Public Reaction to Pharmaceutical Preannouncements on Social Media: A Signaling Perspective

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Abstract

Pharmaceutical companies frequently use strategic communication during research and development (RD), especially when developing high-stakes products like vaccines. During the COVID-19 pandemic, preannouncements became critical tools for companies such as Pfizer, Moderna, and AstraZeneca to signal progress in vaccine development, aiming to manage public expectations and influence competitors and regulators. This study explores the public's reaction to these preannouncements using Twitter data, sentiment analysis, and Named Entity Recognition (NER) with GliNER to extract and analyze mentions of pharmaceutical companies and related side effects. By focusing on NER—a relatively underutilized method in marketing research—we aim to uncover patterns in public discourse and engagement that traditional analysis may overlook. Our findings enhance understanding of how preannouncements impact public perception and discourse, contributing to the literature on strategic communication in the pharmaceutical industry.

Keywords: Signaling theory, pharmaceutical marketing, preannouncements, Named Entity Recognition, sentiment analysis

1 Introduction

Pharmaceutical companies rely heavily on strategic communication throughout the research and development (RD) process, particularly when developing high-stakes products such as vaccines. In the context of the COVID-19 pandemic, preannouncements became critical tools for companies like Pfizer, Sanofi, and AstraZeneca. These companies used preannouncements to signal progress in their vaccine development efforts, not only to manage public expectations but also to influence competitors and regulators. The public's reaction to these preannouncements, especially on social media platforms like Twitter, is an important indicator of how these signals are interpreted and acted upon.

While previous research in finance has focused on the stock market's reaction to new product announcements in the pharmaceutical industry (Schatzel 2006; Eddy and Saunders 1980; Prasad Mishra and Bhabra 2001), the literature has largely overlooked the public's response to these announcements, particularly in the context of social media engagement (Li, Larimo, and Leonidou 2023). As social media becomes an increasingly important tool for companies to communicate directly with consumers, understanding how these announcements shape public sentiment is crucial (Hennig-Thurau, Hofacker, and Bloching 2013). Social media platforms enable rapid dissemination and amplification of information, which can significantly influence public perception and behavior (Iyengar, Van Den Bulte, and Valente 2011).

During the COVID-19 crisis, the urgency to develop vaccines was unprecedented. Regulatory bodies such as the European Medicines Agency (EMA), ANSM (Agence Nationale de Sécurité des Médicaments)[1], and others rapidly coordinated approvals, while pharmaceutical firms raced to gain first-mover advantages. This environment created a unique setting for 'market preemption', where early or frequent pre-announcements could discourage competitors and reassure governments and the public about progress.

Drawing on signaling theory (Akerlof 1978; Spence 1973; Porter 1998), this study explores the public reaction to pre-announcements in the pharmaceutical industry. We examine how these signals are perceived and how their impact varies across different audience segments. Specifically, we analyze a dataset of tweets related to major pharmaceutical companies, employing textual analysis, sentiment analysis, and Named Entity Recognition (NER) with GliNER (Zaratiana et al. 2024) to extract key entities for side effects.

2 Theoretical Framework

2.1 Signaling Theory and Preannouncements in the Pharmaceutical Industry

Signaling theory, initially developed in economics and later extended into marketing and management, focuses on how information asymmetries between companies and their audiences are reduced through strategic communication. Companies use signals to convey valuable information to various stakeholders in markets characterized by high uncertainty and information asymmetry, such as the pharmaceutical industry (Eliashberg and Robertson 1988).

In the pharmaceutical industry, where RD processes are long, expensive, and uncertain, preannouncements serve as key signals to multiple stakeholders—competitors, regulators, and the public. By communicating the progress of drug development, companies aim to:

1. Convey commitment and build trust: Preannouncements signal the company's dedication to developing new products, thereby reducing uncertainty and building trust among

[1]The Agence nationale de sécurité du médicament et des produits de santé (ANSM) is the public agency responsible for ensuring access to healthcare products in France on behalf of the state. It also oversees the safety of these products throughout their lifecycle, a role that became particularly critical during the COVID-19 pandemic.

investors and consumers (Su and Rao 2010).

2. Influence competitor behavior: Companies might use preannouncements to deter competition, induce a rival to exit, or preempt the market (Robertson, Eliashberg, and Rymon 1995; Ofek and Turut 2013).

3. Manage regulatory relationships: Keeping regulators informed can facilitate smoother approval processes and demonstrate compliance with regulatory requirements (Wettermark et al. 2009).

The urgency and high stakes of the COVID-19 pandemic amplified the strategic importance of preannouncements. As detailed in Table 1, the compressed timeline of clinical trials and EMA approvals highlights how pharmaceutical firms like Pfizer/BioNTech, Moderna, and AstraZeneca utilized preannouncements to signal progress and assert competitive positioning. For instance, Pfizer/BioNTech and Moderna communicated efficacy rates of 95% and 94.5%, respectively, in November 2020. Shortly afterward, AstraZeneca announced interim Phase 3 results, reporting an average efficacy of 70%, emphasizing its readiness to compete in the market[2].

