



Facultad de Ciencias Económicas y Empresariales | ICADE

**DO HEALTH WARNINGS AND
REGULATIONS MATTER? AN EVENT
STUDY ON THE STOCK MARKET
IMPACT OF REGULATORY
ANNOUNCEMENTS IN THE ALCOHOL
AND TOBACCO SECTORS**

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ABSTRACT

This thesis examines whether regulatory announcements, health warnings, and other policy-related measures affecting the alcohol and tobacco industries generate statistically significant reactions in the stock prices of firms operating in these sectors. While prior literature frequently emphasizes the high regulatory risk associated with these industries, it also highlights structural characteristics, such as strong market concentration, inelastic demand, and high profit margins, that may make these companies relatively resilient to adverse events. This creates an open empirical question regarding how financial markets actually respond to such announcements.

To address this issue, the study conducts an event study on a sample of 32 publicly traded firms (7 tobacco companies and 25 alcohol companies). Two complementary methodologies are employed: the traditional event study framework following MacKinlay (1997) and a Panel Event Study approach. The events analyzed include regulatory measures, health-related disclosures, and other policy actions targeting alcohol and tobacco consumption. The results obtained from both methodologies consistently indicate a clear negative and statistically significant impact on stock prices around the event date. These findings suggest that, despite their structural resilience, regulatory and health-related announcements are interpreted by financial markets as adverse shocks that negatively affect the valuation of alcohol and tobacco firms

KEY WORDS

Event Study, Regulatory Risk, Alcohol Industry, Tobacco Industry, Stock Market Reaction, Panel Event Study, Health Warnings, Financial Markets.

RESUMEN

Este trabajo analiza si los anuncios regulatorios, advertencias sanitarias y otras medidas de política pública dirigidas a las industrias del alcohol y el tabaco generan reacciones estadísticamente significativas en los precios de cotización de las empresas que operan en estos sectores. Aunque la literatura previa suele destacar el elevado riesgo regulatorio asociado a estas industrias, también señala la existencia de ciertas características estructurales, como una alta concentración del mercado, una demanda relativamente inelástica y elevados márgenes de beneficio, que podrían hacer que estas compañías sean relativamente resilientes frente a eventos adversos. Esto plantea una cuestión empírica relevante acerca de cómo reaccionan realmente los mercados financieros ante este tipo de anuncios.

Para abordar esta cuestión, el estudio realiza un Event Study sobre una muestra de 32 empresas cotizadas (7 compañías de tabaco y 25 de alcohol). Se emplean dos metodologías complementarias: el enfoque tradicional de Event Study siguiendo a MacKinlay (1997) y una metodología de Event Study basada en datos de panel. Los eventos analizados incluyen regulaciones, divulgaciones sobre efectos perjudiciales para la salud y otras medidas de política pública dirigidas al consumo de alcohol y tabaco. Los resultados obtenidos con ambas metodologías muestran de forma consistente un efecto negativo y estadísticamente significativo en los precios de las acciones alrededor de la fecha del evento. Estos hallazgos sugieren que, a pesar de su resiliencia estructural, los anuncios regulatorios y sanitarios son interpretados por los mercados financieros como shocks adversos que afectan negativamente a la valoración de las empresas de alcohol y tabaco.

PALABRAS CLAVE

Event Study, Riesgo regulatorio, Industria del alcohol, Industria del tabaco, Reacción del mercado bursátil, Event study de panel, Advertencias sanitarias, Mercados financieros.

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1. Introduction

Alcohol and tobacco companies have historically attracted strong investor interest due to their ability to generate solid and persistent returns over long periods of time (Dimson et al., 2015). However, the existing literature repeatedly emphasizes that alcohol and tobacco companies are particularly exposed to regulatory risk (Babor et al., 2023; Rehm et al., 2023). Their products are frequently targeted by governments and public authorities through taxation measures, advertising restrictions, packaging requirements, consumption limits, health warnings, and broader public health campaigns (Chaloupka et al., 2012; World Health Organization, 2023). In addition, the disclosure of new evidence regarding the harmful effects of alcohol and tobacco consumption may also affect the perception of these industries among consumers, regulators, and investors (Starr & Drake, 2017). From this perspective, such announcements should represent negative shocks for the firms involved, as they may reduce expected demand, increase compliance costs, damage reputation, or intensify future regulatory pressure. As a result, prior research often presents these sectors as especially vulnerable to policy interventions and health-related disclosures.

At the same time, the existing literature also associates these firms with high profitability, stable cash flows, and business models capable of performing well even under unfavourable macroeconomic conditions (Babor et al., 2010; Blitz & Fabozzi, 2017; Branston, 2021). Such literature highlights several structural features that may make alcohol and tobacco firms more resilient than other companies when facing adverse events: high market concentration (Gilmore, 2012; Anderson et al., 2018), significant barriers to entry (U.S. Department of the Treasury, 2022), and relatively inelastic demand (Blecher & Bertram, 2019). Moreover, the firms operating in these sectors usually benefit from strong pricing power and attractive profit margins (Babor et al., 2010; Branston, 2021), which may allow them to absorb part of the negative effects associated with regulation or reputational pressure. In this sense, the same literature that identifies alcohol and tobacco companies as highly exposed to regulatory risk also suggests that they possess business characteristics that may protect them from severe market reactions.

This creates a relevant tension in the previous literature. On the one hand, these firms appear to face a substantial and persistent risk arising from regulation, health warnings, and similar announcements. On the other hand, their economic fundamentals suggest that they may remain robust even when confronted with negative external shocks. Consequently, it is not

entirely clear whether these events actually produce a meaningful and statistically significant decline in stock prices. This question becomes particularly relevant in the absence of a recent and focused empirical analysis examining whether such announcements continue to affect the market valuation of alcohol and tobacco companies.

To address this issue, this thesis conducts an Event Study on listed alcohol and tobacco firms. The purpose is to determine whether announcements related to regulations, health warnings, and similar measures generate a negative and statistically significant effect on the stock prices of these companies. More specifically, the study seeks to test whether, despite the strong and resilient characteristics commonly associated with these industries, the market still reacts adversely when new regulatory or health-related information becomes public. By doing so, the dissertation aims to contribute to the understanding of regulatory risk in sectors that have historically combined strong financial performance with elevated political and social scrutiny.

This analysis is relevant for several stakeholders. First, it is useful for investors who actively invest in alcohol and tobacco companies and want to better assess the regulatory risk embedded in these sectors. Second, it is relevant for investors who exclude these firms from their portfolios for ethical or sustainability reasons, as it helps identify the type of risk they avoid by doing so. Finally, the study is also of interest to policymakers, since it provides evidence on whether anti-alcohol and anti-tobacco measures have an immediate effect on the stock market valuation of the firms concerned, beyond their possible influence on consumption habits or broader public health outcomes.

2. Literature Review

2.1. Historical Performance of Alcohol and Tobacco Companies

Alcohol and tobacco companies have a long history of robust stock market performance, often outperforming the broader market over extended periods. A wealth of empirical evidence supports this outperformance. For instance, Dimson et al. (2015) document that from 1900 to 2014, tobacco industry stocks in the U.S. delivered an annualized excess return of about 4.5% over the overall equity market (and about 2.6% in the UK). These are remarkable premiums sustained over more than a century. Likewise, Hong and Kacperczyk (2009) find a significant “sin stock” effect: a U.S. portfolio long in tobacco, alcohol, and gaming stocks earned approximately 0.29% higher returns per month than a comparable portfolio, even after controlling for standard risk factors. Such evidence has led to the notion of a “sin stock premium”, wherein investors in these industries have historically been rewarded with superior returns relative to the market (Richey, 2017; Hong & Kacperczyk, 2009). In fact, some of the best-performing individual stocks of the 20th century have come from the tobacco sector: Philip Morris (now Altria) being a prominent example, compounding extraordinary gains over decades (Siegel, 1998). These outcomes have made alcohol and tobacco firms attractive to certain investors despite ethical reservations, giving rise to investment vehicles like “vice funds” that explicitly focus on these industries (Agapova et al., 2025).

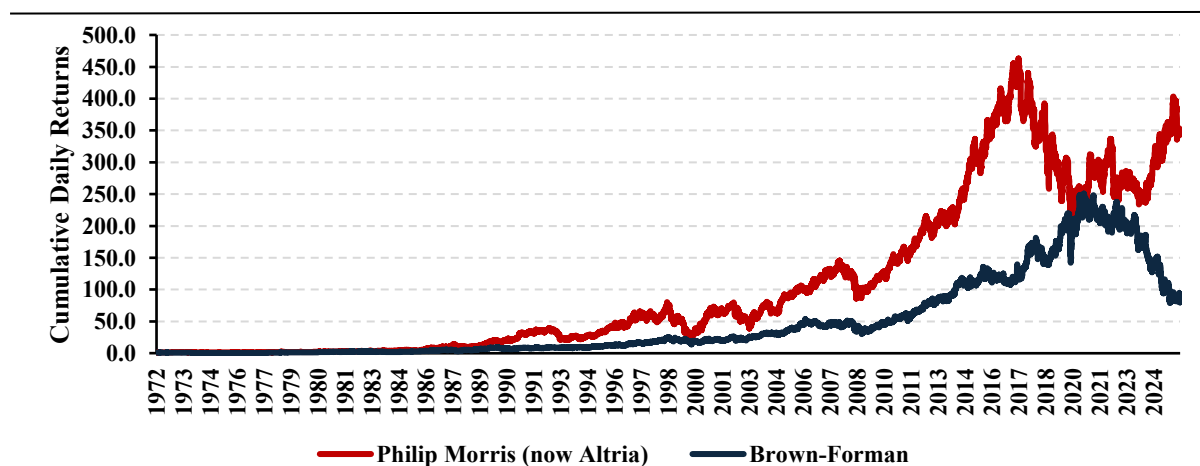


Figure 1. Cumulative Daily Returns of Philip Morris and Brown-Forman, Base 1972 = 1 (Source: FactSet, 2026; Own elaboration)

Several factors underlie why alcohol and tobacco companies have delivered such strong long-term performance, making them appealing investments. One explanation is related to market neglect and investor preferences. Because many institutional investors and pension funds avoid sin industries for ethical or regulatory reasons, the stocks may trade at depressed valuations, thus offering higher subsequent returns for those willing to hold them (Hamdan et al., 2024). In equilibrium, this shunning effect raises the cost of capital for alcohol and tobacco companies and, conversely, their expected returns (Alessandrini & Jondeau, 2019). Another explanation is that these firms often exhibit strong fundamental factors that drive performance. Blitz and Fabozzi (2017) show that the excess returns of these kinds of stocks can be largely explained by classic “quality” factors, notably, above-average profitability and low investment rates. Tobacco and alcohol firms tend to be highly profitable (with strong margins) and reinvest conservatively, which maps into Fama-French factors for profitability and asset growth, respectively (Fama & French, 2015). When such factors are accounted for, the sin stock anomaly disappears (Blitz & Fabozzi, 2017), suggesting that investors in these firms are effectively rewarded for their superior business economics rather than for some unpriced ethical risk. Additionally, these companies have historically paid generous dividends and undertaken share buybacks, contributing to investors’ total returns (Eriksson et al., 2023). This income component, combined with resilient earnings, has also allowed alcohol and tobacco equities to hold up well even during market downturns, cementing their reputation as defensive stocks (even though they are not perfectly defensive) (Salaber, 2009).

2.2. Regulatory Risk and Negative Externalities in Alcohol and Tobacco Industries

Notwithstanding their financial performance, alcohol and tobacco companies are consistently exposed to regulatory risks and negative externalities stemming from the harmful nature of their products (Babor et al., 2023; Rehm et al., 2023). Governments and international bodies have long viewed tobacco and alcohol consumption as public health issues, leading to a wide array of regulatory actions intended to curb use, mitigate health costs, and internalize the externalities (World Health Organization, 2023). These industries thus operate under some of the most stringent regulatory regimes in the corporate world. Key regulatory measures include excise taxation, marketing and advertising bans, mandatory health warnings, product content restrictions, age limits for purchase, and even outright usage prohibitions in certain contexts (e.g. smoking bans in public places) (Chaloupka et al., 2012; Ince, 2024). For example,

the WHO's Framework Convention on Tobacco Control, implemented in 2005, committed 180+ countries to implement high tobacco taxes, comprehensive advertising bans, and other strong tobacco control policies (World Health Organization, 2003). Such measures directly threaten tobacco companies' sales volumes and marketing freedoms (Wagenaar et al., 2009). Similarly, alcohol firms face regulations on advertising (such as limits on liquor ads or sponsorships), restrictions on outlet density and hours of sale, and rising taxes on beer, wine, and spirits to discourage excessive consumption (Giesbrecht et al., 2024).

