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IMPACT OF TAKEOVER BID RUMOURS ON LIQUIDITY: THE CASE OF CANADIAN TARGET FIRMS

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ABSTRACT

By essence, rumours are known to carry uncertain and unverified information. However, despite their lack of reliability, rumours significantly affect the behavior of their "public"; subsequently leading to major impacts on individuals, industries, and even societies at large. The impact of rumours ultimately lies with people's perception and reaction to them rather than the veracity of the information they carry.

In the financial market, takeover rumours have often proven to have significant and atypical consequences on the rumoured target firms before an actual takeover bid is announced. This study examines the short-term impact of takeover rumours on the stock prices and the liquidity of Canadian target firms listed on the Toronto Stock Exchange. We collect the data on 21 published takeover rumors between 1998 and 2015. We find that this type of unofficial information can significantly affect the target companies; leading to abnormal prices and trading volumes around the date of their appearance in the media (websites, newspapers, newsletters, and other published sources). The best performance of target shares is observed one day before the dissemination of the rumours in the media, with an average daily return of 0.0318. However, on the day of the publication itself, no significant reaction can be observed in the market. Those results are similar to the findings of Zivney, Bertin, & Torabzadeh (1996) for rumours published in both the HOTS and the "Abreast of the Market" (AOTM) column in the Wall Street Journal.

Keywords: Takeover Rumours; Financial Rumours; Canadian Targets; Event Study

Part 1. INTRODUCTION

Background of the Study

New and faster forms of communication have emerged with the advent of the Internet; providing the ultimate platform for rumours to run rife on a global scale. In the financial market, as it is the case in other industries, rumours carry unbridled, un-remedied, unrefined, and occasionally unsubstantiated information that spreads through word of mouth or published media (digital, audio, or audiovisual); affecting the decision of market participants. When it comes to rumours, the question of credibility requires even more scrutiny; however, investors hoping to benefit from rumours only have a small window of opportunity; decisions must be taken quickly. The previous statement is perfectly summarized by the popular adage “Buy the Rumour, Sell the News” (BRSN); how does it apply to takeover rumours?

Pound and Zeckhauser (1990) explain that takeover rumours can significantly influence the stock price trends of the target firms before an actual takeover bid is announced. Roughly a year earlier, Jarrell and Poulsen (1989) proved that since 1980, the stock price of the average takeover target moved to incorporate about one-third of the ultimate takeover premium before any formal public news of the bid. The latter analysis suggests that the information from the rumour was progressively incorporated to the stock price. These researches among others attest to the disproportionate consequences of takeover rumours with regard to standard and rational expectations; which in turn, substantiates the increasing interest in the impact of takeover rumors on publicly traded companies and the market at large. The lag in response to the information convey through the rumour challenges the Efficient Market Hypothesis. This statement raises many concerns; should all information be treated equally? Could it be that unverified information like those carried by rumours follow a different path? Adepts of the BRSN believe that prompt actions upon the apparition of rumour will help generate gain before the market efficiently adjusts to published takeover rumours. In other words, they believe that investors capable to correctly assess the average probability that the rumour will ultimately be followed by a takeover bid (Pound & Zeckhauser, 1990) could benefit from them. We believe that the public's reaction to rumours, whether they are right or wrong, play an important role in their effects on the market. In such light, it is important to understand rumours and recognize what set them apart from other forms of news.

In theory, investors are expected to be rational individuals expected to make informed decisions. However, the idea of investment decisions made in the spur of the moment to take advantage of financial rumours challenges this assumption. In such light, the apparition of takeover rumours seems to temporarily invalidate the neoclassical financial theory.

Statement of the Problem

So far, most researches about the impact of takeover rumours were either conducted on countries like the United States and Australia; or with a complete disregard for any form of geographic limitations. What if different markets had different responses to takeover rumours? Recent researches have been oriented toward a more diverse demographic; but still, very little is known about their consequences on rumoured Canadian target firms. Eckbo and Thorburn (2000) conducted a study on the performance of post-takeover Canadian bidder firms; but information about Canadian rumoured targets before the official takeover news is yet to be explored.

Our study will attempt to fill this gap by providing a detailed analysis of the impact of takeover bids rumours on the liquidity of rumoured Canadian target firms. Following the researches of Laouiti, Habib, & Ajina (2015), who similarly explored this subject for rumoured French target firms, this paper centers on the impact of takeover rumours not only on the stock price but also on the trading volumes, which is used as a measure of liquidity throughout this study. The first part will focus on questions like - What are takeover rumours, and how do they affect the market? - What could be their implications for the financial market? – What can we learn from prior studies and their findings? The insight obtained from the first part of this paper will guide our subsequent analysis as well as the interpretation of our results in the last part of this research. In case of variations between our results and prior works, can we identify the agent(s) of these differences? The review of prior literatures coupled with our attempt to answer these questions will provide a great deal of insight in the interpretation of the final results.

Understanding Rumours

Rumours are inherently part of all societies; they spring out of thin air, proliferate, and influence the behavior of their "public"[1]. Robert Knapp (1944) describes rumour as a proposition for belief of topical reference disseminated without official verification. The more they are relayed, the further their content might deviate from their original form; rumours are open to recurrent deformations until an official confirmation or denial is finally issued (Borodina & Zheltukhin, 2013). At times, rumours persist even after being denied through official channels. Based on Knapp's definition, we were able to identify two types of rumours; spontaneous

[1] In this context, "Public" implies all individuals exposed to the rumours

rumours and engineered rumours. Spontaneous rumours can be defined as improvised news resulting from a process of collective discussions that aim at giving meaning to important, ambiguous, and unexplained events (Shibutani, 1977). On the other hand, we gather that engineered rumours are false news carefully designed to trigger a specific feeling and behavior from a pre-selected group of individuals. The labelled engineered rumours are often designed for the sole advancement of a military, political, or economic agenda. For example, in 2016, during the US campaign for the presidential elections, in less than a week, the initial rumour that Hillary Clinton and her top aides were involved in various crimes snowballed into a wild conspiracy theory suggesting that they were running a child-trafficking ring out of a Washington pizza parlor (Silverstein, 2016). This powerful mix of fake news and social media resulted in the raid of the pizza parlor by an armed civilian attempting to rescue the alleged victims (Kang & Goldman, 2016). The rumour turned out to be false, and the whole incident ended peacefully. Similarly, it was later reported that many of the false rumours in circulation during the 2016-US campaign were the nicely orchestrated work of teenagers in Macedonia. From a single town in the Former Yugoslav Republic of Macedonia, these teenagers were allegedly running more than a hundred websites generating countless false rumours in exchange for economic incentives (Smith & Banic, 2016). Those are examples of engineered rumours designed to aid one's political ambitions. Whether they are false or true, rumours provide a great insight into the fears, concerns, and/or hopes of a community at a specific point in time. Likewise, they are undeniably dangerous and potent at influencing the behavior of their public.

The ambiguity surrounding the rumour coupled with people's desperation to uncover the truth about the puzzling events it depicts also aggravates its dispersal. Indeed, spreading rumours is the result of a collective creation and a collective attempt to explain problematical and emotive situations (Zheltukhina, Slyshkin, Ponomarenko, Busygina, & Omelchenko, 2016). The keywords here are “emotive” and “collective”; every single person exposed to the rumour becomes a conduit for its diffusion by the intermediary of family members, friends, acquaintances, and anyone he/she comes in contact with in real life or online. As a matter of fact, the extensive range of computer internet technologies has given an unprecedented platform for people to communicate and rumours to run rife; blurring the barriers between countries and even continents; information is only a click away. Continually bombarded with news, people are now prone to information overload; struggling to decipher truth from lies, fact from fiction, and rumours from authentic news. In many cases, the very origin of the news remains unknown and nearly impossible to trace. As reliable information become increasingly difficult to come across, a shift of problematic is to be considered. It is no longer about giving everyone access to information as it was the issue half a century ago, but rather a matter of discerning quality information among the multitude of reports unceasingly being proffered. In other words, the veracity of public information has progressively become more dubious as its velocity has amplified. In the midst of this chaos, investors, speculators, and any other economic agent find themselves struggling to secure actionable information. The field of behavioral finance might help us understand the economic agent’s behavior in presence of unverified information like financial rumours.

Rumours in the Financial Market.

The financial Market is where people’s savings are channelized into more productive uses for the benefit of both the investor and the borrower, but also for the benefit of the economy at large. As such, it is constantly scrutinized by all stakeholders, trying to adapt to the ever-changing nature of the market. From public and private entities protecting their investments and constantly looking for opportunities to grow their capital, to businesses and their employees apprehensive about their future prospects and trying to secure their position; financial markets are massive platforms of exchange driven not only by information per se, but rather by the behavior of all their participants in response to that very information. With so many livelihoods tied to the financial market, any unexplained event can easily eventuate into a full-blown rumour unless an official and convincing statement from the involved parties is released. Rumour-mongering is a way of trying to explain what is happening and why - it becomes a mean by which people try to uncover the truth about important events in an attempt to reduce their psychological discomfort and relieve their fears (Kimmel, 2004). Thus, financial rumours are only the natural consequences of any financial market (Kapferer, 1990). However, there are also instances where rumormongers intend to mislead or manipulate the market by spreading engineered rumours, which are often nothing more than deliberately added noise (Admati and Pfleiderer, 1986, 1988).

While a takeover bid is a type of corporate action in which an acquiring company makes an offer to a target company's shareholders to buy the target company's shares in order to gain control of their business (Kenton, 2018); a takeover bid rumour can be define as an imprecise and unconfirmed information about an impending takeover announcement (Chou, Tian, & Yin, 2010). Since the second half of the twentieth century, capitalistic societies have been home of an incessantly growing number of mergers and acquisitions. Not surprising that this common practice among developed nations would cause so much chatters in the financial sphere. With an average of 2,593 deals announced over the past five years, economic agents are always on the qui-vive for upcoming announcements.

From the various types of financial rumours available, takeover rumours have the most dramatic impacts on stakeholders. The unpredictability of takeovers announcements as opposed to recurring earnings announcements and other corporate activities, combined with their steadily growing popularity turn them into the answer of choice when, out of anxiety, people start speculating about unexplained events. The fact that the rumours collected for our studies were all advanced as an explanation to prior events only confirms the previous statement. For example, in 2011, a meeting between executives from Research in Motion (RIM) and Samsung Electronics Co. Ltd. was immediately interpreted as an attempt to discuss a potential takeover bid from Samsung for RIM shares. After being picked up by major financial news outlets, the rumour was then denied by both companies (Gongloff, 2011). In agreement with Kapferer (2017) and Kimmel (2004), we gather that takeover rumours are characterized by three main factors: (1) the forthcoming takeover has not yet been confirmed by any official sources (2) it is somewhat believable as it springs from raw unexplained facts that could be used as evidence (3) it is important in current goings-on.

Takeovers rumours might not only affect the market value of both the target and the acquiring firms, but also the viability of the deal itself; indeed, not all announced takeovers live to see the light of day. For market participants, these rumours are often perceived as an opportunity to realize significant profits; a gamble that if played right, will boost their gain. However, if proven true, the investor's ability to consistently gain from rumours will challenge the pre-established norms of neoclassical finance in more than one way.

The earliest the trader act on the rumour, the greater its chances to benefit from them. This (expected) gain represents the difference between the current price of the stock and its subsequent value, resulting from the market’s reaction to rumours. Phrases like "Stock X soared amidst rumors of ... " can be read or heard almost on the daily basis in the media; as if takeovers were an explanation to most if not all unexpected events; especially when the alleged target firm is seen as undervalued or in financial troubles. Notwithstanding the fact that rumours only spread unverified information, the market still overreact; maybe as an attempt to grasp the value of an eventual takeover, and/or in response to the anxiety and confusion generated by a stimulus, the rumour. As takeover rumours spread to a gradually larger public, more and more people will start trading based on this piece of unverified information - the more people's decisions are influenced by the rumour, the worthier the rumour becomes even when on its own, it does not carry any weight or trading value. This frenetic buying spree will subsequently result in the rise of the target stock price. Investors hoping to benefit from rumours will want to seize that opportunity; sometimes even when the rumour cannot be substantiated. This phenomenon is paradoxical as trading based on unreliable information, without due diligence, is irrational and unsupported by the neoclassical theory. However, one could argue that ultimately, it is the underlying investor's motivation to trade that gives him justification as of whether there is a logic in his actions or not. In other words, maybe trading on rumours can also be interpreted as a rational response if the agent's incentive to trade is not just a bandwagon effect, but rather a thought-through strategy designed to maximize his profits. For example, experienced news traders[2] would focus on trading in the time leading up to the news or when the market is reacting to the news by rationally assessing the event and making decisions based on the expected market's reaction to the rumour instead of jumping in following the mass without any logical assessment or established strategy. Very aware that there is a high amount of volatility in the

[2] Define news traders

period leading up to an actual news release and/or when the market is adjusting to a recent release; news traders abide to the adage “buy the rumour, sell the news” which essentially highlights the fact that rumours and news can have very opposite effects on the stock price of the target firm (Chen, 2018). Skilled news traders rationally evaluate and assess information looking for patterns they can rely on to elaborate viable and successful investment strategies. They leverage various strategies that mainly focus on market psychology and historical data analysis.

Investors’ rational intentions can be hindered by their intuitions and emotions. For example, in “Thinking Fast and Slow” (TFaS), Kahneman explains that heuristics and cognitive biases are often the traders’ main obstacles in the marketplace. After dividing people’s decision-making process into two broad categories, system 1 and system 2, Kahneman explains the limitations of both systems, and by extension, the limitations of people’s ability to remain rational at all time. Unlike what the neoclassical theories lead us to believe, economic agents are not always rational. Through series of experiments, Kahneman demonstrates that people are most likely to give into system 1, described as fast, intuitive, emotional, and easier to access; rather than system 2, known to be slow, more deliberate and logical. In other words, by default, people are compelled to use their intuition (system 1) which is a seemingly effortless process in comparison to system 2. Unfortunately, when making important decisions, relying on system 1 alone will most likely result in unfavorable outcomes. Despite years of training and professional experiences, traders like anyone else often make investing decisions based on their intuition when they should rationally assess the event to avoid biases, fallacies, and other mental glitches. We will all agree that by nature financial rumours tend to attract system 1 rather than system 2 thought process.

Trading on Rumours: Rumortrage.

Rumours are unauthoritative and highly uncertain; thus, assessing the credibility of the information they carry must be done with extra care. Their volatility coupled with an uncanny ability to spread fast only leave a narrow window of time for any rewarding action to be taken. In presence of rumours, a common market practice is to “Buy the Rumour, Sell the News” (BRSN); traders would buy shares of the target company under the assumption that the stock price will go up; then close their position around, or at the moment the rumour becomes a public and confirmed piece of information (news). Findings supporting the BRSN strategy mainly show concerns for (1) its severity - the more severe the information the faster it travels - and (2) investors ability to quickly take action. Here, traders must act fast and think even faster; sometimes at the expense of any form of structured and rational analysis… there goes system 2 out the window! Like other strategies designed for the same purpose, the BRSN is a form of rumortrage. In the financial market, rumortrage is used to describe trading that occurs on the basis of rumors of a takeover. This financial term is a combination of "rumour" and "arbitrage," and involves quick decision-making with respect to going long and short securities subject to takeover rumours (Kenton, 2018). Indeed, some market participants would rather act on incomplete, raw, and sometimes wrong information relayed through rumours than wait too long and risk to lose their perceived advantage over the market. They would do so at the detriment of proper analysis and evaluation of their position; sometimes destabilizing their own investment strategy. When it comes to rumours, timing is critical and might be the only thing standing between a big loss and a gain. Studies reveal that those able to promptly react to rumours actually benefit from the slower ones even when the information is later proven wrong. Thus, fast traders, including but not limited to traders with insider information, can close their position when the rumour is at its peak, and still make a profit even if the information is later denied. As previously mentioned, these traders are betting on the expected market overreaction to the news, rather than the veracity of information itself. Slower traders on the other hand are prone to losses as they tend to be used as liquidity for the earlier traders (McInish & Upson, 2012).

Any evidence that the benefit of takeover rumours comes from the trader's ability to predict the market's subsequent reaction, and act accordingly might just be enough to show that fast traders remain rational while the rest might display a lack of clear judgement. Even though rumours are not expected to carry any actionable information, they still significantly impact the market. Some studies show that the stock price rises around or at the apparition of the rumour; then, adjust to reach what is perceived as the fair market value of the security upon the official release of the news. This situation could be explained by the emotional state of the economic agents in presence of rumours. Indeed, puzzled by the unorthodox and unstable nature of the rumour, their actions might not be as logical as they usually are. In general, the stock price of a firm is expected to rise if it is undervalued; thus, making a good takeover target. However, in the market, value is not always determined based on the underlying change in the stocks achieved revenues or earnings. Indeed, stock traders also change their view about the worth of a stock when there is a more positive outlook for the future of the company. What if the information acquired through the rumour was being prematurely incorporated into the stock price as if the takeover had been confirmed? In other word, what if the previously mentioned positive outlook on the future was being acknowledged and integrated to the value of the stock even before confirmation of the rumours. Investing in a stock only in hopes that a rumoured takeover will happen is a rash decision, and more of a straight-out gamble than anything else. Such a decision is not a sign of rationality, and will most likely make a sorry trader. Though rational, investing in potential takeover targets based on insider information exposes investors to monetary penalties and incarceration[3].

Backed up by prior studies on takeover rumours, our observations challenge two essential financial notions, the rational expectations theory and the efficient markets hypothesis. As any other type of rumours, financial rumours spread quickly and require a tantamount swift response from investors hoping to benefit from them. Thus, they only leave a very narrow window of action for any rewarding strategy to be implemented. Either in an attempt to confirm and analyze the rumour, or unable to have access to the rumour as early as fast traders; some market participants fail to seize the potential bargain generated by the rumour; a bargain that one could argue should not exist in the first place.

We believe that when confronted with rumours, investors' behavior digresses from conventional economic assumptions of rationality to an emotionally charged response. The impact of rumours on the financial market calls for a certain understanding of the underlying mechanisms by which hearsay affects human behavior and decision processes (Difonzo & Bordia, 1997). Such knowledge is exactly what the field of behavioral finance is aiming for.

Neoclassical Paradigm in Finance

While most financial models (e.g. model CAPM capital asset evaluation or Markowitz portfolio theory) stem from the assumption that investors always behave "rationally"; trading based on unconfirmed and often unsubstantiated news seems far from a rational behavior.

[3] The legal definition of insiders can vary based on jurisdiction - In Canada, insiders are those with knowledge of the impending event due to a "special relationship" with the company whose shares are purchased or sold (Shecter, 2013)

Investors have voiced their reluctance and concerns about trading on takeover rumours. For example, an article by George Linton for The Globe and Mail (1981) adduces a collection of quotes from various financial market specialists sharing criticisms on investment decisions based on takeover rumours. Albeit investors often claim that rumours are non-credible and that they should not and do not influence investors trading decisions; an increasing trading volume around the apparition of the rumour in the media would rather contradict that claim. When dealing with rumours, investors' claim does not always align with their actions. Despite their inability to rationally justify rumortrage, investors still engage in this practice more often than they would like others to believe.

The neoclassical economic models assume that participants make decisions based on all available information and use this information fully and in an unbiased way. This assumption takes root in the Efficient Market Hypothesis (EMH) and also asserts that all market participants are rational. By postulating that prices always fully reflect all available information (Fama, 1970; Jensen, 1978), the EMH implies that information flow freely and expeditiously in the marketplace; leaving no opportunity for investors to reap an above average return trading on an event. Simply said, investors cannot perform better than the market. However, economic agents hoping to make a profit on takeover rumours believe otherwise; thus, challenging the very idea conveyed by the EMH. How do takeover rumours affect the financial market? Are traders actually able to successfully beat the market? If yes, does this lack of consistency between theory and reality suggest that the Efficient Market Hypothesis should be discarded? How does the implications for the Canadian market relate to other markets? Our study shed some light on the impact of takeover rumours on Canadian public companies as an addition to prior studies.

The Efficient Market Hypothesis relies on three important assumptions; (1) investors are rational, (2) information is free and available to all, and (3) the stock price instantaneously reflects all known information. However, studies and observations often challenge these assumptions. Indeed, investors from all levels of expertise are often influenced by emotional factors, leading to rather irrational trading decisions. Are these anomalies frequent enough to warrant a public outcry?

Despite the phenomenal growth of information technologies, information lag is still an issue when dealing with rumours. As a result, information symmetry might not be as effective as we are led to believe. This study evaluates the impact of takeover rumours in the Canadian financial market by assessing the returns generated by the target stocks around the day of the first publication. We also evaluate the trading volume of the target stocks over the same period. As per our hypothesis, the presence of abnormal returns and abnormal trading volumes would suggest that some of the previously stated assumptions are being challenged; and may lead to the subsequent failure of the EMH as well as other theories that hold any of these assumptions as a fundamental requirement to their existence. On the other hand, the absence of significant anomalies in the marketplace would suggest that the EMH applies to the Canadian financial market.

