**The Rich Get Richer and the Poor Get Poorer:**

**Behavior of Investors in Biotechnology Firms Post-IPOs**

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**Abstract**

This paper analyzes stocks’ return after initial public offering (IPO) events of biotechnology firms and explores the role of social media in determining this return. Results indicate positive yet insignificant cumulative average abnormal returns (CAAR) of 1.97% in the first 20 days following an IPO until the end of quiet period, and a decline of tens of percents over the following three years. However, when dividing the sample into two subsamples according to firm size, using a separation market value of $500M, the overall picture changes dramatically. Firms with a market value lower than $500M yielded negative CAAR from the very beginning, however this negative CAAR become significant from day 50 onwards. Firms with a market value higher than $500M experienced a positive CAAR from the very beginning, when this positive CAAR become significant from day 50 and throughout the following year. These findings can be attributed to the limited investors' attention. Attention to new IPOs increases until the end of quiet period and, in the case of small-sized firms, diminishes during the post-IPO years. An examination of social media and share returns demonstrates a robust correlation between the two, which may indicate that investors’ attention to firms is also reflected in social media.

**Keywords:** behavioral finance; biotechnology companies; financial markets; IPO; social media

**JEL Classification:** D8 (Information, Knowledge, and Uncertainty); G11 (Portfolio Choice; Investment Decisions); G14 (Information and Market Efficiency; Event Studies); G17 (Financial Forecasting and Simulation).

1. **Introduction**

The pharmaceutical industry develops, produces, and markets drugs to be used as medications. According to its revenues and capitalization, it is one of the world’s top five industries, with total annual revenues worldwide of 1.25 trillion US dollars in 2019 and 1.27 trillion US dollars in 2020 (statista.com), most of which are generated by multinational pharmaceutical giants that have been dominating the industry for decades. The United States alone is responsible for almost 50% of these amounts.

The “new world” of biotechnology companies seeking to develop one or more drugs started to emerge a decade ago when technology became less expensive. While biotechnology project risk tends to decrease with each stage in the product development cycle, the absolute capital requirements are increasing over multiple years of product development, hence, finding financing is critical.

The Jumpstart Our Business Startups (JOBS) Act, enacted in the United States in April 2012, was designed to help revitalize the IPO market by providing a series of regulatory, accounting, and disclosure easements for Emerging Growth Companies (EGC). EGCs are characterized by annual gross revenues of less than US $1 billion over the year prior the IPO. Dambra et al. (2015) documented a 25% increase in new IPOs annually in the two years following enactment of the law compared to the two years preceding the law’s enactment. In addition, offerings of EGC and non-ECG firms increased by 53% and 10% respectively following enactment of the law. Of these, pharmaceutical or biopharmaceutical companies had the greatest increase in activity, as they were more likely to take advantage of the act’s risk reduction provisions which permit firms to file their IPO confidentially while making overtures to qualified institutional buyers. IPOs, in addition to increasing firm’s equity, significantly increases its exposure to the public as well as to other pharma companies. This exposure was well utilized in the years 2013-2020 when biotech companies raised additional significant financing through $100M+ acquisitions and alliances. 146 companies raised $85.9B in pre-IPO deals, 133 companies raised $113.2B in post-IPO deals and 40 companies were acquired for a total amount of $83.8B. (Edwards 2021)

This paper focuses on the “new world” of biotech firms that perform an IPO between 2013 and 2019 after the JOBS act was enacted. The first part of the paper examines how the new Jumpstart Our Business Startups Act (JOBS Act) has influenced investors’ activity during the three years post-IPO as reflected in their cumulative average abnormal return (CAAR).

Numerous studies have attempted to explore variables that might affect the behavior of stock prices after an IPO, part of them dealt with media coverage, whether it was originated by the firm, like press releases or publications originating outside the firm, yet very few studies investigated the relations between tweets and returns, and hence we wish to contribute of filling this gap by focusing on Twitter. Thus, in the second part we investigate the relation between the volume of the text messages posted on Twitter known as “tweets” and stock returns. The decision-making process of participants in financial markets is not always rational and is often influenced by motives other than risk and return, such as the perceived quality of a firm. One of the channels for shaping investors’ perceptions is publishing posts about a firm through social media channels, from online message boards to Facebook and Twitter. We choose to focus on Tweeter, as it enjoys increasing popularity and because tweets are characterized by non-scrutinized, unstructured, informal, and very short texts. In a world where there is almost an endless amount of available information, firms’ competition for investors’ attention has become fiercer than ever. We were therefore interested in exploring how the volume of tweets, without any potentially controversial evaluation of their content, influence main capital market variables after the IPO. The contribution of this paper is twofold, first, our focus on the biotechnology sector, which despite of being one of the leadings based on its revenues, got relatively low academic attention, and second, analyzing the relation between investors’ attention as reflected in the sheer Twitters’ discourse level and stock returns.

The rest of the paper is organized as follows: section 2 contains literature review of relevant studies. Section 3 analyzes the behavior of CAAR post IPO, section 4 analyzes the relations between tweets volume and stock behavior, and section 5 contain discussion and conclusions.

**2. Literature Review**

**2.1 IPO and** Long Run **Stock Performance**

While numerous issues involving IPOs have been widely studied, those most relevant to this study analyzed the performance of stocks, that were issued in the United States, up to three years following the IPOs, and optional factors that may influenced these performances. We will mention a few of than in chronological order. Jain and Kini (1994) investigate firms that were issued between 1976 and 1988 and found significant decline in operating performance for up to three years after the offering. In addition, they found a significant positive relation between post-IPO operating performance and equity retention by the original entrepreneur. Loughran and Ritter (1995) analyzed companies going public between 1970 and 1990 and reported that IPO stocks yielded an average of 8.4% for the three -year post-IPO, compared to 35% for a comparably non-IPO benchmark. In a seminal paper, Ritter and Welch (2002) investigated the long-term performance of IPOs issued between 1980 and 2001 and found that the three-year average market-adjusted return was a negative -23.4%. Gao at al. (2006) analyzed firms that were issued between 1980 and 2000 and documented a negative -38.48% excess return over NASDAQ for the 3 years following the IPO, their findings suggests that wider divergence of opinion in the IPO market leads to greater long-term underperformance. Lin et al. (2021) used IPOs data from 1970 to 2008 to investigate the role of “Hot market” and earnings management in explaining IPO’s long-running underperformance. Their findings suggest that, because the information asymmetry is more severe in hot market condition, IPOs issued in hot market tend to exhibit poorer returns than those issued in cold market. Earnings management no longer exhibits significant explanatory power when the IPOs are issued in the cold market.