These regulatory actions and related negative publicity can have adverse impacts on stock prices and investor sentiment (Vasileiou et al., 2025). When new regulations or government actions are announced, investors often anticipate higher costs or lower future demand for the affected companies, leading to negative abnormal returns around such events (Zhang et al., 2024). Prior studies have shown that tobacco stock prices react negatively to major regulatory events (Adda et al., 2012). For instance, Sloan et al. (2005) analysed the U.S. tobacco industry regulations and found that announcements of tighter regulations or tax increases led to significant short-term declines in tobacco company share prices (signalling a loss of shareholder wealth). Large-scale litigation events have had a similar effect: the 1998 Master Settlement Agreement in the United States, in which tobacco firms agreed to pay over \$200 billion to state governments and accept advertising restrictions, initially sent tobacco stocks downward, reflecting investor concern over the financial burden (Sloan et al., 2005). In the alcohol sector, regulatory shocks such as sudden tax hikes or advertising bans (for example, a ban on spirits advertising on TV in certain countries) can likewise jolt stock prices as the market reassesses growth prospects (Zhang et al., 2024). Overall, because these industries' profitability is so directly tied to public policy, regulatory news is a major source of return volatility for sin stocks.

Beyond formal regulations, reputational risk and changing social norms also pose challenges to alcohol and tobacco companies. There is a growing movement toward ESG investing, wherein many investors exclude unsustainable or harmful industries from their portfolios (Li, 2022). For example, Storebrand Asset Management, an institutional investor with a strong sustainability mandate, explicitly prohibits investment in both sectors (Storebrand Asset Management, 2025). Similarly, the Tobacco-Free Finance Pledge, launched in 2018, has attracted banks and asset managers representing trillions in assets who commit to avoid financing tobacco (UNEP Finance Initiative, 2018). While such divestment campaigns may

only marginally impact a company's day-to-day operations, they can affect stock valuations by shrinking the pool of potential investors and increasing the equity risk premium required by the remaining investors (Hong & Kacperczyk, 2009).

2.3. Structural Resilience of Alcohol and Tobacco Firms

Despite the formidable risks outlined above, it is also stated in previous literature that alcohol and tobacco firms have demonstrated notable structural resilience in their business models (Meehan & Corbet, 2025). Several interrelated factors contribute to this resilience:

- **Inelastic demand and product addictiveness:** Because tobacco and alcohol products are addictive or habit-forming, consumers are less sensitive to changes in price than they might be for other goods (Blecher & Bertram, 2019). Empirical research consistently finds that the price elasticity of demand for these substances is low. For instance, Nelson (2013) found alcohol price elasticities of approximately -0.3 for beer and around -0.5 to -0.6 for wine and spirits, implying that a 10% increase in alcohol prices is associated with an average reduction in consumption of roughly 3–6%. By comparison, Colchero et al. (2015) report substantially higher own-price elasticities for non-alcoholic beverages, estimating -1.06 for soft drinks and -1.16 for sugar-sweetened beverages, which implies that a similar price increase would reduce consumption by approximately 10.6–11.6%. Similarly, cigarette demand is notoriously inelastic; recent studies in the United States confirm that sizable tax or price hikes lead to proportionally smaller declines in cigarette sales (Cotti et al., 2022). For example, one analysis found that substantial increases in cigarette prices driven by tax changes were associated with price elasticities well below -1 , often around -0.3 to -0.4 for higher-income consumers, indicating that despite higher prices, a large share of smokers continued purchasing cigarettes (Guindon et al., 2014). Figure 2 shows the revenues of Philip Morris International (one of the largest tobacco product companies in the world) and Diageo (a multinational beverage company known for producing and distributing alcoholic drinks such as spirits and beer). It illustrates how the revenues of these companies remain consistent over time, without significant declines or particularly bad years to consider.

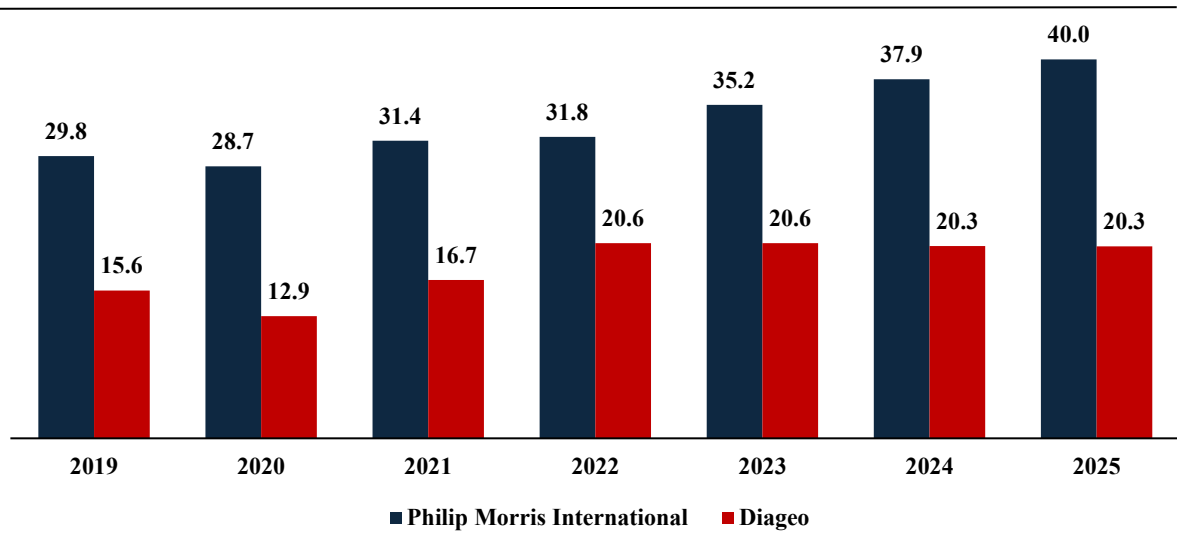


Figure 2. Annual Revenues of Philip Morris International and Diageo, 2019–2025 (USD billions) (Source: Company reports; Own elaboration)

- High barriers to entry:** The regulatory and legal environment that punishes tobacco and alcohol use ironically creates a protective barrier for incumbent firms. It is extraordinarily difficult for new entrants to establish themselves in these industries (U.S. Department of the Treasury, 2022). Would-be competitors face not only the usual start-up challenges but also regulatory hurdles, such as licensing requirements, advertising bans (making it hard to build a brand), and strict age-restricted distribution channels. The incumbents, meanwhile, have decades of experience navigating regulations and large compliance departments to handle legal risks (Levy et al., 2019). Moreover, the controversial nature of these products means new entrants struggle to raise capital since few investors or banks want to back a sin product startup (McDonald & Fauver, 2012). As a result, the market structure for both cigarettes and alcoholic beverages is oligopolistic. A handful of large multinational corporations dominate global sales (e.g. AB InBev, Diageo, and Pernod Ricard in alcohol; Philip Morris International, BAT, and Altria in tobacco). These dominant firms benefit from economies of scale and entrenched distribution networks that a new competitor simply could not replicate (Institute of Alcohol Studies, 2020).
- Industry consolidation and market power:** Over time, both the tobacco and alcohol sectors have seen significant consolidation through mergers and acquisitions. Larger firms have acquired smaller rivals, leading to highly concentrated industries (Gilmore,

2012; Anderson et al., 2018). This consolidation has several benefits that bolster resilience. Firstly, it allows companies to diversify across products and geographies, for example, a big tobacco firm might sell cigarettes in dozens of countries and also own smokeless tobacco or vaping brands (Levy et al., 2019), while a big alcohol firm might have a portfolio ranging from beer to whiskey (Anderson et al., 2018). Such diversification can spread and reduce risk (geographic diversification insulates against any one country's regulatory shock). Secondly, with few competitors left, firms can achieve implicit pricing coordination: while overt collusion is illegal, a small number of players can often sustain higher prices since aggressive price-cutting would hurt everyone (Levy et al., 2019). The market power gained through consolidation also grants more influence over supply chains and lobbying: large firms can better negotiate with regulators or at least adapt quickly to new rules, using their scale to absorb compliance costs that would bankrupt smaller rivals (Cowgill et al., 2024). Figure 3 shows how concentrated the U.S. cigarette market is, where just two competitors account for nearly 80% of the market share (Gong et al., 2025). Figure 3 shows the market share of the main cigarette companies in the USA, highlighting how concentrated the industry is. The two main players, British American Tobacco and Altria Group, together hold close to 80% of the market share.

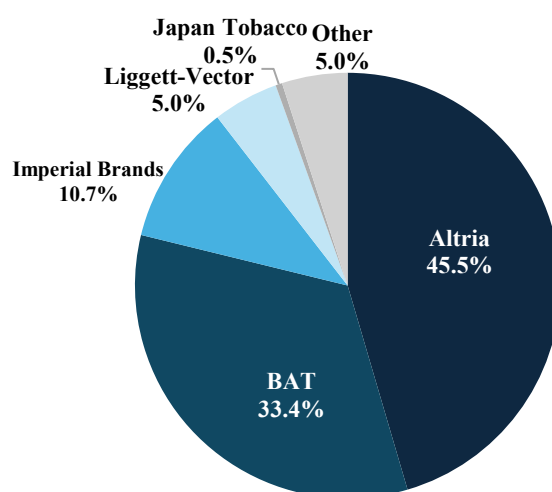


Figure 3. U.S. Cigarette Market Share by Company, as of 2022 (Source: Gong et al., 2025; Own elaboration)

- **Strong cash generation and financial flexibility:** A direct consequence of the above factors is that alcohol and tobacco firms generate abundant cash profits relative to their sales (Babor et al., 2010), and great profit margins (Branston, 2021). This allows firms to consistently reward shareholders (through dividends and buybacks) which keeps investors loyal even if growth prospects are limited. It also provides funds for innovation and diversification: for example, tobacco giants have invested in next-generation products like e-cigarettes and heated tobacco devices (Mathers et al., 2019), and alcohol companies have developed low-alcohol or non-alcoholic product lines, as a hedge against changing consumer preferences or future regulations (Critchlow et al., 2025). Finally, ample cash reserves mean that when faced with one-time liabilities (e.g. legal settlements or tax hikes), the firms can often pay the cost without jeopardizing the core business.

These resilience factors help explain the apparent paradox that despite facing continual regulatory and social pressures, tobacco and alcohol companies have historically managed to prosper. The tension between Section 2.2 and Section 2.3 is therefore central: on one hand, sin industries bear extraordinary external risks; on the other hand, they possess internal strengths that have allowed them to weather those risks and continue delivering returns. This tension creates an open empirical question about how markets respond to new information in these sectors. Do investors penalize sin stocks when negative events (like new regulations or health disclosures) occur, or do they largely discount such events knowing the firms' resilience? The answer is not obvious *ex ante*, which is precisely why an Event Study is warranted. By examining actual stock price reactions to relevant events, we can observe which force dominates: the negative shock of regulatory news or the countervailing confidence in structural resilience.

2.4. Event Study Methodology in Financial Literature

An Event Study is a statistical method used to assess the impact of a specific event on the value of a firm (or firms). It has become a standard tool in financial economics for analyzing how new information (earnings announcements, mergers, regulatory changes, etc.) affects stock prices (MacKinlay, 1997; Brooks, 2014). The core principle behind event studies is that in an efficient market, any value-relevant event will be quickly reflected in security prices. By

isolating the period when the event occurs and comparing actual returns to a benchmark of normal returns, researchers can infer the event’s economic significance.

2.4.1. The Classical Event Study Approach (MacKinlay, 1997)

The classical Event Study as formalized by MacKinlay (1997) proceeds in several well-defined steps. First, one must identify the event of interest and the event window. The event is typically a specific announcement or occurrence at a known date (denoted as time $t=0$). The event window is the short time period over which the market reaction is expected to occur, for example, $-1, +1$ days around the event to capture the immediate reaction on the day of the announcement and one day before/after. Next, one defines an estimation window prior to the event (for instance, $t = -120$ to $t = -21$, a 100-day period ending 21 days before the event) during which normal return behaviour is observed. No events or contaminating information should occur in the estimation window.

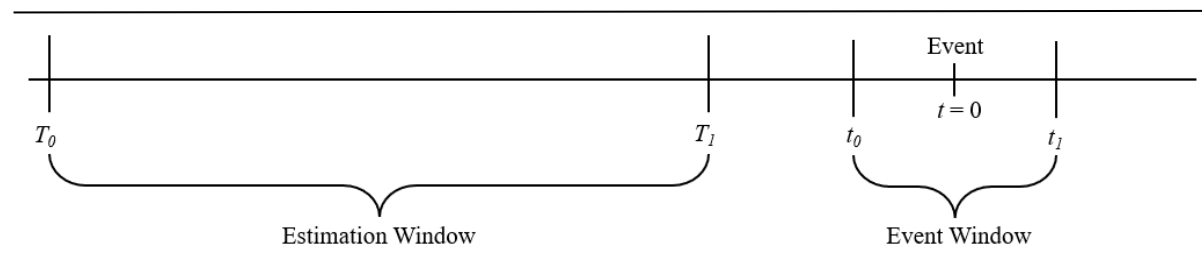


Figure 4. Graphical Illustration of MacKinlay’s Event Study Framework (Own elaboration)

Using the data from the estimation window, a normal return model is estimated for each stock. The simplest specification is the one assuming a constant mean return, in which the expected return is assumed to be equal to the average return of the stock over the estimation window (Brooks, 2014). While straightforward, this approach does not control market-wide movements.

