and August 2024.



Descriptive Statistics

Table 2 provides descriptive statistics about the acquisition activity of acquirers, grouped by their primary stock exchange. LSE has the largest number of acquirers which are listed for more than 10 years.

Table 2. Summary Table of acquisition activity of acquirers

Acquiror Primary Stock Exchange	Average number of acquisitions per acquirer	Max. number of acq. per acquirer	Standard error	Number of Acquirors listed more than 10 years
Euronext	9,54054054	99	13,4999703	107
Frankfurt	6,34745763	169	11,0905062	172
Luxembourg	3,79310345	22	4,4431272	2
Madrid	6,50531915	54	7,66302138	55
Milan	7,03571429	67	8,47971949	134
London	6,11632904	182	9,93841817	3258

Table 3 provides a comprehensive summary of acquirers and their listing durations across different stock exchanges, differentiating between all acquirers and serial acquirers. LSE has the highest number of serial acquirers (181) but a relatively lower average listing duration for both all acquirers (5.38 years) and serial acquirers (16.7 years). The Luxembourg Stock Exchange has only one acquirer; therefore, it is excluded from future analysis. Table 4 summarizes the availability of deal value information for acquisitions across different stock exchanges. Milan

stock exchange leads with the highest percentage of known deal values (63.15%), suggesting a strong tendency for deal value transparency.

Table 3. Summary of acquirers and their listing durations

Acquirer Primary Stock Exchange	Number of acquirers	Average Listing Duration of Acquirers (in years)	Number of serial acquirers	Average Listing Duration of Serial Acquirers (in years)
Euronext	296	8.06062119614481	30	18.38
Frankfurt	708	5.84961542477291	46	17.75
Luxembourg	29	3.37010550166395	1	18.35
Madrid	188	7.10623734836239	12	20.54
Milan	420	7.44162836934911	29	19.13
London	691	5.37992140513876	169	16.7

Table 4. Summary Table of deal value information

Acquiror Primary Stock Exchange	Amount of known deal values	Total number of acquisitions	Percentage of Known values
Euronext	1056	2824	37.39
Frankfurt	1180	4494	26.25
Luxembourg	61	110	55.45
Madrid	701	1223	57.32
Milan	1866	2955	63.15

Methodology

This study aims to measure the impact of serial acquisitions on the stock price performance of acquiring firms. M&A pays for target firm shareholders, when a firm gets acquired. According to the Fundamentals of Corporate Finance Textbook, shareholders in acquirer firms seem to neither win nor lose very much, on average. The explanations for that are 1) if managers of acquirer firms overestimate the gains from acquisitions, then the prices for acquirers may drop as anticipated merger gains are not completely achieved, 2) acquirer firms tend to be larger than target firms, so the gain is not substantial.

To understand the average effect of acquisitions and identify patterns, this study leverages a dataset of **serial acquirers**. Analyzing a large sample of acquisitions helps address variability in outcomes and provides robust insights into long-term stock price performance. To isolate the effect of acquisitions on stock price performance, it is essential to account for market returns. Market returns represent the general movement of the stock market, which can influence individual stock prices irrespective of firm-specific events.

1. Regression with event dummies

1.1 Firm-by-Firm OLS

The simplest and most traditional approach to capturing stock price patterns is through the use of event dummies. Running a firm-by-firm regressions is used to

analyze the heterogeneity in stock price reactions across different firms. This method proves useful in avoiding aggregation bias, since aggregating stock price reactions may yield a misleading “flat” average.

The regression with dummies is presented as follows:

$$R_{i,t}^e = \alpha_{i,0} + \sum_{l=-K}^L \gamma_{i,l} E_{i,t-l} + \beta_{i,1} R_{M,t}^e + \beta_{i,2} SMB + \beta_{i,3} HML + \epsilon_{i,t}$$

$$R_{i,t}^e = \alpha_{i,0} + \sum_{l=-K}^L \gamma_{i,l} E_{i,t-l} + \beta_{i,1} R_{M,t}^e + \epsilon_{i,t}$$

(2)

Excess returns are denoted as $R_{i,t}^e$ which is the return above risk-free rate. Event dummy is represented as $E_{i,t}$ and each coefficient $\gamma_{i,l}$ represents an estimate of the average abnormal return for firm i in the l th week where the event windows are $[-K, \dots, L]$ around the announcement. This study focuses on the pre-event and post event period, where $-K$ is 1, meaning that we observe the effect of one week before the event.

The next step after running firm-by-firm regressions is to compare positive and negative significant coefficient groups in terms of Cumulative Abnormal Returns and factor sensitivities, by simply taking averages and standard deviations of the

coefficients. After this procedure, investigating whether positive and negative significant coefficient groups yield systematic differences will provide if there is an asymmetry between them.

1.2 Panel Regression

The next approach is to run a panel regression with fixed effects, so that the analysis is improved by using a one-time estimation through a panel approach. By running a panel regression with fixed effects, we can get a common set of coefficients for all stocks. The advantages of this approach are, first, we don't need to calculate the t-test using equations (10-11), as the t-test of panel regression takes into account the correlations of all the residuals across stocks and second, it places less emphasis on noisier stocks, making the estimate more accurate. The disadvantage of running a panel regression, namely aggregation bias, can be viewed as an advantage of running firm-by-firm regressions. Panel regressions may produce a 'flat' averages.

1.2.1 Calculating Cumulative Abnormal Returns (CARs)

To quantify the market's response to acquisition announcements, CARs were calculated for all event windows [-1, 7] based on the coefficients obtained from the panel regressions, by taking a linear combination of coefficients corresponding to specific event weeks.

$$\text{CAR}(W) = \sum_{t \in W} \gamma_t \quad (3)$$

Where: γ_t are the estimated coefficients for each week in the event window.

The t-statistics for CARs are computed to test their statistical significance, using the variance-covariance matrix to compute the standard error for each linear combination.

1.3 Conditioning on the 1-week-before effect

From firm-by-firm regression results, the division of the dataset was implemented based on the sign of the coefficient of 1_week_before variable, which represents an estimate of the average abnormal return for the week leading up to the event. The motivation to separate the dataset into two subsets is to **isolate and study the dynamics of price adjustments after announcement**. This manipulation not only serves as a robustness check, but also will enable us to examine how different market behaviour influences CAR patterns.

- 1) After dividing the dataset based on the 1-week-before effect, the next procedure is to perform firm-by-firm regressions separately for each subset to capture firm-specific variations.
- 2) Running panel regressions for each subset will give the comprehension of whether group-level patterns exist. This step examines the distinctions

between firms with positive and negative pre-event reactions, focusing on how these differences influence their post-event CAR trajectories.

1.4 Industry-Specific Panel Regressions

In order to capture industry-specific reaction patterns, separate panel regressions are conducted for each industry using subsets of the dataset corresponding to industry classifications. Additionally, the fact whether industries exhibit different within-window CAR dynamics will be assessed.

2. A modified Almon Pattern for Post-Event Reactions

In this study, the modified Almon pattern is used to model the post-event stock price reactions following acquisition announcements. The regression with event dummies, which relies on a series of dummy variables representing each week within the event window, can produce noisy patterns. Therefore, adopting a parsimonious model can better capture the smooth transitions in price movements.

The modified Almon pattern uses a smooth quadratic function $d(w)$ of event time w , which captures both the initial price movement and its gradual fade-out over the event window.

A smooth function $d(w)$ is composed of two parameters, $\phi(t)$ and $\psi(t)$.

The function is expressed as:

$$D(w) = \eta[\phi(w) + b\psi(w)]$$

(4)

where:

- $\phi(w)$ captures rapid price movements, decaying faster due to the $1/w$ factor.
- $\psi(w)$ represents slower fading.

- η controls the amplitude and direction of the return pattern, and b influences the shape of the curve.

The parameters are calculated as follows where $w=1$ is event week, and $w=W(=7)$ is the end of event window:

$$\phi(T(j, m) + w - 1, m) := \begin{cases} \frac{1}{w} \left[\frac{w-W}{1-W} \right]^2, & 1 \leq w \leq W \\ 0, & \text{otherwise} \end{cases},$$

$$\psi(T(j, m) + w - 1, m) := \begin{cases} \left[\frac{w-W}{1-W} \right]^2, & 1 \leq w \leq W \\ 0, & \text{otherwise} \end{cases}.$$

(5), (6)

$D(t,m)$ was defined for each takeover in calendar time, assigning zeros outside the event window for that specific takeover. Summing these values across multiple mergers creates a general regressor. When event windows for takeovers overlap, the total expected return for period t is considered to be the cumulative effect of the individual takeovers.

$$\begin{aligned}
\delta_t &= \sum_{m=1}^M D(t, m), \\
&= \eta \sum_{m=1}^M \phi(t, m) + b \eta \sum_{m=1}^M \psi(t, m), \\
&=: \eta U_t + b \eta V_t.
\end{aligned}$$

(7)

The regression model Doan and Sercu (2020) used involves the modified Almon pattern for the abnormal returns, which they modeled as follows:

$$R_{j,t}^e = \alpha_{j,0} + \alpha_{j,1} E_{j,t} + \beta_{j,0} R_{M,t}^e + \eta_j U_{j,t} + \eta_j b_j V_{j,t} + \epsilon_{j,t}. \quad (8)$$

So, the modified CARs are calculated as follows:

$$\begin{aligned}
CAR(w) &= \alpha_1 + \sum_{\omega=1}^w [\eta \phi(\omega) + \theta \psi(\omega)], \\
&= \alpha_1 + \eta \left[\sum_{\omega=1}^w \phi(\omega) \right] + \theta \left[\sum_{\omega=1}^w \psi(\omega) \right], \\
&=: \alpha_1 + \eta \Phi(w) \quad + \theta \Psi(w).
\end{aligned}$$

(9)

Main Results

1. Firm by Firm regression results

After running firm-by-firm regressions across European stock exchanges - namely the UK, Frankfurt, Milan, Madrid, and Euronext (Tables 12 - 17), the common pattern is only detected in the market factor. The market factor consistently exhibits a strong positive impact across all regions, highlighting that overall market trends have a significant influence on firm outcomes.

For the UK companies, the announcement week shows a modest positive average coefficient, which explains the slight positive effect on excess return. For the acquirers of Frankfurt Stock Exchange, the event week's impact is mixed, with both positive and negative coefficients. Additionally, applying the Fama-French three factor model to European and the UK data accentuates the weighty influence of market excess returns, with consistently strong positive average coefficients. Overall, pre-event and post-event weeks show mixed and mostly insignificant effects, with average coefficients becoming negative in later weeks.

In Tables 12 - 17, I provide a summary of the firm-by-firm regression results for each stock exchange, including the average coefficient, standard deviation, t-statistic, number of positive and negative coefficients, and the counts of significant positive and negative coefficients at the 5% level.

Panel regressions

The panel regression analysis, spanning the period from 2000 to 2024, reveals and confirms the firm-by-firm regression results that the market factor consistently exerts a strong, positive, and statistically significant impact on excess returns across all regions analyzed.

Event-week effects are significant in most regions, with the events contributing to an increase in excess returns by 0.4% for UK acquirers and 0.5% for acquirers listed on the Euronext Stock Exchange. For the UK, the week-after effect remains positive and significant, contributing to an increase of 0.2% in excess returns.

However, pre-event and long-term post-event effects are generally weaker and less consistent, which explains that the immediate event window holds the most explanatory power.

