STOCK JUMPS: ANALYZING TRADITIONAL AND BEHAVIORAL PERSPECTIVES

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Abstract

Our aim is to define the concept of stock jumps from a practitioner's perspective and to give an insightful overview of the topic. We provide different technical and practical definitions from distinct points of view: mathematical, risk managerial, trading and investing. We verify the robustness of some common stylised facts for three major stock indices, and we derive an approximated jumps distribution. We finally provide some innovative insights from a behavioral perspective, and how to account for behavioral biases in this context.

Keywords: Stock Market, Stock Jumps

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1 Introduction

Any practitioner has experienced how hard and frustrating may be trying to forecast the stock price variations on a daily basis, as well as on longer periods. If one assumes that the Efficient Market Hypothesis (Fama, 1970) holds, then the prediction is quite impossible unless possessing some private information. Hence, sometimes a trader misses a profit opportunity from a certain transaction because she did not expect such a sudden swing. Some other times, she tries to guess *ex-ante* what is going to be tomorrow (and maybe she guesses right), but she is not able to act promptly or to close the position as she would.

Trading nowadays is becoming a mix of art and science, a bundle of technological skills, financial ability and intuition. With so many agents participating in the market, it is really unlikely to make substantial profits each day and on each transaction. The first inner principle on which the market is built is indeed a law of nature, i.e., “the survival of the fittest”. Only the ones who are able to perform better over a long period will remain in the market. And, no matter of what kind of trader you are or what stock you trade, one of the factor that many times determines who stays in and who has to leave is the ability to forecast the unexpected. Hence, among the most important aspects that every practitioner should take care of are when, why and how the asset he is trading is going to have an unexpected large increase (or decrease). As a matter of fact, while some traders are able to make money on average, the really huge gain opportunities come from the ability to invest quickly on something is drastically going to change his price, before others do the same. In other words, you make money when you are able to forecast whether and when your stock will “jump”. This is one of the reasons why jumps are so important in practice. However, it is also important to analyze them from a theoretical point of view because there are different definitions and ideas of what a jump is. Hence, our aim is to provide a common definition of what a jump is and how to deal with them from several sides. We neither aim to fully cover all the aspects related to jumps models, nor to deal with every mathematical detail. Our goal is rather to review some technical concepts under a tenuous light, and to approach the issue from different perspectives. Indeed, a vast literature exists on this subject. The first work that discusses about discontinuous trajectory for the stock price path (Merton, 1976) embeds a Poisson process into a classical Black and Scholes option-pricing model. The novelty of Merton’s work lies in the idea of assuming that the extra randomness coming from the jumps may be diversified, so that even if we would be in an incomplete market with several states (more than the assets), we would anyway be able to set a unique price for the options (Carr, 2005). Chang and Chiarella (2011) modify the Merton's model, changing the market measure to a martingale one, thus being able to price the jump-risk and provide an innovative hedging technique. Cont and Tankov (2004a) arrange an extensive list of more than 400 scientific papers on the topic, while Tankov and Voltchkova (2009) propose an merely technical review of tools to deal with jump-diffusion models. According to them, this class of models is indeed practically important for basically two reasons. First, the options out of the money are more expensive in practice than what predicted in theory, and only allowing for the price to jump and to suddenly move an option in the money it is possible to fix this puzzle. Second, in the real incomplete (and discontinuous) market a perfect hedging is indeed impossible, and this is why the option finds room for hedging purposes. If it was not so, we would be able to hedge everything using only the underlying. Moreover, Maheu and McCurdy (2004) study GARCH-jump diffusion models. More in general, in the last twenty years scholars created a new branch in the field, analyzing non-constant volatility models, such as stochastic volatility jump-diffusion models (Bates, 1996a), or time-varying jumps (Andersen et al., 2002), both in returns and volatility (Eraker et al., 2003; Eraker, 2004), but also jump-diffusion models with uniform-jump amplitude (Hanson and Westman, 2002). Jorion (1988) instead focuses on the sudden movements observed in the foreign exchange market, that he claims to be more relevant and obvious with respect to the stock market ones.

2 Jumps: alternative definitions

The multiple definitions and interpretations of what a stock jump is mainly depend on how investors use information. Thus, in the following section we discuss jumps in financial markets from distinct perspectives.

2.1 The mathematician's perspective

The mathematician's view mostly concerns the formal and rigorous definition of a jump, and how to find a common language that every actor may use when she builds a pricing or hedging model. In any basic course on quantitative finance, the first typical model used to price fluctuations is the Brownian motion (Bachelier, 1900), afterwards adapted by Black and Scholes (1973) and named Geometric Brownian motion:

$$\frac{dS_t}{S_t} = \sigma dW_t + \left(\mu + \frac{\sigma^2}{2}\right) dt \tag{1}$$

