Master's Program: Banking and Finance

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"Measuring the effects of the fluency of company names and tickers on the stock returns"

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Abstract:

Previous research in behavioral finance field shows that the fluency effect exists. In my thesis, I determine whether name and ticker fluency affect stock returns in any way. I find that stocks with fluent names and tickers do not yield higher abnormal returns relative to nonfluent stocks. I show that neither the name, nor the ticker fluency effect influences the stock returns significantly in the long run. Moreover, I show that after controlling for a large vector of company characteristics, as well as firm and time effects, the joint influence of name and ticker fluency on stock returns is statistically not significant. The presented results imply that investors are not able to exploit the fluency effect on stock returns. Furthermore, using event study analysis, I determine that a change of a company ticker to a more fluent one affects both the biggest and medium-sized companies' stock abnormal returns positively in the short and the long run, leading to significant outperformance compared with the stocks that lowered their fluency levels when Carhart Four Factors and several firm and event characteristics are controlled for.

JEL classification: G12, G14, G41.

Keywords: Fluency; Investor recognition; Company names; Company tickers; Stock returns.

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Contents

1. Introduction

Throughout this thesis, I seek to answer the question if the companies with more fluent names and tickers outperform firms with less fluent names and tickers in the long run. I do that by analysing the panel data of monthly returns for the U.S. companies in years 1980-2021. It is an element of novelty with regard to the original setup, because until now, researchers (Green and Jame, 2013; Montone et al., 2021) have covered data until December 2008. I also expand on the fluency measure created by Green and Jame (2013) by adding the ticker fluency to the original fluency model. My thesis is the first to assess the ticker fluency using an objective, mathematical model instead of survey methods that make it impossible to include huge numbers of companies in the analysis, and are prone to several biases (Gilbert and Malone, 1995; Olson, 2006). This expansion allows to combine two major channels through which the fluency may affect the stock returns. I determine that the name and ticker fluency are not significant stock returns predictors and that they do not affect the stock returns in the long run. Neither a name, nor a ticker fluency is a significant stock returns determinant as a standalone variable. Additionally, if measured jointly, they also do not influence the stock returns when a vector of companies' characteristics as well as firm and year effects are controlled for. On the other hand, even though fluency is not a significant stock returns predictor, the effect of a change in ticker fluency is significant in both short and long run. The Cumulative Average Abnormal Return analysis of the stock returns shows that a change of a ticker to a more fluent one as well as an action of a ticker change when the fluency level is maintained both generate higher abnormal returns in the short run when compared with lowering the ticker fluency. In the short run, the fluency change effect is pronounced mainly among the companies with the highest market valuation. Through the long run analysis of Average Buy and Hold Abnormal Return, I determine that a change of a ticker symbol, when the fluency level is increased or maintained, is associated with higher abnormal returns in the year following the event than the action of lowering the ticker fluency. The magnitude of the effect is economically large among the biggest and medium-sized companies.

A lot has been written about the influence of the company name fluency on the stock valuation (Green and Jame, 2013; Chan et al., 2018; Fang and Zhu, 2019), but measuring this effect with regard to stock returns is rather a new topic in the behavioural finance field. Additionally, the literature on the fluency effect of the ticker symbol is even scarcer. The most recent academic papers find that the name fluency effect on the stock returns is positive in the long run, however when it comes to the ticker symbol effect, a scientific consensus is still not reached and especially this channel of influence needs to be explored further. Having already some evidence that the fluency effect may exist in general, some clever executives can try to exploit it and influence the company valuation and stock returns through changing the company name and ticker. The effect of such a change has been measured with regard to valuation and is deemed to be significantly positive.

There are two possible and opposing to each other explanations when it comes to the effect that the fluency may have on the stock returns. In the first setting, the naive investors may believe that the companies with more fluent names and ticker codes have better and more profitable projects, i.e., they are more successful, and consequently it leads to overpricing of their stocks. Consecutively, following Statman et al. (2008), the returns of such stocks are lower in comparison to the stock returns of less fluent stocks. According to the second setting, the fluent companies indeed have better and more profitable projects that yield higher expected payoffs, but since the investors are naive, they seem to neglect this information. Consequently, the stocks of fluent companies become under-priced, which leads to higher returns than in case of the less fluent stocks. Since the effect of the company name fluency on stock returns is positive (Montone et al., 2021), and due to the fact that ticker is an integral part of company identity along with the legal name (Michayluk, 2008), the effect of a change of the ticker to a more fluent one on the stock returns should be positive in the short and the long run when compared with a change of a ticker to a less fluent one. Several papers analyse the influence of a ticker change on abnormal stock returns in general (Kadapakkam and Misra, 2007; Chen et al., 2004), however my thesis is the first to analyse the effect of a change in ticker fluency in both short and long run.