Assuming that our hypothesis proves to be right, how should these results be interpreted? Does it mean that the EMH should be totally discarded? Or, does it simply imply that the EMH comes with limitations and should be reviewed? What if the EMH is only a partial portrayal of reality? The presence of abnormal returns and volumes could also be the product of mere anomalies due to variations in methodology, inputs, or length and period of the study. Could it be that the variations in regulations and laws in Canada as opposed to other financial markets influenced our results? This study fuels ongoing debates about the legitimacy of the Efficient Market Hypothesis as well as other neoclassical theories built on the same assumptions.

Investors Emotions.

Strictly formulated under the assumption that market participants are rational, the EMH does not always offer a truthful representation of the financial market. Unlike earlier belief that rational decisions are natural and therefore not in need of explanation (Cosmides & Tooby, 1994); a growing number of studies have shown that investors from all levels of expertise are often influenced by emotional factors. These emotions will in turn lead to lapses in judgement and irrational trading decisions. Some of these studies will be discussed in greater details later in this paper.

When faced with rumours, traders have the tendency to act irrationally for reasons we are still trying to grasp. To this day, number of studies evinces the failures of the rational choice theory; the difficulty always revolves around the inability to accurately model the behaviors of human traders. We emphasize the word "human" since emotions and psychological predispositions do not apply to algorithmic traders[4]. Indeed, algo-trading only follows a set of purely rational rules based on a predetermined trading strategy; its sole purpose is to realize optimum profits thanks to its superior analytic capabilities and speedy delivery. Another challenge with the rational choice theory is that behavioral patterns may vary from one individual to the next, and from one situation to another; making accurate market predictions even more difficult. In that perspective,

[4] Automated trading systems that utilizes advanced and complex mathematical models and formulas to make high-speed decisions and transactions in the financial markets. Also referred to as algo trading or black box trading, algorithmic trading involves the use of fast computer programs and complex algorithms to create and determine trading strategies for optimal returns. Chan, E. P. (2013). *Algorithmic trading: Winning strategies and their rationale*. Hoboken, NJ: Wiley.

the assumption that traders are always rational make it easier and more practical to design financial models and come to a consensus; even though their depiction of the financial market leaves us with unexplained patterns and unanswered questions.

The rational choice theory is an economic principle that reveals that individuals always make prudent and logical decisions; these decisions are drafted to provide people with the greatest benefit or satisfaction given all available choices. Under this theory, the financial market is only made of homogeneously and globally rational people whom greatest satisfaction is to lower their risk and increase their profit (Amadae, 2017). Though studies have shown that the previous statement is not always true; what if there were clear instances when previous and regular rational agents would behave irrationally?

To evaluate traders' reaction to rumours we categorize market events according to specific criteria; anticipated or scheduled events versus unanticipated events. Prior studies like the one conducted by Kim and Verrecchia (2001) have shown that traders would mostly remain the same when it comes to scheduled activities. However, unanticipated events tend to create a very different behavior. These unanticipated events act as stressors; triggering an irrational behavior from numbers of human traders. A research conducted by Christopher Simms of Dalhousie University in Halifax, Canada, postulated that when people are anxious, they fail to make rational decisions (Simms, 2016). Anxiety has been shown to actually suppress parts of the brain that aid in rational decision-making (Ganti, 2019). By extension, his study supports the idea that people rely on system 1 in period of anxiety. Unanticipated events are perceived as dangerous because they were never part of the original plan. As a disturbance, they leave the participants without much control over the possible and expected outcomes. They come as a surprise and do not leave much room nor time for traders to adjust to the shock. Financial rumours alter one's pre-existing equilibrium resulting in an apprehensive uneasiness that will then open the way for anxiety to kick in and affect one's choices and decisions… not necessarily for the best. Indeed, confused and desperately trying to make sense of the events they are facing; people would rely on the creativity of system 1 to quickly come up with "a plausible story, an explanation for what is happening, relying on associations and memories, pattern-matching, and assumptions."[5] Kahneman (2013) explains the following:

> The measure of success for System 1 is the coherence of the story it manages to create. The amount and quality of the data on which the story is based are largely irrelevant. When information is scarce, which is a common occurrence, System 1 operates as a machine for jumping to conclusions. (p. 85)

This explanation applies to both the rumour itself, and the subsequent irrational response of the market participants. Unfortunately, by jumping to conclusion and identifying causal connections between events, sometimes even when the connection is spurious; people may give into heuristics and fallacies.

Rationality as portrayed by the rational choice theory does not grasp the full spectrum of the economic agent's behavior and cognitive process in the marketplace. Even though the definition of a rational investor does not reflect the demeanor of real-life human beings, it does not necessarily mean that those who fail to fit into this rather utopic box are truly irrational. Maybe it is the rational-agent model that need to be adjusted. In regards to this issue, Kahneman (2013) writes:

> I often cringe when my work with Amos is credited with demonstrating that human choices are irrational, when in fact our research only showed that Humans are not well described by the rational-agent model (p. 411).

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[5] Ranadive, A. (2017, February 20). What I learned from "Thinking Fast and Slow". Retrieved from https://medium.com/leadership-motivation-and-impact/what-i-learned-from-thinking-fast-and-slow-a4a47cf8b5d5

In a confusing environment, system 2 is a lot more helpful than system 1. Unfortunately, by default, people tend to rely on System 1 unique abilities to concoct very convenient stories out of vague events. People jump to conclusions on the basis of limited information and ignore absent evidences; this phenomenon is known as the WYSIATI or "what you see is all there is" (Ranadive, 2017). According to Kahneman (2011) the impressions and intuitions created by System 1 under the WYSIATI are quickly endorsed by System 2 and turn into deep-rooted values and beliefs.

To sum up, we can agree that the rational choice theory is a rather idealistic representation of people's reactions and decision-making process. It fails to account for individual's emotional and impulse-driven actions; instead, it only vindicates people's rational conduct. The market's anomalies are proofs that securities do not always align with the established financial fundamentals. Unexpected events like takeover rumours tend to act as stressors, triggering a momentary emotional response that might progressively adjust to conventional expectations as reliable information is eventually released in an attempt to either confirm or deny the rumour. Ergo, out of anxiety and confusion generated by unexpected events, people are less likely to remain rational.

Starting in the 1970's, series of studies have explored and established a cognitive basis for common human errors that arise from heuristics and biases.[6] As a result of these studies, we know that investors are often influenced by extraneous factors (personal beliefs, environment specific influences, etc.) that eventually impel them to make irrational trading decisions.

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[6] Kahneman, D. (2013, November 26). Daniel Kahneman on Controlling Irrational Tendencies. *BigThink*. Retrieved from https://www.google.com/amp/s/bigthink.com/daniel-kahneman-on-controling-irrational-tendencies-2604469874.amp.html

Kahneman's contribution was instrumental to these discoveries; along with other acclaimed scholars like Amos Tversky, Paul Slovic, and Richard Thaler among others. Kahneman's extensively researched the mental tricks we could all be victims of as avid users of System 1 (Kahneman & Tversky, 1973; Kahneman, Slovic & Tversky, 1982; and Kahneman, 2011). De Bondt and Thaler (1985) noticed that people systematically overreact to unexpected and dramatic news events, which in turn result in substantial inefficiencies in the stock market. Keeping in mind that unanticipated events are source of anxiety; the study performed by De Bondt and Thaler is complementary to Christopher Simm[7]'s findings discussed a little earlier as they both ultimately link anxiety to a lack of efficiency in the marketplace. Various behavioral biases have been studied over the years; some of them more relevant to trading and decision-making in the marketplace than others. Biases are complex and can affect both professional and non-professional market players in the same manner. According to Kent Baker and Victor Ricciardi (2014), some of the most widely spread behavioral biases in financial decision making are representativeness, anchoring, hindsight, trend-chasing, regret aversion, disposition effect, familiarity, and self-attribution among others. Kahneman was the first to build the bridge between human's default decision making process (System 1) and the repetitive errors in judgement people were inadvertently responsible for. He also pushed it further in Thinking Fast and Sow (TFaS) (2011) by offering ways to recognize and avoid these errors.

The broad range of behavioral anomalies observed in the financial sphere comes to support scholars' dissatisfaction with the rational choice theory. To account for irregularities and

[7] Ganti. A. (2019, April 1). Rational Choice Theory. Retrieved from https://www.investopedia.com/terms/r/rational-choice-theory.asp

alleviate the gap between what the neoclassical financial theories would like to be true and what is actually happening, academics turned to behavioral finance. Dissenters of the rational choice theory rallied behind this new field of study in an attempt to understand the cognitive psychology that lies behind human behavior and actions in the marketplace.

During the second half of the 1900's, Herbert Simon introduced the theories of the bounded rationality. Through series of studies centered around human decision making, Simon devised a more positive and formal characterization of the mechanisms of choice under conditions of bounded rationality, taking into account not only the man's economic behavior, but also his environment. Simon pointed out that global rationality in the neoclassical theory requires a complete knowledge and anticipation of the consequences that will follow each choice; no psychological theory is needed other than a theory of wants and needs. Thus, there is no need to understand human thought process in order to carry out economy analysis; instead, it is sufficient to know how people ought to behave, since the neoclassical theory assumes that people will do things that are objectively rational (Simon, 1956). Simon's main idea was to replace the unrealistic representation of the economic man, who is characterized by global rationality, with a behavior that is still rational, but that is compatible with the access to the information and the computational capacities that the man actually possesses in the environment where he lives. Thus, with the bounded rationality, Simon developed a concept that represents the key interface between his works in economics and psychology (Schilirò, 2013). Simon believes that rationality is bounded since the quality of information used is poor and the cognitive capacity of an individual is limited (Simon, 1955). In other words, people might make decisions that appear irrational from the perspective of conventional economic wisdom; even though they are typically the right ones for the one making them (Schilirò, 2013). Individuals can only choose from the array of alternatives available to them at a particular point in time; this statement implies that information symmetry is non-existent in such environment. According to Simon (1956), the incapacity of exercise of global rationality makes the economic agents beings endowed with the bounded rationality. The bounded rationality is Simon's attempt to include the whole range of human limitations that prevent real-world economic actors from behaving as predicted by the neoclassical theory (Simon, 1947). Simon explains that the key to the simplification of the choice process is the replacement of the goal of maximizing with the goal of satisficing, of finding a course of action that is 'good enough' (Simon, 1947).

These studies have illustrated that the rational expectations theory is not representative of investors' decision-process in its entirety. Investment decisions are the result of a more complex mechanism than neoclassical financial theories cares to admit. The market overreaction to rumours, the existence of emotionally charged trading patterns like behavioral biases, and the bounded rationality theory are all elements that prompt us to question any mainstream financial assumptions built on the sole belief that all investors were rational, and therefore actively try to maximize their expected utility. Seeing that rumours initiate a wave of irrational[8] behavior from the market participants; it leaves us pondering about their impact on the target firm and the market at large. In the event of rumours, does the more acute lack of rationality from the market participants destabilize the EMH, allowing traders to successfully beat the market?

The Efficient Market Theory.

"Abnormal profits" are defined as any above average return yield from trading on an event in the capital market (there is no need to understand human thought process in order to carry out

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[8] Irrational based on neoclassical standards and strictly

economy analysis; instead, it is sufficient to know how people ought to behave). Bargaining on rumours evidences the underlying belief that there are anomalies in the marketplace to be exploited. For decades, financial and economics scholars have studied the concept of efficiency applied to capital markets with the Efficient Market Hypothesis (EMH) being at the center of the debate. Views on the EMH are very divergent; for each article that confirms the hypothesis, there is another that invalidates it (Titan, 2015). While the variation of results observed between studies could be justified by the dissimilarity of techniques and methodologies used, pressing us to believe that the capital market is efficient; others seem to believe that the EMH is a faulty hypothesis, since it is based on assumptions that often do not hold in real life. Consistent with both beliefs we have active traders (anomalies hunters), always looking for events to benefit from; and passive traders, who believe in the supremacy of the market, and do not expect the return of their portfolio to surpass the market's. At first, the Efficient Market Hypothesis was very well received; the idea of a fair and homogeneous market was certainly appealing to most. However, around 1980's, criticisms started to rise, backed up with studies pointing out the shortcomings of the EMH. The last financial crisis rallied even more dissenters of the EMH as number of acclaimed financial specialists blamed the unjustified faith in the Efficient Market Hypothesis to be the underlying cause of the last financial crisis. Among these publications, a respected market strategist pejoratively referred to the EMH as theory designed to fulfill "their desire for mathematical order and elegant models," he also mentioned that "the economic establishment played down the role of bad behavior."[9]

[9] Nocera, J. (2009, June 06). Poking Holes in a Theory on Markets. Retrieved from https://www.nytimes.com/2009/06/06/business/06nocera.html

The first formal definition of market efficiency was proposed by Eugene Fama in 1970. The efficient market was defined as "a market with great number of rational profit-maximizers actively competing with each other, trying to predict future market values of securities, and where current important information is almost freely available to all participants."[10] Along with the previous definition, Fama (1970) also offered the distinction between all three forms of market efficiency – weak, semi-strong and strong. He categorized the market efficiency based on the nature and availability of information. The weak form of EMH represents a market within which the current prices of financial assets incorporate, at any moment, all the existing historical financial information. Thus, future prices cannot be predicted by analyzing past prices. It supports the idea that investors cannot obtain long term abnormal profits from investing in financial assets. This degree of EMH implies that prices will exhibit a random walk. While a technical analysis will fail to consistently produce any excess return; some fundamental analysis practices might successfully help secure above-market returns.

The semi-strong form is described as an addition to the weak-form of EMH. As such, the current prices of financial assets incorporate, at any moment, all existing historical financial information, as well as any other new public information released in the market at all time. In presence of this form of EMH, neither technical nor fundamental analysis can determine the way an investor should split his funds so that his expected profit is higher than that achieved in case of investment in a random portfolio of financial assets (Kenton, 2019).

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[10] Fama, E. F., "Efficient Capital Markets: A Review of Theory and Empirical Work", Journal of Finance, Volume 25, Issue 2, Papers and Proceedings of the Twenty-Eighth Annual Meeting of the American Finance Association New York, N.Y. December, 28-30, 1969 (May, 1970), pp. 383-417

The strong form of market efficiency is one level above the semi-strong form. It represents a market in which all available information, whether public or private, are instantaneously incorporated in the stock's price. This degree of market efficiency is very difficult to achieve; especially when all financial markets have legal barriers established to maintain a safe and reliable trading environment. Hence, neither technical analysis nor fundamental analysis nor inside information can consistently predict future price movements; the market cannot be surpassed. As a general rule the more efficient the market, the more random the sequence of price change. Empirical evidences supporting the market efficiency theory only discuss two degree of efficiency: the weak and the semi-strong forms of EMH. To my knowledge, there is no evidence of a financial market being endowed with the strong form of market efficiency.

Assuming that all financial markets accommodate a certain level of efficiency; if proven right, the semi-strong form of market-efficiency contradicts any suggestion that market participants could benefit from financial rumours. As such, the presence of excess returns around the publication of the rumours would suggest that the market is not efficient at the semi-strong level, including the strong one by extension. In that case, we are left with two other alternatives; we might be facing a weak form of market efficiency, or perhaps, the market does not meet any known standard of efficient. In 2003, Malkier defined an efficient capital market as being a market in which "prices fully reflect all known information, and even uninformed investors buying a diversified portfolio at the tableau of prices given by the market will obtain a rate of return as generous as that achieved by the experts". Malkier's definition is very similar to Fama's semi-strong form of market efficiency; hence, the presence of excess returns does not align with any of these definitions of market efficiency. With the last financial crisis, critics of the EMH have grown to a much larger number. Experts like Paul Volcker [11]and Richard Posner[12] among other public personae, believe that the misplaced and overzealous trust of financial leaders in the Efficient Market Hypothesis played a significant part in the financial crisis.

As previously discussed, financial rumours tend to drive the stock price up as they propagate to a larger public. This apparent overreaction to unverified information stem from people's anxiety; however, once the ambiguity is cleared up, stock prices progressively recede to their expected value. Assuming that our assumption is true, the idea that the market participants are not always rational cripples the EMH. Furthermore, significant overreaction to rumours also means that the market does not immediately adjust to new information. Thus, proving that there might exist patterns to be exploited in the market.

Fama (1998) explains that what one's possibly sees as market inefficiency might be subject to misconception due to failure to categorize and accordingly analyze these anomalies. According to Fama an efficient market sometimes generates categories of events that individually suggest that prices overreact, or underreact to information. However, in an efficient market, apparent under-reaction will be about as frequent as overreaction. Consequently, if anomalies split randomly between under-reaction and overreaction, they are still consistent with the EMH (Fama, 1998). Looking at the long- term return anomalies, Fama (1998) also comes to the same conclusion; if the anomalies are so large that they cannot be attributed to chance, then an even split between over- and under-reaction is also a pyrrhic victory for market efficiency (Fama, 1998). He also demonstrates that long-term anomalies are sensitive to methodology, and tend to become marginal or disappear when exposed to different models, or when different statistical

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[11] former US Federal Reserve chairman

[12] Renowned American economist and jurist

approaches are used to measure them. Thus, even viewed one-by-one, most long-term return anomalies can reasonably be attributed to chance (Fama, 1998).

Neoclassical economic models assume that participants make decisions on the basis of all available information and that they use this information fully and in an unbiased way; however, Simon shows that it is only presumptuous to assume that everyone will have access to the same information in the same manners and at the same time. The bounded rationality put forward some of the limitations of the EMH. Furthermore, the existence of late responders being used as liquidity for the earlier responders also defeats the idea of markets participants being able to fully use all available information. The shortcomings of the Efficient Market Hypothesis lays in its inability to account for all human behaviors involved in the decision-making process. With rumours, these shortcomings are only amplified, economic agents find themselves in uncharted territory, often mistakenly relying on instincts rather than logic. Confusion can be an opportunity for those able to remain clear-headed.

Part 2. LITERATURE

The literature on takeover rumours has long speculated on their impacts and consequences on the stock market. Even though there is no doubt that these rumours can influence the stock price trends of target firms before an actual takeover bid is announced; there is still a great deal of polemic about this subject. One major concern is whether the price run-up frequently highlighted in previous studies and articles, might challenge the pre-established neoclassical theories of finance discussed earlier. So far, studies about takeover rumours mainly focused on the U.S. market (Pound and Zeckhauser (1990); Zivney et al. (1996); Gao and Older (2008)), or the Australian market (Clarkson et al. (2006); Bujera et al. (2014); Aspris et al. (2012)). This study contributes to the existing literature by shedding new insights into the impacts of takeover bid rumours on short-term stock return patterns and pricing of target companies listed on the Canadian Stock Exchange. While studies about the Canadian market's reaction to M&A announcement has been tackled in previous studies (Gratton (2003); and Aintablian and Roberts (2005)); very little, if any at all, is known about the impact of takeover rumours on the Canadian market despite the recurrent price run-ups to possible takeover bid announcements published in the media about Canadian targets.

Prior studies on takeover rumours were conducted from two different perspectives. On one side, we have studies designed to assess the behavior of the acquired firms on the period leading up to the official announcement of the merger. This model best fit the assumption that there is information leakage before the official announcement; thus, the market gradually adjust to the official news release as bits of information are leaked to the public. The information leakage mentioned earlier is explained by the presence of takeover rumours (including but not limited to insider information); however, it only focuses on those rumours that were later proven to be true (Keown and Pinkerton (1981), Jarrell and Poulsen (1989), Aktas et al. (2002), Chou et al. (2010); Gao and Oler (2012) among others). On the other side, we have studies that regard takeover rumours as a distinctive type of information. As such, they can account for all types of takeover rumours, the standalone rumour events are gathered before any official news release or takeover announcement is made. At this point, there is no sure way for investors to know whether the information is right or wrong; thus, any decision to enter a deal express his/her willingness to be exposed to considerable risk. Studies following this logic rely on a collection of takeover rumours data available in print and/or digital forms (Pound and Zeckhauser (1990); Zivney et al. (1996) among others). While the previous type of studies is looking backward from the official announcement of M&A, the latter assesses the broad range of takeover rumours and accommodates for better analysis of their causes and consequences. Even though these studies follow a very different approach; they both evaluate the returns and/or volumes of the target stocks over a given period (the pre-announcement period, or the period around the apparition of the takeover rumour).