In continents other than the US: Goergen et al. (2009) studied long run performance of U.K IPOs between 1991 to 1995 and found a negative -19.94% adjusted return for the 3 years post IPO; Small firms suffer from worse long-run performance than large firms. The percentage of equity issued and the degree of multinationality of a firm are key predictors of its performance after the IPO. Berk and Peterle (2015) analyzed IPOs in central and eastern Europe between 2000 and 2009 and found 3 years underperformance of -14% to -31% depends in the benchmark. Like Georgen et al. (2009) they found that smaller IPOs exhibit greater long-run underperformance compared to their larger counterparts. Shimizu and Takei (2016) examined IPOs stock behavior during 2004 to 2011 at three different stock exchange markets in Japan. For two of the three exchanges the CAAR was not statistically significant 3 years post IPO, in the third exchange CAAR was -30.08% on month 36. Boubaker at al. (2020) investigate the underperformance of 402 French firms that went public during 1998 – 2011. Their finding suggests that excess control (the difference between control rights and cash flow rights) is negatively associated with long-term performance because it increased the likelihood that controlling shareholders extract private benefits of control to the detriment of minority shareholders. Kumar and Sahoo (2021) who analyzed the Indian market IPOs from 2009 to 2014 reported a negative average CAAR of -41.05% in the 36 months post IPO.

Evidence regarding the importance of innovations in the pharmaceutical industry was studied by Chen and Xu (2015) who found that firms with higher level of pre-IPO innovation outcome have a higher buy and hold abnormal return in 24 and 36 months after IPO. Guo and Zhou (2016) studied post-IPO performance of 151 biotech IPO firms from 1991 to 2012. They found that innovation capability is critical to contemporaneous stock performance and eventual firm survival. Biotech IPO firms are more likely to succeed in the long run, if they can expand the scale of their research undertakings and make progress in these research activities.

Komenkul and Kiranand (2017) investigated 76 health care and biopharmaceutical IPOs in ASEAN (Association of Southeast Asian Nations) countries between 1986 and 2014 and found positive and significant CAAR of 5.57% 36 months post-IPO. Malaysia and Singapore present the highest and lowest CAARs of 57.25% and -39.4%, respectively. Thakor et al. (2017) tracks pharma firms from 1930 to 2015. They found that from 1930 to 2015, the pharma industry outperforms the market with 3% per year, however the biotech sector which began in the 1980s underperform the market by 5% per year in the years 1980-2015. They confirm that almost all biotechnology companies are loss-making enterprises.

**2.2 Media and (IPOs) Stock Performance**

According to Merton (1987), the most common way to boost investors’ awareness is to promote the visibility of the firm through the media. Shiller (2000) wrote:

*"The role of the news media in the stock market is not, as commonly believed, simply as a convenient tool for investors who are reacting directly to the economically significant news itself. The media actively shape public attention and categories of thought, and they create the environment within which the stock market events we see are played out*."[[1]](#footnote-1)

Shiller (2000) found that extra media coverage draws investors’ attention to these stocks. This leads to a positive feedback effect, in which big returns are followed by more big returns because of increased media coverage. In contrast, Fang and Peress (2009), found that a portfolio of stocks not covered by the media outperformed a portfolio of stocks with high media coverage by 3% per year following portfolio formation. In their view, the “no media premium” may stem from limitations on trading or to compensation for little or lack of information. Bhattacharya at, et al. (2009) explored the role of the media in the internet IPO bubble between 1996 and 2000. They found that media coverage was much more intense for internet IPOs. There were more total new items, good and bad for internet IPOs than for a matching sample of non-internet IPOs. The effect on daily abnormal returns, which was lower for internet IPOs, especially during the bubble period, indicates that the market largely discounted the media hype. Siev (2014) documented that firms publishing a low number of press releases enjoy higher returns than those publishing a high number of press releases (PR). firms that enjoy a high level of public attention due to a much higher volume of annual PRs get noticed more, which leads to overpricing, which can ultimately yield lower returns.

In addition to the information generated by the firms and the press, discussed in the previous section, firm-related information is also disseminated using online social media. One of the earliest studies conducted about internet stock messages boards was that of Wysocki (1998), who found that firms whose stocks receive the highest volume of posted messages were characterized by: extreme returns, high market value and high trading volume. An increase in overnight message postings led to a positive abnormal return on the next day. Studies on the online social networks effect, such as that of Antweiler and Frank (2004) determined that when many messages were posted on a given day, there was a negative return on the next day. Das and Chen (2007) found a negative correlation between changes in the number of messages and changes in the contemporaneous stock prices. Gilbert and Karahalios (2010) used over 20 million posts from the LiveJournal website to create an index of the national mood in the United States, when this index rose sharply, the S&P 500 Index ended the same day marginally lower than was expected. According to Chen et al. (2014), the views expressed in both articles and commentaries posted on a popular social media outlet predicted future stock returns for a period of three months after their publication.

The few studies that investigated the role of Twitter tweets on stock returns, had mainly dealt with their sentiment and not with the volume of tweets per se. Zhang et al. (2011) analyzed a sample of Twitter posts for six months to measure collective fear and hope. Examining whether these collective emotions correlated with major stock indices in the U.S. market, the authors found that “emotional tweet percentage significantly negatively correlated with Dow Jones, NASDAQ and S&P 500, but displayed significant positive correlation to VIX[[2]](#footnote-2).” Forbergskog and Blom (2014) demonstrate that the positive and negative sentiment extracted from tweets could predict both positive and negative S&P 500 returns the following day. Furthermore, Sul, et. al. (2014) showed that sentiment polarities extracted from tweets positively correlated with intraday returns of the S&P 500, and Twitter users with more followers had greater influence on the returns.

Even fewer studies analyzed the role of Tweeter on IPOs. Liew and Wang (2016) documented a contemporaneous positive correlation between IPOs’ tweet sentiment and returns in the first trading day. In addition, they found that tweet sentiment in the days preceding the IPO could predict the IPO’s first day returns from opening price to closing price. Gregori et al. (2020) analyzed Tweets in the 3 months prior to each IPO for a sample of 412 US IPOs between 2010 and 2016. Results show that the more favorable the sentiment, the closer the offer price is set to the maximum achievable to the benefit of the issuer; on the contrary, negative sentiments seem to play no effect on the pricing, supporting the idea that investors are net buyers of attention-grabbing news. The number of Tweets shows no effect as well. Kwan (2015) found that higher Twitter volume on the first trade day is correlated with higher first day returns and did not find a significant predictive relationship between Tweets volume and IPO performance.

