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The Impact of Celebrity Endorsement Announcements

An Empirical Study of the Stock Market Reaction to Celebrity Endorsement Deal Announcements in the USA and Europe

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Acknowledgments

This thesis finalizes our master's degree in Economics and Business Administration at the Norwegian School of Economics, majoring in Financial Economics.

The journey of writing this thesis has been an educational and inspiring experience. During the writing of this thesis, we have had the privilege of applying the knowledge acquired during our five years of economic studies. Additionally, we have substantially expanded our expertise in event studies and regression analysis.

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Abstract

Do celebrity endorsements impact the stock price? In this thesis, we aim to answer this by analyzing a unique sample of 155 announcements from 2009 to 2023 by firms listed in Europe and the USA, using announcements from social media, press releases, and news sources. Employing the event study methodology, we observe no significant abnormal returns on the announcement day. However, in the USA, significant negative returns occur two days before announcements, indicating potential information leaks, followed by positive returns post-announcement. In Europe, we document no significant abnormal returns, indicating that the benefits of celebrity endorsements are closely equivalent to their costs. In addition, we examine if the abnormal returns depend on several characteristics. Our findings suggest lower returns for male celebrities compared to women. Additionally, the celebrity-firm match-up negatively influences abnormal returns in the USA. In Europe, celebrity popularity negatively affects the stock price, and technology firms experience a significantly positive impact from endorsements.

Keywords – Celebrity Endorsement Announcements, Abnormal Stock Return, Event Study, Europe, USA

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1. Introduction and Literature Review

Celebrity endorsement is a popular marketing strategy used by companies for decades (Jones, 2023). Estimates suggest that 25-30% of advertisements in Western countries utilize celebrities when endorsing (Schimmelpfennig, 2018), and that 10% of an advertiser's budget involves celebrity endorsement (Agrawal & Kamakura, 1995). In the financial year of 2023 alone, Nike's advertising and promotion costs amounted to $4.06 billion (Tighe, 2023). An illustrative case of the financial magnitude of such endorsements is the 10-year contract Nike signed with football star Erling Haaland in 2023, where he receives approximately $25 million annually (Corbella, 2023). Additionally, celebrities may boost firms' performance through endorsements, as highlighted by Forbes in 2017, estimating that Cristiano Ronaldo generated an impressive $500 million for Nike in 2016 alone through his extensive social media presence (Badenhausen, 2017).

Several papers and articles focus on the positive aspects of celebrity endorsements. One of the key benefits of using celebrities in advertisements is the ability to make ads appear more credible and influence consumer behavior (Kamins et al., 1989). Additionally, celebrities enhance brand recognition and promote positive attitudes toward the endorsed brand (Petty & Lindsey-Mullikin, 2006; Kamins et al., 1989). Furthermore, retailers using celebrity endorsements have a better chance of effectively communicating a wanted message to consumers (Choi & Rifon, 2007).

The cases mentioned underscore celebrity endorsements' potential positive influence on sales and consumer attitudes. They support the belief that celebrity endorsements can positively impact a firm's stock price. Agrawal and Kamakura (1995) exemplify this by hypothesizing that the announcement of a celebrity endorsement contract serves as critical information for investors, helping them assess the contract's potential benefits and impact on the endorser's future profitability. Their analysis of 110 contracts involving 35 firms and 87 celebrities reveals a significant positive effect, with an average abnormal return of 0.44% on the announcement day. Abnormal returns are earnings on a stock or portfolio that exceed or fall short of the market's expected performance. This finding suggests that celebrity endorsements can be a worthwhile investment in advertising.

Our thesis builds upon the studies by Ding et al. (2011) and Prentice and Zhang (2017), which examine the impact of celebrity endorsement announcements on a firm's stock price.

Moreover, they explore how individual firm and celebrity characteristics impact the abnormal return. Ding et al. (2011) examine a sample of 101 celebrity endorsement deals involving 40 firms and 85 celebrities from the USA, which document statistically insignificant abnormal returns on the announcement day. When investigating the characteristics, they find both endorsements of technology products and the celebrity-product match-up to show positive and statistically significant abnormal returns.

Prentice and Zhang (2017) analyze a sample of 87 announcements from China. Their findings are mostly consistent with Ding et al. (2011). They find insignificant results around the announcement day and that the celebrity-product match-up endorsements positively affect the abnormal returns. In contrast to Ding et al. (2011), they find a negative effect on celebrities endorsing high-tech products. The mixed results regarding the stock market responses to celebrity endorsement announcements in the mentioned studies motivate us to investigate whether the market reacts positively or negatively to such announcements. Moreover, Ding et al. (2011) and Prentice and Zhang (2017) inspire us to examine whether the characteristics of the firms and celebrities affect the abnormal returns on the firms' stock prices.

Previous studies focused primarily on singular regions and countries. Building upon these studies, we examine regional discrepancies, particularly in the USA and Europe. A study from Morgan State University in 2021 sheds light on the different advertising approaches in Europe and the USA. American companies are known to invest more in advertising than their European counterparts (Thompson, 2021). Additionally, European firms often encounter stricter regulatory requirements, leading them to adopt more conservative marketing strategies (Thompson, 2021). These inequalities lead to our interest in examining Europe and the USA and their regional discrepancies.

Social media is more prominent now than ever (Jones, 2023). In 2021, the GameStop incident demonstrated social media's power in stock market dynamics, where social media users dramatically influenced the company's stock price (Umar et al., 2021). As companies increasingly recognize social media's potential as a marketing tool, we aim to explore whether social media announcements have an additional impact on celebrity endorsements.

The studies by Ding et al. (2011) and Prentice and Zhang (2017) incorporate firm size factors by including variables such as market capitalization and book value. However, to our knowledge, existing literature has not attempted to assess a celebrity's popularity. Our study aims to address this by quantifying the popularity and fame of each celebrity through their followership on social media platforms. A substantial following may translate into a significant influence on consumers and investors. As mentioned, Cristiano Ronaldo, the world's most-followed celebrity (Dixon, 2023), generated $500 million for Nike in a single year (Tighe, 2023). In contrast, the popularity of such figures most likely entails higher contract costs for firms, which ultimately can lead to a negative return on such announcements. Consequently, it becomes compelling to examine if the size of the celebrity's followership and popularity influences abnormal returns when announcing an endorsement.

In our study, we gathered data on 155 endorsement announcements from 2009 to 2023, where 80 observations are from Europe and 75 are from the USA. We collect our data using social media platforms, press releases, and credible news sources. Our observations are more recent compared to earlier studies like Ding et al. (2011) and Prentice and Zhang (2017), which compiled their data between 1998 and 2008. A more recent data sample provides benefits, such as increased relevance to today's societal context. In addition, our dataset is more extensive than those in prior studies, which typically consist of less than 110 observations (Ding et al., 2011; Prentice & Zhang, 2017; Agrawal and Kamakura, 1998). A larger sample size offers several advantages, including increased statistical precision, which enhances the identification of effects and the credibility of our findings (MacKinlay, 1997). Furthermore, we categorize the endorsements into seven distinct variables, grouped into three broad segments: endorsers (gender, age, fame, match-up), firms (market capitalization, industry), and the announcements themselves (focusing on social media announcements).

To answer our research questions, we use the event study methodology by MacKinlay (1997) to examine the data and understand the stock market reaction to celebrity endorsement announcements. This is achieved by using financial market data, such as closing prices, to assess the effect of a firm-specific event on the company's value. MacKinlay (1997) further explains that "given rationality in the marketplace, the effect of an event is reflected immediately in security prices. Hence, a measure of the event's economic impact can be constructed using security prices observed over a relatively short period" (MacKinlay, 1997). The methodology forms the foundation for our analysis of celebrity endorsements.

After conducting the analysis, we find no significance in the abnormal returns on the announcement day, aligning with findings from previous studies (Ding et al., 2011; Prentice & Zhang, 2017). The negligible returns suggest that the benefits of endorsements match the cost associated with the deal. Furthermore, looking at the total sample, our study reveals that endorsements involving male celebrities yield significantly lower abnormal returns compared to those with female celebrities post-announcement. Additionally, we find that higher-valued firms experience a significantly negative impact on abnormal returns from celebrity endorsements.

When examining regional differences, Europe exhibits lower abnormal returns compared to the USA, which shows significant positive returns during the post-announcement period. Additional regional differences emerge considering the characteristics of the endorsers. In the USA, the match-up between the celebrity and the product has a significant negative impact on the stock returns, contradicting the findings of several previous studies (Ding et al., 2011; Prentice & Zhang, 2017). Conversely, in Europe, celebrity fame significantly adversely affects stock prices. Moreover, European technology companies experience a significant positive impact from such endorsements.

This thesis unfolds systematically, beginning with Section 2, which provides the development of our research questions. Subsequently, Section 3 details the event study methodology by MacKinlay (1997), the foundation of our analysis. Section 4 describes our data set and justifies the methods and choices behind our data collection. The core of our work is in Section 5, where we unveil, interpret, and discuss our results, enabling a comparison with prior studies. Section 6 delves into a robustness analysis, exploring the impact of various research models on the outcome of our analysis. Finally, the thesis culminates in Section 7, drawing conclusions and discussing potential future research.

2. Research Development Question

This section outlines the main hypothesis, which probes the overall influence of endorsement deals on abnormal returns. Additionally, we formulate six subsidiary hypotheses that focus on discerning the effects of specific factors on the sample.

H0 Abnormal Returns

The central aspect of our study, and indeed of prior studies in this domain as noted by Ding et al. (2011), Agrawal and Kamakura (1995), and Prentice and Zhang (2017), is to understand the effect of endorsement deal announcements on abnormal stock returns. Therefore, we articulate our central hypothesis from earlier studies mentioned in the introduction and review of existing literature:

H0: Celebrity endorsement deal announcements significantly impact abnormal returns.

H1 Personal Traits

Previous studies indicate that personal traits can influence abnormal returns. Ohanian (1990) states that endorsements become more effective when people perceive the endorsing celebrity as an expert, trustworthy, attractive, familiar, and likable. However, the influence of a celebrity's demographic background, such as age and gender, remains debatable. While Ding et al. (2011) suggest that these factors have minimal effect on endorsement success, other studies highlight that sports stars tend to appeal more to a large portion of consumers and investors (Fink et al., 2004; Fizel et al., 2008).

Regarding gender, multiple studies find that consumers tend to prefer celebrity endorsers of their own gender (Hsu & McDonald, 2002; Boyd & Shank, 2004). On the other hand, Constanzo and Goodnight (2006) delve into the possibility that respondents might better recall female celebrities. Other studies also incorporate age as a variable. For instance, Hsu and McDonald (2002) discover that age significantly impacts abnormal returns. The results from these studies create the foundation for this hypothesis:

H1: The personal traits of the celebrity influence the abnormal return of the endorsing company's stock prices.

H2 Market Capitalization

Clark et al. (2009) employ assets as a metric for firm size, concluding that more prominent firms tend to have more advantages from endorsement deals. The concept of firm size is also used by Clark et al. (2002) and Cornwell et al. (2001) as an influential factor in their studies. Both studies document significant adverse outcomes associated with endorsement announcements. The studies present contrasting views on the relationship between endorsement announcements, stock returns, and the firm's size. In some instances, leveraging a celebrity for companies with weak financial standing can negatively impact shareholder value and lead to potential agency risks (Prentice & Zhang, 2017). These perspectives inform our following hypothesis:

H2: The market capitalization of the endorsing company significantly impacts its abnormal return.

H3 Match-Up

Past studies suggest that the impact of celebrity endorsements is enhanced when there is a match-up between the celebrity and the product they are endorsing (Prentice & Zhang, 2017; Kamins et al., 1989). When harmony exists between the brand and the celebrity, it boosts brand memory, emotional connection to the brand, and the intent to buy (Kamins, 1990; Misra & Beatty, 1990; Kamins & Gupta, 1994). Additionally, Koernig and Boyd (2009) document that sports consumers exhibit more favorable attitudes when athletes endorse sports-related brands compared to unrelated products. Ding et al. (2011) find that match-up endorsements yield significant positive abnormal stock returns. Moreover, Mittelstadt et al. (2000) argue that the congruence in match-up endorsements holds more weight than the celebrity's fame. These insights set the stage for the following hypothesis:

H3: Match-up endorsement positively impacts the abnormal return of the endorsing company's stock prices.