After incorporating other two factors, the results show that SMB is negative for European companies but positive for UK companies, while HML is positive and significant for both. Event-week effects are consistently positive and significant for both European and UK companies. For both groups, the week-after effect remains positive and significant (for European countries at 10%).

CARs

The analysis of CARs across London, Milan, Madrid, Frankfurt, and Euronext Stock Exchanges gives impactful insights about regional differences in market reactions to events. London Stock Exchange CARs show the strongest immediate impact, with significant positive CARs during the event week and the following periods (from CAR1 till CAR4), showing diminishing returns. Milan and Euronext exhibit delayed but sustained positive abnormal returns, peaking at CAR4 and CAR2-CAR3, respectively.

In contrast, Madrid and Frankfurt Stock Exchanges show weaker and less consistent responses, with limited significance.

After incorporating other factors and consolidating European stock exchanges, we get positive and declining CARs for the European market. The UK companies show the immediate reaction at event week and have stronger response, while European stocks show a delayed but sustained positive impact. (Fig. 3)

Table 5. CAR results for panel regressions with 1 factor.

CAR Label	London		Milan		Madrid		Frankfurt		Euronext	
	CAR	t_stat	CAR	t_stat	CAR	t_stat	CAR	t_stat	CAR	t_stat
CARm1	-0,00067	-0,92049	-0,00074	-0,45569	-0,00066	-0,29398	0,000334	0,188919	-0,00057	-0,37816
CAR0	0,006073	3,717531	0,003248	1,431631	-0,00082	-0,26068	0,003301	1,337044	0,004137	1,959489
CAR1	0,006073	4,918597	0,006582	2,389318	0,002967	0,779706	0,004181	1,3987	0,005532	2,161401
CAR2	0,005592	3,965437	0,008547	2,719217	0,004468	1,030546	0,002882	0,843802	0,006326	2,163476
CAR3	0,004207	2,695861	0,01293	3,720868	0,00241	0,500951	0,00325	0,858488	0,006815	2,111709
CAR4	0,003596	2,124871	0,015749	4,180355	-0,0008	-0,15332	0,003752	0,914227	0,006102	1,746586
CAR5	0,00265	1,464801	0,014124	3,50116	-0,00149	-0,26399	0,003146	0,717996	0,004571	1,227981
CAR6	0,00237	1,237962	0,01176	2,746783	0,000441	0,073734	0,005678	1,227737	0,003034	0,773638
CAR7	0,002173	1,08152	0,009002	1,996989	0,000217	0,034321	0,004379	0,905045	0,001508	0,367975

Fig. 3. CAR Graphs for 1-factor panel regressions

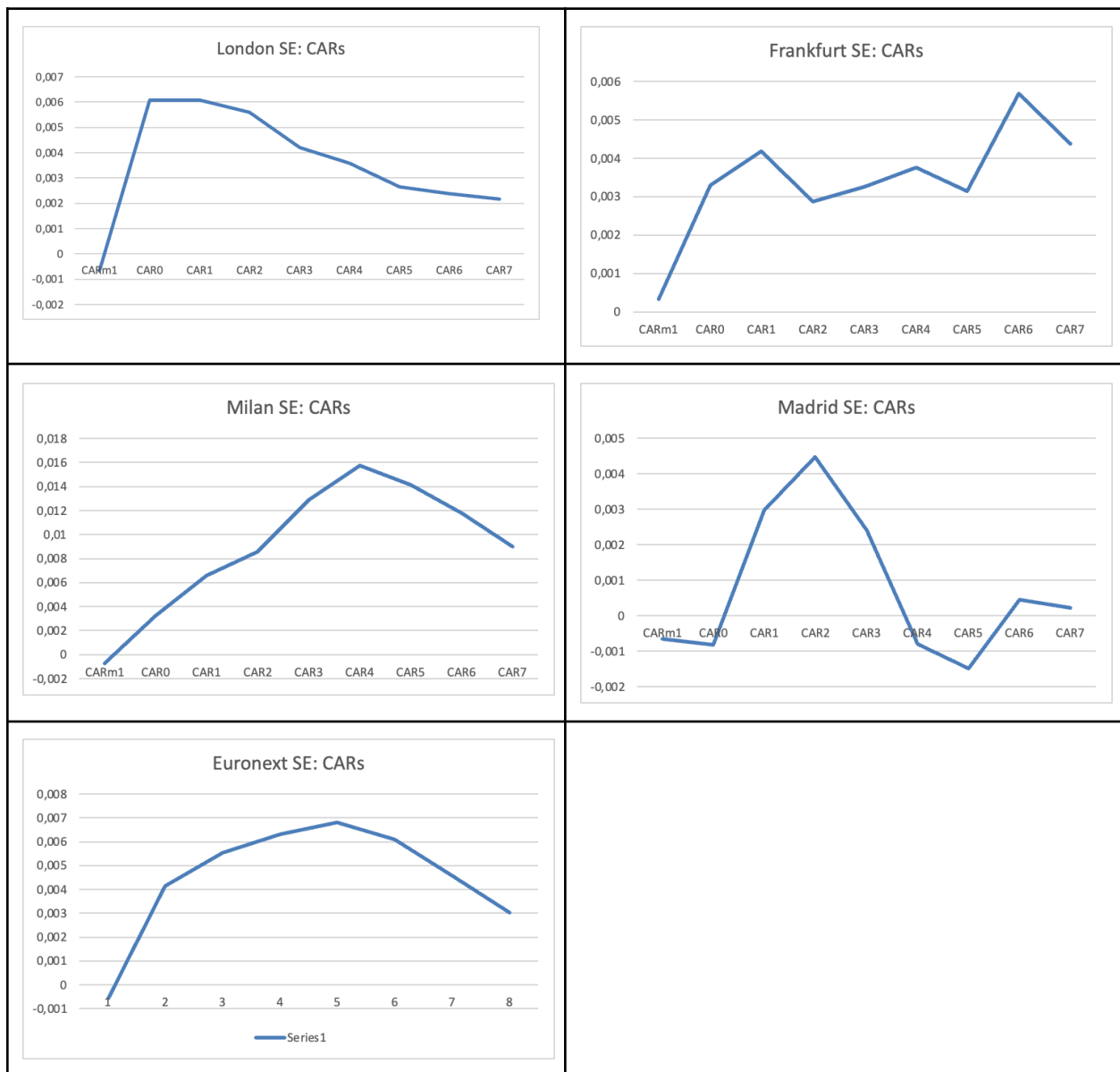
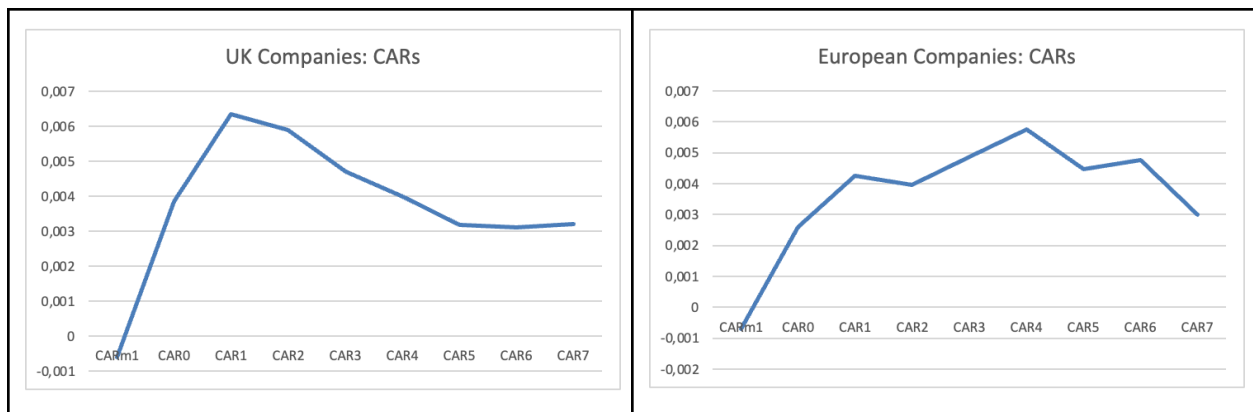


Table 6. CAR results for panel regressions with 3 factors.

	UK		European	
CAR_Label	CAR	t_stat	CAR	t_stat
CARm1	-0,00061	-0,8331	-0,0007	-0,75508
CAR0	0,003851	3,7432	0,002598	1,997856
CAR1	0,006351	5,097753	0,00427	2,710121
CAR2	0,0059	4,145736	0,00396	2,201278
CAR3	0,004704	2,986353	0,004885	2,455658
CAR4	0,00398	2,330286	0,005765	2,674148
CAR5	0,003176	1,739795	0,004483	1,947545
CAR6	0,003106	1,607349	0,004774	1,963323
CAR7	0,003212	1,584164	0,00299	1,173852

Fig. 4. CAR Graphs for 3-factor panel regressions



2. Conditioning on positive 1_week_before

Firm-by-Firm

After conditioning on the positive 1_week_before variable, the results for the UK are mixed. The difference between the number of positive and negative significant event dummies is negligible, indicating no discernible pattern. For Milan Stock Exchange acquirers, while the number of positive significant coefficients slightly

exceeds the negative ones, the difference is statistically insignificant. Similarly, for other stock exchanges and the three-factor models for the UK and European markets, the distribution of positive and negative coefficients is comparable, with few significant coefficients overall. These findings suggest that conditioning on the positive 1_week_before variable does not provide clearer or more conclusive results across the examined markets.

Panel Regressions

After conducting panel regressions for each stock exchange and conditioning on the positive1_week_before variable, the results yield limited significance across the examined periods. For the UK, the event_week variable is statistically significant at the 1% level, while 1_week_after is marginally significant at the 10% level. Similarly, for Euronext, the event_week is statistically significant.

In the case of the Milan stock exchange, the findings indicate that 3_weeks_after is significant at the 1% level, and 6_weeks_after is significant at the 5% level. Notably, Milan exhibits smaller p-values overall compared to the other stock exchanges, meaning relatively stronger relationships between the variables with excess return.

However, despite these observations, conditioning on the 1_week_before variable does not lead to substantial changes to the overall findings. The inconsistent significance across periods points to the fact that the conditioning on positive

1_week_before variable didn't provide additional clarity or didn't improve the robustness of the results.

The analysis of CARs reveals statistically significant results ($t\text{-stat} > 2$) for the UK, Milan, and Euronext. For Euronext, the CARs exhibit a consistently increasing trend, starting at 0.0078 for CAR0 and rising steadily to 0.0178 for CAR4, followed by a slight stabilization. In the UK, CARs are significant until CAR4, with a declining trend overall. The CARs start at 0.006 for CAR0 and decrease to 0.002 by CAR7, having a diminishing effect over time. For Milan Stock Exchange, the CARs have a pattern that depicts a short-term cumulative positive effect that diminishes over time, as it increases sharply until CAR4 (0.0231), and then begins to decline thereafter, falling to 0.0097 by CAR7. (Fig.5)

When comparing UK and European companies, it is evident that the UK experiences a strong immediate market reaction during the event week, but the effects tend to diminish over time. In contrast, European companies exhibit more sustained positive abnormal returns, with significant impacts persisting over a longer period. (Table 8)

Table 7. CAR results for panel regressions with 1 factor.