**3. Stock Behavior Post-IPO**

3.1. **Research Goals and Hypotheses**

In the first 25 days after an IPO is priced and opens for trading, underwriters and their affiliated analysts are not allowed to publish any research about the company. Consequently, the stock trades as an “uncovered” stock. The ending of this quiet period is important because the simultaneous launching of coverage by several underwriters on that day can have a significant impact on the stock price. The duration of this period has changed over the years, and the SEC recently shortened it to 10 days after the IPO. However, most investment banks still observe the 25-day rule, so that outside coverage commences 25 days after first day of the IPO pricing. Our goal was to investigate CAAR behavior from the IPO date to the end of the quiet period and thereafter. Thus, it can be expected to see an upward trend in CAAR during the quiet period and a downward trend after it ends. An increase in CAAR is expected due to the natural hype immediately following the IPO. The later downward trend can be explained, in part, to the publishing of numerous reports about the company and future forecasts by affiliated analysts.

Biotechnology drug development is a long and expensive process. Hundreds of millions of dollars are needed to develop a biotechnological drug and the chances of success of a product developed in the laboratory to pass the experiments in animals and humans and reach the market, are one in ten thousand. Naturally, large-sized firms are likely to have more experience, more available resources, and a bigger product portfolio. The presence of these factors is likely to enhance a large firm’s potential for future success as well as to attract greater attention from investors. Accordingly, we assume that bigger firms will perform better than smaller ones. (See also Georgen et al. (2009) and Berk and Peterle (2015)). To that end, we divided the sample into two subsamples according to firm size, we expect to observe better performance among large-sized firms. We formulated the following hypotheses to reflect these expectations:

***H1: Quiet Period:* Stock’s return until the end of the quiet period:**

The natural hype from the new IPO will yield positive CAAR from the IPO date until the end of the quiet period.

***H2: Quiet Period:* Stocks return post-quiet period:**

As coverage initiates by underwriters and their affiliated analysts at the end of the quiet period, and as the initial hype diminishes, the stock will experience a negative CAAR.

***H3:* Sock returns and market capitalization:**

Large-sized firms are likely to perform better than small-sized firms, due to their higher potential for future success and their greater share of investor attention.

**3.2 Data and Method**

Our initial database consisted of all biotech companies that issued IPOs in the period from January 2013 to December 2019. Data was extracted from the EvaluatePharma database and NASDAQ web site and consisted of 434 companies.[[3]](#footnote-3) We focused on companies traded in the United States, thus excluding firms traded on non-U.S. stock exchanges. We also excluded firms that became private or were merged into or acquired by others from the time of the IPO until three years following the IPO. Our final database consisted of 367 firms. Table 1 displays the number of IPOs per year in our final database.[[4]](#footnote-4)

Table 1: Number of IPOs per year

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **year** | **total** | **biotech.** | **biotech (%)** | **sample** |
| 2013 | 248 | 52 | 17% | 30 |
| 2014 | 312 | 85 | 24% | 70 |
| 2015 | 200 | 64 | 27% | 49 |
| 2016 | 128 | 33 | 25% | 29 |
| 2017 | 210 | 51 | 24% | 50 |
| 2018 | 258 | 82 | 32% | 82 |
| 2019 | 266 | 69 | 26% | 57 |
| Total | 1,622 | 403 |  | 367 |

Note: This table presents the number IPOs that took place in the USA during the years of the sample, the number of Biotech IPOs in these years and the number of IPOs included in the sample.

A prominent feature of the firms in our sample is their relatively low market capitalization,[[5]](#footnote-5) as displayed in Table 2. The average market value is $556M, and the median market value is $297M. Years 2018 - 2019 are characterized by higher market value than 2013-2017 $708M versus $461M due to two extreme values[[6]](#footnote-6). It appears that Biotech companies have well utilized the JOBS ACT that enable ECG companies to issue shares to the public. Overall, the average size of biotech firms in our sample is very small in terms of average issue size and is about 27% of the size of firms that issued in those years. According to data from Ritter (2020), the average size of a firm issued in the years 2013-2019 was $2,024M and the median was $1,202M compared to $556M and $297M in our sample (Table 2).

Table 2: Descriptive statistics for Market Value ($M) as of the end of the IPO year

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **2013** | **2014** | **2015** | **2016** | **2017** | **2018** | **2019** | **2013-2019** |
| **Average** | 487 | 405 | 489 | 425 | 499 | 766 | 650 | 556 |
| **Median** | 374 | 229 | 287 | 299 | 368 | 337 | 301 | 297 |
| **Min** | 45 | 11 | 1 | 9 | 19 | 12 | 8 | 1 |
| **Max** | 2,308 | 2,165 | 2,347 | 1,843 | 2,685 | 11,528 | 7,166 | 11,528 |
| **Std. Dev** | 456 | 452 | 576 | 444 | 521 | 1,600 | 1,129 | 964 |
| **Count** | 30 | 70 | 49 | 29 | 50 | 82 | 57 | 367 |

Note: This table presents descriptive statistics of the market capitalizations of the firms studied.

The event study approach (see: Binder, J. (1998)) was employed to examine market reaction to IPO events. The actual date of the IPO was marked as t=0 and the daily stock prices extracted from the NASDAQ website and Yahoo Finance were applied for the period t=0…755 (three years post-IPO), to calculate daily logarithmic returns. We chose the logarithmic calculation returns on a simple gross return calculation because of the continuous accumulation feature of Ln, where the cumulative return is the sum of the periodic returns. Two return benchmarks were utilized: the IXJ Healthcare Index, and the S&P 500 Market Index. The Abnormal Return (AR) was calculated for each stock by subtracting the benchmark returns from the stock return. CAR was calculated for each stock by summing the ARs from day 0 to day t and, Cumulative Average Abnormal Return (CAAR) was calculated by averaging the firms CAR, each day relative to the IPO date. As no stock prices exist prior to the IPO, conditional return using the market model was not calculated. We calculated the CAAR for the entire sample, and in addition, we divided our database into two subsamples of small and large firms and calculated the CAAR for each of them. The average rounded market value of $500 million was chosen as a threshold to differentiate between small-sized and large-sized firms. Given that the MV series is not normally distributed, one can argue that using the median as a separation value between small and large firms is as good as the average. We chose a number close to the average, because we assume the market value of $500M is better perceived as a separator between small-sized and large-sized firms.

