The Stock Exchange of Influencers: A Financial Approach for Studying Fanbase Variation Trends

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***Abstract*—In many online social networks (OSNs), a limited portion of profiles emerges and reaches a large base of followers, i.e., the so-called social influencers. One of their main goals is to increase their fanbase to increase their visibility, engaging users through their content. In this work, we propose a novel parallel between the ecosystem of OSNs and the stock exchange market. Followers act as private investors, and they follow influencers, i.e., buy stocks, based on their individual preferences and on the information they gather through external sources. In this preliminary study, we show how the approaches proposed in the context of the stock exchange market can be successfully applied to social networks. Our case study focuses on 60 Italian Instagram influencers and shows how their followers short-term trends obtained through Bollinger bands become close to those found in external sources, Google Trends in our case, similarly to phenomena already observed in the financial market. Besides providing a strong correlation between these different trends, our results pose the basis for studying social networks with a new lens, linking them with a different domain.**

***Index Terms*—Social Networks, Influencers, Followers, Google Trends, Instagram, Stock Market, Bollinger bands**

I. Introduction

In the last two decades, Online Social Networks (OSNs) have become increasingly popular and are nowadays part of everyday life and a fundamental means of communication. According to the Digital 2021 Global Statshot Report[1], Facebook and Instagram are used by 2.8 and 1.3 billion users worldwide. In this large and complex ecosystem, a limited portion of social profiles emerges and reaches a large base of followers. One of the main goals of these so-called *influencers* is to increase their fanbase engaging users through the content they offer. In many cases, social celebrities monetize their social presence, offering brands a practical way for marketing [1], [2]. As such, users in OSNs can be roughly divided into two non-exclusive categories: *regular users*, that consume the content of the *influencers* they follow.

In this work, we propose a parallel between the ecosystem of OSNs and the stock exchange market. Influencers can be seen as stocks with a market value, and their goal is obviously to increase this value. Their follower base quantifies the market value. Regular users act as private investors, and they follow (buy) influencers based on their individual preferences and on the information they gather from external sources. In this work, we exploit this analogy and provide a preliminary investigation on the use of techniques and approaches from the stock exchange field to shed some light on the dynamics in OSNs. Bollinger bands and other techniques have been used within decision support system applications to give traders recommendations about transaction on stocks [3]. Similarly, in the field of social networks, this tools may provide influencers, advertisers and social platforms a support for shaping their strategies.

From the end of the 2000s, scholars and practitioners have started to include web interest metrics, such as Google Trends, to complement technical analyses on stocks. For example, Choi et al. [4] studied weekly search volume data for various search terms from 2004 to 2010. They found a link between search volume data and financial market fluctuations, observing that weekly transaction volumes of S&P 500 companies are correlated with the search volume of the corresponding company names. Increasing transaction volumes of stocks coincides with an increasing search volume and vice versa. Preis et al. [5], instead, make a similar hypothesis, using Google Trends as an external measure. They claim that, even if Google Trends might not be useful to predict the future, it certainly helps in predicting and describing the present. For example, the volume of queries on a particular brand of cars during the second week in June helps to estimate (and predict) the June sales report for the brand, a number that might be available much later. Such kind of prediction is also referred to as *nowcasting*. In the context of social networks, the fusion of data from different social networks has already been studied [6]. However, less work has been done in studying the contribution of data coming from external sources, with a focus on Twitter only [7], [8]. In our previous work [9] we assessed the external impact of Covid-19 on trends in OSNs, both considering influencers and followers, while in [10] we studied variation in coordinated trends of followers around politicians during the elections.

In this preliminary work, we show how an approach proposed in the context of the stock exchange market can be successfully applied to social networks. Our idea is to expand those techniques belonging to the financial world to the

[1] https://datareportal.com/reports/digital-2021-april-global-statshot

scope of social network influencers. Our case study targets 60 popular Instagram influencers with various follower base sizes and shows how the Google Trend historical data is instrumental for nowcasting the follower base variation. We show that indicators derived from the Bollinger bands often used in the financial field are instrumental for this objective, catching the underlying short-term phenomena. To the best of our knowledge, we are the first to: (i) Use Bollinger bands in the context of social networks, and (ii) Compare oscillations in Google Trends and in the followers growth rate. We believe that the study of novel usage of financial metrics in social networks, where this work represents the first step, would improve the understanding of social network dynamics and provide tools for decision support systems.