The results of the research are especially useful for the listed companies, portfolio managers, and other investors. The executives of the given companies can use the outcome to adjust their company names and stock tickers in a way they are more fluent in order to affect the performance of the stocks. In case of portfolio managers and investors, the fluency effect may become a useful tool to maximize the portfolio returns.

The paper is organized as follows. Next section presents a brief literature review of papers from the fluency and behavioural finance field. Subsequently, the third section describes the data used in empirical tests and section four specifies the methods which I use to assess whether fluency is a principal factor determining the stock returns. Section five presents the results. Section six concludes the findings.

2. Literature Review

Prices of the stocks are not necessarily an exact reflection of the company value. This statement would have been bold and controversial if it were written half a century ago, however nowadays researchers and investors are well aware that the Efficient Market Hypothesis may not always hold as it would mean that capital markets would not allow investors to earn abnormal returns without accepting abnormal risks (Malkiel, 2003; Jagric et al., 2005). Moreover, the model itself is built on the assumption that the asset prices reflect only the economic fundamentals based on particular company performance, and macroeconomic factors, which define the systematic risk for the number of various companies. Because of that fact, the decades of 1980s and 1990s brought with themselves new pricing models and redefined the determinants of the stock returns creating the pillars of the behavioral finance. The new school of finance suggests that the investors' behavior is not as rational as it was described in the classic models.

The investment process is complex and finding the best possible asset to invest in is generally a perplexing task, especially for the unsophisticated investors. Additionally, the abundancy of listed companies makes it impossible to analyze all the stocks on the market, not mentioning any other financial instruments. Therefore, in order to simplify the decision-making process, people tend to make use of heuristics (Gigerenzer, 1997). Heuristics can be defined as mental shortcuts and generalizations that allow us to solve complicated problems using a rule of thumb. Although they are time efficient, they not always lead to rational solutions as they are often linked with suboptimal outcomes (Tversky and Kahneman, 1973), but also systematic and repeated errors in judgment (Tversky and Kahneman, 1974; Otuteye and Siddiquee, 2015). It leads to a conclusion that the whole decision-making process in terms of investment may be biased.

The recently emerged concept of the "fluency effect" is an example of such a bias that becomes more and more widely popular in the world of finance. The phenomenon is based on several psychological studies, which suggest that people tend to prefer information or stimuli, which are easier to process. Furthermore, easy to understand stimulus is seen as more familiar and likeable, which means that the companies with understandable, short names should be preferred over stocks with complex names (Alter and Oppenheimer, 2006). That would imply that the investors would accept paying the familiarity premium for the fluent stocks and most importantly, that these stocks would offer lower returns. However, according to Montone et al. (2021), stocks with more fluent names yield higher abnormal returns than the stocks with less fluent names. The fluency effect in this case is concentrated among smaller companies.

Moreover, according to Head et al. (2009), the company ticker conveys the information for the investors as well. Consequently, the firms with memorable, i.e., more familiar ticker symbols outperform the overall market in the long run. On the other hand, Durham and Santhanakrishnan (2016) find that the stocks with fluent tickers have lower returns than stocks with nonfluent tickers during periods preceded by high investors' sentiment. Consequently, there is no scientific consensus about the strength and direction of the ticker fluency effect. Therefore, my paper adds to the literature by studying the influence of the fluency effect of both company name and the ticker symbol on the stock returns in the long run. I determine if these effects exist, but also whether they cohabit or whether one of them prevails over the second. Taking into consideration all the mentioned papers on the fluency measure, I expect the combined fluency effect on the stock returns to be jointly significant, positive and persistent in the long run despite the mixed results and lack of scientific consensus when it comes to the direction of influence of the ticker symbol. Therefore, my first hypothesis is that:

H1: The companies with more fluent names and tickers outperform the companies with less fluent names and ticker codes.