Normalized trading volumes were computed as a proxy for market attention. For each firm in the sample, the natural logarithm of the daily trading volume throughout the period t=0…755 was recorded, and each observation was normalized by subtracting the mean and dividing by the standard deviation calculated over the period. Then, the average across all firms for each day relative to the IPO date was calculated.

3**.3 Results**

The CAAR results for selected time periods during the three years post-IPO are presented in Table 3. The CAAR results are presented using two return benchmark and were calculated for the entire sample, for a subsample of small-sized firms with a market capitalization ≤ $500 million (68% of the sample), and for the large-firms with a market capitalization higher than $500 million (32% of the sample). Figure 1 graphically illustrates the results of Table 3 and the normalized trading volumes over the 3 years post IPO. As the CAAR results relative to the two benchmarks are similar, reference will be made only to the sector index benchmark.

As shown in Table 3, the CAAR for the first 20 trading days post-IPO for the entire sample is positive and equals 1.71% (t = 0.34). These results are in the spirit of H1 hypothesis yet due to its insignificance, we reject H1. After 20 trading days, performance began to decrease, diminishing significantly until the 50th trading day, with CAAR = -1.99% (t = -0.40). One hundred trading days post-IPO, CAAR = -7.10% (t = -1.54); 200 trading days post-IPO, CAAR = -21.46% (t= -4.62); 250 trading days post-IPO CAAR = -26.74% (t = -5.71); two years (550 trading days) post-IPO, CAAR = -58.61% (t = -11.92); and three years (755 trading days) post-IPO, CAAR = -84.08% (t = -19.00). The results demonstrate a CAAR decline that is consistent from day 20 onward. These results are consistent with previous literature and support hypothesis H2.

With respect to small-sized firms, CAAR exhibits decline from the very beginning yet becomes significant from day 50 onward. Fifty trading days post-IPO, CAAR was -8.22% (t = -1.65); 100 trading days post- IPO, CAAR was -15.64%, (t = -3.46); one-year post-IPO, CAAR = -40.56% (t = -8.46). The results for large-sized firms reveal a completely different picture. CAAR is positive from the very beginning yet gain significance from day 50 onward, with CAAR = 9.05%, (t = 1.8); after 100 trading days CAAR = 12.91% (t = 3.14). One year after the IPO, CAAR = 6.00% (t = 1.58) and 3 years post-IPO CAAR=-38.45% (t=-11.55). CAAR reaches its peak of 14.76% (t=3.56) 108 post-IPO and begins to decline from that point until it disappears completely 299 days post-IPO. To conclude, investors’ activity post-IPO differs significantly depending on the firm’s size. Small-sized firms exhibited negative CAAR in the first year post-IPO and large firms exhibited positive CAAR in the first year post-IPO. These findings support hypothesis H3 and are in line with Georgen et al. (2009) and Berk and Peterle (2015).

To pinpoint firm value of $500M as a separator value between small-sized firms (“poor”) and large-sized firms (“rich”), we repeated CAAR calculation for large-sized firm subsample using $100M, $200M, $300M and $400M as a separator value. The results presented in Appendix A support our choice and indicating that for values smaller than $500M, the positive CAAR is either not significant or does not last beyond the first 100 days post-IPO.

In terms of trading volumes, the IPO day was characterized by the highest trading volume during the entire three-year post-IPO period. On the second trading day, trading volumes decreased substantially and from that point on, trading volumes showed an increasing growth trend over time for both small and large firms (Figure 1).

**Table3: Post-IPO CAARs, +1 to +755 days**

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **Sector Index** | | | | | |  | **Market Index** | | | | | |
| Days | **All sample** | | **Large Firms** | | **Small Firms** | |  | **All sample** | | **Large Firms** | | **Small Firms** | |
| CAAR | t-stat. | CAAR | t-stat. | CAAR | t-stat. | CAAR | t-stat. | CAAR | t-stat. | CAAR | t-stat. |
| 1 to 10 | 0.21% | 0.04 | 2.39% | 0.43 | -0.66% | -0.12 |  | 0.35% | 0.06 | 2.54% | 0.46 | -0.80% | -0.14 |
| 1 to 20 | 1.71% | 0.34 | 5.58% | 1.20 | 0.25% | 0.05 |  | 1.97% | 0.39 | 5.69% | 1.21 | -0.08% | -0.01 |
| 1 to 50 | -1.99% | -0.40 | 9.05% | 1.80 | -8.22% | -1.65 |  | -1.44% | -0.29 | 9.60% | 1.88 | -8.54% | -1.71 |
| 1 to 100 | -7.10% | -1.54 | 12.91% | 3.14 | -15.64% | -3.46 |  | -6.31% | -1.36 | 13.78% | 3.25 | -16.38% | -3.62 |
| 1 to 150 | -16.04% | -3.55 | 9.07% | 2.26 | -26.80% | -5.99 |  | -15.08% | -3.29 | 10.20% | 2.47 | -27.70% | -6.28 |
| 1 to 200 | -21.46% | -4.62 | 12.47% | 3.28 | -36.35% | -7.77 |  | -20.53% | -4.32 | 13.88% | 3.55 | -37.06% | -8.09 |
| 1 to 250 | -26.74% | -5.71 | 6.00% | 1.58 | -40.56% | -8.46 |  | -25.21% | -5.33 | 7.81% | 2.03 | -41.89% | -8.84 |
| 1 to 375 | -36.80% | -8.03 | 5.96% | 1.49 | -55.31% | -12.01 |  | -36.72% | -7.84 | 6.26% | 1.54 | -55.30% | -12.32 |
| 1 to 550 | -58.61% | -11.92 | -4.09% | -1.11 | -83.62% | -16.24 |  | -60.40% | -12.07 | -5.62% | -1.51 | -81.71% | -16.23 |
| 1 to 755 | -84.08% | -19.00 | -38.45% | -11.55 | -104.17% | -22.45 |  | -85.40% | -19.19 | -38.46% | -11.39 | -102.3% | -22.10 |
| Obs. | 367 | | 116 | | 251 | |  | 367 | | 116 | | 251 | |

Note: This table displays Cumulative Average Abnormal Return for the entire sample and the two subsamples of firms with market valuations below $500M (small) and above $500M (large) as of December of the IPO year. CAAR is presented for selected time periods relative the IPO date.