II. Instagram and Google Trends Data

In this work, we take as case study 60 Italian public figures popular in Instagram. For them, we collect historical data on their activity on Instagram as well as the search engine volume using Google Trends. The collected data on the two platforms span more than 3 years, from November 2017 to March 2021.

To get popular profiles on Instagram, we exploit the online analytics platform hypeauditor.com, offering per-country and category ranks. We conduct our analysis on three categories of profiles: (i) Singers/Musicians, (ii) Athletes, and (iii) VIPs. We make the list of influencers publicly available.[2] For each profile, we download the corresponding metadata, i.e., the profile information, and the generated posts, using the CrowdTangle tool.[3] CrowdTangle is a content discovery and social analytics tool owned by Facebook, which is open to researchers and analysts worldwide to support research, upon having a partnership agreement. It also offers an historical perspective, which allows us to download the time series of number of followers of an influencer in the past.

We use Google Trends[4] as an external source of data regarding the influencers. Google Trends is a service that analyses the popularity of top search queries in Google Search across various regions and languages. Through this service we can compare the search volume of different queries over time. We exploit the Google Trends API to download the historical trends for our set of influencers. For each one, we use as search keyword his/her name, or, in case, the stage name. We collect the Search Volume Index (SVI) of Google Trends, a time series with monthly granularity representing search queries normalized over the maximum value observed in the considered period.

III. Bollinger bands and trend comparison

We start our analysis by considering the efficient-market hypothesis (EMH) used in the finance. The EMH is a cornerstone yet debated hypothesis about financial economics proposed in 1970 by Eugene Fama [11]. Essentially, it states that: (i) Current prices of stocks incorporate all available information and expectations, and (ii) Current prices of stocks are the best approximation of their intrinsic value.

Some investors do believe that the market is efficient, others do not [12]. In an inefficient market, there is a period of time, following a news or financial statement, during which an asset could be mispriced, i.e., its current price does not coincide with its intrinsic value [13]. Thus, trying to predict its intrinsic value, e.g., by means of fundamental analysis techniques, could drive investors to bet in such a way to anticipate the equilibrium. Conversely, in an efficient market, prices change (almost) instantaneously according to market news and similar relevant external factors. In this work, our influencers represent stocks, which we put in relationship with the search volume SVI.

We study the trends for an asset by exploiting a classical financial technical analysis tool: the *Bollinger bands*. The purpose of Bollinger bands is to provide a relative definition of high and low prices. Bollinger bands are an upper and lower price range levels delimited by standard deviation (or a multiple of it) above and below a moving average of the price. Because the distance of the bands is based on standard deviation, they dynamically adjust to volatility oscillations in the underlying price. Therefore, three curves over time characterize the Bollinger bands: (i) A Simple Moving Average (SMA) looking back at T time units, and (ii) two bands, upper and lower, respectively obtained by adding and subtracting C times the standard deviation (also computed looking back T time units) of the quantity of interest measured by the signal to the SMA. Notice that C regulates the amplitude of bands and is typically set around two [14].

By definition, prices are high at the upper band and low at the lower band. Typically, Bollinger bands are used in conjunction with other indicators to understand if the price of the stock is overpriced/underpriced with respect to its intrinsic value. An extensive dissertation about the topic can be found in [14]. Bollinger bands have already been applied to other contexts, such as to identify the start and end of demand for pediatric intensive care in real-time [15]. The time window T, typically days in finance, is months in our study, and the signal under analysis is the absolute variation of followers or search volume in place of the variation in price.

Here, we want to characterize and compare the trends observed on these two signals, similarly to what has been done for the stock market [5]. To this end, we use a popular indicator derived from the Bollinger bands called the *%B* and defined as follows:

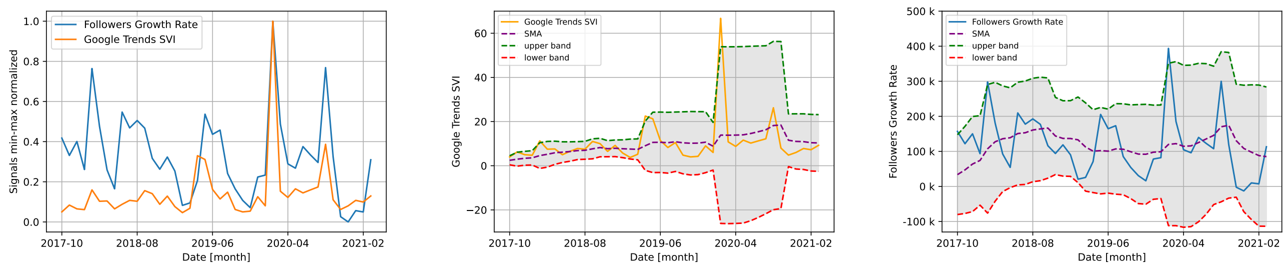
$$\%B(t) = \frac{Signal(t) - LowerBand(t)}{UpperBand(t) - LowerBand(t)}$$

%B measures the relative position of the signal with respect to the band interval. In such a way, we get rid of the differences brought by the different order of magnitude and the different volatility over time. Intuitively, a %B close to 1 (or even exceeding it) indicates that the asset (the influencer in this

[2]It is available online at: https://smartdata.polito.it/osn-trends/

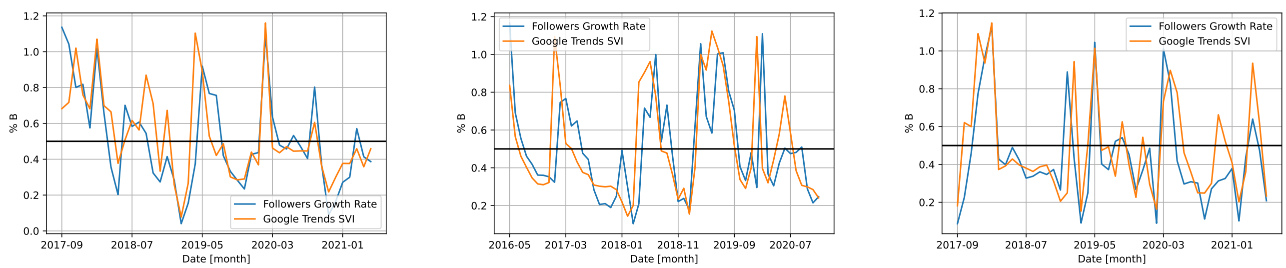
[3]https://www.crowdtangle.com/

[4]https://trends.google.com/trends/



(a) Static normalization for Google Trends SVI and Followers Growth Rate (b) Bollinger bands for the Google Trends SVI (c) Bollinger bands for the Followers Growth Rate

Fig. 1: Original time series and Bollinger bands of the two signals for Elettra Lamborghini



(a) Elettra Lamborghini (singer) (b) Elodie (singer) (c) Michelle Hunziker (VIP)

Fig. 2: Three cases of influencers with dynamic normalization through Bollinger bands

case) is undergoing an intense short-term increasing trend, while, conversely, a %B close to 0 indicates a decreasing one. When %B is ≈ 0.5 no quick variations are occurring. In the following, we show how short-term phenomena co-occur with similar intensity both in the SVI and in the fanbase trends. In particular, we observe that, while the long-term trends may diverge, short-term ones, pinpointed using %B, are often similar. To quantify them, we define an *Efficiency* measure that quantifies how %B curves are close. We define the Efficiency as the complement of the average absolute difference between the two curves, i.e.:

$$\text{Efficiency} = 1 - \frac{\sum_t |\%B(t)_{Followers} - \%B(t)_{SVI}|}{\sum_t 1}$$

where $\%B(t)_{Followers}$ is the curve for the followers growth rate and $\%B(t)_{SVI}$ is the curve for Google Trends SVI. The denominator simply counts the number of observations. An efficiency of 1 indicates that the two %B signals overlap, meaning that the fanbase trends closely follow those in the search volume. This corresponds to the case where the EMH hypothesis perfectly holds. Instead, an efficiency approaching 0 translates into completely opposite trends, i.e., an inefficient market.