H4 Technology Companies

Ding et al. (2011) observe a positive stock market response to celebrity endorsements in technology companies. Additionally, Clark et al. (2009) identify a positive link between abnormal returns and technology firms announcing sponsorships. These endorsements suggest that investors may perceive a technology company's sponsorship announcement as a positive indicator, showing the company's financial capability to have significant long-term marketing expenses. Furthermore, Biswas et al. (2006) find a positive effect between celebrity and expert endorsements for high-technology-oriented products. Following these studies, we will investigate the following hypothesis:

H4: Technology Companies positively impact abnormal returns in the event of an endorsement deal, compared to other sectors.

H5 Celebrity Fame

A study on different social platforms found that the number of followers can reliably predict daily stock prices (Coyne et al., 2019). Consumers today are rapidly making attitudes and negative reactions to unreliable and unrealistic brands, and the behavior of mindlessly following celebrities is decreasing (Garthwaite, 2014). To our knowledge, other studies have not yet quantified a celebrity's popularity when analyzing celebrity endorsements. As the introduction highlights, high-profile celebrities may generate substantial revenue for companies (Tighe, 2023). These studies help us formulate the following hypothesis:

H5: *Celebrity fame significantly impacts abnormal returns in the event of an endorsement deal announcement.*

H6 Social Media Announcements

In the domain of how celebrity endorsements influence stock prices, no study has specifically investigated the role of social media. However, there are extensive studies on how social media impacts stock prices. For instance, Ranco et al. (2015) discover a notable correlation between Twitter posts and abnormal returns during peak activity. In addition, Carlsson and Ek (2022) document that posts on Instagram notably influence stock prices in four out of thirteen cases for Swedish companies. Paniagua and Sapena (2014) find that followers and likes positively influence a firm's share value, but only after the firm attains a critical mass of followers. Understandably, isolating the effect of social media announcements is challenging due to the simultaneous publishing of press releases and news outlets. Therefore, our approach aims to test whether announcements on social media platforms have an additional impact or not. These factors motivate the following hypothesis:

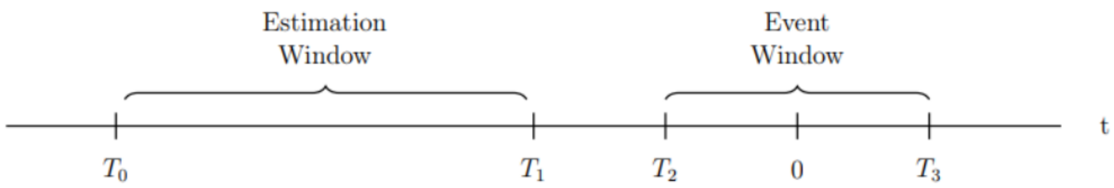
H6: Social media announcements significantly impact abnormal returns in the event of an endorsement deal announcement.

3. Methodology

Under the efficient market hypothesis, stock prices will reflect new value from relevant information introduced to the stock market (Malkiel, 1989). The event study approach measures the effect by calculating the abnormal returns from a given event. The approach implies that the announcement of celebrity endorsements will generate stock price reactions, but only if the information is regarded as value-relevant by investors. This section will detail the methodology of the event study approach.

3.1 The Event Study Methodology

Figure 3.1: The Event Study Timeframe



In our study, the initial task is to calculate the expected returns. By analyzing this, one can understand an endorsement deal's impact on the stock performance. To approximate the expected performance, we analyze financial data on returns during a specified period leading up to the event. Figure 3.1 shows this period as $[T_0, T_1]$, where T_0 is the start time and T_1 the end time, this timeframe is the estimation window.

There is no correct answer to the length of an estimation window. However, longer windows offer greater precision due to larger return samples but may include unrelated events, leading to biased estimates. A meta-analysis by Holler (2012) encompassing more than 400 event studies reveals that estimation windows typically range from 30 to 750 trading days. Other studies by Armitage (1995) and Park (2004) suggest that increasing the estimation window above 100 days does not notably affect the results. Based on these studies, we use an estimation window of 200 trading days, set from [-210, -10]. The event's timing, designated as $(t = 0)$, is the date of the celebrity endorsement announcement. The estimation window is defined before $(t = 0)$, and therefore, of negative values.

In addition, we need to define the event window $[T_2, T_3]$ in Figure 3.1. Based on the definition of $(t = 0)$, the stock price may reflect the impact of endorsement deals before and after the event date. A study by Oler et al. (2007) reveals that the preferred duration for an event window is five days. In order to capture the complete impact of the endorsement announcements, our analysis adopts an 11-day event window, spanning from five days before to five days after the event, covering the timeframe [-5, 5]. The full timeframe thus spans [-210, 5], where the estimation window concludes five days prior to the start of the event window.

We use the estimation window to calculate expected returns on the stock. The abnormal returns AR_{iT} on the stock are given by subtracting the expected returns $E(R_{iT} \mid X_T)$ from the actual return R_{iT}:

$$AR_{iT} = R_{iT} - E(R_{iT} \mid X_T) \tag{3.1}$$

given firm i and date T.

3.2 Expected Stock Performance

We can estimate the expected returns of the stock using multiple methods. According to MacKinlay (1997), there are two main approaches: statistical and economic. Statistical models utilize statistical assumptions about the behavior of returns. Economic models include investor behavior in addition to statistical assumptions (MacKinlay, 1997). We choose to use the market model because studies frequently observe that more intricate models fail to surpass the performance of the market model (Warner & Brown, 1985). One significant advantage of the market model lies in encompassing each stock's sensitivity to market returns.

3.2.1 The Market Model

The market model assumes a consistent linear association between asset and market portfolio returns. This model's specification is derived from the assumed joint normality of asset returns, as proposed by MacKinlay (1997). For any given security i, the market model is given as:

$$\begin{gathered} R_{i\tau} = \alpha_i + \beta_i R_{m\tau} + \epsilon_{i\tau} \\ E(\epsilon_{i\tau} = 0) \qquad Var(\epsilon_{i\tau}) = \sigma_{\epsilon_i}^2 \end{gathered} \tag{3.2}$$

where $R_{i\tau}$ represents the anticipated return for security i at time τ, whereas $R_{m\tau}$ denotes the return of the market portfolio at time τ. The disturbance term is $\epsilon_{i\tau}$ and is characterized by an expected value of zero and a variance indicated by $\sigma_{\epsilon_i}^2$. The parameters α_i and β_i are estimated through ordinary least squares (OLS) using the data from the specified estimation window. When applying this model, it is common to use a broad-based stock index as the market portfolio, as suggested by MacKinlay (1997). For instance, we use the S&P 500 as the benchmark for the USA.

3.3 Measuring Abnormal Returns

The market model employs two key parameters: α_i and β_i. These parameters determine the anticipated return of a company's stock price during the event window. Therefore, using the market model, the abnormal return can be given as:

$$AR_{i\tau} = R_{i\tau} - \left(\hat{\alpha}_i + \hat{\beta}_i R_{m\tau}\right) \tag{3.3}$$

Under the null hypothesis, the $AR_{i\tau}$ (abnormal return) is set to zero. According to MacKinlay (1997), the $AR_{i\tau}$ is expected to have a joint normal distribution, characterized by a conditional mean of zero and a conditional variance, denoted as σ^2. The conditional variance is defined as:

$$\sigma^2(AR_{i\tau}) = \sigma_{\epsilon_i}^2 + \frac{1}{L_1}\left[1 + \frac{(R_{m\tau} - \hat{\mu}_m)^2}{\hat{\sigma}_m^2}\right] \tag{3.4}$$

Equation 3.4 comprises two main parts. The initial component is the disturbance variance, represented as $\sigma_{\epsilon_i}^2$, same as in Equation 3.2. The subsequent component arises from the sampling error associated with α_i and β_i. As the equation suggests, when the duration of the estimation window (L_1) increases, the impact of the sampling error diminishes. Given that we utilize an estimation window of 200 days, the influence of the second component can be disregarded. Consequently, the variance $\sigma^2(AR_{i\tau})$ is effectively equivalent to $\sigma_{\epsilon_i}^2$, that is $\sigma^2(AR_{i\tau}) \approx \sigma_{\epsilon_i}^2$ (MacKinlay, 1997).

3.3.1 Cumulative Abnormal Returns

To make overall inferences about the events of interest, it is imperative to aggregate the abnormal returns over both time and securities, as highlighted by MacKinlay (1997). The AAR

(Average Abnormal Return) represents the mean abnormal return across N securities. Thus, the AAR provides the average abnormal returns across all securities for a specific day within the event window. The formula is as follows:

$$AAR_\tau = \frac{1}{N}\sum_{i=1}^{N} AR_{i\tau}$$
$$Var(AAR_\tau) = \frac{1}{N^2}\sum_{\tau_1}^{N} \sigma_{\epsilon_i}^2 \tag{3.5}$$

Cumulative Abnormal Returns (CAR) are essential to our regression analyses. CAR is the sum of all abnormal returns for a specific company, i, during the defined event window (τ_1, τ_2). Under the assumption of no event-date clustering, CAR is typically normally distributed, and we can apply the significance tests directly. CAR is given as:

$$CAR_i(\tau_1, \tau_2) = \sum_{\tau=\tau_1}^{\tau_2} AR_{i\tau} \tag{3.6}$$

Furthermore, where there are numerous instances of specific event types (endorsement deals announcements), the Cumulative Average Abnormal Returns (CAAR) can be computed. CAAR provides the average value across all companies and days, and is given as follows:

$$CAAR = \sum_{\tau=\tau_1}^{\tau_2} AAR_\tau$$
$$var[CAAR(\tau_1, \tau_2)] = \sum_{\tau=\tau_1}^{\tau_2} var(AAR_\tau) \tag{3.7}$$

Therefore, the CAAR provides a singular value that encapsulates the combined average abnormal returns across the event window, which is important to understand the total impacts from the sample.

3.4 Cross-Sectional Significance Test

We can use a modified version of the Student's t-test to understand the significance of how endorsement deals influence a company's stock. The initial assumption (null hypothesis) is that these abnormal returns average to zero. For a single event, the Student's t-test is optimal. However, we must address certain complexities when examining multiple events simultaneously. The cross-sectional significance test employs the cross-section of cumulative abnormal returns to derive an estimator for the variance. Once the variance is estimated, we can determine if the abnormal returns significantly differ from zero. The formula for the variance is:

$$Var(CAAR(\tau_1,\tau_2)) = \frac{1}{N^2}\sum_{i=1}^{N}(CAR(\tau_1,\tau_2) - CAAR(\tau_1,\tau_2))^2 \tag{3.8}$$

Once we have the variance, we can calculate the t-statistic for the CAAR. This t-statistic follows a normal distribution and can indicate if the event significantly affected the stock price. The t-statistic is given as:

$$t_{CAAR(\tau_1,\tau_2)} = \frac{CAAR(\tau_1,\tau_2)}{var(CAAR(\tau_1,\tau_2))^{\frac{1}{2}}} \sim N(0,1) \tag{3.9}$$

3.5 Cross-Sectional Regression Analysis

As a final step of the event study methodology, we perform cross-sectional regressions to analyze stock market responses linked to variables of interest. As MacKinlay (1997) suggests, abnormal returns during the event window are often tied to specific firm characteristics. This association is not solely due to the valuation effect of the event but also stems from a correlation between the firm's attributes and the degree to which the event is foreseen. Given our sample of N observations of CAR and M characteristics, we employ the following regression model:

$$\begin{gathered} CAR_j = \delta_0 + \delta_1 x_{1j} + \cdots + \delta_M x_{Mj} + n_j \\ E(n_j) = 0 \qquad\qquad var(nj) = \sigma_{nj}^2 \end{gathered} \tag{3.10}$$

The CAR is used as the dependent variable. x_{Mj} is an indicator of the specific characteristic M for the j^{th} observation. We employ seven variables representing the x_{Mj}, which is described in section 4. The error term is given by n_j with an expected value of zero and variance of σ_{nj}^2. Note that the error term is not correlated with the specific characteristics x.

