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Facultad de Ciencias Económicas y Empresariales | ICADE

MARKET EFFICIENCY IN THE SPANISH CONTINUOUS MARKET: A PANEL EVENT STUDY OF M&A ANNOUNCEMENTS

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MADRID | APRIL 2024

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ABSTRACT

This paper investigates the efficiency of the Spanish Continuous Market by analyzing how stock prices react to the announcement of corporate events. In particular, merger and acquisition ("M&A") announcements are used as a natural experiment and both target and acquirer firms are studied. A panel event study methodology is employed, which addresses some of the limitations of traditional event studies by accounting for cross-sectional and temporal variations in stock returns. By analyzing abnormal returns around the announcement dates, the research aims to provide insights into the speed and manner in which information is assimilated into stock prices. Additionally, the behavior of abnormal returns in the days leading up to the announcement is examined as a means to investigate the presence of potential insider trading in the Spanish market. The findings suggest a precise assimilation of information into market prices, evidencing efficient responses to new information in the Spanish Continuous Market.

KEY WORDS

Efficient Market Hypothesis, Panel Event Study, Spanish Continuous Market, Merger and Acquisition Announcements, Abnormal Returns.

RESUMEN

Este trabajo investiga la eficiencia del Mercado Continuo español analizando cómo reaccionan los precios de las acciones ante el anuncio de eventos corporativos. En particular, se utilizan los anuncios de fusiones y adquisiciones ("M&A") como experimento natural y se estudian tanto las empresas objetivo como las adquirentes. Se emplea una metodología de estudio de eventos de panel, que resuelve algunas de las limitaciones de los estudios de eventos tradicionales al tener en cuenta las variaciones transversales y temporales de los retornos bursátiles. Mediante el análisis de los retornos anormales próximos a las fechas de anuncio, la investigación pretende aportar datos sobre la velocidad y la manera en que la información se asimila en los precios de las acciones. Además, se examina el comportamiento de los retornos anormales en los días previos al anuncio como medio para investigar la presencia de posibles operaciones con información privilegiada o *insider trading* en el mercado español. Los resultados sugieren una asimilación precisa de la información en los precios de mercado, evidenciando respuestas eficientes a la nueva información en el Mercado Continuo español.

PALABRAS CLAVE

Hipótesis del Mercado Eficiente, Estudio de Eventos de Panel, Mercado Continuo Español, Anuncios de Fusiones y Adquisiciones, Retornos Anormales.

1. INTRODUCTION

The idea of market efficiency has been the cornerstone of modern financial economics and asset pricing theory. Broadly expressed, the Efficient Market Hypothesis asserts that asset prices reflect all available information at any given time so that investors cannot consistently achieve returns that are disproportionate to the level of risk assumed (Fama, 1970). Moreover, in an efficient market new information is rapidly incorporated into asset prices by the interaction of investors that react to the news by buying or selling financial assets (Fama, 1965; Grossman & Stiglitz, 1976).

The Efficient Market Hypothesis has been the subject of much debate since its formulation in the 1970s with no consensus in the literature on its validity (Boettke, 2010). A large number of studies have focused on analyzing the efficiency of different financial markets, with the majority of the research being focused on US capital markets. While some studies have covered other European countries, market efficiency in Spain remains a novel topic in the literature.

Market efficiency has been traditionally tested through what became known as "event studies", which are used to assess the impact of a given event on a subject of study (Kothari & Warner, 2007). During the 1980s and 1990s, the methodology of these studies became standardized, and despite its limitations most event studies in the field of finance today continue to follow the same structure (MacKinlay, 1997). However, promising developments in the event study methodology, such as the use of panel data, have started to appear in other fields, particularly in the study of the impact of public policies.

This paper will cover the development of the event study methodology and contribute to the understanding of market efficiency by addressing the gap in the literature concerning Spanish financial markets. To this end, a novel panel event study will be performed, analyzing the reaction of target and acquirer firms from the *Spanish Continuous Market* to merger and acquisition announcements.

2. THEORETICAL FRAMEWORK

2.1. THE EFFICIENT MARKET HYPOTHESIS

2.1.1. Introduction

The effort to evaluate and quantify the impact of an event or policy on a given subject of study has been a constant in the various fields of research, from economics and finance to the social sciences or medicine. In finance, this eagerness was initially channeled through the development of what is now known as event studies.

The event study methodology is grounded on the *Efficient Market Hypothesis* ("**EMH**") which posits that the price of an asset exchanged in a financial market reflects all the available and relevant information at any given time (Fama, 1970). Therefore, in an efficient market stock prices can only change as market participants react to that new information by buying or selling stock. Furthermore, in such a market, on average, the complete impact of new information is typically incorporated into actual prices almost immediately (Fama, 1965; Grossman & Stiglitz, 1976). The underlying idea is that stocks follow a random walk, meaning that future price movements are independent of past trends and are determined primarily by the influx of new and unpredictable information, making consistent forecasting of prices impossible (Samuelson, 1965).

It follows that investment strategies based on technical or fundamental analysis cannot consistently beat the market, as the information that could be derived from them is already incorporated into the quoted price (Malkiel, 2016). This idea is consistent with previous research on the performance of mutual funds which found that, after adjusting for risk, such funds do not generate returns in excess of the market index portfolio (Jensen, 1968).

2.1.2. The Three Forms of Market Efficiency

Despite the popularity of the general formulation of the EMH, Fama argued that the empirical demonstration of the theory required it to be expressed in more specific terms. Thus, he proposed three different formulations of the EMH, each corresponding to a different level of information efficiency (Fama, 1970).

The first level of market efficiency is known as *weak form efficiency*, and its central postulate is that all past trading information is already incorporated into the quoted price. By trading information, Fama (1970) referred to historical stock prices or returns.

However, he would later acknowledge that this first category of market efficiency also covers other trading-related variables such as volume, bid-ask spreads, dividend yields, and interest rates as well as anomalies such as the size effect or the January effect (Fama, 1991). In short, in a weak-form efficient market, the analysis of technical indicators will not result in investment decisions that yield profits beyond the market return, on a risk-adjusted basis, as the insights they provide are already priced in.

A higher form of efficiency, namely *semi-strong form efficiency*, asserts that market prices reflect all publicly available information, which in addition to technical indicators, includes other forms of information such as financial reports, macroeconomic circumstances, news related or unrelated to the company, etc. In a market that is efficient at this level only investors possessing insider information will be able to consistently obtain higher risk-adjusted returns than those of the market since publicly available information —technical or fundamental— has already been considered by market participants.

Finally, the highest level of efficiency a market can reach, *strong form efficiency*, implies asset prices reflect all available information, both public and insider. Therefore, in a strongly efficient market, no investor can achieve risk-adjusted returns that are consistently above those of the market portfolio, regardless of the kind of information he has access to. However, as Fama (1970) noted, this extreme level of efficiency should not be expected of actual markets, but rather be used as a benchmark against which to evaluate market efficiency.

Clearly, the three levels of efficiency are cumulative; thus, a market with strong-form efficiency is also efficient in both the semi-strong and weak forms.

2.1.3. Criticism of the Efficient Market Hypothesis

After its formulation by Fama in 1970, the EMH was broadly welcomed by the academic community. However, the emergence of new evidence towards the end of the 20th century began to dent its support. Today the discussion is still not settled and supporters and detractors of the EMH are equally divided. The purpose of this end-of-degree dissertation is not to provide an exhaustive review of the arguments and empirical evidence that supports or attempts to refute this theory. However, given the research presented intends to determine whether the *Spanish Continues Market* is efficient, it is appropriate to briefly review some of the present-day arguments against the EMH and how its supporters respond to them.

The first wave of criticism towards the EMH has come from the field of *behavioral finance*. Behavioral economists argue that investors are not entirely rational subjects, solely driven by a profit-maximizing urge (Barberis et al., 1998). They argue that cognitive biases can lead to asset mispricing and opportunities, though limited, for arbitrage. In this context, Nobel laureate Robert J. Shiller (2003) highlights the role of feedback models, where rising speculative prices attract investor attention and create a cycle of increasing demand and prices, potentially leading to unsustainable "bubbles" that eventually burst when the expectation-driven high prices cannot be maintained.

This kind of behavior certainly seems to discredit EMH as current prices are derived only from expectations of higher prices in the future, unbacked by the available information which would lead to much lower asset prices. In other words, it is prices that drive themselves and thus returns do not follow a random walk. A similar argument can be made based on Carhart's (1997) momentum factor, which has empirically shown that stocks performing well in a given year tend to outperform in the following year. Similarly, stocks that have performed poorly are likely to continue underperforming in the subsequent year. Such behaviors reflect a valuation of assets that is contrary to the rational interpretation of available information.

After reviewing the literature on the matter, Schiller argues that certain phenomena cannot be explained within the framework of the EMH and that the existence of some rational investors in the market is not always sufficient to counteract the actions of emotional investors. Therefore, he concludes that, while EMH should not be discarded completely, a better understanding of financial markets will only come through the integration of traditional financial models and behavioral finance.

Another source of criticism of the EMH has an empirical nature and is related, but different from the feedback mechanism critique previously described. That criticism had to do with irrational behavior by certain investors leading to mispricing and, in the most serious cases, financial bubbles. This other criticism, on the other hand, has to do with the inability of the markets to react to mispricing that may eventually occur.

According to EMH, mispricing should temporarily give rise to arbitrage opportunities, leading rational market participants to sell (buy) and short (long) overvalued (undervalued) assets, rapidly bringing prices down (up) to an equilibrium and eliminating such arbitrage opportunities. While evidence exists that financial bubbles offer rational investors arbitrage opportunities allowing them to temporarily obtain a disproportionately high return relative to the risk assumed (Mitchell & Pulvino, 2012), these opportunities are usually not so straightforward to exploit.

In a seminal paper by Shleifer and Vishny (1997), they contend that arbitrageurs may find it challenging to capitalize on such opportunities due to capital constraints that limit the amount of investment they can deploy, the tangible costs associated with implementing arbitrage strategies, and the inherent risks posed by potential worsening of mispricing in the short term. In other terms, market mechanisms are not always able to correct deviations in asset prices from their fundamental value, providing evidence that markets may not be efficient.

Voices against the EMH became more vocal after the global financial crisis of 2008, with some academics going so far as to blame the theory for having pushed prices beyond what was reasonable, inflating a bubble with consequences that would prove catastrophic. Paul Krugman (2009), in his weekly column in the New York Times, only a year after being awarded the Nobel Prize in Economic Sciences, would say:

> *"In short, the belief in efficient financial markets blinded many if not most economists to the emergence of the biggest financial bubble in history. And efficient-market theory also played a significant role in inflating that bubble in the first place"*.

The advocates of this theory, nevertheless, argue that such criticisms are the consequence of an erroneous understanding of EMH postulates. The EMH does not claim that prices provided by the market are always correct, nor does it imply that financial asset price bubbles cannot occur. Malkiel (2012) argues that the essence of the EMH is that arbitrage opportunities for excess risk-adjusted returns cannot exist in an efficient market, and should they momentarily occur, they are short-lived.

In summary, over the last two or three decades, and in particular after the 2008 financial crisis, criticisms of the EMH have gained momentum. Although the evidence presented is inconclusive, it seems more inclined to refine and adapt the EMH than to reject it altogether. Today most authors continue to defend EMH in its essence while recognizing the need to incorporate insights from the field of behavioral economics.

2.1.4. The Efficient Market Hypothesis and Event Studies

The principles of the EMH constitute the basis on which the event study methodology has been developed. The EMH posits that markets react only to the emergence of new information and that such information is quickly incorporated into the quoted price. In this sense, event studies provide a framework to measure stock price reactions to the emergence of new information.

The idea is that by measuring the difference between observed market returns and expected returns conditional on the event not having occurred, one can estimate the event's impact and the speed at which the new information is assimilated. This can then be used to test the hypotheses on market efficiency (Ball, 2015). If the event causes a shock in returns that extends over a prolonged period of time, then markets will have failed to quickly incorporate the new information into asset prices, contrary to the postulates of the EMH. On the other hand, if the shock in returns is limited to a short period of time around the event, then there will be evidence that the market is capable of rapidly pricing in new information, as the EMH posits (Kothari & Warner, 2007). In this sense, Fama, Fisher, Jensen, and Roll (1969) conducted the first test of market efficiency by analyzing the reactions to stock split announcements, finding evidence in support of market efficiency.

While event studies can offer insights on the different levels of efficiency, they are most widely used to test for semi-strong form efficiency, as will be the case of this end-of-degree dissertation.

2.1.5. Why Use Merger and Acquisition Announcements to Test Market Efficiency?

Upon designing this study, one of the initial decisions to be made was selecting an appropriate type of event. This choice is critical as different corporate actions like merger and acquisition ("**M&A**") operations, earnings announcements, policy changes or management transitions have a distinct informational content and trigger different reactions in the markets.

In order for the event study to produce clear and meaningful conclusions on market efficiency, the type of event selected for the analysis must meet certain criteria. Firstly, data on the selected category of events must be available. Additionally, the event must have a significant and quantifiable impact on the companies involved, and these companies must be clearly identifiable.

Finally, to assess how quickly the market assimilates new information, it is essential to choose an event whose effects are known and uniformly understood by the market. Investors should be able to gain immediate awareness of the event's effect and their interpretation must be widely accepted among market participants. If the chosen event is not immediately understood by market participants, abnormal returns could persist over an extended period (Bloomfield, 2002). In such cases, a prolonged reaction might

not contradict the EMH, which posits that investors react rapidly to new information, but instead signal that investors are still digesting complex information (Oler et al., 2007). Additionally, if investors have varied interpretations of the event's impact, positive and negative reactions could cancel each other out due to the averaging of returns, making it difficult to clearly observe the effect in question (Satryo & Wijayanto, 2019).

Considering these criteria, M&A announcements were a clear choice. M&A announcements significantly affect the companies involved in the transaction. Additionally, identifying the firms involved and measuring the event's effect is straightforward, especially when the affected companies are publicly traded.

Furthermore, a consensus exists in the literature on the market reaction to M&A announcements: they are followed by large positive abnormal returns in the case of target firms, while acquirers experience close to zero or negative abnormal returns (Agrawal & Jaffe, 2000; Tunyi, 2021). This is specially the case when the target is a publicly listed firm (Jaffe, et al., 2015; Moeller, et al., 2003).

Finally, information on M&A announcements involving public firms is widely available due to legal requirements for disclosure and approval of such transactions. This has led finance information providers, including *FactSet*[1], *Bureau van* Dijk[2], and *Bloomberg*[3], to offer extensive databases on these transactions.

2.2. THE FIRST EVENT STUDIES

The origin of the event study's methodology, according to MacKinlay (1997), can be traced back to James Dolley's (1933) work on the impact of the decision to carry out a stock split on firms' share price. However, most authors agree that the event study methodology was first formalized in Ball and Brown's (1968) and Fama et al.'s (1969) seminal papers.

In their study, Ball and Brown investigated the market reaction to earnings releases and, in particular, whether that reaction was consistent with the efficient market hypothesis. After performing their analysis, they found that following earnings releases

[1] For detailed insights on FactSet Merger database, visit https://www.factset.com

[2] For a detailed insight on Bureau van Dijk Orbis M&A database, visit https://www.bvdinfo.com

[3] Bloomberg's database on global M&A deals can be accessed through the Bloomberg Terminal. For more information, visit https://www.bloomberg.com

that surprised the market —i.e., the reported net income was different than expected— the firm's stock experienced returns that could not be explained by market-wide factors. Those returns were positive when the expected net earnings were lower than those finally reported and negative when the opposite occurred. That allowed them to conclude that market participants view accounting information as a useful insight into a company's operation and that the information they provide is quickly incorporated into the price as it becomes public.

The initial methodology of event studies, as implemented in Ball and Brown (1968), and followed by others in the subsequent decades is based on the concepts of "event window", "abnormal returns", "expected returns" and "cumulative abnormal returns" (Peterson, 1989). The steps outlined below constitute the basic structure of what will be referred to in this end-of-degree dissertation as a "single-event study" or simply an "event study". The methodology of an event study comprises the following stages:

1. Identification of the event date and determination of the event and estimation windows.
2. Estimation of the expected stock returns within the event window and computation of abnormal returns.
3. Aggregation of individual abnormal returns to derive cumulative abnormal returns.
4. Assessment of the statistical significance of the cumulative abnormal returns.

The following section will provide a detailed exploration of each step and discuss the evolution of this methodology, highlighting how advancements in research and practice have enhanced the approach over time.

2.3. THE DEVELOPMENT OF SINGLE-EVENT STUDIES

2.3.1. Event Date, Event Window and Estimation Window

A) Event Date

The initial step in conducting a traditional event study involves defining the *event date*. Typically, pinpointing the event date is straightforward when an official announcement of the event exists. However, one should be mindful of possible leaks or rumors that may justify choosing an earlier date as the event date. For instance, a press leak can lead to the market becoming widely aware of a given event days before its official announcement. In the context of M&A, however, early research found that the

official announcement date should generally serve as the event date (Dodd, 1980). Around the event date, an event window will also be defined. Additionally, an estimation window that precedes the event date is typically used.

B) Event Window

The *event window* can be defined as the period of time around the event that includes at least the day of the event itself, but usually also an additional period before and after the event. The definition of the event window is critical for the outcome of the event study as it needs to be sufficiently long to capture all of the market reaction, but not so long that extraneous information dilutes the true effect of the event and confounds the analysis (Krivin, et al., 2003).

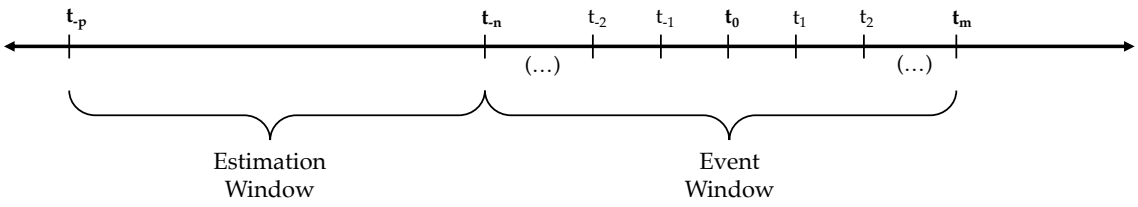

Figure 1 Overview of an Event Study Timeline (Source: Author)

The initial event studies aimed to analyze the impact of significant events for which it was difficult to determine when the market had finished assimilating the new information into the price. This made it common to use broad event windows, which could span several months, in an attempt to capture the full extent of the reaction. For example, Binder (1985) analyzes the impact of some twenty regulatory changes on the share price of affected companies using time windows extending an average of 21.5 months.