A more refined and commonly used specification in event studies to construct expected returns is the market model, which consists of a one-factor OLS regression of the stock’s returns on a market index return:

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

where $R_{i,t}$ is the return of stock i on day t and $R_{m,t}$ is the return of the market portfolio (or a broad index) on day t . The coefficients α_i and β_i are estimated over the pre-event period for each firm i . This model controls systematic market movements and typically provides more precise estimates of expected returns than the mean-adjusted model (MacKinlay, 1997).

Beyond these simpler specifications, the literature also proposes more sophisticated multifactor models to estimate expected returns. In particular, the Fama-French three-factor model and its extension, the Fama-French five-factor model, incorporate additional risk factors related to size, value, profitability, and investment (Fama & French, 1993; Fama & French, 2015). Similarly, the Carhart four-factor model augments the framework by including a momentum factor (Carhart, 1997). While these models are not implemented in this study, they are often preferred when analyzing longer event windows, as they better capture multiple sources of systematic risk. In contrast, simpler models such as the mean-adjusted or market model are generally considered sufficient for short event windows.

The next step is to calculate abnormal returns (AR) for each company at each point in time within the event window. Using the market model, the abnormal return is defined as the difference between the actual return and the model's predicted return (Brooks, 2014):

$$AR_{it} = R_{it} - E(R_{it})$$

In essence, AR_{it} measures how much stock i outperformed or underperformed what would have been expected given general market movements on day t . Under the null hypothesis of no impact, the AR should average around zero (MacKinlay, 1997).

Often, we are interested in the total impact over a multi-day window, especially if information leaks or if the market takes time to fully digest news. Thus, one computes the cumulative abnormal return (CAR) for each stock i by summing the abnormal returns over the event window (MacKinlay, 1997; Brooks, 2014). For an event window from T_1 to T_2 , the CAR is:

$$C\hat{A}R_i(T_1, T_2) = \sum_{t=T_1}^{T_2} \hat{A}R_{it}$$

For example, if the event window is -1 to +1, $C\hat{A}R_i(T_1, T_2)$ would aggregate the abnormal returns on the day before, day of, and day after the event for stock i . This represents

the total excess return attributable to the event. MacKinlay (1997) notes that the *CAR* is the primary metric for gauging an event's economic magnitude, and its variance can be derived from the variance of the underlying AR_{it} (Brooks, 2014). Under the null hypothesis, *AR* and *CAR* are normally distributed (MacKinlay, 1997), which facilitates statistical inference.

Once all statistics associated with the Event Study have been computed, the final step consists of conducting a hypothesis testing procedure to determine whether the events under analysis have a statistically significant impact on stock prices. The null hypothesis (H_0) states that the events do not affect the returns of the firms included in the sample (MacKinlay, 1997). Formally, under the null hypothesis, the expected value of both abnormal returns and cumulative abnormal returns is equal to zero:

$$H_0: E(AR_{i,t}) = 0 \text{ and } E(CAR_{i,[T_1,T_2]}) = 0$$

The hypothesis testing method adopted in this thesis is based on the Standardized Cumulative Abnormal Return (SCAR), which focuses on cumulative abnormal returns at the firm level and allows for a direct aggregation across entities. Such SCAR statistic is constructed using the average cumulative abnormal return across firms and its corresponding variance:

$$SCAR(T_1, T_2) = \frac{C\hat{A}R(T_1, T_2)}{[\hat{\sigma}^2(CAR(T_1, T_2))]^{1/2}}$$

where $C\hat{A}R(T_1, T_2)$ is the sum of $\hat{A}R_t$ (the average abnormal return per company at each time t) between T_1 and T_2 ; and $\hat{\sigma}^2(CAR(T_1, T_2))$ denotes the variance of the firms' $C\hat{A}R_i$ (Brooks, 2014). Under the null hypothesis that the analysed events have no effect on stock prices, the population mean of cumulative abnormal returns is assumed to be zero and that is why there is just $C\hat{A}R(T_1, T_2)$ in the numerator. Consequently, the SCAR statistic follows a normal distribution (0,1):

$$SCAR \sim \mathcal{N}(0,1)$$

Statistical significance is therefore assessed by computing the corresponding p-value from the standard normal distribution of SCAR. The null hypothesis is rejected if the p-value

is lower than the chosen significance level α , indicating that the event has a statistically significant impact on stock prices.

The classical Event Study approach has been extensively applied in finance research. It was popularized by early studies like Fama et al. (1969) on stock splits and has since been used to analyze virtually every type of corporate or regulatory event. In the context of alcohol and tobacco companies, however, relatively few modern studies have focused on regulatory and health-related events using this method. More commonly, sin stock studies have been about long-run performance or the effects of social norms (Hong & Kacperczyk, 2009) rather than short-run event analysis and have largely focused on sin stocks as a broad category, with limited attention to specific sectors such as tobacco and alcohol. This suggests a gap: the classical Event Study methodology can and should be employed to measure how capital markets react to policy or health news affecting tobacco and alcohol firms, something our thesis will undertake. MacKinlay's framework provides a rigorous way to do so, by quantifying abnormal returns around events and testing their significance. A strength of this approach is its clarity and focus on the immediate market reaction, which is ideal for capturing the impact of news in the highly liquid equity markets for large tobacco/alcohol firms.

However, an important methodological limitation that exists in classical Event Study approach is the so-called joint hypothesis problem (Fama, 1970). When conducting an Event Study, the statistical test simultaneously evaluates two hypotheses: (1) whether abnormal returns are present, and (2) whether the underlying asset pricing model used to estimate expected returns is correctly specified. Consequently, if significant abnormal returns are detected, it is not possible to determine with certainty whether they reflect the true impact of the event or instead arise from misspecification of the expected return model. Additionally, the framework generally assumes that the event window is short and that effects are transitory; it may not fully capture longer-term adjustments or multiple overlapping events. To address some of these limitations, we consider an alternative approach below.

2.4.2. Panel-Based Event Study Methodology

Traditional event studies (e.g. the approach of MacKinlay, 1997) were developed primarily in financial economics using time-series data for single events. In contrast, the more recent panel-based Event Study methodology extends the Difference-in-Differences (DiD) framework to settings with panel data and staggered treatment timing (Clarke & Tapia, 2020).

At its core, the panel Event Study is a dynamic DiD design. The DiD framework estimates treatment effects by comparing two differences: (1) the difference in outcomes over time (before vs. after the event), and (2) the difference in outcomes between a treated group and a control group.

The panel Event Study generalizes this idea by allowing for multiple time-relative treatment effects (leads and lags) instead of a single post-event indicator (Clarke & Tapia, 2020). This design is particularly useful when an event or policy occurs at different times across units (e.g. firms or states), so that units not yet treated (or never treated) serve as the control group for those already treated. By examining outcome differences between treated and control units around the time of event adoption, relative to a pre-event baseline, the method estimates a sequence of dynamic effects that can be plotted to visualize the causal impact of the event (Clarke & Tapia, 2020). A central identifying assumption of this approach (as in standard DiD) is the parallel trends assumption (Clarke & Tapia, 2020). This assumption states that, in the absence of treatment, the treated group and the control group would have followed parallel outcome trajectories over time. In other words, any difference between the two groups observed before the event would have remained constant in the post-event period had the treatment not occurred. The inclusion of lead indicators allows researchers to test this assumption empirically: statistically insignificant pre-treatment coefficients provide support for parallel trends (Clarke & Tapia, 2020).

Model Setup: Formally, consider a panel of observational units indexed by s (e.g. firms) observed over time periods t . Some units belong to the treated group and experience the event at time $Event_s$, while others belong to the control group and do not experience the event at that time. Let y_{st} denote the outcome of interest for unit s at time t . Following Clarke and Tapia (2020), the Panel Event Study regression model is specified as:

$$y_{st} = \alpha + \sum_{j=2}^J \beta_j (Lag\ j)_{st} + \sum_{k=1}^K \gamma_k (Lead\ k)_{st} + \mu_s + \lambda_t + X'_{st} \Gamma + \varepsilon_{st}$$

where μ_s and λ_t are unit and time fixed effects, X'_{st} is a vector of control covariates, and ε_{st} is the error term (Clarke & Tapia, 2020). The inclusion of unit fixed effects (μ_s) controls for unobserved heterogeneity that is invariant across units over time (e.g. firm-specific

characteristics), while time fixed effects (λ_t) control for shocks common to all units in a given period (Clarke & Tapia, 2020). This two-way fixed effect's structure is a key advantage of the panel design, as it eliminates bias from unobserved factors that are constant across either the cross-sectional or time dimension.

The event's dynamic impact is captured through time-relative dummy variables. The (Lag j) and (Lead k) indicators are defined exactly as in Clarke & Tapia (2020), identifying periods before and after the event. One relative-time indicator must be omitted to avoid perfect multicollinearity. Consistent with Clarke and Tapia (2020), the omitted category is typically the period immediately before the event ($j = 1$). This period serves as the reference baseline, representing the last moment in which treated and control groups are assumed to be evolving in parallel. All estimated coefficients are therefore interpreted relative to this pre-event baseline period. This normalization is crucial for interpreting both regression tables and event-study graphs. Clarke and Tapia's notation defines these indicators as follows:

- $(Lag\ J)_{st} = \mathbf{1}[t \leq Event_s - J]$, for periods at least J periods before the event (the most distant pre-event period included).
- $(Lag\ j)_{st} = \mathbf{1}[t = Event_s - j]$ for $j \in \{1, \dots, J - 1\}$, to indicate exactly j periods before the event.
- $(Lead\ k)_{st} = \mathbf{1}[t = Event_s + k]$ for $k \in \{1, \dots, K - 1\}$, to indicate exactly k periods after the event.
- $(Lead\ K) = \mathbf{1}[t \geq Event_s + K] = \mathbf{1}$, for periods K or more periods after the event (the most distant post-event period grouped).

Here J and K denote the number of pre- and post-event periods (lags and leads) to include in the regression. The final lag ($Lag\ J$) and lead ($Lead\ K$) are accumulated indicators that soak up all periods beyond the chosen horizon J or K . By construction, one of the relative period dummies must be omitted to serve as a reference baseline and avoid perfect multicollinearity.

Units that never experience the event serve as the control group in the standard panel Event Study framework (Clarke & Tapia, 2020). These units have all lag and lead indicators equal to zero and provide the counterfactual trend against which treated units are evaluated. However, in the present study, a market index is used as a benchmark to approximate the counterfactual evolution of returns. This approach effectively constructs a control comparison using aggregate market performance rather than untreated firms. Finally, because the panel Event Study

generalizes DiD it avoids the joint hypothesis problem mentioned in the MacKinlay Event Study framework. By modeling time relative to treatment, it reduces the bias that may appear when treatment effects differ across cohorts (Goodman-Bacon, 2018, as discussed in Clarke & Tapia, 2020).

3. Problem Definition and Study Objectives

As discussed in the previous sections, the existing literature shows a certain inconsistency in the way alcohol and tobacco companies are understood in relation to negative regulatory events. On the one hand, these firms are usually considered to be strongly exposed to regulatory risk, since their business activity is frequently affected by new regulations, health warnings, advertising restrictions, taxation measures, and other policy interventions. From this perspective, such announcements should have a negative effect on investor expectations and, consequently, on stock prices. On the other hand, the literature also suggests that alcohol and tobacco companies have several characteristics that may make them relatively resilient in the face of adverse events. These firms often operate in highly concentrated markets, benefit from strong pricing power, and tend to generate stable revenues and high profitability. As a result, it is not entirely clear whether regulatory and health-related announcements actually translate into a significant negative market reaction.

In this context and given the lack of recent Event Study evidence focused specifically on this issue, the main objective of this dissertation is to examine whether announcements related to regulation, health warnings, and similar measures affecting the alcohol and tobacco industries produce a statistically significant negative effect on the stock prices of these companies. More specifically, the study aims to test whether these events are interpreted by the market as value-relevant negative shocks for firms operating in these sectors. An Event Study is the chosen methodology to test this.

4. Methodology

As mentioned before, in this study, an Event Study methodology is employed to analyze the impact of various regulatory actions, policy measures, and public health disclosures related to alcohol and tobacco on the stock performance of companies in these sectors. The Event Study approach allows for examining how such events influence the stock returns of affected firms around the time of the announcement. The following sections detail the steps followed in implementing this methodology.