where S_t is the stock price, σ and μ respectively the volatility and the drift, while the W_t independent process with stationary increments is the standard Brownian motion, which follows a Gaussian distribution. This model has been widely used for decades because it owns several nice properties, such as continuity, scale invariance (the properties do not depend on the time scale), positivity (since it models the log prices), and tractability. From it, an extensive class of models arose, as for instance the local volatility models (Dupire, 1994; Derman, 1994). However, although the model was implemented and exploited for years, in practice the stock returns are not perfectly normally distributed. In fact, the distribution presents a higher concentration of events with an extremely high or low magnitude (*fat tails*). To give a numerical explanation of this idea, we are going to use a classic example (Cont and Tankov, 2004a): if we assume the distribution to be normal, statistical theory would suggest that an event with a magnitude of six times the standard deviation of the price is going to occur with a very low probability (around 10^{-18}), that in practice would mean only once each million of years. This conclusion is quite counterintuitive for who works in financial markets, because events like that happen much more often than what are predicted. However, even if it may appear trivial to be specified, the market underestimated this probability of extremely (unlikely) events until the 1987 crash, when it actually became aware of the volatility smile caused by fat tails distribution (the Black and Scholes model assigns a higher implied volatility to the options out/in the money). From that time on, market participants started considering these “black swan” events as not so impossible to occur, but rather as something that their models have to necessarily deal with. These are some of the reasons why the mathematicians ended up with three distinct basic models for financial applications, which would allow them to take into account discontinuous trajectories and to address the fat tails puzzle:

- **Poisson process:** most basic model that involves discontinuous trajectories, commonly known as *counting* process, since it counts the number of events (jumps) in a given time interval. More formally, given a sequence of independent exponential random variables with parameter λ, the process

$$N_t = \sum_{n\geq 1} \mathbf{1}_{t\geq T_n} \tag{2}$$

is a Poisson process with intensity λ. This simple process has many useful characteristics that make it an essential building block for the jump modeling: it is indeed “memoryless”, i.e., the probability of the event to occur is not affected by the time elapsed. The process follows a Poisson distribution:

$$P(N_t = n) = e^{-\lambda t}\frac{(\lambda t)^n}{n!} \tag{3}$$

i.e., the jumps arrive randomly both in size and time in an independent way.

- **Lévy process:** A stochastic process (a generalization of the Poisson) with stationary independent increments and infinite divisibility, i.e., it may be represented by the sum of an arbitrary number of independent identical distributed random variables. This class of process is not able to perfectly capture every jump, because of a series of pitfalls, i.e., the skew vanishes fast, the mean reversion effect, and the lack of time clustering (Dupire, 2014).
- **Jump-diffusion models:** a particular case of exponential Lévy processes, used as building blocks for a wider class of models such as the stochastic volatility ones (Bates, 1996a; 1996b):

$$dS_t = \mu S_{t-}dt + \sigma S_{t-}dZ_t + S_{t-}dJ_t \tag{4}$$

where Z_t is a Brownian motion, and J_t a compound Poisson process, i.e., the waiting times between the jumps are exponentials although their sizes may be arbitrarily distributed (Cont and Tankov, 2004b; Cont and Voltchkova, 2003; 2005; Kou, 2002; Kou et al., 2003; Kou and Wang, 2004).

In conclusion, no matter the method or the formal definition the mathematicians choose to use, what they focus on is looking at the stock path and at the jumps from a frequentist perspective: how many times the stocks jump over a certain period? With which intensity do they jump? This is a strong simplification, of course, but it seems to give a rough idea concerning the technical approach to this problem.

2.2 The risk manager's perspective

From a risk manager's point of view, jumps are seen as nothing more than a component of the risk you bear when buying a stock. In particular, they measure how likely your stock price unusual and intensive variations are going to occur in a short time interval and what would be their impact on your portfolio. The problem that a risk manager (or, more generally, a hedger) has to consider is then how to replicate his portfolio in order to be immune - even if sometime not completely - from the risk coming from a certain activity and/or asset. The Black and Scholes model suggests a strategy that would eliminate any risk arising from any option position, i.e., the "delta-hedging strategy". Indeed, buying a portion of underlying assets exactly equal to the option price sensitivity makes the portfolio immune to any variation. Despite any anomaly that may characterize financial data (skewness, excess kurtosis, volatility clustering, etc.), delta hedging is still commonly used because of his simplicity and tractability. Unfortunately, this strategy is not consistent with the real market when we normally observe jumps in the stock price, because we do not know in advance the jump size, and thus we will not be able to perfectly hedge our portfolio, but rather we try to minimize the effect of such events on our positions. Hence, what a risk manager is interested to look at is when and whether his portfolio may be compromised by an unexpected stock price variation. In other words, there will be an event I would not be able - or it would be too difficult - to hedge? The jump seems then to be defined as that threshold value which could undermine the portfolio integrity. In the last years, scholars coined a new term for this threshold value, i.e., *Value-at-Risk* (VaR). The VaR is a technique that measures the risk of losses on a specific portfolio within a certain confidence interval, and for any probability p, it is defined as a value such that the probability that the losses exceed that value is exactly p. So, for a weekly 5% VaR of $10 million, the probability that in one week the value of the asset will fall over $10 million is exactly 5%. On the other hand, to understand the magnitude of any jump and to identify them, risk managers developed a very useful tool called "stress test", which assesses and simulates the effect of large variations on their own portfolios.