Literature Based on Official Takeover Announcements

Using a sample of 194 firms; Keown and Pinkerton (1981) evidences excess returns earned by investors in acquired firms prior to the first public announcement of planned mergers. They find that the price run-up observed before the announcement date is largely explained by the media speculations; and also notice the presence of a higher trading volume for 64 percent of their sample target firms three weeks before the announcement. Similarly, with a sample data of 172 target stocks going all the way back to 1962, Jarrell and Poulsen (1989) demonstrate that the stock price of the average takeover target moves to incorporate about 40 percent of the ultimate takeover premium before any formal public news of the bid. They conclude that the presence of takeover rumours in the media is the strongest variable in explaining unanticipated premiums and pre-bid run-up for tender-offer targets. More recently, Gao and Oler (2012) also enquire into trading activity in the days preceding the official acquisition announcements, and detect an abnormally high trading volume over the 20 days preceding the official announcement of the offer. They find that for companies that have not been the subject of rumors, abnormal volumes are observable only from the sixth day before the announcement.

Unlike previously discussed researches, using court information, Meulbroek (1992), and Cornell and Sirri (1992) show in their respective work that some of the pre-trade volume is driven by illegally informed trade. In the same year, Sanders and Zdanowicz find no evidence of the pre-announcement date average abnormal trading volume noted by previous researchers; instead, they find average abnormal volume beginning with the first public information regarding the transaction. They also find no evidence suggesting that insider trading is the mechanism through which information regarding the impending bid is leaked to the market. However, the recent study of Augustin et al (2014) shows that informed trading also plays a significant role in the statistically significant abnormal trading volumes observed in call options written on the targets, prior to M&A announcements, with particularly pronounced effects for OTM calls (Out of the money). This evidence is confirmed both overall, and in a sample of strongly unusual trades, where the incentives for informed trading seem particularly striking, given the comparison to the volume of trades in random samples. Stepping away from the American market, Aspris et al. (2012) examines the impact of changes in substantial shareholdings ahead of 450 Australian takeover offers between the years 2000 and 2009. Their findings show no significant pre-bid run-up for takeover targets. Thus, they conclude that any previous findings attributing pre-bid share price run-up to illegal insider trading may overstate the existence of such conduct.

In 2005, King and Padalko publish their work on the price-volume dynamics ahead of takeover announcements for 420 Canadian firms from 1985 to 2002. They find that pre-bid run-ups in the target firm’s shares occurred shortly before the announcement and were of comparable magnitude to the run-ups documented for U.S. takeovers, which suggests a similar amount of price discovery in both countries. They finally establish that the average takeover in this sample exhibits a price–volume dynamic that is more consistent with the predictions of the market anticipation hypothesis than the information leakage hypothesis. However, they do not discard the possibility of illegal insider trading in any of the individual takeovers in our sample. In 2009, King decides to explore the latter topic in greater details. With a sample of 399 Canadian takeover announcements from 1985 to 2002, he finds evidence consistent with insiders trading illegally, creating both abnormal returns (ARs) and abnormal turnover (AT) ahead of the announcement. The rise in AT begins far ahead of the actual announcement, accompanied by ARs in the last five trading days, consistent with more informed trading. Data on disclosed insider trading indicate a sharp increase in volume prior to the takeover announcement, suggesting that insiders make use of private information. In both studies, the samples are based on Canadian takeover announcements; to our knowledge, there is no literature about the Canadian market response to takeover rumours.

One particularity of studies based on pre-announcement trading period is that researchers consistently try to determine whether the abnormal returns and/or volumes could be explained by insider trading and/or the media's speculations about imminent takeovers. As previously illustrated, most studies establish that takeover rumours published in the media successfully explain most of the market anomalies, if any. However, often time, scholars find evidences of insider trading. Perhaps, beyond the variety of methods used for their analysis, factors like industries and locations also influence these results due to the legal and economic barriers specific to each one of them.

Literature based on Takeover Rumours Published in the Media

In this type of studies, takeover rumours are directly collected from one or multiple sources of media. Even though the method applied to the data follow the same idea as the one used in the previous type of studies, the variation in the nature and origin of the data might ultimately affect the results. Thanks to their traceability (access to the publication time and location), this technique offers a more in-depth assessment of the actual events.

Pound and Zeckhauser (1990) evaluates 42 takeover rumours published in the column "Heard on the Street" of the Wall Street Journal between 1983 and 1985. Although on average, the target stocks display significantly positive excess returns in the 20 trading days before the rumour publication; there is no reaction to the rumour on the actual date of its publication. Lastly, they find that the market reacts to rumors efficiently as trading on the rumours cannot not generate any profit. In other words, the market processes incomplete information as well as it does more complete and specific information, such as the value of an actual takeover bid or earnings reports. Few years later, Zivney et al. (1996) argue that Pound and Zeckhauser (1990) should have used the first publication of the rumours. Consequently, they extend the work of Pound and Zeckhauser (1990) by including the first publication of the rumours in their research. Once they realized that the rumours published in the "Heard on the Street” (HOTS) column of the WSJ were first published in the "Abreast of the Market" (AOTM) column of the same journal; Zivney et al. conduct a separate assessment of both types of rumours. They realize that rumours in the AOTM column are associated with short-term overreactions, while those in the HOTS column exhibit rapid price stabilization following the rumor publication. Trading on these overreactions would have resulted in annualized excess returns averaging 20 percent with 70 percent of the trades being profitable. The profitability of this trading strategy suggests that the market overreacts to takeover rumors. More recently, Antweiler and Frank (2004), examines 1.5 million messages published at Raging Bulls and Yahoo! finance for 45 companies, including stocks of the Dow Jones Industrial Average, and find that the Internet messages allow the prediction of market price fluctuations. Furthermore, a positive rumor usually results in a positive return in the next trading day, while a negative message yields to the opposite result.

Moving away from the American market, Durand et al. (2003) examine the Australian market reaction to the rumours generated for 88 internet and technology companies. They discover an average of over 24% abnormal return during five days [-4, 1] around the time of the publication. Likewise, Clarkson, Joyce, and Tutticci (2006) investigate the market reaction to takeover rumor postings on the Hotcopper, an Australian internet discussion site. Their findings show that rumours are associated with an abnormal return and trading volume during the 10-minute posting interval and an abnormal trading volume in the 10 minutes immediately preceding the posting. More recently, Tavor (2013) uses a combination of rumours from different and independent Israeli websites. He finds that for positive excess return companies prior to the event, excess return will decrease during the following period. For companies that have yielded no returns or yielded negative excess return during the period preceding the event, the trend is reversed, the excess return will increase during the period to follow.

The overreaction observed in previous literatures is consistent with the more general findings of Hoitash and Krishnan (2008), who suggest that investors overreact for firms showing a high degree of speculative intensity. Thus, takeover rumours should be perceived as a symptom of this speculative intensity. This deduction is supported by the findings of Jensen and Ruback (1983) who argue that some skilled investors, like researchers and analysts, may be able to anticipate the takeover using publicly available information. Consequently, the trading activities of these investors impound this anticipation into the prices. This hypothesis is also consistent with the common investment adage ‘‘buy on the rumor, sell on the news.’ In the same logic, our study proposes an analysis of the impacts of takeover rumours published in the media. Unlike prior investigations on Canadian takeover rumours that only move backward from the official announcements; this study only utilizes actual takeover rumours published by reliable news media available online and/or in printed press. Furthermore, while previous researches focus on rumours from specific and limited websites; we track and gather the first apparition of the published takeover rumours. Collecting data around the first apparition of the published rumours allows us to adequately capture the flow of rumours, and reduce the risk of errors during the interpretation of our results.

Part 3. METHODOLOGY

The goal of this study is to explore the impacts of takeover bid rumours on target stocks traded on the Toronto Stock Exchange, and their repercussions on the Efficient Market Hypothesis. Our methodology takes root in the research of Laouiti et al. (2015) on French target stocks; similar techniques were also used in number of studies on mergers and acquisitions, and takeover rumours; some of them are discussed in this paper.

We proceed with an evaluation of both the stock prices and the trading volumes of our pre-selected sample. This process allows us (1) to understand the behavior of rumour during, before, and after the apparition of the rumour in the media, and (2) to ascertain the short-term implications of our findings on the market’s efficiency. Unlike prior studies that either tackled liquidity or efficiency; we offer an assessment of both instances. Among others, the work of Chordia et al. (2007) and Hodrea (2015) have shown that liquidity boosts/increases the market efficiency.

Liquidity is defined as the easiness to trade shares with minimum price disturbance; pertaining to rumours, the demand must be sufficient to support the price during the course of the transactions. The most useful measure of liquidity for any stock is its average daily trading volume or ADV (Cogger and Emery, 1982); the highest the ADV, the more liquid the security. Another useful measure of liquidity is the turnover ratio which is obtained by dividing the trading volume by the total number of outstanding shares. Part of our analysis will focus on comparing the variation in prices to the variation in volumes over the study window. A significant trading volume spread in presence of a minor price spread is also a sign of liquidity; which as mentioned earlier, intensifies market efficiency. On the other hand, a lower-level of liquidity around the apparition of the rumours in the media would demonstrate a decrease in market efficiency driven by the price volatility at that time.

We organize our analysis around the following hypothesis:

H0: There is no significant price abnormalities around the publication of takeover rumours in the Canadian market. We are in presence of the semi-strong form of market efficiency; at any moment, all existing historical financial information, as well as any other new public information are incorporated in the current price of Canadian securities.

H1: There is significant price abnormalities around the publication of takeover rumours in the Canadian market. The EMH is challenged; new information is not systematically incorporated within the price of Canadian securities.

Pursuant to the assumptions we made earlier in this paper; we expect the null hypothesis (H0) to fail, in favor of the alternate hypothesis (H1). In order to test our hypothesis, we analyze the results obtained from a randomly selected sample of publicly traded Canadian securities. Our step-by-step approach is detailed within the next two subsections under “the sample selection” and “the research design”.

The Rumours Selection

One essential part of this analysis is the sample selection. First, we establish the inclusion and exclusion criteria of our sample. Then, we gather and organize all events matching those criteria. Our data pool is obtained from this sample over a predetermined period of time. Takeover rumours with repetitive, missing and/or incomplete information are discarded.

Even though all rumours are first shared by word of mouth, there is also a more formalized networks for rumour dissemination that give us access to traceable and publicly available rumours. Using published rumours, we are able to easily comb through for irrelevancy; but more importantly, we can gather tangible and traceable news made available to the general public at once. We collect takeover rumours from Factiva, Dow Jones global news database, to perform our study. For the purpose of the present study, a takeover rumour describes a publication (online post or article) containing an unofficial proposition that a TSX listed company will be, should be or could be taken over. We use different combinations of keywords to find a suitable sample. Keywords like acquisition rumours, buyout rumours, takeover rumours, and takeover bids are combined to other keywords like Canada targets, TSX or TSE or Toronto Stock Exchange, Canadian or Canada. We also play with the spelling of rumour, going back and forth between the American and the British spelling (rumor vs rumour for the latter). Our initial sample collection period was from 1995 to 2017; however, the final sample will only be made of rumours published between 1998 and 2015. We obtain a raw sample of more than a thousand takeover rumours to which we then apply our selected criteria.

We rule out all articles covering (1) the actual announcements of takeover bids or other types of acquisition or buyout announcements, (2) companies that were not listed on the Toronto Stock Exchange that managed to slip through our research perimeter, and (3) announcements within one day of the publication of the rumours. This step significantly reduces our raw sample size. We also create a spreadsheet to catalog our search results with columns for acquirer, target, industry, financial market, target's ticker, name of the article, source of publication, publication date, and a summary section that put those rumours into context. This spreadsheet allows us to get rid of articles with identical content (articles discussing about the same takeover rumour but published by a different media outlet). We only keep the first publication of each takeover rumours discussing the same acquirer and target. Since some rumours are recurring, we keep those that reappear after about 60 days. Most of the rumours in our sample were published in the Reuters News, the Canadian Press, the Globe and Mail, Benzinga, Dow Jones Business News, Canada Stockwatch, and some local journals like Guelph Mercury, Edmonton Journal, Toronto Star, among others. At this stage, we end up with a sample of 146 takeover rumours. Unfortunately, due to the limited resources available on campus for financial researches, we have to alter our original design, and once again reduce our sample size. Unable to secure data for delisted targets, we remove them from our selection. Our final sample is now made of 21 takeover rumours. It is important to note that this adjustment might considerably affect our study as most delisted stocks are those acquired firms. Our final sample only reflect takeover rumours that were either never confirmed; or failed somewhere down the line, even after an official takeover bid announcement. Unlike our initial goal, not all types of takeover rumours are represented in our sample. Important rumours that turned out to be true, like the takeover of Provigo by Loblaws, among others, had to be removed due to the unavailability of historical prices and volumes.

Table 1. Selected events between 1998 and 2015

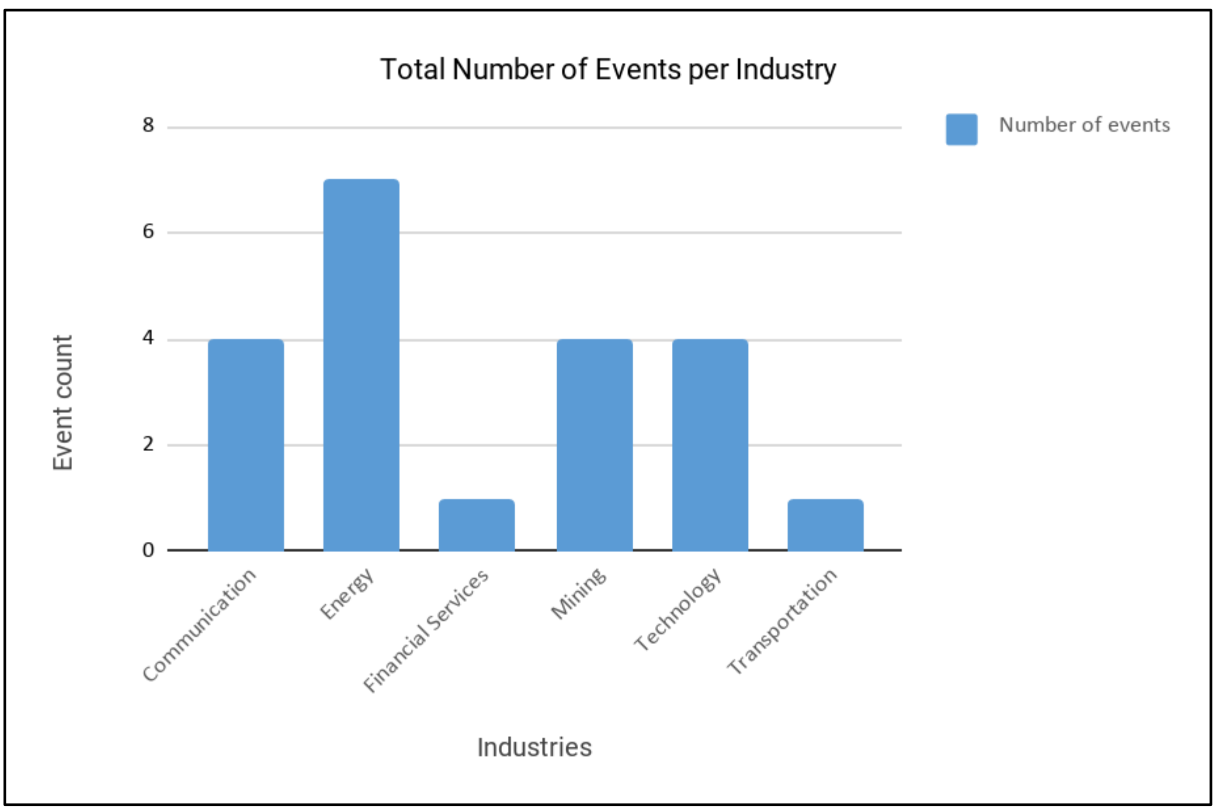
Event ID	Firm Name	Ticker	Industry	Article Date
511801	Bell Canada	BCE	Communication	11/17/1999
511802	Bell Canada	BCE	Communication	11/25/2000
511803	Bell Canada	BCE	Communication	3/30/2007
511804	Blackberry	BB	Technology	8/1/2003
511805	Blackberry	BB	Technology	10/5/2011
511806	Blackberry	BB	Technology	1/18/2012
511807	Blackberry	BB	Technology	1/15/2015
511808	Canadian Natural Rscs.	CNQ	Energy	1/6/2004
511809	Canadian Pacific Rail.	CP	Transportation	7/18/2007
511810	EnCana	ECA	Energy	10/19/2005
511811	Husky Energy	HSE	Energy	9/6/2001
511812	Husky Energy	HSE	Energy	2/19/2002
511813	Husky Energy	HSE	Energy	11/27/2004
511814	Imperial Oil	IMO	Energy	5/24/2007
511815	Jaguar Mining	JAG	Mining	4/16/2012
511816	Kinross Gold	K	Mining	3/25/2002
511817	National Bank	NA	Financial Svces.	2/25/2000
511818	Osisko Mining	OSK	Mining	6/18/2009
511819	Osisko Mining	OSK	Mining	5/18/2010
511820	Shaw Communications	SJR.B	Communication	7/25/2007
511821	Suncor Energy	SU	Energy	3/18/2002
Total	**21 Events**		**6 Industries**	

This table summarizes the total firm-events obtained from Factiva (Dow Jones) after filtering for takeover rumours involving Canadian target stocks, duplicates or re-published rumours, and delisted companies. Our final sample is made of 21 events from 6 industries.

Table 2. Total Number of Events per Industry

Industries	Number of events per industry
Communication	**4**
Energy	**7**
Financial Services	**1**
Mining	**4**
Technology	**4**
Transportation	**1**

Chart 2. Total Number of Events per Industry



Research Design

Determining the study parameters.

In addition to a carefully selected sample, we need to identify 3 essential elements to perform our analysis: (1) the event date, (2) the estimation window, and (3) the study window. One key element at play in the determination of all three elements is to identify the correct event date. The event date is an 'anchor' for the whole analysis (Schimmer, Levchenko, & Müller, 2015); once determined, we can then establish the lengths and positions of the estimation and event windows.

The event date: the first publication.

Identifying the event date is not always a simple task. In the case of takeover rumours, the rumour is bounced around, and reported by multiple sources with often few variations. With each new report, determining the adequate event date to be analyzed can be confusing. We came to the realization that after the first publication, subsequent articles discussing the same rumour are mere echoes of that original one. Later publications could potentially be collected to measure the rate of propagation of the rumour; or even assess its seriousness or intensity. However, to capture the full impacts of the rumours on the stock market; we need to assess the market response after the initial publication, as everything afterward can also be viewed as a response to that initial article. In the same manner, in the context of M&A, Dodd explains that past investigations on this issue found the information content of the first official announcement being highest and therefore representing the correct event date (1980). Accordingly, the event date (t_0) is set to be the date the rumour was first published in an official media source accessible to the general public.

The study window.

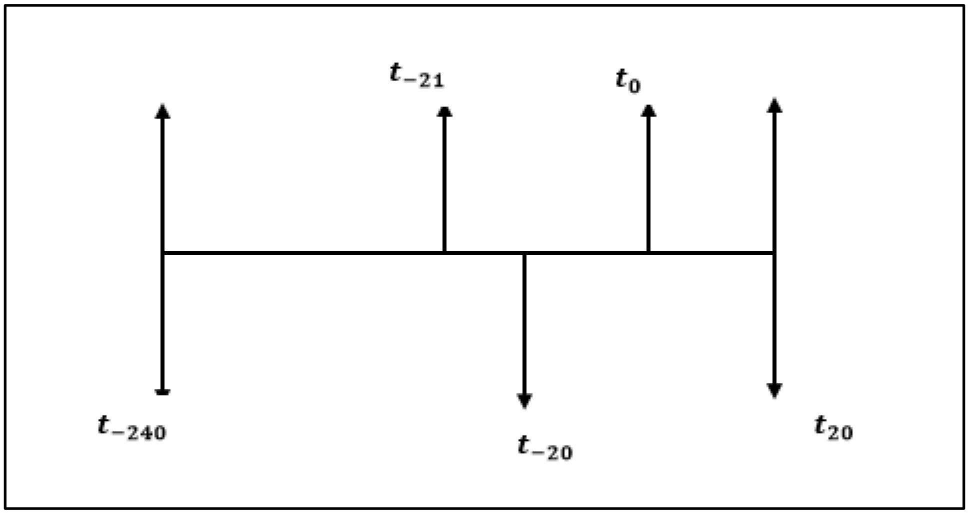
The study window is an interval around the event date (t_0) that varies from 10, 20, to 40 days around the announcement date (Armitage, 1995). According to Pound and Zeckhauser (1990), rumours spread up to 40 days around their date of appearance. In an effort to grasp the full impact of these events, we pick a 41 days study window. Our analysis is based on data collected 20 days prior, and 20 days after each event. The somewhat long study window helps us understand the mechanism behind the price variation. Then, we focus the rest of our analyses on a smaller window of study based on the previous observations. Our final window of study is [-10, 10].

