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Acquisitions of artificial intelligence companies. What are the effects for the acquiring firms' stock price?

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In a sample of acquirer companies from USA, which are dominant in the field of artificial intelligence, I analyze the returns after M&A activity. I find that the cumulative abnormal returns are higher for the targets that are related to artificial intelligence. Consistent with previous results, I also find that returns tend to be higher if the acquisition is not domestic, implying that returns of acquisitions of domestic companies not related to artificial intelligence are the lowest.

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1. Introduction

In this paper, I examine how acquisition announcements affect the stock price of acquiring company if the acquiring firm is specializing in artificial intelligence (AI) and compare it to other acquisitions. This is an important research because money invested in artificial intelligence has been sharply increasing in the past several years and the technology has been firmly progressing. AI investments and its research in many companies and countries has been made a priority. For example, in United States of America (USA) the increase in investments in artificial intelligence have been robust – from more than $1,1 billion in 2013 to $9,3 billion in 2018. The sharpest increase so far has been recorded from 2017 to 2018 amounting to almost $4 billion (PwC & CB Insights, 2018). The amounts invested can be interpreted as a technological competition between companies to secure the leading role in their field.

With advancing technology and its importance, a higher AI investment tendency can be seen from the largest international firms. This is due to the fact that in such a way innovation-led growth can be stimulated. This grants an ability for the companies to escape competition by innovating the technological field. The lack of competitors gives an opportunity for the companies to exercise their monopoly positions by imposing greater fees for the services provided, which could potentially yield huge profits as well as constantly increasing growth potential (Aghion, P., Jones, B. F., & Jones, 2017). Moreover, the majority of the countries have been devoting vast amounts of money and resources into AI. AI investments have even been prioritized by governments all over the world including China, France and others. What is more, many public figures like Elon Musk and Stephen Hawking have expressed their opinions warning about the consequences that could arise if AI is not regulated and the largest firms continue to control this field. The leading companies would be dominating society and dictating the rules in the upcoming years (Agrawal, Gans, & Goldfarb, 2018).

A common and the most expensive way to invest in artificial intelligence is acquiring a startup or a distinguished company that specializes in AI field. Distinctly high amount of research has been previously conducted on the stock price reactions of firms after an acquisition of a company. Surprisingly, the literature suggests that in many cases mergers and acquisitions (M&A) do not deliver profits for the acquiring firms. According to Bruner (2003), the acquisitions do not pay off for the acquiring companies in 60-70% of the time. This paper was based on data from 130 different event studies during 1971-2001. The author states that the majority of bidder firms' shareholders lose money on their investments or break even at best but, nonetheless, there were few cases that had positive returns.

Furthermore, some more similar papers have been written analyzing M&A activities. For example, mixed but comparable results have been recorded in another paper, which analyzed acquisition returns in the previous century. The conclusions made suggest that short-term gains vary a lot and are dependent on the characteristic and the period of the acquisition (Martynova & Renneboog, 2008). Therefore, it is apperent that further research could be done in analyzing the performance of stock price behaviour after acquisitions with respect to the various influencing factors.

After observing the increase of investments into artificial intelligence and its growing importance for competetiviness of the companies, some questions emerge. The main research question is, do acquisitions of AI companies provide higher short-term returns than the rest of the acquisitions? Moreover, has the perception of financial importance of artificial intelligence increased during the last few years according to companies and shareholders? How returns after an acquisition are dsitributed on a daily basis for both AI and non-AI companies? These are vital questions that would help unfolding investment possibilities and stock price movements.

To my knowledge, no previous research has been conducted on how AI influences stock price movements after an acquisition. However, some papers have been published analyzing how different types of acquisitions affect the stock price returns. Papers published by Dranev, Frolova, & Ochirova (2019), Ma, Whidbee, & Zhang (2019), and Mccarthy & Aalbers (2016) research different characteristics of M&A. The papers include various acquisition types like technological and fintech, which are partly related to this topic. The results report that acquisitions related to technology do provide positive returns after occurrence of an event. Therefore, this suggests that stock price reactions after an acquisition is dependent on the target and its characteristics.

Following the methods used in the previously mentioned papers, I have used event study to analyze stock price movements. To answer the research question I will calculate the abnormal returns of all the acquisitions made by several firms during the period of 2012-2019. To test the difference between the returns I will divide the acquisitions in 2 groups, where target company is associated with AI and the rest.

In this paper I find that the acquisitions of firms, specializing in artificial intelligence on average have higher returns than those of firms, which are not related to AI. The coefficient of AI acquisition target variable is positive in all the models used and equals from 0.3 to 0.9 depending on the model, however it is not significant. I also find that returns for AI targets increase and are positive on the day of the event unlike the returns from non-AI targets. However, during the days +1 and +2 the returns for both types of acquisitions drop down to similar level and are negative.

The paper is organized as follows. In section 2, I will overview the relevant literature with respect to event studies, preceding research carried out on AI and in analyzing M&A activities. In this section I will also form expectations of the study and hypotheses based on other research. Section 4 describes the data and research method used in performing the study. Section 5 provides the results and relates it to the stated hypotheses. I conclude in section 6.

2. Literature review and hypotheses

In order to fully assess how M&A activities affect stock price movements and how influential AI is, it is first necessary to review existing literature. First, it is important to analyze the technique that is going to be used in this paper to generate the results. Furthermore, to construct hypotheses precisely, it is necessary to grasp the importance of AI and the reason why companies have been increasing investments towards it. Moreover, the analysis of the effects of previous merger activities is essential in order to comprehend past stock price reactions and anticipate factual results. In this section, I will first explain the basics of an event study. Then, I will review the level of AI's advancement and economic research done in this field. Next, papers analyzing previous M&A activities will be analyzed in order to scope out the historical data and return tendencies of acquisitions. Throughout the chapter hypotheses will be formed in accordance with the literature findings.

2.1. The principles of an event study

Event study methodology has been introduced by Fama et al. (1969) and has been widely used to examine security prices behavior for events like earnings announcements, changes in regulations or accounting rules and money supply announcements. Event study has now become a standard technique to test security price reaction after an announcement or event (Binder, 1998). Following other papers and according to the type of events that are tested in the paper I will also be using event study methodology since it is the most fitting for my study.

The goal of an event study is to evaluate whether there are any abnormal or excess returns earned by security holders characterizing specific events. When there is no occurrence of any event normal or predicted returns for a security should be observed. These returns are commonly assessed over the time period, which is not surrounding the period of an event, which is called estimation window. These returns are then compared to the period around the event called event window to see if different returns would be generated (Peterson, 1989).

The stock market's reaction to the introduction of new information is reflected by abnormal returns (AR). To get the full view of AR during the whole event period we can cumulate the returns over number of days used in the event window (Mcwilliams & Siegel, 1997). This derives a measure of cumulative abnormal returns (CAR). There are several different ways to calculate abnormal returns, which is more generally discussed in section 3.1.2., where research methodology is explained.

2.2. Previous research on artificial intelligence

Artificial intelligence is a capability to develop self-learning software and smart machines emulating the traits of human mind in problem solving, reasoning, decision making (Educba, 2017). AI is nowadays commonly used in many different fields and has been implemented in companies all over the globe. According to a survey of 1624 data professionals with diverse job functions, 61 percent indicated that AI is the most significant aspect of data strategy in their companies for the upcoming year. Moreover, 88 percent of the respondents revealed that AI and machine learning (ML), which is considered a subset of AI, has already been or is about to be implemented in their companies. This suggests that artificial intelligence is currently one of the top business priorities (O'Reilly Media, 2018). Companies such as Google, Facebook, Amazon, Apple are currently controlling the digital field in terms of social network, mobile, web search and so on. They greatly rely on AI and invest immense amounts of money into it, which are increasing every year (Gartner, 2016). It is clear that dependency on AI is vastly increasing and firms ought to follow the tendency in order to stay competitive in the rapidly evolving world.