4.1. Sample Selection and Preparation

4.1.1. Data Collection

The selection of companies for the analysis was guided by the Q2 2025 exclusion list of Storebrand Asset Management, a leading Norwegian investment manager renowned for its strict ESG criteria and exclusion policies. Storebrand's exclusion list identifies companies involved in industries or practices deemed unsustainable or unethical, including firms in the alcohol and tobacco sectors (Storebrand Asset Management, 2025). From this list, only companies with operations at an international level (as opposed to purely local businesses) and whose primary business is the production or sale of alcohol or tobacco were chosen. This filtering ensures that the companies in the sample are truly representative of the global universe of major alcohol and tobacco firms. Applying these criteria yielded a final sample of 32 companies, comprising 7 tobacco companies and 25 alcohol companies. For each of these 32 firms, historical daily stock price data were collected through the FactSet financial database (FactSet, 2026).

In addition to the company data, a broad market index was selected to serve as both a benchmark for the classic Event Study methodology and as a control group for the panel Event Study. For this purpose, the S&P Global 1200 Industrials index was used. This index is a stock market index that aggregates the performance of leading industrial-sector companies worldwide, within the broader S&P Global 1200 universe of global large-cap stocks (S&P Dow Jones Indices, 2026). The S&P Global 1200 Industrials index provides a diversified international benchmark, and its inclusion allows the analysis to account for general market movements unrelated to the specific events. The daily price history of the S&P Global 1200

Industrials index was also obtained from FactSet (FactSet, 2026). Table 1 provides a summary of the companies selected for the sample, as well as the S&P 1200 Industrials index.

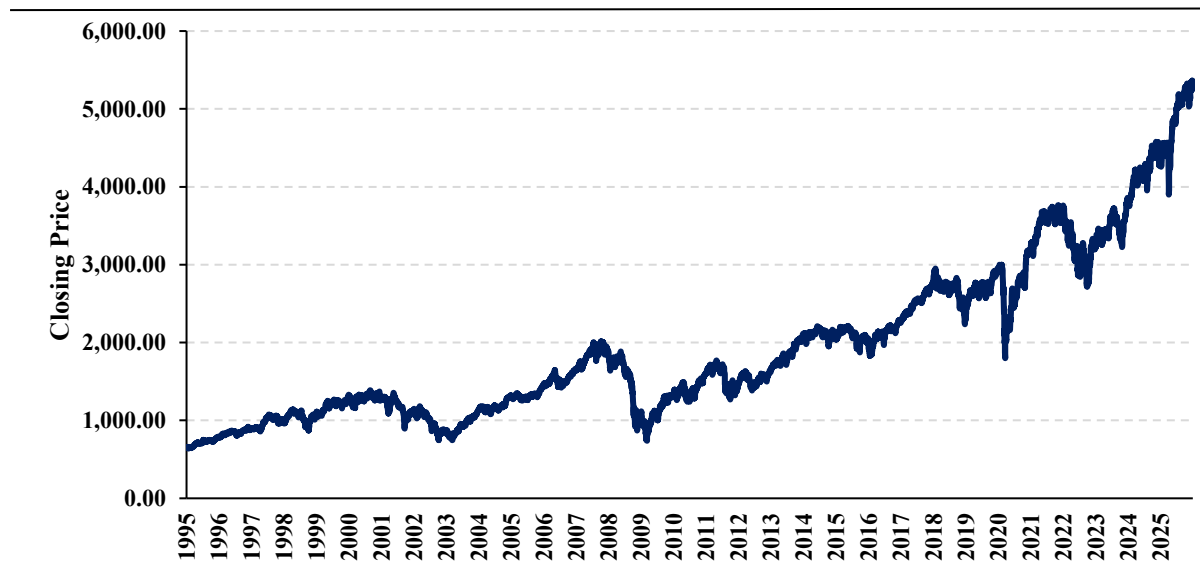


Figure 5. Daily Closing Price of the S&P 1200 Industrials Index, 1995–2025 (Source: FactSet; Own elaboration)

Furthermore, a risk-free rate series was gathered for use in the classical Event Study calculations (specifically for computing expected returns and abnormal returns under the market model approach). For simplicity and consistency across an international sample, the chosen proxy for the risk-free rate was the U.S. 1-Year Treasury Bill yield. The U.S. 1-Year T-Bill rate is used as a global risk-free benchmark due to the widespread acceptance of U.S. Treasury bills as a risk-free asset and the strong presence of U.S.-based firms in the S&P Global 1200 index. Furthermore, this choice of risk-free rate aligns with practices in prior research, such as Grimme (2023), which states, “the risk-free rate is the 1-year government bond yield of the respective country” (p. 147). The daily yield data for the 1-Year T-Bill (expressed as a percentage yield) was retrieved from the financial platform Investing.com (Investing.com, n.d.).

4.1.2. Sample Preparation

After collecting the necessary price data, the next step was to prepare the data for analysis. First, the historical daily prices of each of the 32 sample companies and the S&P Global 1200 Industrials index were compiled and converted into daily returns. Specifically, for each trading day, the daily logarithmic return was calculated using the price data. This was done to

normalize the return distributions and to ensure additive properties over time. These return calculations were performed using Microsoft Excel for accuracy and consistency across all series, using the following formula for each day and each company:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right)$$

where R_t is the logarithmic return of the company on day t , P_t is the company's stock price on day t , and P_{t-1} is the company's stock price on the previous day.

The 1-Year T-Bill risk-free rate series was then integrated into the dataset. Since the T-Bill data was already in the form of a daily yield (which can be interpreted as a daily return on a risk-free asset), it was added directly without further transformation.

Lastly, for both Event Study methodologies (MacKinlay's and Panel), each date was re-indexed relative to the event date for the corresponding company. In practice, this means that for each firm, the event date is labelled as day 0, the days before the event are labelled with negative indices (-1 for one trading day before the event, -2 for two days before, and so on), and the days after the event are labelled with positive indices (+1 for the first day after, +2 for the second day after, etc.). This re-indexing allows the returns of all companies to be analysed in a common event-time framework, even though the actual calendar dates of events differ by company. (For the full list of the companies included in the sample and a brief description of each, see **Annex 1**)

In addition to the returns' dataset, an event list was prepared to identify the event date for each entity in the sample. This event list is a simple two-column table containing the entity identifier (company ticker or index name) and the corresponding event date for that entity. There are 33 entries in this event list: one for each of the 32 companies and one for the control group index. This list is used in both the MacKinlay and panel Event Study analyses to ensure that each company's returns are aligned correctly with its specific event date in the calculations. Each company in the sample has one unique event associated with it. These events were chosen to be highly relevant regulatory or public health announcements that could reasonably be expected to impact the company's valuation. For example, a new law, regulation, or government health policy targeting alcohol or tobacco that directly affects a given firm's business. Because the sample includes companies from different countries, the chosen event

for each firm is specific to that firm's context (for instance, a regulatory change in the United States for an American tobacco company, which might not affect a brewery in Europe or Asia, and vice versa). The events were identified through reports in reputable financial news outlets such as Reuters, *the Financial Times*, CNBC, and Bloomberg, among others. Table 1 provides a summary of the sample, including the event date corresponding to each entity.

Table 1. Overview of Sample Companies and the S&P 1200 Industrials Index (Own elaboration)

Company Name	Ticker	Country	Sector	Data Start Date	Event Date
Altria Group	MO	USA	Tobacco	4 Jan. 2010	28 Jul. 2017
Anheuser-Busch InBev SA/NV	ABI	Belgium	Alcohol	4 Jan. 2010	3 Jan. 2025
Anhui Gujing Distillery Co Ltd	000596	China	Alcohol	4 Jan. 2010	29 Oct. 2018
Anhui Yingjia Distillery Co Ltd	603198	China	Alcohol	28 May. 2015	18 Oct. 2021
Asahi Group Holdings Ltd	2502	Japan	Alcohol	4 Jan. 2010	6 Jan. 2025
Beijing Yanjing Brewery	000729	China	Alcohol	4 Jan. 2010	21 Nov. 2022
British American Tobacco Plc	BATS	UK	Tobacco	4 Jan. 2010	28 Jul. 2017
Brown-Forman Corp	BF.B	USA	Alcohol	4 Jan. 2010	12 Mar. 2025
Carlsberg AS	CARL-B	Denmark	Alcohol	4 Jan. 2010	17 Aug. 2011
China Resources Beer Holdings Co Ltd	291	China	Alcohol	4 Jan. 2010	29 Oct. 2018
Constellation Brands Inc	STZ	USA	Alcohol	4 Jan. 2010	2 Sep. 2025
Davide Campari-Milano	CPR	Italy	Alcohol	4 Jan. 2010	3 Jan. 2025
Diageo plc	DGE	UK	Alcohol	4 Jan. 2010	3 Jan. 2025
Endeavour Group Ltd	EDV	Australia	Alcohol	24 Jun. 2021	17 Jul. 2023
Heineken NV	HEIA	Netherlands	Alcohol	4 Jan. 2010	28 Jul. 2025
Imperial Brands	IMB	UK	Tobacco	4 Jan. 2010	26 Sep. 2019
Japan Tobacco	2914	Japan	Tobacco	4 Jan. 2010	4 Dec. 2012
Jiangsu King's Luck Brewery Ltd	603369	China	Alcohol	3 Jul. 2014	20 Aug. 2021
Jiangsu Yanghe Brewery JSC Ltd	002304	China	Alcohol	4 Jan. 2010	10 Oct. 2018
Kirin Holdings Co Ltd	2503	Japan	Alcohol	4 Jan. 2010	6 Jan. 2025
KT&G Corp.	033780	S. Korea	Tobacco	4 Jan. 2010	11 Sep. 2014
Kweichow Moutai Co Ltd	600519	China	Alcohol	4 Jan. 2010	27 Mar. 2012
Luzhou Laojiao Co Ltd	000568	China	Alcohol	4 Jan. 2010	20 Aug. 2021
Molson Coors Beverage	TAP	USA	Alcohol	4 Jan. 2010	3 Jan. 2025
Pernod Ricard SA	RI	France	Alcohol	4 Jan. 2010	7 Feb. 2025
Philip Morris International	PM	USA	Tobacco	4 Jan. 2010	29 Apr. 2022
Royal Unibrew A/S	RBREW	Denmark	Alcohol	4 Jan. 2010	14 Nov. 2025
Smoore International Holdings	6969	Hong Kong	Tobacco	10 Jul. 2020	22 Mar. 2021
Treasury Wine Estates	TWE	Australia	Alcohol	11 May 2011	27 Nov. 2020
Tsingtao Brewery Co Ltd	168	China	Alcohol	4 Jan. 2010	10 Oct. 2022
United Spirits Ltd	532432	India	Alcohol	4 Jan. 2010	03 Apr. 2017
Wuliangye Yibin Co Ltd	000858	China	Alcohol	4 Jan. 2010	19 Aug. 2021
S&P 1200 Industrials	N/A	N/A	N/A	4 Jan. 2010	N/A

4.2. Implementation of the Event Study

Before implementing the traditional Event Study methodology (as per MacKinlay) (MacKinlay, 1997), it is necessary to define two key horizons: an estimation window and an event window. In our case, we choose an estimation window from $t = -150$ to $t = -50$ relative to the event date (where $t = 0$ denotes the event day). This setup ensures that the estimation period is sufficiently long to yield reliable parameters but does not include the event or any days immediately around it, preventing contamination of the normal return estimation by the event itself. Indeed, leaving a gap between the estimation window's end ($t = -50$) and the start of the event window analysis (the earliest event window begins at $t = -5$) is recommended in order to avoid any influence of the event on the parameter estimates. The 100-trading-day length of our estimation window (approximately five months) is in line with common practice (e.g. ~ 120 days is often used), balancing the trade-off noted by Brooks (2014) that longer estimation windows improve precision but risk including structural breaks.

Instead of using a single event window, we consider three event windows of different lengths: $[-1,0]$, $[-3,+3]$, and $[-5,+5]$. This multi-window approach allows us to observe how the results change across various horizons and thus determine whether the event's impact is immediate, progressive, or persistent. The shortest window $[-1,0]$ focuses on the immediate effect of the event (capturing the event day and the day before, to account for any slight anticipatory price movement). The intermediate window $[-3,+3]$ captures a moderate horizon, since it includes a few days before and after the event, which can reveal information leakage or a gradual price adjustment in the days surrounding the event. Finally, the longest window $[-5,+5]$ covers an extended period to check for any persistent or lingering effects beyond the immediate aftermath of the event. In essence, a very narrow window like $[-1,0]$ isolates the event-day impact most cleanly, whereas a broader window like $[-5,+5]$ provides insight into market efficiency by showing whether abnormal returns appear or continue outside the immediate event day. By comparing these three event windows, we can assess if the market reaction is largely concentrated on the event day (immediate), unfolds gradually over several days (progressive), or if the impact remains detectable over a longer period (persistent).