Beyond signaling, preannouncements also played a critical role in market preemption. By rapidly communicating trial results, firms sought to establish an early foothold in the market and influence stakeholder expectations. AstraZeneca's announcement exemplifies this strategy. While its average efficacy was lower than that of Pfizer/BioNTech and Moderna, AstraZeneca strategically framed its results by combining two dosing regimens—one with 90% efficacy (half-dose followed by full-dose) and another with 62% efficacy (two full doses)—to present a competitive narrative (Callaway 2020). This approach signaled readiness and adaptability, helping AstraZeneca secure attention from regulators, competitors, and the public.

The dual nature of pre-announcements, serving both as signals and as preemptive moves, underscores their strategic complexity. Pre-announcements not only reduce uncertainty, but also discourage competitors from capturing market share by demonstrating progress and commitment (Robertson, Eliashberg, and Rymon 1995; Ofek and Turut 2013). The swift announcement of AstraZeneca, which came shortly after Pfizer / BioNTech and Moderna, highlights its intention to remain in the competitive race despite lower efficacy rates.

However, the duality of signaling poses challenges, as signals intended for one audience may be perceived differently by others. Signals aimed at competitors or regulators can be misinterpreted by the public, whose reaction is crucial to trust and reputation (Eliashberg and Robertson 1988).

2.2 Emotional and Sentiment Responses to Positive and Negative Signals

Research in marketing and psychology has consistently demonstrated that negative events elicit stronger emotional reactions than positive ones, a phenomenon widely known as *negativity bias* (Baumeister et al. 2001). This bias suggests that bad news, such as adverse events or delays, tends to dominate public discourse and shape perceptions more profoundly than positive announcements. Within the pharmaceutical industry, where public trust and perception are critical, this dynamic is particularly pronounced.

Pharmaceutical preannouncements, such as those related to vaccine efficacy or adverse side effects, serve as strategic tools to influence stakeholder perceptions in highly uncertain environments (Eliashberg and Robertson 1988). Positive signals—like announcements of high efficacy rates—can foster trust among regulators, investors, and the public, highlighting the company's commitment to innovation and transparency (Su and Rao 2010). Conversely, negative signals,

[2]AstraZeneca Press Release, available at: https://www.astrazeneca.com/media-centre/press-releases/2020/azd1222hlr.html#

such as concerns over adverse side effects[3], can pose significant reputational risks and amplify public scrutiny, particularly in the context of the pandemic. During this period, daily updates on vaccine efficacy often fueled conspiracy theories and skepticism, leading individuals to doubt not only the safety of vaccines (Dubé et al. 2013), but also their choice among the available options. This created an additional layer of complexity for pharmaceutical companies, which had to manage public perception while navigating a highly volatile informational environment.

The emotional impact of such announcements is not limited to immediate reactions but can also create a backlash effect, where negative sentiment escalates over time, particularly when amplified by social media. These dynamics highlight two key phenomena:

- **H1: Asymmetry of Positive vs. Negative Signals.** Positive preannouncements—such as high efficacy rates—are expected to increase positive sentiment, whereas negative preannouncements—such as side-effect concerns—generate a disproportionately stronger surge in negative sentiment.
- **H2: Backlash Effect.** Sentiment initially aligns with the direction of the signal (positive or negative) but subsequently reverses, reflecting a backlash or rebalancing over time.

3 Methodology

3.1 Data Collection

We analyzed a subset of French-language tweets (2020–2021) focused on major pharmaceutical companies involved in COVID-19 vaccine development, including Pfizer, Moderna, AstraZeneca, Johnson Johnson, BioNTech, Sanofi, and Valneva. The tweets were selected from a large-scale dataset using hashtags and keywords such as "covid," "coronavirus," and "covid19." From an initial dataset of 1.4 million tweets, extracted with regular expressions to capture various brand name spellings, preprocessing steps—such as removing retweets, spam, and duplicates—yielded a final cleaned dataset of 150,564 unique, original tweets in French.

Due to low mention frequencies, only Pfizer, Moderna, AstraZeneca, and BioNTech were retained for analysis. The dataset spans early 2020 to the end of 2021, excluding two brief gaps (February 18–28 and June 20–30, 2021). Significant Twitter peaks corresponding to key preannouncement events were identified (see Figure 1), enabling a focus on moments of heightened public interest for analysis.