For the Buy-and-Hold (BHAR) simulation, we use various curtailed study windows designed to capture the most profitable holding periods around the event date. While the initial interval was selected to analyze the daily variations prior and after the publications in order to determine possible patterns; the intervals designated for the BHARs are shorter, and designed to evaluate the possible accumulated gain investors could make when the stock price rises. We evaluate BHAR over different intervals in order to understand based on the following assumptions. (1) Entering a long position before the rumour becomes public, and closing the position after the announcement; (2) Entering a long position once the rumour becomes public, and closing the position few days later; (3) Entering a long position after the rumour becomes public, and closing the position he position few days later. These intervals help ascertain the degree of abnormal returns, if any, with regard to investor’s timing, illustrating the concept of fast versus slow trader in the case of rumours. The length of these intervals is motivated by the recent paper by Allen, Harrison, & Oler (2007) explaining that the most common choice for event window length is 5 days; representing 76.3% of the reviewed studies.

The estimation window.

Recent meta-research reviewing 400 event studies shows that the average estimation window lengths ranges from 30 to 750 days (Holler, 2014). Further studies investigating the sensitivity of results (e.g., the predicted return on the event date) suggest that results are not sensitive to varying estimation window lengths as long as the window lengths exceed 100 days (Armitage, 1995). Supporting these findings, Peterson (1989) and Armitage (1995) found that the estimation period is typically between 100 and 300 days for daily studies. Based on these prior findings and the nature of our study, we opt for a 220 days estimation period ending 21 days prior the event. Our estimation window is similar to the one observed by Lahouti et al. in a study covering the French market, with a slightly shorter estimation period. The similarity of criteria we create between our study and the one previously conducted by Lahouti et al. will allow us to compare both markets at the end of our analysis.

Figure 1. An illustration of the time parameters



With,

t_0= Event date, first publication of the rumour in the media;

t_{20}= End of the study window, 20 trading day after the event;

t_{-20}= Beginning of the study window, 20 trading day before the event;

t_{-21}= Last day of the estimation window, 21 trading day before the event; and

t_{-240}= First day of the estimation window, 220 trading days before the first publication date.

Calculating abnormal returns: the market model.

The goal is to estimate the expected future values based on the past values; the norm is what should be expected under normal circumstances. Consequently, any drastic variation from the norm is an anomaly.

Calculating abnormal returns: the market model.

The expected returns.

The expected returns can be approximated using various tools. We use the "Event Study Tools" to perform our analysis. The application gives us access to seven of the most prominent financial models used to predict future prices. In turn, each of the predicted benchmark values are deducted from the actual stock returns for calculating 'abnormal returns' (Schimmer et al., 2015). With this application, expected returns can be obtained through (1) the market model, (2) the market adjusted model, (3) the comparison period mean adjusted model, (4) the Scholes/Williams model, (5) the Fama-French 3 Factor model, (6) the Fama-French-Momentum 4 Factor model, (7) GARCH and EGARCH. For the purpose of our study, we use the market model to conduct our analysis. Unlike other models that focuses on resolving the shortcomings related to the CAPM, the market model takes root in the CAPM without any attempt to alter its assumptions. The capital asset pricing model describes the relationship between the systematic risk (β) and expected return for assets by multiplying the market return with the firm individual β factor (βi): $\alpha_i - \beta_i (R_{mt})$ (Schimmer et al., 2015).

The market model.

The market model was developed by Fama, Fisher, Jensen, & Roll (1969) to provide an estimate of the expected profitability of the shares in terms of the risk incurred (CAPM risk) and the marked return.

We have:

$$R_{it} = \alpha_i - \beta_i (R_{mt}) + \varepsilon_{it}$$

Where: t ∈ [-240, -21]

R_{it}: Realized returns of share i at date t

R_{mt}: Market return

ε_{it}: Model error

α_i & β_i : Coefficients to be estimated through the ordinary least squares method.

First, the coefficients α_i and β_i are estimated through the ordinary least square model; then, we deduct the expected returns of share i at date t (return under normal conditions). We now have:

E (R_{it})= $\alpha_i{}'$-$\beta_i{}'$ (R_{mt})

Where: t ∈ [-20, +20]

E ($\mathrm{R_{it}}$): expected returns in the absence of event of share i at date t;

$\mathrm{R_{mt}}$: market return at date t,

$\mathrm{\alpha_i}'$ & $\mathrm{\beta_i}'$: are the coefficients estimated using the ordinary least squares method.

The abnormal return (AR_{it}) is the excess return obtained in the presence of takeover rumour, calculated for each firm-event from to first day of the study window to the last one. If the takeover bid rumours include relevant information not being captured within its current price, the difference between the observed returns and the theoretical returns will capture the anomaly resulting from that event.

$\mathrm{AR_{it}} = \mathrm{R_{it}} - \mathrm{E(R_{it})}$; t ∈ $[-20, 20]$

Where,

$\mathrm{R_{it}}$: Observed return of share i at time t

$\mathrm{R_{mt}}$: Market return

Now that we have AR_{it} , we can calculate the following values.

- Average abnormal return of the N firm-events at time t (AAR_t);

$$AAR_t = \frac{1}{N}\sum_{i=1}^{N} AR_{it}$$

- Cumulative abnormal return ($CAR_{(t,T)}$) over a chosen interval;

$$CAR_{(t,T)} = \sum_{t=1}^{T} AR_{it}$$

- Cumulative average abnormal return ($CAAR_{(t,T)}$) over a chosen window

$$CAAR_{(t,T)} = \sum_{t=1}^{T} AAR_t$$

Following the above-mentioned logic and steps, the Event Study tools computes the potential abnormal returns generated by the events from the carefully collected data. Three types of spreadsheets have to be created when using the Event Study tools; one for each type of data required for our analysis. We need spreadsheets for the firm data, the market data, and the request file. These spreadsheets are then uploaded to the application.

The firm and market data are collected from Yahoo Finance. From the study window to the estimation window, we need to collect enough data to cover about 260 trading days per firm-event. However, when it comes to the market data, we need a pool of data large enough to capture the estimation window covered by all the events, from the latest estimation window to the most recent study window; more precisely, we want to gather enough market data to cover [t_{-240}; t_{20}] for both the earliest and the latest firm-events. We choose the S&P/ TSX as index representative of the Canadian market; it also offers the best representation of our data pool.

More about the requirements of these spreadsheets is available on the Event Study Tool website. Once all spreadsheets are completed, we load them to the website for processing.

Calculating abnormal volumes.

Calculating abnormal volumes, just like abnormal returns, can be done through various models. The Event Study tool for abnormal volumes called "trading volume event study" gives us access to four different methods (1) the market model, (2) the Scholes/Williams model, (3) the market adjusted model, and (4) the comparison period mean adjusted. For our analysis, we use the comparison period mean adjusted. Here, the abnormal volume in the event window is the volume of observation *i* on day *t* minus the average volume of the observation *i* in the estimation window.

Prior May 2002, the TSX66 was known as the TSE 300 Composite Index, and comprised of 300 large caps common equities from 14 different sectors. After its conversion to the S&P/ TSX in the same month, it changed from a fixed to a floating index. Since then, revisions have been occurring about every quarter ending in March, June, September, and December; with intra-quarterly reviews whenever needed (Shams, 2015). With a floating number of constituents; there has been no need to add a new stock after deleting one. Given all the variables in play, complying with the requirements related to the use of the market model when dealing with abnormal volumes can be challenging. Ideally, we would have used the same model for both returns and volumes. However, without access to the historical composition of the index, the comparison period mean adjusted is our best option. Indeed, when it comes to volumes, the market model uses the mean of log percentage of trading volume of the index that we can only accurately calculate using values from the index constituents.

We collect the raw firm data from Yahoo.ca, and uploaded them to the application. Here, the trading volume metric underlying our simulations is the daily log percentage of outstanding shares traded on a given day (V_{it}), also known as the daily log modified volume turnover. We must gather enough data to cover both the estimation and the study intervals; create three semicolon separated files (request file, firm data, and market data), and upload them to the Event Study Tool website. Even though the market data are not relevant to our chosen method, we still have to upload it along with the other two files. V_{it} is obtained through the application based on the following formula.

$$V_{it} = log\left(\frac{N_{it} + .000255}{S_{it}} \times 100\right)$$

N_{it}, the number of shares traded for firm *i* on day *t*;

S_{it}, the outstanding share of firm *i* on the trading day.

We use the log-transformed volumes as recommended by Ajinkya and lain (1989), Campbell and Wasley (1996), and Cready and Ramanan (1991) among others. However, to avoid a log-transformation of zero, we use the same technique as Llorente, Michaely, Saar and Wang (2001), and add the constant .000255 to the number of traded shares. The ultimate goal is to calculate the difference between the observed V_{it} (V_{it} over the study window) and the average V_{it} or $\overline{V_{\imath t}}$ (obtained from the estimation window).

We have:

$$AV_{it} = V_{it} - \overline{V_{\imath t}}$$

Where,

$$\overline{V_{\imath t}} = \frac{1}{T}\sum_{t=-240}^{t=-21} V_{it}$$

t ∈ [t_{-240}, - t_{-21}] and T = 220

This logic is what drives the analysis performed on the Event Study Tools comparison period mean adjusted in the case of volumes. In this model, the abnormal volume (AV_{it}) in the event window is the log modified volume turnover of event i on day t (V_{it}) minus the average daily log modified volume turnover of event i (V_{it}) in the estimation window.

Calculating BHAR.

We also measure the short-term performance of each target stocks subject to takeover rumours in terms of returns generated by a buy-and-hold abnormal return (BHAR) strategy. Barber and Lyon (1997) explain that this strategy provides a measure of the investors' experience over the period under study. The authors recommend using this estimator to calculate short-term performance.

The returns generated by the buy-and-hold strategy, also known as the time-weighted return, is simply the return generated from buying the stock and holding onto it for a period of time. BHAR is estimated for each company in our sample and measured according to the following formula: (adjust formula using wiki)

$$BHAR_{\ i(t,T)} = \prod_{t=0}^{T}(1 + r_{it}) - \prod_{t=0}^{T}(1 + E(r_{it}))$$

Where:

r_{it} : Observed returns of share i at date t

$E(r_{it})$: Expected returns of share i at date t estimated through the market model.

$\prod_{t=0}^{T}(1 + r_{it})$: Observed time-weighted return over [t, T]

$\prod_{t=0}^{T}(1 + E(r_{it}))$: Expected time-weighted return over [t, T] [t, T] is set for multiple 5 days intervals; [-4, 0], [-3, 1], [0, 4], [1, 5], [3, 7].

The first part of the formula is the observed time-weighted return over our interval; and the second part is the expected time-weighted return for the same period. The difference between both values for each company gives us the buy-and-hold abnormal return for each company.

From the previously determined BHARs, we are able to calculate the average buy-and-hold abnormal return ($ABHAR_t$) over the same hold period according to the following formula:

$$ABHAR_t = \frac{1}{T}\sum_{t=1}^{T} BHAR_{\ i(t,T)}$$

Testing for Statistical Evidence

In order to test the statistical significance of the results for the abnormal returns, the abnormal trading volumes, and the buy-and-hold abnormal return; we rely on the test statistics. The test statistic tells us whether to reject the null hypothesis, or not. Over time, more test statistics have been developed in order to overcome the shortcomings of the earliest models. With these alternatives, researchers are less likely to under or over reject the null hypothesis. There are two main categories of test statistics, the parametric and the nonparametric tests. While the parametric tests make assumptions about the parameters of the population from which the studied sample is drawn, the nonparametric test do not make such assumptions. As such, the use of a specific type of test depends on the research setting and the statistical issues the analyzed data holds. For example, Brown and Warner (1985) explain that in presence of increasing event-related variance, nonparametric tests (which do not use the return variance) may perform better than parametric tests that assume stable variances.

As documented in the work of Schipper and Smith (1983) among others, we complement the commonly used parametric test with a nonparametric test for all average values in order to reduce errors due to outliers or extreme values, and volatility. Unlike the parametric test statistic (Pts), the nonparametric test statistic (NPts) does not require normality to achieve proper specification under the null hypothesis. Below is summarized the test statistics used throughout our analysis.

Table 3. Summary of Test Statistics

Null hypothesis	**Parametric**	**Nonparametric**
H0: AR= 0	T test	
H0: AAR= 0	Cross-Sectional Test	Generalized Rank Test
H0: CAR= 0	T test	
H0: CAAR= 0	Cross-Sectional Test	Generalized Rank Test
H0: BHAR= 0	T test	
H0: ABHAR= 0	Cross-Sectional Test	

Some of the commonly used nonparametric tests are the rank test, the generalized rank test, the sign test, and the generalized sign test. Our choice of test statistic is based on their characteristics with regards to our research setting and the statistical issues within our sample. Corrado (1989), and Corrado and Sinewy (1993) show that the rank test is robust for single event day, and loses power when dealing with long interval of cumulative abnormal values. The sign test has a poor performance for longer event windows (Schimmer et al., 2015). We are then left with the generalized rank test (GRANK), and the generalized sign test (GSIGN). Cowan (1992) demonstrates that the generalized sign test becomes relatively more powerful as the length of the event window increases. It also remains consistent in presence of extreme values and increased variance. The generalized rank test or GRANK can be used to test both single abnormal returns as well as cumulative abnormal returns; and is robust for abnormal return serial correlation and event-induced volatility (Kolari and Pynnonen, 2011). In their study, Kolari and Pynnonen (2011) also show that the GRANK test often has superior (empirical) power relative to popular parametric tests at all event window lengths. After taking their respective characteristics into account, we decide to rely on the GRANK test throughout this study.

The formulas used in our study are detailed below. Let L1 = T1 −T0 +1 the estimation period length, L2 = T2−T1 as the event period length, and the combined estimation period and event period length as T = L1 + L2.

With,

T0 as the 'earliest' day of the estimation window;

T1 the 'latest' day of the estimation window relative to the event day;

T2 as the 'latest day' of the event window relative to the event day;

N as the sample size (number of events);

S_{ARi} Represents the standard deviation as produced by the regression analysis over the estimation window;

Mi refers to the number of non-missing returns.

The test statistic and formulas used in this study were all obtained from Schimmer et al. (2015) through the Event Study Tools.

T test-statistics.

The T test is used for single firms in each time point *t* under the null hypothesis for both abnormal returns and cumulative abnormal returns.

Abnormal Returns (AR_{it}), with H0: AR_{it}= 0

$$t_{(AR_{it})} = \frac{AR_{it}}{S_{AR_i}}$$

Where $S^2_{AR_i}$ is the standard deviation of the abnormal returns in the estimation window?

$$S^2_{AR_i} = \frac{1}{Mi - 2} \sum_{t=T0}^{T1} (AR_{it})^2$$

Cumulative Abnormal Returns (CAR_{it}), with H0: CAR_{it}= 0

$$t_{CAR} = \frac{CAR_i}{S_{CAR}}$$

S^2_{CAR} is the standard deviation of the cumulative abnormal returns in the estimation window?

$$S^2_{CAR} = L_2\left(S^2_{AR_i}\right)$$

Cross-Sectional Test (CSect T).

The CSect T test is used for average, and cumulative average abnormal returns,

Average Abnormal Returns (AAR_t), with H0: AAR_t= 0

$$t_{AARt} = \sqrt{N}\,\frac{AAR_t}{S_{AARt}}$$

Where S_{AARt} is the standard deviation across firms at time *t*.

$$S_{AARt}^2 = \frac{1}{N-1}\sum_{i=1}^{N}(AR_{it} - AAR_t)^2$$

Cumulative Average Abnormal Returns (AAR_t), with H0: $CAAR$= 0

$$t_{CAARt} = \sqrt{N}\ \frac{CAAR}{S_{CAAR}}$$

Where S_{CAARt} is the standard deviation of the cumulative abnormal returns across the sample.

$$S_{CAAR}^2 = \frac{1}{N-1}\sum_{i=1}^{N}(CAR_i - C\mathrm{AAR})^2$$

Generalized Rank T Test (GRANKt).

Here, we assume that there are no missing values in estimation or event window for each firm. In order to account for possible event-induced volatility, the GRANK test squeezes the whole event window into one observation, the so-called 'cumulative event day' (Schimmer et al., 2015).

First, define the standardized cumulative abnormal returns of firm *i* in the event window

$$SCAR_i = \frac{CAR_i}{S_{CARi}}$$

Where $SCAR_i$is the standard deviation of the prediction errors in the cumulative abnormal returns of firm *i*,

$$\mathrm{S_{CARi}^2} = \mathrm{S_{CAR_i}}\ (\mathrm{L} + \frac{\mathrm{L_2}}{\mathrm{L_1}} + \frac{\sum_{\mathrm{t=T1+1}}^{\mathrm{T2}}(\mathrm{R_{mt}} - \overline{\mathrm{R}}_{\mathrm{mt}})^2}{\sum_{\mathrm{t=T0}}^{\mathrm{T1}}(\mathrm{R_{mt}} - \overline{\mathrm{R}}_{\mathrm{mt}})^2})$$

The standardized CAR value $SCAR_i$ has an expectation of zero and approximately unit variance. To account for event-induced volatility $SCAR_i$ is re-standardized by the cross-sectional standard deviation.

$$SCAR_i^* = \frac{SCAR_i}{S_{SCAR}}$$

Where,

$$S_{SCAR}^2 = \frac{1}{N-1}\sum_{i=1}^{N}(SCAR_i - \overline{SCAR})$$

And,

$$\overline{SCAR} = \frac{1}{N}\sum_{i=1}^{N} SCAR_i$$

By construction $SCAR_i^*$ has again an expectation of zero with unit variance. Now, let's define the generalized standardized abnormal returns (*GSAR*):

$GSAR_{it}$ = {$SCAR_i^*$for t in event window; $\overline{SCAR}_{it}$ for t in estimation window}

The CAR window is also considered as one time point, the other time points are considered GSAR is equal to the standardized abnormal returns. Define on this $L_1 + 1$ points the standardized ranks:

$$\overline{K}_{it} = \frac{RANK(GSAR_{it})}{L_1 + 2} - 0.5$$

Then the generalized rank t-statistic for testing *H0: CAAR = 0* is defined as:

$$t_{grank} = Z\left(\frac{L_1 - 1}{L_1 - Z^2}\right)^{1/2}$$

With,

$$Z = \frac{\overline{K}_0}{S_{\overline{K}}}$$

T = 0 indicates the cumulative event day, and

$$S_{\overline{K}}^2 = \frac{1}{L_1 + 1} \sum_{t \in CW} \frac{N_t}{N} (\overline{K}_T)^2$$

With CW representing the combined window consisting of estimation window and the cumulative event day and $\overline{K}_t$ as detailed below

$$\overline{K}_t = \frac{1}{N} \sum_{i=1}^{Nt} K_{it}$$

t_{grank} is t-distributed with $L_1 - 1$ degrees of freedom.

Formulas testing on a single day (H0: AAR = 0) are straightforward from the ones shown above (Schimmer et al., 2015).

Part 4. RESULTS AND DISCUSSIONS

We proceed with the Event Study Tool as previously discussed. Unfortunately, the rather small size of our sample significantly decreases the statistical power of our analysis. Our findings are provided and discussed below.

Abnormal Returns

We track abnormalities up to 20 days prior and 20 days after the first publication of the rumour. The longer event window helps us understand the overall trend of the stocks. From these observations, we subdivide our event window into shorter intervals of 5 days around the event date. The length of the mini-intervals is motivated by the paper of Allen et al (2007) which explains that the most common choice for event window length is 5 days; representing 76.3% of the reviewed studies. The subsequent cumulative abnormal returns are computed over these mini study intervals. This subdivision helps us determine the period around the events with the highest concentration of abnormal values.