As mentioned before, the view on the AI's impact is indecisive. On one hand, it creates tremendous technological growth opportunities and innovation possibilities. On the other hand, it generates doubts whether the consequences are going to be entirely beneficial. According to evidence from a survey in Japan, people have generally positive views on robotics and AI and forecast an advantageous impact on their businesses. It is expected to enhance the potential of growth of advanced economies. Furthermore, companies operating in global markets also predict favorable outlook on AI and suggest that implementation of new technologies supplement the globalization of economic activities (Morikawa, 2017). Nonetheless, Google, Facebook and other multinational companies enjoy monopoly positions in their fields and persevere the barriers to enter the industry. This can be influenced by the difficulty to access data as well as large fees to enter the market industry (Aghion, P., Jones, B. F., & Jones, 2017). Despite the effect that the diffusion of AI brings, investments into AI generate high added value for a company due to its obscure potential.

As already mentioned before the investments into AI by companies has greatly increased. At the same time AI has been boosting not only the growth of the companies but economy of the countries as well. According to a research done by Accenture and Frontier Economics, the impact of AI has a potential to double the annual economic growth of the countries. In the study 12 developed economies have been analyzed using baseline growth levels with assumptions used in 2016 and growth levels with AI integrated into economic process. The results show that by the year 2035 the annual economic growth would be highest for USA amounting to 4.6% with and 2.6% without the absorbed impact of artificial intelligence. The research also suggests that the impact on other countries would be tremendous as well, with growth rates more than tripling for Japan and doubling for the Netherlands. Furthermore, the productivity of labor is also expected to be significantly influenced, reaching up to 40% labor boost for the analyzed countries (Purdy & Daugherty, 2016).

In addition to creating macroeconomic growth opportunities AI has also huge potential in boosting growth and profits in different industries. Another research conducted by the same institution similarly compared data analyzing potential of 16 different industries with and without the help of AI by year 2035. The research reveals that the highest advancement is expected in Information and Communication, Manufacturing and Financial Services sectors. The increase in these sectors amounts to 4.8%, 4.4% and 4.3% respectively with almost double the growth rate compared to the increase without further influence of AI. What is more, the profits in each industry would also be greatly increased with highest boost in Education totaling up to 84% (Purdy & Daugherty, 2017). These findings suggest that AI implementation in companies is crucial despite the field that they are operating in. These arguments lead to the following hypothesis:

H1: the acquirers' average cumulative abnormal return on AI acquisition announcements will be increasing every year relative to the acquisitions of non-AI targets in the short term ($CAR_t < CAR_{t+1}$).

Although more and more companies are now investing in AI, some firms have been dominating this field for a while now. Google is currently the leading investor into AI with the most AI acquisitions made. Accordingly, it has the most publicly disclosed money invested in AI with more than $3.7 billion already. Google is being followed by companies like Amazon, Intel, Twitter, Microsoft, Apple and Facebook on the all-time money invested in AI list (Guta, 2019). Even though Apple is the second company with the highest amount of acquisitions made, it takes only sixth place on the money spent on AI acquisitions. Apple was also one of the first companies to start investing into the field. However, after acquiring Siri in 2010 Apple slowed down and made no acquisitions for the upcoming six years before entering the field again. Meanwhile, the tendency in AI acquisitions for other companies began in 2012 (CB Insights, 2018).

It is hard to imagine how these leading companies would function without implementation of AI in their daily operations. The technology is being utilized almost in every operational aspect of the firms. For example, not to mention the most known Google's efforts to further AI in translation or computer training, they also use AI to optimize energy use. After implementing AI in the usage of air conditioners, Google managed to decrease energy consumption by 40 percent in its data centers. Moreover, Google uses Smart Reply for its email service – Gmail. AI can generate three possible responses for the users to pick from after scanning the incoming email. After its implementation in 2018, 10 percent of the letters from 1.4 billion Gmail accounts have been responded using Smart Reply (Agrawal, Gans, & Goldfarb, 2019).

Other companies have been also implementing AI effectively in various fields. The most essential uses of AI by Amazon is for products such as Alexa, Amazon Go Store and Amazon recommendation engine. The engine alone generates 35% of the company's revenue only by creating personalized purchase list by individual customer preferences (Morgan, 2018). Furthermore, Microsoft is utilizing AI in developing autonomous vehicles by partnering with another companies, advancing ML and healthcare division. The main goal of the latter is to develop analytic tools discovering people's medical diseases and alerting them as well as recommending treatments for it (Marr, 2017). As a result of these arguments another hypothesis can be formulated:

H2: the average CAR on AI relative to non-AI target acquisitions in the short term will be higher for the companies that invest more often into AI ($CAR_{highN} > CAR_{lowN}$).

As witnessed before, AI is highly popular in digital field, nevertheless, it is not the only industry that is implementing the technology. Banks have also been using ML to solve financial problems. One of the common uses of it is detecting credit card fraud. Another newly employed strategy not only by banks but also by nonfinancial firms are development of the chatbots. They are useful in helping out as a customer service and providing information. Furthermore, AI is being used for picking stocks, which consequently lays off employees such as portfolio managers. A famous US bank JP Morgan is also using ML to execute trades in equity markets (Wall, 2018). Even more applications of AI are underway to be implemented with the quickly advancing technology and diminishing limitations. Therefore, based on all these findings following hypothesis can be made:

H3: the acquirers' stock returns after announcements of AI targets' acquisition will outperform non-AI targets' acquisition in the short term ($CAR_{AI} > CAR_{non\text{-}AI}$).

2.3. Previous research on M&A

Mergers and acquisitions have been a common investment strategy for more than a century. Hence, a lot of research has been done in this field. As mentioned before, several papers suggest that majority of the results exhibit negative returns for acquiring firms' shareholders. However, some acquisitions also have positive returns.

Paper published by (Martynova & Renneboog, 2008) has analyzed acquisitions research made from 1963 till 2001. When taking into account short event windows varying form [-1, +1] to [-5, +5] days mixed results were recorded. For period 1963-1984 papers mostly suggest positive returns ranging from +0.52% to +0.97% with some exceptions in smaller periods. On the other hand, during the period 1973-2001, the results in most of the papers show negative returns. They vary from -2.74% to +1.20%. Nonetheless, in some papers positive returns still can be seen mostly in the 1991-2001 period. However, data analyzed by (Andrade, Mitchell, & Stafford, 2001) suggests that from 3,688 acquisition made over 1973-1998 period, on average they had negative returns in every decade for [-1.+1] day window, amounting to -0.3%, -0.4% and -1.0% in each decade, respectively. Therefore, these findings indicate that M&A activities had mixed results and returns depend on the period and event characteristics.

Another paper analyzed acquisitions made by USA acquirers over the 1981-2014 period. The total amount of acquisitions was more than 19 thousand and the returns on these acquisitions averaged around +1.5% while [-5,+1] day period was being applied. The average daily returns highly increase until day +2 and then slowly decrease during the following days (Ma et al., 2019).

When analyzing the research done only for the acquisitions in the last decade relatively similar results can be observed. Alexandridis, Antypas, & Travlos (2017) in their paper have studied US M&A deals announced during 1990-2009 and 2010-2015. The cumulative abnormal returns with [-1;+1] event window for all announcements in the period 2010-2015 were +0.68%, which was 0.25% higher than the ones made during 1990-2009. In addition, the data reports that 54.23% of the returns were positive. Furthermore, the paper unfolds that CARs are even higher for the deals that are priced for more than $500 million. These findings indicate that the returns from US M&A

deals during the last decade have increased and are on average positive. This explains the forth hypothesis:

H4: Deals priced for more than 500 million outperform deals that have lower price both with AI and non-AI targets ($CAR_{mega\text{-}deals} > CAR_{smaller\text{-}deals}$).

After scrutinizing several papers on the acquirer stock performance after an M&A announcement it is still troublesome to determine unanimous results. Some data shows positive returns for deal announcements and some data records negative returns. However, papers analyzing US M&A returns in the past couple decades record on average positive CAR but only slightly more than half of the deals create positive value. Due to the lack of consistent results a more comprehensive research is required to further distinguish the rationale behind stock price reactions after M&A announcements.