As the methodology became more refined and daily price data became more widely available, researchers started using shorter time frames to analyze stock market reactions. Additionally, the popularization of the EMH contributed to this trend. More recently, the accessibility of intraday stock data has accentuated this trend paving the way for even shorter event windows aimed at capturing real-time market reactions throughout a trading day. Marshall, et al. (2019) confirm the robustness of event studies that focus on changes in return in 1-to-30-minute intervals.

It is worth stressing the significance of choosing an appropriate event window as different time horizons give rise to relevant changes in the event study's test properties

(Kothari & Warner, 2007). Moreover, the development of the event study methodology has shown that one-size-fits-all solutions for determining the event window length are not sufficient. Different types of events (e.g., an M&A announcement, an environmental scandal, or a regulatory change) generate reactions at different speeds in the markets and make it necessary to adjust the event window length to the particular characteristics of the event.

But even within the same kind of event, it is not always clear what the appropriate event window is. Regarding this issue, Krivin et al. (2003) analyze three possible approaches to determining the event window length: choosing a predetermined duration, using a flexible approach that adapts to the case at hand, or following a rule that considers how the stock behaves during the event window. The conclusion they reach is that, for studies encompassing numerous events, a standard fixed event window can be used because, according to the Law of the Large Numbers, fluctuations after this period should balance out. By contrast, when the study focuses on a limited number of firms, or even just a single one, selecting an appropriate event window demands more careful consideration. In such cases, tailored solutions based on return volatility might be beneficial.

Undoubtedly, there is a trade-off in the choice between shorter or longer event windows. Opting for a shorter event window minimizes the risk of including abnormal returns attributable to events other than the one studied, which might otherwise bias the analysis. However, is problematic for events that gradually unfold over time. Conversely, wider event windows are more appropriate for this kind of events as they capture the full extent of the market reaction. Nonetheless, they increase the likelihood of incorporating confounding events.

In any case, most event studies still rely on daily data and use event windows centered on the event date with a span of no longer than 11 days (Holler, 2012). This event-window size is particularly popular in studies analyzing market reactions to merger and acquisition announcements. For instance, in an event study covering 37 M&A announcements by firms listed in Asian markets Shah & Arora (2014) tried different event windows for robustness (±2 days, ±5 days, ±7 days, and ±10 days) and the findings across these windows showed no significant differences. Similarly, in the case of M&A announcements by Turkish firms, Akben-Selcuk & Altiok-Yilmaz (2011) use symmetric 11-day, 7-day, 5-day, and 3-day event windows.

C) Estimation Window

Another decision to make when designing an event study concerns the length of the *estimation or pre-event window*. The purpose of defining an estimation window is to capture the normal behavior of the stock when it has not yet been affected by the event. This window will be used to calculate the regression coefficients which will then be used to estimate expected returns during the event window (Ullah, et al., 2021). Additionally, the estimation window can be useful when analyzing the statistical significance of abnormal returns by comparing the stock's behavior during the event window to its baseline behavior. However, this decision is of minor importance when compared to that regarding the event window, assuming the company did not experience significant alterations in its profitability or core business operations (Krivin et al., 2003).

2.3.2. Expected Returns

Once the event window is established, the key to the analysis lies in the quantification of the market reaction to the analyzed event during the event window. The rationale behind the analysis of the returns generated by a stock following the event is that such returns capture the market's collective response and provide a quantitative measure of its economic impact. However, the mere observation of realized returns does not suffice, as these could be the consequence of several factors, some unrelated to the event. It is essential, therefore, to separate the returns that are exclusively attributable to the event from those that can be explained by market-wide factors.

This leads us to the concept of *abnormal returns*, i.e., the residual returns that remain once we eliminate those attributable to other factors. Consequently, abnormal returns are calculated by subtracting the expected returns conditional on the event not having occurred, from the actual returns observed during the event window.

The challenge lies in selecting a model that can reliably calculate the stock's expected returns. There are various models available, each with its unique features and underlying assumptions. MacKinlay (1997) categorizes these models into two broad classes: those based solely on statistical assumptions and those that include economic assumptions about investor behavior. The first class of models includes the *Constant Mean Return Model* and the *Market Model*, while the *Capital Asset Pricing Model* and other related models are sorted into the second category.

A) Constant Mean Return Model

The first statistical model for expected returns is a rather naïve one as it assumes that market returns are constant. According to the *Constant Mean Return Model* ("**CMRM"**), the stock's expected return during each day of the event window will be equal to the stock's daily average return during the estimation window.

However, the CMRM fails to consider possible market-wide drifts during the event window, sector-specific shocks, or changes in broader economic conditions that make past returns an unreliable estimator of event window returns (Tareq & Horimoto, 2011). Merton (1980) also highlights a limitation of this model, pointing out its failure to consider the impact of variations in market risk levels.

Nonetheless, the CMRM can be used as a benchmark when the stock's historical performance relative to the market is no longer indicative of future returns due to fundamental changes in the company's operation that render more advanced models undependable.

B) Market Model

A more sophisticated, yet statistical, approach to the estimation of expected returns is the utilization of a *Market Model*. This kind of model assumes a linear relationship between the return of an individual stock and the returns of the market portfolio. This model applies regression analysis to determine the beta associated with the stock, which measures the sensitivity of its returns relative to market movements, hence reflecting the systematic risk associated with the stock (De Jong et al., 1992). Systematic risk is considered to be a non-diversifiable risk or market-associated risk. Fama (1973) formally expresses the market model in the following terms:

$$\tilde{R}_i = \alpha_i + \beta_i \cdot \tilde{R}_M + \tilde{\varepsilon}_i \qquad i = 1, 2, \dots, N \tag{1}$$

Where $\tilde{R}_i$ is the return of stock i, $\tilde{R}_M$ is the return of the market portfolio, $\tilde{\varepsilon}_i$ is the value of the residual term or error term, and ~ indicates random variables. Fama (1973) notes that additionally assuming that the expected value of the residual is zero and that the residual and the market portfolio returns are independent leads to the following:

$$E(\tilde{R}_i | R_M) = \alpha_i + \beta_i \cdot R_M \tag{2}$$

The regression coefficients α_i and β_i are obtained by regressing actual stock returns and market portfolio returns during the estimation window. Equation (2) indicates that the expected returns of stock i during the event window conditional on the markets return is a function of α_i, and the market return.

The alpha coefficient (α_i) represents the intercept of the regression, indicating the average return of the stock when the market portfolio's return is zero. The beta coefficient (β_i) has already been expressed as a measure of a stock's return volatility relative to the market portfolio.

C) Capital Asset Pricing Model

The first model that goes beyond purely statistical analysis is the *Capital Asset Pricing Model* ("**CAPM**") developed in the 1960s (Sharpe, 1964). According to this model, the expected return of an asset equals the return that would be expected from investing in the risk-free asset plus a premium that compensates for the higher risk of holding the asset in question. This risk premium is the product of the asset's beta, which measures its sensitivity to market movements, and the market risk premium, which is the excess return expected from the market portfolio over the risk-free rate or risk-free asset's return (R_{rf}). After years of development and following contributions by Sharpe (1964) and Lintner (1965a, 1965b) the CAPM began to be expressed as follows:

$$E(\tilde{R}_i) = R_{rf} + \beta_i \cdot \left[E(\tilde{R}_m) - R_{rf}\right] \tag{3}$$

The CAPM assumes that the market is efficient, investors are risk-averse, and therefore expect to receive an additional return based on the non-diversifiable or systematic risk they are willing to assume. This risk is quantified through beta, such that a beta with an absolute value greater than one indicates that the asset is more volatile than the market portfolio, while a beta with an absolute value lower than one implies the asset is less volatile than the market portfolio.

The CAPM model has enjoyed great popularity because of its elegance and intuitiveness: expected return is explained as compensation for the time value of money —through the risk-free rate— and for the additional risk an investor is willing to take by holding a given asset in comparison to the market portfolio —risk premium—. Even

though this model is still widely used[4], there is empirical evidence that CAPM presents serious flaws.

The main source of criticism of CAPM is that it does not consider all of the factors that affect stock returns. In this regard, Banz (1981) describes a "size effect" after observing that stocks of smaller firms generate higher returns than stocks of larger companies on a risk-adjusted basis. Basu (1983) describes evidence of what he calls an "E/P effect", now commonly referred to as a "value effect", finding that "*common stock of high E/P firms seem to have earned, on average, higher risk-adjusted returns than the common stock of low E/P firms*" (p. 150).

While the size and value effects are the most significant empirical sources of criticism against the CAPM, several other misspecifications have been documented in the literature. For instance, Jegadeesh and Titman (1993) describe a "momentum effect" and find that, for holding periods of less than a year, investment strategies that consist of buying and holding stocks that have performed well in the recent past and selling those that performed badly yields positive abnormal returns after adjusting for risk[5].

The size and book-to-market anomalies were further reported by Fama and French (1992) showing the CAPM beta, and the market factor alone could not fully explain the variations in stock returns, thus providing compelling evidence against the sufficiency of the model. Fama and French did not reject the explanatory power of beta but rather argued it should be considered only within a multi-factor model.

D) Fama-French Three-Factor Model

Following their 1992 paper, Fama and French (1993) built upon the CAPM and introduced the *Fama-French Three-Factor Model* ("**FF3FM**"). This new model extended CAPM by adding two new factors (size and value) enhancing its explanatory power. The FF3FM has been formally expressed as follows:

$$(4) \qquad E(\tilde{R}_i) = R_{rf} + \beta_{M,i} \cdot \left[E(\tilde{R}_M) - R_{rf}\right] + \beta_{SMB,i} \cdot SMB + \beta_{HML,i} \cdot HML + \alpha$$

[4] In a survey of over 300 professionals performed by the Association for Financial Professionals 90% of them admitted to using CAPM, despite having been challenged by empirical evidence (Jacobs & Shivdasani, 2012).

[5] *Cfr.* Section E) on page 21 on Carhart's (1997) momentum factor for an explanation of a similar phenomenon.

The *size factor* or *"small minus big"* ("**SMB**" or "size premium") attempts to capture the excess return that firms with a lower market value have historically earned over the return of firms with a higher market value. A rationale behind the size effect is that smaller firms are often considered riskier than larger, better-established companies, due to their higher volatility, capital constraints, liquidity risks, and more significant idiosyncratic risks (Dhawan, 2001; Acharya & Pedersen, 2005). However, the phenomenon has also been attributed to several factors: the enhanced growth prospects of smaller firms (Gala, 2006), the premium linked to the reduced liquidity of their securities (James & Edmister, 1983), and the higher risk of information asymmetry resulting from less equity coverage (Berk, 1995).

For these reasons, rational risk-averse investors demand higher returns in compensation for the higher risk they are willing to assume when holding stocks of smaller firms. The evidence suggests that such risks were not adequately reflected in the CAPM beta. Thus, adding the SMB factor was necessary (Chan, Chen, & Hsieh, 1985).

Similarly, the *value factor* or *"high minus low"* ("**HML**" or "value premium") attempts to capture the historical excess return that so-called "value stocks" have earned over "growth stocks". Value firms are those with high book-to-market ratios, i.e., those firms with a high shareholder's equity —assets minus liabilities— relative to their market value, suggesting that their market value may be low relative to their fundamental value. The value premium has been attributed to a variety of factors, including temporary setbacks, market overreaction to bad news, or a general market undervaluation of the asset's potential. Conversely, growth firms are those that trade at a low book-to-market ratio indicating a possible overvaluation by the market or investors' anticipation of future earnings that will justify a higher current price (Bourguignon & De Jong, 2003). Nonetheless there remains some debate as to whether this premium is in fact compensation for greater risk or stems from another cause. For instance, Lakonishok et al. (1994) suggest that the superior returns of value strategies are due to exploiting suboptimal typical investor behaviors rather than inherently higher risk.

E) Carhart's Four-Factor Model

The FF3FM model was revised by Carhart (1997), who proposed extending it to incorporate an additional factor. The expansion of the Fama-French model was driven by its shortcomings in explaining a specific market dynamic: stocks that previously outperformed the market tend to show higher returns in the short term, and vice versa for those that underperformed (Jegadeesh & Titman, 1993). This phenomenon, known as the momentum effect, was not adequately addressed by the original three-factor model. *Carhart's Four-Factor Model* can formally be expressed as:

(5) $$E(\tilde{R}_i) = R_{rf} + \beta_{M,i} \cdot \left[E(\tilde{R}_M) - R_{rf}\right] + \beta_{SMB,i} \cdot SMB + \beta_{HML,i} \cdot HML + \beta_{MOM,i} \cdot MOM + \alpha$$

Where MOM is the *momentum factor* calculated as the difference in the average returns of two portfolios comprised of the top and bottom 30% of firms ranked by their eleven-month returns with a one-month lag and equally weighted firms (Carhart, 1997). Carhart finds that the Four-Factor Model using a one-year momentum factor significantly outperforms both CAPM and FF3FM. However, this momentum-driven overperformance disappears after one year so past performance can only explain a part of short-term future performance. Carhart's findings are not inconsistent with the EMH as underperformance of most funds is roughly equivalent to their investment expenses and overperformance of funds in the top decile only allows them to cover their investment costs.

F) Fama-French Five-Factor Model

Finally, it is worth referring to the *Five-Factor Model presented by Fama French* ("**FF5FM**") as an extension of his previous Three-Factor model (Fama & French, 2015). The FF5FM intends to address the anomalies in stock returns presented in the literature following the development of the FF3FM. This way, much of the FF5FM builds on previous findings regarding the positive abnormal returns of more profitable firms and the lower expected returns of firms with higher-than-average investment ratios (Fama & French, 2006).

Those anomalies led to the extension of the FF3FM model by including a *profitability factor* (or "*robust minus weak*", "**RMW**") and an *investment factor* (or "*conservative minus aggressive*", "**CMA**"). The RMW factor addresses the higher returns that firms with higher operating profitability —computed by dividing a measure of gross profits by the book value of equity— tend to yield. The CMA factor allows the model to consider evidence that firms that invest conservatively tend to outperform firms with more aggressive investment strategies. The investment rate is proxied by dividing the year-to-year growth in the book value of assets by the previous year's total book value of assets. Formally, the FF5FM can be expressed as follows:

(6) $$E(\tilde{R}_i) = R_{rf} + \beta_{M,i} \cdot \left[E(\tilde{R}_M) - R_f\right] + \beta_{SMB,i} \cdot SMB + \beta_{HML,i} \cdot HML + \beta_{RMW,i} \cdot RMW + \beta_{CMA,i} \cdot CMA + \alpha$$

2.3.3. Abnormal Returns and Cumulative Abnormal Returns

The next step in performing a single-event study is calculating the abnormal returns ("**ARs**") for each period included in the event window. Returns identified as abnormal are simply those returns experienced by a given stock that cannot be explained by the chosen model of expected returns. Formally:

$$AR_i = R_i - E(\tilde{R}_i) \tag{7}$$

Where AR_i represents the abnormal return for security i, R_i is the actual return of security i, and $E(\tilde{R}_i)$ is the expected returns of security i conditional on the event not having occurred. Commonly, abnormal returns of every period included in the event window are summed to derive the cumulative abnormal returns ("**CARs**"), which quantify the total impact of the event. Thus, under a null hypothesis that the event had no impact on the stock's return, the expected value of the CARs is zero.

However, even if the event had no influence, CARs could differ from zero due to market noise and model imperfection. As previously mentioned, financial markets are inherently volatile; stock prices naturally fluctuate in response to an array of new information. Therefore, a divergence between the actual returns and those predicted by the model may simply reflect normal market movements or reflect the inability of the model for expected returns to perfectly predict actual returns, rather than being an indication of the event's impact.

2.3.4. Tests of Statistical Significance

As covered in the previous section, CARs may differ from zero for reasons other than the impact of the event. This makes the analysis of the CARs' statistical significance a crucial step in discerning whether CARs can genuinely be considered an estimation of the event's impact, or they simply fall within the realm of chance and ordinary market volatility.

The methods used to determine the statistical significance of the CARs can be broadly classified into two types: parametric and non-parametric. Parametric tests are those that rely on certain assumptions about the parameters and distribution of the population from which the data are obtained (Dutta, 2014). The main advantage of parametric methods is that, in those cases where the assumptions are correct, they are more powerful and precise than non-parametric alternatives. However, these tests are

sensitive to such assumptions, so when the assumptions are not met, the results are often not reliable. By contrast, non-parametric methods do not make assumptions about the population, which makes them useful for assessing statistical significance of data with a skewed distribution or outliers (Corrado, 2011). Nonparametric test, however, are found to be less reliable for longer event window spans (Kolari & Pynnonen, 2011).

Considering the scope of the end-of-degree dissertation, the large number of existing tests of statistical significance and that the appropriateness of each of them is largely dependent on the particular characteristics of the study at hand, this section will be limited to the implementation of a *traditional Student's t-test*.

Student's t-test is used to determine, with a certain level of confidence, whether the means of two population groups are significantly different from each other. However, event studies typically lack two independent samples for direct comparison. Instead, the test adapts to examine if the mean of (cumulative) abnormal returns significantly deviates from zero, known as a one-sample t-test.

The t-test assumes that abnormal returns are independently and identically distributed and that they follow a normal distribution. Additionally, homoscedasticity is assumed meaning that variances are assumed to be constant.

The performance of a t-test is comprised of three fundamental steps: the definition of the null and alternative hypotheses; the calculation of the test statistic; and the calculation of the p-value to determine whether or not to reject the null hypothesis at the chosen level of confidence.

In an event study, the null hypothesis can be defined as the event studied having no impact on stock returns. The alternative hypothesis will often simply deny the null hypothesis. Formally:

(8) $H_0: \overline{AR} = 0$ or $H_0: CAR = 0$

(9) $H_1: \overline{AR} \neq 0$ or $H_1: CAR \neq 0$

The test statistic (t) is calculated as expressed in equation (10) and follows a t-Student distribution with $n - 1$ degrees of freedom:

(10) $$t = \frac{\bar{X} - \mu^{H0}}{\frac{\sigma}{\sqrt{n}}} \sim T_{n-1}$$

Where $\bar{X}$ is the sample mean —in an event study it is the mean abnormal return or the cumulative abnormal return —, μ^{H0} is the mean under the null hypothesis — which is zero—, and $\frac{\sigma}{\sqrt{n}}$ is the standard error of the mean calculated dividing the sample standard deviation (σ) by the square root of the sample size (n). It is important to note that σ should be calculated using data from the estimation window.

Finally, the p-value is calculated using the test statistic and the degrees of freedom that determine the exact shape of the distribution, and a decision is made. For a significance level α the null hypothesis is rejected if the p-value is less than or equal to α.

While common, the t-test presents several potential issues due to its underlying assumptions. First, results may not be reliable if returns are not normally distributed, which is not unusual. Issues caused by non-normality can be mitigated if a large sample size is employed as the Central Limit Theorem states that, given a sufficiently large sample size, the distribution of the sample mean will approach normality, regardless of the distribution of the underlying population. However, this is not possible in a single-event study where only one event is analyzed or in event studies with a low number of instances.