Table 4. Estimated α_i and β_i over the 220 days estimation window

Event ID	Firm	Est. Window Length	Actual Stock Return	Actual Market Return	Alpha	Beta	Residual STD	Exp. Market Return	1st order Autocorrelation
511801	Bell Canada	220	-0.0148	0.0015	0.0012	1.6178	0.0127	0.0037	0.1406
511802	Bell Canada	220	-0.0095	-0.0117	0.0009	0.9939	0.0235	-0.0107	0.1438
511803	Bell Canada	220	0.0185	-0.007	0.0004	0.2324	0.015	-0.0012	0.0654
511804	Blackberry	220	0.1211	-0.0054	0.0018	2.1568	0.0342	-0.0099	-0.0725
511805	Blackberry	220	0.0982	0.0247	-0.0022	1.2336	0.0301	0.0283	0.0039
511806	Blackberry	220	-0.0165	0.0077	-0.0051	1.1998	0.0352	0.0042	-0.0159
511807	Blackberry	220	-0.2178	-0.003	0.0001	0.895	0.029	-0.0026	-0.0029
511808	Natural Rsces.	220	-0.0391	0.0028	0.0011	0.452	0.0117	0.0023	0.1979
511809	C. P. Railway	220	0.1442	0.0139	0.001	0.8193	0.0102	0.0124	-0.1816
511810	EnCana	220	0.0933	0.0078	0.0012	2.1425	0.0133	0.0178	-0.0564
511811	Husky Energy	220	0.1024	-0.0043	0.0009	0.0907	0.0202	0.0005	-0.0436
511812	Husky Energy	220	0.1285	-0.0117	0.0008	0.4613	0.0241	-0.0045	-0.06
511813	Husky Energy	220	-0.0518	0.0038	0.001	1.3605	0.0134	0.0061	0.072
511814	Imperial Oil	220	-0.0209	-0.014	-0.0006	1.3908	0.0136	-0.02	0.0186
511815	Jaguar Mining	220	-0.0375	-0.0002	0.0011	1.5205	0.0461	0.0008	-0.0655
511816	Kinross Gold	220	0.0101	-0.0134	0.0035	-0.3106	0.0452	0.0076	0.0323
511817	National Bank	220	0.1373	-0.008	-0.0017	0.6736	0.0139	-0.0071	-0.0959
511818	Osisko Mining	220	0.0754	0.0055	0.0027	0.6624	0.0594	0.0063	-0.0128
511819	Osisko Mining	220	-0.0309	-0.0041	0.0002	1.2988	0.0238	-0.0051	-0.1411
511820	Shaw Comm.	220	0.021	0.0026	0.0012	0.7123	0.0129	0.0031	0.0465
511821	Suncor Energy	220	0.06	0.0058	0.001	0.4391	0.0172	0.0036	0.1298

The estimated coefficients for each event are listed in table 6. The coefficients α_i and β_i will then be used to calculate the expected returns, and subsequently compute the abnormal returns. The first-order autocorrelation coefficients measure the degree of correlation between consecutive errors, or serial correlation. An autocorrelation of positive 1.0 represents a perfect positive correlation (an increase seen in one time series leads to a proportionate increase in the other time series); and an autocorrelation of negative 1.0 represents perfect negative correlation (an increase seen in one time series results in a proportionate decrease in the other time series) (Smith, 2019). However, a coefficient with a value of zero means that there is no autocorrelation between consecutive errors, as required under the classical assumptions supporting the regression model. Given that the twenty-one first-order coefficients (ρ_i) are close to zero; we conclude that the errors are not serially correlated. Furthermore, the residual standard deviations shown in table 4 give us a sense of how close the estimates are to the observed data. The smaller the residual standard deviation, the closer is the fit of the estimate to the actual data. In other words, the magnitude of the residual standard deviations is a typical indicator of the model's predictive power. The twenty-one residual standard deviations listed in table 6 are very small, and attest to the goodness of fit of our model. Despite the small size of our sample, the absence of autocorrelation and the small residual standard deviations support our model, and strengthen the degree of reliability of our results.

Daily abnormal returns, AR_{it}

The abnormal returns and their corresponding t-statistics are shown in the tables below. The tables 5a to 5d show the abnormal returns (AR_{it}), and the tables 5e to 5h show the t-values over the study window [-20, 20].

H0: AR = 0

H1: AR ≠0

For AR ≠0, we use the t-value to determine whether the difference between the predicted return and the observed return is significant.

The critical value t_α for a significance level α = 0.05, and a degree of freedom of 856.

Here,

The degree of freedom, df = M_i- 2, where M_i refers to the number of non-missing (i.e., matched) returns; we have 858 matched returns. Thus, using the t-table the matching t-statictic is:

t_α = 1.96 (two-sided test).

Then,

If t_α< t_{ARit} (absolute value)**,** we reject the null hypothesis

If t_α > t_{ARit} (absolute value)**,** we fail to reject the null hypothesis

The results of our analysis are shown in the tables 5a to 5h, please see appendices. Within these tables, P: N will always stand for "Positive: Negative" count.

The highlighted cells in tables 5e to 5h represent the statistically significant t-values over our study period. We compare the critical t-value to the absolute value of every single t values in the table in order to unveil any significant abnormal returns. Based on our results, only few of the abnormal returns are not due to randomness, with the most important concentration of intrinsic abnormal returns observed on the day of the announcement. There is a high concentration of meaningful abnormal returns one day prior and after the event day at T0. The overall trend of the abnormal returns shows that one day prior the public announcement of the rumour, the returns significantly exceeded their expected values. Then, the abnormal returns keep climbing for very few events on the apparition of the rumour in the press; before a substantial decrease the following day. The highest abnormal return is observed on the apparition of the takeover rumour of the Canadian Pacific Railroad, AR_{it} = 0.1318. While a cumulation of significant abnormal returns is observed on the event day for most (11 out 21 events), few events display significant abnormal returns one day prior the announcement (6 out 21 events). For almost each one of them, a decline is observed the day following the surge in price. For example, the share prices that reached their peak at T (-1), decrease at T (0); and those reaching their peak at T (0), decrease at T (1).

These results might be relevant when we take a look at single events, but they are not reliable when looking at the Canadian market as a whole. Instead, using the average and/or the cumulative abnormal returns will allow us to capture the market behavior when faced with takeover rumours while taking into account the shortcomings resulting from the small size of our sample. Indeed, the rather large degree of freedom associated with the daily abnormal returns exposes us to significant sampling errors if we were to extend our finding to the market as a whole. The results from the average abnormal returns, the cumulative abnormal, and the cumulative average abnormal returns are respectively in table 6, table 7, and table 8. Figure 2 also offers a graphic comparison of the cumulative abnormal return over smaller intervals of five days.

Average abnormal returns, AAR_t

Hypothesis Testing:

H0: AAR = 0

H1: AAR ≠ 0

If t_α< t_{AARt} (absolute value)**,** we reject the null hypothesis

If t_α > t_{AARt} (absolute value)**,** we fail to reject the null hypothesis

For the Csect T test, the critical value t_α = 2.086 when the significance level α= 0.05 (two-sided) and the degree of freedom df = 20

With, df = N- 1; N represents the total number of events

For the Grank T test, the critical value t_α = 1.97 when significance level α = 0.05 (two-sided), and a degree of freedom, df = 219

With df = L1 - 1; where L1 is the length of our estimation window.

The results of our analysis are shown in the table 6, below. Within this study, P:N will always stand for "Positive: Negative" count. The highlighted cells in tables 6 represent instances when t_α< t_{AARt} resulting in the rejection of the null hypothesis. We use two different tests here, the Csect T test with t_α= 2.086 and the Grank T test with t_α = 1.97. The small difference in value between both test-statistics could be explained by the presence of few outliners; however, both parametric and non-parametric test lead to the same conclusion.

Table 6. Average Abnormal Returns (AAR_t) over an interval of [-20, 20]

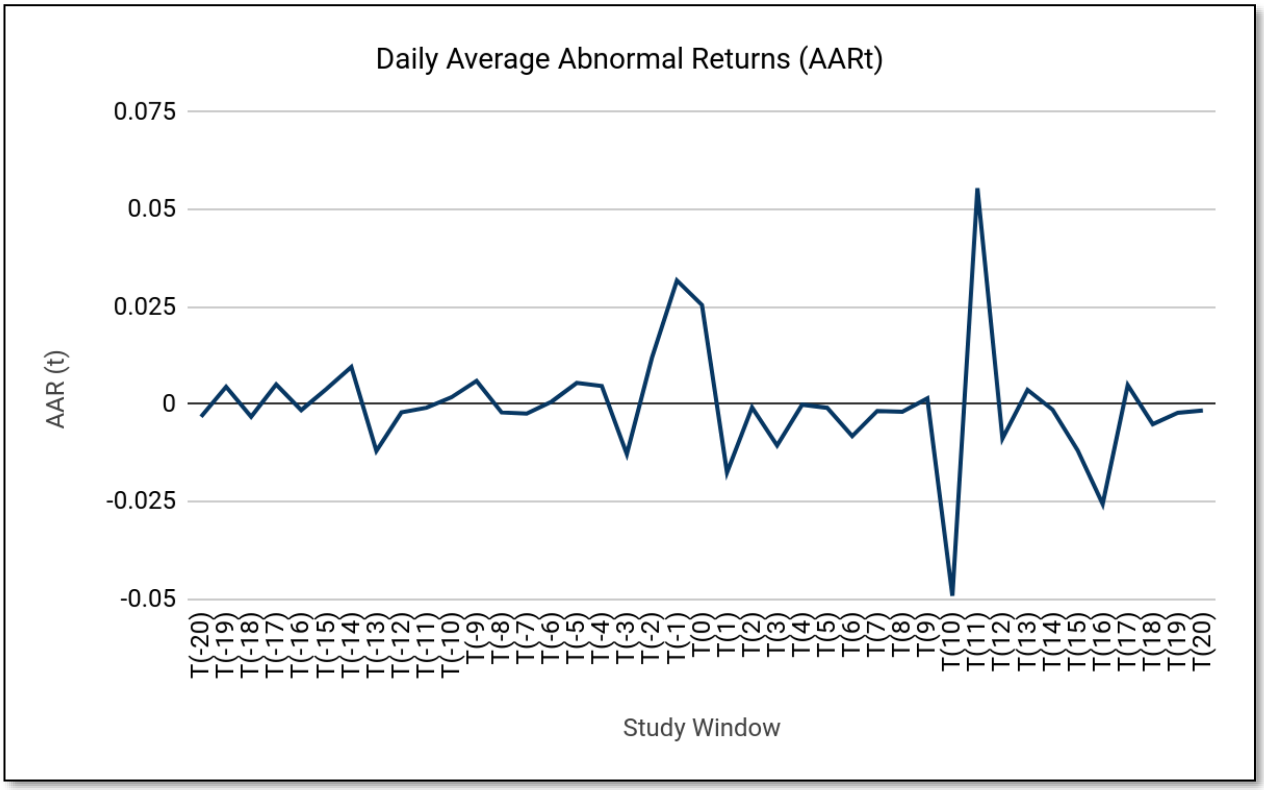
Study Window	AAR (t)	P:N	Csect T	GRank T
T(-20)	-0.0032	10:11	-0.4105	0.1048
T(-19)	0.0045	12:9	0.8359	0.7812
T(-18)	-0.0032	10:11	-0.7903	-0.0909
T(-17)	0.0051	10:11	0.7412	0.7756
T(-16)	-0.0015	8:13	-0.4	-1.0029
T(-15)	0.0039	9:12	0.6898	0.0454
T(-14)	0.0096	14:7	2.0289	1.7291
T(-13)	-0.012	8:13	-1.2092	-0.3908
T(-12)	-0.0021	15:6	-0.3919	0.6361
T(-11)	-0.0009	11:10	-0.1738	0.5204
T(-10)	0.0018	9:12	0.5032	0.3949
T(-9)	0.006	12:9	1.3451	1.6787
T(-8)	-0.0021	11:10	-0.4582	-0.1958
T(-7)	-0.0024	11:10	-0.7154	-0.1573
T(-6)	0.0007	9:12	0.1949	0.1258
T(-5)	0.0055	10:11	1.2329	0.731
T(-4)	0.0047	7:14	0.5126	-0.0629
T(-3)	-0.0128	11:10	-0.8948	0.0734
T(-2)	0.0119	15:6	2.3571	2.5918
T(-1)	0.0318	13:8	2.2631	2.125
T(0)	0.0255	13:8	1.3802	1.6708
T(1)	-0.0175	6:15	-3.0787	-2.8047
T(2)	-0.0008	9:12	-0.1211	-0.7411
T(3)	-0.0106	9:12	-1.5958	-0.5831
T(4)	-0.0001	11:10	-0.0143	-0.3845
T(5)	-0.0009	10:11	-0.1168	-0.1713
T(6)	-0.0082	7:14	-1.653	-1.8664
T(7)	-0.0017	10:11	-0.3594	-0.4023

T(8)	-0.0019	7:14	-0.5148	-0.7342
T(9)	0.0015	9:12	0.2695	0.0804
T(10)	-0.0492	11:10	-0.881	0.4746
T(11)	0.0555	10:11	0.978	0.7921
T(12)	-0.0088	7:14	-2.1421	-2.0783
T(13)	0.0037	11:10	0.3562	0.3147
T(14)	-0.0014	12:9	-0.1868	-0.0035
T(15)	-0.0118	5:16	-2.6873	-3.0383
T(16)	-0.0256	8:13	-1.2576	-1.2219
T(17)	0.0049	8:13	0.5371	-0.3774
T(18)	-0.0051	11:10	-1.1701	-0.8771
T(19)	-0.0022	11:10	-0.4704	0.1607
T(20)	-0.0016	10:11	-0.3053	0.2274

At T (-2), T (-1), T (1), T (12), and T (15), the absolute values of the matching t-statistics are all superior to 2.086 for the Csect T test, and all superior to 1.97 for the Grank T test. Thus, the average abnormal returns at T (-2), T (-1), T (1), T (12), and T (15) are statistically significant; we reject the null hypothesis in favor of the alternate hypothesis. AAR (-2) and AAR (-1) are positive and rising while AAR (1) shows a decrease in the market value of the stocks resulting in an average negative return for the twenty-one target stocks. Over 10 days after the event, the price of the stocks significantly decreases, resulting in an average negative abnormal return at T (12) and T (15). Those observations apply to both, the parametric and the nonparametric tests.

On average, we observe a significant increase in the average abnormal returns starting two days prior the apparition of the rumours in the media. On the day of their first publication, the phenomenon tends to die down; this is explained by the absence of any significant average abnormal returns at T (0). Then, on the day following the events, we observe a significant decrease in the average abnormal returns. Figure 2 offers a graphic representation of these findings.

Figure 2. Average Abnormal Returns Chart



Cumulative abnormal returns (CAR_i) & buy-and-hold abnormal returns (BHAR)

Hypothesis Testing:

H0: CAR = 0

H1: CAR ≠ 0

If $t_\alpha < t_{CAR}$ (absolute value)**,** we reject the null hypothesis

If $t_\alpha > t_{CAR}$ (absolute value)**,** we fail to reject the null hypothesis

Here, as for the abnormal returns (AR_{it}), we use a regular t test based on the information below.

For a significance level $\alpha = 0.05$ (two-sided). The critical value $t_\alpha = 2.78$.

With a degree of freedom df = 4 (the total number of observations minus one)

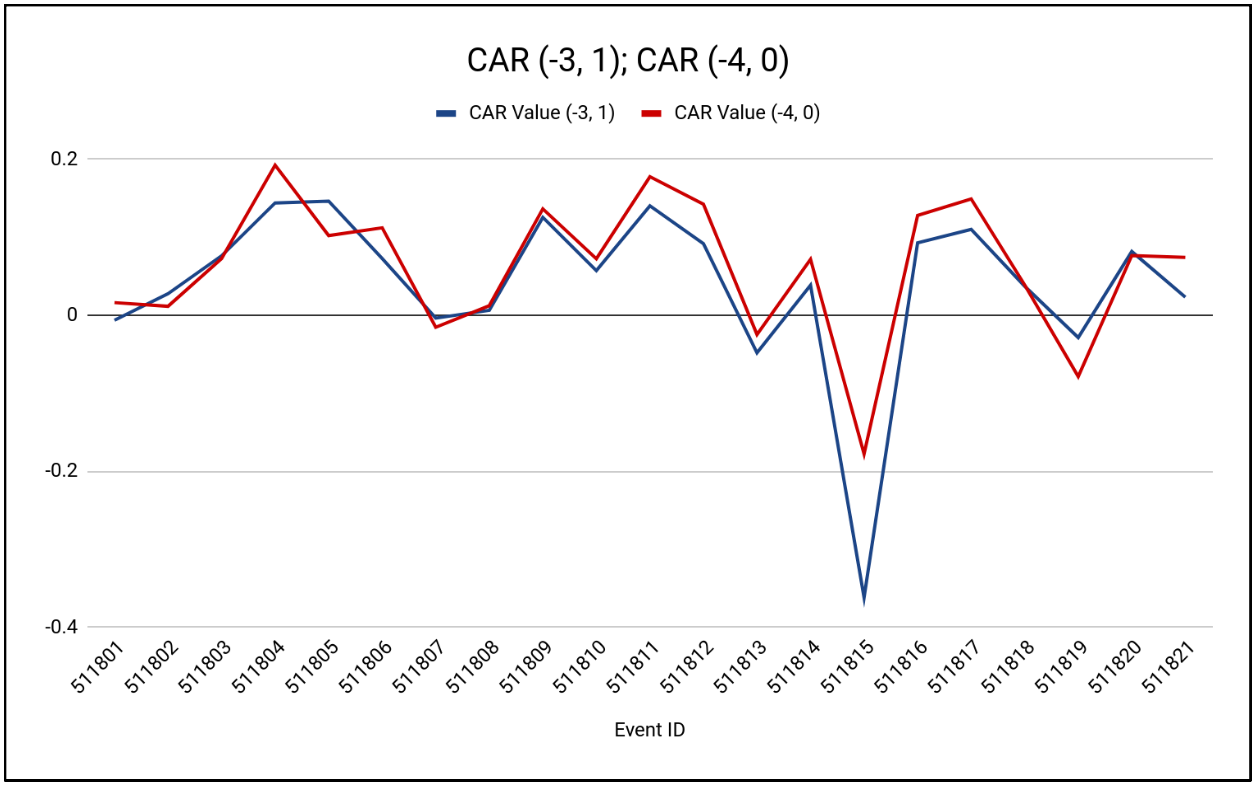
The results of our analysis are shown in the table 7. The highlighted cells in tables 7 represent instances when $t_\alpha < t_{CAR}$ resulting in the rejection of the null hypothesis. We only use a parametric test here. Based on the results obtained for the abnormal returns (AR_{it}), we set shorter 5 days intervals of study to capture the price surge over these two intervals, [-4, 0] and [-3, 1].

Over [-4, 0], 3 out of the 21 events present significantly positive cumulative abnormal returns, we do not have any significantly negative cumulative abnormal returns. Over [-3, 1], 4 out of the 21 events present significantly positive cumulative abnormal returns, and 1 out of the 21 events presents significantly negative cumulative abnormal returns. The events 511809, 511811, 511817, and 511820 are significantly positive on both intervals. Only 511815 is significantly negative for [-3, 1]. The figure 3 offers a graphic comparison of both intervals.

Table 7. Cumulative Abnormal Returns (CAR_i) and Buy-and-Hold Abnormal Returns (BHAR)

Event ID	Window	CAR	BHAR	CAR test	Window	CAR	BHAR	CAR test
511801	(-4, 0)	0.016	0.015	0.5634	(-3, 1)	-0.0065	-0.0071	-0.2289
511802	(-4, 0)	0.0113	0.0111	0.215	(-3, 1)	0.0274	0.0272	0.5214
511803	(-4, 0)	0.0724	0.0729	2.1586	(-3, 1)	0.076	0.0769	2.2659
511804	(-4, 0)	0.1922	0.1968	2.5133	(-3, 1)	0.1438	0.1346	1.8804
511805	(-4, 0)	0.1019	0.0997	1.514	(-3, 1)	0.1461	0.1521	2.1707
511806	(-4, 0)	0.1119	0.1128	1.4217	(-3, 1)	0.0724	0.0719	0.9198
511807	(-4, 0)	-0.0156	-0.0689	-0.2406	(-3, 1)	-0.0038	-0.0592	-0.0586
511808	(-4, 0)	0.0121	0.0097	0.4665	(-3, 1)	0.0062	0.0037	0.239
511809	(-4, 0)	0.1362	0.1387	5.9716	(-3, 1)	0.1253	0.1251	5.4937
511810	(-4, 0)	0.0722	0.0677	2.4277	(-3, 1)	0.057	0.048	1.9166
511811	(-4, 0)	0.1774	0.1851	3.889	(-3, 1)	0.1401	0.1408	3.0713
511812	(-4, 0)	0.1422	0.1438	2.6387	(-3, 1)	0.0915	0.0847	1.6979
511813	(-4, 0)	-0.0249	-0.0272	-0.831	(-3, 1)	-0.0484	-0.0501	-1.6153
511814	(-4, 0)	0.0715	0.0707	2.3512	(-3, 1)	0.0384	0.037	1.2627
511815	(-4, 0)	-0.1779	-0.2119	-1.7258	(-3, 1)	-0.3619	-0.3474	-3.5108
511816	(-4, 0)	0.1277	0.1342	1.2635	(-3, 1)	0.0927	0.0931	0.9172
511817	(-4, 0)	0.1489	0.1468	4.7907	(-3, 1)	0.1099	0.1048	3.5359
511818	(-4, 0)	0.0386	0.0339	0.2906	(-3, 1)	0.037	0.0332	0.2786
511819	(-4, 0)	-0.0787	-0.0746	-1.4788	(-3, 1)	-0.0288	-0.0277	-0.5412
511820	(-4, 0)	0.0763	0.0772	2.6451	(-3, 1)	0.0815	0.0816	2.8254
511821	(-4, 0)	0.074	0.075	1.9241	(-3, 1)	0.023	0.0208	0.598

Figure 3. Comparing CAR over (-3, 1) and (-4, 0)



Cumulative Average Abnormal Returns and Average Buy-and-Hold

Hypothesis Testing:

H0: CAAR = 0 *H0: ABHAR = 0*

H1: CAAR ≠0 *H0: ABHAR ≠0*

If t_{α}< t_{CAARt}(absolute value)**,** we reject the null hypothesis

If t_{α} > t_{CAARt}(absolute value)**,** we fail to reject the null hypothesis

The same applies to ABHAR t statistics.