3.2 Named Entity Recognition (NER)

To extract mentions of pharmaceutical companies and vaccine-related side effects, we used the GLiNER model, a zero-shot[4] Named Entity Recognition (NER) tool. NER identifies and classifies entities in text, such as organizations, products, and attributes like side effects (Nadeau and Sekine 2007). GLiNER enhances this by detecting semantic variations and spelling differences without relying on predefined lists, identifying unexpected side effects, and enabling scalable, detailed trend analysis (Hartmann and Netzer 2023). Chi-squared analyses identified significant discrepancies in how specific side effects are associated with various vaccine brands (see Figure 2 for the distribution of statistically significant signals and Figure 3 for observed vs.

[3]Following reports of thrombotic events associated with its COVID-19 vaccine, AstraZeneca released a detailed update on 14 March 2021 to reassure the public and stakeholders about its safety. The statement emphasized that a review of data from over 17 million vaccinated individuals in the EU and UK found no evidence of increased risks of pulmonary embolism, deep vein thrombosis (DVT), or thrombocytopenia. Full details are available in the press release: https://www.astrazeneca.com/media-centre/press-releases/2021/update-on-the-safety-of-covid-19-vaccine-astrazeneca.html#.

[4]Zero-shot learning allows recognizing entities without prior task-specific fine-tuning. The model is available on Hugging Face: https://huggingface.co/urchade/gliner_multi-v2.1.

expected counts). To refine the analysis, multiple variants of similar symptoms were recoded into unified groups, addressing minor orthographic or morphological differences. Table 2 lists the 15 recoded side-effect categories with the highest overall frequency in the dataset.

3.3 Sentiment Analysis

To assess public sentiment towards preannouncements, we employed the twitter-XLM-roBERTa-base model[5]. This transformer-based model is fine-tuned on multilingual tweets related to COVID-19, covering eight languages, including French (Barbieri, Anke, and Camacho-Collados 2021). Tweets were classified into three sentiment categories: positive, neutral, and negative, with associated probabilities (sentiment score) ranging from 0 to 1 (representing the model's level of certainty for each category). This classification enables the analysis of emotional responses to key events, such as announcements of vaccine efficacy or concerns about side effects. Sentiment was analyzed across three time periods: "Before", encompassing all tweets prior to the preannouncement date; "On", representing tweets published on the day of the preannouncement; and "After", including all tweets posted after the preannouncement.

4 Results

4.1 Contextualizing NER Findings in a Marketing Strategy Framework

AstraZeneca exhibits disproportionately high mentions of thrombosis and cutaneous reactions ($p < 0.001$). This surge coincides with the March 15, 2021, European suspension (see Figure 1), creating a dominant negative narrative that overshadowed logistical advantages such as easier cold-chain requirements. Pfizer shows higher-than-expected references to fever, pain, cardiac, and neurological issues ($p < 0.001$). Having announced a major efficacy breakthrough (November 9, 2020) earlier than most competitors, and occupying a leading role in France's vaccine rollout, Pfizer became the default target for discussions of vaccine-related problems—highlighting how brand prominence can intensify scrutiny. Moderna records moderate elevations in mentions of cardiac, pain, and muscle issues, albeit less acutely than AstraZeneca or Pfizer. Its mid-November 2020 efficacy announcement (94.5%) nonetheless placed it under heightened public examination of mRNA safety. BioNTech, often mentioned alongside Pfizer in media coverage and public discourse, is rarely discussed independently in relation to side effects. While 283 tweets reference BioNTech when discussing side effects, this figure largely stems from mentions of "Pfizer-BioNTech." When side effects are attributed to a single pharmaceutical company, the number drops to just 5 for BioNTech, highlighting its limited standalone visibility compared to Pfizer.

4.2 Sentiment analysis

The analysis of Pfizer-related tweets ($n = 83,841$) (see Figure 4) revealed significant sentiment shifts across the three periods. Negative sentiment decreased sharply from 41.43% "Before" to 13.10% "On" ($Z = 14.2356$, $p < 0.001$), followed by a rebound to 36.52% "After" ($Z = -16.6987$, $p < 0.001$). Positive sentiment surged "On" (30.28% to 74.22%, $Z = -19.0762$, $p < 0.001$) but dropped significantly "After" to 22.63% ($Z = 41.7676$, $p < 0.001$). Neutral sentiment declined "On" (28.29% to 12.68%, $Z = 8.5937$, $p < 0.001$) and then increased to 40.85% "After" ($Z = -19.6663$, $p < 0.001$). These shifts were corroborated by t-tests, with negative sentiment scores increasing significantly "On" ($t(240.21) = 7.90$, $p < 0.001$) and remaining elevated "After" ($t(319.93) = 8.12$, $p < 0.001$). Positive sentiment scores decreased "On" ($t(339.22) = -4.85$, $p < 0.001$) and stabilized thereafter.