To model expected returns during the estimation window, we employ the CAPM. Specifically, for each company i , we regress its stock returns on the market return over the estimation window in order to estimate the firm-specific intercept (α_i) and slope (β_i) coefficients. These parameters are then used to compute the expected returns during the event window. In this model, we use the S&P Global 1200 Industrials index as the proxy for the market, and the one-year U.S. T-bill rate as the risk-free rate.

Using the estimated parameters, we next project the expected returns for each stock over the event window ($t = -5$ to $+5$). For each day t in the event window, the expected return is given by $E(R_{it}) = \hat{\alpha}_i + \hat{\beta}_i R_{m,t}$. We then calculate the abnormal return (AR) for each firm i on each event-day t .

We implemented the above computations in Python (see [Annex 2](#) for the code). The script compiled daily AR values for each of the 32 companies across the 11-day event window. The output was a three-column table: the first column contains the company's ticker, the second shows the time-to-event for all dates available, and the third reports the AR for each company at each time to event. From these, we then computed the cumulative abnormal returns (CAR) for each company over the full event window.

As explained in section 2.4., the CAR condenses the total impact of the event on stock i over the entire window into a single number. For example, a CAR of 5% means the stock earned +5% cumulatively above expectation during the days surrounding the event. After computing CARs for all firms, we obtained a distribution of 32 CAR values (one per company/event).

Finally, to assess whether the event had a statistically significant impact on the sample as a whole, we conduct a hypothesis test on the abnormal performance. The null hypothesis H_0 is that the events have no effect on stock returns, implying that the expected abnormal return is zero (and hence expected CAR is zero as well) (Brooks, 2014). Under H_0 , any non-zero CAR is due to chance. As explained in section 2.4., we follow the approach in Brooks (2014) to calculate the standardized cumulative abnormal return (SCAR) statistic for the event window. This is essentially a t -statistic that compares the sample average CAR to zero, standardized by the cross-sectional variability of CARs.

Intuitively, SCAR tells us how many standard deviations away from zero the average cumulative abnormal return is. Under the null of no event impact, SCAR should be approximately standard normal $N(0,1)$. We therefore obtain a p-value associated with the observed SCAR, indicating the probability of seeing an average CAR as extreme as ours if H_0 were true. By comparing this p-value to conventional significance levels (e.g. 5% or 1%), we can determine whether to reject the null hypothesis and conclude that the event had a statistically significant effect on stock prices. In sum, this traditional Event Study methodology allows us to rigorously test if the events in question led to abnormal stock returns that deviate from expected performance in a statistically significant manner.

Regarding the panel Event Study methodology, the approach used is the one described in Section 2.4.2 of this thesis, where the panel data methodology is presented following Clarke and Tapia (2020).

5. Results

5.1. Results of the Traditional Event Study Methodology

After preparing and modifying the datasets and establishing the estimation window and event windows as described in the methodology (see Section 4), we applied the traditional Event Study approach of MacKinlay (1997) to our data using a Python script (see [Annex 2](#) for the full code). The results obtained from this procedure (using the three different event windows defined above) are presented below. Note that we will analyze the evolution of AR, SAR, CAR, and SCAR throughout the event window in order to determine the impact of the events on the companies' stock prices. Furthermore, the SCAR for the different cases corresponding to various event window lengths will be analysed to compute a p-value in order to conduct a statistical significance test on the effect of the events on stock prices.

As illustrated in Figure 6, abnormal returns exhibit a pronounced negative reaction on the event day, following a relatively stable pattern beforehand. In parallel, the cumulative abnormal returns show a clear and sharp decline at the time of the event and remain at lower levels in the subsequent days without a noticeable rebound. Overall, the visual pattern suggests a persistent negative market response around the event window, consistent with an adverse impact on the valuation of firms in the alcohol and tobacco sector following the introduction of the related health regulations and disclosures.

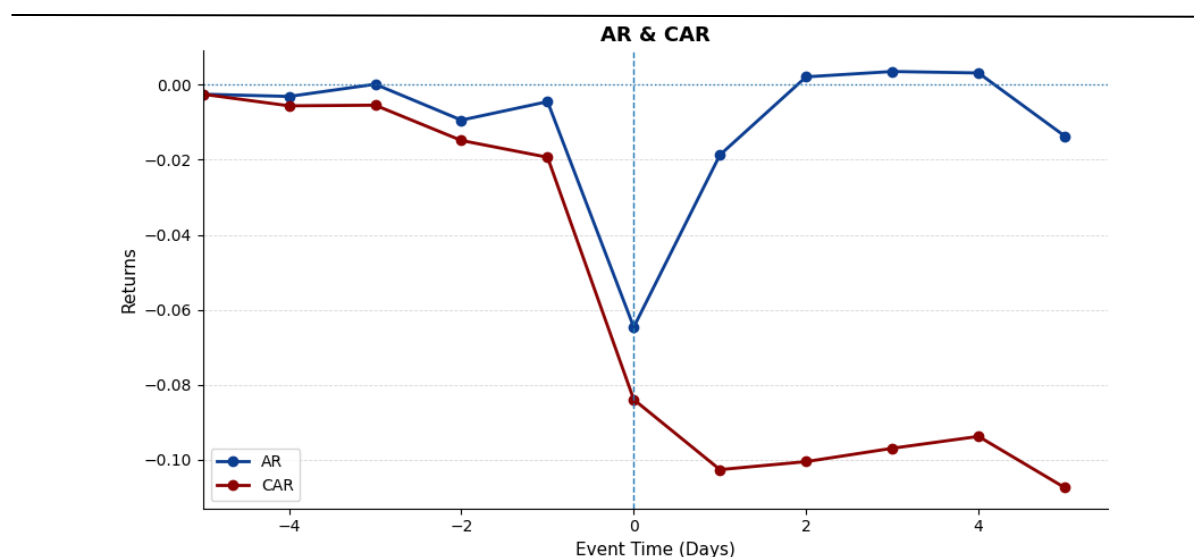


Figure 6. Traditional Methodology: AR & CAR, Event Window [-5,+5] (Own elaboration)

Furthermore, regarding the statistical significance test, for the event window $[-1,0]$, the average CAR per company by the event day ($t = 0$) is around -7% . The corresponding SCAR is -11.88 , which yields a p-value effectively equal to 0 (i.e. much smaller than a 1% significance level). This indicates that, on average, companies experienced a sharply negative abnormal return on the event day (relative to the prediction from the estimation period), with a test statistic so extreme that the result is statistically significant at the highest confidence levels.

With an event window of $[-3,+3]$, the average CAR per company at the end of this window ($t = +3$) is -8.01% . The SCAR for the $[-3,+3]$ period is -7.98 , which is somewhat less extreme than the SCAR for the $[-1,0]$ window but still yields a p-value practically **equal to 0** (well below a 1% significance threshold). Figure 6 illustrates the average CAR per company for each day relative to the event in the $[-3,+3]$ window, showing how abnormal returns evolve from 3 days before the event to 3 days after. Notably, the negative impact is evident, and the inclusion of a few days around the event still results in a strongly significant cumulative effect.

Finally, for the broader event window $[-5,+5]$, the average CAR per company by the end of the window ($t = +5$) is -8.79% . The SCAR over this longer window is -6.98 . These values are very similar to those observed for the $[-3,+3]$ window, though both the CAR and SCAR are slightly less negative in magnitude than those in the shortest window $[-1,0]$. Nonetheless, this SCAR still corresponds to a p-value essentially equal to 0, again far below a 1% significance level. Figure 6 shows the average CAR per company for each period within the $[-5,+5]$ window, depicting the trend of cumulative abnormal returns from 5 days before the event to 5 days after. In summary, across all three event windows, we find a pronounced negative abnormal return around the event date, with test statistics indicating a highly significant impact under each window length. (The detailed numerical results per company for the $[-5,+5]$ event window are summarized in Table 2). As shown in the Figure 7, SAR displays a marked negative reaction on the event day and at the same time, SCAR experience a sharp decline at the moment of the event and remain at depressed levels in the following days, without showing a clear recovery. Overall, the pattern suggests a sustained negative response around the event window that is statistically significant.

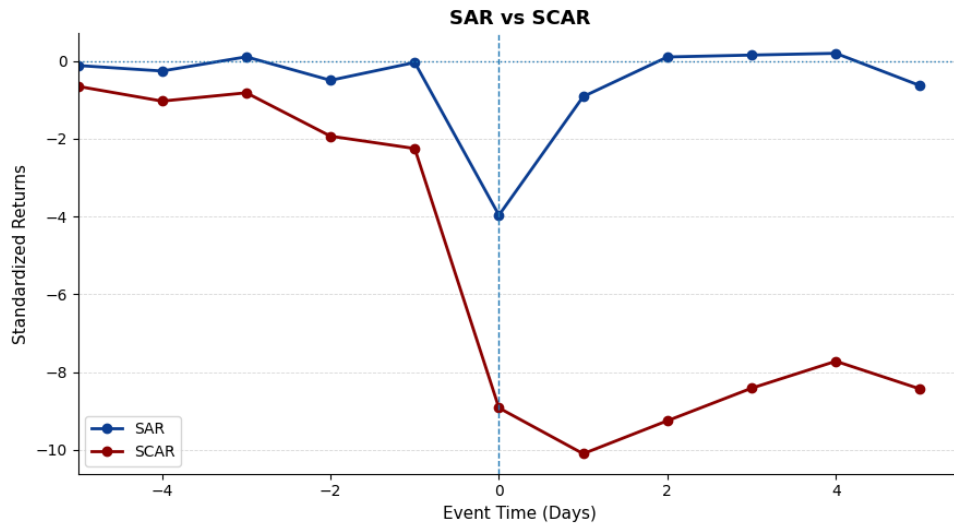


Figure 7. Traditional Methodology: SAR & SCAR, Event Window [-5,+5] (Own elaboration)

Table 2. Firm-Level Event Study Results, Event Window [-5,+5] (Own elaboration)

Company Ticker	$\sigma^2(\text{AR})$	CAR	$\sigma^2(\text{CAR})$
000568	0.001399	-0.100997	0.015393
000596	0.000955	-0.190238	0.010507
000729	0.000578	-0.199543	0.006353
000858	0.000850	-0.172194	0.009353
002304	0.000621	-0.047513	0.006832
033780	0.000183	-0.037321	0.002009
168	0.000932	-0.049853	0.010257
2502	0.000339	-0.082599	0.003725
2503	0.000139	-0.074671	0.001528
291	0.000510	0.044943	0.005615
2914	0.000343	-0.031966	0.003770
532432	0.000374	-0.161152	0.004114
600519	0.000295	-0.038035	0.003245
603198	0.001526	-0.033478	0.016790
603369	0.000769	-0.036230	0.008454
6969	0.001089	-0.316685	0.011983
ABI	0.000125	-0.078023	0.001379
BATS	0.000076	-0.065381	0.000837
BF.B	0.000318	0.074343	0.003499
CARL-B	0.000108	-0.251694	0.001185
CPR	0.000348	-0.072488	0.003827
DGE	0.000150	-0.047093	0.001645
EDV	0.000158	-0.029817	0.001743
HEIA	0.000342	-0.154597	0.003757
IMB	0.000260	-0.141361	0.002863
MO	0.000035	-0.109426	0.000390
PM	0.000109	-0.063855	0.001202
RBREW	0.000139	0.059425	0.001524
RI	0.000233	-0.084654	0.002562
STZ	0.000239	-0.112230	0.002634
TAP	0.000184	-0.136585	0.002025
TWE	0.001016	-0.070409	0.011178

5.2. Results of the Panel Event Study Methodology

As evidenced in Figure 8, the Panel Event Study results indicate that the regulatory announcements included in the sample are associated with a statistically significant effect on the stock prices of alcohol and tobacco companies at the time the event occurs. The clearest result appears at $t = 0$, which corresponds to the event date itself. At this point, the estimated coefficient is negative and highly statistically significant, while the t-statistic is extremely large in absolute value and the p-value is effectively zero. This combination provides strong evidence against the null hypothesis that these events have no impact on firm valuation. In statistical terms, such a low p-value implies that observing a result of this magnitude under the assumption of no true effect would be extraordinarily unlikely. Therefore, the null hypothesis that the events have no effect on market returns can be rejected at conventional significance levels, and the evidence supports the existence of a negative market reaction on the event day.