CAR_Label	UK		Frankfurt		Milan		Madrid		Euronext	
	CAR	t_stat	CAR	t_stat	CAR	t_stat	CAR	t_stat	CAR	t_stat
CAR0	0,006072557	3,717503	0,001822	0,830313	0,00224	0,943241	-0,00013	-0,04392	0,007828	2,888728
CAR1	0,006072557	4,918597	0,00436	1,427097	0,006872	2,066263	0,001583	0,375572	0,009197	2,409879
CAR2	0,005592255	3,965437	0,004027	1,089498	0,010682	2,648371	0,002874	0,563679	0,013261	2,851942
CAR3	0,004207394	2,695861	0,004115	0,97944	0,019102	4,164339	0,000682	0,117592	0,015401	2,883516
CAR4	0,003595957	2,124871	0,005179	1,115186	0,023077	4,571897	0,000629	0,09767	0,017838	3,007465
CAR5	0,002650042	1,464801	0,004439	0,885803	0,01904	3,498613	-0,00112	-0,15918	0,016466	2,554417
CAR6	0,002370331	1,237962	0,00835	1,56875	0,014262	2,460538	0,000307	0,040763	0,016773	2,430323
CAR7	0,002173225	1,08152	0,005673	1,015328	0,009687	1,585406	0,002313	0,290105	0,016987	2,322465

Fig. 5. CAR Graphs for 1-factor panel regressions with significant t-stat

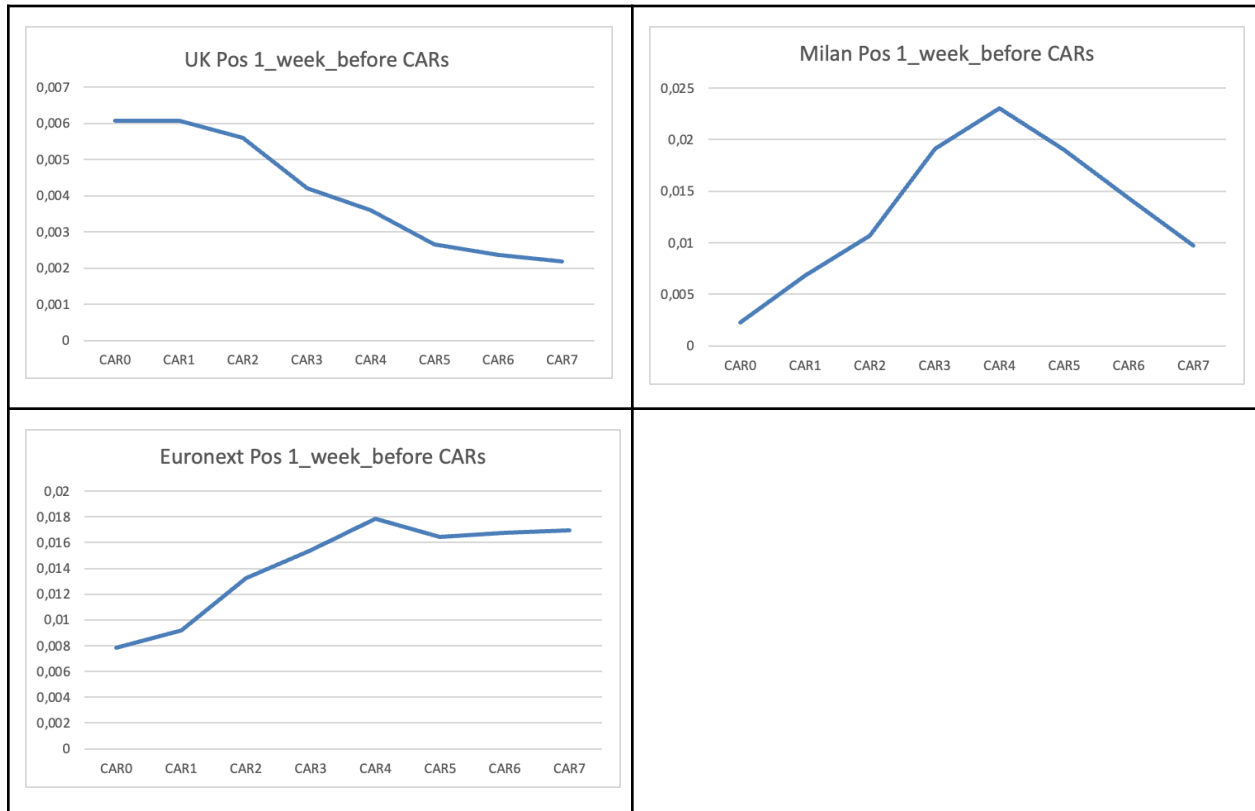


Table 8. CAR results for panel regressions with 3 factors.

	UK		European	
CAR_Label	CAR	t_stat	CAR	t_stat
CARm1	-0,00061	-0,8331	-0,0007	-0,75508
CAR0	0,004481	4,253726	0,002578	1,781871
CAR1	0,006622	4,515836	0,004575	2,264951
CAR2	0,005495	3,103182	0,005391	2,200284
CAR3	0,004958	2,458223	0,007126	2,550328
CAR4	0,003092	1,388683	0,008864	2,868591
CAR5	0,001655	0,687408	0,007669	2,294981
CAR6	0,001737	0,677429	0,008861	2,48845
CAR7	0,001815	0,671422	0,006813	1,815203

3. Conditioning on negative 1_week_before

After conditioning on the negative 1_week_before variable, for the UK, we can infer some insights - both the 1-factor and 3-factor firm-by-firm regressions show 10 and 11 positive significant coefficients, respectively, for the event week. This indicates that firms experience a positive impact during the event week, following a decline observed in the period before the announcement. This pattern points to a rebound effect as markets react positively to the announcement after the pre-event decline.

However, the firm-by-firm analysis does not yield statistically significant coefficients for other stock exchanges. In the Milan and Frankfurt stock exchanges, no significant negative coefficients are observed, and only a small number of positive coefficients are present. Similarly, for the other stock exchanges, only a minimal number of significant coefficients (1-2 for both positive and negative) are

identified. These results suggest that the firm-by-firm regressions fail to provide conclusive insights under this conditioning.

Panel regression on the subset with negative 1_week_before reveals significant positive effects during the event week for the Milan and Frankfurt stock exchanges, indicating strong investor reactions. In the UK, the event week and 1_week_after variables remain positively significant. When incorporating two additional factors, the UK model also shows significance for 3_week_after, though with a negative coefficient.

Based on the statistically significant CARs, only the UK exhibits a declining pattern in CARs over time. However, when incorporating two factors, the diminishing pattern shifts to an increase two weeks after the event, followed by a slight decrease, with all coefficients remaining statistically significant.

Table 9. CAR results for conditioning on negative 1_week_before.

	UK		Frankfurt		Milan		Madrid		Euronext	
CAR_Label	CAR	t_stat	CAR	t_stat	CAR	t_stat	CAR	t_stat	CAR	t_stat
CAR0	0,006073	3,717503	0,004792	2,053796	0,005962	2,752219	-0,00051	-0,1509	0,002613	1,473677
CAR1	0,006073	4,918597	0,003171	0,973172	0,007893	2,600255	0,005736	1,213145	0,00417	1,679112
CAR2	0,005592	3,965437	0,000513	0,129416	0,007851	2,126493	0,007607	1,328085	0,002758	0,920332
CAR3	0,004207	2,695861	0,001286	0,282397	0,007729	1,827657	0,005898	0,901397	0,002207	0,646976
CAR4	0,003596	2,124871	0,000904	0,178416	0,009174	1,951966	-0,00096	-0,13727	-0,00058	-0,15533
CAR5	0,00265	1,464801	0,000755	0,136458	0,010281	2,006709	-0,00043	-0,05455	-0,00215	-0,5308
CAR6	0,00237	1,237962	0,001328	0,223522	0,010578	1,917037	0,002076	0,244483	-0,00483	-1,12565
CAR7	0,002173	1,08152	0,00207	0,327487	0,009908	1,679634	-0,00093	-0,10259	-0,00752	-1,66962

Fig. 6. CAR Graphs the UK companies conditioning on negative 1_week_before.

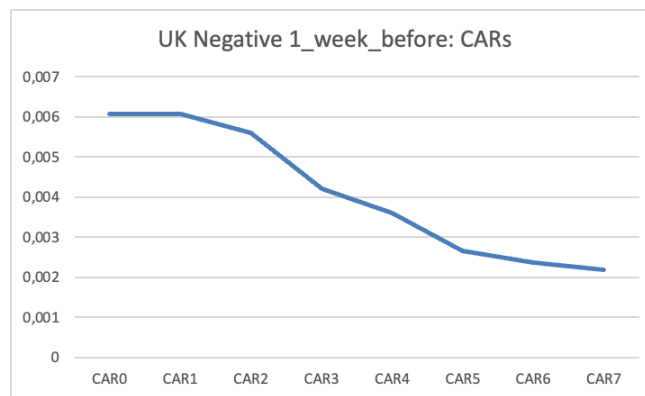
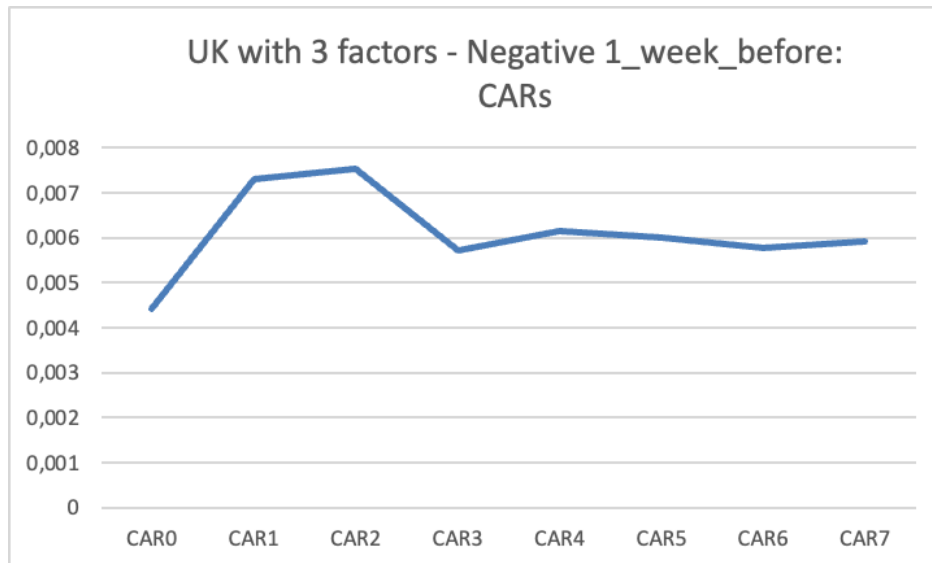


Table 10. CAR results for conditioning on negative 1_week_before.

	UK		European	
CAR_Label	CAR	t_stat	CAR	t_stat
CAR0	0,004427	4,304228	0,003902	3,569699
CAR1	0,007316	5,06124	0,005268	3,439915
CAR2	0,00754	4,298042	0,003979	2,14506
CAR3	0,005726	2,848789	0,004171	1,967975
CAR4	0,006153	2,75799	0,00428	1,827026
CAR5	0,005994	2,47178	0,00289	1,137356
CAR6	0,005787	2,225474	0,002403	0,884531
CAR7	0,005928	2,147455	0,000809	0,281282

Fig. 7. CAR Graphs the UK companies (with 3 factors) conditioning on negative 1_week_before.



4. Functional Form

After running firm-by-firm regressions with $\phi(t)$ and $\psi(t)$ as regressors, the UK data presents a clear pattern. Positive and statistically significant $\psi(t)$ coefficients are prevalent, with 13 significant coefficients observed. This indicates that the effect captured by $\psi(t)$ tends to fade positively over time, suggesting that the market adjusts favorably and gradually to the event after the announcement.