2.3 The trader's perspective

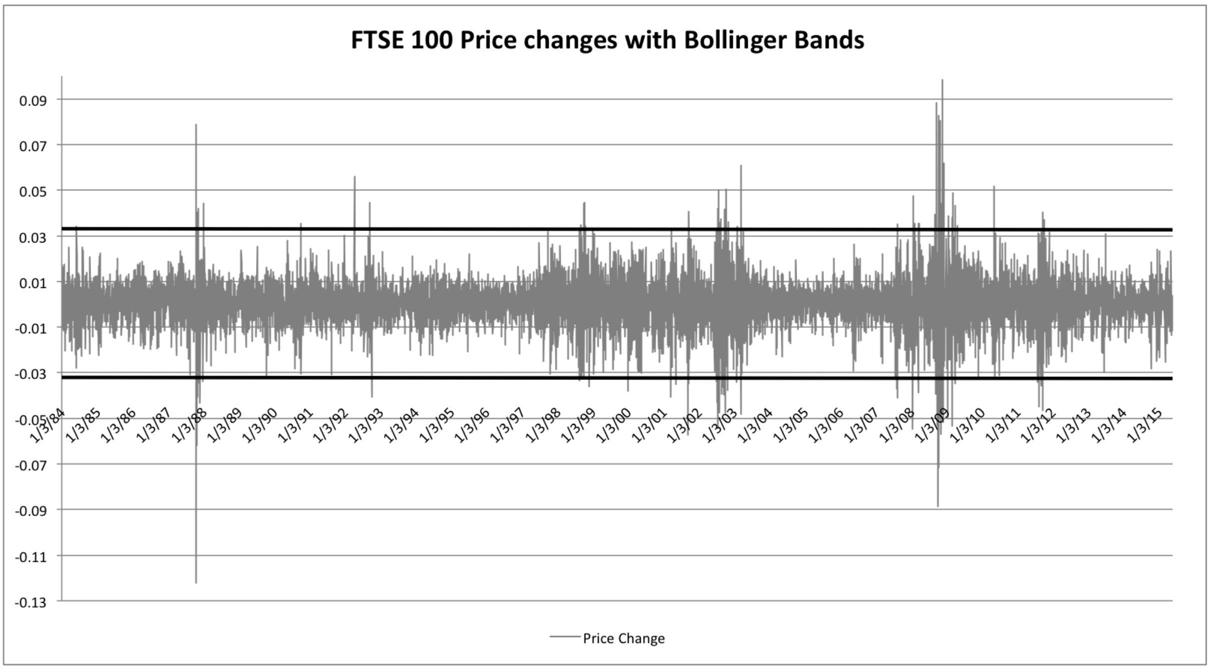
What in practice a trader struggles with is how to distinguish a jump from normal volatility. Understanding whether the price is going to be unexpectedly higher or lower is a source of competitive advantage for a trader. Hence, she would basically focus on two aspects: trying to forecast when a jump may occur, and identifying a jump – distinguishing it from normal volatility – when it indeed occurred in the past. Of course, the first aspect is extremely difficult to deal with, because of the intrinsic nature and definition of jumps: they could arrive at any random time, without forewarning. Although this is true in general, there are circumstances in which jumps are so to say "predictable". One particular case is due to the arrival of new information (usually private and not release to the market yet), or to some analysis related to market inner structure (e.g., in the energy market: if you would be able to perfectly forecast that in two hours is going to be extremely warm, you may infer that the demand for electricity will have a sudden spike). On the other side, it is also true that trading floors are fast-pace environments, so traders should be rapid to identify when something weird is happening.

A quick way to see whether the last variation was indeed a jump or a normal swing is to set a "volatility range" in "normal" situations. Assuming that a jump should rarely occur by definition (otherwise it would only be a high stock variation), in this way the trader would easily see using for instance a *three-sigma rule of thumb* that only the rough 0.3% of variations are real jumps. In the same fashion, he could build a basic *Bollinger's bands* tool, creating a normality range for the volatility around a simple weekly or monthly moving average

$$\boldsymbol{MA_t = \frac{1}{t}\sum_{i=0}^{t-1} P_{t-i}} \tag{5}$$

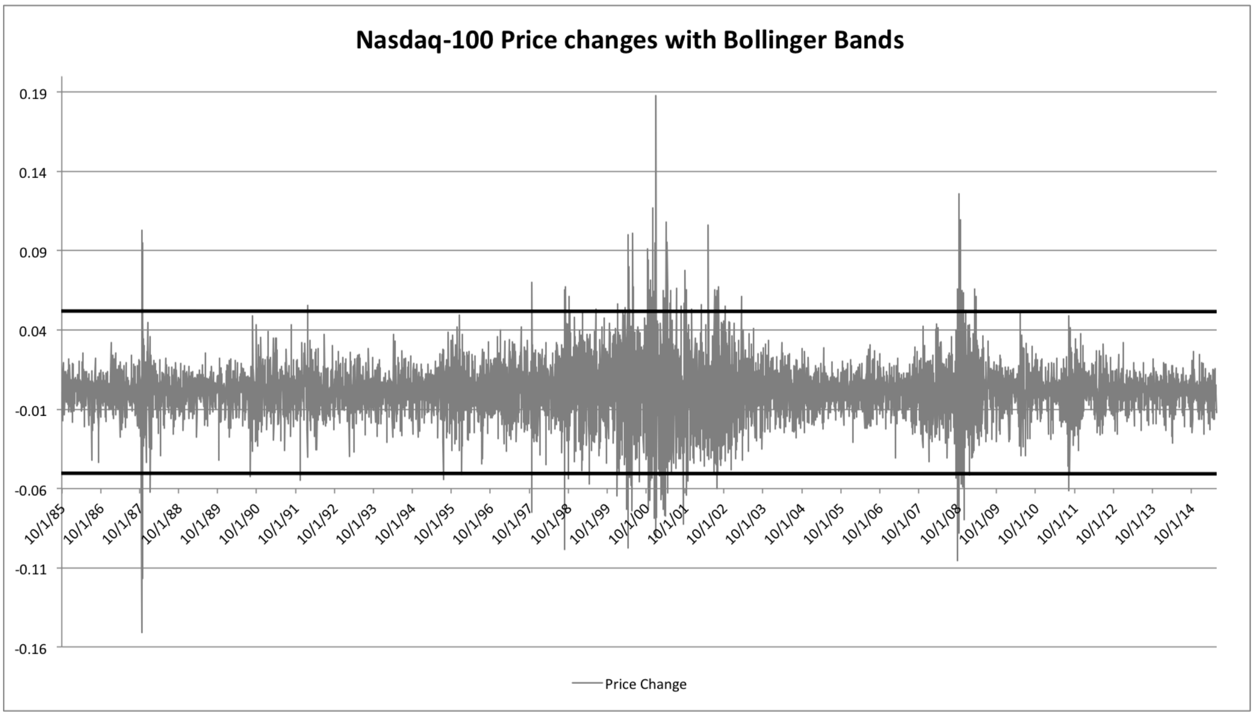
As we can see in Figures 1 to 3, the three-sigma moving average Bollinger's bands, with respect to the percentage changes in prices, is indeed a good instrument for assessing at a glance whether there was an anomaly in the prices oscillations. The data for the FTSE 100, the Nasdaq 100 and the S&P 500, have been extracted from Yahoo!Finance, and are updated to May, 26, 2015.