It can also be the case that the assumption of constant variance is violated — heteroscedasticity issues—. Additionally, the literature has reported that M&A announcements are followed by event-induced variance which might not be accounted for in a t-test (Aktas et al., 2009).

2.4. THE LIMITATIONS OF SINGLE-EVENT STUDIES

The event study methodology described so far has been widely used to assess the impact of certain corporate events or policies through an isolated consideration of the event or policy impact on the share price of the affected company. This has then been used to gather insight on market efficiency. However, the restriction of the analysis to individual companies presents some limitations.

Focusing on a single firm limits the efficacy of event studies as a result of the narrow data scope. This issue can be aggravated when selection bias —i.e., the choice of firms is influenced by their visibility or by the availability of data (Holmen & Nivorozhkin, 2009)— or survivorship bias —i.e., when only surviving firms are studied (Sandler & Sandler, 2014)— are present. These issues limit the generalizability of results to contexts other than the specific one under analysis.

However, a more serious limitation of traditional event studies lies in their inability to control for effects attributable to other factors that are concurrent with the event. In a single-event study, the aim is to quantify the impact of the event by comparing the actual stock returns that follow the event with those expected in its absence. The expected returns are calculated by applying a set of betas estimated using pre-event data to a given model, such as any of the factor models.

As a result, actual and expect returns differ in two fundamental ways. Expected returns correspond to a firm that (i) did not experience the event and (ii) are estimated using the pre-event period characteristics of the firm and the market. On the other hand, actual returns are those of a firm that (i) did experience the event and (ii) are the result of present time characteristics of the firm and the market. In other words, two relevant variables exist: the occurrence of the event and the passage from one temporary state to another (Huntington-Klein, 2021).

However, traditional event studies assume that any difference observed between the actual and the expected return is solely attributable to the event. They ignore that any difference between actual and expected returns could be owed simply to changes in firm-specific characteristics or market conditions as we move from one temporary state to the next.

Therefore, single-event studies overlook the potential influence of factors other than the event but simultaneous to it and that may also contribute to the change in performance. Some traditional event studies, such as Morse, et al. (2011), try to account for confounding variables by eliminating from the analysis the instances in which these variables are most evident. This is clearly insufficient as it does not account for unobserved confounding variables and it impedes the analysis of such instances, even though they might be relevant for the study.

Finally, a concern regarding single-event studies lies in their inability to address the heterogeneity of the impact of events that occur in a non-simultaneous manner. While some events may be experienced by all the affected firms at the same time (e.g., as can be the case when regulatory changes are analyzed), more typically events occur in a

staggered sequence (e.g., as is usually the case with the announcement of M&A operations), which may lead firms to react differently to similar events. Traditional event studies focus on average effects and often do not consider this diversity of company reactions. As a result, the risk of oversimplifying the analysis and misrepresenting the true impact of the event on the various entities exists.

2.5. A New Age of Event Studies: The Panel Methodology

2.5.1. A General Characterization of the Panel Event Study

In the field of event studies, the literature is shifting towards the combination of the traditional methodology described above with techniques of panel data analysis. *Panel event studies*, while rooted in the foundational principles of traditional event studies, innovate by incorporating elements from the difference-in-differences approach. This addresses some of the inherent limitations of single-event studies, particularly when the events under analysis are not simultaneous.

The primary characteristic of panel event studies is their use of panel data, i.e., datasets containing repeated observations from multiple entities (e.g., countries or companies) over time as exemplified in the table below. The treatment of the data in a multidimensional way allows the analysis to be simultaneously carried out both across time and across entities (Clarke & Tapia-Schythe, 2021).

Table 1 Representation of Panel Data Structure (Source: Author)

Entity	Time Period	Variable A	Variable B
Entity 1	1	45	0.30
Entity 1	2	48	0.06
Entity 1	3	65	0.27
Entity 2	1	68	0.47
Entity 2	2	68	0.81
Entity 2	3	20	0.48
Entity 3	1	84	0.39
Entity 3	2	22	0.43
Entity 3	3	37	0.54

A second distinctive feature of panel event studies is that they allow to control for unobserved heterogeneity which refers to the variation in the dependent variable that is

not explained by the independent variables included in the model. This can be achieved through different approaches, and potentially through their combination, as will be discussed in a later section.

Finally, a third distinctive feature of panel event studies is the incorporation into the analysis of lags and leads which allows for a comprehensive analysis of staggered events (Borusyak & Jaravel, 2018). The lags keep track of the number of periods remaining until the event date and capture any pre-event trends or anticipatory effects. Leads, on the other hand, reflect the number of periods since the event date and capture both immediate and longer-term effects of the event.

In an analysis in which events occur in a staggered manner for each entity, lags and leads are used to align timelines. Moreover, they help in analyzing how the event's impact evolves over time. This provides the analysis with greater depth than is possible with single-event studies in which the entire impact of the event is usually summarized in the cumulative abnormal return, a metric that does not consider the timing of the effects.

2.5.2. Panel Data Regression

As previously discussed, a key feature of panel event studies is the use of datasets comprising observations from multiple entities over time. This approach captures two types of variations: the cross-sectional variation, which is the difference between entities at a given time, and the time-series variation, which tracks changes within each entity over time.

To analyze these variations, linear regression methods derived from the *Ordinary Least Squares* ("**OLS**") are commonly used. In the OLS model, the relationship between the dependent variable and each of the independent variables in the dataset is defined by the regression coefficients or betas. These coefficients indicate both the magnitude and the direction of the effect that each independent variable exerts on the dependent variable (Rencher & Schaalje, 2007).

Graphically, the OLS method can be understood as a process of fitting a line —in two dimensions— or a hyperplane —in higher dimensional spaces— to the data points. The objective is to find the line or hyperplane that minimizes the sum of the squares of the vertical differences between the observed data points and the predicted values. In

other words, it is a matter of finding the line or hyperplane that passes as close as possible to all the observed points (Dismuke & Lindrooth, 2006).

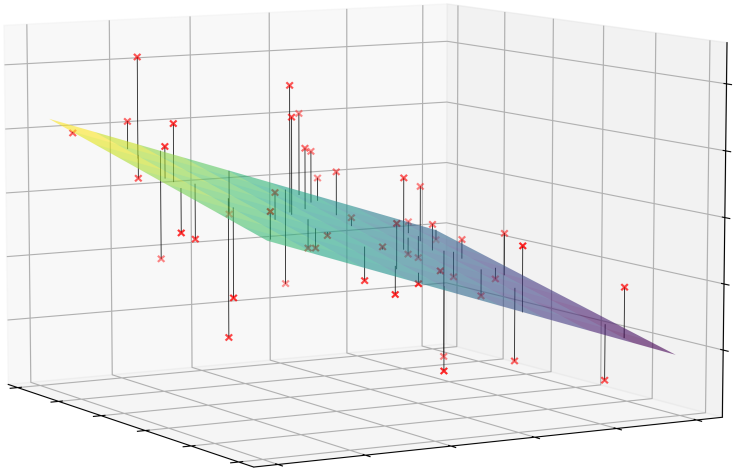

Figure 2 Conceptual Illustration of a Linear Regression Model. This figure represents a generic example with hypothetical data points and a hyperplane. Its purpose is to demonstrate the principles of linear regression analysis (Source: Author)

While OLS establishes the basic of linear regression, it cannot be directly applied to panel data due to its inherent structure. *Pooled OLS* offers a most simple solution to this issue by ignoring that the data has a panel structure. This way each row in the panel is treated as a separate observation, as if the data had a cross-sectional or time-series structure (Novales, 2011). Then a regression is performed as if the panel were a large set of independent observations. This results in a single set of regression coefficients that is assumed to be valid for all entities and time periods. In other words, pooled OLS assumes that the effect of the independent variables on the dependent variable is consistent across all units and time (Gil García & Puron-Cid, 2014).

However, this assumption can be too restrictive, especially in cases where entity or time-specific effects are present. In such cases, pooled OLS might lead to a biased estimation of the true effect of the explanatory variables (Cameron & Trivedi, 2005). For this reason, models that control for unobserved heterogeneity are often preferred.

2.5.3. Controlling for Unobserved heterogeneity

A major advantage of panel event studies over traditional single-event studies lies in their ability to control for unobserved heterogeneity. Unobserved heterogeneity arises from either characteristics inherent to each entity under analysis or from time trends that uniformly affect all entities (Bartolucci et al., 2015). In any case, these factors are

unrelated to the event itself but affect the dependent variable. Thus, they must be controlled for as failure to do so may result in the analysis being influenced by extraneous factors, leading to an inaccurate estimation of the event's true impact.

This section covers certain methods for controlling unobserved heterogeneity. *Difference-in-Differences* does this by using untreated entities as pure controls, while fixed and random effect models aim at finding the specific effects of unobserved factors intrinsic to each entity or time period.

A) Difference-in-Differences

The *Difference-in-Differences methodology* ("**DiD**") is a statistical technique used in the analysis of causal relationships. In an ideal world, when it comes to assessing the impact of an event occurring at time t on a given entity A, one would be able to observe two versions of entity A at t+1: one that experienced the event and one that did not. However, in real-world scenarios, this is not possible as the occurrence of the event precludes the possibility of observing a future no-event scenario.

DiD techniques overcome the lack of a perfect counterfactual by establishing control groups. The goal is to better isolate the impact that is solely attributable to the analyzed event by considering the effect that other factors may have had. Thus, in its simplest version, the DiD methodology will require identifying two comparable groups, one of which will have experienced the event —i.e., the treated group— and one of which will not —i.e., the control group— (Goodman-Bacon, 2021).

This set of techniques assumes that the changes observed in the treated group after the event can be partially attributable to the event itself and partially to various other drivers. The effect these other drives have on the dependent variables is assumed to be equal to the variation experienced by the control group. Thus, the event's impact on the target group is isolated by subtracting the variance experienced by the control group form the total variance measured in the treated group (Miller, 2023).

As can be observed, a key, tough questionable, assumption of DiD is that, in the absence of the event, both the control and treated groups would have followed parallel trends (Parker et al., 2011).

On a practical note, DiD studies —or two-way fixed effects— are performed by introducing a single dummy variable that takes the value 1 for those observations corresponding to a treated entity. Then a regression is performed as follows (Clarke & Tapia-Schythe, 2021):

(11) $$y_{st} = \alpha + \beta \cdot PostEvent_{st} + \mu_s + \lambda_t + X'_{st} + \varepsilon_{st}$$

Where $PostEvent_{st}$ is the dummy variable, μ_s is the entity fixed effect, λ_t is the time fixed effect, and X'_{st} are optional time or entity-varying controls.

B) Fixed and Random Effects Models

Contrary to DiD, fixed and random effect models do not necessarily use a pure control group to account for unobserved heterogeneity. Therefore, the parallel trends assumption need not hold.

The underlying idea to *fixed-effect models* is that some of the variance in the dependent variable is not attributable to the selected independent variables, but rather to some other factors that are unknown or that cannot be precisely measured (Brüderl & Ludwig, 2015). These models typically focus on entity-fixed effects but can also be applied to account for time-fixed effects or both.

Entity-fixed effects refer to the unique characteristics of each entity (e.g., individuals, firms, or countries) that do not change over time. Entity-fixed effect models are based on two fundamental assumptions (Wooldridge, 2010):

1. The entity-specific effect is constant over time. This means that while the observed independent variables may vary, the unobserved characteristics captured by the fixed effect are stable.

2. The entity-specific effect is unique to each entity and can be arbitrarily correlated with the independent variables.

To control for these entity-specific effects, fixed effects models focus on within-entity variations across time. Within a regression model, this is can be achieved by including an entity-specific intercept so that the value of the dependent variable for each entity has a unique baseline that is constant over time but different from that of other entities (Adeleke, Binuomote, & Adeleke, 2020). These intercepts capture all the variation specific to each entity, effectively isolating the impact of the measured independent variables.

This way the regression coefficients of the independent variables reflect solely the effects of variations that occur within each entity over time, as confounding effects due to constant, but unmeasured characteristics specific to each entity are removed (DeHaan, 2021). In other words, fixed effects models ensure that the coefficients of independent

variables precisely reflect their unique impact, allowing for a more precise interpretation of how the independent variables affect the dependent variable.

Similarly, time fixed effects can be included to address time-related factors that affect all entities equally at a given moment but that vary over time. This way we can control for trends that impact all entities similarly during specific time periods. This could be important in a panel event study such as the one performed in this end-of-degree dissertation in which the relevant event happens in a staggered manner for each entity.

Random effects models follow a different approach as their key assumptions are (Wooldridge, 2010):

1. The entity-specific effect is a random variable drawn from a population following a certain distribution, typically a normal distribution.

2. The entity-specific effect or random effect is uncorrelated with the independent variables.

If these assumptions are met, random effects models are often preferred for two primary reasons (Huntington-Klein, 2021). Firstly, they provide more precise estimates of the entity effects. This precision arises because random effects models assume that all entity effects are drawn from a common distribution. This assumption allows the model to use data from all of the observed entities, and not just from the specific entity when estimating its entity-specific effects. Secondly, this approach leads to results that can be more easily generalized to larger populations. Since the model treats the sampled entities as a random selection from a broader population, it facilitates extrapolation of the findings beyond the specific entities studied.

2.5.4. The Role of Lags and Leads

Lags and leads are crucial for analyzing how stock prices react before and after the announcement of an M&A deal. *Lags* are defined as the periods leading up to the M&A event, while *leads* are the periods following it.

The importance of lags and leads is twofold. On the one hand, they allow us to temporally align the impact of the events that happen at different times for different firms, providing a common basis for comparison (Borusyak & Jaravel, 2018). By using lags and leads, we can standardize the timeline in which the effects of the event are

examined, thus allowing to assess how stock prices react on average across firms. The importance lies in the time relative to the event, not in the specific date, which varies from firm to firm.

At the same time, lags and leads capture the dynamic effects of these events on stock prices. This means that we can observe how the impact of the M&A announcement unfolds over time (Clarke & Tapia-Schythe, 2021). Lags can reveal whether there was a build-up of expectations or changes in market behavior prior to the official announcement of the event, which may indicate the presence of inside information or rumors in the market. Leads help to understand the short- and medium-term consequences of M&A transactions on the value of the companies involved. This includes the immediate market reaction and subsequent adjustments as investors assess the long-term impact of the merger or acquisition.

In short, unlike what happens in a traditional event study, by incorporating lags and leads it is not only possible to measure the total impact of the event, but also how it progresses over time. This will be relevant to test the validity of the efficient market hypothesis in the *Spanish Continuous Market*.

2.6. A FINAL ISSUE OF EVENT STUDIES: THE JOINT HYPOTHESIS PROBLEM

Every study that focuses on evaluating market efficiency faces a problem that was identified in the event studies literature early on. This issue received the name of the "*joint hypothesis problem*" which refers to the challenge of distinguishing between market inefficiency and an incorrect model of market equilibrium (Jensen, 1978). Essentially, the joint hypothesis problem is rooted on the fact that when testing for market efficiency one must assume a specific model that describes how the markets should behave in absence of the event. Thus, as noted by Fama (1991), when anomalous return behaviors are observed, it's unclear whether to attribute these anomalies to market inefficiency or to a flawed model of market equilibrium.

In other words, drawing conclusions on the efficient market hypothesis through the calculation of abnormal returns requires some expected returns to be estimated. This estimation relies on models such as CAPM or FF3FM, but these are just simplified representations of reality, crafted to explain complex market behaviors. Different models might yield varying predictions for expected returns, and most likely none of them are entirely correct. This issue is common to traditional and panel event studies as the later

ones also rely on such models, even if the estimation of expected returns is not as evident.

In principle, the joint hypothesis problem implies it is not possible to know whether results that contradict market efficiency are owed to actual inefficiencies, to an incorrect model, or to both. It follows that event studies are a joint test of market efficiency and the validity of the asset pricing model (Kothari & Warner, 2007). Nonetheless, results are often only interpreted in terms of market efficiency, especially when the joint-hypothesis problem is mitigated through robustness checks and by incorporating factors to adjust for known biases into the asset pricing model. Furthermore, Fama (1991) notes that the use of daily data can reduce or completely address the joint-hypothesis problem.

3. OBJECTIVES

The purpose of this end-of-degree dissertation is to evaluate the efficiency of the *Spanish Continuous Market* using the announcements of M&A transactions involving Spanish listed companies as a natural experiment. The main objective is to verify the validity of the efficient market hypothesis in the Spanish context and, more specifically, to determine whether the market is efficient at the semi-strong level.

To this end, the reaction of investors to the aforementioned announcements will be studied through the analysis of returns obtained by shares of the firms involved during a 100-day event window symmetrically distributed around the announcement date.

This study specifically focuses on the semi-strong form of market efficiency, which involves analyzing how quickly and accurately market prices reflect publicly available information. Given the fundamental and not technical nature of M&A announcements, weak-form efficiency will not be specifically tested. Additionally, while findings might provide insights into strong form efficiency, which posits that market prices reflect all information, both public and private, the study does not test for this level of efficiency as it is often regarded as an ideal or theoretical benchmark rather than a practical level of efficiency achievable in real-world markets.

In any case, as was discussed earlier, efficiency levels are cumulative. Therefore, if the Spanish market is found to be semi-strong efficient, then it would also meet the weak form efficiency criteria. Conversely, rejecting the hypothesis stating the market is semi-strong efficient implies a rejection of strong-form efficiency.

Consequently, the null and the alternative hypothesis can be formulated as follows:

- Null hypothesis (H_0): the Spanish market is not efficient or exhibits only weak efficiency.
- Alternative hypothesis (H_1): the Spanish market exhibits semi-strong efficiency.

The interpretation of results will depend on whether acquirer or target firm's returns are analyzed. As discussed, M&A announcements are followed by significant positive abnormal returns in the case of target firms. On the other hand, acquirers are found to experience zero or slightly negative abnormal returns. Therefore, only target firms provide an appropriate framework in which to test the EMH. Nonetheless, a separate regression will also be performed on a panel of acquirer firms as a way of testing the validity of the model used to estimate abnormal returns. If the model is correctly specified one should expect acquirers' abnormal returns to be close to zero around the

event date. Therefore, the panel of acquirer firms is used to evaluate the robustness of the methodological framework employed in this end-of-degree dissertation, mitigating the joint hypothesis problem.

As for the target firms, to convincingly reject the null hypothesis in favor of the alternative hypothesis of semi-strong efficiency, a prompt and precise market response to M&A announcements should be observed before rapidly disappearing, reflecting the efficient assimilation of news implications into market prices (Andrade, Mitchell, & Stafford, 2001). Graphically, this would be indicated by a noticeable surge or drop in returns immediately following the announcement, swiftly reverting to typical return levels thereafter. In terms of accumulated returns, this reaction would imply the initial surge or drop in returns is followed by a flat accumulated return.