Panel regression

In the panel regressions, the results indicate that the UK, Frankfurt, and Euronext exhibit positive and statistically significant $\psi(t)$ variables, pointing out a gradual positive fading effect in these markets. In contrast, Milan shows a positive and

statistically significant $\phi(t)$ variable, suggesting a stronger immediate reaction or spike in abnormal returns following the event.

CARs for panel regression with a modified Almon Lag part

Overall, applying a functional form provided a smoother representation of CARs over time. The London Stock Exchange and Euronext exhibit a gradual upward trend, with minor abrupt fluctuations observed between the third and fourth weeks. Milan and Madrid demonstrate a convex rising pattern, reflecting a consistent positive adjustment over the event window. In contrast, Frankfurt shows a decline, with CARs falling below zero starting from the week following the event.

Figure 8. CARs for panel regression with a modified Almon Lag part(with 1 factor).

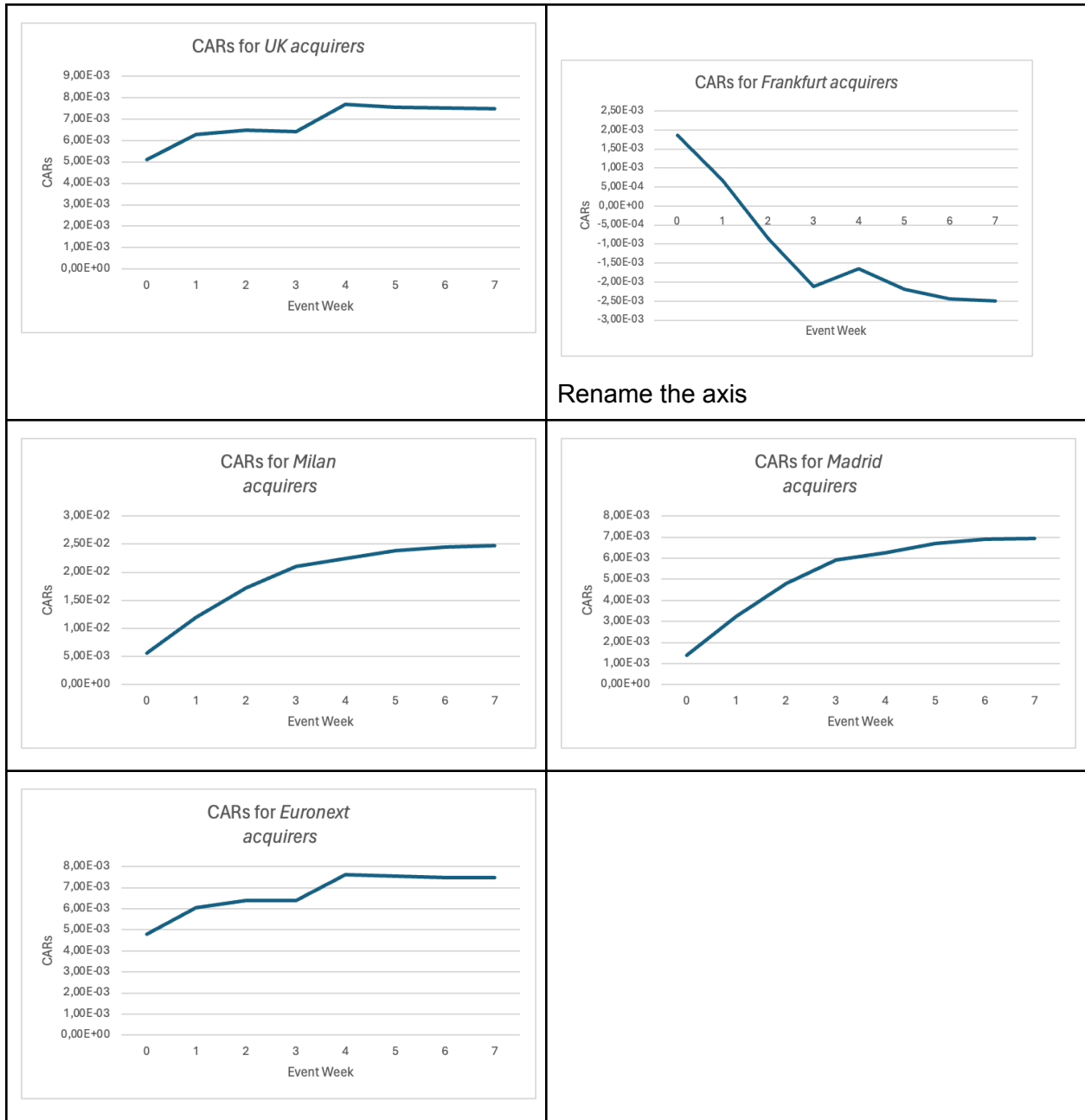
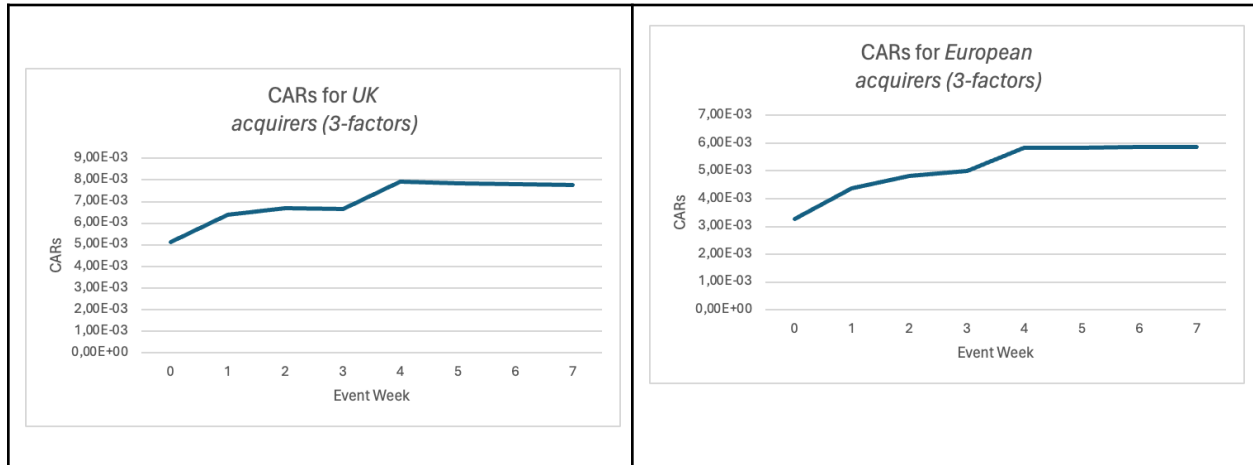


Figure 9. CARs for panel regression with a modified Almon Lag part(with 1 factor).



Industries

The panel regression analysis conducted for individual industries did not yield statistically significant results. This lack of significance may be attributed to the limited sample size within each industry and the unbalanced nature of the panel, which could result in reduced statistical power.

Conclusion

With an emphasis on UK and European companies, this thesis examines the long-term effects of serial acquisitions on acquirers' stock performance between January 2000 and August 2024. The study offers important insights into the dynamics of stock price behavior after acquisitions through the use of event study approaches, such as event dummy regressions and a modified Almon-lag methodology. Across the UK and Europe, the market factor consistently exhibits a strong positive impact on excess returns, showing the crucial role of the broader market in shaping acquirer company performance. The event-week effects are often substantial, with European acquirers—especially those on Milan and Euronext—showing a more prolonged but delayed positive impact, whereas UK acquirers see an instantaneous positive market reaction. The positive event-week effect demonstrates that the acquisition has a positive impact on an excess return. Additionally, the incorporation of $\psi(t)$ and $\phi(t)$ variables into the regressions provides an understanding of how abnormal returns evolve over time. While the UK and Euronext reflect a gradual positive adjustment, Milan demonstrates a stronger immediate impact, aligning with regional market dynamics.

Conditioning on pre-event variables, such as positive or negative performance one week before the event, yields mixed results. Conditioning factors generally do not add substantial clarity or robustness to the findings.

Analysing at industry level and across regions highlights heterogeneity in market reactions. However, panel regressions for individual industries did not yield statistically significant results, potentially due to limited sample sizes and unbalanced panel structures.

Limitations and Future Research

For industry-specific analysis, the dataset has an unbalanced nature which causes reduction on the statistical strength for many regressions. Also, for the firm-by-firm regressions, the t-statistics can be calculated using these equations. A key limitation of this thesis was the challenge of estimating the average rho, which was constrained by the characteristics of the dataset.

$$\text{(test for all } \gamma\text{s being zero:)} \quad t(\text{avg}(t)) = \text{avg}(t) \sqrt{\frac{1 + (N - 1)\bar{\rho}}{N}}.$$

(10)

$$\text{(test for a zero average } \gamma\text{:)} \quad t(\text{avg}(t)) = \frac{\text{avg}(t)}{\text{std}(t)} \sqrt{\frac{1 + (N - 1)\bar{\rho}}{N}},$$

(11)

Also, for future research, others can incorporate the relative size of takeover and experience interactions into the regression with a functional form. However, this approach could not be implemented in this study due to the limited dataset, as the data spans varied across stocks, resulting in cropped and inconsistent data availability.

Appendices

Table 11. Average deal values over time.

Year	Euronext	Frankfurt	Luxembourg	Madrid	Milan(EUR)	London (GBP)
2000	519.98383553751	921.449063552944	109.660680480175	83.4864106167681	399.766495371407	147.145107020956
2001	497.2897226248	769.364150232493	1001.13327227323	104.210715793422	230.245808890415	53.9830660675873
2002	118.649112248781	418.686682558173	64.1190583195601	190.543878462797	265.947243895938	78.6996056396239
2003	140.679187675646	240.451294270771	65.8131227338072	226.451920541224	344.87102624354	52.5442876779533
2004	166.144871624434	236.875216768772	41.071	497.015813710959	380.721446964468	47.7639422420323
2005	271.097304026007	744.703394088157	348.137749544766	920.939393880584	278.090376844817	81.4496184416349
2006	189.466488279911	373.960329820303	31.541622907225	499.016749004072	611.750689766882	73.2410160668589
2007	507.431332646569	616.1468939459	217.589904438714	355.274094584515	571.063119553921	73.04078377996
2008	728.729120816925	387.146311980155	74.5849879984226	620.015079563164	141.622891765442	72.7004366779987
2009	108.584728561474	379.365901472347	31.1927254029386	249.473483093153	108.419000569726	54.2063680448933
2010	78.0900063557083	88.4551206734129	4.113	717.91352932949	85.2884604437898	108.23540980962
2011	130.572520525556	100.089098382721	15.88	364.239632	55.5559949746153	112.543908328926
2012	279.230246131522	237.597564934923	NA	NA	148.82102258355	129.691420349455
2013	119.501786791106	409.500815922146	23.4312374891683	NA	172.065010423491	59.0141209766185
2014	322.963561611366	606.720203284008	107.55936	433.058833180405	223.430050241219	120.13235725079
2015	6793.83462085675	240.60836289841	46.625075	185.263522996183	254.977469626115	139.196339086822
2016	170.892132665223	338.593607309538	24.7069540315588	297.209511373839	90.8619120586257	164.46692272853
2017	189.871536887898	491.473921455838	20.2532016705427	NA	88.6973920659554	129.284473422065
2018	307.074401297931	515.229593357942	209.818866850885	NA	129.205522794517	164.54308566291
2019	452.042973883553	573.467528266542	28.7610427293637	179.996029858212	192.292620287082	146.3910221231
2020	446.681776348052	491.203677458201	NA	315.277839312967	290.720593336365	374.914647114893
2021	454.677146813827	644.309115285551	87	339.115678461569	201.555646852022	106.510821057632
2022	871.43089862874	554.340904247828	72.5	168.363399010071	150.692280747761	121.804479160388
2023	411.058921192484	286.211354973889	110	247.532792653695	196.573814805165	140.95744781328
2024	170.087015350209	252.472634633626	NA	179.823	415.005463379086	281.928147058823