Even though no previous research has been done analyzing the effects of AI on firms, a comparable researches to the one executed in this paper have been done before but instead of testing AI related acquisitions, technological acquisitions have been used. Lusyana & Sherif (2016) examined the performance of bidders acquiring high tech companies. They find that during 2007-2014 these takeovers accumulate significant positive returns. Additionally, they observe higher acquirer returns for domestic acquisitions rather than cross-border.

Furthermore, another paper has analyzed data with 178 different fintech M&As in 2010-2017. Fintech is a technology-enabled innovation in financial services. They found out that the average abnormal returns during [0,+1] day event window for acquirer companies that are fintech related and non-fintech related were 2.05% and 0.76%, respectively. When taking into account longer event window, they report a constant return increase until day +2 and then a slight fluctuation of returns till day +10. Moreover, they found out that more value has been created by cross-border acquisitions (+1.58%) rather than domestic ones (+0.82%) for developed countries (Dranev et al., 2019). These results suggest that technological acquisitions are valued positively in the short term. On the other hand, these papers provide different results for the returns from cross-border and domestic acquisitions. However, none of these studies analyze how different are the returns generated by non-technological targets. According to these findings, following two hypotheses can be made:

H5: the average CAR for AI targets will increase for the day of the announcement and at least one day after ($CAR_{-1} < CAR_0 < CAR_{+1}$).

H6: the acquisition of AI targets will positively affect the average cumulative abnormal returns of the acquiring company in the short term.

The performance after technological acquisitions has also been tested by incorporating different a type of development measure instead of stock returns. Mccarthy & Aalbers (2016) has analyzed whether technological acquisitions increase the number of patents made after an acquisition by the company and compared it to predicted forecast of both acquirer and the target. According to data with a set of 3683 M&A deals announced between 2003-2008, the results show that in the first year on average +2.16 more patent applications were made but only 21% of the companies beat their forecast. They also showed that technological M&A have higher expected patent number when deals were international – averaging around +4.12 patents in the first year. These results are for the most part consistent with other technological M&A studies and imply that technological acquisitions create positive short-term value on firms performance. It also supports the theory that international deals outperform domestic ones. Therefore, as a result of all these findings following hypothesis can be formulated:

H7: the cross-border acquisitions of AI targets will perform better than domestic acquisitions in the short term ($CAR_{cross\text{-}border} > CAR_{domestic}$).

3. Research methodology and data sample

In this section, I will describe the methodology that is going to be adopted to carry out the event study and test previously formulated hypotheses. Thereafter I will discuss the approaches used to calculate abnormal returns. Lastly, I will describe the data sample that is employed in this research.

3.1. Research methodology

3.1.1. Event study

The most frequently used methodology for examining the post M&A returns is event study. The advantage of an event study is that in the case of rational markets the impact of an event can be seen right away in the changes of security prices (Mackinlay, 1997). Moreover, the results using the method can be produced without the dependence on difficult to acquire data or complicated instruments. According to Fama (1991) : "The results stand up to replication and the empirical regularities, some rather surprising, are the impetus for theoretical work to explain them. In short, on all counts, the event-study literature passes the test of scientific usefulness". Hence, event study should be the method suiting this research the best.

Over the last years there have not been recorded any fundamental changes in the methodology of an event study. Same approaches have been used for measuring the cumulative mean abnormal returns and the mean of sample securities centering around the time of observed event. The only notable changes are the daily data usage instead of monthly and the increase of sophistication level in the usage of methods measuring abnormal returns and verifying their statistical significance (Khotari & Warner, 2006). Evidently, daily returns are used in conducting this study as well.

In event study it is essential to identify the exact effect of the event without interference and make valid conclusions about the result significance. According to Mcwilliams & Siegel (1997) there are three general assumptions that need to be met to ensure the significance:

(i) Markets have to be efficient. It means that all relevant information is incorporated in stock prices and any kind of recent information disclosed to the investors would immediately be reflected in the stock prices.

(ii) Events are not anticipated. This suggests that no previous information about the event was available to the investors until it was officially revealed.

(iii) There are no confounding effects. It assumes that the effect of an event is not affected by any other occurrences. The longer the event window, the larger the chance of violating this assumption because of the increased probability of other influential events occurring during the period.

In my study, multinational companies are being used in the sample, due to the fact that AI acquisitions are mostly made by M&A heavy companies that dominate their industries. Therefore, these firms are frequently acquiring other companies and startups. Consequently, event windows are kept short in order to hinder breaking (iii) assumption and prevent confounding effects.

One of the most important aspects in conducting a successful event study is determining the appropriate event and estimation windows, which are shown in Figure 1. These windows have been already briefly discussed in the 2.1. section. Event window includes the day of the announcement but in practice a longer period is taken including some days before and after the occurrence of an event. This provides the possibility to show the stock price effects after the closure of a stock market on the announcement day as well as capture the pre-event returns in case of information leakage and its accessibility some time prior to the actual announcement of the event (Mackinlay, 1997). In the past literature short-term event windows were selected as [-1, +1]; [-5, +5] or [-10, +10] days. The most common choice is [-1, +1] but longer events windows are taken when the actual date of the announcement is not entirely clear (Martynova & Renneboog, 2008).

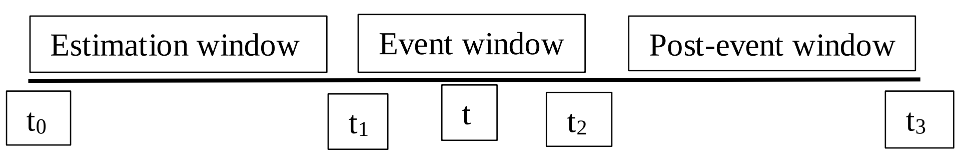


FIGURE 1. ILLUSTRATION OF AN EVENT STUDY

In this paper I test the abnormal returns using [-1, +1], [-3, +3] and [-5, +5] event windows. This allows me to test the daily returns few days before and after acquisition announcements and contrast the effects of the announcement between longer short-term periods. Nevertheless, it is crucial to keep in mind that with longer event windows comes the possibility of confounding effects' interference due to the companies' high level of activity frequency.

In the most studies estimation windows are generally being chosen around [-250; -30] days. However, the problem of biased results can sometimes be caused by the possibility of unrelated events occurring in the period of the estimation (Aktas, de Bodt, & Cousin, 2007). Hence, it is important to verify that the estimation period was not contaminated by confounding events. In this case, I use [-240, -10] trading days event window . The event window should be long enough for the estimation not to be contaminated by the effect of one exceptional event. The amount of events occurring during the 230 days period for the selected firms are quite high. This eliminates thus the possibility of an exceptionally anomalous period and should provide a conforming estimation basis.

3.1.2. Abnormal returns

Abnormal returns can be calculated using various different methods. These methods include: capital asset pricing model, mean adjusted returns model, market adjusted returns model, market and risk adjusted returns model (MRAR) (Brown & Warner, 1980), Fama-French 3 factor model (FF3F) (Fama & French, 1993) and Carhart 4-factor model (Carhart, 1997). The AR calculation is generally expressed in the following equation :

$$(1) \qquad AR_{it} = R_{it} - R^*_{it}$$

where AR_{it} are the abnormal returns of underlying asset i for the time period t, R_{it} are the returns for asset i for time period t and R^*_{it} is the varied calculation depending on the model used.

According to one of the research analyzing 400 event studies, in almost 80% of the cases MRAR model was used to calculate abnormal returns (Holler, 2014). The further calculation for this model would be expressed as follows :

$$(2) \qquad R^*_{it} = \alpha_i + \beta_i * R_{mt}$$

where α_i and β_i are the parameters of regression equation, with β_i being the beta value of the asset i and R_{mt} is the reference market returns on day t.

Nonetheless, this model has a disadvantage. The risk free rate in this case is included in α factor and is assumed to be constant, which is not in line with the assumption of market returns varying over time (Cable & Holland, 2002). Despite that MRAR is one of the models that is going to be used in this research due to its acceptance and employment in the majority of previous event studies.