3.6 Event Study Assumptions

For an event study to accurately capture the influence of a specific event, certain fundamental assumptions must hold. The three main assumptions are: (1) markets operate efficiently, (2) the event in question is unexpected, and (3) no other overlapping or confounding events occur within the event window (Warner & Brown, 1985).

The initial assumption originates from the efficient market hypothesis. If the stock prices under consideration fail to integrate all accessible information in their valuation, the event study is unlikely to produce meaningful outcomes. Generally, the consensus is that stock markets exhibit semi-strong efficiency, which means that the market efficiently incorporates public information into stock prices (Fama, 1991). The second assumption states that for an event to impact investors, it must bring new information. If this is the case, the unexpected profits are likely due to the market's response to this new information from the event (Warner & Brown, 1985). The third assumption specifies that only the event under investigation occurs within the event window, excluding other confounding events (Warner & Brown, 1985).

It is challenging to fully isolate the effects of confounding events, given the numerous factors that can influence stock prices. For example, during the event window, a company might release financial data, announce dividends, or enact stock splits, which can influence the stock price and violate the third assumption. Moreover, companies that frequently collaborate with celebrities understand the significance of maintaining relevance. As such, they consistently engage in public relations efforts, introducing new endorsement deals or other events that accumulate publicity (Elberse & Verleun, 2012). This may result in new endorsement deals having no effect on abnormal returns, as the anticipation of these endorsements is already factored into the stock price.

4. Data

Our dataset consists of 155 endorsement deals from Europe and the USA. The dataset includes announcements from 2009 to 2023 and information on 54 distinct firms and 112 celebrities. In this data section, we systematically describe our data sample, beginning with data collection, followed by data processing, and lastly, descriptive statistics.

4.1 Data Sources and Collection

Since celebrity endorsement contracts are not consistently labeled, we had to conduct our search process manually. The initial studies used newspapers to collect data (Agrawal & Kamakura, 1995). However, our approach is similar to that of Ding et al. (2011) and uses search engines such as Google and Yahoo to find endorsement deal announcements. It is worth noting a fundamental limitation with this manual procedure: the search engines may not align the timing of news articles with the actual day of a company's press release, often prioritizing articles with higher click-through rates (Google, 2023). Consequently, official press releases may rank lower in search results because other news sources have more engaging and clickable titles.

Further, our next step is to determine the precise announcement date. Rumors regarding endorsement deals between celebrities and firms often circulate prior to the formal announcement and contract signing. This information leak raises the question of which date should be used in the analysis. To find the most accurate date, we investigate the social media accounts of both the endorsing company and celebrity, differentiating our approach from previous studies. In the absence of social media announcements, we refer to press releases aimed at investors. Notably, some companies only keep current endorsements, discarding older, irrelevant ones. When social media and press releases are unavailable, we use credible news outlets like CNN, Reuters, and WSJ to determine the announcement date by cross-referencing articles to confirm the accuracy of the chosen event day. Additionally, when an announcement falls on a weekend, we consider the subsequent trading day as the actual announcement date. This approach accounts for the first day when trading activities can react to the announcement, potentially impacting the stock price.

For the market model (MacKinlay, 1997) to accurately represent market returns, we incorporate one index for the USA and two for Europe. The S&P 500 serves as an appropriate benchmark for the NYSE and Nasdaq firms, encapsulating 500 leading companies and representing around 80% of the American market capitalization. We use the CAC 40 for companies listed on the Paris Stock Exchange, an index of the 40 most prominent stocks on the exchange. Meanwhile, the DAX Performance Index is the benchmark for securities on Xetra. The DAX includes the 40 primary blue-chip firms from the Frankfurt Stock Exchange. To simplify, and due to time constraints, we only include data from companies in France and Germany, which constitute about 40% of the European GDP (The World Bank, 2023). This is assumed to represent the European economy substantially in this thesis.

4.2 Data Processing

Before processing the data, we had a total of 188 observations. A comprehensive data review is essential to uncover confounding effects to ensure an unbiased sample. Confounding effects are factors influencing stock performance other than the endorsement announcement in the chosen timeframe. We examine news messages released within the [-5, 5] event window for every observation in our sample. This 11-day span should be sufficient to exclude any potential significant impact on the endorsement announcement. Examples of confounding events include earning announcements, dividends, and other unexpected and noteworthy news. If such events occur within the examined window, we omit the related endorsement announcement from the data sample. By using databases like Nexis Uni and YCharts to identify news and other company-specific events, we have excluded 33 contaminated events. We also exclude observations if the given firm (celebrity) announces a partnership with multiple celebrities (firms) in the event window.

In our analysis, we encounter instances of missing stock price data within the estimation windows. In these instances, we modify the 200-day estimation window to encompass 200 data points consistently. Consequently, this adjustment requires extending the window's start beyond the usual 200 trading days prior to the event, thereby altering the estimation window. For example, if two trading days are absent in the estimation window, the window is expanded to [-212, -10].

In the final step, we analyze data outliers. We examine each endorsement within the $[-5, 5]$ window to identify any substantial returns. To understand how including the different outliers affects the result, Pritamani and Singal (2001) employ two distinct criteria, 5% and 10% (max daily returns of a given stock within the timeframe). Their findings remain consistent regardless of the chosen threshold. Of the total 188 observations, only 14 had returns surpassing 5%. When observing stocks with large returns, we cross-check them with search engines and news outlets to ensure that no other major events might account for these returns. We also exclude the Oprah Winfrey and WW International endorsement deal from our analysis. This case had an extraordinary 73% return on the event date, attributed solely to the endorsement, marking it as an extreme outlier in the data set. We include the 13 remaining observations and test the effect without these in the robustness analysis.

Appendix A1 contains the observations included in the sample. Meanwhile, Appendix A2 lists the observations excluded due to the factors we mention in this section.

4.3 Descriptive Statistics and Variable Description

This subsection provides an overview of the sample in more detail. Firstly, Table 4.1 displays the annual count of announcements for the total sample, Europe and the USA. Secondly, we will present the variables used in the regression analysis.

Table 4.1: Yearly summary of endorsement deal announcements for the total sample, Europe and the USA.

Year	Total	Europe	USA
2009	2	2	0
2010	7	3	4
2011	4	3	1
2012	9	4	5
2013	15	6	9
2014	13	7	6
2015	19	13	6
2016	9	5	4
2017	17	5	12
2018	18	9	9
2019	14	7	7
2020	9	5	4
2021	6	4	2
2022	6	3	3
2023	7	4	3
Total	155	80	75

Table 4.1 presents 155 observations collected between 2009 and September 2023. European companies include 80 observations (55 listed on Xetra and 25 on the Paris Stock Exchange), whereas 75 (50 listed on the New York Stock Exchange and 25 on Nasdaq) are from American companies.

Table 4.2 outlines our seven variables and provides total and separate counts for Europe and the USA. We choose the variables for their potential relevance and influence in the study. This approach allows for a comprehensive understanding of the various factors that may affect the outcomes of the hypotheses. We introduce the variables in the text following Table 4.2.

Table 4.2: Summary of dataset variables.

	Total	Europe	USA
Males	87	38	49
Social Media Posts	49	22	27
Match-Up	24	14	10
Technology	33	10	23
Market Cap (brackets in billions)			
[0, 25]	51	29	22
[26, 75]	46	25	21
[76, 125]	24	13	11
[>126]	34	13	21
Age (brackets in age)			
[0, 20]	8	4	4
[21, 30]	85	47	38
[31, 40]	37	18	19
[41, 50]	20	7	13
[>51]	5	4	1
Celebrity Size (brackets in millions of followers)			
[0, 25]	60	31	29
[26, 75]	38	23	15
[76, 125]	15	9	6
[>126]	42	17	25

Note: All numbers are observations relevant to the variable mentioned

1. Males: The number of male subjects in the dataset. The data includes 87 males and 68 females. In the regression, we include the dummy variable $MALE_j$, which takes the value of 1 if the celebrity is male and 0 if the celebrity is female.

2. Social Media Posts: The count of social media posts included in the dataset. In this thesis, "social media" refers to instances where the company or celebrity has publicly communicated, posted, or mentioned the announcement on a social media platform. As described in Table 4.2, 49 of the included events are posted on social media, 22 in Europe and 27 in the USA. In the regression, we include the dummy variable $SOCIALMEDIA_j$, which takes a value of 1 if the endorsement deal was additionally announced on a social media platform, and 0 if it was announced only through traditional news sources or press releases.

3. Match-Up: A successful pairing of a celebrity and a product occurs when the celebrity's image aligns well with the characteristics of both the product and the company. To determine if there is a match-up, we adopt the method outlined by Amos et al. (2008). This approach evaluates the match-up based on relevance, credibility, and trustworthiness. As listed in Table 4.2, we have 24 companies and products that match up. In the regression, we use the dummy variable $MATCHUP_j$, which takes a value of 1 if the celebrity's public image or industry aligns with that of the firm (e.g., a sports celebrity endorsing a sports brand), and 0 if there is no match-up.

4. Technology: This variable represents a count of technology firms. In our sample, we have chosen to also include car manufacturers within this category due to their substantial use of technology in vehicle production and research. In the regression, we include the dummy variable $TECHNOLOGY_j$, which takes the value of 1 if the firm operates within the technology industry, and 0 if operating in another sector.

5. Market Capitalization (in billions USD): This shows the distribution of market capitalization across four intervals: $[0, 25], [26, 75], [76, 125]$, and over $125 billion. We measure the firm's size based on its market capitalization, taken on the exact date of the event under consideration. The regression includes the numerical variable $MARKETCAP_j$, which indicates the firm's market capitalization at the time of the event.

6. Age (in years): This variable shows the number of subjects or data points falling into different age intervals: $[0, 20], [21, 30], [31, 40], [41, 50]$, and over 50 years of age. Our approach uses the celebrity's age at the event's occurrence date. In the regression, we include the numerical variable AGE_j, which represents the celebrity's age at the event's time.

7. Celebrity Fame (in millions of followers): This reflects the number of celebrities within specific intervals of followers: $[0, 25]$, $[26, 75]$, $[76, 125]$, and over 125 million followers. For consistency, the analysis presumes that the celebrities in question maintained a comparable level of fame throughout the sampling period. Therefore, the selected measure of popularity is the follower count of each celebrity in October 2023. In the regression, we include the numerical variable $CELEBRITYFAME_j$, which states the number of celebrity followers on social media.

4.4 Data Limitations

As mentioned, our data consists of 155 observations. A larger sample can lead to higher statistical power. However, in the endorsement deal studies, it is worth highlighting that our sample size is larger than most studies in this field, which typically range from 50 to 110 observations, as noted by Ding et al. (2011), Agrawal and Kamakura (1995), and others. Since we removed a few observations, the reduced sample size can increase the variance and subsequently affect the significance of the results, as Equation 3.8 demonstrates.

As previously highlighted, every firm in our data sample appears on public stock exchanges. However, a few observations from smaller firms have infrequent trading volume during the event window. Due to such infrequent trading, the actual impact of the endorsement deal might not be comprehensively reflected, especially in less liquid markets.

Another potential limitation of our dataset is its representation of the European market, which we collect from stocks in Germany and France. While these countries account for approximately 40% of the European GDP, suggesting a dense representation, the inclusion of additional countries would likely provide a more comprehensive reflection of the overall European economy.

5. Results and Discussion

The results described in this section are based on the methodology presented in section 3 and the data introduced in section 4. Our initial focus is presenting the abnormal returns, establishing the basis for our research: whether endorsements generate abnormal returns. We examine this across the entire dataset, highlighting contrasts between the USA and Europe. Finally, our analysis uses a cross-sectional regression to deepen our understanding of the hypotheses based on the endorsement characteristics mentioned in section 4.3.

5.1 Stock Markets Reaction to Endorsement Announcements

We organize this section into two separate parts. Initially, our focus will be on the Average Abnormal Return, or AAR, for each day within the event window. Following this, the focus moves to the Cumulative Average Abnormal Return, or CAAR, a singular value that compiles the average abnormal returns from all events within the event window. Analyzing these factors is crucial for determining endorsements' impact on stock prices.