**Figure 1: Post-IPO CAARs, +1 to +755 days**

**Panel A: CAAR to Sector**



**Panel B: CAAR to Market**



Note: These figures present daily CAAR after the IPO from day 1 to day 755. Panel A presents CAAR that was calculated versus the sector index and panel B displays CAAR that was calculated versus the S&P500.

We will turn now to examine the level of activity on the Twitter social media platform before and after the IPO and its relation to stock returns. In addition, based on the results above, we look at the relation between the firm size and the Tweet volume, analyzing, inter alia, whether firms use social media as a tool to promote a successful IPO.

**4. Tweets and IPOs return**

When considering the volume of tweets as a reflection of the level of attention a firm has attracted, it should be noted that the volume of tweets has been weighted relative to the tweet volume of other firms. As a result, even a low tweet volume can stand out in an environment where comparable firms have a lower volume or no tweets at all, thereby creating an impact, perhaps even similar to that of a firm with very high tweet volume in an environment of high tweet volumes. Therefore, the mere number of tweets itself is often meaningless; the number becomes more meaningful only when compared with others in the comparable sector. For that reason, the number of tweets above and below the median for each year relative to the IPO have been characterized as High Twitter Volume (HTV) and Low Twitter Volume (LTV) respectively.

**4.1 Research Goals and Hypotheses**

Our goal was to analyze the correlation and possible causality between the annual volume of tweets about a firm and that firm’s main capital market variables. The expectation was that a positive relationship would be found, so that large-sized firms, high trading volumes and high returns would increase investor interest, which would be reflected in a higher volume of tweets, and, conversely, that higher volumes of tweets would draw investors’ attention, which would be reflected in higher market activity.[[7]](#footnote-7) In addition, it was expected to find causality between the annual volume of tweets about a firm and that firm’s returns, so that a high volume of tweets in a given period would have positive impact on returns in the ensuing period.

We formulated the following hypotheses to reflect these expectations:

***H4: Correlation:*** There will be a positive correlation between Twitter volume and capital market variables: risk, returns, trading volume and market capitalization**.**

***H5:*** C***ausality:*** a: There will be a positive causality between the annual volume of tweets

about a firm and its annual returns.

b: There will be positive causality between the volume of tweets a firm

receives in periods of less than one year, one week, two weeks and

one month prior to the IPO, and returns in parallel periods post-

IPO.

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**4.2 Data and Method**

For each firm in our sample, we downloaded its related tweets using Python programing[[8]](#footnote-8), starting from one calendar year preceding the IPO day and up to three calendar years post-IPO. We extracted all tweets containing: full company name, $ + firms’ ticker and the company’s twitter username if there was one, such as @chimerix for Chimerix. Next, we excluded all unrelated tweets in which the company name appeared in a non-company context, such as “Adam Kadmon” for Kadmon. Our Twitter database consisted of daily tweets for each company and contained over 1.5 million tweets. Table 4 displays descriptive statistics regarding the annual volume of tweets. The actual date of the IPO was marked as t=0, we name the pre-IPO days -250 – (-1) as IPO year-1, post-IPO days 0–250 as IPO year, post-IPO days 251–501 as IPO year+1 and post-IPO days 502–755 as IPO year+2.

**Table 4: Volume of Tweets: Descriptive Statistics**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **IPO Year-1** | **IPO Year** | **IPO Year+1** | **IPO Year+2** |
| **Average** | 359 | 2,237 | 3,083 | 3,558 |
| **Median** | 246 | 1,524 | 2,377 | 2,326 |
| **Std. Dev.** | 377 | 2,690 | 2,978 | 3,976 |
| **Min.** | 0 | 0 | 197 | 15 |
| **Max.** | 2,035 | 26,126 | 20,022 | 27,579 |
| **No. of Tweets** | 65,349 | 407,067 | 548,815 | 542,232 |
| **No. of firms** | 182 | 182 | 178 | 147 |

Note: This table presents Twitter volume descriptive statistics for one year before the IPO up to two years after the IPO. Tweets were extracted only for firms that performed IPO between 2013 – 2017.

Two main findings emerged, as presented in Table 4. First, the average annual number of tweets increased over the years, from 359 during the year preceding the IPO, through 2,237 tweets during the IPO year and up to 3,558 tweets two years after the IPO. The second notable observation is the huge variance in the annual volume of tweets among the firms. For example, in Adverum Biotechnologies’ IPO year, it had zero tweets, while Juno Therapeutics had over 26,000 related tweets in its IPO year. The growing number of annual tweets reflects both the growth in Twitter’s popularity and the increased interest in firms over time.

To explore the relations between the volume of tweets and capital market variables, both univariate and multivariate analyses were employed. In the univariate analysis, several capital market variables were calculated for each firm in our database and compared the average of these variables between the LTV and HTV groups. The compared variables were Return (t), the rate of return on a firm’s stock at period t; Trading volume (t), a firm's daily average trading volume at period t; Std. Dev. (t), the standard deviation of daily returns calculated over the period and used as a proxy for total risk and beta is a proxy for systematic risk coefficients. For the IPO year beta was estimated using the market model regression on both Indexes based on the first 50 trading days after the IPO for the IPO year+1 and IPO year+2 beta was estimated using daily returns of a time window that ends ten trading days before the beginning of that year. Market value (t) was calculated as the number of shares for December of that year multiplied by the stock price of that day.

While there are many parameters that attempt to explain stocks return, our goal was to shed light on the relationship between returns and their contemporaneous tweets volume. This goal guided our choice of the explanatory variables in the multivariate section. The multivariate analysis employs two sets of ordinary least squares (OLS) linear regressions to analyze the contemporaneous relation between annual volume of tweets and the annual returns and abnormal returns. The regression equations were:

(1)

(2)

Explained variables were returns and abnormal returns. The abnormal return was calculated relative to two benchmarks: The S&P 500 Index and the IXJ index. Explanatory variables are Rm market return for the S&P500 and IXJ index; Beta- as described above; HTV as a dummy variable that receives 1 for companies with a high volume of tweets and 0 otherwise. The dummy variables for the IPO years 2013–2017 are Y2013 to Y2016, which are aimed at capturing potential influence during a given year. Normalized Market Value (NMV) was calculated for each firm for each year relative to the IPO date by subtracting the firms’ average market value from a firm’s value and dividing by standard deviations of the firms’ market value.[[9]](#footnote-9) Additional multivariate analyses employing causality tests will be detailed later.

**4.3 Results**

**4.3.1 Univariate Analysis**

Table 5 presents descriptive statistics for some capital market variables for the years following the IPO. Panel A presents the IPO year, panel B presents IPO year+1, panel C presents IPO year+2 and Panel D presents absolute tweets volume for small-sized and large-sized firms.