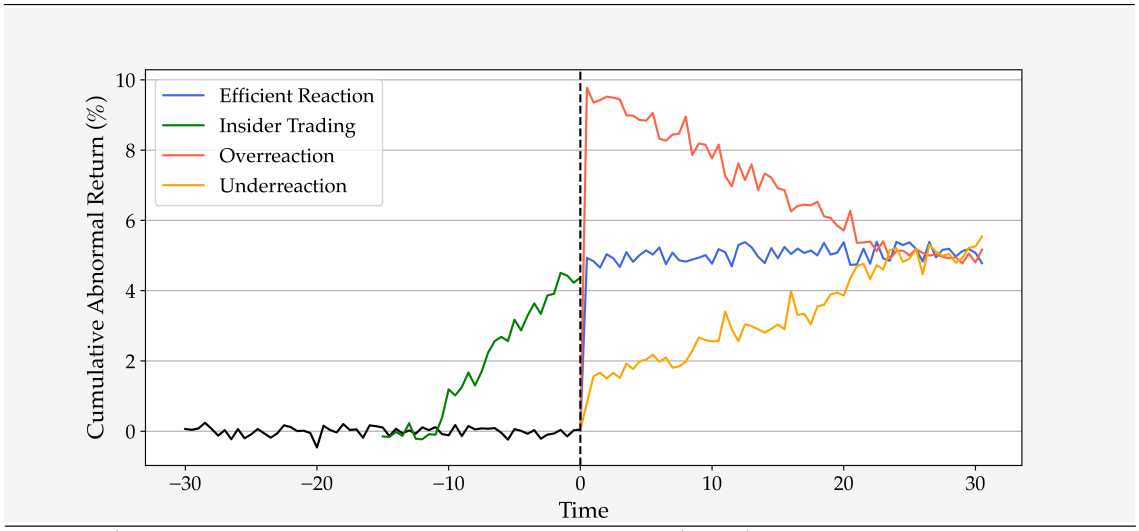

Figure 3 Theoretical Reactions to an Event (Source: Adapted by the author from M. Brunnermeier, "Lecture 10: Market Efficiency", https://markus.scholar.princeton.edu/sites/g/files/toruqf2651/files/13lecture.pdf)

Conversely, scenarios in which high positive abnormal returns are followed by negative ones —or vice versa—, indicate an initial mispricing of the announcement. This creates an opportunity for traders to achieve higher risk-adjusted returns by capitalizing on publicly available information, which is contrary to semi-strong efficient market postulates. In these scenarios, the surge or drop in accumulated returns would be followed by a progressive decline or increase in such returns respectively.

Furthermore, the presence of significant abnormal returns in the days leading up to the announcement of the transaction would demonstrate the existence of traders investing with insider information. This would provide evidence against strong form efficiency, as it shows that investors with access to privileged information can obtain risk-adjusted returns above those of the market (Rozeff & Zaman, 1988; Wong, 2002).

4. METHODOLOGY

4.1. DATA PREPARATION

The first step in the implementation of the panel event study panel is the collection of the necessary data and its subsequent manipulation and organization into an appropriate format.

4.1.1. Data Collection

Two types of data had to be obtained for the development of this work: data on the M&A transactions that meet the criteria defining the scope of the analysis and data on the share prices of various Spanish companies. The information on M&A transactions was obtained through *FactSet Research Systems Inc.* which provides a detailed database on global M&A transactions.

In addition, *FactSet* offers a filtering service that allows to obtain a refined dataset, including only those operations that, according to the selected criteria, are of interest. In particular, this study required two datasets to be obtained: one including those operations in which a Spanish company acted as the acquirer firm and one in which a Spanish company was the target of the operation.

The filtering process to gather both datasets is explained below. Additionally, for a comprehensive visual understanding of this process, Figure 4 includes a flow chart detailing each of the steps in the filtering procedure. Furthermore, Annex 1 contains a table portraying the target firms and M&A deals' description included in the panel.

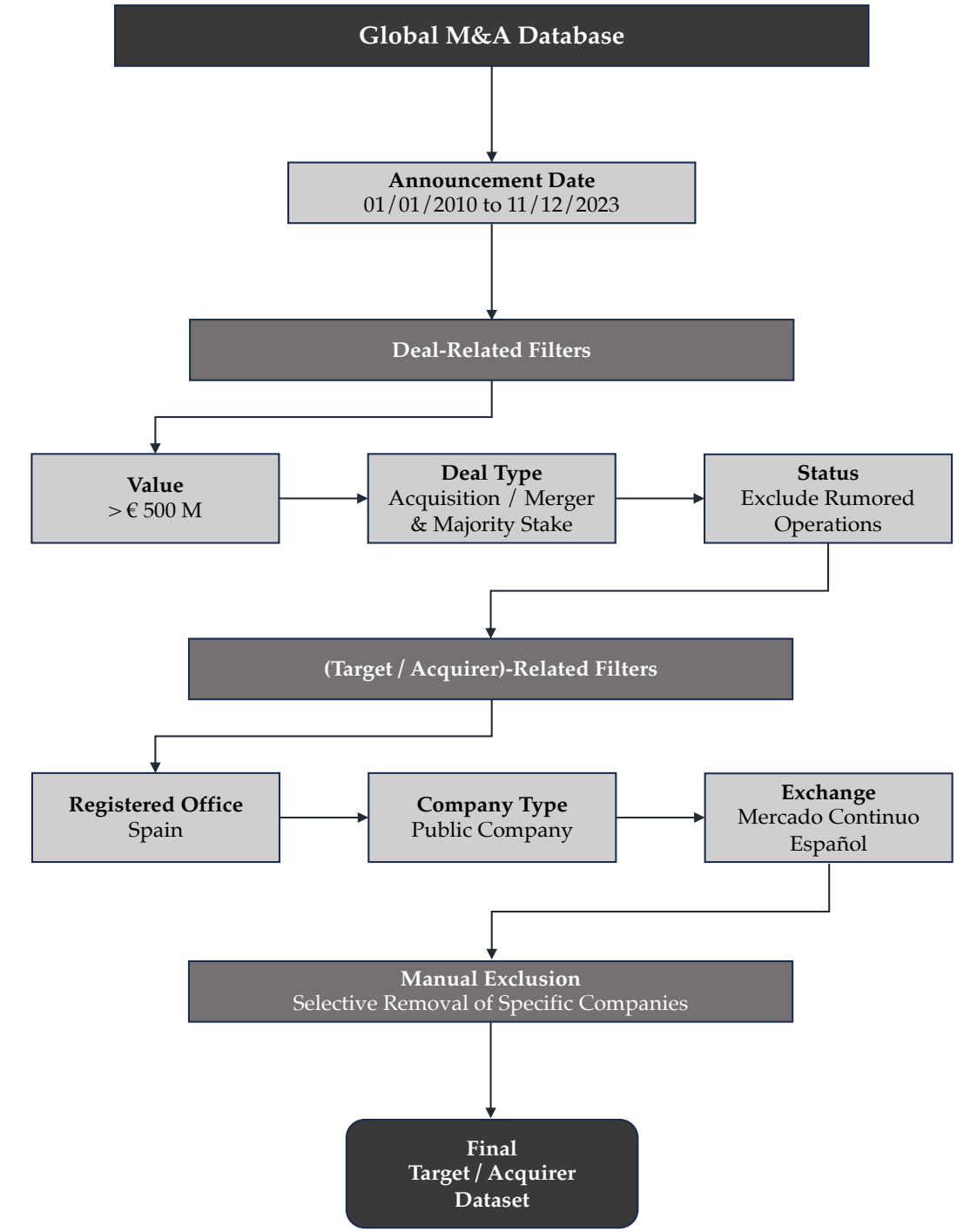

Figure 4 Flow Chart Detailing the Data Filtering Procedure (Source: Author)

First, only transactions announced between January 1, 2010, and December 31, 2023, were considered. In addition, a filter was applied to include only those transactions in which the relevant firm had its registered office in Spain. After this filtering, *FactSet* reported 240 transactions with Spanish acquirers and 306 with Spanish targets.

FactSet also offers the possibility of filtering on four different classes of M&A transactions: "Acquisition/Merger", "Majority Stake", "Minority Stake" and "Spinoff". A filter was applied to keep only Acquisition/Merger operations, defined as those in which the acquirer seeks to obtain 100% of the target company, and Majority Stake which refers to cases where the acquirer, initially owning less than 50% of the shares, seeks to increase its stake to more than 50% but without reaching a 100% stake.

The exclusion of Minority Stake and Spinoff is crucial for the proper testing of the hypothesis of interest. Minority Stake transactions typically have limited impact on corporate management and strategy, while Spinoffs are a completely distinct form of corporate restructurings and where therefore removed.

Additionally, to ensure that the transactions could have a measurable impact on the stock price, an additional filter was applied to exclude transactions with a value of less than 500 million euros.

At this stage the dataset encompassed actual and only rumored M&A operations Including these rumored operations presents a challenge: without an official announcement, it's uncertain whether the market believed and reacted to these rumors or largely ignored them. Thus, rumored operations were excluded. Consequently, the dataset now includes only those M&A operations officially announced, regardless of whether the operation was ultimately completed, is still in progress, or was eventually cancelled.

Given the impact of M&A announcements is assessed though changes in share prices, the datasets were further restricted to public companies, which *FactSet* defines as those that have *"issued securities through a public offering and whose shares are owned by many different investors and are traded on an open market, generally through a stock exchange"*. Moreover, only firms listed in the *Spanish Continuous Market* were considered. This focus is relevant as it ensures that included stocks have sufficient liquidity, enabling a reliable measurement of market reactions to M&A announcements. Incorporating stocks listed on the *BME Growth* —formerly *Mercado Alternativo Bursátil*—, which are typically less liquid and more volatile could distort the true impact of M&A announcements making findings less reliable.

After completing the filtering process, a dataset including 72 transactions where both the transaction and the acquiring company met the described criteria was obtained. A second dataset was generated with 32 transactions where both the operation and the target companies matched the established conditions.

Additionally, several transactions from both datasets were manually excluded for various reasons. For example, the announcement on 19 April 2023 of *Abengoa SA's* acquisition by *Cox Energy America SAB* was removed from the target firm's dataset. The reason is that *Abengoa* had been suspended from trading since 14 July 2020 by the Spanish *Comisión Nacional del Mercado de Valores*, citing circumstances potentially disrupting normal stock operations, making it impossible to assess the market's reaction to the announcement.

Operations involving companies with missing price data around the event date — as was the case of *Mediaset España Comunicación SA*— were also excluded. This missing information could be attributed to the stock's low liquidity or data collection issues by *FactSe*t. Furthermore, firms like *Testa Residencial SOCIMI SA* were excluded due to their very low level of free float. This is common with *SOCIMIs*, as trading on a stock market is a requisite for benefiting from the special *SOCIMI* tax regime. Typically, most of their equity is held by a limited number of shareholders, with only a small proportion of shares being traded on the market to fulfill these requirements.

Once the M&A operations datasets were refined, price information for all the companies listed on the *Spanish Continuous Market* was downloaded from *FactSet*. This included both firms participating in M&A operations during the period under study and other firms which would serve as controls when performing the regression analysis.

Finally, daily SML, HML, risk-free rate, and market excess returns were gathered from Kenneth R. French's publicly available data library to be used as control variables in the regression[6].

4.1.2. Data Processing and Formatting

After acquiring the data, several steps are required to prepare and structure it in a panel format suitable for conducting linear regression. For that purpose, I merged the dataset containing price information with the dataset involving transactions where the Spanish company was the target. The same was done with the dataset concerning Spanish acquirer firms.

Subsequently, I defined a *time_to_event* function, which is responsible for calculating the time distance between the announcement date of the M&A operation or event date

[6] The data library can be accessed at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french

and each of the daily records of the companies in the treated group. The *time_to_event* function accounts for the stock market calendar so that the days in which it remained closed are not considered. Furthermore, if an event occurred after the market close, the first trading date following the announcement is considered to be the event date.

At this stage, the dataframe had over half a million rows as it included daily price data for over a hundred companies spanning longer than a decade. To optimize the handling and processing of data the dataframe was trimmed to keep only the daily records that fell within a 100-day window before or after any of the analyzed M&A transaction announcements. In essence, this step involved defining an event window within which the study would be conducted. Those observations corresponding to dates that did not fall within any of the event windows were removed.

The next fundamental step in the formation of the panel is the creation of *dummy variables* representing the lags and leads around the event. These variables are assigned a value of 1 in the row corresponding to a date that falls within a specified number of days before the M&A event; otherwise, it is assigned a 0. Similarly, a lead dummy variable takes a value of 1 for those observations that fall within a specified number of periods after the event. This way, each day in the dataset is marked to indicate its relative position before or after the M&A event. Those firms that belong to the control group and therefore have no associated event date simply have only zeros in all their lags and leads.

		-10	-9	-8	-7	-6	-5	-4	-3	-2	-1	...	1	2	3	4	5	6	7	8	9	10
symbol																						
ABE-ES	230612	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	230613	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	230614	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	230615	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	230616	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
	230628	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0
	230629	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0
	230630	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0
	230631	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0
	230632	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0

Figure 5 Representation of Lags and Leads (Source: Author)

Once the dummy variables for lags and leads have been created, they are merged into the main dataframe. However, before carrying out the linear regression, an

additional step is necessary: eliminating the dummy variables corresponding to one of the lags or leads. This step is required to avoid the perfect multicollinearity that would otherwise occur. Once a lag or a lead has been removed, the panel is ready to be regressed.

An additionally possibility regarding lags and leads is to *collapse the tails* of the dataframe. This refers to aggregating those lags and leads that are furthest from the event into single observations as exemplified. Figure 6 exemplifies the collapsing of lags and leads over a ±9-day interval.

Collapsing the tails reduces the complexity of the model by decreasing the number of dummy variables for which a beta will need to be estimated while maintaining a longer event window. When the tails are collapsed, the betas associated with furthermost lag and lead capture the event's effect in all the periods that were collapsed. For this study I collapsed the lags and leads that were beyond a ±30-day window into the 30-day lag and the 30-day lead.

		-9	-8	-7	-6	-5	-4	-3	-2	-1	0	1	2	3	4	5	6	7	8	9
symbol																				
ABE-ES	230612	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	230613	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	230614	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	230615	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
	230616	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
	230628	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0
	230629	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0
	230630	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	0.0
	230631	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0
	230632	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0

Figure 6 Collapsing the Tails (Source: Author)

Finally, Fama-French factors were added to the panel as controls. This reduces the risk of omitted variable bias by better estimating the return that can be attributed to factors other than the event. Therefore, by accounting for the effect that market returns, size and book-to-market ratios have on a stock's performance, a more accurate estimation of abnormal returns that can be attributed to the event is possible.

4.2. REGRESSION ANALYSIS

As previously discussed, there are several methods to perform a regression on panel data. For this analysis, I utilized *PanelOLS* from Python's *linearmodels* package[7]. *PanelOLS* can estimate a variety of panel data models, including pooled OLS, fixed effects, and random effects models.

Pooling and the random effects models were discarded because, according to existing literature, M&A announcements do not uniformly affect all firms, with certain firm and time-specific characteristics playing a significant role. Particularly, the potential correlation between entity-specific effects and some of the independent variables included in the model like firm size and book-to-market factors meant that a crucial assumption of the random effects model could not be sustained.

Consequently, a fixed effects model was deemed appropriate for carrying out the regression. *PanelOLS* permits the incorporation of either entity or time-specific fixed effects, or both of them. In the analysis I found that incorporating time-specific effects did not significantly alter the results. However, including them forces the model to drop the HML, SML and excess market return independent variables as they only vary over time but are consistent across entities on a given date. This is logical as time-fixed effects aim to capture the effect of time-varying —but not entity-specific— characteristics, i.e., the dropped factors would be somewhat captured in the time-fixed effects.

These variables displayed very low p-values, suggesting high explanatory power so in the trade-off between omitting these significant variables or foregoing the time-effects, I chose the latter.

The specific equation used to model this relationship in the *PanelOLS* analysis is as follows:

$$return_{it} = \alpha + \sum_{j=0}^{J} \beta_j \left(Lag_j\right)_{it} + \sum_{k=1}^{K} \gamma_k (Lead_k)_{it} + \mu_i + \lambda_t + \beta_M \cdot (RM_t - RF_t) + \beta_{SMB} \cdot SMB_{i,t} + \beta_{HML} \cdot HML_{i,t} + \varepsilon_{it} \quad (12)$$

[7] For more details, see the PanelOLS documentation at https://bashtage.github.io/linearmodels

(13) $$(\text{Lag } J)_{it} = \mathbb{I}[t \leq Event_i - J]$$

(14) $$(\text{Lag } j)_{it} = \mathbb{I}[t = Event_i - j] \text{ for } j \in \{0, \dots, J-1\}$$

(15) $$(\text{Lead } k)_{it} = \mathbb{I}[t = Event_i + k] \text{ for } k \in \{1, \dots, K-1\}$$

(16) $$(\text{Lead } K)_{it} = \mathbb{I}[t \geq Event_i + K]$$

Where $return_{it}$ is the dependent variable for firm i at time t, α_i represents entity's i specific intercept —its fixed effect—, $Lag_j \; and \; Lead_j$ represents the lags and leads included in the regression —one for each day in the event window, but excluding one of them to avoid perfect multicollinearity and the ones that were collapsed—, μ_i and λ_t are the entity and time fixed effects, $(RM_t - RF_t)$ is the excess market return, and $SMB_{i,t}$ and $HML_{i,t}$ are two remaining Fama-French factors included as controls.

Additionally, *PanelOLS* allows for different covariance estimators to be used, from which "robust" was selected to instruct the model to provide standard errors that are robust to the homoskedasticity —i.e., constant variance of errors— assumption in linear regression. This is typically of special important when using panel data as varying error variances across entities (cross-sectional heteroskedasticity) or over time (temporal heteroskedasticity) is more likely.

In addition to the "*robust*" covariance *estimator*, "*clustered*" and "*kernel*" —specified as "*bartlett*"— were also tried. The "clustered" covariance estimator was utilized to account for potential within-group correlation in the error terms. The "*kernel*" covariance estimator was selected to adjust for potential autocorrelation within the panel data, heteroskedasticity and cross-sectional dependence. Despite these methodological variations, no significant alterations in the results were observed.

5. RESULTS

5.1. TARGET FIRMS

The regression was performed using the *PanelOLS* function. Tables displaying the estimation summary and the parameter estimates for each lag, lead and Fama-French can be found in Annex 2A.

The R-squared, which measures the proportion of variance in returns that can be explained by the independent variables included in the model, is found to be lower than 10%. By contrast, the F-statistic of the model is high, which suggests that the overall significance of the regression is high and that the independent variables, considered as a group, explain the variability in returns in a statistically significant way.