PanelOLS Estimation Summary						
Dep. Variable:	Metric	R-squared:	0.1487			
Estimator:	PanelOLS	R-squared (Between):	0.4422			
No. Observations:	4428	R-squared (Within):	0.1411			
Date:	Sun, Mar 08 2026	R-squared (Overall):	0.1487			
Time:	19:12:16	Log-likelihood	1.272e+04			
Cov. Estimator:	Robust	F-statistic:	77.150			
Entities:	33	P-value	0.0000			
Avg Obs:	134.18	Distribution:	F(10,4418)			
Min Obs:	10.0000					
Max Obs:	3986.0	F-statistic (robust):	8.5266			
		P-value	0.0000			
Time periods:	4004	Distribution:	F(10,4418)			
Avg Obs:	1.1059					
Min Obs:	1.0000					
Max Obs:	7.0000					

Parameter Estimates						
	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
-5.0	0.0034	0.0025	1.3472	0.1780	-0.0016	0.0084
-4.0	-0.0023	0.0030	-0.7709	0.4408	-0.0081	0.0035
-3.0	-0.0067	0.0047	-1.4239	0.1545	-0.0158	0.0025
-2.0	-0.0090	0.0072	-1.2490	0.2117	-0.0232	0.0051
0.0	-0.0625	0.0074	-8.4648	0.0000	-0.0770	-0.0480
1.0	-0.0255	0.0170	-1.5018	0.1332	-0.0587	0.0078
2.0	0.0038	0.0052	0.7303	0.4653	-0.0064	0.0141
3.0	-0.0020	0.0058	-0.3516	0.7252	-0.0135	0.0094
4.0	0.0112	0.0051	2.1656	0.0304	0.0011	0.0212
5.0	-0.0003	0.0023	-0.1194	0.9050	-0.0047	0.0042

Figure 8. Panel Event Study Results (Own elaboration)

Furthermore, the negative value of the coefficient at $t = 0$ indicates that, on average, these announcements are associated with a decline in stock market performance for the firms in the sample. This suggests that investors interpret this type of news as unfavourable for the expected profitability or future outlook of alcohol and tobacco companies. The immediate negative response is consistent with the idea that the market rapidly incorporates new information when announcements related to regulation, health warnings, or similar restrictions become public.

Figure 9 displays the abnormal returns (AR) estimated across the event window, together with their confidence intervals. The dots represent the point estimates at each t , while the shaded area corresponds to the confidence interval, allowing for a visual assessment of statistical significance. It can be observed that at $t = 0$, corresponding to the event day, the estimated effect is clearly negative and its confidence interval does not include zero, confirming its statistical significance (consistent with the nearly zero p-value obtained). In contrast, for the remaining periods, both before and after the event, although the point estimates may be positive or negative, their confidence intervals do include zero, indicating that these effects are not statistically significant. This pattern is typical in panel Event Study methodologies, where the impact is concentrated at the time of the event and dissipates in surrounding periods. The graphical representation is particularly useful, as it provides an immediate overview of the magnitude, direction, and precision of the estimates, thereby facilitating a more comprehensive assessment of the robustness of the results.

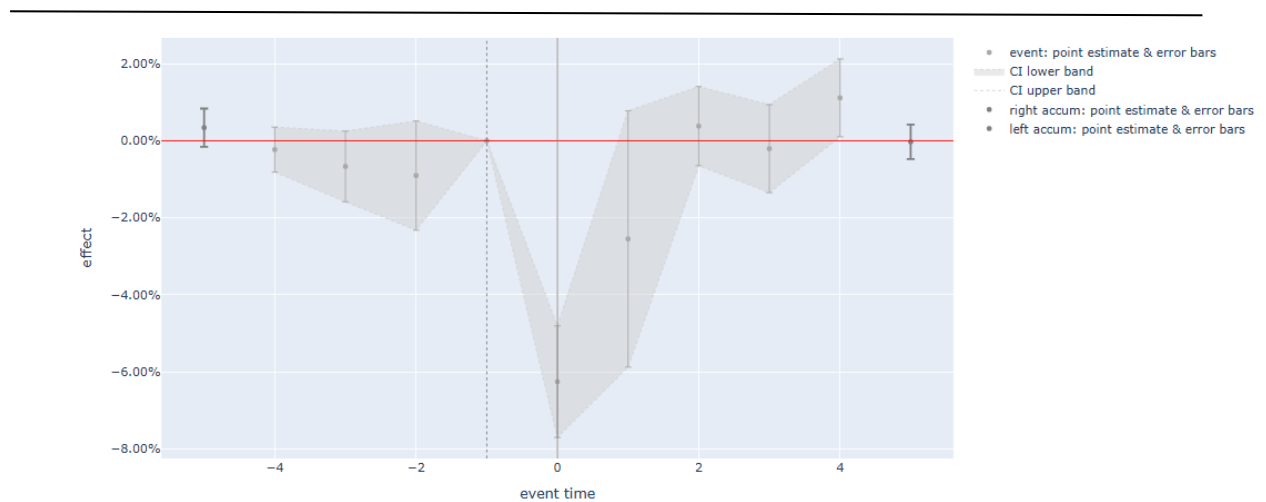


Figure 9. Panel Methodology: AR, Event Window [-5,+5] (Own elaboration)

Following the analysis of abnormal returns, Figure 10 also presents the CAR over the event window within the panel framework. The graph shows how the effects accumulate over time, providing a clearer picture of the overall impact of the event. Consistent with the AR results, the CAR exhibits a pronounced drop around $t = 0$, reflecting the significant negative effect observed on the event day. Beyond this point, the trajectory of the CAR tends to stabilize, suggesting that there is no strong evidence of persistent or additional cumulative effects after

the initial impact. Overall, this pattern reinforces the conclusion that the market reaction is concentrated at the time of the event and does not generate prolonged abnormal performance.

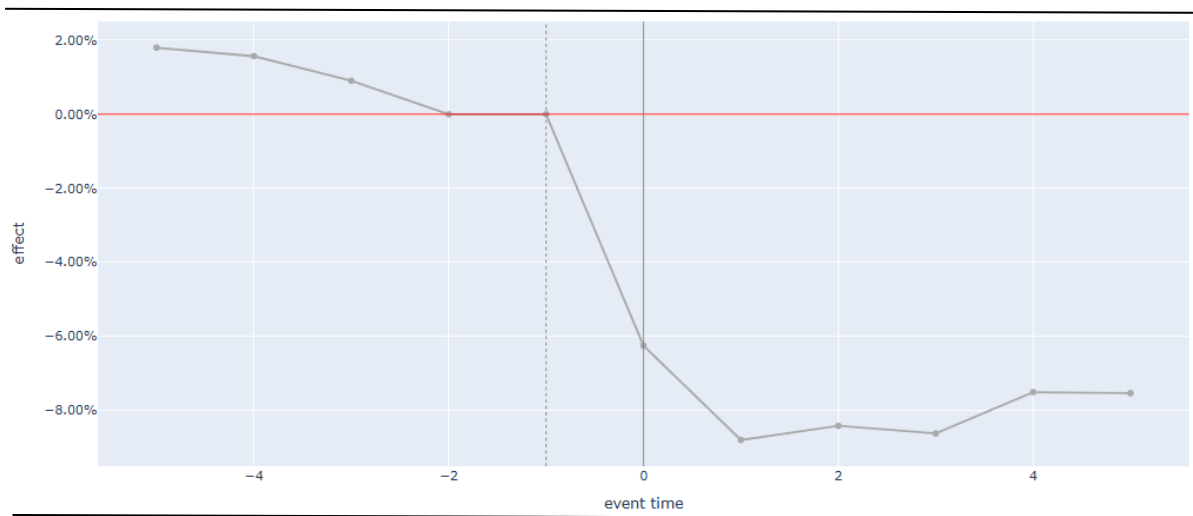


Figure 10. Panel Methodology: CAR, Event Window [-5,+5] (Own elaboration)

6. Conclusions

The findings of this study indicate that announcements related to regulations, health warnings, and similar policy measures affecting the alcohol and tobacco industries are associated with a negative and statistically significant impact on the stock prices of firms operating in these sectors. This result is supported by both empirical approaches applied in the study (Traditional and Panel Event Study methodologies). The fact that both methods lead to a consistent interpretation strengthens the overall robustness of the evidence and suggests that these events are perceived by the market as adverse news for alcohol and tobacco companies. In both cases, the results point in the same direction: regulatory and health-related announcements tend to reduce firm value, at least in the short term, by negatively affecting investor expectations. As discussed in the thesis, this pattern is also consistent with prior literature (Ince, 2024; Vasileiou et al., 2025; Wagenaar et al., 2009).

An important aspect of the results is that the effect appears to be concentrated on the event day itself. The strongest and clearest reaction is observed at the moment when the announcement becomes public, while no statistically significant effects are generally found in the days before or after the event. This pattern suggests that the market reaction is immediate rather than gradual. The absence of significant effects in the pre-event period indicates that there is no clear evidence of systematic information leakage or anticipation by investors before the announcement date. At the same time, the lack of persistent effects in the post-event period suggests that the market incorporates the information rapidly, without a delayed adjustment process. Taken together, these results are consistent with a relatively efficient market response, in which new public information is quickly reflected in stock prices (Fama, 1970).

These findings have several relevant implications: for investors who are actively exposed to alcohol and tobacco companies, the results highlight the importance of regulatory risk as a relevant source of short-term market volatility. In practical terms, investors in these industries must consider that unexpected announcements concerning new restrictions, health warnings, taxation changes, or similar measures may generate an immediate negative reaction in stock prices, which means that there is a clear event-driven regulatory downside risk that may affect portfolio performance. For investors who choose to exclude alcohol and tobacco firms from their portfolios, avoiding these sectors not only responds to ethical, social, or sustainability considerations, but may also reduce exposure to specific regulatory downside risks affecting firm valuation. In that sense, the exclusion of alcohol and tobacco stocks may reduce exposure

to adverse price reactions associated with sudden policy announcements. However, it is also important to consider that such screening narrows the investment universe, potentially limiting diversification benefits. Finally, the findings are relevant for policymakers and regulators, since they suggest that the market clearly interprets regulatory announcements and health-related policy measures as economically meaningful events for alcohol and tobacco companies. This means that such measures do not remain merely at the level of public debate or social signalling but instead have observable financial consequences for the firms concerned.

This dissertation is not without limitations. First, the sample is restricted to a specific set of events and firms, which may limit the generalizability of the results across periods, countries, or regulatory contexts. Second, although both Event Study methodologies provide consistent evidence, event studies are designed to identify short-term market reactions and do not capture longer-term effects on firm performance or investor behaviour. Third, different regulatory announcements may vary in intensity, credibility, and expected economic impact, while the present analysis necessarily groups together a range of related events under a broader common framework. Future research could therefore extend the sample to a larger set of firms and jurisdictions, distinguish more explicitly between different types of regulatory and health-related announcements, and analyse whether the magnitude of the market reaction varies depending on firm characteristics such as size, leverage, geographic exposure, or product diversification. It would also be useful to explore longer-term effects beyond the immediate event window, in order to determine whether the negative impact observed at the announcement stage is temporary or whether it leads to more persistent valuation consequences over time.

7. Statement of Use of Generative AI Tools


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

Por la presente, yo, Ignacio Ruesta Llorente, estudiante de ADE y Business Analytics (E-2 + Analytics) de la Universidad Pontificia Comillas al presentar mi Trabajo Fin de Grado titulado “*Do health warnings and regulations matter? an Event Study on the stock market impact of regulatory announcements in the alcohol and tobacco sectors*”, declaro que he utilizado la herramienta de Inteligencia Artificial Generativa ChatGPT u otras similares de IAG de código sólo en el contexto de las actividades descritas a continuación:

1. **Referencias:** Usado conjuntamente con otras herramientas, como Science, para identificar referencias preliminares que luego he contrastado y validado.
2. **Interpretador de código:** Para realizar análisis de datos preliminares.
3. **Corrector de estilo literario y de lenguaje:** Para mejorar la calidad lingüística y estilística del texto.
4. **Sintetizador y divulgador de libros complicados:** Para resumir y comprender literatura compleja.
5. **Traductor:** Para traducir textos de un lenguaje a otro.

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

Fecha: 18/04/2026

Firma: 

Ignacio Ruesta Llorente

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9. Annexes

Annex 1 – Company Descriptions

- **Altria Group (MO)** – U.S. tobacco company best known for cigarettes and smoke-free nicotine products.
- **Anheuser-Busch InBev SA/NV (ABI)** – World’s largest brewer, producing global beer brands like Budweiser and Stella Artois.
- **Anhui Gujing Distillery Co Ltd (000596)** – Chinese producer of traditional baijiu spirits.
- **Anhui Yingjia Distillery Co Ltd (603198)** – Chinese baijiu distiller focused on regional premium spirits.
- **Asahi Group Holdings Ltd (2502)** – Japanese beverage group producing beer, soft drinks, and food products.
- **Beijing Yanjing Brewery (000729)** – Chinese state-linked brewery known for Yanjing Beer.
- **British American Tobacco Plc (BATS)** – Global tobacco company producing cigarettes, vaping and nicotine products.
- **Brown-Forman Corp (BF.B)** – U.S. spirits company famous for Jack Daniel’s and other premium liquor brands.
- **Carlsberg AS (CARL-B)** – Danish multinational brewer with large European and Asian operations.
- **China Resources Beer Holdings Co Ltd (291)** – Major Chinese brewery, owner of the Snow Beer brand.
- **Constellation Brands Inc (STZ)** – U.S. producer of beer, wine, and spirits, including Corona (U.S. rights).
- **Davide Campari-Milano (CPR)** – Italian spirits company behind Campari, Aperol, and other iconic beverages.
- **Diageo plc (DGE)** – UK-based global leader in spirits and beer, owning Johnnie Walker and Guinness.
- **Endeavour Group Ltd (EDV)** – Australian retailer and operator of liquor stores, pubs, and beverage services.