The univariate analysis indicates that firms characterized by a high volume of tweets (HTV) are larger, with higher trading volumes, volatility, and stock returns. For example, differences in returns reached: 7% (p-value = 0.08) in the IPO year, 51% (p-value = 0.001) in the following year and 29% (p-value = 0.04) in the IPO year+2. Trading volumes for the HTV firms were 2.7–2.8 times higher than for the LTV firms and market value was 1.7–2 times higher for the HTV firms. As presented in Panel D, large-sized firms were also characterized by a higher tweets volume in the year before the IPO and in the IPO year. These results support our H4 hypothesis.

**Table 5: Capital Market Variables: Descriptive Statistics for HTV and LTV Firms**

**Panel A: IPO Year**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **LTV** | **HTV** | **Diff** | **P-Value** |
| Market Value ($M) | 322.74 | 585.66 | 262.91 | 0 |
| Return | 0.05 | 0.12 | 0.07 | 0.08 |
| Trading Volume | 94,321 | 267,332 | 173,011 | 0 |
| Return’s Volatility | 0.05 | 0.12 | 0.07 | 0.14 |
| Beta (50 Days) | 0.68 | 1 | 0.31 | 0.03 |
| Observations | 91 | 91 |  |  |

**Panel B: IPO Year+1**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **LTV** | **HTV** | **Diff.** | **P-Value** |
| Market Value ($M) | 418.17 | 844.56 | 426.38 | 0.001 |
| Return | -0.15 | 0.36 | 0.51 | 0.001 |
| Trading Volume | 162,046 | 441,602 | 279,556 | 0 |
| Return’s Volatility | 0.044 | 0.057 | 0.013 | 0.001 |
| Beta (former year) | 0.65 | 0.87 | 0.22 | 0.07 |
| Observations | 89 | 89 |  |  |

**Panel C: IPO Year+2**

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **LTV** | **HTV** | **Diff.** | **P-Value** |
| Market Value ($M) | 493.44 | 841.79 | 348.35 | 0.017 |
| Return | 0 | 0.29 | 0.29 | 0.043 |
| Trading Volume | 244,890 | 660,862 | 415,973 | 0 |
| Return’s Volatility | 0.04 | 0.06 | 0.01 | 0 |
| Beta (former year) | 0.83 | 1.26 | 0.43 | 0.00 |
| Observations. | 75 | 72 |  |  |

**Panel D: Absolute Tweet Volume per Firm Size**

|  |  |  |  |
| --- | --- | --- | --- |
| **Absolute Tweet Volume** | **Small** | **Large** | **P-value** |
| IPO Year -1 | 310 | 474 | 0.01 |
| IPO Year | 2,068 | 2,636 | 0.07 |
| IPO Year+1 | 3,063 | 3,135 | 0.43 |
| IPO Year+2 | 3,404 | 4,001 | 0.20 |

Note: Panels A to C present descriptive statistics of market variables for the sample firms divided into LTV and HTV firms. The beta displays in this table estimated using the sector index. Panel D presents absolute annual tweet volume from one year before the IPO through three years after the IPO.

**4.3.2 Multivariate Analysis**

Considering the positive correlation found between annual tweets volume and stocks return in the univariate analysis, we conducted the regression analysis as set forth in equations 1 and 2. The regression results are displayed in Table 6. Panel A (B) displays the results for the return (Abnormal Return) as the dependent variable. Due to high correlation coefficient of 0.27 between tweets volume and the control variable normalized market value, we repeated the regressions without NMV as an explanatory variable (model 2)[[10]](#footnote-10). The regressions results are presented relative to the sector index only due to similarities between results using the two selected benchmarks.

**Table 6: The Effects of Tweet Volume on Returns and Abnormal Returns (AR): Regression**

**Results**

**Panel A: Explaining Returns**

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **IPO Year** | | | **IPO Year +1** | | | **IPO Year +2** | | |
|  | **Model 1** | **\*Model 2** | | **Model 1** | **Model 2** | | **Model 1** | **Model 2** | |
| Intercept | 1.09 (0.07) | | 1.21 (0.05) | -0.14 (0.44) | | -0.21 (0.26) | -0.05 (0.80) | | -0.05 (0.79) |
| Year 2013 | -1.06 (0.05) | | -1.23 (0.03) | 0.00 (0.98) | | 0.00 (0.99) | -0.55 (0.08) | | -0.54 (0.08) |
| Year 2014 | -1.03 (0.05) | | -1.23 (0.03) | -0.12 (0.61) | | -0.08 (0.75) | -0.03 (0.88) | | -0.04 (0.85) |
| Year 2015 | -1.45 (0.02) | | -1.61 (0.01) | 0.03 (0.88) | | -0.07 (0.71) |  | |  |
| Year 2016 | -1.28 (0.02) | | -1.49 (0.01) |  | |  |  | |  |
| Rm\_sector | 1.60 (0.20) | | 1.64 (0.20) | 2.13 (0.05) | | 2.69 (0.02) | 1.2 (0.37) | | 1.2 (0.36) |
| NMV | 0.22 (0.00) | |  | 0.26 (0.00) | |  | 0.03 (0.74) | |  |
| HTV | 0.18 (0.21) | | 0.30 (0.04) | 0.36 (0.01) | | 0.47 (0.00) | 0.46 (0.01) | | 0.47 (0.01) |
|  |  | |  |  | |  |  | |  |
| Adjusted R2 | 0.19 | | 0.15 | 0.23 | | 0.16 | 0.06 | | 0.07 |
| F stat (p-value) | 7.08 (0.00) | | 6.18 (0.00) | 9.86 (0.00) | | 7.68 (0.00) | 2.96 (0.01) | | 3.69 (0.00) |
| Obs. | 182 | | 182 | 178 | | 178 | 147 | | 147 |