The regression analysis also reveals that none of the beta coefficients corresponding to the dummy variables for the lags and leads around the event date are statistically significant at the 0.001, 0.05 or 0.1 levels. The only exception is the beta for the dummy variable representing the event date itself, which is significant with a p-value of 0.0014. Moreover, Fama-French factors are significant at every relevant level.

A separate regression using CAPM (i.e., including the excess market return factor, but not the size and value factors) was performed. Results can be found in Annex 2B. The regression based on the *Fama-French Three-Factor Model* was preferred as it had a slightly higher R-squared and the size and value factors' p-values were found to be significant at every relevant level. In any case, as can be seen by comparing the tables in Annexes 2A and 2B, the results concerning the relevant lags and leads are mostly unchanged.

Figure 7 depicts the values of the regression coefficients corresponding to each lag and lead —except for the one that was dropped to avoid perfect linear multicollinearity and the ones collapsed— around the occurrence of the event.

Figure 8 displays the cumulative abnormal returns during the event window as well as the associated confidence intervals. These results show a build-up of relevant negative CARs in the days preceding the event. In the days that immediately follow the event,

CARs are large and positive. However, these returns get halved one month after the event.

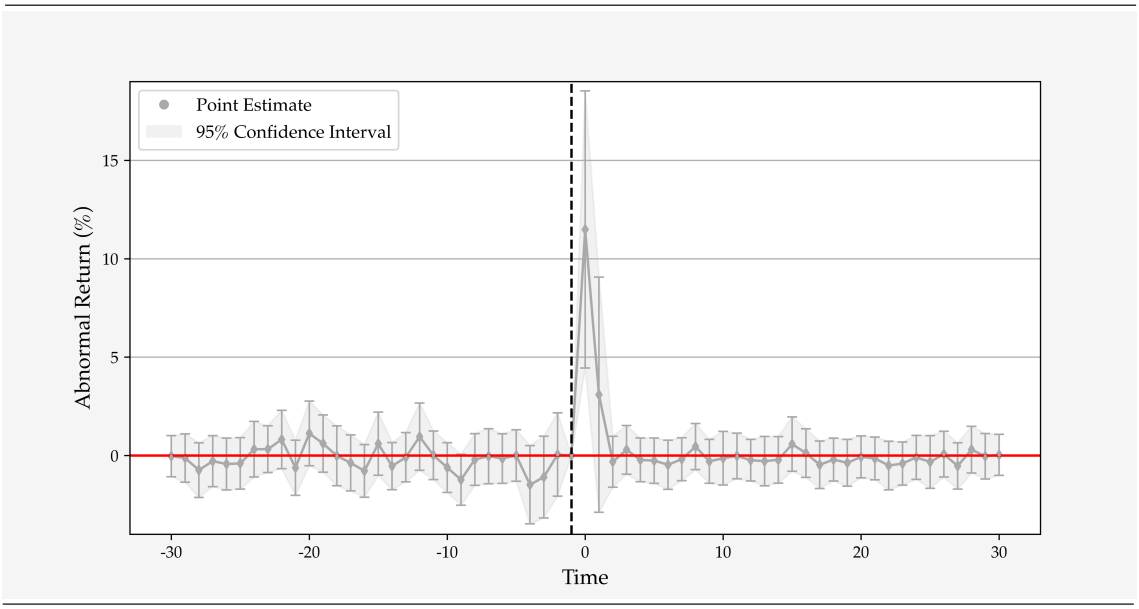

Figure 7 Target Abnormal Returns During the Event Window (Source: Author)

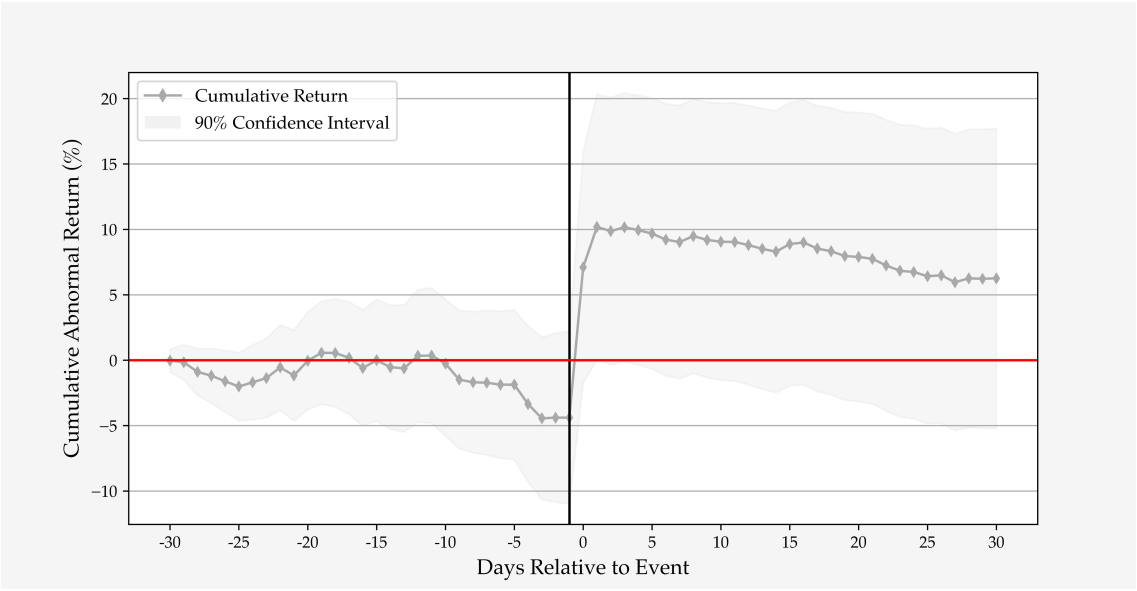

Figure 8 Target Cumulative Abnormal Returns During the Event Window (Source: Author)

These regression coefficients showed in Figure 7 quantify the abnormal returns of firms that are the target of an M&A operation. As can be seen, abnormal returns are approximately zero for every lag and lead, except the one corresponding to the event date itself in which large positive abnormal returns are observed, highlighting a large event impact. The second day after the event also experiences larger than usual positive abnormal returns, but the confidence interval also extends into the negative region.

These results were not significantly affected by changes in the length of the event window or the collapsing of tails.

One aspect to be noted is that the initial positive market reaction is followed by small but consistently negative abnormal returns in the weeks that follow as graphing the cumulative abnormal returns evidence. This contrasts with the abnormal returns observed in the weeks leading to the event which split almost halfway between positive and negative value.

The regression was specified to include entity fixed effects to control for individual firm characteristics that remain constant over time. These account for variations in firm returns that are not captured by the independent variables included in the model, but attributable to other firm-specific characteristics. Figure 9 depicts the fixed effects estimated for the target firms —fixed effects were also estimated for control firms but are not represented in this graph for clarity—. For instance, *Banco Popular* (*POP-ES*) has some characteristics that makes it different from other firms and that consistently have the effect of subtracting approximately 0.6% from its return.

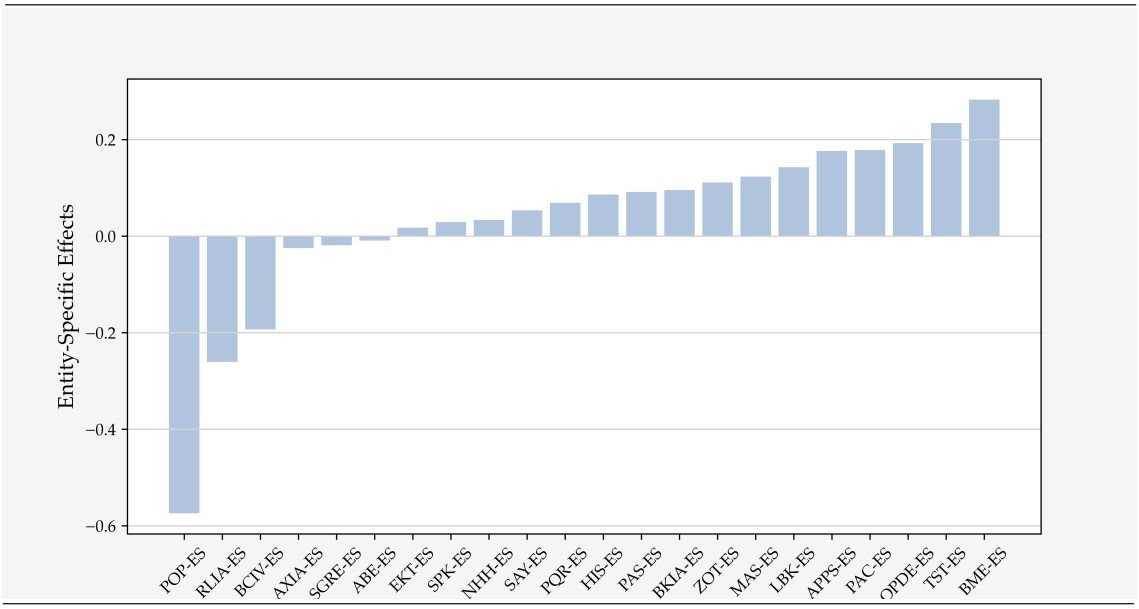

Figure 9 Target Entity Fixed Effects (Source: Author)

5.2. ACQUIRER FIRMS

The estimation summary and parameter estimate for the regression of the acquirer firms panel including the Fama-French factors can be found in Annex 3A. The R-squared value associated with the regression analysis of the panel containing acquirer firms'

reactions to M&A announcements is also found to be lower than 10%. The F-statistic also suggests that the regression is significant and that the factors included in the regression allow for a better fit than the intercept-only model would.

A separate regression using CAPM (i.e., including the excess market return factor, but not the size and value factors) was also performed in the case of acquirer firms. Results can be found in Annex 3B. Again, the regression based on the *Fama-French Three-Factor Model* was preferred as it had a slightly higher R-squared and the size and value factors' p-values were found to be significant at every relevant level. In any case, as can be seen by comparing the tables in Annexes 3A and 3B, the results concerning the relevant lags and leads are similar.

The majority of the regression coefficients for the lags and leads around the M&A announcement dates exhibit slightly negative values, yet they are mostly not significant at any relevant level. Specifically, the p-values for the coefficients that are closest to the event date show minimal significance. For instance, the p-value for the coefficient corresponding to the event date itself is 0.9005. Furthermore, despite the estimated coefficients leading toward the negative, the upper bounds of their confidence interval are often positive. Fama-French factors, on the other hand, are statistically significant. As occurred with the target firms panel, variations in the event window length did not significantly alter the results.

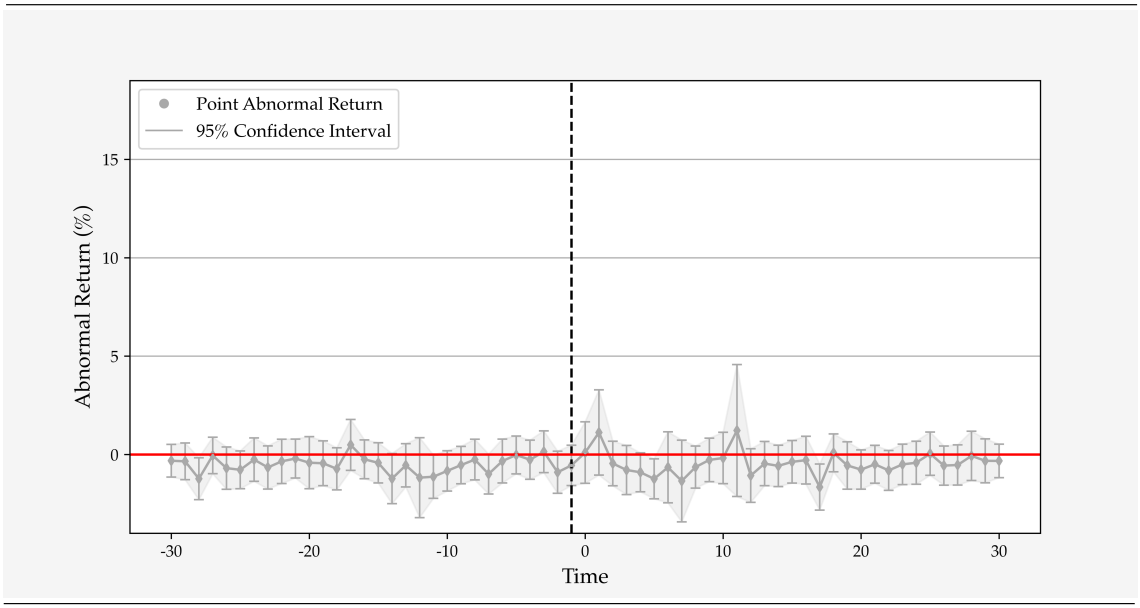

Figure 10 Acquirer Abnormal Returns During the Event Window (Source: Author)

Entity fixed effects were also estimated for the panel of acquirer firms. In contrast with the fixed effects estimated for the target firms, every acquirer had characteristics that added to the return of those firms.

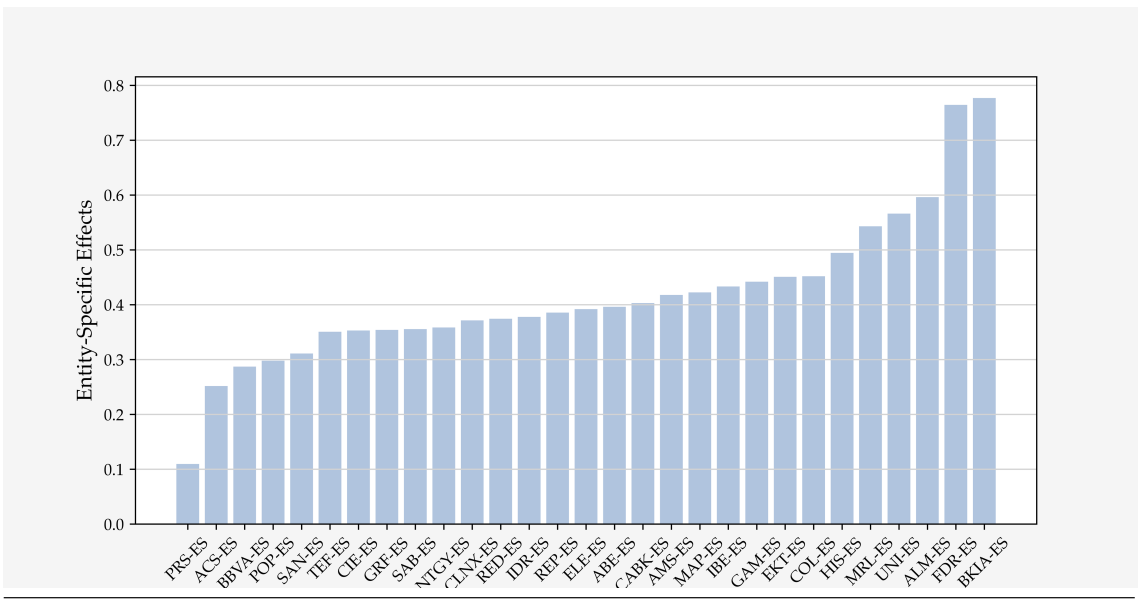

Figure 11 Target Entity Fixed Effects (Source: Author)

6. DISCUSSION AND CONCLUSION

6.1. SIGNIFICANCE OF THE REGRESSION ANALYSIS

As reported in the results section, the R-squared for the regression of both the target and the acquirers panel was below 10%. This would indicate that while the independent variables have some explanatory power, they leave a large portion of the variance in returns unaccounted for. While this value might appear low, it is not unusual —and in fact should be expected— when dealing with panel data.

When models like CAPM or Fama-French are applied to estimate the returns of a single company, the R-squared is typically much higher. The reason is that in such cases the regression coefficients are calibrated to fit the unique risk profile and characteristics of a single firm, i.e., a single set of betas is estimated for each firm. However, when performing panel data regression, a single set of coefficients is estimated for the entire set of firms. In our particular case, over one hundred firms operating in a variety of industries and with unique risk profiles are included. Therefore, it should not come as a surprise that estimating a single set of betas leaves out a large portion of the variation in the returns of firms that are so different. In short, a low R-squared in this context is not a concern.

The primary objective of the regression when performing an event study is to estimate the abnormal returns that, on average, follow a given event. The emphasis of the analysis is on understanding the impact the event has on firms that experience it. Therefore, the validity of our findings should be judged using the p-values associated with the lags and leads. More specifically, the p-values associated with the relevant lags and leads, as high p-values of lags or leads that are distant from the event date are themselves a finding. Precisely, the low p-value associated with the event date dummy coefficient reported in the results section indicates that the abnormal returns of target firms estimated to follow an M&A announcement are significant.

The validity of the model is also sustained by the fact that results for the acquirers' panel regression are found to be in line with the existing literature. As presented when discussing the use of M&A announcements as a natural experiment to test for market efficiency, a consensus exists in the academic community that acquirer firms experience zero or close to zero negative abnormal returns following an M&A announcement, which is the same we observe in this study. The fact that results for the acquirer's dataset are consistent with the literature enhances the credibility of the methodology followed in the study and serves the purpose of testing the robustness of the model. As a result, the confidence in the significance of the results observed for target firms is reinforced

and the joint hypothesis problem is mitigated, allowing conclusions on market efficiency to be drawn from this study.

6.2. IMPLICATIONS FOR THE EFFICIENT MARKET HYPOTHESIS

The regression coefficients for each lag and lead included in the regression measure the abnormal returns of firms that experienced the event on the day corresponding to relevant the lag or lead. These abnormal returns reflect the part of the actual returns of those firms that cannot be attributed to the market's overall movement or to other firm-specific characteristics. These returns are thus attributed solely to the impact of the event itself. Furthermore, lags and leads allow not only to quantity the impact of the event, but also to discern how the event unfolds over time.

Our confidence in attributing these returns to the event lies in the fact that the model is capable of controlling for various factors that can also influence returns. Firstly, broader market performance is accounted for by incorporating the market portfolio return over the risk-free rate as a factor in the regression. Similarly, other firm-specific characteristics are considered by introducing the Fama-French factors for size and value. All three factors are found to be significant at every relevant level, indicating that these factors play an important role in explaining the variation in stock returns across different firms, which helps to better isolate the variation in stock returns that is attributable to the M&A announcement.

Other firm-specific, but unknown or unmeasurable characteristics are also controlled for by estimating the entity fixed effects. Moreover, the use of panel methodology strengthens the conclusions on causal inference and market efficiency by employing control groups. In this sense, firms that did not experience the event but were included in the panel serve as pure controls. Additionally, given the staggered nature of the event, firms that did experience the event, but at a different moment, are also used as controls for the remaining firms.

The distribution of abnormal returns during the event window, in the case of target firms, provides compelling evidence against the null hypothesis that the *Spanish Continuous Market* is not efficient or exhibits only weak form efficiency.