5.1.1 Average Abnormal Returns

Table 5.1 and Figure 5.1 display the AAR for the total sample and separately for Europe and the USA. Figure 5.1 illustrates these returns across the event window of [-5, 5]. Table 5.1 shows the AAR for the total dataset with a significant decline at $(t = -2)$ and a significant positive abnormal return at $(t = 1)$. Additionally, the USA shows significance at $(t = -2)$. In contrast, Europe's AAR remains relatively stable, showing no significance.

Table 5.1: AAR by total sample, Europe, and the USA.

Day	AAR Total	AAR Europe	AAR USA
[-2]	-0.0027*	0.0002	-0.0057**
	(-1.9376)	(0.151)	(-2.3057)
[-1]	-0.0005	0.0000	-0.001
	(-0.45)	(0.0012)	(-0.6812)
[0]	0.0012	0.0005	0.002
	(1.1055)	(0.3664)	(1.1684)
[1]	0.0017*	0.0018	0.0016
	(1.6697)	(1.5195)	(0.946)
Observations	155	80	75

Note: T-statistics in parenthesis; *p<0.1, **p<0.05, ***p<0.01

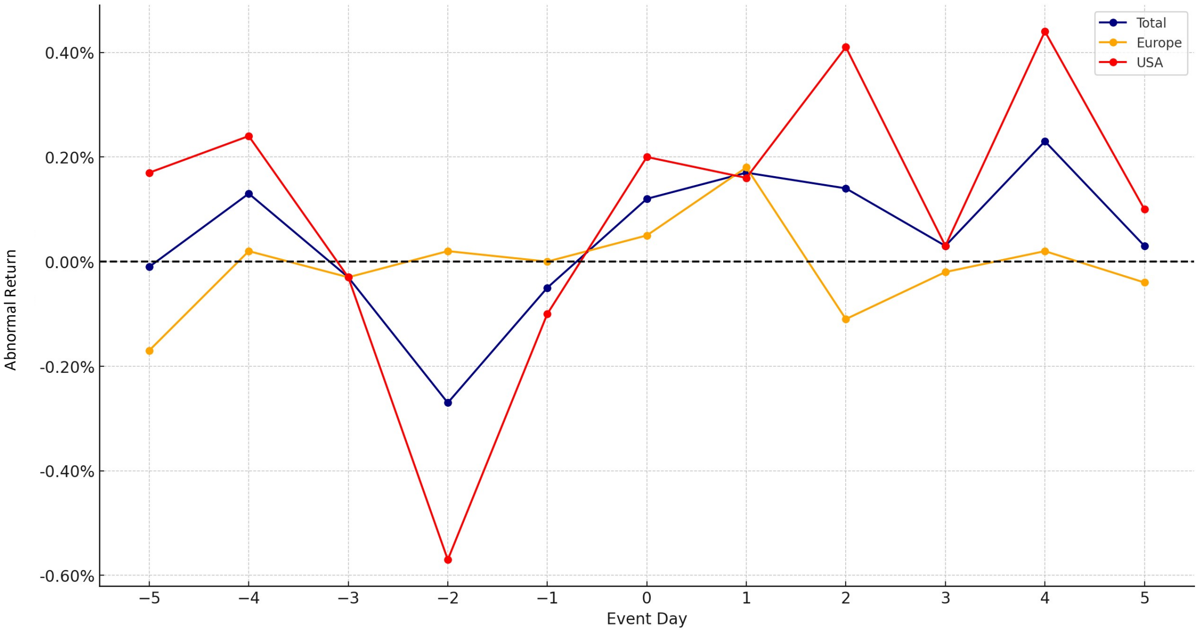


Figure 5.1: AAR through the event window for Europe (yellow), the USA (red), and combine (blue).

The significant negative outcome at $(t = -2)$ for the total data and in the USA may be due to an early reaction to information leakage before the actual event. Investors frequently view endorsement deals as costly marketing ventures and risk a negative investment if the endorsed celebrity fails to yield positive outcomes (Prentice & Zhang, 2017). Investors might also see this as a risk if they believe that the selected celebrity is a bad fit for the company's brand image, potentially leading to negative abnormal returns before the event and the following reveal of the celebrity. Bartz et al. (2013) discover that celebrity endorsers involved in negative publicity can significantly impact abnormal returns. In this case, if a celebrity has a controversial background, investors might become skeptical. This skepticism can explain the negative abnormal returns before the event due to circulating rumors.

As mentioned, at $(t = 1)$, we find a significant positive return for the total sample. Given that 97 of the observations are derived only from credible news sources, as opposed to direct communication from the company via press releases or social media posts, the speed of information transmission is an essential factor. While news outlets can distribute information quickly, there seems to be an implication that the complete information dissemination process may be slower, potentially due to the time needed for investors to digest and react to the news. This lag can account for the delay in the significance of abnormal returns at $(t = 1)$, reflecting a gradual integration of information into market prices.

Previous studies in the field, such as those by Ding et al. (2011) and Prentice and Zhang (2017), support our findings of no immediate impact on $(t = 0)$. This can be because the market has already incorporated the costs and expected profits from endorsements into its pricing. On the other hand, the significant findings at $(t = 0)$ by Agrawal and Kamakura (1995) and our significant results at $(t = 1)$ may imply a delay in the market's response. This suggests that investors hesitate to react to initial news, requiring time to verify and process information before making investment decisions. As Garthwaite (2014) notes, the trend of mindlessly following celebrities and unrealistic brands is diminishing and may explain the delayed effect.

The observed negative trend in AAR before the event date in the USA, as indicated in Table 5.1, suggests that the market might be either receiving premature information about a contract or accurately anticipating it. This is not unique to the American market; similar results were reported in China by Prentice et al. (2017), who observed significant negative results prior to the event at $(t = -3)$.

Overall, there appears to be an asymmetry in the effects of endorsement deals between Europe and the USA. Endorsement deals' effect on abnormal returns, or hypothesis 0, is supported by the total sample and the USA. Conversely, Europe shows no significance, which contradicts hypothesis 0. This disparity can stem from cultural variations among investors, consumers, or media in these regions.

5.1.2 Cumulative Average Abnormal Returns

The CAAR will provide additional insights into the findings discussed in the previous section. By calculating CAAR, we aim to understand better the overall impact across various timeframes. Figure 5.2 presents the CAAR over a specified event window, comparing Europe (in yellow), the USA (in red), and a combined dataset (in blue). The timeframe on the x-axis suggests a periodical assessment, with data points representing intervals like [-5, -1], indicating the CAAR from five days before the event until one day before.

Figure 5.2 shows fluctuations in CAAR for each region, with the combined data following the trend of the USA but with less volatility. For the USA, the trend shows a downward shift at $(t = -2)$, continuing into $(t = -1)$, but changing to a more positive trend after the event. On the other hand, Europe's CAAR remains relatively stable, with a slight downward trend towards the end of the event window. Overall, the CAAR shows less effect in Europe throughout the event window, while the CAAR in the USA exhibits a more volatile trend.

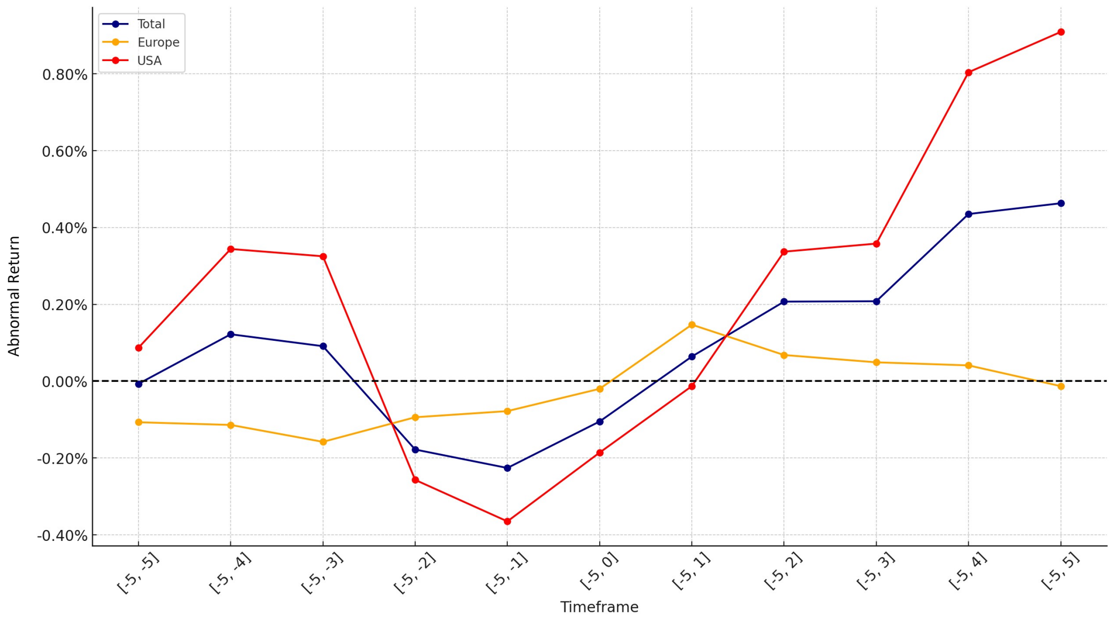


Figure 5.2: CAAR through the event window for Europe (yellow), the USA (red), and combined (blue).

Table 5.2 highlights a positive significance for the USA and the total sample following the event. This reveals a regional disparity in the post-event window [0, 5], where the USA shows a significant positive impact, while Europe shows non-significant results. The European results are consistent with previous studies, like Ding et al. (2011) and Prentice and Zhang (2017), which also report minimal effects.

Table 5.2: CAAR by total sample, Europe, and the USA.

Timeline	CAAR Total	CAAR Europe	CAAR USA
[-5, 5]	0.0046	-0.0009	0.0105
	(1.1301)	(-0.207)	(1.4731)
[-2, 2]	0.0012	0.0012	0.0011
	(0.4573)	(0.3958)	(0.2641)
[-1, 1]	0.0024	0.0022	0.0026
	(1.222)	(0.8399)	(0.8822)
[-5, 0]	-0.0011	-0.0012	-0.0009
	(-0.3895)	(-0.347)	(-0.2166)
[0, 5]	0.0069**	0.0008	0.0134**
	(2.1687)	(0.2308)	(2.4483)
Observations	155	80	75

Note: T-statistics in parenthesis; *p<0.1, **p<0.05, ***p<0.01

Our results show that the impact varies between Europe and the USA, highlighting regional variations in our data set. Notably, the significant negative effect preceding the event in the USA is possibly due to information leakage. Furthermore, the effects following the event are more pronounced in the USA than Europe, as Figure 5.2 illustrates. The significant positive trend in the USA can be attributed to the greater financial resources allocated to advertising in the American market, as opposed to the European (Thompson, 2021).

Europe shows no significance in either of the timeframes, indicating that, on average, the market anticipates the returns from endorsement contracts to be negligible. This suggests that the advantages of celebrity endorsements are typically balanced out by their costs. Additionally, European firms often encounter stricter regulatory requirements, leading them to adopt more conservative marketing strategies (Thompson, 2021). Our results suggest that investors perceive the endorsements as profitable in the USA compared to Europe after the event.

Overall, the USA and the total sample support hypothesis 0 with significant positive returns after the event. On the other hand, given our lack of statistical significance in Europe and other timeframes, reaching solid conclusions about endorsement announcements on abnormal returns and Hypothesis 0 is challenging.