Table 12. Firm-by-firm coefficients summary: UK

Coefficient Type	Average Coefficient	Standard Deviation	t-stat	# of Positive Coefficients	# of Negative Coefficients	# of Positive Significant (5%)	# of Negative Significant (5%)
(Intercept)	0,001205	0,001907	0,048917	139	28	14	5
Mkt.RF	0,782656	0,410375	0,147582	165	2	156	0
1_week_before	0,000183	0,012123	0,001168	77	88	3	5
event_week	0,0049	0,012529	0,030263	110	55	16	1
1_week_after	0,00338	0,010459	0,025011	101	64	7	1
2_weeks_after	-0,00012	0,009155	-0,00104	79	86	3	1
3_weeks_after	-0,00148	0,012393	-0,00925	68	97	4	3
4_weeks_after	-0,00048	0,010532	-0,00354	78	87	4	1
5_weeks_after	-0,00027	0,009568	-0,00217	79	86	4	6
6_weeks_after	-0,00041	0,010184	-0,00308	81	84	4	6
7_weeks_after	-0,00057	0,008591	-0,00512	75	90	5	1

Table 13. Firm-by-firm coefficients summary: Milan

Coefficient Type	Average Coefficient	Standard Deviation	t-Statistic	# of Positive Coefficients	# of Negative Coefficients	# of Positive Significant (5%)	# of Negative Significant (5%)
(Intercept)	0,000592	0,002265	0,052301	20	5	2	1
Mkt.RF	0,731463	0,230223	0,635439	25	0	25	0
1_week_before	-0,00116	0,008084	-0,02862	13	12	0	0
event_week	0,004681	0,015138	0,061851	14	11	4	0
1_week_after	0,003695	0,008174	0,090422	18	7	0	0
2_weeks_after	0,002602	0,009973	0,052185	14	11	1	0
3_weeks_after	0,004269	0,00997	0,085648	17	8	3	0
4_weeks_after	0,003275	0,009603	0,068216	14	11	1	0
5_weeks_after	-0,00139	0,007852	-0,03545	12	13	1	0
6_weeks_after	-0,00273	0,008425	-0,06483	10	15	0	0
7_weeks_after	-0,00399	0,009292	-0,08592	9	16	0	1

Table 14. Firm-by-firm coefficients summary: Madrid

Coefficient Type	Average Coefficient	Standard Deviation	t-Statistic	# of Positive Coefficients	# of Negative Coefficients	# of Positive Significant (5%)	# of Negative Significant (5%)
(Intercept)	0,000263	0,000799	0,116494	5	3	0	0
Mkt.RF	0,995545	0,280884	1,253108	8	0	8	0
`1_week_before`	-0,00089	0,005759	-0,05486	4	4	0	0
event_week	-0,00038	0,008434	-0,01586	3	5	0	1
`1_week_after`	0,003821	0,006928	0,194998	6	2	1	0
`2_weeks_after`	0,002248	0,007382	0,107687	4	4	0	0
`3_weeks_after`	-0,00136	0,006355	-0,0758	3	5	0	0
`4_weeks_after`	-0,00254	0,007341	-0,12255	4	4	0	0
`5_weeks_after`	0,000255	0,007504	0,012025	2	6	0	1
`6_weeks_after`	0,001192	0,004454	0,094599	5	3	1	0
`7_weeks_after`	-0,00141	0,006889	-0,07244	4	4	0	1

Table 14. Firm-by-firm coefficients summary: Frankfurt

Coefficient Type	Average Coefficient	Standard Deviation	t-Statistic	# of Positive Coefficients	# of Negative Coefficients	# of Positive Significant (5%)	# of Negative Significant (5%)
(Intercept)	-0,0005	0,003217	-0,02376	26	16	2	0
Mkt.RF	0,816876	0,329791	0,382202	42	0	38	0
`1_week_before`	-3,1E-05	0,011649	-0,00042	23	18	1	1
event_week	0,00319	0,014128	0,034836	24	17	4	2
`1_week_after`	0,002283	0,014811	0,023783	21	20	1	1
`2_weeks_after`	-0,00143	0,008783	-0,02506	13	28	0	0
`3_weeks_after`	0,000262	0,009676	0,004177	20	21	2	0
`4_weeks_after`	0,001784	0,010396	0,026482	19	22	0	0
`5_weeks_after`	0,000861	0,012504	0,010625	24	17	1	2
`6_weeks_after`	0,001968	0,0121	0,025099	27	14	1	0
`7_weeks_after`	-0,00152	0,010598	-0,02212	20	21	0	2

Table 15. Firm-by-firm coefficients summary: Euronext

Coefficient Type	Average Coefficient	Standard Deviation	t-Statistic	# of Positive Coefficients	# of Negative Coefficients	# of Positive Significant (5%)	# of Negative Significant (5%)
(Intercept)	0,000272	0,003322	0,015176	22	7	2	2
Mkt.RF	0,892758	0,319719	0,518521	29	0	29	0
1_week_before	-0,00121	0,01007	-0,02224	10	18	1	2
event_week	0,004135	0,006513	0,1179	20	8	1	0
1_week_after	0,002401	0,008192	0,054432	17	11	3	0
2_weeks_after	-0,0002	0,008844	-0,00427	14	14	0	1
3_weeks_after	-0,00036	0,008328	-0,00793	12	16	2	0
4_weeks_after	-0,00116	0,006659	-0,03247	11	17	1	1
5_weeks_after	-0,00134	0,006823	-0,0365	14	14	0	1
6_weeks_after	-0,0006	0,007675	-0,01461	10	18	0	1
7_weeks_after	8,14E-05	0,009989	0,001513	8	20	2	0

Table 16. Firm-by-firm coefficients summary: UK - 3 factors

Coefficient Type	Average Coefficient	Standard Deviation	t-Statistic	#of Positive Coefficients	# of Negative Coefficients	# of Positive Significant (5%)	# of Negative Significant (5%)
(Intercept)	0,001097965	0,002134559	0,039923287	131	35	17	5
Mkt.RF_w	0,670891054	0,312817362	0,166458933	162	4	157	0
SMB_w	0,277384745	0,617357749	0,034873186	111	55	85	35
HML_w	0,034348764	0,431633815	0,006176488	94	72	45	31
`1_week_before`	6,02735E-05	0,011976434	0,000390611	77	87	2	4
event_week	0,004989236	0,01259859	0,030736758	104	60	18	0
`1_week_after`	0,003594977	0,010069779	0,027709084	103	61	9	1
`2_weeks_after`	6,77378E-05	0,009025143	0,000582536	84	80	2	3
`3_weeks_after`	-0,00142578	0,012773685	-0,008663278	65	99	3	3
`4_weeks_after`	-0,000563812	0,010565063	-0,004141981	74	90	3	1
`5_weeks_after`	8,84287E-06	0,009998721	6,86427E-05	76	88	5	5
`6_weeks_after`	-0,000136448	0,01025625	-0,001032585	83	81	4	7
`7_weeks_after`	-0,000487396	0,009166191	-0,004127047	81	83	6	2

Table 17. Firm-by-firm coefficients summary: Europe - 3 factors

Coefficient Type	Average Coefficient	Standard Deviation	t-Statistic	# of Positive Coefficients	# of Negative Coefficients	# of Positive Significant (5%)	# of Negative Significant (5%)
(Intercept)	1,28E-05	0,002653	0,000471	68	36	9	3
Mkt.RF_w	0,783473	0,293208	0,262019	103	1	101	0
SMB_w	-0,07159	0,518094	-0,01355	56	48	26	37
HML_w	0,093204	0,601961	0,015183	60	44	41	26
`1_week_before`	-0,00105	0,009878	-0,01038	44	58	1	3
event_week	0,003392	0,012476	0,026661	62	40	7	5
`1_week_after`	0,002439	0,010448	0,022896	57	45	5	1
`2_weeks_after`	-0,00026	0,009381	-0,00274	42	60	2	3
`3_weeks_after`	0,000906	0,008906	0,00997	50	52	6	0
`4_weeks_after`	0,001574	0,010029	0,015389	53	49	2	1
`5_weeks_after`	-0,00047	0,010332	-0,00447	49	53	3	4
`6_weeks_after`	0,00033	0,009448	0,003422	49	53	1	3
`7_weeks_after`	-0,00171	0,009525	-0,01763	43	59	4	5

Table 18. Panel regression results for 1-factor.

	<i>Dependent variable:</i>				
	Frankfurt (1)	Madrid (2)	Milan (3)	Euronext (4)	UK (5)
Mkt.RF	0.855*** (0.010)	0.995*** (0.011)	0.733*** (0.008)	0.892*** (0.010)	0.855*** (0.005)
X1_week_before	0.0003 (0.002)	-0.001 (0.002)	-0.001 (0.002)	-0.001 (0.002)	-0.001 (0.001)
event_week	0.003* (0.002)	-0.0002 (0.002)	0.004** (0.002)	0.005*** (0.002)	0.004*** (0.001)
X1_week_after	0.001 (0.002)	0.004* (0.002)	0.003** (0.002)	0.001 (0.002)	0.002*** (0.001)
X2_weeks_after	-0.001 (0.002)	0.002 (0.002)	0.002 (0.002)	0.001 (0.002)	-0.0005 (0.001)
X3_weeks_after	0.0004 (0.002)	-0.002 (0.002)	0.004*** (0.002)	0.0005 (0.001)	-0.001* (0.001)
X4_weeks_after	0.001 (0.002)	-0.003 (0.002)	0.003* (0.002)	-0.001 (0.001)	-0.001 (0.001)
X5_weeks_after	-0.001 (0.002)	-0.001 (0.002)	-0.002 (0.002)	-0.002 (0.001)	-0.001 (0.001)
X6_weeks_after	0.003 (0.002)	0.002 (0.002)	-0.002 (0.002)	-0.002 (0.001)	-0.0003 (0.001)
X7_weeks_after	-0.001 (0.002)	-0.0002 (0.002)	-0.003* (0.002)	-0.002 (0.001)	-0.0002 (0.001)
Observations	44,765	8,664	28,295	32,162	164,132
R ²	0.146	0.507	0.220	0.209	0.132
Adjusted R ²	0.146	0.506	0.219	0.208	0.131
F Statistic	767.396*** (df = 10; 44713) 889.576*** (df = 10; 8646) 794.782*** (df = 10; 28260) 849.509*** (df = 10; 32123) 2,495.302*** (df = 10; 163954)				

Note: *p<0.1; **p<0.05; ***p<0.01

Table 19. Panel regression results for 3-factors.