[5]For more details, visit https://huggingface.co/cardiffnlp/twitter-xlm-roberta-base-sentiment

For Moderna ($n = 29,463$) (see Figure 5), a similar pattern emerged. Negative sentiment decreased "On" (24.90% to 8.47%, $Z = 8.9465$, $p < 0.001$) but rebounded "After" to 35.76% ($Z = 15.5208$, $p < 0.001$). Positive sentiment surged "On" (33.62% to 67.99%, $Z = -14.3669$, $p < 0.001$) but declined "After" to 24.63% ($Z = -26.8902$, $p < 0.001$). Neutral sentiment fell "On" (23.54%, $Z = 7.9117$, $p < 0.001$) but recovered "After" (39.61%, $Z = 8.9274$, $p < 0.001$). T-tests confirmed these findings, with significant shifts in sentiment scores across the periods.

AstraZeneca ($n = 40,384$) (see Figure 6) displayed more pronounced shifts due to safety concerns. Negative sentiment spiked "On" (48.58% to 82.68%, $Z = -27.5238$, $p < 0.001$) and remained high "After" (50.75%, $Z = 26.4366$, $p < 0.001$). Positive sentiment decreased "On" (21.88% to 8.82%, $Z = 13.0623$, $p < 0.001$) and showed limited recovery "After" (17.12%, $Z = -9.224$, $p < 0.001$). Neutral sentiment decreased "On" (29.55% to 8.50%, $Z = 19.0821$, $p < 0.001$) but increased "After" (32.13%, $Z = -21.2193$, $p < 0.001$). T-tests corroborated these results, with negative sentiment scores increasing "On" ($t(2628.7) = -11.31$, $p < 0.001$) and slightly decreasing "After" ($t(14464) = 6.85$, $p < 0.001$).

Table 3 summarizes the support for Hypotheses 1 (Asymmetry of Positive vs. Negative Signals) and 2 (Backlash Effect). For Pfizer and Moderna, both hypotheses are supported, as positive announcements generated initial optimism followed by a backlash. For AstraZeneca, Hypothesis 1 is supported due to the dominance of negative sentiment "On," but Hypothesis 2 is partially supported, as negative sentiment remained the dominant force "After."

5 Discussion

Effective vaccine communications during the COVID-19 crisis exemplify the strategic importance of signaling theory in competitive and uncertain markets. Preannouncements served as key signals to manage uncertainty, preempt competitors, and build trust among stakeholders. However, the public's perception of these signals—shaped by both positive achievements, such as efficacy rates, and negative events, like adverse side effects—plays a critical role in determining their impact. Understanding and responding to these perceptions requires advanced tools that go beyond traditional analysis.

The NER technique is more than a text-mining exercise; it serves as a strategic tool for identifying adverse-event themes that resonate in public discourse and assessing their potential to damage reputations. By aligning these themes with market dynamics and regulatory events, companies can pinpoint moments of heightened risk and respond effectively. For instance:

Brand Leadership and Vulnerability: Pfizer's position as a leading vaccine provider in France exemplifies the duality of visibility—early achievements attract attention but also amplify scrutiny and reputational risks.

Crisis Communication Strategies: AstraZeneca's challenges with thrombosis reports demonstrate how even rare adverse events can dominate narratives if they coincide with official actions, underscoring the need for timely, transparent communication to mitigate public anxiety.

Brand Differentiation: Moderna's and BioNTech's experiences show that clear and well-timed messaging about novel technologies, such as mRNA vaccines, can either alleviate or exacerbate public concerns, depending on the precision of their communication strategies.

These insights highlight the strategic complexity of managing vaccine communications in unpredictable environments. Real-time detection and categorization of side effects through NER allow pharmaceutical companies to refine risk communication, collaborate effectively with regulators, and maintain public trust.

When paired with sentiment analysis, NER provides a comprehensive and proactive understanding of how public emotions evolve. Positive announcements, such as efficacy rates, can generate optimism, but this sentiment may quickly fade if adverse events dominate the discussion. Monitoring both the content of discourse (via NER) and its emotional tone (through sentiment analysis) enables companies to adapt their messaging dynamically.