- **Heineken NV (HEIA)** – Dutch multinational brewing company known for Heineken and over 300 local brands.
- **Imperial Brands (IMB)** – UK tobacco company producing cigarettes, rolling tobacco, and vaping products.
- **Japan Tobacco (2914)** – Japanese tobacco and food conglomerate selling cigarettes and reduced-risk products.
- **Jiangsu King's Luck Brewery Ltd (603369)** – Chinese baijiu producer focused on premium and mid-range spirits.
- **Jiangsu Yanghe Brewery JSC Ltd (002304)** – Leading Chinese baijiu distiller with strong national presence.
- **Kirin Holdings Co Ltd (2503)** – Japanese beverage and food company producing beer, soft drinks, and biotech products.
- **KT&G Corp. (033780)** – South Korean tobacco company manufacturing cigarettes and ginseng products.
- **Kweichow Moutai Co Ltd (600519)** – China's most valuable distiller, producing the premium Moutai baijiu.
- **Luzhou Laojiao Co Ltd (000568)** – One of China's oldest baijiu distilleries, specializing in strong-aroma spirits.
- **Molson Coors Beverage (TAP)** – North American brewer producing brands like Coors, Miller, and Blue Moon.
- **Pernod Ricard SA (RI)** – French multinational spirits group behind Absolut, Chivas, and Jameson.
- **Philip Morris International (PM)** – Global tobacco company focused on smoke-free products like IQOS.
- **Royal Unibrew A/S (RBREW)** – Danish beverage company producing beer, soft drinks, and malt beverages.
- **Smoores International Holdings (6969)** – Chinese manufacturer of vaping devices and e-cigarette technology.
- **Tsingtao Brewery Co Ltd (168)** – One of China's largest breweries, known for Tsingtao Beer.
- **Treasury Wine Estates (TWE)** – Australian wine company producing Penfolds and other global wine brands.
- **United Spirits Ltd (532432)** – India's largest spirits producer.

- **Wuliangye Yibin Co Ltd (000858)** – Chinese premium baijiu distiller famous for Wuliangye spirits.

Annex 2 - Python Script: MacKinlay Event Study

1. Installation of required libraries and packages

```
# Package installation
!pip install linearmodels

# Import of necessary libraries and packages
from linearmodels import PanelOLS as PanelRegression
from linearmodels import OLS as CrossSectionOLS
import numpy as np
import pandas as pd
import plotly.graph_objects as go
import plotly.express as px
from scipy.stats import norm
import matplotlib.pyplot as plt
```

2. Importation of the databases

```
# Load daily return data for firms, control group and risk-free rate
returns_long = pd.read_excel('/content/Logarithm Returns - Event Study MacKinlay.xlsx')

# The dataset is initially structured in long format
returns_long

# Load the event-date information associated with each firm
# Entity "SGBXX003" has no event date because it represents the control group
event_calendar = pd.read_excel('/content/Event dates - Event Study.xlsx')

event_calendar
```

3. Data adaptation and handling

```
# Convert daily returns from long to wide format
# If a firm does not trade on a given date, its return is set to 0

returns_wide = (returns_long.pivot(index="Date", columns="Entity",
values="Metric").fillna(0))

# Create a sequential trading-day index (1, 2, 3, ...)
returns_wide["Day"] = np.arange(1, len(returns_wide) + 1)

# Build a mapping between calendar dates and event-study day numbers
date_day_map = (returns_wide.reset_index().loc[:, ["Date", "Day"]])
```

```

# Drop the Date column and set Day as the index of the returns matrix
returns_wide = (returns_wide.reset_index(drop=True).set_index("Day"))

returns_wide.head()
event_calendar.head()

# Replace event dates with their corresponding day index on the "event_calendar" dataframe
# This allows both datasets to be aligned using the Day variable

event_calendar = (
    event_calendar
        .merge(
            date_day_map,
            left_on="EventDate",
            right_on="Date",
            how="left"
        )
        .drop(columns=["EventDate", "Date"])
)

# Exclude the control entity (SGBXX003) from the event dataset
event_calendar = (event_calendar.loc[event_calendar["Entity"] != "SGBXX003"])

# Define the relative time interval used to construct the estimation window
estimation_start = -150
estimation_end = -50

# Define market index and risk-free rate identifiers
market_proxy = "SGBXX003"
risk_free_rate = "United States 1-Year Bond Yield"

ols_results = []

for _, event_row in event_calendar.iterrows():
    firm = event_row["Entity"]
    event_day = event_row["Day"]

    # Define the estimation window relative to the event date
    estimation_start_day = event_day + estimation_start
    estimation_end_day = event_day + estimation_end

    # Extract returns for the firm, market index, and risk-free rate
    estimation_window = (
        returns_wide.loc[
            estimation_start_day:estimation_end_day,
            [firm, market_proxy, risk_free_rate]
        ]
        .dropna()

```

```

)

# Dependent variable: firm returns
y = estimation_window[firm].to_numpy()

# Independent variable: market excess returns
x = (estimation_window[market_proxy] - estimation_window[risk_free_rate]).to_numpy()

# Design matrix: constant term and market factor
X = np.column_stack((np.ones(len(x)), x))

# Estimate alpha and beta using OLS
alpha, beta = np.linalg.lstsq(X, y, rcond=None)[0]

# Store estimated coefficients
ols_results.append(
    {"Entity": firm, "alpha": alpha, "beta": beta}
)

coefficients = pd.DataFrame(ols_results)

# Add the event-day index to the table containing alpha and beta estimates
coefficients["Day"] = event_calendar["Day"].to_numpy()

coefficients

# Daily factor: market return minus risk-free rate (Rm - Rf)
factor = returns_wide[market_proxy] - returns_wide[risk_free_rate]

ar_blocks = []

for _, c in coefficients.iterrows():
    entity = c["Entity"]
    alpha = c["alpha"]
    beta = c["beta"]

    # Abnormal return:
    #  $AR_{i,t} = R_{i,t} - \alpha - \beta \times (R_{m,t} - R_{f,t})$ 
    ar_series = returns_wide[entity] - alpha - beta * factor

# Convert to long format and attach auxiliary information
ar_blocks.append(
    pd.DataFrame({
        "Day": ar_series.index,
        "Entity": entity,
        "AR": ar_series.values,
        "alpha": alpha,
        "beta": beta,
    })
)

```

```

        "factor": factor.values
    })
)

# Combine all firm-level abnormal returns into a single long DataFrame

abnormal_returns = pd.concat(ar_blocks, ignore_index=True)
abnormal_returns

# (Entity, alpha, beta) → corresponding event day
# Add a column indicating the event day for each firm

key_to_day = (
    coefficients
    .set_index(["Entity", "alpha", "beta"])["Day"]
    .to_dict()
)

abnormal_returns["DateOfEvent"] = list(
    map(
        key_to_day.get,
        zip(
            abnormal_returns["Entity"],
            abnormal_returns["alpha"],
            abnormal_returns["beta"]
        )
    )
)

abnormal_returns

# Create a column measuring time relative to the event date
# This is computed using the Day and DateOfEvent columns
abnormal_returns["TimeToEvent"] = (
    abnormal_returns["Day"] - abnormal_returns["DateOfEvent"]
)

abnormal_returns

```

4. Table of Abnormal Returns by Company and Time to Event

```

# Create a new DataFrame containing abnormal returns by firm and time relative to the
event
# This DataFrame is built by selecting the relevant columns from abnormal_returns
AR_all = abnormal_returns[["Entity", "TimeToEvent", "AR"]].copy()

# Display the AR_all table
AR_all

```

5. Variance and Standard Deviation of AR_{it}

```
# 1) Filter the estimation window (including boundaries)
estimation_window = AR_all.loc[AR_all["TimeToEvent"].between(estimation_start,
estimation_end, inclusive="both"),["Entity", "TimeToEvent", "AR"]
].dropna(subset=["Entity", "AR"])

# 2) Brown & Warner (1980):
# var(AR_it) = sum(AR_it^2) / (T - 2) -> where AR_it are the residuals from the market
model

# Number of observations (T) per entity
T = (estimation_window.groupby("Entity")["AR"].apply(lambda x: x.notna().sum()))

# Sum of squared AR (residuals) per entity
sum_sq = (estimation_window.groupby("Entity")["AR"].apply(lambda x: (x ** 2).sum()))

# Variance following Brown & Warner (1980): sum_sq / (T - 2)
AR_variance = sum_sq / (T - 2)

# Standard deviation
AR_std_dev = np.sqrt(AR_variance)

# Final summary table (same output as your function)
Summary_table = pd.DataFrame({
    "T": T,
    "AR_variance": AR_variance,
    "AR_std_dev": AR_std_dev
}).reset_index()

Summary_table
```

6. Cumulative Abnormal Returns (CAR) by Entity

```
# 1) Define the event window
event_window_start = -5
event_window_end = 5

# 2) Filter ARs in the event window and compute CAR per firm as the sum of ARs
event_window = AR_all.loc[AR_all["TimeToEvent"].between(event_window_start,
event_window_end, inclusive="both"),["Entity", "TimeToEvent",
"AR"]].dropna(subset=["Entity", "AR"])
```

```

car_by_firm = (event_window.groupby("Entity",
as_index=False) ["AR"].sum()).rename(columns={"AR": "CAR"})

# 3) Merge CAR into Summary_table
Summary_table = Summary_table.merge(car_by_firm, on="Entity", how="left")

Summary_table

```

7. Variance and Standard Deviation of CAR_i

```

# 1) Length of the event window
L = event_window_end - event_window_start + 1

# 2) Variance and standard deviation of CAR for each firm
#  $Var(CAR_i) = Var(AR_i) * (T2 - T1 + 1)$ 
Summary_table["CAR_variance"] = Summary_table["AR_variance"] * L

# Standard deviation of CAR
Summary_table["CAR_std_dev"] = Summary_table["CAR_variance"] ** 0.5

# Store event window length for reference
Summary_table["L"] = L

Summary_table

```

8. Plot: Mean AR and CAR by company over the event window

```

# 1) Filter the event window
event_window = AR_all[
    (AR_all["TimeToEvent"] >= -5) &
    (AR_all["TimeToEvent"] <= 5)
].copy()

# 2) Compute AAR (Average Abnormal Return)
aar = (
    event_window
    .groupby("TimeToEvent") ["AR"]
    .mean()
    .sort index()
)

# 3) Compute CAR (Cumulative Average Abnormal Return)
car = aar.cumsum()

# 4) Combined plot
plt.figure(figsize=(9, 5))

```

```

# AAR line (navy blue)
plt.plot(
    aar.index,
    aar.values,
    linewidth=2,
    color="#0b3d91",    # navy blue
    marker="o",
    label="AR"
)

# CAR line (dark red)
plt.plot(
    car.index,
    car.values,
    linewidth=2,
    color="#8b0000",    # dark red
    marker="o",
    label="CAR"
)

# Reference lines
plt.axvline(0, linestyle="--", linewidth=1)
plt.axhline(0, linestyle=":", linewidth=1)

# Styling
plt.grid(axis="y", linestyle="--", linewidth=0.6, alpha=0.5)
plt.xlim(left=min(aar.index))
plt.xlabel("Event Time (Days)", fontsize=11)
plt.ylabel("Returns", fontsize=11)
plt.title("AR & CAR", fontsize=13, weight="bold")

# Legend
plt.legend()

# Remove top and right spines
plt.gca().spines["top"].set_visible(False)
plt.gca().spines["right"].set_visible(False)

plt.tight_layout()
plt.show()

```

9. SCAR (Standardized Cumulative Abnormal Return)

```

# 1) Number of firms
N = Summary_table["CAR"].notna().sum()

# 2) Mean CAR across firms (under H0: population mean = 0)
mean_CAR = Summary_table["CAR"].sum() / N

```

```
# 3) Aggregate variance term in the denominator
denominator_std = np.sqrt(Summary_table["CAR_variance"].sum() / (N ** 2))
```

```
# 4) SCAR statistic
SCAR = mean_CAR / denominator_std
```

```
SCAR
```