Moreover, to measure the abnormal returns more accurately and avoid errors Fama-French 3 factor model will be used as an alternative. This model controls for the size and includes market capitalization as well as risk factor in returns related to book-to-market equity. The model should do a better job in isolating the firm-specific components in returns (Fama & French, 1993). The calculation for FF3F model is done as follows :

$$(2) \qquad R_{it}^{FF} = \alpha_{it} + \beta_{1i} * R_{mt} + \beta_{2i} * SMB_t + \beta_{3i} * HML_t + \varepsilon_{it}$$

R_{it}, and R_{mt} are the monthly return on stock "i" and the market portfolio respectively. SMB_t shows the difference between the monthly return of small size and big size stocks and HML_t shows the difference between the monthly returns of high book-to-market value stocks and low book-to-market value stocks at time t; ε_{it} is the random error.

As reported in previous research, FF3F model largely captures the average returns on US portfolios due to extra factors included. Therefore, FF3F model provides a more accurate estimation than the capital asset pricing model and improves its errors (Carhart, 1997; Davis, Fama, & French, 2000). However, FF3F model is not always so common for event studies. According to simulations and empirical tests, one factor model using market as an index is a completely solid and sufficient method in adopting abnormal performance (C. J. Campbell, Cowan, & Salotti, 2010). The absence of FF3F model is also practically always observable in multi-country event studies. This is most likely due to the lack of available data on size and book-to-market factors outside the US and extreme difficulty in creating them from scratch (Lundgren & Olsson, 2010).

Furthermore, after calculating AR, they can be accumulated over the whole estimation period. This obviates the uncertainty of exact event date and captures the full effect of asset price changes. Cumulative abnormal returns are calculated as a sum of all the abnormal returns for the event period [t_1; t_2] (Elad & Bongbee, 2016). This can be expressed as.

$$(3) \qquad CAR_{t_1;t_2}^{i} = \sum_{t_1}^{t_2} AR_{it}$$

Following the H_0 hypothesis the distribution of cumulative abnormal returns would be :

$$(4) \qquad CAR_i(t_1, t_2) \sim N(0, \sigma_i^2(t_1, t_2))$$

with a mean distribution of 0 and variance of σ_i^2. In order to test whether the actual value of the parameter is not 0 a t-test can be used.

$$(5) \qquad t_{CAR} = \frac{CAR_{i,t}}{\sqrt{h} * \sigma_{CAR_i}}$$

where h equals to the amount of days in the event window and σ_{CAR_i} is the average standard deviation of CAR. The underlying assumption in the test is that variance is constant over time and abnormal returns are uncorrelated. The interpretation of the test – that the larger t value is, the less it is likely for the value of the parameter to be 0 (Patell, 1976). If the absolute value of test is larger than 1.96, then the average abnormal return for that stock is significantly different from zero at the 5% level. The value of 1.96 comes from the standard normal distribution with a mean of 0 and a standard deviation of 1. 95% of the distribution is between ±1.96 (J. Y. Campbell, Lo, & MacKinlay, 1997).

Moreover, after calculating the cumulative abnormal returns for single events, they can be aggregated by taking the mean of all the events tested.

$$(6) \qquad \overline{CAR}_{t_1;t_2} = \frac{1}{N}\sum_{i=1}^{N} CAR_i(t_1;t_2)$$

N in this case is the number of different acquisitions tested and $\overline{CAR_{\iota t}}$ is the cumulative abnormal returns of all observations. The test statistic with all the acquisitions would be calculated :

$$(7) \quad t_{CAR} = \frac{\overline{CAR_{\iota t}}}{\sqrt{h} * \sigma_{CAR_{it}} / \sqrt{N}}$$

σ in this case is the CAR standard deviation of the acquiring firms (Mackinlay, 1997). The t-test for all the acquisitions will help to determine how significant are the CAR from the event study on average.

3.2. Data sample

My sample of acquisitions and the industry categories of acquired companies is retrieved from Crunchbase. The data involves deals announced between January 2012 and April 2019 period. The acquirers consist of listed US firms that are heavily dominating in AI industry and have made expensive acquisitions: Amazon, Facebook, Google, Intel, Microsoft, Oracle, Twitter. My stock price data is retrieved from Factset. Some of the transactions have been excluded due to stock price unavailability for 230 days prior to the acquisition announcement or event dates from the same company interfering with each other. One case has also been removed because of extremely high influence on the whole estimation with the value of Cook's coefficient of around 0.85, while other influential cases were not higher than 0.07.

The final sample includes a total of 346 deals. Table 1 displays the fundamental information about the sample. To separate AI and non-AI targets all the acquisitions have been included and divided according to the target company's type. The total amount of acquisitions made when the target company is associated with AI is 51. The most (18) of these acquisitions are made by Google, while Twitter in this sample has acquired only 2 AI firms. The total amount of cross-border

COMPANY	TOTAL AI	TOTAL NON-AI	INTERNATIONAL AI	INTERNATIONAL NON-AI	PRICE DISCLOSED AI	PRICE DISCLOSED NON-AI	MEGA DEALS
AMAZON	8	30	0	7	3	9	7
FACEBOOK	5	30	1	7	0	6	3
GOOGLE	18	90	7	16	0	14	5
INTEL	7	29	1	13	3	10	3
MICROSOFT	7	63	3	19	2	12	3
ORACLE	4	44	2	1	1	14	11
TWITTER	2	9	1	0	1	3	0
TOTAL	51	295	15	63	10	68	32

TABLE 1. SAMPLE DESCRIPTION

Notes: The sample includes 346 acquisitions announced between January 2012 and April 2019 period. Table shows the amount of acquisitions made by different companies. TOTAL (NON-)AI is the amount of acquisitions when the target company is (not) associated with artificial intelligence; INTERNATIONAL (NON-)AI is the amount of deals when the target company is not based in the US with (NON-)AI targets; PRICE ANNOUNCED (NON-)AI is the amount of deals when the transaction price is diclosed with (NON-) AI targets; MEGA DEALS is the amount of deals when the purchase price is higher than $500 million. *Source:* Crunchbase.

acquisitions made is 15 for AI targets and 63 for non-AI targets. Google is the company that is investing into AI internationally the most with 7 acquisitions, which is almost a half of the deals compared to all the other firms in this sample. When looking at the cross-border non-AI acquisitions nearly all the companies are expanding internationally except for Oracle and Twitter making few acquisitions worldwide.

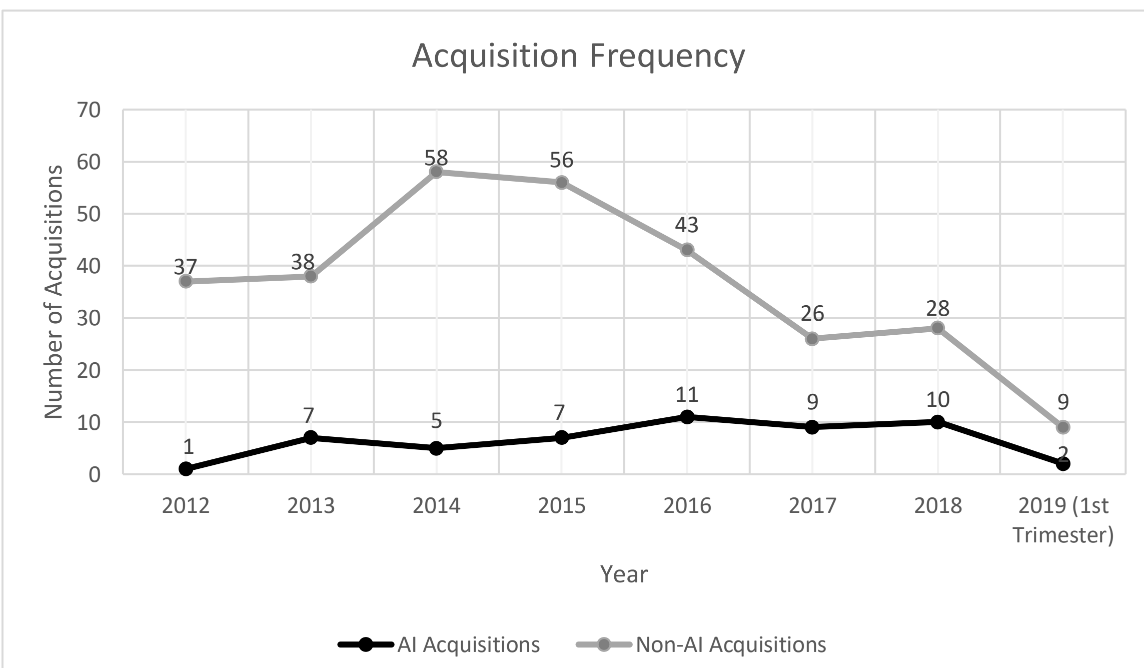
Table 1 also shows how many deals have their transaction price disclosed. Only around 20% of both AI an non-AI deals make the price public. Intel has the highest percentage of deal prices disclosed with around 43% of the transactions for AI and 34% for non-AI. The sample also lists mega deals, which are transactions with the purchase price higher than $500 million. As much as 41% of the purchases that have their price announced are mega deals, which is not entirely surprising since the companies in the sample are large and dominant in their field. Oracle has made the most high price transactions with 73% from the ones that have their price announced, while Twitter invested the high amounts of money the least into a single company with no mega deals.