5.2 Cross Sectional Regression

In this section, we examine whether the impact of celebrity endorsements on stock market performance depends on firm and endorser characteristics. We regress individual stocks' CAR on various characteristics, including firm size, match-up, social media announcements, age, industry, gender, and level of fame based on social media followership. Specifically, the regression looks as follows (see section 4.3 for the variable definitions):

$$CAR_j^{[t_0,t_1]} = \delta_0 + \delta_1 MALE_j + \delta_2 AGE_j + \delta_3 MARKETCAP_j + \delta_4 CELEBRITYFAME_j \\ + \delta_5 MATCHUP_j + \delta_6 TECHNOLOGY_j + \delta_7 SOCIALMEDIA + n_j$$

In the regression with the full sample, we incorporate a regional dummy $EUROPE_j$ to discern any regional differences and take the value of 1 for Europe and 0 for the USA. This results in the following regression:

$$CAR_j^{[t_0,t_1]} = \delta_0 + \delta_1 MALE_j + \delta_2 AGE_j + \delta_3 MARKETCAP_j + \delta_4 CELEBRITYFAME_j + \delta_5 MATCHUP_j + \delta_6 TECHNOLOGY_j + \delta_7 SOCIALMEDIA_j + EUROPE_j + n_j$$

The regressions employ three distinct timeframes when calculating CAR: [-5, 5], [0, 5], and [-1, 1]. The [-5, 5] timeframe encompasses a broader period to capture the overall effect and account for any potential information leakage in the sample, while [-1, 1] offers a more focused view. When examining the [0, 5] timeframe, we aim to analyze the impact of endorsement deals on the period following the event. The timeframes help us understand how different proximities to the event affect the abnormal returns.

We bifurcate our regression analysis into two distinct segments. Initially, we address the entire sample in Table 5.3, discussing hypotheses 1 and 2. Furthermore, the regression in Table 5.4 of the European and the USA samples corresponds to exploring hypotheses 3, 4, 5, and 6. This allows us to align our discussion with the regressions that yielded significant results.

5.2.1 Cross-Sectional Regression of Full Sample

In Table 5.3, regression (1) denotes timeframe [-1, 1], (2) timeframe [-5, 5], and (3) timeframe [0, 5]. The regional dummy variable shows significance at the 10% level for the [-5, 5] timeframe and at the 5% level for the [0, 5] timeframe. The negative coefficient indicates that Europe has significantly less impact than the USA, and it reveals that Europe experiences 1.6% lower abnormal returns in both event windows. This result further substantiates the finding in the AAR and CAAR, reinforcing the notion that Europe demonstrates a lesser effect on abnormal returns compared to the USA. Interestingly, the regional difference in other timeframes is absent in the regression analysis for the [-1, 1] timeframe. From the AAR, as illustrated in Figure 5.1, it is evident that the abnormal returns exhibit similar patterns in both Europe and the USA in the [-1, 1] interval. Furthermore, we will discuss the findings in our designated variables.

Table 5.3: Regression of the total sample in timeframes [-1, 1], [-5, 5], and [0, 5]

	Dependent variable:		
	CAR [-1, 1] (1)	CAR [-5, 5] (2)	CAR [0, 5] (3)
Male	-0.004	-0.009	-0.013^{**}
	(-0.959)	(-1.060)	(-1.990)
Age	0.0002	0.0002	0.00004
	(0.707)	(0.382)	(0.107)
Market Cap	-0.00001	-0.00003	-0.0001^{*}
	(-0.835)	(-0.885)	(-1.891)
Celebrity Fame	-0.00001	-0.00001	-0.00000
	(-0.437)	(-0.338)	(-0.153)
Match-Up	-0.002	0.014	-0.005
	(-0.383)	(1.215)	(-0.546)
Technology	0.010^{**}	-0.007	0.003
	(1.984)	(-0.607)	(0.400)
Social Media	-0.005	-0.008	-0.003
	(-1.163)	(-0.851)	(-0.440)
Europe	-0.0001	-0.016^{*}	-0.016^{**}
	(-0.013)	(-1.880)	(-2.373)
Constant	0.001	0.018	0.027^{*}
	(0.129)	(0.950)	(1.873)
Observations	155	155	155
R^2	0.056	0.044	0.072
Adjusted R^2	0.004	-0.008	0.021
Note:			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Hypothesis 1 – Personal Traits

In Table 5.3, within the [0, 5] timeframe, the "male" variable is significantly negative at the 5% level. We interpret this as males having 1.3% less effect on the CAR compared to women. These findings align with Klaus and Bailey (2008), who observe a positive response to advertisements featuring female celebrity endorsers. On the other hand, all other regressions show insignificance in the "male" variable and align with other studies, such as those by

Prentice and Zhang (2017) and Ding et al. (2011). Furthermore, the "age" variable consistently shows insignificance in the analyses. These two coefficients – male and age – are pivotal in testing Hypothesis 1, which relates to the influence of personal traits on abnormal returns.

Understanding the underlying reasons for these findings can be complex. For instance, the sample's nature might influence the MALE coefficient's significant result in the [0, 5] timeframe. Over half of the male sample involves athletes endorsed by firms such as Adidas, Nike, and Puma. These firms frequently enter endorsement contracts, often on a weekly basis, for instance, with new football players. This high frequency of contract signings may dilute the impact of any new information, providing the investors with no additional incentive to invest in the firm.

The support for hypothesis 1, primarily driven by the "male" variable, suggests that personal traits may influence abnormal returns. However, this effect seems weak and confined to the aftermath of the event date.

Hypothesis 2 – Company Size

Within the [0, 5] event window, market capitalization emerges as a significant factor at the 10% level, with a coefficient of -0.001%. The coefficient suggests that an increase of one billion USD in market capitalization is associated with a decrease of 0.001% in abnormal returns. The previous study by Clark et al. (2009) observe that larger firms reap more benefits from endorsement deals. Similarly, the study by Prentice et al. (2017) identifies a significant positive impact of larger company size on abnormal returns, particularly in the [0, 10] timeframe, which contradicts our negative results from the [0, 5] timeframe. In our case, it seems that for higher-valued firms, the cost of a new contract outweighs the deal's benefits. For example, Nike often engages in a multitude of endorsement deals simultaneously. Consequently, initiating another deal might be considered an unnecessary expenditure, not contributing additional value to the firm, but rather a negative impact, as the findings suggest.

As mentioned in section 4.2, we exclude the Oprah Winfrey and WW International deal because it was an extreme outlier. WW International was the smallest company in our initial dataset. The negative findings suggest that for small companies, partnering with a celebrity might have a more pronounced impact than it would for larger companies. Therefore, a smaller firm collaborating with, for example, Haaland can potentially experience a greater value creation than the athlete endorsing Nike.

In the other regressions, the “market capitalization” variable does not show significance. This lack of consistent significance across different timeframes and samples limits the support for Hypothesis 2. This finding aligns with the results given by Ding et al. (2011), who also report no significant impact of firm size on abnormal returns in varied timeframes. These contrasting results from different studies highlight the complexity and context-specific nature of the relationship between company size and the financial impact of celebrity endorsements (Ding et al., 2011; Prentice & Zhang, 2017; Clark et al., 2009).

5.2.2 Cross-Sectional Regression of Europe and the USA

Table 5.4 introduces an additional model that bifurcates the dataset into two distinct regional segments: Europe and the USA. This approach entails conducting separate regression analyses for each region, employing the timeframe [-1, 1]. Regression (1) is for Europe, and (2) is for the USA. We did the same regression for timeframe [-5, 5] and [0, 5], which shows no significance in any of the variables, and we include these in Appendix A4.

The results from the [-1, 1] timeframe in Table 5.4 are indeed more compelling, showing variations in variable significance between the regions of Europe and the USA. This suggests that the variable coefficients are more pronounced within a closer range to the event, as broader timeframes have less impact on outcomes.

Table 5.4: Regression of Europe and USA in timeframe [-1, 1]

	Dependent variable:	
	CAR	
	Europe	USA
	(1)	(2)
Male	-0.005	-0.003
	(-1.024)	(-0.458)
Age	0.0002	0.0001
	(0.659)	(0.322)
Market Cap	-0.00004	-0.00001
	(-1.239)	(-0.566)
Celebrity Fame	-0.00004^{*}	0.00001
	(-1.841)	(0.640)
Match-Up	0.010	-0.016^{*}
	(1.360)	(-1.785)
Technology	0.018^{**}	0.004
	(2.239)	(0.565)
Social Media	0.0002	-0.008
	(0.028)	(-1.262)
Constant	0.001	0.004
	(0.117)	(0.331)
Observations	80	75
R^2	0.168	0.084
Adjusted R^2	0.087	-0.012
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$	

H3 – Match-Up Between Celebrity and Firm

The concept of "Match-Up" is a key element in endorsement deal studies and research on the alignment between the characteristics of a celebrity endorser and the endorsed product. Extensive studies in this area often indicate a positive link between a good match-up and increased abnormal returns (Atkin & Block, 1983; Baker & Churchill, 1977; Erdogan, 1999; Ding et al., 2011). In Table 5.4, such alignment appears to impact the CAR in the USA. The result suggests that if the celebrity and the firm match, the abnormal returns are 1.6% lower, contrasting the studies mentioned. The effect is specific to the USA, as it does not manifest in European markets in any of the regressions.

The underlying reason for the negative outcomes might be that the benefits of these well-matched contracts might not surpass the non-matched counterparts and their benefits. Another plausible explanation for the adverse effect in the USA can be because of our specific sample. Notably, seven out of ten observations in the USA involve the match of athletes endorsing sports brands or models endorsing beauty products. For instance, Nike's decision to endorse an additional athlete can be unnecessary, considering they already have numerous well-matched representatives, which also can explain the insignificant results from Europe. The expectation of well-matched announcements may not provide any novel information to investors.

Overall, in proximity to the event in the USA, a well-matched celebrity endorsement does suggest significant negative results. In addition, the absence of effect in most timeframes suggests that a match-up does not necessarily translate into positive financial returns for the firm, as earlier studies find (Atkin & Block, 1983; Baker & Churchill, 1977; Erdogan, 1999; Ding et al., 2011).

H4 – Technology Firms

The technology variable stands out in both Tables 5.3 and 5.4, showing significance at the 5% level. Celebrities endorsing technology firms in Europe are associated with a positive effect on abnormal returns, quantified at 1.8%. In Europe, the significant impact between technology firms and abnormal returns aligns with earlier research such as Ding et al. (2011), which observe a similar positive relationship in the USA. However, the American market did not show any significant effect in this study on its own.

The specific market dynamics of the region can likely explain the positive outcome in Europe. High-technology car manufacturers heavily influence the European technology sector, which plays a crucial role in the economy. According to Cornet et al. (2023), car manufacturers contribute about 7% to Europe's GDP, highlighting the impact of the automotive industry on the economy. In our European sample, car manufacturers constitute 80% of the technology firms. Our findings support Ding et al. (2011), which also find positive effects from the technology industry. This indicates that the announcement of celebrity endorsements in technology firms might be perceived as a financially positive factor for investors.

In contrast, various companies, including giants like Apple, Mastercard, Ford, and AT&T, characterize the USA technology sector in our sample. The lack of significance in the relationship between technology firms and abnormal returns in the USA can be because of the diversity, different market conditions, and consumer behaviors compared to Europe. As technology has become more commonplace and integrated into everyday life, its novelty and unique appeal may have diminished (Palandrani, 2022). The ubiquity of technology may lead to the combination of a celebrity and a "technology firm" not carrying the same weight as it did during the early 2000s and in previous studies (Ding et al., 2011; Prentice and Zhang, 2017). These studies' findings have datasets from early 1998 to 2008, a period characterized by substantial technology-firm investments. During this period, an endorsement announcement might be a positive signal to invest in technology firms, but this effect seems to have diminished today.

Our analysis reveals a positive coefficient for Europe, suggesting a significant relationship. Conversely, the USA's data does not show a significant effect, which may be attributed to its technology sector's heterogeneity and evolving dynamics. Overall, the novelty of celebrity endorsements in technology firms seems less impactful than in earlier studies.

H5 – Celebrity Fame

In the European dataset, the "celebrity fame" variable holds significance at the 10% level. This suggests that each additional million followers on Instagram lead to a decrease of 0.004% in abnormal return. The finding suggests an inverse relationship between the prominence of the celebrity and the CAR, implying that more popular celebrities may yield lower returns in Europe.

This outcome can be attributed to the perception among investors that contracts with high-profile celebrities are costly, potentially leading to concerns about future expenses and the overall financial implications for the company. The results also highlight a regional disparity in celebrity endorsements between Europe and the USA. Our results indicate that investors in Europe tend to view high-cost celebrity endorsements more skeptically. At the same time, in the USA, the practice seems more commonplace and widely accepted.