**Panel B: Explaining AR to Sector**

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  | **IPO Year** | | **IPO Year +1** | | **IPO Year +2** | | |
|  | **Model 1** | **Model 2** | **Model 1** | **Model 2** | **Model 1** | **Model 2** | |
| Intercept | 0.20 (0.59) | 0.31 (0.42) | -0.13 (0.38) | -0.22 (0.16) | 0.07 (0.74) | | 0.06 (0.77) |
| Year 2013 | -0.18 (0.64) | -0.32 (0.42) | -0.05 (0.80) | -0.05 (0.80) | -0.58 (0.02) | | -0.58 (0.02) |
| Year 2014 | -0.08 (0.84) | -0.24 (0.53) | -0.34 (0.03) | -0.37 (0.02) | -0.02 (0.91) | | -0.03 (0.87) |
| Year 2015 | -0.69 (0.07) | -0.84 (0.03) | -0.04 (0.82) | -0.16 (0.34) |  | |  |
| Year 2016 | -0.36 (0.35) | -0.54 (0.18) |  |  |  | |  |
| Beta\_sector | -0.19 (0.00) | -0.19 (0.00) | -0.03 (0.78) | 0.07 (0.49) | -0.08 (0.52) | | -0.08 (0.54) |
| NMV | 0.18 (0.00) |  | 0.25 (0.00) |  | 0.03 (0.69) | |  |
| HTV | 0.08 (0.4) | 0.18 (0.07) | 0.19 (0.09) | 0.27 (0.03) | 0.49 (0.01) | | 0.50 (0.01) |
|  |  |  |  |  |  | |  |
| Adjusted R2 | 0.22 | 0.17 | 0.16 | 0.06 | 0.04 | | 0.05 |
| F stat (p-value) | 8.43 (0.00) | 7.06 (0.00) | 6.55 (0.00) | 3.14 (0.01) | 2.25 (0.05) | | 2.79 (0.03) |
| Obs. | 182 | 182 | 178 | 178 | 147 | | 147 |

Note: This table displays the results of OLS regressions in which the dependent variables were Return and Abnormal Return. P-values are displayed in parentheses. Tweets data ends in 12/1/18, therefor observations of firms for which the IPO took place after Dec. 1, 2017, were excluded from the IPO year +1 and IPO year +2 analysis., firms for which the IPO took place after Dec.1, 2016 were excluded from the IPO year +2 analysis.

The contemporaneous correlation between tweet volume and returns found in the univariate analysis, was also recorded in the multivariate analysis, indicating that the difference in returns between HTV and LTV firms is tens precents every year in favor of the HTV firms. The HTV coefficient is 0.3 (p=0.04) for the IPO year, (Panel A, model 2); 0.36 (t=0.01) for the year IPO+1 (model 1) and 0.46 (p=0.01) for the year IPO+2 (model 1). Regarding AR (Panel B model 2), the results are similar, firms with HTV presents higher AR of 0.18 (p=0.07) in the IPO year (model 2); 0.19 (t=0.09) in the IPO year+1 (Model 1) and 0.49 (p=0.01) in the IPO year +2 (Model 1).

Normalized market value is positively correlated with returns and Abnormal Returns in the first two years as was also demonstrated in the former CAAR analysis section. For example (panel A, model 1) 0.22 (P=0.00) in the IPO year; 0.26 (p=0.00) in the IPO year+1 (Model 1) and 0.03 (p=0.74) in the IPO+2 year (Model 1). The Rm-sector variable proves to be significant in the first two years, however, lost its significance in the third one.

We turn now to examine the causality between tweets volume and returns. We conducted three sets of regressions. First, we examined whether tweets volume in a certain year affected stock returns in the following year. Specifically, we conducted the following regressions:

(3) - (4)

Despite our expectation of finding a causality link between tweet volume and returns, no such link was uncovered in the various regressions we conducted. Considering these results, we analyzed whether high or low tweets volume one week, two weeks or one month before the IPO affected one week, two weeks or one-month post-IPO returns. Here, too, no causality was found. We suggest that the absence of causality may stem from the relatively long periods of time we examined. It may be that the effect of tweets is myopic or short-sighted in nature and affects time periods of hours or days, as was shown by Forbergskog and Blom (2013), Sul, et al. (2014) , Zhang et al. (2011) and Kwan (2015). The relatively long timeframes examined in this study constitute a limitation. Further research is needed to examine causation during shorter-term time periods.

**5. Discussion and Conclusions**

During the last few decades, psychological aspects of decision-making have been successfully integrated into economic modeling, adding to the descriptive power of the traditional normative approach based on rational expectations. Numerous study results indicating individuals’ cognitive limitations have been documented as part of this trend.

Our contribution to this line of work is in several aspects, first, we have focused on the post-IPO period of biotechnology firms representing the “new world” of firms. Most of these are small-sized firms developing one or only a few drugs. Therefore, investors’ attention has enormous influence on companies’ share prices. The phenomenon of a collapse in shares’ CAAR after IPO has been well known for years (see Loughran and Ritter, 1995 and Ritter and Welch, 2002). However, only a small portion of the studies have focused on the biotechnology sector, despite this sector being ranked as a leading one based on its revenues. Second, we investige small-sized firms’ behavior after the change in regulations signified by the passage of the JOBS Act in 2012 which has dramatically altered investors’ approach to these kinds of small-sized firms, resulting in these firms receiving more attention from capital markets. Third, finding the $500M as the necessary minimal market value for firms seeking to perform a successful IPO. We suggest that firms’ with smaller market values are being perceived with small likelihood to survive which leads to share underperformance in the years following the IPO. And fourth, this study sheds light on the behavior of market participants for whom a prominent presence social media as reflected in high tweets volume contributes to the firm’s perceived quality. This higher perceived company image bias and boost financial trading activity and stock pricing, which in turn affects stock rates of return in the contemporaneous year.

This study documents CAAR's behavior following IPOS of innovative biotechnology firms. The overall picture of stock performance after IPOs indicates that firms receive short-term hype immediately after the IPO with positive yet insignificant CAARs that peak close to the end of the quiet period 20 days after the IPO. This increase in CAAR is followed by a consistent and long decline of tens of precents in the subsequent three years. These results reflect a market inefficiency in its weak form, providing yet another example of individuals’ cognitive limitations. These findings also indicate that the changes engendered by the 2012 JOBS Act have not actually changed long-term negative CAARs post-IPO, a result found in similar studies (see Loughran and Ritter, 1995 and Ritter and Welch, 2002) conducted before the enactment of the Act.

Unexpected results emerged when analyzing investors’ activity according to firm size. In our sample, small-sized firms demonstrated negative CAAR, while large-sized firms enjoyed positive CAAR in the post-IPO years. We suggest that this dramatic difference in results experienced by small-sized firms and large-sized firms can be attributed to the ability of the firms to meet investor expectations of a desirable growth rate of revenues and profits. Large companies, which are likely to rely on a broad product line, find it easier to meet or exceed market expectations in that regard, as evidenced by their positive yet volatile CAAR in the years following the IPO (table 3, Panels A and B), (for the perceived value of innovations see Guo and Zhou (2016) and Cau et al. (2015)). It appears that the volatility reflects close monitoring by the market, responses to the results of trials, and adherence to drug development timelines. Small-sized firms rely on one or a few products. Any delay in development or experimental failure makes it difficult for these small firms to meet investors’ expectations regarding desirable growth rates of revenue and profits. Failing to meet these expectations can lead to negative CAARs. This make-or-break situation for small-sized firms may affect the optimal timing for IPO.