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Figures

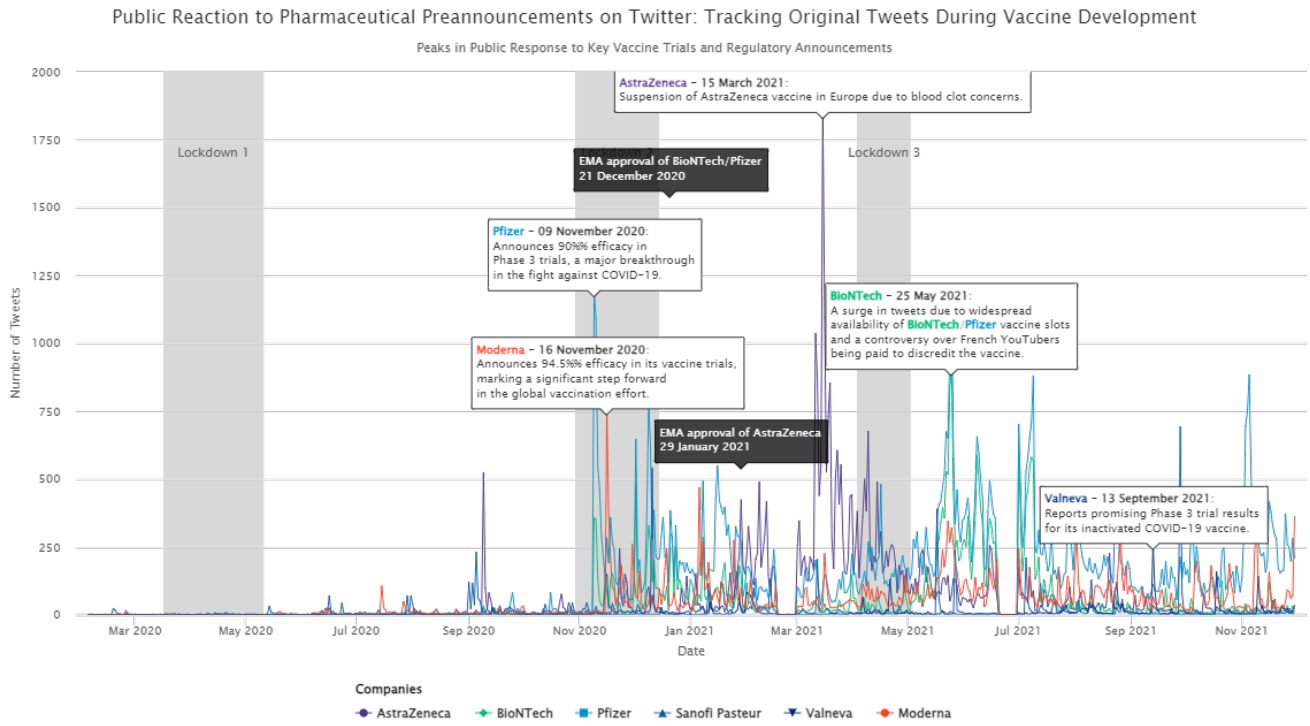

Figure 1: Public Reaction to Pharmaceutical Companies on Twitter.