Erdogan (1999) notes that the risk of a celebrity overshadowing the brand becomes more significant when the celebrity substantially influences consumer behavior and serves as a role model for many. The risk of overshadowing may follow with the size of the celebrity's following: the more considerable the following, the greater their influence. Consequently, investors may perceive the endorsement of a highly influential celebrity as a potential negative for the firm, fearing that the celebrity's presence can become the focus in front of the brand itself. As Cooper (1984) says, "The product, not the celebrity, must be the star."

Overall, we uncover a regional variation in the impact of celebrity endorsements on abnormal returns, with Europe showing weak adverse effects for larger celebrity endorsements – supporting hypothesis 5. In contrast, the USA indicates a more indifferent investor perspective.

H6 – Social Media

Our study aims to determine if social media presence has an additional impact on abnormal returns. At the same time, endorsements in the sample are also shared through news sources and press releases. This aspect is analyzed using the "social media" variable. Previous studies have mainly used news sources and press releases (Agrawal & Kamakura, 1995; Ding et al., 2011).

The study reveals that public announcements of endorsement deals on social media platforms do not add additional influence on abnormal returns. This finding is consistent across various timeframes and remains unchanged. Additionally, we replace the "social media" variable from the primary models with the "press release" variable, assigning a value of 1 to endorsements announced via press releases and 0 if through news sources, as shown in Appendix A3. These regressions show that press releases significantly impact abnormal returns positively at the 10% level, in the [-5, 5] and [0, 5] timeframes. This indicates that the announcement method, particularly press releases, significantly affects financial outcomes in these periods. The negligible effect of social media announcements likely originates from the targeted audience. Press releases are typically aimed directly at investors and carry more weight in their decision-making, whereas social media posts are generally directed at a broader, consumer-oriented audience.

In summary, social media's influence on abnormal returns is negligible, which contradicts hypothesis 6. Contrarily, traditional press releases show significance, likely due to the targeted audience.

6. Robustness Analysis

In this chapter, we delve deeper into the reliability of the results discussed in section 5 by conducting a comprehensive robustness analysis. Our primary objective is to explore the effects of various methodological decisions. Initially, we will apply stricter criteria than those used in the analysis section to identify and remove outliers. In addition, as outlined in the Methodology section, we will implement the constant mean model to conduct an event analysis using this framework. Finally, we apply a cross-sectional regression to the two methods. This will allow us to compare the results obtained using different models.

6.1 Omitting Outliers

When collecting and analyzing our sample, we excluded the endorsement deal between Oprah Winfrey and WW International. This exclusion was because of an extraordinary 73% return attributed solely to the endorsement, classifying it as an extreme outlier. In this part of our analysis, we apply stricter criteria. We exclude any observations that show a return exceeding 5% in the event window [-5, 5]. This approach results in removing an additional 13 observations from our dataset. Tables 6.1 and 6.2 explain the differences before and after removing the outliers.

Table 6.1: CAAR, comparing effects with and without outliers.

Timeline	With Outliers	Without Outliers
[-5, 5]	0.0046	-0.0003
	(1.1301)	(-0.0867)
[-2, 2]	0.0012	0.0018
	(0.4573)	(0.7487)
[-1, 1]	0.0024	0.0027
	(1.222)	(1.3259)
[-5, 0]	-0.0011	-0.0013
	(-0.3895)	(-0.5442)
[0, 5]	0.0069**	0.0015
	(2.1687)	(0.6124)
Observations	155	142

Note: T-statistics in parenthesis; *p<0.1, **p<0.05, ***p<0.01

Table 6.1 presents the CAAR, with and without outliers. The data reveals a notable change in the significance of returns in the [0, 5] timeframe upon removing outliers, suggesting that the excluded observations substantially impact the results following the event. Additionally, in the periods closer to the event, specifically in the [-1, 1] and [-2, 2] timeframes, there is an observed increase in abnormal returns, though these findings are not statistically significant. The analysis also indicates that the overall effect across the broader timeframe of [-5, 5] is negligible, with a result of -0.03%, demonstrating the diminished impact when we remove the outliers. After removing outliers, the insignificance of results in the [0, 5] timeframe slightly alters our previous results. Aside from this change, the conclusions remain consistent with earlier findings, indicating insignificant results for all other timeframes.

Table 6.2: AAR, comparing effects with and without outliers.

Day	With Outliers	Without Outliers
[-1]	-0.0005	0.0003
	(-0.45)	(0.2773)
[0]	0.0012	0.0005
	(1.1055)	(0.5035)
[1]	0.0017*	0.0019**
	(1.6697)	(1.9991)
Observations	155	142

Note: T-statistics in parenthesis; *p<0.1, **p<0.05, ***p<0.01

The robustness analysis yields some notable results concerning abnormal returns on specific days. Initially, $(t = 1)$ shows statistical significance at the 10% level in the AAR. However, after removing outliers, this significance improved to the 5% level, strengthening the findings of hypothesis 0 described in section 5.1.1.

The expectation of removing outliers is a less significant result, which we find in [0, 5]. Although not significant, contrary to expectations, the abnormal returns increase in both timeframes of [-2, 2] and [-1, 1]. The results also reveal less impact over broader timeframes and a more substantial effect from the day after the event.

6.2 Alternative Expected Performance Models

We determine the abnormal return by employing expected performance models, which estimate the stock's performance in the absence of the event. In this thesis, we use the market model because of its favorable qualities and because it is commonly used in event studies

(MacKinlay, 1997). However, the choice of expected performance models influences the results. Therefore, we compare the Market Model and the Constant Mean Model estimation of AAR and CAAR. We estimate the model by using the following equations:

$$R_{i\tau} = \mu_i + \epsilon_{i\tau}$$
$$\hat{\mu}_i = \frac{1}{L_1}\sum_{\tau=T_0+1}^{T_1} R_{i\tau} \qquad E(\epsilon_{i\tau} = 0) \qquad var(\epsilon_{i\tau}) = \sigma^2_{\epsilon_i} \tag{5.1}$$

where $R_{i\tau}$ is the anticipated return on the security i at time τ; $\hat{\mu}_i$ denotes the mean return of the asset over the estimation window employed; $\epsilon_{i\tau}$ represents the error term, characterized by an expected value of zero and a variance denoted by $\sigma^2_{\epsilon_i}$. Finally, L_1 corresponds to the number of observations within the selected estimation window.

According to MacKinlay (1997), the market model is seen as a potential enhancement over the constant mean return model because it "eliminates the component of the return linked to market return fluctuations, thereby decreasing the variance of abnormal returns" (MacKinlay, 1997). Table 6.3 shows the results of the market model and the constant mean model regarding the CAAR.

Table 6.3: CAAR, comparing expected performance models.

Timeline	Market Model	Constant Mean Model
[-5, 5]	0.0046	0.0057
	(1.1301)	(1.1902)
[-2, 2]	0.0012	0.0024
	(0.4573)	(0.8263)
[-1, 1]	0.0024	0.0025
	(1.222)	(1.0499)
[-5, 0]	-0.0011	0.001
	(-0.3895)	(0.3185)
[0, 5]	0.0069**	0.006
	(2.1687)	(1.6253)
Observations	155	155

Note: T-statistics in parenthesis; *p<0.1, **p<0.05, ***p<0.01

Table 6.3 reports similar effects on significance as reported in removing outliers. The results become insignificant when using the constant mean model in [0, 5], going from significant on the 5% level to no significance. In contrast to the omitting outliers section, the constant mean model reports higher CAAR values in all instances except for the [0, 5] timeframe. We also change from negative CAAR to positive in the [-5, 0] timeframe.

Table 6.4: AAR, comparing expected performance models.

Day	AAR Market Model	AAR Constant Mean
[-1]	-0.0005	-0.0013
	(-0.4549)	(-0.922)
[0]	0.0012	0.0014
	(1.1055)	(1.0953)
[1]	0.0017*	0.0024*
	(1.6697)	(1.9293)
Observations	155	155

Note: T-statistics in parenthesis; *p<0.1, **p<0.05, ***p<0.01

Table 6.4 indicates that the AAR exhibits similar patterns in terms of statistical significance. On day [1], the results are more pronounced, yet they do not reach the threshold required for a 5% significance level. Generally, the results across all days appear marginally higher than those calculated by the market model.

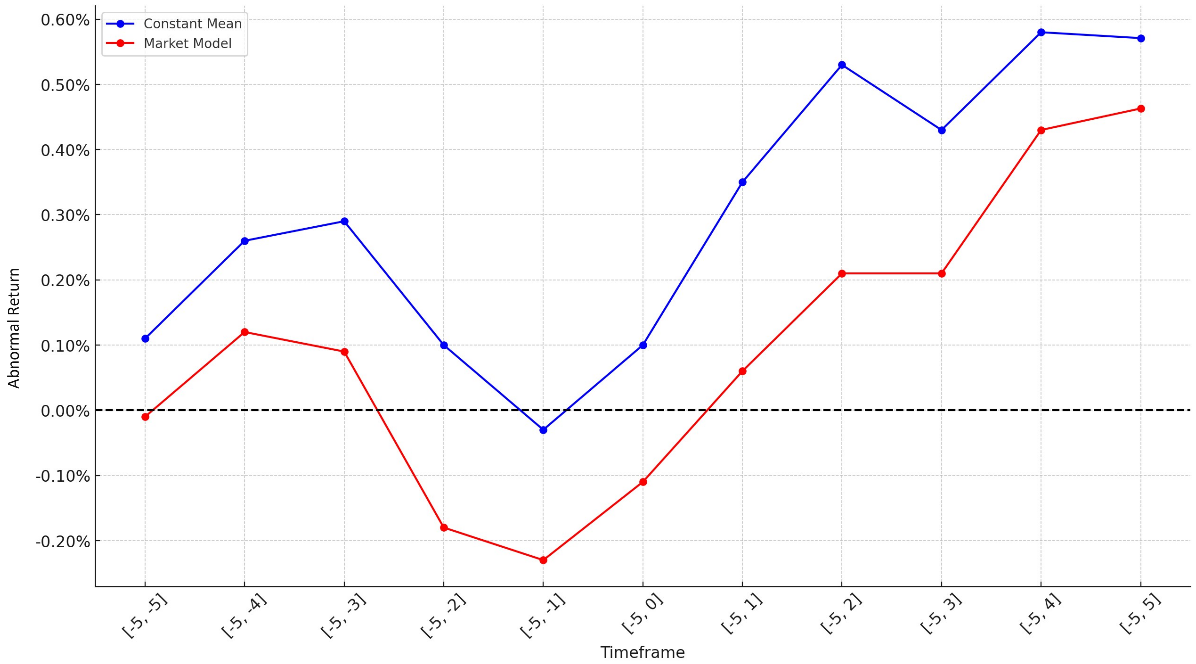


Figure 6.1: Aggregated CAAR, comparing expected performance models.

The analysis of CAAR from Figure 6.1 shows a somewhat equal trend. Notably, higher CAAR values from the constant mean model lead to increased values throughout the timeframe. When comparing the results from the constant mean model to those of the market model, the former displays slightly higher values. However, these results' significance levels remain unchanged, except for the time window [0, 5], where there is a notable difference of non-significance.

6.3 Cross-Sectional Regression on the Robustness Models

We employ CAR values derived from two distinct models to conduct our regression in the robustness analysis. Table 6.5 details the results of these regressions. Model (1) represents the original regression, model (2) uses results from the constant mean model and model (3) uses the omitted outlier's model results. All regressions use the CAR values extracted from the relevant model. While the first two models include 155 observations, the model excluding outliers comprises 142 observations. We use the [-5, 5] timeframe in the regression outlined in Table 6.5.

The results across the models are mostly consistent with the original results. The outliers model produces the most noticeable variation, where the regional "Europe" variable lost statistical significance. The statistical change can be because of removing 13 observations, 10 of which are from the USA. The results indicate a more substantial impact of outliers in the USA compared to Europe. Consequently, removing these outliers might diminish the significance of the regional variable. This implies that endorsement deals may have a more pronounced impact in the USA than in Europe, a conclusion that aligns with our results in Section 5. This reinforces the findings that a difference between the USA and Europe persists in the context of this sample.