Figure 1. Price percentage changes (i.e., returns) for the FTSE 100 Index



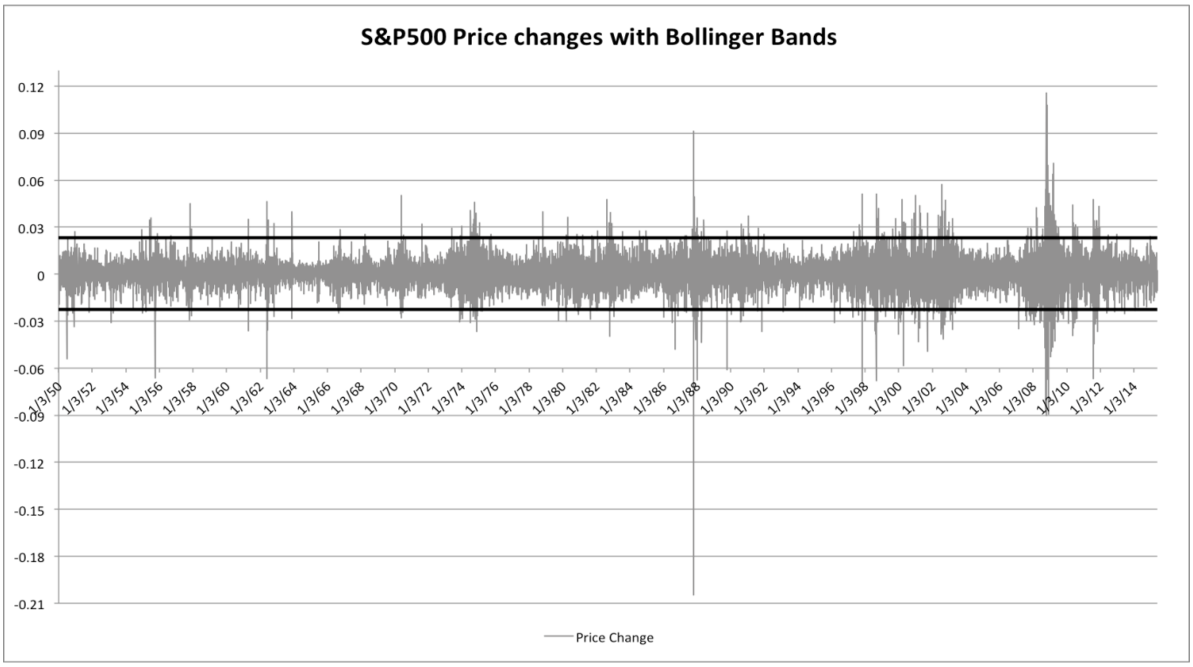
The black lines represent instead the three-sigma Bollinger bands, computed with respect to the five-days price changes moving average

Figure 2. Price percentage changes (i.e., returns) for the Nasdaq 100 Index



The black lines represent instead the three-sigma Bollinger bands, computed with respect to the five-days price changes moving average

Figure 3. Price percentage changes (i.e., returns) for the Nasdaq 100 Index



The black lines represent instead the three-sigma Bollinger bands, computed with respect to the five-days price changes moving average.

2.4 The investor's perspective

From an investor's side, jumps may or may not be a real concern depending on the individuals' investment horizons. Indeed, as we will see in the next section, jumps usually are temporary and last for a very short time interval - they tend to mean-revert.