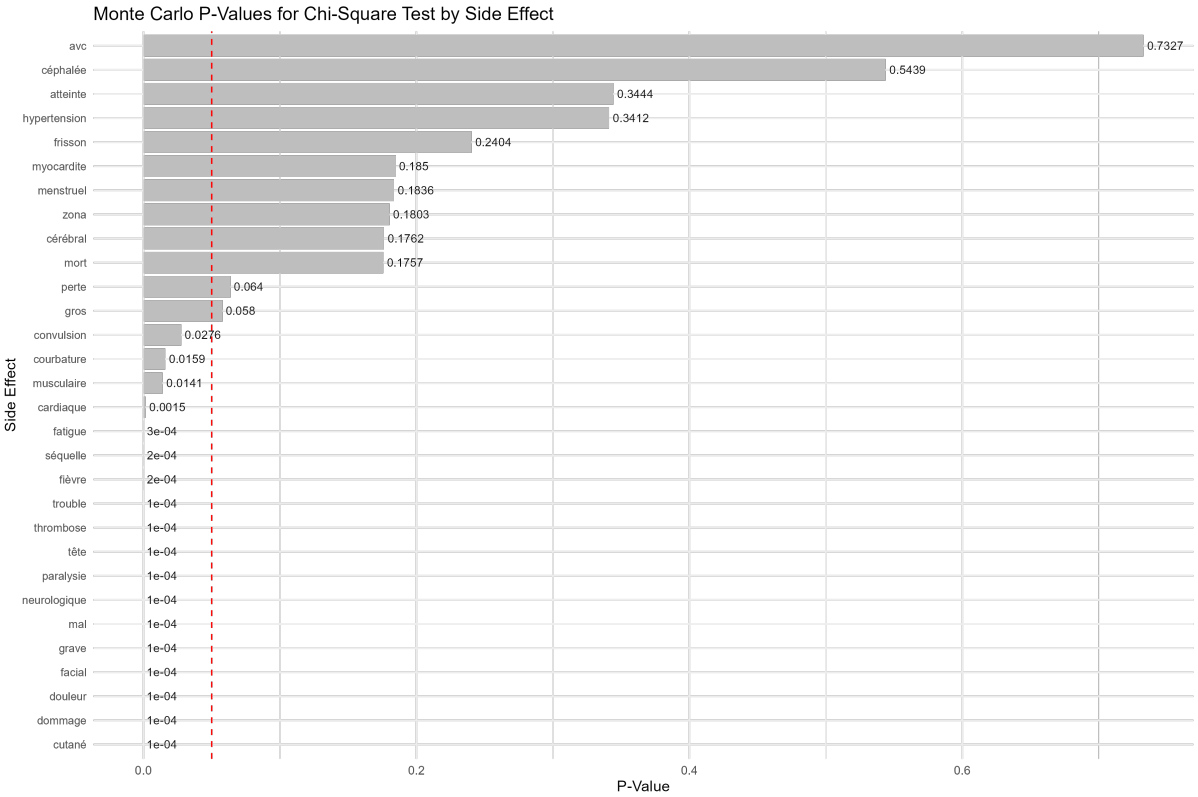

Figure 2: Significant Side Effects

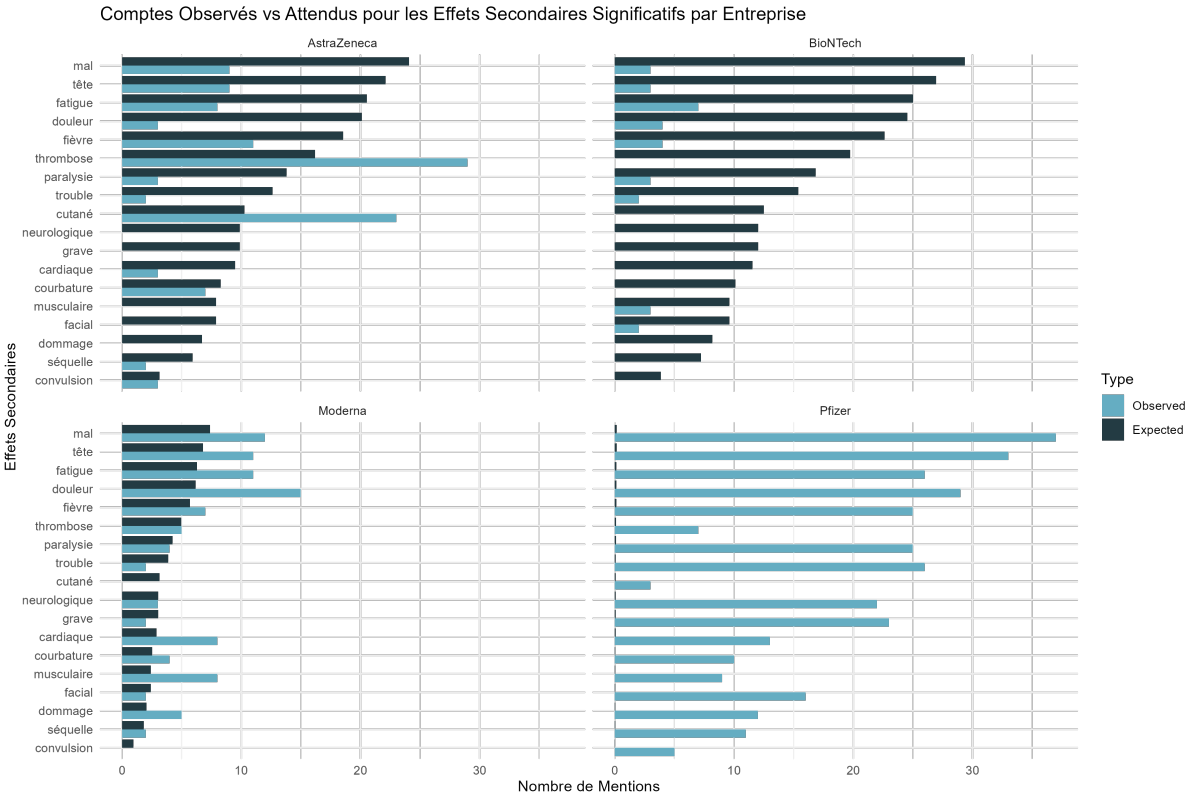

Figure 3: Side Effects Expected/Observed for Each Pharmaceutical Company

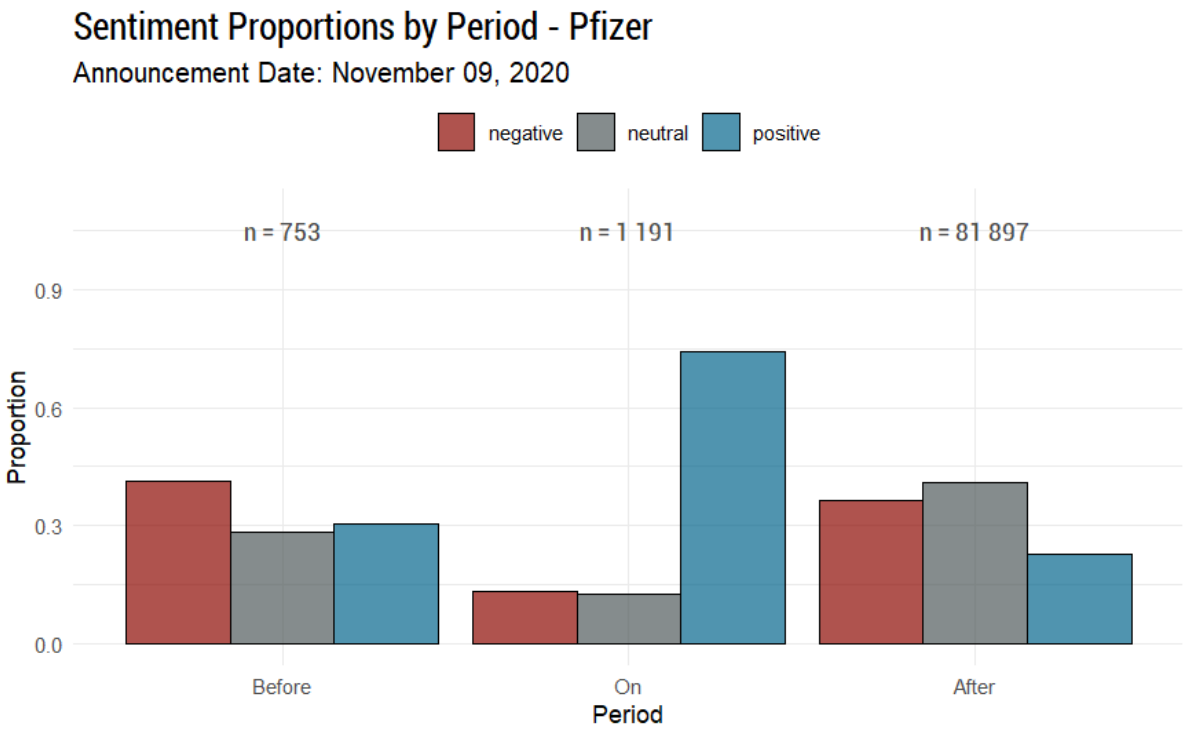

Figure 4: Sentiment Proportions before/after preannouncement - Pfizer

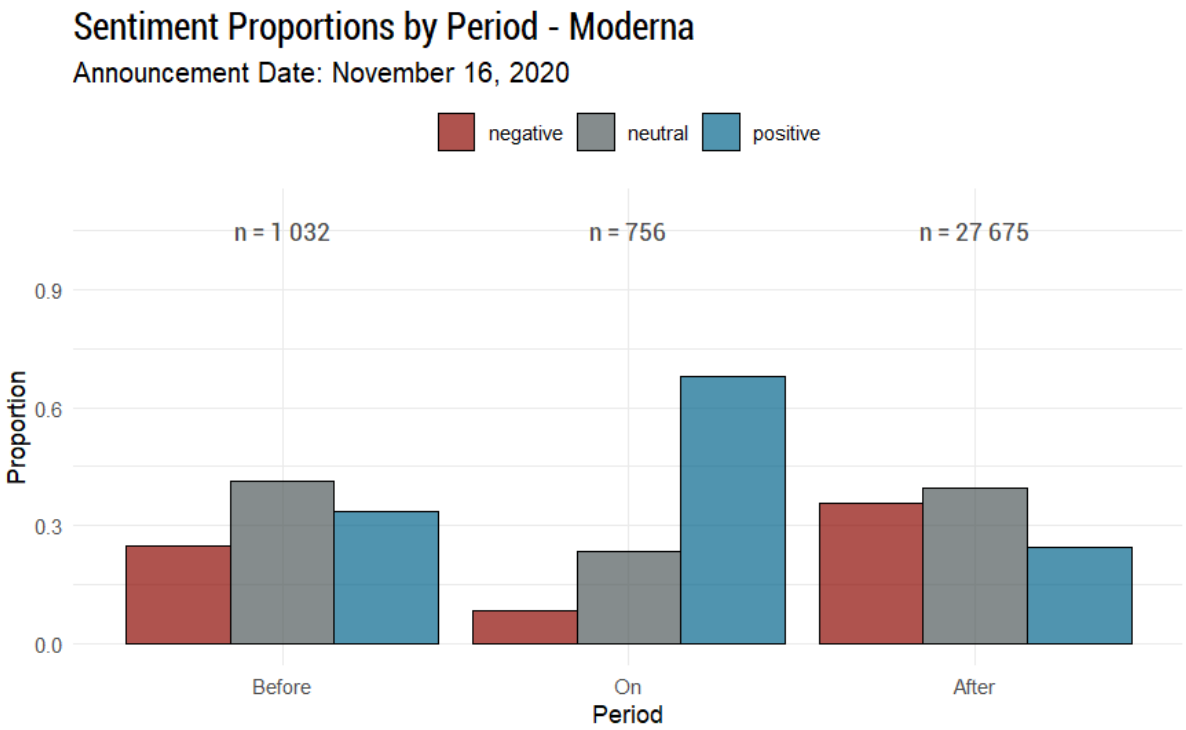

Figure 5: Sentiment Proportions before/after preannouncement - Moderna

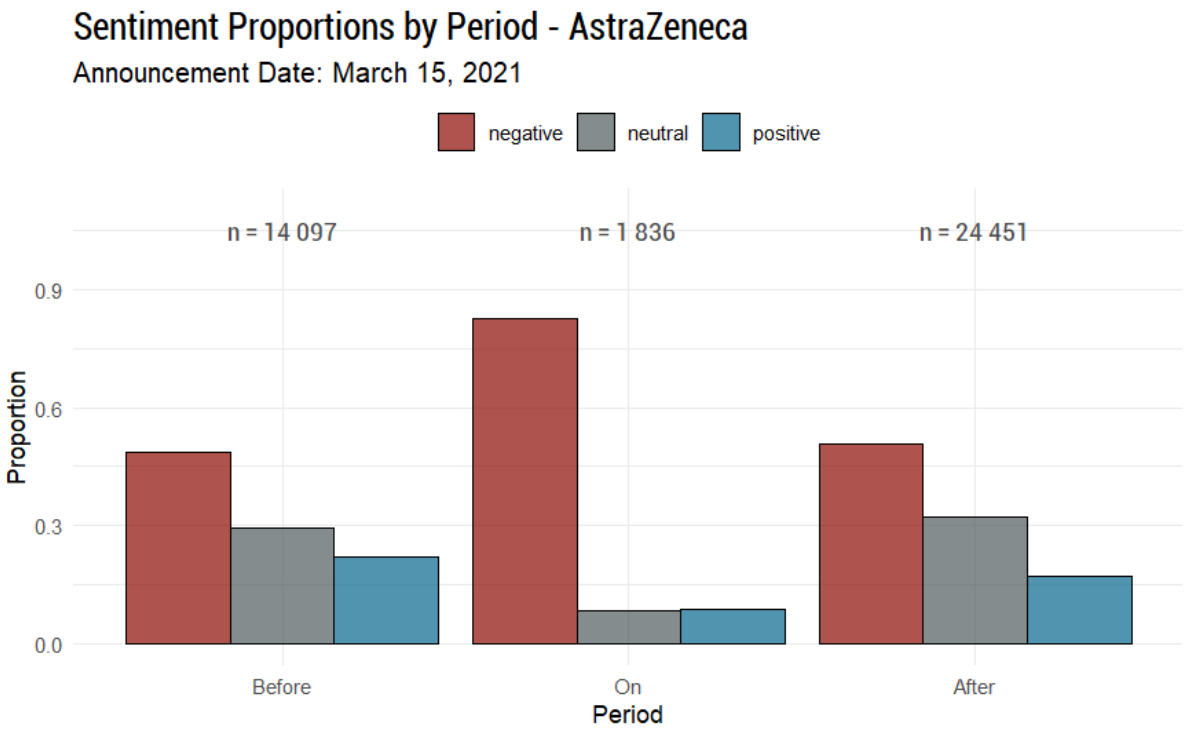

Figure 6: Sentiment Proportions before/after preannouncement - AstraZeneca

Tables