The first relevant insight is drawn from the spike in abnormal returns on the event date. This immediate and sharp reaction to the information as it becomes publicly available suggests that market participants are capable of rapidly reacting to new information.

Furthermore, the subsequent quick disappearance of abnormal returns in the days after the event date is also revealing. Figure 7 shows that once new information is absorbed and reflected in that target firm's price, the market rapidly returns to a state of equilibrium, leaving no opportunity for arbitrage. This suggests that not only the market is reactive to new information but also that information is quickly assimilated. In fact, the market is shown to have priced in the news after just one, or at most, two trading days, aligning with the notion of semi-strong efficiency.

A second insight emerges from the observation of an absence of significant abnormal returns in the days and weeks that lead up to the event date. The lack of pre-event abnormal returns suggests that the market did not anticipate the announcement and that no relevant insider trading took place during the event window. This aligns with the postulate of strong form efficiency that no investor, regardless of whether he has access to insider information, is consistently capable of achieving excess risk-adjusted returns. While strong form efficiency is often regarded as an idealistic benchmark and not as an actual level of achievable efficiency, the evidence is relevant given the cumulative nature of efficiency levels. Indeed, the lack of insider trading supports strong form efficiency, so it also provides evidence that the conditions of semi-strong efficiency are also met.

Even though these insights favor the rejection of the null hypothesis, Figure 8 representing the cumulative abnormal returns experienced by target firms, offers a contrast. In the objectives section of this end-of-degree dissertation, we affirmed that a reaction consistent with semi-strong efficiency would be characterized by a noticeable surge or drop in cumulative abnormal returns followed by a flat accumulated return —as illustrated in Figure 3—. Figure 8, however, shows that the initial surge in CARs is followed by a progressive decline, which would signal a market overreaction to the news and a subsequent correction. Such a reaction diminishes the idea that the market is semi-strong efficient as investors who follow the rule that target firms should be shorted once the first-day reaction to M&A announcements occurs would find this strategy profitable.

However, it should also be noted that this evidence against market efficiency is not definitive. As reported in the results section, while the event date abnormal return is statistically significant, the same cannot be said the days in which the correction takes place. Furthermore, while these returns may be slightly negative on average, thus lowering CARs, the confidence interval for all of them well extends into the positive range. This indicates a level of statistical uncertainty and suggests that the observed correction in CARs after the event date, while notable, cannot be taken as conclusive and final evidence against market efficiency.

All in all, the evidence presented leads to the rejection of the null hypothesis that the *Spanish Continuous Market* is not efficient or exhibits only weak form efficiency. The immediate and pronounced reaction to M&A announcements, together with the rapid disappearance of abnormal returns, supports the idea that markets reflect all publicly available information and that when new information becomes available it is rapidly assimilated into asset prices. Therefore, we can affirm the *Spanish Continuous Market* exhibits signs of semi-strong efficiency.

6.3. STUDY LIMITATIONS AND FURTHER RESEARCH

The study performed in this end-of-degree dissertation presents some limitations that highlight the need for further research. The first class of limitations affects the generalizability of the results and conclusions presented. The companies considered for the event study represent only a fraction of all the publicly traded companies in Spain. Specifically, those firms traded on markets other than the *Spanish Continuous Market*, in which only the largest and more liquid firms are quoted, were omitted. As a result, extending the study to other markets, such as the *BME Growth* for growing small and medium-sized companies, would favor the generalizability of the results.

Furthermore, this study has focused only on a very specific kind of event. While M&A announcements are relevant and offer an opportunity to examine market reactions to new information, future research on the reaction to other events would offer additional insights into market efficiency and contribute to the extrapolation of results.

Another serious limitation regarding data availability lies in the frequency of the data employed in this study. While using daily price data is still the most common option when performing an event study, the use of intraday data could provide a more detailed understanding of how the market reaction to the analyzed event unfolds. Additionally, future research could benefit from considering the use of dependent variables other than stock prices. In this sense, event studies have been performed in other countries using volume or bid-ask spreads to unveil reactions that might not be evident just by looking at prices due to a canceling-out effect when positive and negative reactions to an event exist.

From a methodological perspective, potential limitations may derive from the ability of the model to accurately estimate the returns that can be attributed to the event and not to other factors —i.e., the abnormal returns—. To isolate the portion of the actual returns that was linked to the event, this study incorporated the Fama-French factors

and included entity fixed effects. Thus, the assumption is that the Fama-French factors would capture the variance in returns driven by market, size, and value factors; and that the fixed effects would capture the remaining unobserved heterogeneity. This assumption, however, could be oversimplistic.

As regards the Fama-French factors, while they have proven robust, they do not capture all of a firm's characteristics that influence returns. In this sense, future research might consider including additional factors in the regression, such as Carhart's momentum factor, to account for other return-affecting firm characteristics. Additionally, Kenneth French's European factors, calculated using a portfolio of companies from 16 European countries, were used. However, research suggest that in some cases these factors might be country-specific so the assumption that European factors can be directly applied to Spanish firms could be more carefully revisited.

Finally, with respect to the use of entity-fixed effects, although they rely on less stringent assumptions than random effects models, they still presume that the firm-specific effect remains constant over time. While this is not a wild assumption, considering firms are unlikely to experience significant changes during a 100-day event window, it may not hold in every case, especially considering the impact an M&A operation can have on a business structure. Therefore, future studies should examine — and possibly adjust— the methodology employed to control for unobserved heterogeneity.

7. STATEMENT OF USE OF GENERATIVE AI TOOLS

ADVERTENCIA: Desde la Universidad consideramos que ChatGPT u otras herramientas similares son herramientas muy útiles en la vida académica, aunque su uso queda siempre bajo la responsabilidad del alumno, puesto que las respuestas que proporciona pueden no ser veraces. En este sentido, NO está permitido su uso en la elaboración del Trabajo fin de Grado para generar código porque estas herramientas no son fiables en esa tarea. Aunque el código funcione, no hay garantías de que metodológicamente sea correcto, y es altamente probable que no lo sea.

Por la presente, yo, Alejandro Larrea Rodríguez, estudiante de Derecho y Business Analytics (E-3 Analytics) de la Universidad Pontificia Comillas al presentar mi Trabajo Fin de Grado titulado "*Market Efficiency in the Spanish Continuous Market: A Panel Event Study of M&A Announcements*", declaro que he utilizado la herramienta de Inteligencia Artificial Generativa ChatGPT u otras similares de IAG de código sólo en el contexto de las actividades descritas a continuación:

1. **Referencias:** Usado conjuntamente con otras herramientas, como Science, para identificar referencias preliminares que luego he contrastado y validado.

2. **Interpretador de código:** Para realizar análisis de datos preliminares.

3. **Corrector de estilo literario y de lenguaje:** Para mejorar la calidad lingüística y estilística del texto.

4. **Generador de datos sintéticos de prueba:** Para la creación de conjuntos de datos ficticios.

5. **Traductor:** Para traducir textos de un lenguaje a otro.

Afirmo que toda la información y contenido presentados en este trabajo son producto de mi investigación y esfuerzo individual, excepto donde se ha indicado lo contrario y se han dado los créditos correspondientes (he incluido las referencias adecuadas en el TFG y he explicitado para que se ha usado ChatGPT u otras herramientas similares). Soy consciente de las implicaciones académicas y éticas de presentar un trabajo no original y acepto las consecuencias de cualquier violación a esta declaración.

Fecha: 05/04/2024

Firma:

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9. ANNEXES

ANNEX 1 – TARGET PANEL

PROFILE OF TARGET FIRMS AND DEAL OVERVIEW

Firm	Sector / Date of Announcement / Deal Value (MM)	Description
Abertis Infraestructuras SA	• Toll Road Management • 14-3-2018 • 31.246,16	A consortium of infrastructure companies, Hochtief AG, Atlantia SpA and ACS Actividades de Construcción y Servicios SA, acquired Abertis Infraestructuras SA through a cash tender offer. This deal involved the creation of a new holding company to manage Abertis Infraestructuras SA. Regulatory approvals were required for this transaction.
Applus Services SA	• Quality Control • 28-6-2023 • 2.041,86	Applus Services SA, a company providing inspection, certification, and other technical services, was acquired by private equity firm Apollo Global Management Inc through a cash tender offer. This deal faced a competing bid from another private equity consortium. Regulatory approvals were required for this transaction.
Axiare Patrimonio SOCIMI SA	• Commercial and Logistics Real Estate • 13-11-2017 • 842,95	Inmobiliaria Colonial SOCIMI SA, a competitor in the commercial property investment market, acquired an additional 58.1% stake in Axiare Patrimonio SOCIMI SA in cash, increasing its ownership to 86.9%. This deal strengthens Inmobiliaria Colonial SOCIMI SA's presence in Spain and Europe.
Banca Cívica SA	• Banking • 26-3-2012 • 956,39	Acquired by CaixaBank SA through a stock swap. This deal occurred within a context of consolidation in Spanish banking sector following the 2008 financial crisis.

Banco Pastor SA	• Banking • 7-10-2011 • 1.047,01	Acquired by Banco Popular Español SA through a stock exchange offer. The deal allowed Banco Pastor SA to retain its brand but integrated it under Banco Popular Español SA's ownership. Regulatory approvals were required for this transaction.
Banco Popular Español SA	• Banking • 7-6-2017 • 3.800,00	Acquired by Banco Santander SA in a fire sale for a symbolic €1 due to Banco Popular's financial difficulties. This deal allowed Banco Santander to expand its presence in Spain and Portugal. The deal was approved by the European Comission.
Bankia SA	• Banking • 3-9-2020 • 4.293,57	CaixaBank acquired Bankia through a stock swap in a transaction closing in March 2021. The deal, approved by regulators and shareholders, aimed to create a stronger entity with a wider product range and efficiencies. Merging operations led to potential job cuts and branch closures under CaixaBank's brand.
Bolsas y Mercados Españoles	• Stock Exchange Operator • 18-11-2019 • 2.719,96	SIX Group Ltd acquired Bolsas y Mercados Españoles, the Spanish stock exchange operator, through a voluntary tender offer. This deal enabled SIX Group Ltd to expand its reach globally. The transaction required approval from Spanish authorities and closed in September 2020.
Euskaltel SA	• Telecommunication • 28-3-2021 • 3.461,45	Kaixo Telecom SAU, a subsidiary of Másmovil Ibercom SA, acquired Euskaltel SA, a telecommunications provider, through a cash tender offer. The deal, approved by regulatory bodies and shareholders, was completed in July 2021.
Hispania Activos Inmobiliarios SOCIMI SA	• Residential and Commercial Real Estate • 5-4-2018	Blackstone Group LP acquired a majority stake in Hispania Activos Inmobiliarios, a Spanish real estate investment trust (REIT). Through a cash tender offer, Blackstone aimed to gain control and eventually delist the company from the stock exchange. Regulatory approvals were required for this transaction.

	• 1.474,81	
Iberdrola Renovables SA	• Renewable Energy Generation • 8-3-2011 • 2.540,21	Iberdrola SA, a Spanish energy company, fully acquired its subsidiary Iberdrola Renovables taking it private and delisting it. The deal involved a combination of cash and stock issuance, allowing Iberdrola to diversify its business portfolio while maintaining its exposure to renewable energy sources.
Liberbank SA	• Banking • 5-10-2020 • 758,09	Unicaja Banco merged with its competitor Liberbank in a stock swap deal. This move aimed to create a stronger financial institution in Spain by combining the networks and client bases of both banks. The merged entity retained the Unicaja Banco name, solidifying its position in the Spanish banking sector.
Másmovil Ibercom SA	• Telecommunications (Mobile Network) • 1-6-2020 • 4.706,51	A consortium led by private equity giants KKR, Cinven, and Providence Equity Partners acquired a controlling stake in Másmovil Ibercom, a leading Spanish telecom provider. The deal involved a cash tender offer. Regulatory approvals were required, and the consortium planned to delist the company from the stock exchange after the acquisition.
NH Hotel Group SA	• Hotels and Tourism • 5-6-2018 • 1.198,65	Minor International, a hospitality company, acquired an additional 47.76% stake in NH Hotel Group, a Spanish hotel operator, through a mandatory tender offer. The deal was financed through Minor's existing cash and credit lines. The transaction was approved by relevant authorities and shareholders. Following the acquisition, Minor now owns over 94% of NH Hotel Group.
Opdenergy Holding SA	• Renewable Energy Generation • 12-6-2023 • 1.416,30	Antin Infrastructure, an investment firm, agreed to acquire Opdenergy Holding, a Spanish renewable energy company, through a cash tender offer and subject to a 46% price premium to the pre-announcement closing price. The deal is subject to regulatory approvals. The acquisition will complement Antin's infrastructure portfolio.

Papeles y Cartones de Europa SA	• Paper and Pulp Packaging • 4-6-2018 • 1.802,92	DS Smith, a British packaging company, acquired Papeles y Cartones de Europa, a Spanish paper and cardboard products manufacturer. The deal was financed through a rights issuance and debt. The acquisition will expand DS Smith's business and strengthen its supply chain. The transaction required regulatory approvals and was approved by shareholders of both companies. After the acquisition, DS Smith delisted Papeles y Cartones de Europa from the stock exchange.
Parques Reunidos Servicios Centrales SA	• Amusement Parks and Leisure Facilities • 26-4-2019 • 1.511,40	A consortium led by EQT Partners, Groupe Bruxelles Lambert, and Corporacion Financiera Alba acquired a majority stake in Parques Reunidos, a Spanish leisure park operator. The acquisition followed a tender offer, required regulatory approvals including the European Commission and BaFin, and was financed by several major banks. The deal concluded with the delisting of Parques Reunidos, aligning with the consortium's strategic goals for the company.
Realia Business SA	• Residential and Commercial Real Estate • 20-11-2014 • 521,31	Hispania Activos Inmobiliarios, proposed to acquire Realia Business through a tender offer, aiming to expand its portfolio in the Spanish real estate market. The transaction required regulatory approvals and set a minimum acceptance threshold. Amidst this competitive interest, including a notable counteroffer from Inmobiliaria Carso, Hispania ultimately decided to withdraw its bid for Realia Business.
Saeta Yield SA	• Renewable Energy Generation • 15-1-2018 • 2.397,39	TerraForm Power, a Brookfield Asset Management subsidiary, successfully acquired Saeta Yield, a renewable energy firm, through a tender offer. The acquisition, supported by significant shareholder commitments and financed through equity offerings, emphasized TerraForm's expansion into the renewable energy sector in Spain. The transaction involved regulatory approvals and concluded with Saeta Yield's delisting.
Siemens Gamesa Renewable Energy SA	• Engineering and Wind Turbine Manufacturing • 18-5-2022	Siemens Energy AG completed the acquisition of a 32.9% minority stake in Siemens Gamesa Renewable Energy SA, thereby increasing its ownership to 92.72%. This move allows Siemens Energy to fully integrate Siemens Gamesa into its operations, reflecting a significant premium over Siemens

	• 4.048,50	Gamesa's closing price prior to the acquisition announcement. The deal, financed through a combination of equity, debt, and cash, was subject to regulatory approvals.
Solarpack Corporación Tecnológica SAU	• Renewable Energy Generation • 16-6-2021 • 1.210,10	EQT Partners AB, part of EQT AB, successfully acquired Solarpack Corporación Tecnológica SA, enhancing its portfolio with a significant stake in the solar energy sector. The transaction was underpinned by irrevocable agreements from major shareholders. Following regulatory approvals, the acquisition culminated in a squeeze-out procedure, resulting in Solarpack's delisting from several stock exchanges.
Testa Inmuebles en Renta SA	• Residential and Commercial Real Estate • 8-6-2015 • 1.555,24	MERLIN Properties SOCIMI SA acquired a 74.6% additional stake in Testa Inmuebles en Renta SA from Sacyr SA, bringing its total ownership to 99.6%. This strategic acquisition was part of a phased transaction, initially bolstering MERLIN's stake through a capital increase, followed by a mandatory offer for the remaining shares. The deal, supported by shareholder approval reinforces MERLIN's position as a dominant player in Spain's rental real estate sector.
Zardoya Otis SA	• Elevator Manufacturing • 23-9-2021 • 1.662,51	Opal Spanish Holdings SAU, part of Otis Worldwide Corp, acquired the remaining 49.8% of Zardoya Otis SA, bolstering Otis's presence in the elevator sector. Financed via a bridge loan and notes offering, the acquisition enhances Otis's earnings. Following regulatory approvals, Otis exceeded 95% ownership, leading to Zardoya Otis's delisting from Spanish exchanges, marking a strategic expansion for Otis Worldwide.