Figure 2 shows the number of both AI and non-AI acquisitions made every year. From the graph we can see that the number of AI acquisitions are increasing almost every year with only one acquisition made in 2012 and 10 in 2018. The difference between the number of AI and other acquisitions is also decreasing, which complies with the previously written data that investments into AI are growing every year. This suggests that companies are investing more money into AI every year and allocating even bigger percentage of their funds to advance their AI-related technology.

The main purpose of the paper is to test if and how different are the stock price reactions of announcements of AI from non-AI target acquisition. In order to do this I perform a series of cross-sectional regressions clustered at firm level. The dependent variable is cumulative abnormal returns, which are determined after the running an event study with MRAR and FF3F models using [-5,+5], [-3,+3] and [-1;+1] event windows.

To analyze what affects the acquirer returns several independent dummy variables are constructed. First estimator is Artificial Intelligence and it is used to determine, whether the target company specializing in AI field is affecting the CAR of the announcement. This variable is

FIGURE 2. ACQUISITION FREQUENCY DURING 2012-2019 PERIOD



constructed as a dummy, where it is coded 1 if the target company is specializing in artificial intelligence or machine learning. The variable is coded 0 if target firms are not related to AI. Second independent variable is Target Country, which is also coded as a dummy with value 1 if the target country is located in the USA and 0 if it is not part of the USA. This variable allows us to test hypothesis, whether cross-border acquisitions outperform domestic ones.

The analysis is also focused on determining if the market view on AI target acquisitions has improved in the past few years. To test this I compare yearly returns on AI and non-AI acquisitions to see if the difference is increasing. In addition, I examine the daily average abnormal returns for 5 days before and after the announcement to identify the short-term market reactions on a daily basis.

Furthermore, in order to see the return differences between AI and non-AI acquisition announcements I compare the CAR using some other specifications. I take into account and contrast the results between all the companies in the sample. I also estimate how different the CARs are when the acquisition price is disclosed or the transaction price is higher than 500 million dollars. This allows us to see what effect the transaction price has.

4. Empirical results

In this section, I will discuss results analyzing the factors influencing M&A returns with respect to AI targets. First I discuss the daily short-term average abnormal returns for AI and non-AI related acquisitions. Next, I look at the regression results of all models. Then I test other factors that could affect acquisitions, which were mentioned in the hypotheses section.

4.1. Average daily abnormal returns.

Firstly, I examine how abnormal returns are evolving during the event day period. To test that I apply both MRAR and FF3F methods to calculate abnormal returns and analyze [-5;+5] event day window. Table 2. Average daily abnormal returns shows the results with CAR for each day around the acquisition announcement as well the percentage of positive abnormal returns that were recorded during that day.

When analyzing the results generated by MRAR model, we see that before the acquisition announcements of AI companies they have positive returns on all days except for the 4th day prior to the event. For non-AI targets the returns before the event day are negative on the 5th and the 1st day prior to the event. During the pre-event period AI firms have higher abnormal returns on days -5, -2 and -1. However, it is important to note that due to the high frequency of M&A activity of these companies, a few acquisitions in my sample were made within 5 trading days between one another. Hence, some confounding effects could be seen when analyzing periods longer than 3 days before and after the event. For this reason, more attention in this paper is paid for the period that is within the 3 days around the event announcement. The amount of deals that have positive returns before the event is a little higher for AI targets on day -2 and -1 but lower on day -3. The returns calculated by FF3F model do not deviate very much from the MRAR model and provide the same results for the pre-event period.

On the event day market model shows comparably high and positive returns for AI companies and slightly negative results for non-AI companies, amounting to 0.25 and -0.03, respectively. FF3F model also predicts positive, although slightly lower returns for AI and negative returns for non-AI transactions equal to 0.11 and -0.04, respectively. Consequently, the percentage of the deals

TABLE 2. AVERAGE DAILY ABNORMAL RETURNS

	MARKET MODEL				**FAMA-FRENCH 3 FACTOR MODEL**			
DAY	Average Returns AI	Percent Positive	Average Returns Non-AI	Percent Positive	Average Returns AI	Percent Positive	Average Returns Non-AI	Percent Positive
-5	0.28	57%	-0.05	46%	0.20	51%	-0.05	44%
-4	-0.21	43%	-0.02	49%	-0.22	35%	0.01	51%
-3	0.06	45%	0.13	54%	-0.03	49%	0.14	52%
-2	0.19	53%	0.13	53%	0.19	51%	0.10	47%
-1	0.08	51%	-0.13	48%	0.07	51%	-0.14	46%
EVENT DAY	0.25	63%	-0.03	54%	0.11	59%	-0.04	52%
+1	-0.10	45%	-0.08	47%	-0.11	51%	-0.05	46%
+2	-0.15	45%	-0.16	45%	-0.15	49%	-0.15	46%
+3	0.07	53%	-0.08	44%	-0.01	49%	-0.10	44%
+4	0.14	61%	0.10	54%	0.19	65%	0.06	52%
+5	0.24	57%	0.10	54%	0.14	53%	0.16	56%
AVERAGE CAR [-5;+5]	0.84	57%	-0.09	47%	0.38	57%	-0.06	48%
AVERAGE CAR [-3;+3]	0.40	57%	-0.22	47%	0.06	53%	-0.24	45%
AVERAGE CAR [-1;+1]	0.22	59%	-0.24	48%	0.07	61%	-0.23	46%

Notes: The sample includes 346 acquisitions announced between January 2012 and April 2019 period. Table shows the average daily abnormal returns for [-5;+5] day period. AVERAGE RETURNS AI is the average abnormal returns when the target company specializes in AI; AVERAGE RETURNS NON-AI is the average abnormal returns when the target company is not related to AI; PERCENT POSITIVE shows the percentage of deals that have abnormal returns higher than 0. AVERAGE CAR [-5;+5] is the total average CAR when using [-5;+5] event window. *Source:* Author's calculations.

having positive returns is also higher for AI targets with both models, resulting in 63% for AI deals and 54% for the rest in MRAR model and 59% to 52% in FF3F model. These results indicate that announcements of artificial intelligence target acquisitions do in fact generate higher returns than those not related to AI on the event date.