Often jumps are caused by high-frequency trading that indeed boosts the volatility and makes one of side of the market really inelastic, increasing the likelihood for the price to suddenly react and jump. Because jumps happen at a milliseconds time frame – and then they mean-revert – individual investors might not be able to profit from them, while they are big profitable opportunities for professional traders. However, because they usually come back to a normal and steady level, they are not the main issue neither for a long term non-professional investor (who only cares about a long period) nor for a short term one (who cannot trade by himself in any case at the same speed of institutional traders). Thus, should the investors completely disregard jumps? Not really. Indeed, sometime a stock jumps for a precise reason. Maybe it reflects some fundamental or permanent change in demand or supply, or maybe it is just a final assessment to a new price level. In this case, if the investor had the wrong position before the change occurred, she may find herself in serious troubles. Hence, from an investor point of view, what it is alarming is the case in which jumps are permanent and do not come back to a normal level shortly afterwards. We would like to call this class of jumps *orbital-jumps*, in comparison with the *spring-jumps*, that are the "normal" jumps with a short duration and that come back to a normality range level. Figuratively speaking, the idea is pretty similar to what happens in physics at a molecular level: the electrons can jump between different orbits (orbital-jump) if a certain energy will push them toward a new permanent level, although they somehow oscillate on the same orbital level. So a further question arises, that is whether there exists a threshold that would determine whether a jump is permanent or temporary, or if there is a fix set of conditions which blocks the price at the new level. So far we do not have any evidence to test this hypothesis and conclude in any way, but we do believe that there are some reasons that more than others may cause the price to definitively jump at a new level.

3 Some stylized facts

So far, we presented some perspectives about jumps, but we did not underlined why they are so important and what kind of characteristics a jump is supposed to have. In literature, it seems to be widely accepted that jumps have the following characteristics:

- they are usually downward, i.e., there are more negative jumps than positive. This seems to be verified for the stock market, but a higher symmetry could instead be found in the exchange market (Cont, 2001);

- after a jump, the price comes back to normality (or close to it);
- jumps are time-clustered, i.e., a jump increases the probability that another jump is going to occur.

However, these "stylized facts" in practice do not always hold, at least for the major indices we have considered, i.e., the FTSE 100, Nasdaq-100 and S&P 500, as we can observe from Table 1.

Table 1. Number and magnitude of jumps for three major indices: FTSE 100, Nasdaq 100, and S&P 500. In parenthesis there is the average magnitude for the positive or negative jumps.

	Number of jumps	Number of jumps (+)	Number of jumps (-)	Highest 5 jumps	Lowest 5 jumps
FTSE 100	83	47 (0.044)	36 (-0.048)	0.079	-0.072
Nasdaq 100	84	53 (0.072)	31 (-0.069)	0.108	-0.097
S&P 500	150	91 (0.041)	59 (-0.049)	0.069	-0.083

We anyway believe that those empirical evidences may apply stronger for single stocks, which in general have a greater volatility with respect to the indices. Indeed, if we count as jumps every oscillation greater than the five-days moving-average plus the three-times standard deviation (positive jump), or lower than the five-days moving-average minus the three-times standard deviation (negative jump), we observe that there have been quite a lot anomalous oscillations since the creation of the indices. A result that seems to contradict the literature is that there occurred more positive jumps than negative, regardless of the market we take into account. Hence, the first characteristic does not hold so strongly as claimed in literature, even if the negative jumps have on average a slightly higher magnitude (except for the Nasdaq-100) - the data are shown in parenthesis in the Table 1. Nevertheless, if we tighten our analysis and we look only at the highest and lowest five jumps, we observe the opposite behavior: the positive jumps are much larger than the negative - this is not straightly verified for the S&P 500, but if we further constrain our analysis to the three highest/lowest jumps, we do reach the same conclusions. Furthermore, from the Figures 1 to 3 we infer that the process is quite stationary, so the mean-reversion already found in literature still holds and it is confirmed also by our data. On the other hand though, jumps seem to not be time-clustered: their behavior is quite irregular, since sometime we observe just a single spike, while other times they come banded together. For this phenomenon, there is however an alternative explanation: they indeed cluster only in crisis period (i.e., 2000-2001 period, and 2008-2009). This behavior pushes us therefore to look for a different inner cause for these larger oscillations, i.e., the market sentiment and the behavioral reactions of the investors, as we will explain in the next section.

In order to check for both time clustering and other hidden effects, we also run additional quantitative analysis on the three indices. We indeed implement the two following regressions, respectively a linear probability model (LPM) and an ordinary least square (OLS) regression:

$$\mathbf{Jumps_t = \beta_0 + \beta_1\ Jumps_{t-1} + \beta_2\ Volume_{t-1} +\ } \boldsymbol{e_t} \tag{6}$$

$$\mathbf{Magnitude_t = \beta_1 Magnitude_{t-1} + \beta_2 Volume_{t-1} +} \boldsymbol{e_t} \tag{7}$$

where respectively *Jumps* is a dummy variable with value 1 whether the returns jumped over the threshold (assessed with the three-sigma rule), and 0 otherwise; *Volume* represents the volume of the transaction happened, while *Magnitude* is an interaction variable built as the amplitude of the jump if a jump actually takes place.

Thus, the first regression tells us which is the probability that a stock will jump tomorrow since it jumped today, and also verifies for the number of transactions occurred today. The second analysis instead reveals how much the stock will jump (if it jumps), given how much it jumped today and given the transaction volume. It is a straightforward analysis, but it gives us some insights. As we can see from the Table 2, the relations are always statistically significant, even if the total portion of model explained by our variables is quite low (i.e., the R^2 is low, meaning that additional variables and analysis are needed).