- For the Csect T test, the critical value t_{α} = 2.086

  With,

  Significance level α = 0.05 (two-sided), and a degree of freedom of 20

  df = N- 1; where N represents the total number of events

- For the Grank T test, the critical value t_{α} = 1.97

  With,

  Significance level α= 0.05 (two-sided), and a degree of freedom of 219

  df = L1 - 1; where L1 is the length of our estimation window

Table 8. Cumulative Average Abnormal Returns ($CAAR$) and Average Buy-and-Hold Abnormal Returns (ABHAR) over shorter intervals

Intervals	**CAAR**	**ABHAR**	**P:N CAAR**[13]	**CAAR CsectT**	**CAAR GrankT**	**ABHAR GrankT**	**ABHAR CsectT**
(-4, 0)	0.0612	0.0575	17:4	3.1622	3.6988	3.6155	2.708
(-3, 1)	0.039	0.0354	16:5	1.653	3.1138	3.0443	1.5188
(0, 4)	-0.0035	-0.0053	14:7	-0.1677	0.6711	0.6567	-0.2654
(1, 5)	-0.0299	-0.0304	5:16	-2.2167	-2.8507	-2.7877	-2.3366
(3, 7)	-0.0215	-0.0227	7:14	-2.1836	-1.7692	-1.7308	-2.3164
(-5, 5)	0.0368	0.0321	17:4	1.5074	3.4133	3.3384	1.3284
(-10, 10)	-0.0187	-0.0344	17:4	-0.3197	1.9234	1.8813	-0.4993

The results for both the CAARs and the ABHARs follow the same trend. The CAAR values are consistently larger than the ABHAR values over each one of the intervals. On average, the stock price start increasing few days prior the event; then decreases after the event.

Over (-4, 0), both the CAAR and ABHAR are significant and positive using both types of tests. Over (-3, 1), we are only able to capture the abnormal values using the non-parametric test. The next five days intervals starting after the apparition of the rumour in the media result in significant and negative abnormal values for both the CAAR and ABHAR. From the event day, up to 4 days later, there is no significant values.

[13] *Total number of CAARs considered = 21*

Past the 5 days intervals, we are only able to capture significant abnormal values using a non-parametric test for the 11 days interval (-5, 5). Indeed, the CAAR and ABHAR remain positive, but less significant than what we obtained over shorter intervals starting prior the event day. Over a longer interval, for example (-10, 10), there is no significant abnormal values; the effect of the rumours is diluted over time. The opportunities for gain are only short lived.

Abnormal volumes

Daily abnormal returns, AV_{it}

The analysis performed on the returns in the previous part allows us to reduce our interval of study. The abnormal volumes and their corresponding t-statistics are shown in the tables below. The tables 9 to 10 show the abnormal volumes (AV_{it}), and the corresponding t-values over the study window [-10, 10].

H0: AV = 0

H1: AV ≠0

For AV ≠0, we use the t-value to determine whether the difference between the predicted return and the observed return is significant.

The critical value t_α for a significance level α = 0.05, and a degree of freedom of 441.

Here,

df = M_i- 2, where $M_i$refers to the number of non-missing (i.e., matched) returns.

t_α = 1.97 (two-sided test).

Then,

If t_α< t_{AVit} (absolute value), we reject the null hypothesis

If t_{α} > t_{AVit} (absolute value), we fail to reject the null hypothesis

The results of our analysis are shown in the tables 9a to 9b for the abnormal volumes (AV_{it}), and tables 10a to 10b for the matching test statistics; please see appendices. Within these tables, P: N will always stand for "Positive: Negative" count.

The highlighted cells in tables 10a and 10b represent the statistically significant t-values over our study period. We compare the critical t-value to the absolute value of every single t values in the table in order to unveil any significant abnormal returns. The t-values table shows that we have the highest accumulation of statistically significant abnormal volumes up to two days before the event. After these two days, the number of significant abnormal volumes gradually decreases. Toward the end of our interval of study, there is barely any significant abnormal volumes to be observed. We see that starting at T6, the abnormalities spread out, and are barely noticeable. At T (-2), 7 out of 21 events being studied display significantly abnormal trading volumes. At T (-1), an even larger number of stocks are being traded prior the apparition of the rumour in the news; 12 out of the 21 events being studied are significantly abnormal. A larger than average volume of these stocks is being traded on that day. From T (0) to T (5), about 4 out of 21 events are still trading abnormally high volumes of stocks.

Cumulative abnormal volumes, CAV_i

Hypothesis Testing:

H0: CAV = 0

H1: CAV ≠ 0

If t_{α}< t_{CAV} (absolute value), we reject the null hypothesis

If t_{α} > t_{CAV} (absolute value), we fail to reject the null hypothesis

Here, as for the abnormal volumes (AV_{it}), we use a regular t test based on the information below. For a significance level α= 0.05 (two-sided). The critical value t_{α} = 2.09.
With a degree of freedom df = 20, given that df represents the events window length or the number of observations, minus one)

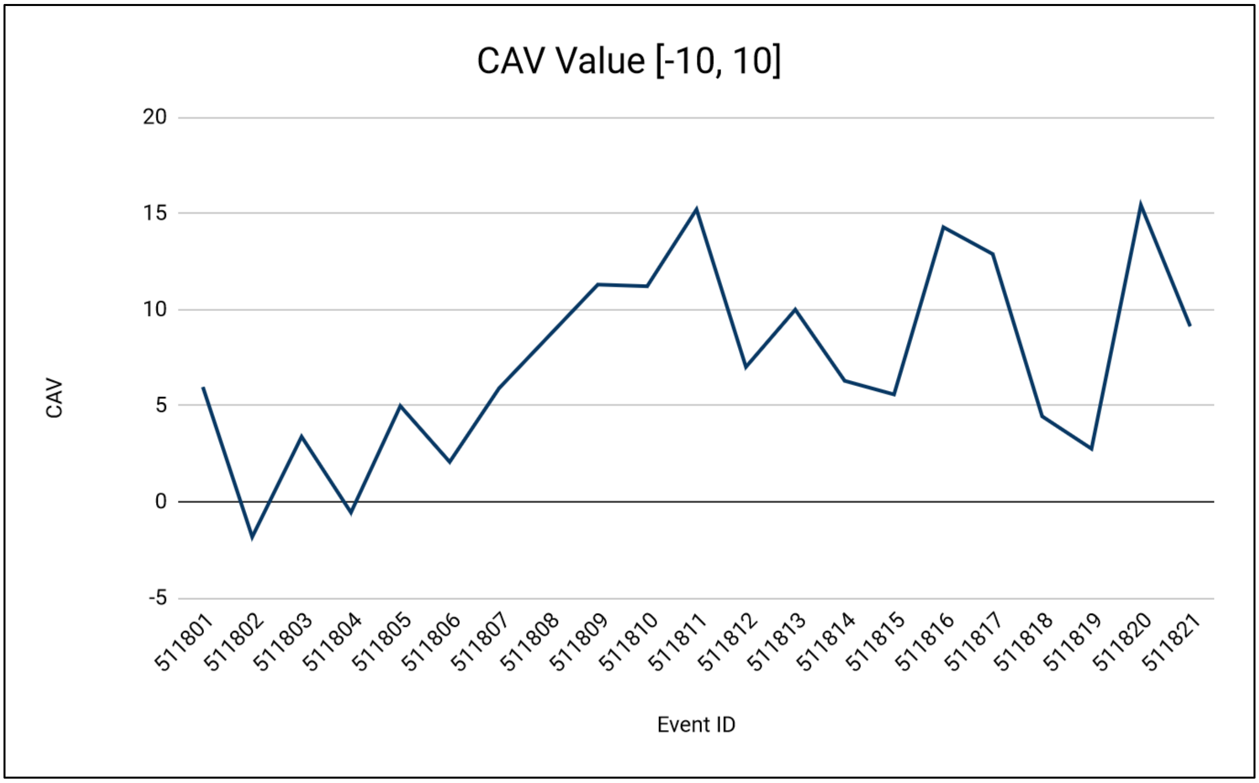
The results of our analysis are shown in the table 11. The highlighted cells in tables 11 represent instances when $t_{\alpha} < t_{CAV}$ (absolute values) resulting in the rejection of the null hypothesis. We can observe variations in the CAV values from one event to the next. These variations can simply be explained by the fact that some events generate more reactions than others; due to factors like the size of the firm, the industry, and/or the source of the rumour. We have positive cumulative abnormal volumes for most of the events, only 511802 and 511804 a close to non-existent to the event, with values very close to zero. The overreaction is not as intense from one stock to the next, but there is indeed an overall significant reaction to the takeover rumours starting before the first apparition of the rumour in the media.

Let’s keep in mind that different methods were employed to calculate the abnormal returns and the abnormal volumes. Over an interval of 21 days, [-10, 10], the abnormal volumes are a lot more intense than their matching abnormal returns; this difference is noticeable in figure 5.

Table 11. Cumulative Abnormal Volumes (CAV), [-10, 10]

Event ID	Window	CAV Value	CAV t-test
511801	(-10, 10)	5.9777	2.921
511802	(-10, 10)	-1.8204	-0.724
511803	(-10, 10)	3.3933	1.3022
511804	(-10, 10)	-0.5501	-0.1868
511805	(-10, 10)	4.9867	2.0475
511806	(-10, 10)	2.0803	0.8949
511807	(-10, 10)	5.9106	2.549
511808	(-10, 10)		
511809	(-10, 10)	11.3012	5.9628
511810	(-10, 10)	11.214	6.1234
511811	(-10, 10)	15.2129	3.5982
511812	(-10, 10)	7.0169	1.6618
511813	(-10, 10)	9.9999	3.5202
511814	(-10, 10)	6.2962	3.3908
511815	(-10, 10)	5.5879	1.6075
511816	(-10, 10)	14.2848	3.3808
511817	(-10, 10)	12.8876	4.9651
511818	(-10, 10)	4.4498	1.0485
511819	(-10, 10)	2.7648	0.8116
511820	(-10, 10)	15.4359	5.3629
511821	(-10, 10)	9.1286	3.8866

Figure 4. Cumulative Abnormal Volumes (CAV), [-10, 10]



Comparing the average abnormal returns and the average abnormal volumes

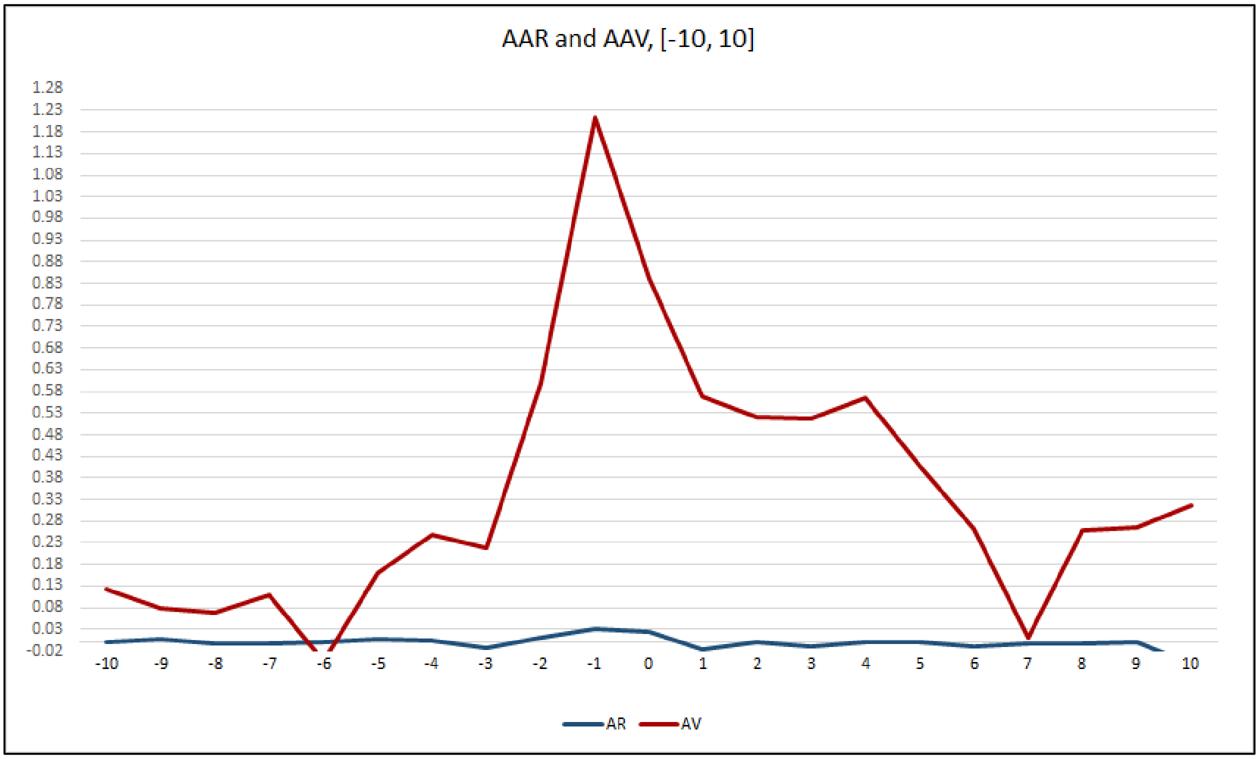
We know that for the Csect T test, the critical value t_{α} = 2.086 when the significance level α= 0.05 (two-sided) and the degree of freedom df = 20. With, df = N N- 1; N represents the total number of events. The degree of freedom (df) is obtained based on the number of events which are here constant and equal to 21 for both the volumes and the returns.

The largest significant and positive values are observed at T (-1) for the average volumes and between T (-1) and T (-2) for the average returns. Even though we are still observing a somewhat significant abnormal volume at T (0), there is no significant reaction for the average returns on that day. We also plugged the daily average abnormal volumes and the daily average abnormal returns over [-10, 10]. The obtained graphs are shown in figure 5. As previously pointed out in our analysis of the average abnormal returns (see figure 2), the average abnormal volumes also reach the highest values at T (-1). On a shorter interval, [-3, 1], we can observe price and volume surge from T (-3) to T (-1) followed by a steep decrease at T (0). Starting at T (1), both the average returns and the average volumes decrease at a slower rate. The average volume significantly rises again at T (3) and T (4), but there is no significant reaction from the average return (please see table 12 and figure 5).

Table 12. Average abnormal returns and average abnormal volumes over [-10, 10]

Day	AAR (t)	Csect T	AAV (t)	Csect T
T (-10)	0.0019	0.5032	0.1211	1.213285
T (-9)	0.006	1.3451	0.0771	0.671521
T (-8)	-0.0021	-0.4582	0.0669	0.300596
T (-7)	-0.0024	-0.7154	0.108	0.531533
T (-6)	0.0007	0.1949	-0.0448	-0.38003
T (-5)	0.0055	1.2329	0.1607	1.08013
T (-4)	0.0047	0.5126	0.2474	2.175496
T (-3)	-0.0128	-0.8948	0.2175	1.488985
T (-2)	0.0119	2.3571	0.5974	2.730361
T (-1)	0.0318	2.2631	1.2156	6.451654
T (0)	0.0255	1.3802	0.8406	2.897344
T (1)	-0.0175	-3.0787	0.5692	3.168648
T (2)	-0.0008	-0.1211	0.5202	3.589939
T (3)	-0.0106	-1.5958	0.5166	5.505883
T (4)	-0.0001	-0.0143	0.5632	3.127368
T (5)	-0.0009	-0.1168	0.4093	2.048724
T (6)	-0.0082	-1.653	0.2615	1.489786
T (7)	-0.0017	-0.3594	0.0118	0.068892
T (8)	-0.0019	-0.5148	0.2582	1.72106
T (9)	0.0015	0.2695	0.2647	1.682065
T (10)	-0.0492	-0.881	0.3159	2.26706

Figure 5. Average abnormal returns and average abnormal volumes over [-10, 10]



Part 5. CONCLUSION

This study examines the impact of takeover rumours on firms listed on the Toronto Stock Exchange. Special attention is devoted to their effects on the return of the target firms, their liquidity around the publication of the rumour in the media, and the implications of these findings with respect to the Efficient Market Hypothesis (EMH). We first take a closer look at the abnormal returns on a broader scale; the daily abnormal returns for each target firm is computed over the interval (-20, 20). Then, based on these findings, we isolate significant interval(s) of 5 days around the event prone to abnormal values. We identify two intervals with the higher concentration of abnormal values fitting the previous description; (-3, 1) and (-4, 0). The Buy-and-Hold returns for each interval is also assessed.

Our sample is representative of published takeover rumours about Canadian target firms between 1998 and 2015. The use of t test statistics for parametric testing make up for the size of our sample. Even though our analysis starts with the abnormal values for each firms at a specific moment (AR_{it} and AV_{it}), the comparisons and conclusions of this study are only based on subsequent cumulative and average values. The results are mainly computed using the "Event Study Tools," a research application. We assess the liquidity of the target stocks using the daily trading volumes. On average, the target firms experience significant abnormal tendencies around the publication of the rumours. We notice substantial and positive average trading volumes before the first appearance of the rumours in the media, (-2, -1). One day before the event, the average abnormal trading volume reaches its apex, rising up to 12.16 % above average. We also have the highest concentration of positive abnormal volumes at T (-2) and T (-1), respectively with 6 out of 21 positive abnormal volumes, and 12 out of 21 positive abnormal volumes (see tables 9 and 10). After reaching a peak at T (-1), the average daily trading volume significantly decreases over the following days. At T (0), the volumes start decreasing, getting closer to the mean average one day at the time (see figure 4 and table 14). The high trading volume preceding the event is a sign of increasing liquidity and also an indicator of a decreasing bid-ask spread. On the other hand, the post-event decreasing daily trading volumes reveals a lower liquidity; which usually suggests that the bid-ask spread is getting wider. In accordance with our findings, Draper and Paudyal (1999) also observe a decrease in the volume of transactions over the post-announcement period of takeover bids. The abnormal returns and the abnormal volumes display a positive relationship over the entire study window as illustrated in figure 4 and table 14. The volume-return dynamic observed in this study supports the findings of Epps (1977) and Harris (1984-1986; who found the presence of significant positive correlation between the daily volumes and the price change of common stocks.

We observe significant positive abnormal returns up to the event day, followed with declining and significantly negative values starting at T (1). The results of our study on abnormal returns share similarities with some of the studies mentioned earlier. On the event day, the average abnormal return observed in the French market is 2.26% (Laouiti et al., 2015) against an average abnormal return of 2.55% in the Canadian market. However, by T (0), the abnormal returns are already decreasing in the case of the Canadian market. Just like the volumes, we actually reach the highest point at T (-1) with an average abnormal return of 3.18%. While the peak for the French market is at T (0), the Canadian target firms reach a peak one day earlier, at T (-1). The market trades on privileged information more heavily than the French market. These results illustrate the impact of takeover rumours (unverified information) on the behavior and beliefs of investors in the market. After the event, there is a significant decline in both the returns and the volumes. Even though the volumes remain significantly positive before and after the event, past T (0), the average abnormal returns are no longer significant. Looking at table 12 we can see that along with the decreasing but significantly positive average abnormal volumes after T (0), the average abnormal returns are also decreasing but non-significant. The high trading volumes after the event could be explained by investors' attempt to close their position while using slower traders as liquidity. The period preceding the event date is representative of what Kahneman refers to as system 1, with people jumping to conclusions on the basis of limited information (Kahneman, 2011). After the event day, the volume-return dynamic becomes more rigid. The published rumour is perceived as negative news and the target stocks are being sold. Though unproven, unofficial, and sometimes unsubstantiated, takeover rumours affect the liquidity of the alleged takeover target's stock.