Our study shows that examining IPOs in terms of the firms’ maturity is critical to the success of the issue. Consequently, a value of $500 million may be viewed as a threshold for biotech firms seeking to go forward with an IPO. We can observe that small-sized firms are overpriced at the IPO stage, while large-sized firms are underpriced. This finding is of great importance to firms aiming to raise money via the capital markets.

Failure to meet market expectations, as explained above, results in limited investor attention, As also reflected in the findings of a significant lower tweets volume for small-sized firm. These findings are consistent with those of Barber and Odean (2007), who measured indirect investor attention using three observable measures that are likely to be associated with attention-grabbing events: media, unusual trading volume, and extreme returns. These findings are consistent with our hypotheses that larger and high yield companies will attract more investor attention, as reflected in the Twitter discourse volume, and that companies attracting more investor attention are larger and enjoy higher yields.

We suggest that the high volume of discourse contributes to investor awareness of the company. The ongoing exposure on Twitter leads to the branding effect of the firm, which increases investor confidence in its reliability and prosperity. The resulting perceived quality of the firm leads to a higher volume of purchases of its shares at a high price. These purchases prove to be justified due to the continued difference in returns in favor of the HTV firms.

To conclude, our findings have implications about investors’ limited attention regarding small-sized firms, which become “off-the-radar” stocks. We assume an IPO ignites a period of investor attention which rises until the end of quiet period and then investors’ attention to small size firms diminishes at the post IPO years as they seek their next lottery like opportunity. Despite the enormous under performance of small firms, performing an IPO increases their exposure and therefore, as suggested by Zingales (1995), Mello and Parsons (1998) and Dambra et al. (2015), an IPO can be a first step towards a future sale. This seems particularly relevant to small pharma firms whose acquisition by an established, asset-rich firm is likely to be the best option to support the drug development process until its successful completion.

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**Appendix A**

Table A: CAAR for “large-sized” firm using different separation market values

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Market Value above | **$100M** | | **$200M** | | **$300M** | | **$400M** | | **$500M** | |
| Days relative to event | CAAR, % | t-stat. | CAAR, % | t-stat. | CAAR, % | t-stat. | CAAR, % | t-stat. | CAAR, % | t-stat. |
| 1 to 10 | 1.70% | 0.31 | 3.15% | 0.58 | 3.10% | 0.56 | 2.59% | 0.47 | 2.54% | 0.46 |
| 1 to 20 | 4.25% | 0.88 | 6.16% | 1.37 | 5.76% | 1.28 | 5.50% | 1.18 | 5.69% | 1.21 |
| 1 to 50 | 3.08% | 0.62 | 6.01% | 1.22 | 9.99% | 2.07 | 9.48% | 1.94 | 9.60% | 1.88 |
| 1 to 100 | 1.16% | 0.25 | 4.87% | 1.10 | 10.23% | 2.32 | 9.38% | 2.11 | 13.78% | 3.25 |
| 1 to 150 | -5.75% | -1.30 | -1.49% | -0.35 | 5.42% | 1.27 | 4.27% | 0.99 | 10.20% | 2.47 |
| 1 to 200 | -9.59% | -2.08 | -3.24% | -0.73 | 5.33% | 1.24 | 5.29% | 1.21 | 13.88% | 3.55 |
| 1 to 250 | -15.43% | -3.31 | -7.14% | -1.67 | 0.44% | 0.10 | -1.61% | -0.37 | 7.81% | 2.03 |
| 1 to 375 | -27.48% | -5.85 | -15.69% | -3.49 | -3.00% | -0.67 | -3.03% | -0.66 | 6.26% | 1.54 |
| 1 to 550 | -48.65% | -9.76 | -38.58% | -7.71 | -19.47% | -3.99 | -11.8% | -2.83 | -5.62% | -1.51 |
| 1 to 755 | -77.80% | -17.7 | -68.63% | -14.9 | -46.55% | -13.20 | -37.4% | -11. 7 | -38.46% | -11.39 |

Note: this table present large-sized firm CAAR results, when using $100M, $200M, $300 and $400M as a separating value between small-sized and large-sized firms.

1. Quoted in Bhattacharya, U., Galpin, N., Ray, R., & Yu, X. (2009). The role of the media in the internet IPO bubble. *Journal of Financial and Quantitative Analysis*, *44*(3), 657-682., p1 [↑](#footnote-ref-1)
2. **VIX**, is a popular measure of the [stock market](https://en.wikipedia.org/wiki/Stock_market)’s expectation of volatility implied by S&P 500 index options. It is calculated and disseminated on a real-time basis by the Chicago Board Options Exchange (CBOE), and is commonly referred to as the fear index or the fear gauge(Wikipedia). [↑](#footnote-ref-2)
3. EvaluatePharma database is one of the top global pharma databases: <http://www.evaluate.com/> [↑](#footnote-ref-3)
4. A detailed list of the companies can be provided upon request. [↑](#footnote-ref-4)
5. Market capitalization for December of the IPO year calculated by multiplying the number of shares appearing in the firms’ profit and loss statement by the stock price on that day. The result was confirmed with the value appearing on the stockraw.com website. [↑](#footnote-ref-5)
6. The companies' market capitalization series is not normally distributed as evidenced by Jarque-Bera Test results. [↑](#footnote-ref-6)
7. One of our goals was to explore whether firms that conduct an active tweeting policy had an advantage over these who do not with respect to returns. Surprisingly, the firms’ activity on Twitter was non-existent or very low. For example, in the IPO year, only 15 out of 182 companies used Twitter and were responsible for less than 0.6% of the total number of tweets. This low participation rate within the total number of tweets rendered this analysis pointless. [↑](#footnote-ref-7)
8. Due to limitations of using Twitter API, we perform this analysis only for the years2013 to 2017. [↑](#footnote-ref-8)
9. Market capitalization is calculated for December of each year relative to the IPO date. [↑](#footnote-ref-9)
10. Despite the relative simplicity of the regression models offered, they are well specified as was proved by heteroscedasticity tests. [↑](#footnote-ref-10)