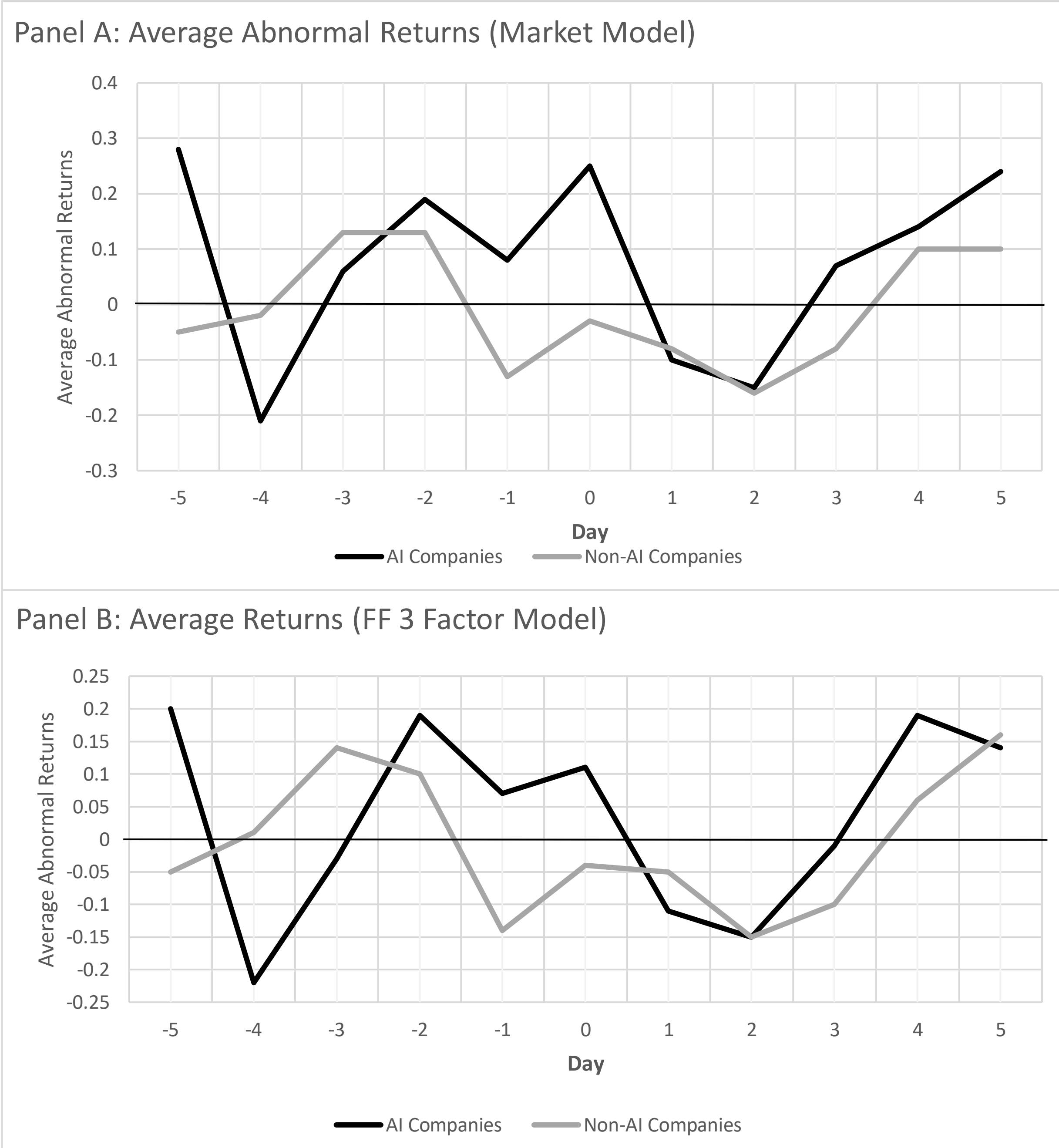


FIGURE 3. AVERAGE ABNORMAL RETURNS

When looking after post-event period both models predict negative and similar returns during the days +1 and +2 for both types of acquisitions. However, during day +3 the returns for AI targets recover and are 0.07 according to MRAR model and -0.01 under the FF3F model. Returns for non-AI acquisitions, on the other hand, stay negative for the day +3 at around -0.1 and do not return to being positive until day +4. The total CARs using any of the event windows are greater for target companies that are related to AI. The total CARs for AI target firms are always positive while they are always negative for non-AI targets. The percentage of the deals having positive returns is also always higher for AI deals. This indicates that AI companies do produce higher shareholders' returns in the short term.

Figure 3 provides two graphs showing the average abnormal returns with MRAR model in panel A and FF3F model in Panel B. These graphs provide a clearer visual view of the return differences between AI and non-AI companies. Notably, we see that average abnormal returns drop on day -1 for both AI and non-AI companies. However, the drop for non-AI companies is even more significant and produces negative returns, while AI targets still generate positive returns according to both models. The return drop one day before the occurrence of the announcement might suggest that there is some negative inside information for some shareholders and investors, who could have anticipated the event before it was officially revealed. This to an extent violates efficient market hypothesis and implies that some people might be trading with knowledge while people in general are lacking the knowledge.

During the event day returns from both AI and non-AI targets increase, implying that there is a positive reaction to an event from the shareholders. The AI returns, however, produce higher returns under both models. When looking at the post-event window a clear decrease can be observed for both types of acquisitions during days +1, +2 and the returns approximately even out between the two. The return drop before and after an event date is consistent with some prior studies. Chen (2017) has also reported in his study that standardized abnormal returns before and after the announcement are consistently negative on the M&A within financial holdings. Moreover, Ma et al. (2019) has also recorded a return drop up to -1.25% for the 1st and 2nd day after an announcement in their study analyzing US public targets. However, in their analysis the returns do not recover or show any increase in the consequent days.

The average abnormal returns start increasing again on the 3rd day after the announcement. It recovers to a positive value for AI targets but still remains negative for non-AI targets. This might suggest that stock returns after an AI acquisition recover quicker after a decrease than non-AI acquisition.

Hence, the hypothesis H5 states that the average CAR of AI targets should increase for the day of the acquisition and one day after. This hypothesis can be rejected due to the notable decline during day +1. However, the returns do rise during the event day. Moreover, hypothesis H6 cannot be rejected, which states that acquisitions of AI targets will positively affect the acquirers' CAR in the short term. This is observed when analyzing the total average CAR of during the [-5;+5] day event window.

4.2. The effects of AI

To further examine the effect that AI has on stock price returns after a M&A announcement I run a cross-sectional ordinary least squares (OLS) regression clustered at the firm level analyzing all the models. Table 3 shows the regression results with CAR as a dependent variable and AI as an independent variable. There are 6 different regressions using both MRAR and FF3F models with [-1;+1], [-3;+3] and [-5;+5] event windows. By looking at the results and t-test values I will

TABLE 3. CAR REGRESSIONS WITH AI

VARIABLES	Market Model [-1;+1]	Market Model [-3;+3]	Market Model [-5;+5]	Fama-French Model [-1;+1]	Fama-French Model [-3;+3]	Fama-French Model [-5;+5]
AI	0.468 (0.273)	0.617 (0.527)	0.932 (0.637)	0.301 (0.301)	0.297 (0.370)	0.439 (0.521)
P-value	0.138	0.286	0.193	0.177	0.454	0.432
T-stat	1.71	1.17	1.47	1.53	0.80	0.84
Constant	-0.243 (0.319)	-0.222 (0.209)	-0.089 (0.424)	-0.229 (0.286)	-0.235 (0.400)	-0.062 (0.400)
Observations	346	346	346	346	346	346
R-squared	0.005	0.004	0.005	0.002	0.001	0.001
Robust P-value	0.173	0.497	0.849	0.120	0.275	0.990
T-test	-0.0396	0.0015	0.0228	-0.0224	-0.0715	-0.0378

Notes: The sample includes 346 acquisitions announced between January 2012 and April 2019 period. This table presents the coefficients, std. errors (in parentheses), P-value and t-statistic of AI independent dummy variable for six OLS regressions based on the whole sample. The dependent variable is CAR. The numbers in square brackets represent the size of the event window. T-test reports the average value of the t-test according to the model used; *Robust P-value* reports the robust P-value of the constant, which represents the significance level of the event study across all companies. Superscripts *** , ** , and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.
Source: Author's calculations.

determine which event window provides the most representative results. The event window the most accurately embodying the results will be used in later analysis.