On average, the volume and return anomalies observed around the event day are very shortly lived. The study of Jean-Francois Gatton (2003) and King and Padalko (2005) about official Canadian takeover announcements also reveal significant market overreaction shortly before the event day. The similarities between the studies about official Canadian takeover announcements and this study can be explained by the fact that before their publications, takeover rumours are regarded as relevant positive and privileged information by market participants. Once the rumour is published, the information loses its value as the market try to adjust to the previous overreaction. To some extent, takeover rumours are being assimilated to official information.

Overall, the abnormal returns and volumes obtained during the run-up period, (-2, -1) reveal the presence of information asymmetry. This discovery corroborates the opinion of Kim and Verrecchia (1994) who suggest that certain information like those pertaining to takeover announcements increase market asymmetry. Easley and O'Hara (1992) also explain that the preevent trading volume increase is the product of information asymmetry; privileged information is being leaked and acted upon by informed traders. In the event that the rumours are finally confirmed, the early abnormalities become illustrative of information leakage between the parties concerned by the offer; privileged information is disguised as a rumour. On the other hand, false rumours are most likely the product of speculations generated by market participants like financial analysts who, based on certain economic and financial indicators, can detect the potential takeover targets, then transmit the information to other market participants. Rumours instigators can also be motivated by a hidden agenda; in such instance, the rumours are methodically crafted to manipulate the public's behavior. Holding an equal-weighted portfolio of our sample from T (-4), prior the price increase, to T (0) results in an excess return of 5.25%. This could be explained by the fact that our sample includes companies from sectors with the highest rating of merger and acquisition announcements. According to the IMAA Institute, the industry with the most active acquirers is the materials sector, with 31% of all Canadian transactions; in second position comes the energy and power industry, with 14.7%; and finally, the high-technology sector, with 12.1% of all deals. In terms of transaction value, the energy and power sector has been the main contributor with 740 billion USD; the second most important industry by value is the materials sector with 680 billion USD worth of transactions. The financial industry comes in third position with 238 billion USD of deals. This demographic is also reflected by takeover rumours in the financial market. Roughly 95.24% of our sample encompasses companies from each one of these industries. With so many ideal takeover targets, the public is inclined to be more sensible to possible takeover rumours.

In presence of rumour, the Canadian market is not efficient at the semi-strong level over shorter intervals (up to eleven days) starting before the event days. The information leakage and the significant abnormal returns observed prior the event support the previous statement. On a five days interval, (-4, 0) consistently display significant abnormal values, increase liquidity, and information leakage. However, on longer intervals, the abnormalities are diluted and become negligible. While prior studies about Canadian takeover targets were only relying on official takeover announcements, this study is the first performed using the first publication of Canadian takeover rumours. Despite the change in methodology and the use of a different type of sample, the results of our analysis are comparable and similar to previous findings about official Canadian takeover announcements. However, the differences observed between our findings prior studies performed on different financial markets like it is the case for the French market, lead us to believe that the variations in rules and regulations governing these markets could explain these disparities.

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List of Tables and Figures

Appendices

Table 5a. Abnormal Daily Returns (-20, -10)

	(-20)	(-19)	(-18)	(-17)	(-16)	(-15)	(-14)	(-13)	(-12)	(-11)	(-10)
511801	-0.0147	0.0022	0.0115	0.0095	0.0359	-0.0087	0.0184	-0.008	0.0271	-0.0392	0.0291
511802	0.0219	0.0067	-0.0074	0.0138	0.0144	-0.0172	-0.015	0.007	0.0082	0.0024	0.0267
511803	0.0004	0.0007	0.0132	0.0049	-0.0086	0.0014	0.0008	-0.0082	-0.0024	0.0051	0.0001
511804	-0.0018	0.0138	0.0125	-0.0118	-0.0084	0.0109	-0.0119	-0.0047	-0.0339	-0.0331	-0.0001
511805	0.0101	-0.0109	-0.0166	0.0417	-0.0129	-0.0138	-0.014	-0.2057	0.0093	-0.0386	-0.0129
511806	-0.1316	-0.0289	-0.049	0.0953	0.0038	-0.0091	0.0557	-0.0051	0.0032	0.0396	-0.0244
511807	-0.0315	-0.0066	0.0287	-0.0041	-0.0179	0.0756	0.002	-0.0146	0.0173	0.0085	-0.0012
511808	-0.0075	0.0155	0.0031	0.0066	-0.0101	0.0051	-0.0092	0.0053	0.0218	0.0458	0.0174
511809	-0.0022	-0.0106	0.0171	-0.014	-0.0143	-0.0061	0.0036	0.0049	0.0008	0.0123	-0.0087
511810	0.0289	0.0291	0.0219	-0.0363	0.008	-0.0136	0.0293	0.0034	0.0097	0.0091	-0.0163
511811	-0.0087	0.0019	-0.0001	-0.0157	-0.0049	0.0071	-0.0075	-0.0018	0.0073	0.0119	-0.0015
511812	-0.0025	-0.0127	-0.0268	0.0403	-0.0124	-0.0006	-0.0048	-0.0101	0.0017	0.0252	-0.0263
511813	0.0091	-0.0029	-0.0262	0.0188	-0.002	0.0361	-0.0119	0.0032	-0.0266	0.0067	
511814	0.0033	-0.0007	0.004	-0.0042	0.0005	-0.0119	0.0055	0.007	0.0024	-0.0051	-0.0067
511815	0.0114	-0.0469	-0.0116	-0.0167	-0.0321	-0.0336	0.0073	-0.0013	-0.052	-0.0174	0.001
511816	-0.018	0.0637	0.0055	-0.0096	-0.0062	-0.0207	0.0022		-0.0694	-0.0243	0.0278
511817	0.0219	0.0031	0.0031	-0.0309	-0.0107	-0.0188	0.0341	-0.0145	-0.0149	-0.0002	0.0194
511818	0.0651	0.0595	-0.0183	-0.0413	0.0205	0.0392	0.0258	-0.0203	0.0109	-0.0279	-0.0045
511819	-0.0092	0.0109	-0.0053	0.0444	0.0316	0.0391	0.0603	-0.0163	0.0108	-0.0165	0.0042
511820	-0.0168	0.0079	-0.013	-0.0017	-0.0209	-0.0012	0.007	0.0041	0.0214	-0.0028	0.0221
511821	0.0048		-0.0131	0.0188	0.0149	0.0234	0.0232	0.0228	0.0042	0.019	-0.0077

Table 5b. Abnormal Daily Returns (-9, 0)

EventID	AR(-9)	AR(-8)	AR(-7)	AR(-6)	AR(-5)	AR(-4)	AR(-3)	AR(-2)	AR(-1)	AR(0)
511801	0.0173	-0.0065	-0.0126	-0.0161	-0.0092	0.0434	-0.0119	-0.0073	0.0103	-0.0185
511802	0.0211	-0.0263	-0.0288	0.0004	0.0462	-0.0038	0.0083	0.0054	0.0002	0.0012
511803	0.0108	0.0025	0.0029	-0.0135	-0.0054	-0.0101	0.0004	0.002	0.0603	0.0198
511804	-0.0403	0.0049	-0.0032	0.0179	0.0237	-0.0249	0.011	-0.0114	0.0865	0.131
511805	0.0507	0.0188	-0.0076	0.0259	0.006	-0.0398	-0.0194	0.0563	0.0349	0.0699
511806	0.0099	0.0362	0.0119	-0.0104	0.0155	0.0576	-0.0051	0.0204	0.0596	-0.0206
511807	-0.0075	0.015	0.0027	0.0007	-0.0124	-0.0164	-0.0106	-0.0382	0.2648	-0.2152
511808	-0.0068	-0.0125	-0.0017	-0.0011	0.0095	-0.016	0.0027	0.0186	0.0482	-0.0414
511809	-0.0127	0.004	-0.0079	-0.0037	0.0202	0.0043	-0.0003	0.0198	-0.0194	0.1318
511810	-0.0152	-0.0464	0.0081	0.01	-0.0143	-0.0182	0.0243	0.0096	-0.0189	0.0754
511811	-0.007	0.0051	0.0113	-0.0028	-0.0059	-0.0004	0.0052	-0.0078	0.0783	0.1021
511812	-0.0076	-0.0242	-0.016	-0.0017	-0.0139	-0.0115	0.0169	0.0106	-0.0068	0.133
511813	0.0046	0.0257	0.0042	0.0278	-0.0145	-0.001	0.0385	0.0024	-0.0068	-0.058
511814	0.0144	0.0031	0.0219	0.0338	-0.0131	0.0316	0.0261	0.0441	-0.0295	-0.0008
511815	-0.0004	-0.0391	-0.0428	-0.0253	-0.0052	0.1526	-0.2883	0.0197	-0.0236	-0.0383
511816	0.0372	-0.0036	-0.0168	-0.026	0.0462	-0.0145	0.0133	0.0562	0.0702	0.0025
511817	0.0072	0.0237	-0.0117	-0.0008	0.0165	0.0201	-0.0204	0.015	-0.0102	0.1444
511818	-0.0143	-0.0087	0.0047	0.0086	-0.0214	-0.0262	-0.0372	-0.0034	0.0363	0.0691
511819	0.0291	0.0081	0.0088	-0.0011	0.0384	-0.0382	-0.0182	0.0126	-0.0091	-0.0258
511820	0.0169	-0.0199	0.0149	0.0106	0.0083	-0.003	0.0009	0.0375	0.023	0.0179
511821	0.019	-0.0031	0.0071	-0.0185	-0.0002	0.0137	-0.004	-0.0115	0.0194	0.0564

Table 5c. Abnormal Returns (1, 10)

EventID	AR(1)	AR(2)	AR(3)	AR(4)	AR(5)	AR(6)	AR(7)	AR(8)	AR(9)	AR(10)
511801	0.0209	0.0013	0.0369	0.0013	-0.0024	-0.0182	0.0019	0.012	-0.0337	0.0177
511802	0.0123	-0.0205	-0.0037	-0.0267	-0.004	-0.0036	-0.0308	-0.002	0.0441	0.0577
511803	-0.0065	0.0031	0.0033	0.0027	-0.0105	0.048	0.0132	0.0013	-0.0006	0.0382
511804	-0.0733	-0.0096	-0.0079	-0.034	-0.0213	0.002	0.0142	-0.0104	0.0126	0.0561
511805	0.0044	-0.0218	0.006	-0.049	0.0082	-0.0095	-0.0392	0.0185	-0.0117	-0.0033
511806	0.0181	-0.0279	-0.1024	-0.0171	0.0712	0.0049	0.0357	0.0245	-0.0171	-0.003
511807	-0.0046	-0.0052	-0.0039	-0.005	0.0515	0.0165	-0.0156	-0.0015	-0.0209	0.0182
511808	-0.0219	-0.0144	0.0175	0.013	0.0155	-0.0054	-0.0323	-0.0083	0.0085	0.0317
511809	-0.0066	-0.0181	0.0021	-0.0144	-0.027	-0.0225	0.0099	-0.0164	-0.0002	0.0079
511810	-0.0334	-0.0004	0.0116	0.0196	-0.0701	-0.0346	-0.0123	-0.0137	0.0076	-0.0045
511811	-0.0377	0.0366	-0.0681	0.0381	0.0029	0.0306	0.007	0.0295	-0.0264	-0.0515
511812	-0.0622	0.0069	-0.0209	0.0014	0.0545	0.0081	-0.005	0.0212	-0.0168	-0.0081
511813	-0.0245	0.0116	-0.0132	-0.0179	0.0174	-0.0065	0.0073	-0.004	0.0314	0.008
511814	-0.0015	-0.0061	0.0098	0.0008	-0.0159	0.0083	-0.0043	-0.0003	0.0116	0.0048
511815	-0.0314	-0.0523	-0.0395	-0.0168	-0.0464	-0.0435	0.0469	-0.0089	-0.0161	-0.0471
511816	-0.0495	0.0998	-0.0368	0.1053	-0.0625	-0.0292	0.018	-0.0419	-0.0246	-1.1594
511817	-0.0189	-0.0213	-0.0013	0.0091	-0.0143	-0.0268	-0.0079	0.0095	0.0103	0.0193
511818	-0.0278	-0.0201	0.0007	0.0017	0.0114	-0.0295	-0.0215	-0.0218	0.0606	-0.0065
511819	0.0117	0.0261	-0.0113	0.0263	0.027	-0.0334	-0.002	-0.0161	0.0399	-0.0263
511820	0.0022	0.0011	-0.0068	-0.0356	0.0007	-0.011	-0.0236	-0.008	-0.0216	-0.01
511821	-0.0373	0.0146	0.0052	-0.0044	-0.0053	-0.0173	0.0052	-0.0034	-0.0048	0.026

Table 5d. Abnormal Returns (11, 20)

EventID	AR(11)	AR(12)	AR(13)	AR(14)	AR(15)	AR(16)	AR(17)	AR(18)	AR(19)	AR(20)
511801	-0.006	0.0036	0.0194	0.0013	-0.0134	-0.007	0.0189	0.01	0.026	-0.0197
511802	0.0011	0.0079	0.0093	-0.0181	-0.005	-0.002	-0.0109	-0.0132	0.017	0.0042
511803	0.0622	-0.0078	0.0043	0.0316	-0.0056	-0.0038	-0.0092	-0.0099	0.0016	-0.0324
511804	-0.0026	-0.0101	0.0603	-0.0244	-0.0196	-0.0167	-0.0066	0.0067	-0.004	-0.0534
511805	0.0069	0.0049	-0.0354	-0.0834	-0.0158	0.0002	-0.0201	-0.0096	-0.0349	-0.0288
511806	0.03	-0.0201	-0.0083	0.0169	-0.0109	-0.0268	-0.0094	-0.032	-0.0151	0.0207
511807	-0.003	-0.0349	-0.037	0.012	0.0019	0.0024	-0.018	0.0122	-0.0016	-0.0175
511808	0.0083	0.0021	0.0052	-0.0126	-0.0028	-0.0243	-0.0383	-0.0266	0.0207	0.0364
511809	-0.0009	-0.0197	0.0133	-0.0063	-0.0132	-0.0042	-0.0093	-0.0175	-0.0313	0.019
511810	-0.0021	-0.0288	-0.0444	0.0147	-0.0277	-0.0342	-0.0087	0.0071	0.0089	0.0253
511811	-0.0438	-0.0303	0.0812	-0.0333	0.0291	-0.0023	-0.0158	-0.0034	-0.0118	0.0299
511812	0.0138	0.0161	-0.0256	0.0039	-0.0071	0.008	-0.0222	0.0055	0.0064	-0.016
511813	-0.0403	0.0104	-0.0001	-0.0183	-0.0143	0.0115	-0.005	0.0115	0.0124	0.0163
511814	0.0088	-0.0002	0.0035	-0.0049	0.0109	-0.0229	0.0075	0.0034	-0.0011	-0.008
511815	-0.0469	-0.0389	-0.0969	0.0826	-0.0651	-0.4278	0.1709	-0.0454	-0.0529	-0.0347
511816	1.184	-0.0324	0.1237	-0.0607	-0.0332	0.0212	0.0176	0.0268	0.0366	0.0137
511817	0.0453	-0.0055	0.021	0.0162	-0.0177	-0.0011	0.0376	0.0095	-0.0154	-0.0025
511818	-0.0289	-0.0011	-0.0446	0.0394	-0.0194	0.0107	0.0077	0.0206	-0.023	-0.0098
511819	-0.0341	0.0334	0.0457	0.0039	0.0192	-0.0247	0.0135	-0.0247	0.004	0.0054
511820	0.0174	-0.0117	-0.0073	0.0097	0.0002	0.0035	0.0157	0.0029	0.001	-0.0018
511821	-0.0039	-0.0219	-0.0096	0.0001	-0.0382	0.0028	-0.013	-0.041	0.0105	0.0196

Table 5e. T.values for Abnomal Returns (-20, -11)

EventID	(-20)	(-19)	(-18)	(-17)	(-16)	(-15)	(-14)	(-13)	(-12)	(-11)
511801	-1.1575	0.1732	0.9055	0.748	2.8268	-0.685	1.4488	-0.6299	2.1339	-3.0866
511802	0.9319	0.2851	-0.3149	0.5872	0.6128	-0.7319	-0.6383	0.2979	0.3489	0.1021
511803	0.0267	0.0467	0.88	0.3267	-0.5733	0.0933	0.0533	-0.5467	-0.16	0.34
511804	-0.0526	0.4035	0.3655	-0.345	-0.2456	0.3187	-0.348	-0.1374	-0.9912	-0.9678
511805	0.3355	-0.3621	-0.5515	1.3854	-0.4286	-0.4585	-0.4651	-6.8339	0.309	-1.2824
511806	-3.7386	-0.821	-1.392	2.7074	0.108	-0.2585	1.5824	-0.1449	0.0909	1.125
511807	-1.0862	-0.2276	0.9897	-0.1414	-0.6172	2.6069	0.069	-0.5034	0.5966	0.2931
511808	-0.6466	1.3362	0.2672	0.569	-0.8707	0.4397	-0.7931	0.4569	1.8793	3.9483
511809	-0.2157	-1.0392	1.6765	-1.3725	-1.402	-0.598	0.3529	0.4804	0.0784	1.2059
511810	2.1729	2.188	1.6466	-2.7293	0.6015	-1.0226	2.203	0.2556	0.7293	0.6842
511811	-0.4265	0.0931	-0.0049	-0.7696	-0.2402	0.348	-0.3676	-0.0882	0.3578	0.5833
511812	-0.1037	-0.527	-1.112	1.6722	-0.5145	-0.0249	-0.1992	-0.4191	0.0705	1.0456
511813	0.6791	-0.2164	-1.9552	1.403	-0.1493	2.694	-0.8881	0.2388	-1.9851	0.5
511814	0.2426	-0.0515	0.2941	-0.3088	0.0368	-0.875	0.4044	0.5147	0.1765	-0.375
511815	0.2473	-1.0174	-0.2516	-0.3623	-0.6963	-0.7289	0.1584	-0.0282	-1.128	-0.3774
511816	-0.3982	1.4093	0.1217	-0.2124	-0.1372	-0.458	0.0487		-1.5354	-0.5376
511817	1.5755	0.223	0.223	-2.223	-0.7698	-1.3525	2.4532	-1.0432	-1.0719	-0.0144
511818	1.096	1.0017	-0.3081	-0.6953	0.3451	0.6599	0.4343	-0.3418	0.1835	-0.4697
511819	-0.3866	0.458	-0.2227	1.8655	1.3277	1.6429	2.5336	-0.6849	0.4538	-0.6933
511820	-1.3023	0.6124	-1.0078	-0.1318	-1.6202	-0.093	0.5426	0.3178	1.6589	-0.2171
511821	0.2791		-0.7616	1.093	0.8663	1.3605	1.3488	1.3256	0.2442	1.1047
P:N	1:1	1:0	0	1:2	1:0	2:0	3:0	0:1	1:1	1:1

Table 5f. T.values for Abnomal Returns (-10, 0)