Table 2. Results of the LPM and OLS regressions for both the jumps occurrence and their magnitude, for each of the indices considered *t*-statistics in parentheses

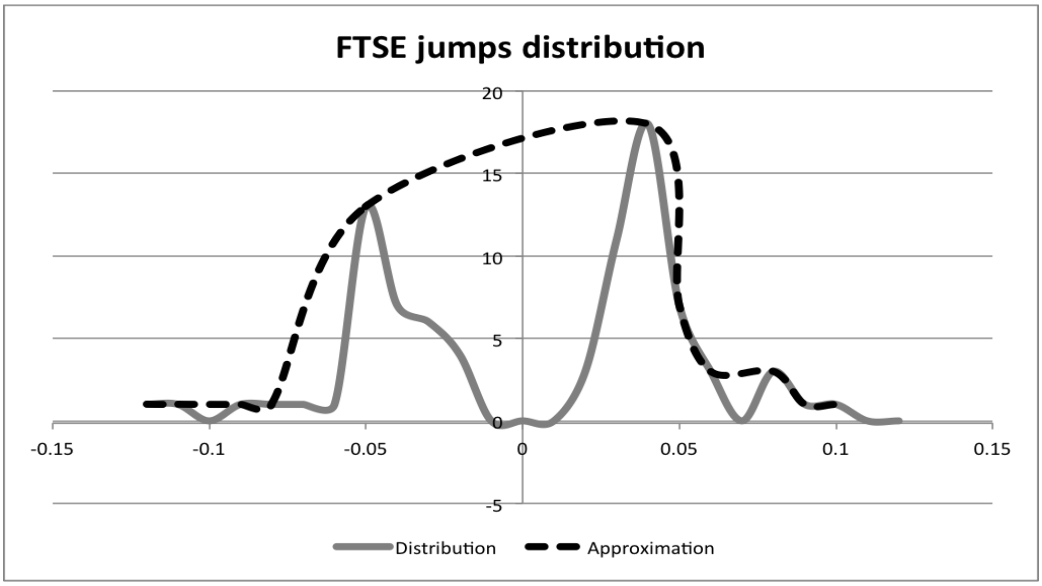
	FTSE		NASDAQ		S&P500	
	Jumps	Magnitude	Jumps	Magnitude	Jumps	Magnitude
Jumps (t-1)	0.129*** (11.19)		0.0985*** (8.10)		0.141*** (17.52)	
Volume (t-1)	1.03e-11*** (5.97)	1.37e-13* (2.22)	8.92e-12*** (5.50)	3.14e-13*** (4.78)	7.49e-12*** (13.54)	3.58e-12** (2.79)
Magnitude (t-1)		0.0430*** (3.91)		-0.0883*** (-7.79)		-0.138*** (-13.25)
Constant	0.00183 (1.18)		-0.00149 (-0.64)		0.00113 (1.26)	

Significance level: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Hence, what the Table 2 shows us is that some degree of clustering exists, because all the coefficients for *Jumps* are positive (i.e., a jump yesterday increases the probability of a jump today), but the effect is extremely low – it may be persistent only in some scenarios, as we claimed before. The volume has an effect as well, and this supports our idea that for instance in high-frequency markets the jumps are more likely to happen. The effect is anyway extremely low, almost irrelevant, and this confirms previous evidences (Joulin et al., 2008). The interaction variable *Magnitude* instead shows an interesting behavior: excluding the FTSE, for the other indices it seems that if a jump of a certain intensity occurred yesterday, the jump that may occur today will have a lower amplitude. This support the idea of a mean-reverting process, and it allows the market to stabilize instead of bursting for a sequence of following higher jumps.

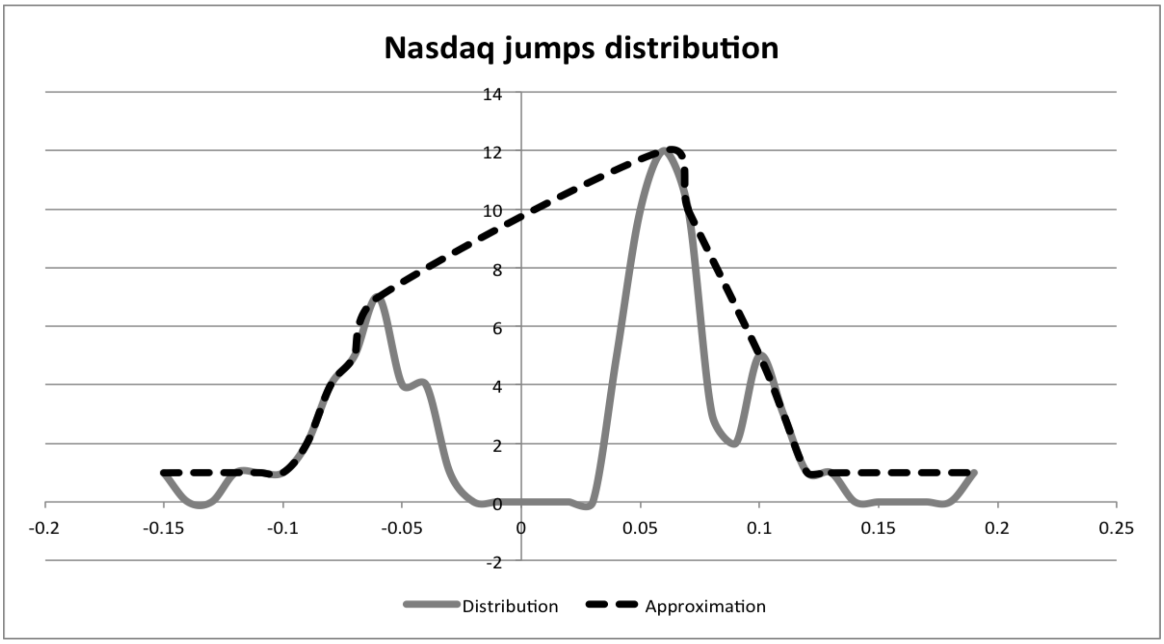
Finally, Figures 4 to 6 display that all the distributions show a negative skewness, while the tails seem to not be extremely fat as expected.