Fluency effect recently receives more and more attention not only among researchers, but also among private business owners. Over the last decade, thousands of companies updated their well-established logos and completely changed the brand design in order to achieve the simplicity (Favier et al., 2019). The oversimplification process becomes more and more widely popular also in terms of company legal names and tickers. That is why, every year several firms update their legal names and tickers and in fact make themselves more fluent. Wheeler (2017) mentions numerous examples of such a change in order to just simplify the name and make it "easier to remember, pronounce and spell". Moreover, Francis et al. (2002) find that the companies during the expansion process, tend to localize their names, i.e., change these names, so they are more understandable both phonetically and semantically on the new market. This phenomenon leads to a crucial question whether the mentioned change affects the company perception among the investors. If so, how does it influence the stock returns in the short and the long run?

The effect of the change has been tested several times on the company name level with regard to the valuation (Bosch and Hirschey, 1989; Karpoff and Rankine, 1994; Asyngier, 2018). Generally, these academics find that name change affects the company valuation positively, however Karpoff and Rankine (1994) point out that the influence is rather weak and highly dependent on the sample selection. Furthermore, Agnihotri and Bhattacharya (2017) touch on the influence of the name change with regard to stock returns and find a positive short run effect. However, they employ only the market adjusted event study methodology, while there are numerous publications suggesting that the size and value of the company should be controlled for, when measuring the fluency effect, as it may be strong only among small-cap firms. Moreover, their research is limited to only Indian stock market, which is still emerging and consequently, different rules may apply, especially in comparison to well-established and significantly bigger U.S. stock market. Therefore, there is still a gap in literature, when it comes to measuring the effect of the company legal name change on the stock returns in both the short and the long run.

Moreover, the literature on the effect of the ticker change on stock performance is even scarcer. Kadapakkam and Misra (2007) find that the ticker change effect exists in the short run and affects negatively both the prices and the trading volume, but they do not control the sample in terms of fluency. Moreover, they use the market model and do not control for the firm size, the value and momentum in their research. Additionally, only the short run effect is taken into consideration by these authors and this kind of approach may lead to a biased conclusion. It is crucial to measure both the short and the long run effect in order to prevent the situation, when the increased awareness in the short run is the principal driver of abnormal stock returns (Chen et al., 2004). Therefore, my thesis adds to the literature by determining if the change of a ticker fluency affects the stock returns in both the short and the long run when all Carhart Four Factors, i.e., market risk premium, company size and value and momentum are controlled for. Consequently, the second and the third hypotheses are:

H2: The effect of a change of the company ticker to a more fluent one on its returns is positive in the short run compared with a change of a ticker to a less fluent one.

H3: The effect of a change of the company ticker to a more fluent one on its returns is positive in the long run compared with a change of a ticker to a less fluent one.

3. Data

As for the fact that my research constitutes of two separate tests, two separate data subsamples will be utilized. In the first part of the research, I update the data set of U.S. companies from Green and Jame (2013), which initially covered the period from 1980 to 2008 for all common stocks in CRSP. Therefore, I analyze the same set of the companies, but over the extended period, i.e. I analyze all the monthly observations from January 1980 to December 2021. I use CRSP database to obtain the stock exchange related variables and Compustat fundamentals to retrieve the accounting variables (i.e., Book-To-Market ratio). The initial sample constitutes of 14,926 different companies and 2,388,797 firm-months observations. The companies for which not even one observation could have been retrieved due to the lack of data on CRSP and Compustat are removed from the sample. The final sample for this part consists of 14,888 companies and 2,122,737 firm-month observations. Table 1 summarizes the selection of companies.