10. Plot: SAR and SCAR over the event window

```
# 1) Keep only firm std. dev. from Summary_table
```

```
sar_data = AR_all.merge(
    Summary_table[["Entity", "AR_std_dev"]],
    on="Entity",
    how="left"
)
```

```
# 2) Compute firm-level standardized abnormal return
```

```
sar_data["SAR"] = sar_data["AR"] / sar_data["AR_std_dev"]
```

```
# 3) Keep event window and compute SAAR_t (average across firms at each t)
```

```
saar = (
    sar_data[(sar_data["TimeToEvent"] >= -5) & (sar_data["TimeToEvent"] <= 5)]
    .groupby("TimeToEvent", as_index=False)["SAR"]
    .mean()
    .sort_values("TimeToEvent")
)
```

```
# 4) Filter ARs within the event window
```

```
ar_event_window = AR_all.loc[
    AR_all["TimeToEvent"].between(event_window_start, event_window_end, inclusive="both"),
    ["Entity", "TimeToEvent", "AR"]
].copy()
```

```
# 5) Sort and compute cumulative CAR per firm (tau = time to event)
```

```
ar_event_window = ar_event_window.sort_values(["Entity", "TimeToEvent"])
ar_event_window["CAR_tau"] = ar_event_window.groupby("Entity")["AR"].cumsum()
```

```
# 6) Add AR variance per firm from Summary table
```

```
scar_path = ar_event_window.merge(
    Summary_table[["Entity", "AR_variance"]],
    on="Entity",
    how="left"
)
```

```
# 7) Length of the cumulative sub-window up to each tau
```

```
scar_path["L_tau"] = scar_path["TimeToEvent"] - event_window_start + 1
```

```

# 8) Variance of cumulative CAR per firm and per tau
scar_path["CAR_tau_variance"] = scar_path["AR_variance"] * scar_path["L_tau"]

# 9) Aggregate by event time to construct SCAR(tau)
scar_series = (
    scar_path
    .groupby("TimeToEvent")
    .apply(lambda df: pd.Series({
        "N": df["CAR_tau"].notna().sum(),
        "mean_CAR_tau": df["CAR_tau"].mean(),
        "denominator_std_tau": np.sqrt(df["CAR_tau_variance"].sum() /
(df["CAR_tau"].notna().sum() ** 2))
    })))
    .reset_index()
    .sort_values("TimeToEvent")
)

# 10) Compute cumulative SCAR statistic for each tau
scar_series["SCAR_tau"] = scar_series["mean_CAR_tau"] / scar_series["denominator_std_tau"]

# 11) Combined plot
plt.figure(figsize=(9, 5))

# SAR line (navy blue)
plt.plot(
    saar["TimeToEvent"],
    saar["SAR"],
    linewidth=2,
    color="#0b3d91", # navy blue
    marker="o",
    label="SAR"
)

# SCAR line (dark red)
plt.plot(
    scar_series["TimeToEvent"],
    scar_series["SCAR_tau"],
    linewidth=2,
    color="#8b0000", # dark red
    marker="o",
    label="SCAR"
)

# Reference lines
plt.axvline(0, linestyle="--", linewidth=1)
plt.axhline(0, linestyle=":", linewidth=1)

```

```

# Styling
plt.grid(axis="y", linestyle="--", linewidth=0.6, alpha=0.5)
plt.xlim(left=min(saar["TimeToEvent"].min(), scar_series["TimeToEvent"].min()))
plt.xlabel("Event Time (Days)", fontsize=11)
plt.ylabel("Standardized Returns", fontsize=11)
plt.title("SAR vs SCAR", fontsize=13, weight="bold")

# Legend
plt.legend()

# Remove top and right spines
plt.gca().spines["top"].set_visible(False)
plt.gca().spines["right"].set_visible(False)

plt.tight_layout()
plt.show()

```

11. P-value

```

# Two-tailed p-value under N(0,1)
p_value_two_tailed = 2 * (1 - norm.cdf(abs(SCAR)))
print(f"SCAR = {SCAR:.6f}")
print(f"Two-tailed p-value = {p_value_two_tailed:.6f}")

```

Annex 3 – Python Script: Panel Event Study

1. Establish the necessary elements and metrics

```
!pip install linearmodels
from linearmodels import PanelOLS, OLS
import numpy as np
import pandas as pd
import plotly.express as px
import plotly.graph_objs as go

BASELINE_LAG = -1

PRE_WINDOW = -10
POST_WINDOW = +10

PRE_EVENT = -5
POST_EVENT = +5

NATURAL_DAY_DIFF = True
OLS_CONSTANT = False
OLS_FIXED_EFFECTS_ENTITY = False
OLS_FIXED_EFFECTS_TIME = False
```

2. Importation of the databases

```
DATA_FILE = '/content/Logarithm Returns - Event Study Panel.xlsx'
EVENTS_FILE = '/content/Event dates - Event Study.xlsx'
data = pd.read_excel(DATA_FILE)
data
df = data.dropna()
df[['Entity', 'Date']].groupby('Entity').agg(['min', 'max'])
events = pd.read_excel(EVENTS_FILE)
events
check_control_group = events[events['EventDate'].isna()]

if check_control_group.empty:
    print("WARNING: No control group found!")

data = pd.merge(data, events, on='Entity')
data
```

3. Calculate “time to event”

```
if NATURAL_DAY_DIFF:
    data['TimeToEvent'] = data['Date'] - data['EventDate']
```

```

data['TimeToEvent'] = data['TimeToEvent'].dt.days

else: # workdays
    # busday_count(...) requires valid dates (no NaT)
    valid_rows = data[['Date', 'EventDate']].notna().all(axis=1)
    data.loc[valid_rows, 'TimeToEvent'] = data[valid_rows].apply(lambda row:
np.busday_count(row['EventDate'].date(), row['Date'].date()), axis=1)

# retain only observations within the window (treated group) or with no event date
(control group)
data = data[ (data['TimeToEvent'].between(PRE_WINDOW, POST_WINDOW)) |
(data['TimeToEvent'].isna())].copy()

# clip time to event to the event range
data['TimeToEvent'] = data['TimeToEvent'].clip(PRE_EVENT, POST_EVENT)

# Plot the average metric by time to event
df = data[['TimeToEvent', 'Metric']].groupby('TimeToEvent').mean()
px.line(
    x=df.index,
    y=df['Metric'],
    title='Average Metric by Time to Event',
    labels={'x':'Time to Event', 'y':'Average Metric'})

# Plot the number of observations per time to event
df = data[['TimeToEvent', 'Metric']].groupby('TimeToEvent').count()
px.bar(
    x=df.index,
    y=df['Metric'],
    title='Number of Observations by Time to Event',
    labels={'x':'Time to Event', 'y':'Number of Observations'})

```

4. Prepare the OLS panel

```

dummies = pd.get_dummies(data['TimeToEvent']).astype(int)
data = data.join(dummies)
data = data.set_index(['Entity', 'Date'])
data

# Debug
x = data.reset_index().reset_index()
x.loc[x.Entity=='North America / Oil & Gas Production - Index']

```

5. Solve fixed-effects panel

```
data = data.dropna(subset=['Metric'])

dependent = data['Metric']
exog = data.drop(columns=['Metric', 'BASELINE_LAG', 'EventDate', 'TimeToEvent'])

if OLS_CONSTANT:
    # add constant?
    exog['const'] = 1.0

fe_model = PanelOLS(
    dependent,
    exog,
    time_effects=OLS_FIXED_EFFECTS_TIME,
    entity_effects=OLS_FIXED_EFFECTS_ENTITY,
    drop_absorbed=False,
    check_rank=True)

fe_result = fe_model.fit(cov_type='robust')

print(fe_result)
fe_result.estimated_effects
```

6. Plot the event

```
result = fe_result

# get confidence interval for given level
alpha = 0.05
solution = result.conf_int(level = 1 - alpha)

# calculate middle of interval (the actual values)
solution['value'] = solution.mean(axis=1)
solution.loc[BASELINE_LAG, 'value'] = 0.0
solution.loc[BASELINE_LAG, 'upper'] = 0.0
solution.loc[BASELINE_LAG, 'lower'] = 0.0

# add constant ??
if 'const' in result.params:
    #solution = solution + result.params['const']
    solution = solution.drop(index=['const'])

solution = solution.sort_index()

solution
```

```

def plotly_event_study(data, baseline, plot_ends, title, filename=None):

    fig = go.Figure()

    # Add a horizontal line at y=0 (or any other y-value you need)
    fig.add_hline(y=0, line={'dash': 'solid', 'width': 1, 'color': 'red'})
    fig.add_vline(x=0, line={'dash': 'solid', 'width': 1, 'color': 'gray'})
    if baseline != 0:
        fig.add_vline(x=baseline, line={'dash': 'dot', 'width': 1, 'color': 'gray'})

    if plot_ends:
        left_end = data.iloc[:1]
        right_end = data.iloc[-1:]
        data = data.iloc[1:-1]

    # point estimate and error bars of left accumulation
    fig.add_trace(
        go.Scatter(
            x=left_end.index, # or another column if your DataFrame has a specific column
for the x-axis
            y=left_end['value'],
            error_y=dict(
                type='data', # indicates that the values for the error bars are given
explicitly
                symmetric=False, # indicates that the error bars are not symmetric
                array=left_end['upper'] - left_end['value'],
                # specifies the length of the portion of the error bar above the value
                arrayminus=left_end['value'] - left_end['lower'],
                # specifies the length of the portion of the error bar below the value
                color='gray',
                thickness=2,
                width=4
            ),
            name='left accum: point estimate & error bars',
            marker=dict(
                color='gray',
                size=5
                # symbol='diamond'
            ),
            mode='markers') # you can change to 'lines' or 'lines+markers' if that's more
appropriate for your data
        )

    # point estimate and error bars of right accumulation
    fig.add_trace(
        go.Scatter(
            x=right_end.index, # or another column if your DataFrame has a specific
column for the x-axis

```

```

y=right_end['value'],
error_y=dict(
    type='data', # indicates that the values for the error bars are given
explicitly
    symmetric=False, # indicates that the error bars are not symmetric
    array=right_end['upper'] - right_end['value'],
    # specifies the length of the portion of the error bar above the value
    arrayminus=right_end['value'] - right_end['lower'],
    # specifies the length of the portion of the error bar below the value
    color='gray',
    thickness=2,
    width=4
),
name='right accum: point estimate & error bars',
marker=dict(
    color='gray',
    size=5
    # symbol='diamond'
),
mode='markers') # you can change to 'lines' or 'lines+markers' if that's more
appropriate for your data
)

# Upper Bound
fig.add_trace(
    go.Scatter(x=data.index,
               y=data['upper'],
               line_color='lightgray',
               line={'dash': 'dot', 'width': 1},
               name='CI upper band',
               mode='lines',
               opacity=0.15)
)

# Lower Bound fill in between with parameter 'fill': 'tonexty'
fig.add_trace(
    go.Scatter(x=data.index,
               y=data['lower'],
               line_color='lightgray',
               line={'dash': 'dot', 'width': 1},
               fill='tonexty',
               name='CI lower band',
               mode='lines',
               opacity=0.15)
)

# event point estimate and error bars
fig.add_trace(

```

```

    go.Scatter(
        x=data.index, # or another column if your DataFrame has a specific column for
the x-axis
        y=data['value'],
        error_y=dict(
            type='data', # indicates that the values for the error bars are given
explicitly
            symmetric=False, # indicates that the error bars are not symmetric
            array=data['upper'] - data['value'],
            # specifies the length of the portion of the error bar above the value
            arrayminus=data['value'] - data['lower'],
            # specifies the length of the portion of the error bar below the value
            color='darkgray',
            thickness=1,
            width=3
        ),
        name='event: point estimate & error bars',
        marker=dict(
            color='darkgray',
            size=5
            # symbol='diamond'
        ),
        mode='markers') # you can change to 'lines' or 'lines+markers' if that's more
appropriate for your data
    )

    #fig.update_xaxes(
    #    dtick=steps_year
    #)

    # use percentages in axes
    fig.update_layout(
        width=1200,
        height=600,
        title=title,
        xaxis_title='event time',
        yaxis_title=r'effect',
        yaxis_tickformat = '.2%'
    )

    fig.show()

    if filename:
        fig.write_image(filename)

plotly_event_study(solution, BASELINE_LAG, (PRE_EVENT, POST_EVENT), 'Event Study')

```

7. Cumulative Abnormal Return (CAR)

```
effect = solution['value']
accum = effect.cumsum()
accum = accum - accum.loc[BASELINE_LAG]
accum = accum.loc[ PRE_EVENT : POST_EVENT ]

fig = go.Figure()

# Add a horizontal line at y=0 (or any other y-value you need)
fig.add_hline(y=0, line={'dash': 'solid', 'width': 1, 'color': 'red'})
fig.add_vline(x=0, line={'dash': 'solid', 'width': 1, 'color': 'gray'})
fig.add_vline(x=BASELINE_LAG, line={'dash': 'dot', 'width': 1, 'color': 'gray'})

fig.add_trace(
    go.Scatter(
        x=accum.index,
        y=accum,
        mode='lines+markers',
        name='Cumulative Effect',
        line=dict(color='darkgray', width=2),
        marker=dict(size=6, color='darkgray'),
    )
)

# use percentages in axes
fig.update_layout(
    width=1200,
    height=600,
    title='Cumulative effect',
    xaxis_title='event time',
    yaxis_title='effect',
    yaxis_tickformat = '.2%'
)

fig.show()
```