Source: Adapted by the author from information retrieved from *FactSet's* Global M&A Database

ANNEX 2 A – TARGET PANEL REGRESSION RESULTS USING THE FAMA-FRENCH THREE-FACTOR MODEL

PANELOLS ESTIMATION SUMMARY			
Dep. Variable:	Price_change	**R-squared:**	0.0655
Estimator:	PanelOLS	**R-squared (between):**	0.0940
No. Observations:	458583	**R-squared (within):**	0.0655
Date:	Sun, Mar 10 2024	**R-squared (overall):**	0.0655
Time:	11:45:23	**Log-likelihood**	-1.1E+06
Cov. Estimator:	Robust		
		F-statistic:	510.05
Entities:	136	**P-value**	0.0000
Avg Obs:	3371.9	**Distribution:**	F(63,458384)
Min Obs:	188.00		
Max Obs:	3984.0	**F-statistic (robust):**	285.20
		P-value	0.0000
Time periods:	3984	**Distribution:**	F(63,458384)
Avg Obs:	115.11		
Min Obs:	114.00		
Max Obs:	120.00		

PARAMETER ESTIMATES						
	Parameter	**Std. Err.**	**T-stat**	**P-value**	**Lower CI**	**Upper CI**
Mkt-RF	0.5107	0.0049	104.56	0.0000	0.5012	0.5203
SMB	0.1186	0.0122	9.6807	0.0000	0.0946	0.1426
HML	0.2831	0.0088	32.102	0.0000	0.2658	0.3004
-30	-0.0323	0.5329	-0.0605	0.9517	-10.768	10.123
-29	-0.1256	0.6266	-0.2004	0.8411	-13.538	11.026
-28	-0.74	0.7093	-10.434	0.2968	-21.301	0.6501
-27	-0.284	0.6611	-0.4296	0.6675	-15.797	10.117
-26	-0.4302	0.6717	-0.6405	0.5219	-17.468	0.8863
-25	-0.3996	0.6674	-0.5988	0.5493	-17.076	0.9084
-24	0.3215	0.7207	0.446	0.6556	-10.911	17.341
-23	0.324	0.6062	0.5345	0.593	-0.8641	15.121
-22	0.8171	0.7562	10.805	0.2799	-0.665	22.992
-21	-0.6214	0.7141	-0.8702	0.3842	-2.021	0.7782
-20	11.266	0.8378	13.447	0.1787	-0.5155	27.686
-19	0.6109	0.7418	0.8236	0.4102	-0.8429	20.647
-18	-0.0138	0.7755	-0.0178	0.9858	-15.338	15.063
-17	-0.372	0.7251	-0.5131	0.6079	-17.931	1.049

-16	-0.7821	0.6831	-1.145	0.2522	-21.209	0.5567
-15	0.6007	0.8182	0.7342	0.4629	-1.003	22.043
-14	-0.5378	0.6106	-0.8808	0.3784	-17.347	0.659
-13	-0.0845	0.6395	-0.1321	0.8949	-13.379	11.689
-12	0.9608	0.8717	11.023	0.2704	-0.7477	26.693
-11	0.0126	0.6294	0.02	0.984	-12.211	12.463
-9	-12.295	0.6597	-18.638	0.0624	-25.224	0.0634
-8	-0.1995	0.6714	-0.2971	0.7664	-15.154	11.164
-7	-0.0333	0.7127	-0.0467	0.9627	-14.302	13.636
-6	-0.1514	0.6434	-0.2353	0.814	-14.124	11.097
-5	0.0036	0.6668	0.0053	0.9957	-13.034	13.105
-4	-14.819	10.143	-1.461	0.144	-3.47	0.5061
-3	-10.941	10.588	-10.333	0.3015	-31.692	0.9811
-2	0.0518	10.802	0.0479	0.9618	-20.655	2.169
-1	0.4896	0.7976	0.6138	0.5393	-10.737	20.529
0	114.868	35.911	31.987	0.0014	44.485	185.252
1	30.909	30.472	10.144	0.3104	-28.815	90.633
2	-0.3163	0.6599	-0.4793	0.6317	-16.096	0.9771
3	0.2913	0.6306	0.4619	0.6441	-0.9447	15.273
4	-0.2186	0.5657	-0.3864	0.6992	-13.274	0.8902
5	-0.2599	0.5881	-0.4419	0.6586	-14.126	0.8928
6	-0.4667	0.6371	-0.7325	0.4639	-17.154	0.7821
7	-0.1853	0.5574	-0.3325	0.7395	-12.778	0.9072
8	0.4576	0.5984	0.7647	0.4445	-0.7153	16.305
9	-0.295	0.5683	-0.5191	0.6037	-14.088	0.8188
10	-0.1357	0.6947	-0.1953	0.8452	-14.973	1.226
11	-0.0207	0.5924	-0.0349	0.9722	-11.818	11.404
12	-0.2374	0.5388	-0.4405	0.6596	-12.934	0.8187
13	-0.2848	0.6405	-0.4447	0.6565	-15.402	0.9705
14	-0.2171	0.6038	-0.3595	0.7192	-14.005	0.9663
15	0.5811	0.705	0.8241	0.4099	-0.8008	19.629
16	0.1241	0.6303	0.197	0.8439	-11.112	13.595
17	-0.4681	0.6149	-0.7613	0.4465	-16.732	0.7371
18	-0.2053	0.5562	-0.3691	0.7121	-12.953	0.8848
19	-0.3681	0.6078	-0.6057	0.5447	-15.594	0.8231
20	-0.0666	0.5449	-0.1222	0.9027	-11.345	10.013
21	-0.1457	0.5554	-0.2623	0.7931	-12.342	0.9429

22	-0.508	0.6284	-0.8084	0.4189	-17.396	0.7236
23	-0.4052	0.5592	-0.7246	0.4687	-15.011	0.6908
24	-0.0924	0.5702	-0.162	0.8713	-12.101	10.252
25	-0.324	0.6828	-0.4746	0.6351	-16.623	10.143
26	0.0715	0.594	0.1204	0.9042	-10.927	12.357
27	-0.5297	0.6002	-0.8826	0.3774	-1.706	0.6466
28	0.2987	0.6052	0.4936	0.6216	-0.8874	14.848
29	-0.0359	0.5889	-0.061	0.9514	-1.19	11.182
30	0.0354	0.5312	0.0666	0.9469	-10.057	10.765

Note: The upper and lower bounds presented in the table represent the 95% confidence interval (CI) for the parameter estimates.

Source: Author

ANNEX 2 B – TARGET PANEL REGRESSION RESULTS USING THE CAPM

PANELOLS ESTIMATION SUMMARY			
Dep. Variable:	Price_change	**R-squared:**	0.0623
Estimator:	PanelOLS	**R-squared (between):**	0.1211
No. Observations:	458583	**R-squared (within):**	0.0623
Date:	Sun, Mar 10 2024	**R-squared (overall):**	0.0623
Time:	11:48:32	**Log-likelihood**	-1.1012+06
Cov. Estimator:	Robust		
		F-statistic:	499.39
Entities:	136	**P-value**	0.0000
Avg Obs:	3371.9	**Distribution:**	F(61,458386)
Min Obs:	188.00		
Max Obs:	3984.0	**F-statistic (robust):**	273.96
		P-value	0.0000
Time periods:	3984	**Distribution:**	F(61,458386)
Avg Obs:	115.11		
Min Obs:	114.00		
Max Obs:	120.00		

PARAMETER ESTIMATES						
	Parameter	**Std. Err.**	**T-stat**	**P-value**	**Lower CI**	**Upper CI**
Mkt-RF	0.5174	0.004	128.93	0.0000	0.5095	0.5252
-30	-0.021	0.5374	-0.0391	0.9688	-10.743	10.323
-29	-0.1065	0.6281	-0.1695	0.8654	-13.376	11.246
-28	-0.7285	0.7193	-10.128	0.3111	-21.384	0.6813
-27	-0.2932	0.6661	-0.4401	0.6598	-15.988	10.124
-26	-0.3892	0.6792	-0.5731	0.5666	-17.204	0.942
-25	-0.3568	0.6709	-0.5319	0.5948	-16.718	0.9581
-24	0.3744	0.7223	0.5183	0.6042	-10.413	17.901
-23	0.3549	0.6077	0.5841	0.5592	-0.8361	15.459
-22	0.8248	0.7701	1.071	0.2842	-0.6847	23.343
-21	-0.5799	0.7225	-0.8026	0.4222	-19.959	0.8362
-20	1.127	0.8523	13.223	0.1861	-0.5435	27.976
-19	0.5789	0.7483	0.7737	0.4391	-0.8876	20.455
-18	0.0236	0.7792	0.0302	0.9759	-15.036	15.507
-17	-0.3547	0.7279	-0.4873	0.626	-17.813	10.719
-16	-0.7321	0.6817	-10.739	0.2829	-20.682	0.604
-15	0.5801	0.8153	0.7115	0.4768	-10.179	21.781
-14	-0.5626	0.6157	-0.9136	0.3609	-17.694	0.6443

-13	-0.1034	0.645	-0.1604	0.8726	-13.675	11.607
-12	0.9347	0.8765	10.664	0.2863	-0.7832	26.525
-11	0.0319	0.6431	0.0497	0.9604	-12.285	12.924
-9	-11.996	0.6647	-18.048	0.0711	-25.024	0.1032
-8	-0.1602	0.6806	-0.2353	0.814	-14.942	11.738
-7	-0.0495	0.7103	-0.0697	0.9444	-14.416	13.426
-6	-0.1709	0.6381	-0.2678	0.7889	-14.215	10.798
-5	-0.0037	0.6711	-0.0055	0.9956	-1.319	13.116
-4	-14.462	10.198	-14.181	0.1562	-3.445	0.5526
-3	-10.591	10.589	-10.002	0.3172	-31.345	10.163
-2	0.057	10.817	0.0527	0.958	-20.631	21.771
-1	0.511	0.7996	0.639	0.5228	-10.563	20.782
0	114.884	35.865	32.032	0.0014	44.589	185.179
1	3.18	30.523	10.418	0.2975	-28.024	91.624
2	-0.2714	0.6599	-0.4113	0.6808	-15.649	1.022
3	0.3478	0.6343	0.5483	0.5835	-0.8954	1.591
4	-0.1907	0.574	-0.3323	0.7397	-13.157	0.9342
5	-0.2737	0.5938	-0.4609	0.6448	-14.375	0.8901
6	-0.4826	0.6432	-0.7504	0.453	-17.432	0.778
7	-0.2205	0.5605	-0.3933	0.6941	-13.191	0.8781
8	0.4341	0.6027	0.7203	0.4713	-0.7471	16.153
9	-0.2637	0.5756	-0.4581	0.6469	-13.919	0.8645
10	-0.1628	0.7013	-0.2321	0.8165	-15.373	12.118
11	0.0022	0.5976	0.0037	0.9971	-11.691	11.735
12	-0.2351	0.5428	-0.433	0.665	-1.299	0.8289
13	-0.2868	0.6461	-0.444	0.6571	-15.532	0.9795
14	-0.2066	0.6111	-0.338	0.7354	-14.043	0.9912
15	0.5979	0.7169	0.834	0.4043	-0.8072	20.031
16	0.1288	0.6391	0.2015	0.8403	-11.238	13.815
17	-0.4813	0.6228	-0.7727	0.4397	-1.702	0.7395
18	-0.1729	0.5612	-0.3081	0.758	-12.728	0.927
19	-0.366	0.6139	-0.5962	0.5511	-15.693	0.8373
20	-0.0408	0.5479	-0.0745	0.9406	-11.146	1.033
21	-0.1393	0.5599	-0.2488	0.8035	-12.368	0.9582
22	-0.5384	0.6411	-0.8398	0.401	-1.795	0.7182
23	-0.4281	0.5648	-0.758	0.4484	-15.351	0.6788
24	-0.0932	0.5721	-0.163	0.8705	-12.145	1.028

25	-0.3021	0.7082	-0.4265	0.6697	-16.901	1.086
26	0.1111	0.6119	0.1816	0.8559	-10.882	13.104
27	-0.5498	0.6058	-0.9075	0.3642	-17.372	0.6377
28	0.3083	0.6132	0.5029	0.6151	-0.8934	15.101
29	-0.0444	0.5962	-0.0745	0.9406	-12.129	1.124
30	0.05	0.5357	0.0933	0.9256	-1	1.1

Note: The upper and lower bounds presented in the table represent the 95% confidence interval (CI) for the parameter estimates.

Source: Author

ANNEX 3 A – ACQUIRER PANEL REGRESSION RESULTS USING THE FAMA-FRENCH THREE-FACTOR MODEL

PANELOLS ESTIMATION SUMMARY			
Dep. Variable:	Price_change	**R-squared:**	0.0477
Estimator:	PanelOLS	**R-squared (between):**	-5.3826
No. Observations:	444069	**R-squared (within):**	0.0477
Date:	Sun, Mar 10 2024	**R-squared (overall):**	0.0475
Time:	18:24:32	**Log-likelihood**	-1.1e+06
Cov. Estimator:	Robust		
		F-statistic:	353.20
Entities:	139	**P-value**	0.0000
Avg Obs:	3194.7	**Distribution:**	F(63,443867)
Min Obs:	201.00		
Max Obs:	3984.0	**F-statistic (robust):**	207.84
		P-value	0.0000
Time periods:	3984	**Distribution:**	F(63,443867)
Avg Obs:	111.46		
Min Obs:	110.00		
Max Obs:	116.00		

PARAMETER ESTIMATES						
	Parameter	**Std. Err.**	**T-stat**	**P-value**	**Lower CI**	**Upper CI**
Mkt-RF	0.4544	0.0049	918.081	0.0000	0.4447	0.4641
SMB	0.1706	0.0123	138.768	0.0000	0.1465	0.1947
HML	0.243	0.0088	277.477	0.0000	0.2259	0.2602
-30	-0.3147	0.4225	-0.7447	0.4565	-11.428	0.5135
-29	-0.3435	0.4751	-0.7231	0.4696	-12.747	0.5876
-28	-12.296	0.5432	-22.637	0.0236	-22.942	-0.165
-27	-0.0476	0.4726	-0.1008	0.9197	-0.9739	0.8786
-26	-0.6902	0.5491	-1.257	0.2087	-17.665	0.386
-25	-0.7752	0.4898	-15.827	0.1135	-17.352	0.1848
-24	-0.2562	0.5617	-0.4561	0.6483	-13.571	0.8447
-23	-0.6557	0.5595	-11.718	0.2413	-17.524	0.441
-22	-0.345	0.5743	-0.6007	0.548	-14.707	0.7807
-21	-0.203	0.5049	-0.4021	0.6876	-11.926	0.7865
-20	-0.4148	0.6752	-0.6142	0.5391	-17.382	0.9087
-19	-0.4426	0.5803	-0.7627	0.4456	-1.58	0.6948
-18	-0.7258	0.5443	-13.334	0.1824	-17.927	0.341
-17	0.492	0.6599	0.7457	0.4559	-0.8013	17.853

-16	-0.2415	0.5023	-0.4808	0.6307	-1.226	0.743
-15	-0.4206	0.5213	-0.8069	0.4197	-14.424	0.6011
-14	-12.215	0.6502	-18.785	0.0603	-24.959	0.053
-13	-0.5465	0.5603	-0.9754	0.3294	-16.446	0.5516
-12	-11.739	10.358	-11.333	0.2571	-32.041	0.8563
-11	-11.259	0.5598	-20.113	0.0443	-22.231	-0.0287
-9	-0.5357	0.4844	-11.059	0.2688	-1.485	0.4137
-8	-0.2542	0.5266	-0.4828	0.6292	-12.864	0.7779
-7	-0.9905	0.5171	-19.154	0.0554	-2.004	0.0231
-6	-0.3293	0.569	-0.5787	0.5628	-14.445	0.7859
-5	-0.0206	0.4905	-0.042	0.9665	-0.9819	0.9407
-4	-0.2628	0.5078	-0.5176	0.6047	-12.581	0.7324
-3	0.144	0.5412	0.266	0.7902	-0.9168	12.047
-2	-0.9	0.5455	-16.498	0.099	-19.693	0.1692
-1	-0.5509	0.5227	-1.054	0.2919	-15.753	0.4735
0	0.0996	0.7966	0.125	0.9005	-14.619	1.661
1	11.224	11.051	10.156	0.3098	-10.436	32.884
2	-0.4532	0.5776	-0.7847	0.4327	-15.853	0.6789
3	-0.7849	0.638	-12.304	0.2185	-20.353	0.4654
4	-0.9017	0.5036	-17.905	0.0734	-18.888	0.0854
5	-12.339	0.5174	-23.848	0.0171	-22.481	-0.2198
6	-0.6488	0.9201	-0.7051	0.4807	-24.521	11.545
7	-13.426	10.596	-12.671	0.2051	-34.194	0.7341
8	-0.637	0.5461	-11.664	0.2434	-17.074	0.4334
9	-0.2726	0.5628	-0.4844	0.6281	-13.756	0.8304
10	-0.1755	0.6665	-0.2633	0.7923	-14.818	11.308
11	1.219	1.71	0.7129	0.4759	-21.325	45.706
12	-10.681	0.6944	-15.382	0.124	-2.429	0.2929
13	-0.4583	0.5732	-0.7995	0.424	-15.817	0.6652
14	-0.5755	0.5364	-1.073	0.2833	-16.268	0.4758
15	-0.3685	0.5507	-0.6691	0.5034	-14.479	0.7109
16	-0.2857	0.6188	-0.4617	0.6443	-14.985	0.9271
17	-16.511	0.5966	-27.673	0.0057	-28.205	-0.4817
18	0.0845	0.4911	0.172	0.8634	-0.8781	1.047
19	-0.5543	0.6143	-0.9023	0.3669	-17.583	0.6498
20	-0.7645	0.509	-15.021	0.1331	-17.621	0.2331
21	-0.4944	0.491	-10.069	0.314	-14.568	0.468

22	-0.8072	0.5155	-15.659	0.1174	-18.175	0.2032
23	-0.5002	0.524	-0.9546	0.3398	-15.272	0.5268
24	-0.4152	0.5567	-0.7458	0.4558	-15.064	0.676
25	0.0446	0.5617	0.0795	0.9367	-10.563	11.456
26	-0.5608	0.5068	-11.066	0.2685	-15.541	0.4325
27	-0.5308	0.521	-10.189	0.3082	-15.519	0.4903
28	-0.0672	0.6378	-0.1053	0.9161	-13.173	1.183
29	-0.3185	0.5697	-0.5591	0.5761	-1.435	0.798
30	-0.323	0.4336	-0.7448	0.4564	-11.728	0.5269

Note: The upper and lower bounds presented in the table represent the 95% confidence interval (CI) for the parameter estimates.