When looking at the results we see that all the models provide positive coefficient for AI variable. According to MRAR model, the coefficient value and standard deviation increases with the amount of days included in the event window. The variable, however, is not significant in any model. The highest P-value and t-statistic can be observed in [-1;+1] event window and is equal to 0.138 and 1.71, respectively. The coefficient for the 3 day event window is equal to 0.468, meaning that acquirer CARs of AI acquisition announcements are 0.468% higher than non-AI.

FF3F model provide similar results with positive coefficient and highest P-value and t-statistic while using [-1;+1] event window. Nevertheless, the coefficients, t-statistic and significance level have slightly lower values with FF3F model than with MRAR model.

Table 3 also reports the robust P-value of the constant and the average value of the t-test. The average test statistic value for all the event windows is lower than 1.96 and thus not significant at 5% level. According to the t-test, MRAR model during the 11 day event window has the highest significance while using FF3F model 3 day event window has the highest t-test value. The robust P-value on the constant from this regression gives the significance of the CAR across all companies. This test is preferable to a t-test because it allows to use robust standard errors. From all the models we see that the P-value is lowest when using [-1;+1] event window. This suggests that even though the event study results are not significant at 5% level, the most representative results are generated using the 3 day event window. In consonance with the OLS and t-test results, we see that [-1;+1] event window most efficiently represents the event study and this model will be used to further test the hypotheses.

4.3. AI influence depending on different factors

To further examine how the AI affects the shareholder returns after an acquisition, I examine the returns using other factors. Table 4 provides the average year-by-year acquirers' CAR for AI and non-AI target M&A announcements. When looking at the market model, we see that the returns for AI targets are generally positive except for 2016 and 2018. However, if the CARs are lower for AI targets they are also lower for non-AI target during the same year. When looking at the difference between AI and non-AI acquisitions we see that it is the highest during 2012 and 2014 although in 2012 only one acquisition of an AI company has been made in the sample.

TABLE 4. YEAR-BY-YEAR CAR

	MARKET MODEL			FAMA-FRENCH 3 FACTOR MODEL		
YEAR	Average CAR AI	Average CAR AI	Difference	Average CAR AI	Average CAR non-AI	Difference
2012	4.06 (1)	0.17 (37)	+3.89	5.12 (1)	0.12 (37)	+5.00
2013	0.35 (7)	0.18 (38)	+0.17	0.38 (7)	0.05 (38)	+0.33
2014	0.25 (5)	-0.94 (58)	+1.19	0.03 (5)	-0.81 (58)	+0.84
2015	0.20 (6)	0.02 (56)	+0.18	-0.42 (6)	0.14 (56)	-0.56
2016	-0.03 (11)	-0.33 (43)	+0.30	-0.03 (11)	-0.13 (43)	+0.1
2017	0.53 (9)	0.11 (26)	+0.42	0.08 (9)	-0.11 (26)	+0.19
2018-	-0.16 (12)	-0.53 (37)	+0.37	-0.18 (12)	-0.72 (37)	+0.54

Notes: The sample includes 346 acquisitions announced between January 2012 and April 2019 period. The results are provided using market and Fama-French 3 factor models and the event window of [-1;+1] days. This table presents acquirers' year-by-year average CAR on AI and non-AI targets and the number of acquisitions made that year (in parentheses). *Difference* indicates the difference between AI and non-AI CAR; *2018-* includes year 2018 and the first trimester of 2019. *Source:* Author's calculations.

FF3F model in Table 4 provides analogous results except for year 2015, where the returns for AI acquisitions are notably lower than non-AI. We can also observe that returns roughly do not really have a pattern but the return difference between AI and non-AI targets have been increasing in the past few years. The AI target returns has been generally outperforming non-AI returns and rising since 2015. Therefore, the hypothesis H1, which states that average CAR on AI target acquisitions should be increasing every year relative to the non-AI targets, cannot be fully rejected. Even though the returns for acquisitions are marginally different every year without any specific pattern, an increase can be recorded when analyzing the difference between AI and non-AI target in the past several years.

In order to test hypothesis H2, I compare the CAR after acquisitions of each acquiring company. Table 5 presents the average CAR and the number of acquisitions made by each company in both AI and non-AI field as well as the difference between the them. When looking at the MRAR model we see that all of the companies except for Intel have better returns for AI target acquisitions rather than non-AI. Whereas FF3F produces slightly different results for Twitter and Intel with respect to the differences between the returns. According to the model, the return difference is negative for Twitter and slightly positive for Intel.

TABLE 5. CAR WITH RESPECT TO THE ACQUIRER

	MARKET MODEL			**FAMA-FRENCH 3 FACTOR MODEL**		
FIRM	Average CAR AI	Average CAR AI	Difference	Average CAR AI	Average CAR non-AI	Difference
AMAZON	0.66 (8)	-0.47 (30)	+1.13	0.51 (8)	-0.44 (30)	+0.95
FACEBOOK	-0.55 (5)	-2.58 (30)	+2.03	-1.09 (5)	-2.23 (30)	+1.14
GOOGLE	0.36 (18)	0.28 (90)	+0.08	0.27 (18)	0.29 (90)	-0.02
INTEL	-0.49 (7)	-0.22 (29)	-0.27	-0.37 (7)	-0.45 (29)	+0.08
MICROSOFT	-0.01 (7)	-0.04 (63)	+0.03	0.33 (7)	-0.12 (63)	+0.45
ORACLE	1.05 (4)	0.09 (44)	+0.96	1.18 (4)	0.08 (44)	+1.10
TWITTER	0.88 (2)	-0.04 (9)	+0.92	0.17 (2)	0.42 (9)	-0.25

Notes: The sample includes 346 acquisitions announced between January 2012 and April 2019 period. The results are provided using market and Fama-French 3 factor models and the event window of [-1;+1] days. This table presents separate acquirer firms' average CAR on AI and non-AI targets and the number of acquisitions made by a company (in parentheses). *Difference* indicates the difference between AI and non-AI CAR. *Source:* Author's calculations.

When looking at the Table 5 in general Facebook has surprisingly the lowest returns after the acquisitions of both AI and non-AI targets. However, the difference between the two is the highest compared to all other firms. Google has the most acquisitions made in AI field but does not produce a clearly diverse results between CAR of AI and non-AI targets. When in fact firms with fewer acquisitions like Oracle and Amazon have profoundly higher returns for M&A of AI targets. Consequently, the hypothesis H2, stating that companies investing more often into AI have comparably higher returns between AI and non-AI targets, can be rejected. The results do not show any patterns suggesting that the returns are higher if the acquirer has more acquisitions in that field.

Furthermore, I analyze if the price of the transactions has any effect on CAR. Panel A in Table 6 presents the average CAR when the price of the transaction has and has not been disclosed for both AI and non-AI target firms as well as the returns for the deals with price higher and lower than $500 million. The results show that the acquisitions of AI targets that have transaction price disclosed have greater returns than AI acquisition with confidential price. However, there are only 10 acquisitions of AI companies with disclosed price which is a rather low sample and the returns could be randomly affected by other factors.