	ExcessReturn	
	European companies (1)	UK companies (2)
Mkt.RF_w	0.792*** (0.006)	0.696*** (0.005)
SMB_w	-0.107*** (0.015)	0.174*** (0.012)
HML_w	0.132*** (0.012)	0.063*** (0.010)
X1_week_before	-0.001 (0.001)	-0.001 (0.001)
event_week	0.003*** (0.001)	0.004*** (0.001)
X1_week_after	0.002* (0.001)	0.003*** (0.001)
X2_weeks_after	-0.0003 (0.001)	-0.0005 (0.001)
X3_weeks_after	0.001 (0.001)	-0.001 (0.001)
X4_weeks_after	0.001 (0.001)	-0.001 (0.001)
X5_weeks_after	-0.001 (0.001)	-0.001 (0.001)
X6_weeks_after	0.0003 (0.001)	-0.0001 (0.001)
X7_weeks_after	-0.002* (0.001)	0.0001 (0.001)
Observations	116,516	164,132
R ²	0.161	0.116
Adjusted R ²	0.161	0.115
F Statistic	1,865.952*** (df = 12; 116400) 1,799.817*** (df = 12; 163952)	

Table 20. Firm by firm coefficients: conditioning on positive 1_week_before: UK

Coefficient Type	Average Coefficient	Standard Deviation	t-Statistic	# of Positive Coefficients	# of Negative Coefficients	# of Positive Significant (5%)	# of Negative Significant (5%)
Mkt.RF	0,795962978	0,392448008	0,23113482	77	0	74	0
event_week	0,004785875	0,012905646	0,042260655	49	28	6	0
`1_week_after`	0,00372663	0,012092079	0,035121246	43	34	4	0
`2_weeks_after`	0,000210845	0,007339678	0,003273711	36	41	2	0
`3_weeks_after`	-0,002366517	0,016100317	-0,016750582	31	46	1	3
`4_weeks_after`	-0,001942687	0,011174532	-0,019811991	33	44	3	1
`5_weeks_after`	-0,000137362	0,009866828	-0,001586508	40	37	1	4
`6_weeks_after`	0,000369576	0,010924548	0,003855273	37	40	3	3
`7_weeks_after`	-0,000933897	0,009186502	-0,011585203	37	40	2	1
`1_week_before`	0,007451144	0,01332126	0,06374297	77	0	3	0

Table 21. Firm by firm coefficients: conditioning on positive 1_week_before: Milan

Coefficient Type	Average Coefficient	Standard Deviation	t-Statistic	# of Positive Coefficients	# of Negative Coefficients	# of Positive Significant (5%)	# of Negative Significant (5%)
(Intercept)	-0,00014	0,002854	-0,0139	9	4	1	1
Mkt.RF	0,747268	0,237057	0,874283	13	0	13	0
event_week	0,000975	0,016809	0,01608	6	7	1	0
`1_week_after`	0,004437	0,008843	0,139169	9	4	0	0
`2_weeks_after`	0,004445	0,012271	0,100477	8	5	1	0
`3_weeks_after`	0,00904	0,009761	0,256867	12	1	2	0
`4_weeks_after`	0,00505	0,012339	0,113513	6	7	1	0
`5_weeks_after`	-0,00366	0,006876	-0,14752	5	8	0	0
`6_weeks_after`	-0,00581	0,006635	-0,24272	3	10	0	0
`7_weeks_after`	-0,00695	0,011031	-0,17477	4	9	0	1
`1_week_before`	0,004651	0,005436	0,237308	13	0	0	0

Table 22. Firm by firm coefficients: conditioning on positive 1_week_before:
Madrid

Coefficient Type	Average Coefficient	Standard Deviation	t-Statistic	# of Positive Coefficients	# of Negative Coefficients	# of Positive Significant (5%)	# of Negative Significant (5%)
(Intercept)	-0,00014	0,000711	-0,10123	2	2	0	0
Mkt.RF	1,027117	0,283408	1,812081	4	0	4	0
event_week	0,001884	0,003401	0,277005	2	2	0	0
`1_week_after`	0,001616	0,002787	0,289909	3	1	0	0
`2_weeks_after`	0,00094	0,008445	0,055678	2	2	0	0
`3_weeks_after`	-0,00212	0,003842	-0,27529	1	3	0	0
`4_weeks_after`	0,001303	0,0056	0,116378	3	1	0	0
`5_weeks_after`	-0,00029	0,007542	-0,01918	1	3	0	1
`6_weeks_after`	0,000411	0,006287	0,032718	2	2	1	0
`7_weeks_after`	0,000242	0,003356	0,036025	2	2	0	0
`1_week_before`	0,003376	0,001852	0,911709	4	0	0	0

Table 23. Firm by firm coefficients: conditioning on positive 1_week_before:
Frankfurt

Coefficient Type	Average Coefficient	Standard Deviation	t-Statistic	# of Positive Coefficients	# of Negative Coefficients	# of Positive Significant (5%)	# of Negative Significant (5%)
(Intercept)	-0,00121	0,00366	-0,06918	10	13	1	0
Mkt.RF	0,865814	0,376133	0,479976	23	0	21	0
event_week	0,000537	0,014727	0,007602	12	11	2	2
`1_week_after`	0,002715	0,009592	0,059021	13	10	0	1
`2_weeks_after`	-0,00081	0,008077	-0,02085	8	15	0	0
`3_weeks_after`	0,00027	0,01057	0,005329	10	13	1	0
`4_weeks_after`	0,001908	0,006824	0,058313	12	11	0	0
`5_weeks_after`	-0,00061	0,011281	-0,01126	14	9	1	2
`6_weeks_after`	0,003746	0,009536	0,081902	18	5	0	0
`7_weeks_after`	-0,0026	0,011582	-0,04673	10	13	0	2
`1_week_before`	0,007479	0,008685	0,179561	23	0	1	0

Table 24. Firm by firm coefficients: conditioning on positive 1_week_before:
Euronext

Coefficient Type	Average Coefficient	Standard Deviation	t-Statistic	# of Positive Coefficients	# of Negative Coefficients	# of Positive Significant (5%)	# of Negative Significant (5%)
(Intercept)	-0,00157	0,005188	-0,09541	5	5	1	2
Mkt.RF	0,866404	0,372376	0,735764	10	0	10	0
event_week	0,007232	0,006244	0,366295	9	1	0	0
`1_week_after`	0,002601	0,00522	0,157574	7	3	1	0
`2_weeks_after`	0,003215	0,007405	0,137301	6	4	0	0
`3_weeks_after`	0,001497	0,009559	0,049524	6	4	1	0
`4_weeks_after`	0,00195	0,007153	0,086224	5	5	1	0
`5_weeks_after`	-0,00101	0,005038	-0,06327	5	5	0	0
`6_weeks_after`	0,001465	0,010329	0,044841	5	5	0	0
`7_weeks_after`	0,001732	0,010007	0,054729	4	6	0	0
`1_week_before`	0,008078	0,010103	0,252839	10	0	1	0

Table 25. Firm by firm coefficients: conditioning on positive 1_week_before:
Europe

Coefficient Type	Average Coefficient	Standard Deviation	t-Statistic	# of Positive Coefficients	# of Negative Coefficients	# of Positive Significant (5%)	# of Negative Significant (5%)
(Intercept)	-0,00076	0,003256	-0,03532	24	20	3	2
Mkt.RF_w	0,782631	0,34308	0,343903	43	1	43	0
SMB_w	-0,07415	0,543238	-0,02058	22	22	8	16
HML_w	0,042191	0,653691	0,00973	25	19	16	12
event_week	0,002166	0,012807	0,025498	23	21	3	3
`1_week_after`	0,002009	0,007771	0,038964	24	20	1	1
`2_weeks_after`	0,000722	0,010566	0,010298	20	24	1	1
`3_weeks_after`	0,002143	0,009853	0,032795	23	21	3	0
`4_weeks_after`	0,002685	0,008029	0,050419	26	18	1	0
`5_weeks_after`	-0,00099	0,009591	-0,01564	21	23	1	2
`6_weeks_after`	0,000971	0,010057	0,01456	25	19	0	2
`7_weeks_after`	-0,00197	0,00886	-0,03347	18	26	1	3
`1_week_before`	0,007235	0,007492	0,145584	44	0	1	0

Table 26. Firm by firm coefficients: conditioning on positive 1_week_before: UK

Coefficient Type	Average Coefficient	Standard Deviation	t-Statistic	# of Positive Coefficients	# of Negative Coefficients	# of Positive Significant (5%)	# of Negative Significant (5%)
(Intercept)	0,000718	0,002499	0,032767	58	19	6	4
Mkt.RF_w	0,688277	0,321858	0,243699	75	2	73	0
SMB_w	0,297794	0,652426	0,052016	52	25	42	15
HML_w	-0,01804	0,455584	-0,00451	38	39	20	15
event_week	0,005848	0,013069	0,050997	48	29	7	0
`1_week_after`	0,003748	0,009851	0,043361	46	31	4	0
`2_weeks_after`	-0,00025	0,00916	-0,00305	40	37	1	2
`3_weeks_after`	-0,00112	0,016312	-0,00783	37	40	1	3
`4_weeks_after`	-0,00263	0,010249	-0,02929	30	47	1	1
`5_weeks_after`	-0,00021	0,011066	-0,00213	33	44	3	3
`6_weeks_after`	0,000109	0,011191	0,001112	37	40	2	4
`7_weeks_after`	-0,00016	0,008729	-0,00208	37	40	2	1
`1_week_before`	0,007362	0,013086	0,06411	77	0	2	0

Table 27. Panel regression results: conditioning on positive 1_week_before

	<i>Dependent variable:</i>		
	ExcessReturn		
	Euronext (1)	Frankfurt (2)	Madrid (3)
Mkt.RF	0.879*** (0.019)	0.913*** (0.013)	1.026*** (0.015)
event_week	0.008*** (0.003)	0.002 (0.002)	-0.0001 (0.003)
X1_week_after	0.001 (0.003)	0.003 (0.002)	0.002 (0.003)
X2_weeks_after	0.004 (0.003)	-0.0003 (0.002)	0.001 (0.003)
X3_weeks_after	0.002 (0.003)	0.0001 (0.002)	-0.002 (0.003)
X4_weeks_after	0.002 (0.003)	0.001 (0.002)	-0.0001 (0.003)
X5_weeks_after	-0.001 (0.003)	-0.001 (0.002)	-0.002 (0.003)
X6_weeks_after	0.0003 (0.003)	0.004* (0.002)	0.001 (0.003)
X7_weeks_after	0.0002 (0.003)	-0.003 (0.002)	0.002 (0.003)
Observations	11,119	24,019	4,332
R ²	0.160	0.174	0.519
Adjusted R ²	0.159	0.173	0.518
F Statistic	235.226*** (df = 9; 11100)	562.174*** (df = 9; 23987)	518.606*** (df = 9; 4319)
<i>Note:</i>			* p<0.1; ** p<0.05; *** p<0.01

	<i>Dependent variable:</i>	
	ExcessReturn	
	UK (1)	Milan (2)
Mkt.RF	0.861*** (0.008)	0.754*** (0.012)
event_week	0.004*** (0.001)	0.002 (0.002)
X1_week_after	0.002* (0.001)	0.005* (0.002)
X2_weeks_after	-0.001 (0.001)	0.004 (0.002)
X3_weeks_after	-0.002 (0.001)	0.008*** (0.002)
X4_weeks_after	-0.001 (0.001)	0.004* (0.002)
X5_weeks_after	-0.001 (0.001)	-0.004* (0.002)
X6_weeks_after	0.0002 (0.001)	-0.005** (0.002)
X7_weeks_after	-0.0004 (0.001)	-0.005* (0.002)
Observations	75,666	14,946
R ²	0.125	0.208
Adjusted R ²	0.124	0.207
F Statistic	1,202.948*** (df = 9; 75580)	435.291*** (df = 9; 14924)
<i>Note:</i>		* p<0.1; ** p<0.05; *** p<0.01