Source: Author

ANNEX 3 B – ACQUIRER PANEL REGRESSION RESULTS USING THE CAPM MODEL

PANELOLS ESTIMATION SUMMARY			
Dep. Variable:	Price_change	**R-squared:**	0.0451
Estimator:	PanelOLS	**R-squared (between):**	-5.2035
No. Observations:	444069	**R-squared (within):**	0.0451
Date:	Sun, Mar 10 2024	**R-squared (overall):**	0.0448
Time:	18:33:04	**Log-likelihood**	-1.1069e+06
Cov. Estimator:	Robust		
		F-statistic:	343.65
Entities:	139	**P-value**	0.0000
Avg Obs:	3194.7	**Distribution:**	F(61,443869)
Min Obs:	201.00		
Max Obs:	3984.0	**F-statistic (robust):**	198.47
		P-value	0.0000
Time periods:	3984	**Distribution:**	F(61,443869)
Avg Obs:	111.46		
Min Obs:	110.00		
Max Obs:	116.00		

PARAMETER ESTIMATES						
	Parameter	**Std. Err.**	**T-stat**	**P-value**	**Lower CI**	**Upper CI**
Mkt-RF	0.4427	0.004	109.67	0.0000	0.4348	0.4506
-30	-0.3081	0.4305	-0.7157	0.4742	-11.519	0.5357
-29	-0.3309	0.4827	-0.6856	0.4929	-1.277	0.6151
-28	-12.323	0.5558	-22.173	0.0266	-23.215	-0.143
-27	-0.026	0.4804	-0.054	0.9569	-0.9675	0.9156
-26	-0.7332	0.5582	-13.136	0.189	-18.273	0.3608
-25	-0.7456	0.4976	-14.983	0.1341	-17.209	0.2298
-24	-0.2942	0.571	-0.5152	0.6064	-14.134	0.825
-23	-0.6888	0.5631	-12.232	0.2213	-17.924	0.4149
-22	-0.3311	0.5814	-0.5695	0.569	-14.705	0.8084
-21	-0.2174	0.5069	-0.4289	0.668	-1.211	0.7761
-20	-0.416	0.6879	-0.6047	0.5454	-17.642	0.9323
-19	-0.4382	0.5867	-0.7469	0.4551	-15.882	0.7117
-18	-0.664	0.5551	-11.962	0.2316	-1.752	0.424
-17	0.4891	0.6574	0.744	0.4569	-0.7994	17.775
-16	-0.2488	0.5053	-0.4925	0.6224	-12.391	0.7415
-15	-0.4259	0.5263	-0.8092	0.4184	-14.575	0.6057
-14	-12.234	0.6608	-18.514	0.0641	-25.185	0.0717

-13	-0.559	0.564	-0.991	0.3217	-16.645	0.5465
-12	-12.026	10.358	-11.609	0.2457	-32.328	0.8277
-11	-11.588	0.5637	-20.558	0.0398	-22.636	-0.054
-9	-0.5381	0.4932	-1.091	0.2753	-15.049	0.4286
-8	-0.2671	0.5311	-0.503	0.615	-1.308	0.7738
-7	-0.9895	0.5228	-18.926	0.0584	-20.143	0.0352
-6	-0.3396	0.5754	-0.5903	0.555	-14.673	0.7881
-5	-0.0346	0.4972	-0.0697	0.9445	-10.091	0.9399
-4	-0.2341	0.5164	-0.4533	0.6504	-12.462	0.7781
-3	0.1371	0.5428	0.2526	0.8006	-0.9268	12.011
-2	-0.9134	0.5559	-1.643	0.1004	-2.003	0.1762
-1	-0.5814	0.5288	-10.994	0.2716	-16.178	0.4551
0	0.1206	0.8065	0.1495	0.8811	-14.601	17.012
1	11.507	11.095	10.372	0.2997	-10.238	33.252
2	-0.4226	0.5957	-0.7094	0.4781	-15.901	0.745
3	-0.7731	0.6409	-12.062	0.2277	-20.293	0.4831
4	-0.8862	0.5111	-17.339	0.0829	-18.879	0.1156
5	-1.23	0.5294	-23.235	0.0202	-22.675	-0.1925
6	-0.6787	0.9206	-0.7372	0.461	-2.483	11.257
7	-13.703	10.611	-12.914	0.1966	-34.499	0.7094
8	-0.6386	0.5523	-11.564	0.2475	-1.721	0.4437
9	-0.3082	0.5662	-0.5443	0.5863	-1.418	0.8016
10	-0.1815	0.6698	-0.271	0.7864	-14.943	11.313
11	12.441	17.136	0.726	0.4678	-21.145	46.026
12	-10.251	0.6924	-14.806	0.1387	-23.822	0.3319
13	-0.4577	0.5802	-0.7888	0.4302	-15.949	0.6795
14	-0.5023	0.5417	-0.9272	0.3538	-1.564	0.5594
15	-0.3522	0.5625	-0.6261	0.5313	-14.546	0.7503
16	-0.2939	0.6277	-0.4682	0.6396	-15.242	0.9363
17	-16.466	0.6013	-27.384	0.0062	-28.251	-0.4681
18	0.0997	0.4988	0.1998	0.8416	-0.878	10.773
19	-0.5401	0.6185	-0.8733	0.3825	-17.523	0.6721
20	-0.7411	0.5156	-14.372	0.1507	-17.518	0.2695
21	-0.4776	0.4921	-0.9706	0.3317	-14.421	0.4868
22	-0.7894	0.5299	-14.896	0.1363	-1.828	0.2493
23	-0.5077	0.5298	-0.9582	0.338	-15.461	0.5308
24	-0.3798	0.5605	-0.6777	0.498	-14.783	0.7187

25	0.0486	0.5838	0.0832	0.9337	-10.957	11.928
26	-0.5381	0.5183	-10.382	0.2992	-15.539	0.4777
27	-0.5168	0.5308	-0.9735	0.3303	-15.572	0.5237
28	-0.0633	0.6423	-0.0986	0.9214	-13.221	11.954
29	-0.3386	0.5749	-0.589	0.5558	-14.654	0.7881
30	-0.3161	0.4414	-0.716	0.474	-11.812	0.5491

Note: The upper and lower bounds presented in the table represent the 95% confidence interval (CI) for the parameter estimates.

Source: Author

ANNEX 4 – PYTHON SCRIPT

I. Libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import glob
import pickle
import linearmodels
import plotly.express as px
import plotly.graph_objs as go
from linearmodels import RandomEffects, PanelOLS, OLS
from matplotlib.lines import Line2D
from matplotlib.patches import Patch
```

II. Data collection

a. Stock prices

```
# Variables contains a list of the relevant columns to be extracted from the
Excel files that were downloaded for each firm from FactSet
variables = [“price”, “price_change”, “price_returns_div_excluded”,
“price_returns_div_received”,
             “price_returns_div_reinvested”, “common_shares_outstading”,
“volume”,
             “market_value_1”, “market_value_2”]

precios_lista = [] # Create an empty list

# Iterate: glob.glob() returns a list with the Excel files (.xlsx) found in
the selected route

for file in glob.glob("./DATOS/Precios/*.xlsx"): # "*" is a wildcard character
    df = pd.read_excel(file)
    df = df[[“date”, “symbol”] + variables] # Keep only the selected columns
    precios_lista.append(df) # Appends each df to the list

precios1_df = pd.concat(precios_lista, axis=0) # Concatenates all dfs in the
list into a single one

precios1_df[“date”] = pd.to_datetime(precios1_df[“date”]) # Change the format
of column "date" to datetime
precios_df = precios1_df.copy()
```

b. Target firms

```
# Load the Excel file with the deals that matched the initial filtering
criteria
targets_df = pd.read_excel("./DATOS/Targets.xls")
```

```
# Keep only the ticker and the announcement date information
lista = [“Target Ticker”, “Announcement Date”]
targets_df = targets_df[lista]

# Add -ES to each ticker to ensure compatibility with the prices df
targets_df["Target Ticker"] = targets_df["Target Ticker"] + "-ES"

# Manually exclude some problematic deals
tickers_to_exclude = ["ABG.P-ES", "CEP-ES", "TL5-ES", "YTST-ES"]
targets_df = targets_df[~targets_df[“Target Ticker”].isin(tickers_to_exclude)]
precios_df = precios_df[~precios_df[“symbol”].isin(tickers_to_exclude)]
```

III. Panel construction

a. Merging prices and target firms dataframes

```
targ_panel_df[“date”] = pd.to_datetime(targ_panel_df[“date”])
targ_panel_df[“event_date”] = pd.to_datetime(targ_panel_df[“event_date”])
```

b. Time to event calculation

```
def calculate_trading_days_to_event(group):

    if pd.isna(group[“event_date”].iloc[0]): # if event_date for the first row
in the group is NaT (i.e., the firm is not a target firm)
        group[“time_to_event”] = pd.NaT # then fill time_to_event for that
group as NaT
        return group

    event_date = group[“event_date”].iloc[0] # otherwise (i.e., if = false)
store the event_date for the group (all rows of the relevant firm)

    # Check whether the event date was a trading day by checking if it exist
in dates (coming from prices)
    if event_date in group[“date”].values:
        event_idx = group[group[“date”] == event_date].index[0] # If the event
date is a trading day, find the index of the event date in the group
    else:
        closest_dates = group[group[“date”] > event_date][“date”] # Else, find
the trading days dates after the event

        if not closest_dates.empty: # Check if there is at least one trading
day after the event date
            closest_date_after_event = closest_dates.iloc[0] # Select the
first trading day after the event date
            event_idx = group[group[“date”] ==
closest_date_after_event].index[0] # Find its index

    # Calculate the time_to_event for each row in the group
    group[“time_to_event”] = group.index.map(lambda x: x - event_idx)
    return group
```

```
# Separate in groups by ticker and pass them to the function
targ_panel_df =
targ_panel_df.groupby(“symbol”).apply(calculate_trading_days_to_event)
```

c. DF with pure controls

```
# Firms with no M&A operations are included to serve as pure controls (DiD
approach)
targ_control_df = targ_panel_df.loc[targ_panel_df["time_to_event"].isnull()]
```

d. Lags and leads

```
targ_panel_df_copia = targ_panel_df.copy()
targ_panel_window = 30 # this will be the max number of lag/lead
targ_event_window = 100 # nº of days in the event window (for tail-collapsing)

# Trim the target df to keep only the rows in an event window
targ_panel_df = targ_panel_df.loc[targ_panel_df["time_to_event"].between(-
targ_event_window,targ_event_window)]
```

e. Collapsing the tails

```
# Create the dummy variables
targ_dummy_df = pd.get_dummies(targ_panel_df["time_to_event"], dtype="float")

# New columns for the last lag/lead
collapsed_lag = np.where(targ_panel_df[“time_to_event”] <= -targ_panel_window,
1.0, 0.0)
collapsed_lead = np.where(targ_panel_df[“time_to_event”] >= targ_panel_window,
1.0, 0.0)

# Eliminate the collapsed lags/leads
cols_to_keep = list(range(-targ_panel_window+1, targ_panel_window))
targ_dummy_df = targ_dummy_df[cols_to_keep]

# Añdd the new columns to the dummies df
targ_dummy_df[-targ_panel_window] = collapsed_lag
targ_dummy_df[targ_panel_window] = collapsed_lead

targ_dummy_df = targ_dummy_df.reindex(sorted(targ_dummy_df.columns), axis=1)
```

f. Merging the target and control dataframes

```
targ_lags_leads_df = targ_dummy_df.join(targ_panel_df[["date",
"symbol","price_change"]]).set_index(["symbol","date"])
targ_lags_leads_df.head() # df of just the target firms

targ_control_df2 =
targ_control_df.set_index(["symbol","date"])[["price_change"]] # df of control
firms
```

```
# Concatenate and fill the N.A. in the lags and leads of the control df with
zeros
targ_final_panel = pd.concat([targ_lags_leads_df, targ_control_df2],
axis=0).fillna(0.0)
targ_final_panel_copia = targ_final_panel.copy()
targ_final_panel
```

g. Adding the Fama-French factors

```
# Load the .txt file
file_path = H./DATOS/Europe_3_Factors.txtH
europe_factors_df = pd.read_csv(file_path, delim_whitespace = True)

europe_factors_df = europe_factors_df.drop(HRFH, axis=1)

europe_factors_df.index = pd.to_datetime(europe_factors_df.index,
format=H%Y%m%dH) # datetime format

europe_factors_df.reset_index(inplace=True) # Reset the index and make it a
column
europe_factors_df.rename(columns={HindexH: HDateH}, inplace=True)

# Resetting the index in targ_lags_leads_df for the merge
targ_final_panel_reset = targ_final_panel.reset_index()

# Left merge using date
targ_final_panel_merged_df = pd.merge(targ_final_panel_reset,
europe_factors_df, how=HleftH, left_on=HdateH, right_on=HDateH)

# Dropping the extra date column and set the double index (ticker + date)
targ_final_panel_merged_df.drop(columns=[HDateH], inplace=True)
targ_final_panel_merged_df.set_index([HsymbolH, HdateH], inplace=True)

targ_final_panel = targ_final_panel_merged_df
```

IV. Regression

```
# Dependent variable for the regression: price_change = return
dependent = targ_final_panel[Hprice_changeH]

# Exogenous variables: lags & leads (except one) and the Fama-French Factors
exog = targ_final_panel.drop(columns = ["price_change", -10])  # Fama-French
#exog = targ_final_panel.drop(columns = ["price_change", -10, "SMB", "HML"])
# CAPM
targ_fe_model = PanelOLS(dependent,
                    exog,
                    time_effects= False,
                    entity_effects=True, # Include entity effects
                    drop_absorbed= False)

targ_fe_result = targ_fe_model.fit(cov_type=HrobustH)
```

```
# Additional estimators:
# Clustering by firm to account for within-firm correlation (observations for
each firm likely not independent)
# Can also cluster by time (probably less necessary, but maybe usefull if
multiple announcements arounf the same time)
# targ_fe_result = targ_fe_model.fit(cov_type="clustered",
cluster_entity=True, cluster_time=True)
#targ_fe_result_kernel = targ_fe_model.fit(cov_type="kernel",
kernel="bartlett", bandwidth=10)
```

V. Visualization

```
# Regression results:
result = targ_fe_result

# Set the confidence level (5%) and find the 95% (1-alpha) confidence interval
alpha = 0.05
data = result.conf_int(level = 1 - alpha)

data["value"] = data.mean(axis=1) # mean of lower and upper bounds of the CI

data = data.drop(["Mkt-RF", "SMB", "HML"]) # Drop this as only lags/leads will
be graphed. (Need to adjust if CAPM is used)

# Artificially fill lag 10 (dropped out to avoid perfect multicollinearity)
mean_values = data.loc[-11].add(data.loc[-9]).divide(2) #mean values of lag -
11 and -9
data.loc[-10] = mean_values

data = data.sort_index() #sort the df by its index to ensure lags/leads are in
the correct order
```

a. Abnormal Returns

```
# Create a numeric index for dataframe's length (to use as an x-axis)
numeric_index = np.arange(len(data))

# Figure
plt.figure(figsize=(10, 5))

# Plot the line
plt.plot(numeric_index, data["value"], color = "darkgray", marker = "d",
markersize = 4, label = "Point Estimate")

# Add confidence interval bands
plt.fill_between(numeric_index, data["lower"], data["upper"],
color="lightgray", alpha=0.3)

# Place them over the point estimates
```

```
plt.errorbar(numeric_index, data["value"], yerr=[data["value"] -
data["lower"], data["upper"] - data["value"]],
             fmt = "o", color = "darkgray", ecolor = "darkgray", elinewidth =
1, capsize = 3, ms = 1)

BASELINE_LAG = -1
data.loc[BASELINE_LAG, "value"] = 0.0
data.loc[BASELINE_LAG, "lower"] = 0.0
data.loc[BASELINE_LAG, "upper"] = 0.0

# Add a vertical line separating pre-event from event & post-event
plt.axvline(x=numeric_index[data.index.get_loc(BASELINE_LAG)], color="black",
linestyle="--")

# Add a horizontal line at zero AR
plt.axhline(y=0, color="red", linestyle="-")

# Set the y-axis limits
plt.ylim(-4, 19)

# Custom
plt.xlabel("Time", fontname="Palatino", fontsize=13)
plt.ylabel("Abnormal Return (%)", fontname="Palatino", fontsize=13)
plt.xticks(numeric_index[::10], data.index[::10], fontname="Palatino",
fontsize=10)  # Show fewer x-axis tick labels
plt.yticks(fontname="Palatino", fontsize=10)

# Custom handles
point_estimate_handle = Line2D([0], [0], color="darkgray", marker="o",
markersize=5, label="Point Estimate", linestyle="None")
error_bar_handle = Line2D([0], [0], color = "darkgray", lw = 1, ls = "-",
markersize = 10, markeredgewidth = 1.5)
ci_band_handle = Patch(facecolor = "lightgray", alpha = 0.3, label = "CI
Band")

# Background and legend
plt.gcf().set_facecolor("whitesmoke")
plt.legend(handles=[point_estimate_handle, ci_band_handle],
           labels=["Point Estimate", "95% Confidence Interval"],
           loc="upper left", prop={"family": "Palatino", "size": 11})

# Grid lines
plt.grid(True, axis="y")

plt.show()
```

b. Cumulative Abnormal Returns

```
# Calculate cumulative standard errors
standard_errors = targ_fe_result.std_errors
cumulative_std_errors = np.sqrt(np.cumsum(standard_errors ** 2)) # Assuming
independence, then:
```

```
# the variance of the sum of independent variables = the sum of their
variances

# Confidence interval
z_value = 1.645  # For a 90% confidence interval

data["cumulative_value"] = data["value"].cumsum()
data["lower_ci"] = data["cumulative_value"] - z_value * cumulative_std_errors
data["upper_ci"] = data["cumulative_value"] + z_value * cumulative_std_errors


# Artificially fill lag -10
mean_lower_ci = (data.loc[-11, "lower_ci"] + data.loc[-9, "lower_ci"]) / 2
mean_upper_ci = (data.loc[-11, "upper_ci"] + data.loc[-9, "upper_ci"]) / 2
data.loc[-10, "lower_ci"] = mean_lower_ci
data.loc[-10, "upper_ci"] = mean_upper_ci
data = data.sort_index()

# Define the numeric index for the x-axis
numeric_index = np.arange(-30, 31)

# Figure
plt.figure(figsize=(10, 5))

# CAR
plt.plot(numeric_index, data["cumulative_value"], color="darkgray",
marker="d", markersize=4, label="Cumulative Return")

# CI bands
plt.fill_between(numeric_index, data["lower_ci"], data["upper_ci"],
color="lightgray", alpha=0.2)

# Add a vertical line separating pre-event from event & post-event
plt.axvline(x=-1, color="black", linestyle="-")

# Horizontal line at zero
plt.axhline(y=0, color="red", linestyle="-")

# Custom axes
plt.xlabel("Days Relative to Event", fontname="Palatino", fontsize=13)
plt.ylabel("Cumulative Abnormal Return (%)", fontname="Palatino", fontsize=13)
plt.xticks(numeric_index[::5], numeric_index[::5], fontname="Palatino",
fontsize=10)
plt.yticks(fontname="Palatino", fontsize=10)

# Background
plt.gcf().set_facecolor("whitesmoke")

# Custom handles for the legend
cumulative_return_handle = Line2D([0], [0], color="darkgray", marker="d",
markersize=5, label="Cumulative Return", linestyle="-")
```

```
ci_band_handle = Patch(facecolor = "lightgray", alpha = 0.3, label = "CI
Band")

plt.legend(handles=[cumulative_return_handle, ci_band_handle],
           labels=["Cumulative Return", "90% Confidence Interval"],
           loc="upper left", prop={"family": "Palatino", "size": 11})

# Gridlines
plt.grid(True, axis="y")

plt.show()
```

c. Fixed Effects

```
targ_entity_effects =
targ_fe_result.estimated_effects.groupby("symbol").mean()
targ_entity_effects = targ_entity_effects.sort_values("estimated_effects")
#order by FE

# Keep only target firms
unique_tickers = targets_df["Target Ticker"].unique().tolist()
targ_entity_effects_filtered =
targ_entity_effects[targ_entity_effects.index.isin(unique_tickers)]
targ_entity_effects_filtered =
targ_entity_effects_filtered.sort_values("estimated_effects")

# Figure
plt.figure(figsize=(10, 5))

# Bar plot
plt.bar(targ_entity_effects_filtered.index,
targ_entity_effects_filtered["estimated_effects"], color="lightsteelblue")

# Custom axes
plt.xlabel("Ticker", fontname="Palatino", fontsize=13)
plt.ylabel("Entity-Specific Effects", fontname="Palatino", fontsize=13)
plt.xticks(rotation=45, fontname="Palatino", fontsize=10)
plt.yticks(fontname="Palatino", fontsize=10)

# Background
plt.gcf().set_facecolor("whitesmoke")

# Gridlines
plt.grid(True, axis="y", color="lightgray")

plt.show()
```