Figure 4. Jumps distribution for the FTSE 100 index



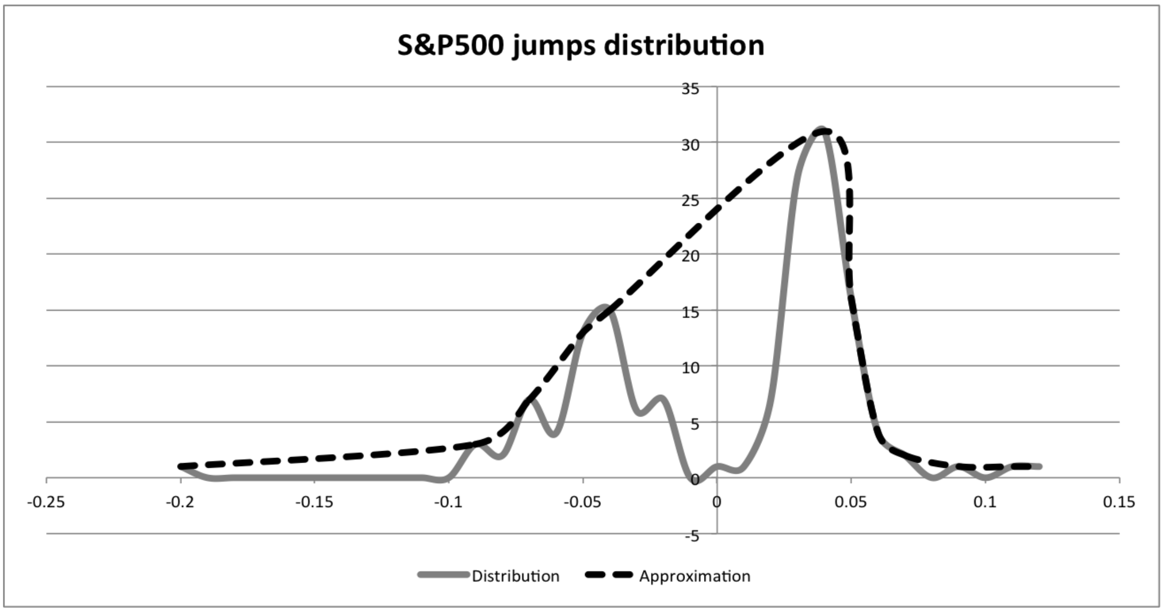
The dash line represents the approximated distribution, which it is showed with the only purpose of making the figure easier to read. The real distribution is instead draw with a lighter color.

Figure 5. Jumps distribution for the Nasdaq 100 index



The dash line represents the approximated distribution, which it is showed with the only purpose of making the figure easier to read. The real distribution is instead draw with a lighter color.

Figure 6. Jumps distribution for the Nasdaq 100 index



The dash line represents the approximated distribution, which it is showed with the only purpose of making the figure easier to read. The real distribution is instead draw with a lighter color.

4 A behavioral perspective

If markets are efficient, then they are supposed to discount all available information into prices. The jumps clearly prove that the theory does not hold so strongly, but what has often been neglected is the *behavioral* side of the jumps. With this term, we mean two distinct issues: first, the motivation or explanation of why jumps exist, and second how to manage them. Indeed, if it is true that a jump may arise from a huge variety of situations such as a change in fundamentals or in the demand of a stock, but it is also true that it could be caused by some human being actions. And, on the other hand, they are causes as well of some phenomena difficult to be explained otherwise.

In fact, if we investigate the jumps existence looking at the human behaviors that may generate them, the first thing we could notice is that people tend to *overreact* (DeBondt and Thaler, 1985) in the markets. The stock price could increase (decrease) suddenly, maybe due to news or to some particular performance we did not expect to have (Lee, 2011), and we thus run to fix our previous misjudgment, as any other person will do. If we instead suffer from herding behavior (or from a *bandwagon* bias (Henshel and Johnston, 1987), it is quite likely that we will follow some big player regardless of any fundamentals. In general, this should not be a problem since the realization period considered in herding environment is quite large (the time between the action and the effect on the prices), but sometime the market is really inelastic, so it accumulates a kind of "*repressed energy*". People would like to buy for instance a certain asset because big funds are doing that, but maybe they cannot due to any kind of constraint (e.g., the minimum amount purchasable is one million dollars), and this creates a repressed potential demand. When that constraint falls down (e.g., the minimum amount purchasable is lowered to $10,000), the demand explodes and so does the price.