Table 1: Clinical Trials and EMA Approval Dates of COVID-19 Vaccines

Company	**Clinical Trial Dates**	**EMA Approval Date**	**Vaccine**
Pfizer/BioNTech	Phase 3 trial concluded in November 2020, demonstrating 95% efficacy.	December 21, 2020	Comirnaty
Moderna	Phase 3 trial results announced in November 2020, demonstrating 94.5% efficacy.	January 6, 2021	Spikevax
AstraZeneca	Interim Phase 3 results published in December 2020, showing an average efficacy of 70%, with variations depending on dosing.	January 29, 2021	Vaxzevria

Table 2: Top 15 Recoded Side-Effect Groups (French Corpus).

Recoded Side-Effect Group	**Total Count**
problèmes neurologiques (paralysie, convulsions, etc.)	60
fièvre	55
maux de tête	54
thrombose	50
douleur musculaire ou articulaire	39
fatigue	36
hémorragies / saignements	36
retards	30
complications	28
problèmes cardiaques	26
symptomes	15
problèmes psychologiques	14
etat grippal	13
problèmes cutanés	11
décès	10

Table 3: Summary of Hypothesis Testing Results

Company	**H1: Asymmetry of Positive vs. Negative Signals**	**H2: Backlash Effect**
Pfizer	Supported	Supported
Moderna	Supported	Supported
AstraZeneca	Supported	Partially Supported