Table 28. Firm by firm coefficients: conditioning on negative 1_week_before: UK

Coefficient	Average Coefficient	Standard Deviation	t-Statistic	# of Positive Coefficients	# of Negative Coefficients	# of Positive Significant (5%)	# of Negative Significant (5%)
Mkt.RF	0,786567532	0,419073502	0,200080369	87	1	82	0
event_week	0,004999824	0,012263989	0,043459195	61	27	10	1
'1_week_after'	0,00307754	0,00884729	0,037081053	58	30	3	1
'2_weeks_after'	-0,000416188	0,010523172	-0,004216011	43	45	1	1
'3_weeks_after'	-0,000705899	0,007858678	-0,00957529	37	51	3	0
'4_weeks_after'	0,000796986	0,009821909	0,008649949	45	43	1	0
'5_weeks_after'	-0,000383775	0,009353195	-0,004373968	39	49	3	2
'6_weeks_after'	-0,001083498	0,009500605	-0,012157261	44	44	1	3
'7_weeks_after'	-0,000249681	0,008074526	-0,003296309	38	50	3	0
'1_week_before'	-0,006176788	0,005862984	-0,112305935	0	88	0	5

Table 29. Firm by firm coefficients: conditioning on negative 1_week_before:
Milan

Coefficient Type	Average Coefficient	Standard Deviation	t-Statistic	# of Positive Coefficients	# of Negative Coefficients	# of Positive Significant (5%)	# of Negative Significant (5%)
(Intercept)	0,001389	0,000989	0,405322	11	1	1	0
Mkt.RF	0,714341	0,23178	0,889689	12	0	12	0
event_week	0,008697	0,012567	0,199788	8	4	3	0
'1_week_after'	0,002892	0,007688	0,108583	9	3	0	0
'2_weeks_after'	0,000606	0,006663	0,026236	6	6	0	0
'3_weeks_after'	-0,0009	0,007543	-0,03439	5	7	1	0
'4_weeks_after'	0,001352	0,005228	0,074678	8	4	0	0
'5_weeks_after'	0,001063	0,008385	0,036584	7	5	1	0
'6_weeks_after'	0,000601	0,009141	0,018965	7	5	0	0
'7_weeks_after'	-0,00079	0,005838	-0,03885	5	7	0	0
'1_week_before'	-0,00745	0,005224	-0,41158	0	12	0	0

Table 30. Firm by firm coefficients: conditioning on negative 1_week_before:
Madrid

Coefficient Type	Average Coefficient	Standard Deviation	t-Statistic	# of Positive Coefficients	# of Negative Coefficients	# of Positive Significant (5%)	# of Negative Significant (5%)
(Intercept)	0,000671	0,000737	0,455163	3	1	0	0
Mkt.RF	0,963973	0,317982	1,515768	4	0	4	0
event_week	-0,00264	0,011864	-0,11129	1	3	0	1
'1_week_after'	0,006027	0,009553	0,315418	3	1	1	0
'2_weeks_after'	0,003557	0,007161	0,248334	2	2	0	0
'3_weeks_after'	-0,00061	0,00883	-0,03452	2	2	0	0
'4_weeks_after'	-0,00639	0,00741	-0,43135	1	3	0	0
'5_weeks_after'	0,0008	0,008585	0,046575	1	3	0	0
'6_weeks_after'	0,001972	0,002265	0,435265	3	1	0	0
'7_weeks_after'	-0,00306	0,009601	-0,15961	2	2	0	1
'1_week_before'	-0,00516	0,005033	-0,51296	0	4	0	0

Table 31. Firm by firm coefficients: conditioning on negative 1_week_before:
Frankfurt

Coefficient Type	Average Coefficient	Standard Deviation	t-Statistic	# of Positive Coefficients	# of Negative Coefficients	# of Positive Significant (5%)	# of Negative Significant (5%)
(Intercept)	0,000274	0,002425	0,026668	15	3	1	0
Mkt.RF	0,791728	0,220628	0,845824	18	0	17	0
event_week	0,006579	0,012934	0,119898	12	6	2	0
1_week_after	0,001731	0,019913	0,020485	8	10	1	0
2_weeks_after	-0,00222	0,009793	-0,05336	5	13	0	0
3_weeks_after	0,000251	0,008702	0,006811	10	8	1	0
4_weeks_after	0,001626	0,013928	0,027509	7	11	0	0
5_weeks_after	0,00274	0,014019	0,04606	10	8	0	0
6_weeks_after	-0,0003	0,014734	-0,00484	9	9	1	0
7_weeks_after	-0,00014	0,009334	-0,00363	10	8	0	0
1_week_before	-0,00963	0,006916	-0,32816	0	18	0	1

Table 32. Firm by firm coefficients: conditioning on negative 1_week_before:
Euronext

Coefficient	Average	Standard Deviation	t-Statistic	# of Positive Coefficients	# of Negative Coefficients	# of Positive Significant (5%)	# of Negative Significant (5%)
(Intercept)	0,001309	0,000894	0,344939	17	1	1	0
Mkt.RF	0,899635	0,305524	0,694041	18	0	18	0
event_week	0,002415	0,006161	0,092376	11	7	1	0
'1_week_after'	0,00229	0,009598	0,056243	10	8	2	0
'2_weeks_after'	-0,0021	0,009192	-0,05391	8	10	0	1
'3_weeks_after'	-0,00138	0,007658	-0,04263	6	12	1	0
'4_weeks_after'	-0,00289	0,00587	-0,11624	6	12	0	1
'5_weeks_after'	-0,00153	0,007771	-0,04628	9	9	0	1
'6_weeks_after'	-0,00175	0,005758	-0,07176	5	13	0	1
'7_weeks_after'	-0,00084	0,010147	-0,01941	4	14	2	0
'1_week_before'	-0,00636	0,005304	-0,28283	0	18	0	2

Table 33. Firm by firm coefficients: conditioning on negative 1_week_before:
Europe - 3 factors

Coefficient Type	Average Coefficient	Standard Deviation	t-Statistic	Number of Positive Coefficients	Number of Negative Coefficients	Number of Positive Significant (5%)	Number of Negative Significant (5%)
Mkt.RF_w	0,791097	0,242317	0,428679	58	0	57	0
SMB_w	-0,07323	0,510978	-0,01882	33	25	18	21
HML_w	0,149992	0,553323	0,035594	34	24	25	13
event_week	0,004322	0,012248	0,046334	39	19	4	2
`1_week_after`	0,002766	0,012149	0,029899	33	25	4	0
`2_weeks_after`	-0,00101	0,008391	-0,01579	22	36	1	2
`3_weeks_after`	-3,4E-05	0,008076	-0,00055	27	31	3	0
`4_weeks_after`	0,000731	0,01131	0,008485	27	31	1	1
`5_weeks_after`	-7,3E-05	0,010926	-0,00088	28	30	2	2
`6_weeks_after`	-0,00016	0,009018	-0,00229	24	34	1	1
`7_weeks_after`	-0,00152	0,010072	-0,01981	25	33	3	2
`1_week_before`	-0,00733	0,006122	-0,15714	0	58	0	3

Table 34. Firm by firm coefficients: conditioning on negative 1_week_before: UK
3-factors

Coefficient Type	Average Coefficient	Standard Deviation	t-Statistic	Number of Positive Coefficients	Number of Negative Coefficients	Number of Positive Significant (5%)	Number of Negative Significant (5%)
(Intercept)	0,001393	0,001634	0,06617	72	15	11	0
Mkt.RF_w	0,66465	0,300748	0,171529	86	1	84	0
SMB_w	0,251342	0,584945	0,03335	57	30	43	20
HML_w	0,077198	0,410308	0,014603	54	33	25	16
event_week	0,004229	0,012193	0,02692	56	31	11	0
`1_week_after`	0,003459	0,010314	0,026031	57	30	5	1
`2_weeks_after`	0,000345	0,008948	0,002989	44	43	1	1
`3_weeks_after`	-0,0017	0,008601	-0,0153	28	59	2	0
`4_weeks_after`	0,001269	0,010559	0,009325	44	43	2	0
`5_weeks_after`	0,0002	0,009011	0,001718	43	44	2	2
`6_weeks_after`	-0,00035	0,009413	-0,00292	46	41	2	3
`7_weeks_after`	-0,00078	0,009577	-0,0063	44	43	4	1
`1_week_before`	-0,0064	0,005527	-0,0899	0	87	0	4

Table 35. Panel regression results: conditioning on negative 1_week_before

	Dependent variable:			
	Frankfurt (1)	Madrid (2)	Milan (3)	Euronext (4)
Mkt.RF	0.818*** (0.012)	0.964*** (0.015)	0.709*** (0.011)	0.893*** (0.011)
event_week	0.005** (0.002)	-0.001 (0.003)	0.006*** (0.002)	0.003 (0.002)
X1_week_after	-0.002 (0.002)	0.006* (0.003)	0.002 (0.002)	0.002 (0.002)
X2_weeks_after	-0.003 (0.002)	0.002 (0.003)	-0.00004 (0.002)	-0.001 (0.002)
X3_weeks_after	0.001 (0.002)	-0.002 (0.003)	-0.0001 (0.002)	-0.001 (0.002)
X4_weeks_after	-0.0004 (0.002)	-0.007** (0.003)	0.001 (0.002)	-0.003 (0.002)
X5_weeks_after	-0.0001 (0.002)	0.001 (0.003)	0.001 (0.002)	-0.002 (0.002)
X6_weeks_after	0.001 (0.002)	0.003 (0.003)	0.0003 (0.002)	-0.003 (0.002)
X7_weeks_after	0.001 (0.002)	-0.003 (0.003)	-0.001 (0.002)	-0.003 (0.002)
Observations	19,882	4,332	13,349	20,145
R2	0.185	0.495	0.239	0.245
Adjusted R2	0.184	0.494	0.237	0.244
F Statistic	500.374*** (df = 9; 19855)	471.244*** (df = 9; 4319)	463.893*** (df = 9; 13328)	725.195*** (df = 9; 20118)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 36. Panel regression results: conditioning on negative 1_week_before: UK

	Dependent variable:
	ExcessReturn UK
Mkt.RF	0.851*** (0.007)
event_week	0.005*** (0.001)
X1_week_after	0.002*** (0.001)
X2_weeks_after	-0.0002 (0.001)
X3_weeks_after	-0.001 (0.001)
X4_weeks_after	0.00004 (0.001)
X5_weeks_after	-0.001 (0.001)
X6_weeks_after	-0.001 (0.001)
X7_weeks_after	-0.00001 (0.001)
Observations	88,241
R ²	0.139
Adjusted R ²	0.138
F Statistic	1,583.355*** (df = 9; 88144)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 37. Panel regression results: conditioning on negative 1_week_before with 3-factors