On the other side, if some behavioral motif may be identified as causing the spikes, it may be also realistic to think that biases such as the *anchoring* effect (Cen et al., 2010) could help us in understanding why the stock price comes back to be normal so quickly. We strongly rely on the information we had on the price, and so on the standard price range we have observed so far. Hence, if there is not any fundamental reason to assume otherwise, we look at any price distortion as temporary by default, and this would explain why jumps are so short-lived. Clearly, this mechanism jams when we are in *hysteria* or *crash-phobia crowd* phenomena, because in those cases the collective behavior fully emphasizes the jump magnitude. However, our general tendency to prefer the *status quo* (Kahneman et al., 1991) pushes us to try to restore anything occurred in the market very quickly.

From the other hand instead, the jump could in turn be the reason why crashes and crisis start. Indeed, people in financial markets are usually *overconfident* (overestimate the returns, Montier, 2013; Odean, 1998) and *optimists* (underestimate the risks, Barberis and Thaler, 2003), and they suffer of what is called *planning fallacy* (Barberis and Thaler, 2003), that means exaggerating personal skills and ability to shape the future and perform a certain task ("*This happens to stocks picked by other people, not to mine*"). So, if you think you would be able to promptly react to anything is going to happen in the market, or you think to be an above-average forecaster and you are wrong, you will probably panic and tend to overreact immediately to fix your misjudgments. Furthermore, jumps clusters may trigger a downturn if you have the tendency to overestimate your ability to control future events (*illusion of control*, Dierkes et al., 2003), because they are quite random and by definition they are usually unpredictable.

Besides the two aspects dealt so far from a behavioral perspective, we claim that other behavioral biases are involved in the world of large stock oscillations. First of all, we would like to provide also a *prospect theory* perspective that stems from the data on jumps (Kahneman and Tversky, 1979). Indeed, as we showed in the previous section, there are definitely more upwards jumps than downwards, but it is also true that the negative jumps have on average a higher magnitude, except for the extremes of the distribution. In fact, the market seems to implicitly compensate to some extent the general loss aversion with a higher number of positive jumps and larger extreme events. The slope of the value function would therefore be different, and the shape would be quite symmetrical with respect to the origin as it is supposed to be. A second interesting anomaly could in case try to explain the time clustering we observe in the jumps distribution, i.e., the *recency* bias (Lim, 2001). We are used to extrapolate recent events into the future indefinitely, so when we see a jump we are led to believe a second one will follow.

Behaviorally speaking, it is also extremely counterintuitive how people seem to not suffer at all of *clustering illusion* bias (Theobald, 2003). Sometimes, human beings tend to see patterns even when there are not, and to overestimate the importance of small clusters when the availability of data is huge, but this does not happen in this context. To some extent, this bias would somehow help the market to be prepared for at least some important and relevant swings, because on average there will be people who would expect them, and the usual informational channels would spread this concern to the investors and the market in general.

With respect to big shocks, what we instead observe is a phenomenon called *hindsight* bias (Gilson and Kraakman, 2003), i.e., seeing past events as predictable where they definitely were not. Furthermore, a *regressive* bias (Edwards, 1968) would justify why people intuitively think that events with an associated low likelihood to take place are usually neglected. More in general, this would also explain why people do not consider a non-insignificant probability that extreme events occur (the so-called *black swan*). Finally, people tend to not plan or react to something they did not think it might happen just because it never happened before (*akinesia* effect).

There also should be take into account the idea of the *availability heuristic* (Kligera and Kudryavtseva, 2010) set into a *negativity* bias framework (Akhtar et al., 2011): in fact, we often tend to overestimate the likelihood of events that we remember clearer than others, and we usually recall better negative events with respect to positive ones –

this may explain why the average for the negative jumps is slightly higher. Hence, many scared investors in 2009-2010 at the first hint of any market downturn, they recollect the experience of the previous financial crisis, and this of course strengthened any unexpected market movement. Another effect is in addition what we defined *denial of similarity*, because we are always led to think that what we experience is not similar at all to what happened in the past (e.g., two crisis are not the same, the periods are different, people are now smarter, the markets are nowadays more efficient, etc.). This would bring us, from one hand, to pretend to not take into account any irregular price oscillations because we do not have the means to forecast them, and from the other to complicate excessively the identification of a jump-cluster.

To conclude, we provided several insights on aspects usually not considered when it comes to market fluctuations. The aim of this section was indeed to stress the importance of the behavioral component in explaining weird stock price variations. A market participant could be affect by some or none of those biases presented, but the point in question is that, in order to reach a better comprehension of this phenomenon, and to achieve new efficient level of understanding on how to manage them, the human component cannot be omitted.

5 Conclusions

The stock jumps are very common in financial markets, although their definition still remain unclear. The purpose of this work is to give an overview on the distinct aspects of the price oscillations, to stress the importance of this phenomenon and to contribute to the academic and professional debate on the topic. We provide four different perspectives (the mathematical one, the risk manager one, the trader and the investor ones). We then analyze the major stock indices such as the FTSE 100, the Nasdaq 100, and S&P 500, in order to test the stylised facts found by the literature, underlining that some of them hold while other do not. We finally provide a new behavioral interpretation on reasons and causes of the price jumps existence. Our comments and results are neither completely conclusive nor to be interpreted as “truth in stone”, but rather as a contribution to this topic that we still barely understand.

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