Additional timeframes, specifically [-1, 1] and [0, 5], are examined, and the findings from these regressions are in Appendix A5 and A6.

Overall, the models yield comparable outcomes. Notably, the model with omitted outliers tends to lose significance more frequently. On the other hand, the constant mean model consistently shows significance in all instances where the original model does. However, there are some disparities between the models. For instance, the constant mean model shows less significance between regions when using the [0, 5] timeframe compared to the original model. This variation indicates subtle differences in how each model interprets the impact of various factors, such as timeframes and regional influences, on the data. The results from these tests show that the differences are not substantial enough to change our conclusions. At the same time, specific observations have a more significant impact than others seen in the omitted outlier model.

Table 6.5: Regression of original, constant mean, and omitted outliers' model.

	Dependent variable:		
	CAR [-5, 5]		
	Original	Constant Mean	Omitted
	(1)	(2)	(3)
Male	-0.009	-0.012	-0.008
	(-1.060)	(-1.171)	(-1.122)
Age	0.0002	0.0003	0.0003
	(0.382)	(0.583)	(0.594)
Market Cap	-0.00003	-0.00003	-0.00001
	(-0.885)	(-0.658)	(-0.382)
Celebrity Fame	-0.00001	0.00000	0.00000
	(-0.338)	(0.023)	(0.175)
Match-Up	0.014	0.016	0.014
	(1.215)	(1.178)	(1.383)
Technology	-0.007	-0.001	-0.011
	(-0.607)	(-0.080)	(-1.262)
Social Media	-0.008	-0.015	0.002
	(-0.851)	(-1.404)	(0.234)
Europe	-0.016*	-0.015*	-0.006
	(-1.880)	(-1.704)	(-0.754)
Constant	0.018	0.014	-0.0002
	(0.950)	(0.642)	(-0.011)
Observations	155	155	142
R^2	0.044	0.041	0.049
Adjusted R^2	-0.008	-0.011	-0.008
Note:			*p<0.1; **p<0.05; ***p<0.01

7. Conclusion

Despite companies investing heavily in celebrity endorsements, studies on how these announcements affect a company's stock value have shown mixed results. We examine this by using a recent sample of celebrity endorsement announcements.

We document no significant abnormal returns on the day of the announcement. On the other hand, when examining the USA, we find significant negative returns before the announcement and positive returns after. While celebrity endorsements can boost attention and brand recognition, prior studies also recognize risks such as high costs and potential controversies. These risks might cause initial negative market reactions, but our findings show investors become more optimistic post-announcement in the USA, likely expecting benefits from the endorsements. When examining Europe, we observe no significant abnormal returns, which indicates that the market anticipates negligible benefits from endorsement contracts. This suggests that the advantages of celebrity endorsements are typically balanced out by their costs. Overall, Europe appears to exhibit a more indifferent attitude towards endorsements compared to the USA.

We also investigate the impact of specific characteristics of endorsers (gender, age, fame, and match-up), firms (market capitalization and industry), and the announcements themselves (social media announcements) on abnormal returns. In most cases, these characteristics do not significantly impact the abnormal returns. Although, we document lower returns for male celebrities, compared to women. Additionally, a higher celebrity following in Europe leads to negative returns, which might be because the substantial cost for high-profile celebrities outweighs the benefits. Moreover, endorsements of European technology firms have a positive return, supporting the findings of Ding et al. (2011). Interestingly, the match-up between the celebrity and the product in the USA demonstrates a negative significance. This contradicts an array of earlier studies, which typically find a positive coefficient in the match-up variable.

For future research, it can be worthwhile to investigate contract costs as these values are often confidential and might influence the returns. Including contract values can answer whether the costs are a primary driver in risks associated with endorsements. Also, expanding the study to include more regions can provide a deeper insight into regional differences in the impact of endorsement deals. While our study focuses on two regions, incorporating countries such as India and China can further determine if regional variations influence abnormal stock returns.

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Appendix

A1 List of Included Events

Table A1: List of included events.

Event ID	Date	Celebrity	Company Name	Benchmark Index
1	10.09.2015	Aaron Rogers	Adidas	DAX
2	27.02.2012	Derrick Rose	Adidas	DAX
3	25.11.2013	Kanye West	Adidas	DAX
4	18.10.2012	Justin Bieber	Adidas	DAX
5	21.11.2012	Selena Gomez	Adidas	DAX
6	31.05.2017	Kendall Jenner	Adidas	DAX
7	07.09.2018	Kylie Jenner	Adidas	DAX
8	14.04.2012	Nicki Minaj	Adidas	DAX
9	04.04.2019	Beyonce	Adidas	DAX
10	19.07.2017	Nina Dobrev	Adidas	DAX
11	27.05.2014	Pharrell Williams	Adidas	DAX
12	09.04.2014	Gareth Bale	Adidas	DAX
13	14.01.2015	Conor McGregor	Adidas	DAX
14	07.09.2020	Jurgen Klopp	Adidas	DAX
15	28.11.2018	Ngolo Kante	Adidas	DAX
16	11.03.2016	Paul Pogba	Adidas	DAX
17	01.02.2023	Jenna Ortega	Adidas	DAX
18	07.06.2022	Carlos Alcaraz	BMW	DAX
19	16.04.2016	Gigi Hadid	BMW	DAX
20	10.06.2019	Keanu Reeves	CD Projekt S.A.	DAX
21	03.06.2015	Johnny Depp	Christian Dior SE	CAC 40
22	17.12.2021	Kylian Mbappe	Christian Dior SE	CAC 40
23	12.06.2013	Robert Pattinson	Christian Dior SE	CAC 40
24	11.06.2015	Jennifer Lawrence	Christian Dior SE	CAC 40
25	25.10.2021	Anya Taylor-Joy	Christian Dior SE	CAC 40
26	16.01.2023	BTS (Jimin)	Christian Dior SE	CAC 40
27	15.03.2015	Rihanna	Christian Dior SE	CAC 40
28	07.06.2010	Natalie Portman	Christian Dior SE	CAC 40
29	08.11.2022	Kylian Mbappe	Danone	CAC 40
30	28.07.2011	David Beckham	H & M Hennes & Mauritz AB	DAX
31	04.11.2016	The Weeknd	H & M Hennes & Mauritz AB	DAX
32	16.07.2015	Katy Perry	H & M Hennes & Mauritz AB	DAX
33	12.04.2021	Maisie Williams	H & M Hennes & Mauritz AB	DAX
34	15.02.2010	Ryan Reynolds	Hugo Boss AG	DAX
35	20.12.2016	Zac Efron	Hugo Boss AG	DAX
36	29.05.2018	Henry Cavill	Hugo Boss AG	DAX
37	12.04.2018	Toni Kroos	Hugo Boss AG	DAX
38	20.03.2018	Harry Kane	Hugo Boss AG	DAX
39	31.05.2020	Snoop Dogg	Just Eat	DAX

40	24.01.2018	Chiara Ferragni	Kering SA	CAC 40
41	03.04.2022	Jack Grealish	Kering SA	CAC 40
42	15.05.2011	Penelope Cruz	L'OREAL	DAX
43	21.02.2014	Ryan Reynolds	L'OREAL	DAX
44	18.07.2023	Kendall Jenner	L'OREAL	DAX
45	22.02.2019	Zendaya	L'OREAL	DAX
46	04.12.2009	Julia Roberts	L'OREAL	DAX
47	09.01.2018	David Beckham	L'OREAL	DAX
48	03.11.2014	Helen Mirren	L'OREAL	DAX
49	29.01.2015	Eva Green	L'OREAL	DAX
50	28.10.2015	Irina Shayk	L'OREAL	DAX
51	15.10.2013	Lara Stone	L'OREAL	DAX
52	14.01.2015	Gigi Hadid	L'OREAL	DAX
53	30.10.2013	Blake Lively	L'OREAL	DAX
54	07.10.2017	Emma Stone	LVMH Moët Hennessy	CAC 40
55	20.04.2023	Zendaya	LVMH Moët Hennessy	CAC 40
56	17.01.2019	Rihanna	LVMH Moët Hennessy	CAC 40
57	03.07.2018	Penelope Cruz	LVMH Moët Hennessy	CAC 40
58	04.06.2019	Dua Lipa	LVMH Moët Hennessy	CAC 40
59	01.07.2021	Alicia Vikander	LVMH Moët Hennessy	CAC 40
60	23.01.2015	Cara Delavigne	LVMH Moët Hennessy	CAC 40
61	08.01.2016	Lea Seydoux	LVMH Moët Hennessy	CAC 40
62	28.04.2014	Cristiano Ronaldo	LVMH Moët Hennessy	CAC 40
63	25.11.2020	Chris Hemswort	LVMH Moët Hennessy	CAC 40
64	15.01.2009	Leonardo Di Caprio	LVMH Moët Hennessy	CAC 40
65	14.10.2015	Tom Brady	LVMH Moët Hennessy	CAC 40
66	27.05.2010	Roger Federer	Mercedes Benz	DAX
67	29.11.2019	The Weeknd	Mercedes Benz	DAX
68	16.06.2011	Li Na	Mercedes Benz	DAX
69	20.05.2015	Lewis Hamilton	Mercedes Benz	DAX
70	01.05.2014	Lady Gaga	Pernod Richard	CAC 40
71	06.11.2015	Penelope Cruz	Piquadro S.p.A.	DAX
72	23.04.2013	Maria Sharapova	Porsche	DAX
73	16.06.2013	Patrick Dempsey	Porsche	DAX
74	12.09.2020	Neymar	Puma	DAX
75	16.12.2014	Rihanna	Puma	DAX
76	16.11.2019	Megan Thee Stallion	Puma	DAX
77	01.10.2018	Adriana Lima	Puma	DAX
78	17.11.2020	Dua Lipa	Puma	DAX
79	20.02.2017	Virat Kohli	Puma	DAX
80	18.09.2017	Selena Gomez	Puma	DAX
81	18.09.2017	Kevin Durant	Alaska Air Group	S&P 500
82	06.11.2010	Phil Mickelson	Amgen	S&P 500
83	01.08.2019	Post Malone	Anheuser-Busch	S&P 500
84	09.09.2020	Lionel Messi	Anheuser-Busch	S&P 500
85	29.01.2018	Chris Pratt	Anheuser-Busch	S&P 500
86	27.05.2017	Conor McGregor	Apple	S&P 500
87	23.07.2017	Dwayne Johnson	Apple	S&P 500