EventID	(-10)	(-9)	(-8)	(-7)	(-6)	(-5)	(-4)	(-3)	(-2)	(-1)	(0)
511801	2.2913	1.3622	-0.5118	-0.9921	-1.2677	-0.7244	3.4173	-0.937	-0.5748	0.811	-1.4567
511802	1.1362	0.8979	-1.1191	-1.2255	0.017	1.966	-0.1617	0.3532	0.2298	0.0085	0.0511
511803	0.0067	0.72	0.1667	0.1933	-0.9	-0.36	-0.6733	0.0267	0.1333	4.02	1.32
511804	-0.0029	-1.1784	0.1433	-0.0936	0.5234	0.693	-0.7281	0.3216	-0.3333	2.5292	3.8304
511805	-0.4286	1.6844	0.6246	-0.2525	0.8605	0.1993	-1.3223	-0.6445	1.8704	1.1595	2.3223
511806	-0.6932	0.2812	1.0284	0.3381	-0.2955	0.4403	1.6364	-0.1449	0.5795	1.6932	-0.5852
511807	-0.0414	-0.2586	0.5172	0.0931	0.0241	-0.4276	-0.5655	-0.3655	-1.3172	9.131	-7.4207
511808	1.5	-0.5862	-1.0776	-0.1466	-0.0948	0.819	-1.3793	0.2328	1.6034	4.1552	-3.569
511809	-0.8529	-1.2451	0.3922	-0.7745	-0.3627	1.9804	0.4216	-0.0294	1.9412	-1.902	12.9216
511810	-1.2256	-1.1429	-3.4887	0.609	0.7519	-1.0752	-1.3684	1.8271	0.7218	-1.4211	5.6692
511811	-0.0735	-0.3431	0.25	0.5539	-0.1373	-0.2892	-0.0196	0.2549	-0.3824	3.8382	5.0049
511812	-1.0913	-0.3154	-1.0041	-0.6639	-0.0705	-0.5768	-0.4772	0.7012	0.4398	-0.2822	5.5187
511813		0.3433	1.9179	0.3134	2.0746	-1.0821	-0.0746	2.8731	0.1791	-0.5075	-4.3284
511814	-0.4926	1.0588	0.2279	1.6103	2.4853	-0.9632	2.3235	1.9191	3.2426	-2.1691	-0.0588
511815	0.0217	-0.0087	-0.8482	-0.9284	-0.5488	-0.1128	3.3102	-6.2538	0.4273	-0.5119	-0.8308
511816	0.615	0.823	-0.0796	-0.3717	-0.5752	1.0221	-0.3208	0.2942	1.2434	1.5531	0.0553
511817	1.3957	0.518	1.705	-0.8417	-0.0576	1.1871	1.446	-1.4676	1.0791	-0.7338	10.3885
511818	-0.0758	-0.2407	-0.1465	0.0791	0.1448	-0.3603	-0.4411	-0.6263	-0.0572	0.6111	1.1633
511819	0.1765	1.2227	0.3403	0.3697	-0.0462	1.6134	-1.605	-0.7647	0.5294	-0.3824	-1.084
511820	1.7132	1.3101	-1.5426	1.155	0.8217	0.6434	-0.2326	0.0698	2.907	1.7829	1.3876
511821	-0.4477	1.1047	-0.1802	0.4128	-1.0756	-0.0116	0.7965	-0.2326	-0.6686	1.1279	3.2791
P:N	1:0	0	0:1	0	2:0	2:0	3:0	1:1	2:0	5:1	8:3

Table 5g. T.values for Abnomal Returns (1, 10)

Event ID	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
511801	1.6457	0.1024	2.9055	0.1024	-0.189	-1.4331	0.1496	0.9449	-2.6535	1.3937
511802	0.5234	-0.8723	-0.1574	-1.1362	-0.1702	-0.1532	-1.3106	-0.0851	1.8766	2.4553
511803	-0.4333	0.2067	0.22	0.18	-0.7	3.2	0.88	0.0867	-0.04	2.5467
511804	-2.1433	-0.2807	-0.231	-0.9942	-0.6228	0.0585	0.4152	-0.3041	0.3684	1.6404
511805	0.1462	-0.7243	0.1993	-1.6279	0.2724	-0.3156	-1.3023	0.6146	-0.3887	-0.1096
511806	0.5142	-0.7926	-2.9091	-0.4858	2.0227	0.1392	1.0142	0.696	-0.4858	-0.0852
511807	-0.1586	-0.1793	-0.1345	-0.1724	1.7759	0.569	-0.5379	-0.0517	-0.7207	0.6276
511808	-1.8879	-1.2414	1.5086	1.1207	1.3362	-0.4655	-2.7845	-0.7155	0.7328	2.7328
511809	-0.6471	-1.7745	0.2059	-1.4118	-2.6471	-2.2059	0.9706	-1.6078	-0.0196	0.7745
511810	-2.5113	-0.0301	0.8722	1.4737	-5.2707	-2.6015	-0.9248	-1.0301	0.5714	-0.3383
511811	-1.848	1.7941	-3.3382	1.8676	0.1422	1.5	0.3431	1.4461	-1.2941	-2.5245
511812	-2.5809	0.2863	-0.8672	0.0581	2.2614	0.3361	-0.2075	0.8797	-0.6971	-0.3361
511813	-1.8284	0.8657	-0.9851	-1.3358	1.2985	-0.4851	0.5448	-0.2985	2.3433	0.597
511814	-0.1103	-0.4485	0.7206	0.0588	-1.1691	0.6103	-0.3162	-0.0221	0.8529	0.3529
511815	-0.6811	-1.1345	-0.8568	-0.3644	-1.0065	-0.9436	1.0174	-0.1931	-0.3492	-1.0217
511816	-1.0951	2.208	-0.8142	2.3296	-1.3827	-0.646	0.3982	-0.927	-0.5442	-25.650
511817	-1.3597	-1.5324	-0.0935	0.6547	-1.0288	-1.9281	-0.5683	0.6835	0.741	1.3885
511818	-0.468	-0.3384	0.0118	0.0286	0.1919	-0.4966	-0.362	-0.367	1.0202	-0.1094
511819	0.4916	1.0966	-0.4748	1.105	1.1345	-1.4034	-0.084	-0.6765	1.6765	-1.105
511820	0.1705	0.0853	-0.5271	-2.7597	0.0543	-0.8527	-1.8295	-0.6202	-1.6744	-0.7752
511821	-2.1686	0.8488	0.3023	-0.2558	-0.3081	-1.0058	0.3023	-0.1977	-0.2791	1.5116
P:N	0:4	1:0	1:2	1:1	2:2	1:2	0:1	0	1:1	3:2

Table 5h. T.values for Abnomal Returns (11, 20)

EventID	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
511801	-0.4724	0.2835	1.5276	0.1024	-1.0551	-0.5512	1.4882	0.7874	2.0472	-1.5512
511802	0.0468	0.3362	0.3957	-0.7702	-0.2128	-0.0851	-0.4638	-0.5617	0.7234	0.1787
511803	4.1467	-0.52	0.2867	2.1067	-0.3733	-0.2533	-0.6133	-0.66	0.1067	-2.16
511804	-0.076	-0.2953	1.7632	-0.7135	-0.5731	-0.4883	-0.193	0.1959	-0.117	-1.5614
511805	0.2292	0.1628	-1.1761	-2.7708	-0.5249	0.0066	-0.6678	-0.3189	-1.1595	-0.9568
511806	0.8523	-0.571	-0.2358	0.4801	-0.3097	-0.7614	-0.267	-0.9091	-0.429	0.5881
511807	-0.1034	-1.2034	-1.2759	0.4138	0.0655	0.0828	-0.6207	0.4207	-0.0552	-0.6034
511808	0.7155	0.181	0.4483	-1.0862	-0.2414	-2.0948	-3.3017	-2.2931	1.7845	3.1379
511809	-0.0882	-1.9314	1.3039	-0.6176	-1.2941	-0.4118	-0.9118	-1.7157	-3.0686	1.8627
511810	-0.1579	-2.1654	-3.3383	1.1053	-2.0827	-2.5714	-0.6541	0.5338	0.6692	1.9023
511811	-2.1471	-1.4853	3.9804	-1.6324	1.4265	-0.1127	-0.7745	-0.1667	-0.5784	1.4657
511812	0.5726	0.668	-1.0622	0.1618	-0.2946	0.332	-0.9212	0.2282	0.2656	-0.6639
511813	-3.0075	0.7761	-0.0075	-1.3657	-1.0672	0.8582	-0.3731	0.8582	0.9254	1.2164
511814	0.6471	-0.0147	0.2574	-0.3603	0.8015	-1.6838	0.5515	0.25	-0.0809	-0.5882
511815	-1.0174	-0.8438	-2.102	1.7918	-1.4121	-9.2798	3.7072	-0.9848	-1.1475	-0.7527
511816	26.1947	-0.7168	2.7367	-1.3429	-0.7345	0.469	0.3894	0.5929	0.8097	0.3031
511817	3.259	-0.3957	1.5108	1.1655	-1.2734	-0.0791	2.705	0.6835	-1.1079	-0.1799
511818	-0.4865	-0.0185	-0.7508	0.6633	-0.3266	0.1801	0.1296	0.3468	-0.3872	-0.165
511819	-1.4328	1.4034	1.9202	0.1639	0.8067	-1.0378	0.5672	-1.0378	0.1681	0.2269
511820	1.3488	-0.907	-0.5659	0.7519	0.0155	0.2713	1.2171	0.2248	0.0775	-0.1395
511821	-0.2267	-1.2733	-0.5581	0.0058	-2.2209	0.1628	-0.7558	-2.3837	0.6105	1.1395
P:N	3:2	0:1	2:2	1:1	0:2	0:3	2:1	0:2	1:1	1:1

Table 9a. Abnormal Volumes (-10, -1)

EventID	AV(-10)	AV(-9)	AV(-8)	AV(-7)	AV(-6)	AV(-5)	AV(-4)	AV(-3)	AV(-2)	AV(-1)
511801	0.5379	0.4635	0.421	0.0996	0.07	0.8032	0.3193	0.0905	0.1797	-0.4433
511802	0.2047	-0.0067	-0.4482	-0.285	-0.2294	-0.3582	0.1131	0.0273	-1.4033	0.267
511803	0.0264	-0.5558	-0.1382	-0.5691	-0.2092	0.074	-0.3424	-0.7216	2.0115	0.7645
511804	-0.8186	-0.2146	-0.5448	0.5969	0.2048	-0.4006	-0.3754	-0.465	1.5225	1.9229
511805	1.0715	0.2997	0.2386	0.7912	-0.0627	0.0552	0.2464	-0.0973	0.8802	1.1627
511806	-0.2004	-0.3472	-0.4136	-0.3461	-0.4491	0.6577	-0.1211	-1.6124	0.9712	0.4065
511807	-0.0514	0.1735	-0.1307	0.1358	-0.1048	-0.0629	-0.143	0.2852	1.0549	1.2227
511808	0.9915	-0.2609	0.3402	-1.0517	-0.4201	-0.5289	-1.3466	-1.0233	0.4342	0.5626
511809	-0.3122	-0.8405	-0.2977	-0.4074	0.3039	-0.5091	-0.6868	0.2254	0.1548	2.2347
511810	0.8933	1.3788	0.7926	0.4188	0.1739	0.8031	0.6585	0.2931	0.0048	0.9927
511811	-1.8137	-2.0594	-0.2606	-0.614	-0.5543	0.194	0.1907	0.3742	2.0535	2.1541
511812	0.1161	-0.4024	0.0607	-0.3356	0.6194	0.7766	0.1471	1.2253	-1.8074	2.0932
511813	0.0209	0.2468	-0.069	0.4042	-0.4518	0.1045	1.3909	0.6932	-0.9718	1.4058
511814	0.1575	0.3904	-0.1419	0.6717	0.4013	0.1834	0.5166	1.1373	0.7763	0.2313
511815	-0.4259	-0.2182	0.1002	-0.0464	-0.7936	1.3132	2.4772	0.9212	0.941	0.5927
511816	0.3837	-0.4815	-0.4342	0.3817	-0.5164	-0.3319	0.5288	0.8632	2.4749	1.7629
511817	-0.1343	1.5866	0.875	0.5205	-0.0189	-0.494	0.6339	0.3346	0.7815	2.2983
511818	0.489	0.0946	0.4944	0.7285	0.2678	-0.0993	0.2019	0.0772	0.285	2.6709
511819	0.5594	0.8304	0.1251	-0.1192	0.647	0.4394	0.1998	-0.0241	-0.4951	-0.0633
511820	0.3202	1.3003	0.6476	1.1566	0.1326	0.5524	0.4497	1.4829	1.0365	1.3697
511821	0.5271	0.2414	0.1875	0.1366	0.0494	0.2022	0.1364	0.4813	1.6606	1.919

Table 9b. Abnormal Volumes (0, 10)

AV(0)	AV(1)	AV(2)	AV(3)	AV(4)	AV(5)	AV(6)	AV(7)	AV(8)	AV(9)	AV(10)
0.384	0.5171	0.5758	0.8923	0.5932	-0.6986	-0.3629	0.2478	0.5635	0.7241	0.3252
0.8351	-0.1425	0.1326	-0.21	-0.2205	-0.5143	0.2652	-0.3337	-0.2865	0.7729	-0.5234
-0.2747	-0.1355	-0.1796	0.3239	-1.0061	1.9129	0.9626	0.4994	-0.2075	1.1578	2.664
1.2513	0.9493	-0.0786	-0.2211	-1.1447	-1.5149	-0.1128	-0.4174	-1.1858	0.4965	0.6085
0.4541	0.0794	0.0794	0.3895	-0.0672	-0.1213	-0.1213	0.1004	0.1664	-0.5582	-0.4847
0.0122	-0.2044	1.0497	1.2248	0.9589	0.4092	0.3207	0.184	0.1329	-0.5532	0.2386
0.6017	-0.5021	0.3772	0.476	1.5189	0.8544	0.0297	-0.0404	0.1141	0.1018	0.4336
0.2767	0.5661	0.7368	0.3134	0.5905	0.1874	-0.1586	-0.0641	0.5406	0.3777	-0.0482
2.1223	1.623	1.1063	0.9863	2.5256	1.147	0.8211	0.1695	0.5519	0.3831	-0.0192
1.5209	0.4062	0.0076	0.0432	1.0069	1.0881	0.3377	0.3078	-0.0651	0.1511	0.0695
1.7562	1.765	1.9869	1.7856	0.6172	1.7864	2.4306	1.6959	1.3994	0.3252	0.7786
1.046	0.7334	-0.2479	0.5986	0.3459	0.7661	0.3711	-0.0449	0.814	0.1416	-0.0516
0.7973	0.9783	1.2476	1.5018	0.6269	0.6416	0.2215	0.8485	-0.209	0.5717	0.0088
0.5144	-0.4658	0.3805	0.3732	0.2731	-0.001	0.3914	0.4208	0.1608	-0.0751	-0.1372
-0.1576	0.4749	0.4749	-0.5059	0.6727	-0.0464	0.6201	-0.6882	-0.2182	0.1002	0.6201
0.6391	2.0627	1.0176	1.1672	1.9133	0.8289	0.5841	0.2687	0.2864	0.8856	0.9308
2.0261	0.9128	0.9851	0.6019	0.5695	0.4133	-0.143	0.2694	0.6492	0.2201	0.6418
1.1916	0.1665	0.4248	-0.4153	0.0616	-0.2974	-0.6706	-0.4468	0.0944	-0.869	-0.3939
0.5391	0.2058	-0.1774	-0.1348	0.3017	0.658	-0.1841	-2.0132	1.4374	0.0329	0.579
1.3133	0.7672	0.5385	0.8802	1.655	0.7258	0.5191	-0.2024	0.347	0.4437	-0.1592
0.8034	1.1949	0.4868	0.7771	0.035	0.3707	-0.6309	-0.5139	0.3357	0.7283	0.5538

Table 10a. T -Test Statistics for Abnormal volumes (-10, -1)

EventID	t-value (-10)	t-value (-9)	t-value (-8)	t-value (-7)	t-value (-6)	t-value (-5)	t-value (-4)	t-value (-3)	t-value (-2)	t-value (-1)
511801	1.1755	1.0129	0.92	0.2177	0.153	1.7552	0.6978	0.1978	0.3927	-0.9688
511802	0.3641	-0.0119	-0.7972	-0.5069	-0.408	-0.6371	0.2012	0.0486	-2.4961	0.4749
511803	0.0453	-0.9538	-0.2372	-0.9767	-0.359	0.127	-0.5876	-1.2384	3.452	1.312
511804	-1.2433	-0.3259	-0.8275	0.9066	0.3111	-0.6084	-0.5702	-0.7063	2.3124	2.9206
511805	1.9675	0.5503	0.4381	1.4528	-0.1151	0.1014	0.4524	-0.1787	1.6162	2.135
511806	-0.3855	-0.6679	-0.7957	-0.6658	-0.864	1.2653	-0.233	-3.102	1.8684	0.782
511807	-0.0991	0.3346	-0.2521	0.2619	-0.2021	-0.1213	-0.2758	0.55	2.0345	2.3581
511808	1.6633	-0.4377	0.5707	-1.7643	-0.7047	-0.8873	-2.259	-1.7167	0.7284	0.9438
511809	-0.7367	-1.9832	-0.7025	-0.9613	0.7171	-1.2013	-1.6206	0.5319	0.3653	5.273
511810	2.1814	3.367	1.9355	1.0227	0.4247	1.9612	1.6081	0.7158	0.0117	2.4242
511811	-1.9184	-2.1783	-0.2757	-0.6495	-0.5863	0.2052	0.2017	0.3958	2.1721	2.2785
511812	0.123	-0.4262	0.0643	-0.3554	0.656	0.8225	0.1558	1.2977	-1.9142	2.2169
511813	0.0329	0.3885	-0.1086	0.6363	-0.7113	0.1645	2.1897	1.0913	-1.5299	2.2132
511814	0.3793	0.9403	-0.3418	1.6178	0.9665	0.4417	1.2442	2.7392	1.8697	0.5571
511815	-0.5479	-0.2807	0.1289	-0.0597	-1.021	1.6894	3.1869	1.1851	1.2106	0.7625
511816	0.4061	-0.5096	-0.4596	0.404	-0.5466	-0.3513	0.5597	0.9136	2.6195	1.8659
511817	-0.2314	2.7336	1.5076	0.8968	-0.0326	-0.8511	1.0922	0.5765	1.3465	3.9599
511818	0.5153	0.0997	0.521	0.7677	0.2822	-0.1046	0.2128	0.0813	0.3003	2.8144
511819	0.7344	1.0902	0.1642	-0.1565	0.8494	0.5769	0.2623	-0.0316	-0.65	-0.0831
511820	0.4975	2.0204	1.0062	1.7971	0.206	0.8583	0.6987	2.3041	1.6105	2.1282
511821	1.0036	0.4596	0.357	0.2601	0.0941	0.385	0.2597	0.9164	3.1618	3.6538
P:N[14]	1:0	3:2	0:0	0:0	0:0	0:0	2:1	2:1	6:1	12:0

[14] "Positive: Negative" count

Table 10b. T -Test Statistics for Abnormal volumes (0, 10)

t-value (0)	t-value (1)	t-value (2)	t-value (3)	t-value (4)	t-value (5)	t-value (6)	t-value (7)	t-value (8)	t-value (9)	t-value (10)
0.8392	1.13	1.2583	1.95	1.2963	-1.5267	-0.7931	0.5415	1.2314	1.5824	0.7107
1.4854	-0.2535	0.2359	-0.3735	-0.3922	-0.9148	0.4717	-0.5936	-0.5096	1.3748	-0.931
-0.4714	-0.2325	-0.3082	0.5559	-1.7266	3.2828	1.652	0.857	-0.3561	1.987	4.5718
1.9005	1.4418	-0.1194	-0.3358	-1.7386	-2.3009	-0.1713	-0.634	-1.801	0.7541	0.9242
0.8338	0.1458	0.1458	0.7152	-0.1234	-0.2227	-0.2227	0.1844	0.3055	-1.025	-0.89
0.0235	-0.3932	2.0194	2.3563	1.8447	0.7872	0.617	0.354	0.2557	-1.0643	0.459
1.1605	-0.9684	0.7275	0.918	2.9294	1.6478	0.0573	-0.0779	0.2201	0.1963	0.8363
0.4642	0.9497	1.236	0.5258	0.9906	0.3144	-0.2661	-0.1075	0.9069	0.6336	-0.0809
5.0078	3.8296	2.6104	2.3273	5.9594	2.7065	1.9375	0.4	1.3023	0.904	-0.0453
3.714	0.9919	0.0186	0.1055	2.4589	2.6571	0.8247	0.7516	-0.159	0.369	0.1697
1.8576	1.8669	2.1017	1.8887	0.6528	1.8896	2.571	1.7938	1.4802	0.344	0.8236
1.1078	0.7767	-0.2626	0.634	0.3663	0.8114	0.393	-0.0476	0.8621	0.15	-0.0546
1.2552	1.5401	1.9641	2.3643	0.9869	1.0101	0.3487	1.3358	-0.329	0.9	0.0139
1.2389	-1.1219	0.9164	0.8988	0.6578	-0.0024	0.9427	1.0135	0.3873	-0.1809	-0.3304
-0.2028	0.611	0.611	-0.6508	0.8654	-0.0597	0.7978	-0.8854	-0.2807	0.1289	0.7978
0.6764	2.1832	1.0771	1.2354	2.0251	0.8773	0.6182	0.2844	0.3031	0.9373	0.9852
3.4909	1.5727	1.6973	1.037	0.9812	0.7121	-0.2464	0.4642	1.1185	0.3792	1.1058
1.2556	0.1754	0.4476	-0.4376	0.0649	-0.3134	-0.7066	-0.4708	0.0995	-0.9157	-0.4151
0.7078	0.2702	-0.2329	-0.177	0.3961	0.8639	-0.2417	-2.643	1.8871	0.0432	0.7601
2.0406	1.192	0.8367	1.3676	2.5715	1.1277	0.8066	-0.3145	0.5392	0.6894	-0.2474
1.5297	2.2751	0.9269	1.4796	0.0666	0.7058	-1.2013	-0.9785	0.6392	1.3867	1.0545
4:0	3:0	3:0	3:0	5:0	3:1	1:0	0:1	0:0	1:0	1:0