No apparent effect of price announcement can be witnessed when looking at the rest of the acquisitions. The CARs almost do not differentiate when looking at non-AI target acquisitions estimated by both MRAR and FF3F models. The mega deals with the transaction price of more than $500 million also do not show any distinct effect and the CARs are on average the same independent of the deal size. These results are not in line with the previous findings of Alexandridis et al. (2017), who observed 2.54% average CAR for mega deals and 1.42% CAR for all the deals during 2010-2015 period. Therefore, we reject the hypothesis H4, which states that the returns of

TABLE 6. CAR DEPENDING ON PRICE AND LOCATION

	MARKET MODEL		**FAMA-FRENCH 3 FACTOR MODEL**	
PANEL A: TRANSACTION PRICE EFFECTS				
	Price announced	Price confidential	Price announced	Price confidential
AVERAGE CAR TOTAL	-0.04 (78)	-0.21 (268)	-0.11 (78)	-0.21 (268)
AVERAGE CAR AI TARGET	0.96 (10)	0.04 (41)	0.93 (10)	-0.14 (41)
AVERAGE CAR NON-AI TARGET	-0.19 (68)	-0.26 (227)	-0.26 (68)	-0.22 (227)
	Mega Deals	Smaller Deals	Mega Deals	Smaller Deals
AVERAGE CAR	-0.10 (32)	-0.01 (46)	-0.10 (32)	-0.12 (46)
PANEL B: TARGET LOCATION EFFECTS				
	Domestic	Cross-Border	Domestic	Cross-Border
AVERAGE CAR AI TARGET	0.20 (36)	0.29 (15)	0.12 (36)	-0.05 (15)
AVERAGE CAR NON-AI TARGET	-0.37 (232)	0.21 (63)	-0.31 (232)	-0.08 (63)
AVERAGE CAR TOTAL	-0.29 (268)	0.22 (78)	-0.25 (268)	0.05 (78)

Notes: The sample includes 346 acquisitions announced between January 2012 and April 2019 period. The results are provided using market and Fama-French 3 factor models and the event window of [-1;+1] days. Panel A presents average CAR on the deals with disclosed and confidential transaction price with AI, non-AI and total targets as well as the number of such acquisitions made (in parentheses). *Mega deals* show the returns if transaction price was higher than $500 million; *Smaller deals* show the returns if the price was announced but it was lower than $500 million. Panel B presents the average CAR on Domestic and Cross-Border acquisitions with AI, non-AI and total targets as well as the number of such acquisitions made (in parentheses).
Source: Author's calculations.

mega deals are higher than returns of smaller deals. The Panel B in Table 6 shows the different CARs for AI and non-AI acquisitions when the target companies are located inside and outside the US. The results from MRAR model suggest that the average CAR on AI target acquisitions do not differentiate if target is located inside or outside of the US but it shows a notably higher returns for cross-border acquisitions with non-AI targets. FF3F model also provides similar results apart from the returns of cross-border AI targets which are lower than the domestic ones.

Both models also indicate that the returns for domestic targets are remarkably higher for AI acquisitions compared to non-AI acquisitions, while for cross-border targets they are fairly equal. Finally, in panel B we see that the total average CARs are higher for cross boarder acquisitions, which goes in line with the previous findings of (Dranev et al., 2019; Mccarthy & Aalbers, 2016). Dranev et al. (2019) reports that cross-boarder acquisitions in developed countries on average generate 1.58% CAR while domestic acquisitions generate 0.82% CAR. This implies that the hypothesis H7 cannot be rejected, which suggests that the CAR for cross-border acquisitions will be higher than domestic ones.

TABLE 7. CAR REGRESSIONS WITH DUMMY VARIABLES

	Market Model			Fama-French 3 Factor Model		
VARIABLES	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
AI	0.468		0.429	0.301		0.278
	(0.273)		(0.297)	(0.197)		(0.210)
Target Country		-0.515**	-0.490**		-0.308**	-0.292*
		(0.190)	(0.199)		(0.118)	(0.122)
Constant	-0.243	0.225	0.142	-0.230*	0.0533	-0.000145
	(0.319)	(0.404)	(0.437)	(0.286)	(0.332)	(0.348)
Observations	346	346	346	346	346	346
R-squared	0.005	0.008	0.012	0.002	0.003	0.005

Notes: The sample includes 346 acquisitions announced between January 2012 and April 2019 period. The results are provided using market and Fama-French 3 factor models and the event window of [-1;+1] days. This table presents the coefficients, std. errors (in parentheses) of the variables. *AI* is an independent dummy variable, where it equals 1 if the target is specializing in AI and 0 otherwise. *Target country* is a dummy variable where it equals to 1 if the target is located in US and 0 otherwise. The dependent variable is CAR. *Model 1* uses only AI variable; *Model 2* uses only Target Country variable; *Model 3* uses both variables. Superscripts *** , ** , and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. *Source:* Author’s calculations.

Finally, to examine the coefficients and the siginificance level of the variables I run the OLS regressions with [-1;+1] event window clustered at the firm level. The dependant variable is CAR and the AI and target country are used as independent variables. Target country is a dummy variable where it has value of 1 if the target firm is located in US and 0 otherwise. The results are presented in Table 7. Model 1, which uses only AI as independent variable was already presented earlier in Table 3 when analyzing the impact of AI with different event windows. Model 2 shows the effect of the location of acquisition target. The variable is negative in MRAR and FF3F models and it is significant at 5% level. When running the regression with both variables in model 3, target country variable is stil significant at 5% level with MRAR model while significance level is at 10% with FF3F model. Despite that, a negative effect can still be seen when the acquisition made is domestic in comparison to a cross-border one.

When comparing to the previous results, Mccarthy & Aalbers (2016) observe postive and significant coeficient at 5% level for international acquisitions. They analyze patent amount of financial companies compared to expectations before the acquisitions and observe a coefficient of 4.12. This suggests that cross-boarder acquisitions generate 4.12 more patents than domestic acquisitions above the expection line if no acquisitions were made, which goes in line with the results observed in this paper.

Moreover, the insignificance for AI could have been influenced by the size of the sample, which was relatively small. In the case of artificial intelligence, there are only few companies that invest huge amounts of money into AI companies, therefore it requires more information in order to test the full effect of AI influence in M&A activities. The problems that event studies face is that the test statistic applied is rather sensitive to outliers. Therefore, the interpretation of significance is quite problematic (Mcwilliams & Siegel, 1997).

Nevertheless, the hypothesis H3, which implies the acquirers' stock returns after announcements of acquisitions of AI targets' will outperform non-AI targets' acquisitions in the short term, cannot be rejected. Even though the coefficient is not significant the returns for AI acquisitions are higher and therefore have positive coefficient. This assumption also holds for almost all the different company returns when they are compared separately.

5. Conclusions and suggestions

In this paper I examined how the fact that target company is specializing in AI affect acquirer's stock price returns after an M&A and the different factors that have been found to have influence in preceding M&A research. I used a sample of giant USA firms', which tend to invest in AI companies quite often, M&A activities during the period from September 2012 to April 2019. The main conclusion of the paper is that AI target companies generate higher but insignificant CAR after an acquisition in the short term than non-AI targets. The insignificance could have been affected by the outlier cases in the sample, which was relatively small due to the lack of firms dominating in AI industry. Therefore, it requires more research.

The results also suggest that hypotheses H1, H3, H6, H7 cannot be rejected. This indicates that the CAR difference between AI and non-AI target acquisitions has been slightly increasing in the past few years although this cannot be applied for the whole period of the sample. Moreover, the returns in the short term are on average positive after M&A activity with AI target firm. Although to my knowledge there has been no research previously done on AI acquisitions, other technological acquisitions have been analyzed. In consonance with those results, I similarly find positive returns after AI acquisitions, which are also a part of technological industry.

In addition, domestic acquisitions have been found to have negative coefficient, which is mostly significant at 5% level. This portends that cross-border acquisitions generate higher returns than domestic ones and goes in line with some of the previously done research on M&A activities. The results also show that AI target has greater positive effect on acquisitions that are domestic. Implying that non-AI and domestic target acquisitions on average produce the lowest and negative CAR.

The results of the paper create a relatively new field for research that is yet to be fully tested since little analysis has been previously done about M&A of AI companies. For that reason, this paper sets the foundation for the topic, which could possibly be broadened even more and suggests that AI has positive effect on the reaction of stockholders. Moreover, due to the relatively low amount of AI acquisitions that has been used in the sample I cannot make distinct conclusions based on the results from the empirical analysis.

To further research this topic, a larger sample could be used including the companies that have made some AI acquisitions but are not dominant in the field. I also included only US acquiring companies but the effects in other countries could be analyzed as well. This could include European and Chinese companies, which are also investing huge amounts of money into AI. Moreover, with a bigger sample AI targets could be scrutinized even more. For example, the developed and emerging market effects could be analyzed, public and private targets could be divided to see the different influence on the returns. Furthermore, acquirers could be divided into separate groups as well related to size of the company and the country they are located in.

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