88	15.05.2014	Jordan Spieth	AT&T	S&P 500
89	13.03.2017	Mark Wahlberg	AT&T	S&P 500
90	31.12.2019	Rafael Nadal	Banco Santander	S&P 500
91	14.05.2018	Chrissy Teigen	Blue Apron	S&P 500
92	25.01.2013	Taylor Swift	Coca Cola	S&P 500
93	29.04.2016	Selena Gomez	Coca Cola	S&P 500
94	09.10.2017	Zac Efron	Columbia Sportswear	S&P 500
95	17.08.2020	Snoop Dogg	Constellation Brands	S&P 500
96	02.11.2018	Post Malone	Crocs	S&P 500
97	01.10.2020	Justin Bieber	Crocs	S&P 500
98	16.03.2015	Rory McIlroy	Electronic Arts Inc.	S&P 500
99	03.08.2017	Neymar	Electronic Arts Inc.	S&P 500
100	11.08.2017	James Harden	Electronic Arts Inc.	S&P 500
101	15.11.2014	Kendall Jenner	Estee Lauder	S&P 500
102	26.02.2021	Ana de Armas	Estee Lauder	S&P 500
103	24.04.2015	Eva Mendes	Estee Lauder	S&P 500
104	17.04.2015	Poppy Delevingne	Estee Lauder	S&P 500
105	01.10.2015	Dwayne Johnson	Ford	S&P 500
106	19.05.2023	Maverick McNealy	Ford	S&P 500
107	04.11.2019	Idris Elba	Ford	S&P 500
108	15.02.2018	Serena Williams	Ford	S&P 500
109	21.08.2014	Matthew McConaughey	Ford	S&P 500
110	11.01.2013	Brad Pitt	General Motors	S&P 500
111	27.11.2017	Jennifer Lopez	Guess?	S&P 500
112	05.06.2013	Cristiano Ronaldo	Herbalife	S&P 500
113	06.04.2022	Doja Cat	Jabil Inc	S&P 500
114	24.01.2018	Priyanka Chopra	Jabil Inc	S&P 500
115	06.03.2016	Stephen Curry	JPMorgan Chase & Co.	S&P 500
116	03.03.2014	DJ Tiesto	Keurig Dr Pepper Inc.	S&P 500
117	20.10.2016	Justin Timberlake	Keurig Dr Pepper Inc.	S&P 500
118	10.04.2018	Lionel Messi and Neymar	MasterCard	S&P 500
119	03.09.2020	Travis Scott	McDonalds	S&P 500
120	19.04.2021	BTS	McDonalds	S&P 500
121	04.10.2018	Conor McGregor	Monster Beverage	S&P 500
122	12.01.2010	Maria Sharapova	Nike	S&P 500
123	10.10.2022	Bronny James	Nike	S&P 500
124	14.01.2013	Rory Mcilroy	Nike	S&P 500
125	15.05.2012	Derek Jeter	Nike	S&P 500
126	06.03.2014	Johnny Manziel	Nike	S&P 500
127	08.07.2017	Kylian Mbappe	Nike	S&P 500
128	11.04.2022	Billie Eilish	Nike	S&P 500
129	04.12.2013	Drake	Nike	S&P 500
130	08.11.2016	Cristiano Ronaldo	Nike	S&P 500
131	22.03.2019	Shaquille O’Neal	Papa John’s International, Inc.	S&P 500
132	10.10.2013	Lionel Messi	PepsiCo	S&P 500
133	09.12.2012	Beyonce	PepsiCo	S&P 500
134	25.01.2019	Cardi B	PepsiCo	S&P 500
135	02.02.2023	Michael B. Jordan	PepsiCo	S&P 500

136	03.05.2012	Katy Perry	PepsiCo	S&P 500
137	19.03.2012	Nicki Minaj	PepsiCo	S&P 500
138	11.01.2014	Scarlett Johansson	PepsiCo	S&P 500
139	02.03.2011	Phil Mickelson	Pfizer Inc.	S&P 500
140	24.07.2013	Shakira	Proctor & Gamble	S&P 500
141	06.11.2013	Sofia Vergara	Proctor & Gamble	S&P 500
142	15.03.2018	Lewis Hamilton	PVH Corp	S&P 500
143	26.03.2015	Kendall Jenner	PVH Corp	S&P 500
144	07.01.2015	Justin Bieber	PVH Corp	S&P 500
145	17.08.2023	Harry Kane	Skechers	S&P 500
146	21.11.2010	Kim Kardashian	Skechers	S&P 500
147	05.03.2019	Ariana Grande	Starbucks	S&P 500
148	01.05.2017	Vin Diesel	Stellantis	S&P 500
149	13.12.2017	Cardi B	Steve Madden	S&P 500
150	06.04.2012	Virat Kohli	Toyota	S&P 500
151	30.03.2013	Stephen Curry	Under Armour	S&P 500
152	06.10.2010	Tom Brady	Under Armour	S&P 500
153	03.07.2019	Lewis Hamilton	Vodafone	S&P 500
154	14.08.2018	Ellen Degeneres	Walmart Inc.	S&P 500
155	29.03.2017	Nicki Minaj	Wilhelmina International	S&P 500

A2 List of Removed Events

Table A2: List of removed events.

Event	Date	Celebrity	Company	Reason for removal
1	11.08.2003	David Beckham	Adidas	Announcement of Q2 at t=-5
2	15.09.2000	Tiger Woods	Nike	Announcement of Q2 at t=2
3	30.01.2013	Alica Keys	Blackberry	Announcement of new phone at t=-0
4	29.01.2020	Cristiano Ronaldo	Italia Independent	Extremely volatile through event window
5	11.02.2017	Lionel Messi	Adidas	Extension deal, we assume no effect
6	08.11.2016	Cristiano Ronaldo	Nike	Extension deal, we assume no effect
7	03.11.2011	David Beckham	Sainsbury	Announcement of Q3 at t=6
8	11.03.2021	Bad Bunny	Adidas	Announcement of Q1 at t=-1
9	20.02.2023	Max Verstappen	Heineken	Announcement of Q4 at t=-5
10	02.05.2019	Liam Payne	Hugo Boss	Announcement of Q1 at t=0
11	31.01.2017	Lady Gaga	LVMH Moët	Announcement of Q4 at t=-5
12	02.05.2023	Floyd Mayweather	LVMH Moët	Dividend Payout at t=-5
13	14.06.2016	Eddie Redmayne	Prada	Dividend Payout at t=-1
14	17.02.2016	Kylie Jenner	Puma	Announcement of Q4 at t=1
15	27.07.2019	Blake Lively	Amazon	Announcement of Q2 at t=-2
16	25.04.2016	Drake	Apple	Announcement of Q1 at t=1
17	30.10.2019	Priyanka Chopra	Crocs	Announcement of Q3 at t=0
18	13.11.2018	Natalia Dormer	Crocs	Announcement of Q3 at t=-5
19	03.02.2023	Max Verstappen	Electronic Arts Inc	Announcement of Q4 at t=-3
20	12.03.2014	Kate Upton	Express	Announcement of Q4 at t=0
21	23.04.2021	Simone Biles	Gap Inc	Dividend Payout at t=5
22	20.03.2023	Kevin De Bruyne	McDonalds	Dividend Payout at t=-5
23	18.10.2019	Beyonce	Netflix	Announcement of Q3 at t=-2
24	31.03.2023	Erling Haaland	Nike	Dividend Payout at t=3
25	24.04.2012	Kyrie Irving	PepsiCo	Announcement of Q1 at t=2
26	28.01.2016	Chiara Ferragni	Proctor & Gamble	Announcement of Q4 at t=-2
27	17.12.2014	Rafael Nadal	PVH Corp	Dividend Payout at t=1
28	17.12.2015	Gigi Hadid	PVH Corp	Dividend Payout at t=1
29	12.02.2019	Ariana Grande	T-Mobil	Announcement of Q4 at t=-5
30	25.01.2016	Dwayne Johnsen	Under Armour	Announcement of Q4 at t=3
31	03.06.2009	Miley Cyrus	Walmart Inc	Dividend Payout at t=-2
32	19.10.2015	Oprah Winfrey	WW International	Outlier, 73% up t=0
33	20.02.2009	Sienna Miller	Hugo Boss	Extremely volatile through event window

A3 Regression with Press Release in timeframes [-5, 5] and [0, 5]

Table A3: Regression of total sample in timeframe [-5, 5] and [0, 5] with press releases instead of social media announcements.

	Dependent variable:	
	CAR [-5, 5] (1)	CAR [0, 5] (2)
Male	-0.008	-0.013*
	(-0.977)	(-1.975)
Age	0.0002	0.0001
	(0.478)	(0.204)
Market Cap	-0.00002	-0.00005
	(-0.566)	(-1.615)
Celebrity Fame	-0.00001	-0.00000
	(-0.222)	(-0.014)
Match-Up	0.015	-0.004
	(1.313)	(-0.510)
Technology	-0.010	0.001
	(-0.873)	(0.067)
Press Release	0.026*	0.020*
	(1.893)	(1.925)
Europe	-0.014	-0.014**
	(-1.605)	(-2.166)
Constant	0.009	0.021
	(0.466)	(1.519)
Observations	155	155
R^2	0.063	0.094
Adjusted R^2	0.011	0.044
Note:	*p<0.1; **p<0.05; ***p<0.01	

A4 Cross-sectional regression of Europe and the USA: [-5, 5] and [0, 5]

Table A4: Regression of Europe and the USA in timeframes [-5, 5] and [0, 5].

	Dependent variable:			
	CAR		CAR	
	Europe	USA	Europe	USA
	[-5, 5]	**[-5, 5]**	**[0, 5]**	**[0, 5]**
Male	-0.010	-0.010	-0.011	-0.014
	(-1.069)	(-0.598)	(-1.566)	(-1.146)
Age	0.00003	0.0002	-0.0001	0.0001
	(0.054)	(0.275)	(-0.266)	(0.133)
Market Cap	-0.00002	-0.00004	-0.0001	-0.0001
	(-0.283)	(-0.754)	(-1.404)	(-1.566)
Celebrity Fame	-0.0001	0.00001	-0.00005	0.00002
	(-1.557)	(0.257)	(-1.533)	(0.575)
Match-Up	0.013	0.015	0.006	-0.019
	(1.051)	(0.663)	(0.691)	(-1.150)
Technology	-0.008	-0.006	-0.004	0.006
	(-0.631)	(-0.342)	(-0.395)	(0.460)
Social Media	0.002	-0.014	-0.003	-0.002
	(0.212)	(-0.878)	(-0.356)	(-0.130)
Constant	0.007	0.016	0.017	0.025
	(0.413)	(0.499)	(1.247)	(0.989)
Observations	80	75	80	75
R^2	0.068	0.036	0.086	0.070
Adjusted R^2	-0.023	-0.064	-0.003	-0.027
Note:		*p<0.1; **p<0.05; ***p<0.01		

A5 Regression using models from the Robustness Analysis: [-1, 1]

Table A5: Regression using the original, constant mean and omitted outlier's models in timeframe [-1, 1].

	Dependent variable:		
	CAR [-1, 1]		
	Original	Constant Mean	Omitted
	(1)	(2)	(3)
Male	-0.004	-0.004	-0.002
	(-0.959)	(-0.812)	(-0.514)
Age	0.0002	0.0002	0.0003
	(0.707)	(0.876)	(1.032)
Market Cap	-0.00001	-0.00002	-0.00001
	(-0.835)	(-1.138)	(-0.783)
Celebrity Fame	-0.00001	0.00001	0.00000
	(-0.437)	(0.577)	(0.031)
Match-Up	-0.002	-0.0003	-0.001
	(-0.383)	(-0.042)	(-0.195)
Technology	0.010^{**}	0.019^{***}	0.009
	(1.984)	(3.134)	(1.607)
Social Media	-0.005	-0.008	-0.004
	(-1.163	(-1.485)	(-0.853)
Europe	-0.0001	0.007	0.001
	(-0.013)	(1.310)	(0.258)
Constant	0.001	-0.007	-0.004
	(0.129)	(-0.641)	(-0.438)
Observations	155	155	142
R^2	0.056	0.103	0.044
Adjusted R^2	0.004	0.054	-0.013
Note:	*p<0.1; **p<0.05; ***p<0.01		

A6 Regression using models from the Robustness Analysis: [0, 5]

Table A6: Regression using the original, constant mean and omitted outlier's models in timeframe [0, 5].

	Dependent variable:		
	CAR [0, 5]		
	Original (1)	Constant Mean (2)	Omitted (3)
Male	-0.013^{**}	-0.019^{**}	-0.009^{*}
	(-1.990)	(-2.466)	(-1.691)
Age	0.00004	0.0001	-0.00005
	(0.107)	(0.211)	(-0.160)
Market Cap	-0.0001^{*}	-0.0001^{*}	-0.00003
	(-1.891)	(-1.909)	(-1.420)
Celebrity Fame	-0.00000	0.00002	0.00000
	(-0.153)	(0.710)	(0.101)
Match-Up	-0.005	-0.010	0.003
	(-0.546)	(-0.961)	(0.411)
Technology	0.003	0.007	0.0004
	(0.400)	(0.745)	(0.064)
Social Media	-0.003	-0.011	0.0003
	(-0.440)	(-1.376)	(0.049)
Europe	-0.016^{**}	-0.014^{*}	-0.008
	(-2.373)	(-1.743)	(-1.465)
Constant	0.027^{*}	0.028	0.014
	(1.873)	(1.637)	(1.209)
Observations	155	155	142
R^2	0.072	0.082	0.048
Adjusted R^2	0.021	0.032	-0.009
Note:			$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$