IV. Early Results on Instagram

We first exemplify our approach by showing the time series for the Italian singer Elettra Lamborghini. We report in Figure 1a the two original signals that we put on the same scale with range $[0, 1]$ using a static min-max normalization. They follow different long-term trends, with the Google Trends SVI (orange line) showing an overall increasing trend, while the follower growth rate (blue line) exhibits seasonal cycles and, in general, more variability. However, the curves have some simultaneous peaks that we aim to pinpoint in the following. These peaks often coincide with external events that boost the popularity of the artist. For example, the peaks in February 2020 are due to the singer participation to the popular *Italian song festival of Sanremo*. In Figure 1b and Figure 1c, we show the signals together with their Bollinger bands for the Google Trends SVI and follower variation, respectively. The dashed purple line depicts the moving average (SMA) computed over 9 months (T), while the grey area delimits the Bands ($C = 2$). In this preliminary work the parameters T and C are equal for both the curves and all influencers and have been manually tuned to obtain a good overlap of the %B signals (see next paragraph), and we leave automatic tuning as future work. We observe how the bands dynamically adjust their range

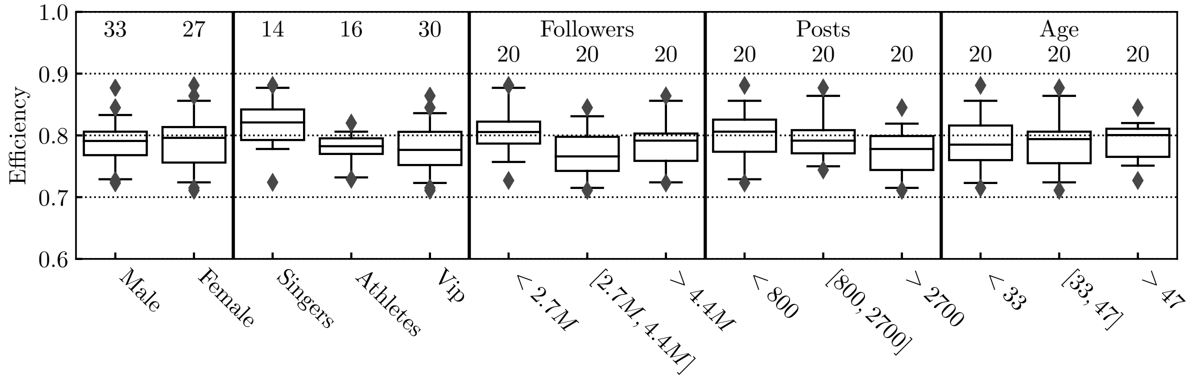


Fig. 3: Efficiency distribution, separately by various influencer characteristics. The numerousness of each box is reported above.

according to the variability of the underlying signal.

The %B metric indicates the relative position of the signal with respect to the range of the bands. We show %B for Elettra Lamborghini and two other influencers in Figure 2. Focusing on the first picture, we observe how the %B time series mostly overlap. If we compare them with the original (but normalized) signals in Figure 1a, Bollinger bands and %B allow us to mine the short-term trends, which we find to co-occur more frequently than long-term shifts. Indeed, the Pearson correlation coefficient on the original signals is 0.63, while the %B are 0.68 correlated. Similar considerations hold for the singer Elodie and the actress Michelle Hunziker. Measuring the Efficiency of the signals, we obtain 0.86 for Elettra Lamborghini, 0.88 for Elodie and 0.86 for Michelle Hunziker.

We now show the efficiency distribution for all 60 influencers and discuss similarities and differences across categories. In general, we observe for all influencers large values of efficiency, hinting that short-term trends co-occur in the Google Trends SVI and the followers variation time series. We show the distribution of efficiency in Figure 3 using boxplots, where the boxes span from the first to the third quartile and whiskers between 5^{th} to the 95^{th} percentiles. The black central stroke represents the median value.

We first compare Male and Female influencers on the left-most box group of Figure 3. The two groups have similar sizes, as shown in the captions above the boxes, and we do not find notable differences in the efficiency, which stands on values around 0.8. Considering the influencer category, conversely, we find that the singers in our dataset tend to have higher efficiency than the athletes and the VIP. Manual inspection reveals that it is often rooted in the launch of new albums and singles, triggering short-term peaks in both domains. In the central box group, we compare influencers with their fanbase size, as measured on March 2021, grouping them in three evenly-sized bins. We observe that influencers with a fewer followers have the most coordinated short-term trends, as they likely still have the potentiality of acquiring new followers if compared with very popular ones. Smaller differences emerge comparing the level of activity (fourth group) – with influencers producing fewer posts showing a slightly higher efficiency – and age (last group) of influencers.