	Dependent variable:	
	ExcessReturn	
	European (1)	UK (2)
Mkt.RF_w	0.798*** (0.007)	0.683*** (0.007)
SMB_w	-0.073*** (0.017)	0.135*** (0.017)
HML_w	0.157*** (0.014)	0.094*** (0.014)
event_week	0.004*** (0.001)	0.004*** (0.001)
X1_week_after	0.001 (0.001)	0.003*** (0.001)
X2_weeks_after	-0.001 (0.001)	0.0002 (0.001)
X3_weeks_after	0.0002 (0.001)	-0.002* (0.001)
X4_weeks_after	0.0001 (0.001)	0.0004 (0.001)
X5_weeks_after	-0.001 (0.001)	-0.0002 (0.001)
X6_weeks_after	-0.0005 (0.001)	-0.0002 (0.001)
X7_weeks_after	-0.002 (0.001)	0.0001 (0.001)
Observations	66,887	87,965
R ²	0.205	0.117
Adjusted R ²	0.204	0.116
F Statistic	1,562.959*** (df = 11; 66818)	1,062.302*** (df = 11; 87867)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 38. Firm by firm coefficients: modified Almon lag pattern, Milan

Coefficient	Average	Standard Deviation	t-Statistic	# of Positive Coefficients	# of Negative Coefficients	# of Positive Significant (5%)	# of Negative Significant (5%)
(Intercept)	-0,00129	0,007115	-0,03615	11	14	1	0
Mkt.RF	0,723518	0,280199	0,516431	25	0	22	0
`1_week_before`	-0,00355	0,023866	-0,02974	9	15	1	0
phi	0,010762	0,024887	0,086489	17	8	2	0
psi	-0,00526	0,030455	-0,03455	11	14	0	1

Table 39. Firm by firm coefficients: modified Almon lag pattern, Madrid

Coefficient Type	Average Coefficient	Standard Deviation	t-Statistic	# of Positive Coefficients	# of Negative Coefficients	# of Positive Significant (5%)	# of Negative Significant (5%)
(Intercept)	-0,00023	0,00281	-0,0292	5	3	0	0
Mkt.RF	0,940665	0,363644	0,914564	8	0	8	0
phi	0,003777	0,012827	0,104097	4	4	0	0
psi	-0,00266	0,01776	-0,05291	4	4	0	0
`1_week_before`	-0,00476	0,013213	-0,1273	3	4	0	0

Table 40. Firm by firm coefficients: modified Almon lag pattern, Frankfurt

Coefficient Type	Average Coefficient	Standard Deviation	t-Statistic	# of Positive Coefficients	# of Negative Coefficients	# of Positive Significant (5%)	# of Negative Significant (5%)
(Intercept)	0,001672	0,006897	0,037862	27	14	0	0
Mkt.RF	0,803435	0,425865	0,294637	39	2	37	0
`1_week_before`	-0,00021	0,033091	-0,00097	18	21	3	1
phi	-0,00512	0,021911	-0,03647	15	26	1	0
psi	0,007459	0,025972	0,044852	25	16	2	1

Table 41. Firm by firm coefficients: modified Almon lag pattern, Euronext

Coefficient type	Average t	Standard Deviation	t-Statistic	# of Positive Coefficients	# of Negative Coefficients	# of Positive Significant (5%)	# of Negative Significant (5%)
(Intercept)	-0,00052	0,005754	-0,01716	11	17	1	0
Mkt.RF	0,887269	0,414559	0,404474	27	1	27	0
phi	0,001255	0,019405	0,012225	13	15	1	0
psi	0,003946	0,017568	0,042444	19	9	0	0
`1_week_before`	-0,00292	0,015138	-0,0365	14	12	0	0

Table 42. Firm by firm coefficients: modified Almon lag pattern, UK - 3 factors

Coefficient Type	Average Coefficient	Standard Deviation	t-Statistic	# of Positive Coefficients	# of Negative Coefficients	# of Positive Significant (5%)	# of Negative Significant (5%)
(Intercept)	4,53E-05	0,00928	0,000381	93	70	3	3
Mkt.RF_w	0,613867	0,506838	0,094576	158	5	137	0
SMB_w	0,193417	0,946313	0,01596	98	65	41	23
HML_w	-0,04617	0,648427	-0,00556	71	92	20	23
`1_week_before`	0,000109	0,026074	0,000327	71	87	2	1
phi	0,000493	0,023898	0,001612	87	76	2	4
psi	0,006457	0,029201	0,017267	97	66	13	1

Table 42. Panel regression results: modified Almon lag pattern

<p>UK</p> <p>Residuals: Min. 1st Qu. Median 3rd Qu. Max. -0.2554919 -0.0205708 -0.0011792 0.0179857 0.7809699</p> <p>Coefficients: Estimate Std. Error t-value Pr(> t) Mkt.RF 0.7834285 0.0225923 34.6768 < 2e-16 *** X1_week_before -0.0031113 0.0035136 -0.8855 0.37593 phi 0.0111262 0.0040048 2.7782 0.00549 ** psi -0.0055123 0.0042352 -1.3016 0.19314 --- Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1</p> <p>Total Sum of Squares: 10.233 Residual Sum of Squares: 7.9144 R-Squared: 0.22659 Adj. R-Squared: 0.2214 F-statistic: 305.653 on 4 and 4173 DF, p-value: < 2.22e-16</p>	<p>Frankfurt</p> <p>Coefficients: Estimate Std. Error t-value Pr(> t) Mkt.RF 0.8797998 0.0191647 45.9073 < 2e-16 *** X1_week_before 0.0013227 0.0024056 0.5499 0.58243 phi -0.0049817 0.0031519 -1.5806 0.11402 psi 0.0068517 0.0033979 2.0165 0.04379 * --- Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1</p> <p>Total Sum of Squares: 21.827 Residual Sum of Squares: 16.963 R-Squared: 0.22283 Adj. R-Squared: 0.21819 F-statistic: 528.009 on 4 and 7366 DF, p-value: < 2.22e-16</p>
<p>Milan</p> <p>Residuals: Min. 1st Qu. Median 3rd Qu. Max. -0.8204737 -0.0200215 -0.0013409 0.0189247 0.7540102</p> <p>Coefficients: Estimate Std. Error t-value Pr(> t) Mkt.RF 0.8299834 0.0118201 70.2178 < 2.2e-16 *** X1_week_before -0.0019293 0.0012028 -1.6039 0.1087 phi -0.0020054 0.0015368 -1.3049 0.1919 psi 0.0071072 0.0016571 4.2889 1.801e-05 *** --- Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1</p> <p>Total Sum of Squares: 76.237 Residual Sum of Squares: 65.31 R-Squared: 0.14332 Adj. R-Squared: 0.13849 F-statistic: 1244.96 on 4 and 29766 DF, p-value: < 2.22e-16</p>	<p>Madrid</p> <p>Coefficients: Estimate Std. Error t-value Pr(> t) Mkt.RF 1.0203945 0.0288710 35.3433 <2e-16 *** X1_week_before 0.0042889 0.0054515 0.7867 0.4316 phi 0.0034154 0.0060116 0.5681 0.5701 psi -0.0020179 0.0062982 -0.3204 0.7487 --- Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1</p> <p>Total Sum of Squares: 2.4695 Residual Sum of Squares: 1.1281 R-Squared: 0.5432 Adj. R-Squared: 0.53842 F-statistic: 312.444 on 4 and 1051 DF, p-value: < 2.22e-16</p>
<p>Euronext</p> <p>Residuals: Min. 1st Qu. Median 3rd Qu. Max. -0.86288835 -0.01847019 -0.00048437 0.01826397 0.75945619</p> <p>Coefficients: Estimate Std. Error t-value Pr(> t) Mkt.RF 0.9281127 0.0187099 49.6054 < 2e-16 *** X1_week_before -0.0016729 0.0022869 -0.7315 0.46449 phi -0.0015408 0.0030114 -0.5117 0.60890 psi 0.0063480 0.0032399 1.9593 0.05012 . --- Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1</p> <p>Total Sum of Squares: 14.505 Residual Sum of Squares: 10.319 R-Squared: 0.2886 Adj. R-Squared: 0.28498</p>	

Table 43. Panel regression results: modified Almon lag pattern: 3-factors

UK					European				
Coefficients:					Coefficients:				
	Estimate	Std. Error	t-value	Pr(> t)		Estimate	Std. Error	t-value	Pr(> t)
Mkt.RF_w	0.6816540	0.0113722	59.9405	< 2.2e-16 ***	Mkt.RF_w	0.81993044	0.01315749	62.3166	< 2.2e-16 ***
SMB_w	0.1025857	0.0267258	3.8385	0.0001241 ***	SMB_w	-0.15391957	0.03106923	-4.9541	7.329e-07 ***
HML_w	-0.0978836	0.0219526	-4.4589	8.270e-06 ***	HML_w	-0.05400802	0.02604002	-2.0740	0.03809 *
X1_week_before	-0.0017499	0.0012153	-1.4399	0.1499051	X1_week_before	-0.00071145	0.00147328	-0.4829	0.62917
phi	-0.0018130	0.0015527	-1.1677	0.2429451	phi	-0.00043861	0.00187752	-0.2336	0.81529
psi	0.0069419	0.0016742	4.1465	3.385e-05 ***	psi	0.00371268	0.00201307	1.8443	0.06516 .
---					---				
Signif. codes:	0 '***'	0.001 '**'	0.01 '*'	0.05 '.'	0.1 ' '				
Total Sum of Squares:	76.226				Total Sum of Squares:	50.305			
Residual Sum of Squares:	66.653				Residual Sum of Squares:	39.548			
R-Squared:	0.12559				R-Squared:	0.21385			
Adj. R-Squared:	0.12059				Adj. R-Squared:	0.20947			
F-statistic:	712.472	on 6 and 29764 DF,	p-value:	< 2.22e-16	F-statistic:	870.633	on 6 and 19204 DF,	p-value:	< 2.22e-16

References

- BONAIMÉ, A., & WANG, Y. (EMMA). (2024). Mergers, product prices, and innovation: Evidence from the Pharmaceutical Industry. *The Journal of Finance*, 79(3), 2195–2236. <https://doi.org/10.1111/jofi.13321>
- Doan, M. P., & Sercu, P. (2021). Merging one's way to the top: AB inbev versus Heineken. *Journal of Wine Economics*, 16(1), 32–55. <https://doi.org/10.1017/jwe.2020.27>
- Hill, C. A., Quinn, B. J. M., & Davidoff Solomon, S. (2016). Mergers and acquisitions: A cyclical and legal phenomenon. *Research Handbook on Mergers and Acquisitions*. <https://doi.org/10.4337/9781784711481.00009>
- Hossain, M., Pham, M. D., & Islam, N. (2021). The performance and motivation of serial acquisitions: Evidence from Australia. *International Review of Financial Analysis*, 77, 101827. <https://doi.org/10.1016/j.irfa.2021.101827>
- HSU, P., LI, K., & TSOU, C. (2023). The Pollution Premium. *The Journal of Finance*, 78(3), 1343–1392. <https://doi.org/10.1111/jofi.13217>
- KEPLER, J. D., NAIKER, V., & STEWART, C. R. (2023). Stealth acquisitions and Product Market Competition. *The Journal of Finance*, 78(5), 2837–2900. <https://doi.org/10.1111/jofi.13256>
- Renneboog, L., & Vansteenkiste, C. (2019). Failure and success in mergers and acquisitions. *Journal of Corporate Finance*, 58, 650–699. <https://doi.org/10.1016/j.jcorpfin.2019.07.010>
- Ross, S. A., Westerfield, R., & Jordan, B. D. (2024). *Fundamentals of Corporate Finance*. McGraw Hill.
- Tunyi, A. A. (2021). Revisiting acquirer returns: Evidence from unanticipated deals. *Journal of Corporate Finance*, 66, 101789. <https://doi.org/10.1016/j.jcorpfin.2020.101789>