V. Conclusions

In the OSN ecosystem, popular influencers compete to attract new followers, increasing their visibility and, thus, their value. This picture has analogies to a stock-exchange market, where investors opt to buy a stock, and stocks with many investors increment their values. In this paper, we proposed to study the dynamics of influencers on OSNs using statistical tools from the financial field. Our early investigations reveal that short-term trends in follower variation tend to co-occur with those found in external sources of data (Google Trends in our case), similarly to what researchers have found for the stock market. The Bollinger bands helps in dynamically compare completely different time metrics. Despite preliminary, this work shows that it is helpful to think of the OSNs ecosystem as a market, and this analogy might help in designing decision support systems to help influencers and advertisers to correctly estimate short-term trends. Moreover, in our future investigation we plan to model the dynamic of the popularity of post and influencers, including well-known phenomena such as exponential fading of interest and log-normal intertime of post creation [16].

Acknowledgements

This work has been supported by the SmartData@PoliTO center for Big Data and Data Science.

References

[1] D. Brown and N. Hayes, *Influencer marketing*. Routledge, 2008.

[2] M. Glucksman, "The rise of social media influencer marketing on lifestyle branding: A case study of Lucie Fink," *Elon Journal of undergraduate research in communications*, vol. 8, no. 2, pp. 77–87, 2017.

[3] A. B. Prasetijo, T. A. Saputro, I. P. Windasari, and Y. E. Windarto, "Buy/sell signal detection in stock trading with bollinger bands and parabolic SAR: With web application for proofing trading strategy," in *2017 4th ICITACEE International Conference*, pp. 41–44, 2017.

[4] H. Choi and H. Varian, “Predicting the present with Google Trends,” *Economic record*, vol. 88, pp. 2–9, 2012.
[5] T. Preis, D. Reith, and H. E. Stanley, “Complex dynamics of our economic life on different scales: insights from search engine query data,” *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, vol. 368, pp. 5707–5719, 2010.
[6] J. Zhang, “Social network fusion and mining: a survey,” *arXiv preprint arXiv:1804.09874*, 2018.
[7] S. A. Myers, C. Zhu, and J. Leskovec, “Information diffusion and external influence in networks,” in *Proceedings of the 18th ACM SIGKDD international conference on Knowledge discovery and data mining*, pp. 33–41, 2012.
[8] M. Mora-Cantallops, S. Sánchez-Alonso, and A. Visvizi, “The influence of external political events on social networks: The case of the Brexit Twitter Network,” *Journal of Ambient Intelligence and Humanized Computing*, pp. 1–13, 2019.
[9] M. Trevisan, L. Vassio, and D. Giordano, “Debate on online social networks at the time of COVID-19: An Italian case study,” *Online Social Networks and Media*, vol. 23, p. 100136, 2021.
[10] C. H. Ferreira, F. Murai, A. P. Silva, J. M. Almeida, M. Trevisan, L. Vassio, M. Mellia, and I. Drago, “On the dynamics of political discussions on Instagram: A network perspective,” *Online Social Networks and Media*, vol. 25, p. 100155, 2021.
[11] E. Fama, “Efficient capital markets: A review of theory and empirical work,” *Journal of Finance*, vol. 25, no. 2, pp. 383–417, 1970.
[12] B. G. Malkiel, “The efficient market hypothesis and its critics,” *Journal of economic perspectives*, vol. 17, no. 1, pp. 59–82, 2003.
[13] P. M. Fairfield, J. S. Whisenant, and T. L. Yohn, “Accrued earnings and growth: Implications for future profitability and market mispricing,” *The accounting review*, vol. 78, no. 1, pp. 353–371, 2003.
[14] J. Bollinger, *Bollinger on Bollinger Bands*. McGraw-Hill, 2002.
[15] C. Pagel, P. Ramnarayan, S. Ray, and M. J. Peters, “A novel method to identify the start and end of the winter surge in demand for pediatric intensive care in real time,” *Pediatric Critical Care Medicine*, vol. 16, no. 9, pp. 821–827, 2015.
[16] L. Vassio, M. Garetto, C. Chiasserini, and E. Leonardi, “Temporal Dynamics of Posts and User Engagement of Influencers on Facebook and Instagram,” in *2021 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM)*, 2021.