	Firms	**Firm-months**
Number of firms/ firm-months	14,926	2,388,797
Firms/ firm-months lost due to unavailable financial data	4	113,384
Number of firms/ firm-months with partial or complete financial data	14,922	2,275,413
Firms/ firm-months lost due to partially incomplete financial data	34	152,676
Number of firms/firm-months in a sample	14,888	2,122,737

Table 1. Selection of firms and firm-months

When analysing the data, I begin with expanding company names abbreviations. For example, “Cognizant Tech Solutions Corp.” is changed to “Cognizant Technology Solutions Corp.”. Sometimes the abbreviation may sound ambiguous, i.e., “Tech” may mean “Technology”, but as well it may stand for “Technical”, and “Info” may stand for “information services” instead of just “information” as in case of “Fidelity National Info”. Therefore, I obtain all the company names directly from the SEC Edgar system to be sure that I use the true legal name for each firm.

The second subset of data consists of companies listed on American Stock Exchange, (i.e., it contains NASDAQ, NYSE, and AMEX firms) that changed their ticker symbols after 2000. The data is downloaded from Capital IQ database and the limit regarding the starting time of the analyzed period is caused by the dataset limitations for ticker changes event study. I begin with excluding duplicates and the observations that happened too late to allow performing long run analysis, therefore, I exclude all companies that changed their credentials after May 2021. Thereafter, I continue with excluding American Depositary Receipts (ADRs), American Depositary Shares (ADSs), Exchange Traded Funds (ETFs), Real Estate Investment Trusts (REITs), warrants and corporation notes from the subsample. Consequently, I exclude the observations with incomplete financial and/or sentiment data. The data regarding stock returns is downloaded from the FactSet database. The financial data is downloaded from CRSP and Compustat Capital IQ. The data regarding investor sentiment index is retrieved from official Jeffrey Wurgler's website.[1] Finally, I download the data regarding the Fama and French Three Factor measures and Carhart momentum factor measures directly from Kenneth R. French website.[2] After collecting all the data and calculating the abnormal returns for all the companies, I exclude the outliers that differ significantly from other observations in the sample. Therefore, I truncate the sample at the 0.5^{th} and 99.5^{th} percentile. The final sample of events that are analyzed in this part of my research consists of 876 companies. Table 2 summarizes the selection process.

	Firms
Number of firms that changed their ticker symbols in 2000-2021	1,564
Number of duplicates and observations that happened after April 2021	447
Number of unique ticker changes in the analysed period	1,117
Firms lost due to incomplete financial and/or sentiment data	232
Firms with complete data	885
Companies lost due to exclusion of the outliers (truncation)	9
Number of firms in the final sample	876

Table 2: Selection of firms for the event study

Table 3 presents the breakdown of the sample of the analyzed events with regard to the occurrence time.

[1] https://pages.stern.nyu.edu/~jwurgler/
[2] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Year	Number of Events	Share	Cumulative
2001-2005	188	21.46%	21.46%
2006-2010	407	46.46%	67.92%
2011-2015	194	22.15%	90.07%
2016-2020	87	9.93%	100.00%
Total	876	100.00%	

Table 3: Event study sample descriptive statistics

The majority (67.92%) of the events that are analyzed in my thesis, occurred in the first half of the sample period. The low number of observations in the last period is due to excluding observations with missing sentiment data, which is unavailable after December 2018.

4. Methodology

In my research, I expand on the fluency measure constructed by Green and Jame (2013). The fluency model they propose measures the fluency of the company name along three principal dimensions, i.e., a given firm receives scores in three categories, which are: length, Englishness, and dictionary. These categories are defined as follows.

The length score is particularly linked with the number of words constituting the legal company name. Shorter words are generally easier to process, therefore they receive higher score in the given model. However, before assigning the final length score to particular company, the dataset needs further clearing, due to the fact that usually there are some parts of the full legal name that are excluded from name under which the company is known or is referred about on a daily basis. The adjustment is done following the original model. Therefore, I exclude expressions like “Co.” “Corp.” “Holding”, “Inc.”, “LTD” and “LLC” if they are the last word constituting the firm name. Conjunctions like “&,” “and,” “or” are also excluded from the name as well as the states of incorporation in a way that “Signature Bank/NY” becomes just “Signature Bank”, and “Clorox CO/DE” becomes “Clorox”. Furthermore, hyphens, dots, commas, quote marks and brackets are excluded from the name. After the adjustments, the companies are given from 0 to 2 points in the length category. The companies with names consisting of one word, i.e., “Apple” or “Tesla” receive the maximum number of two points as the length score. The companies with names consisting of two words like “Goldman Sachs” or “Ralph Lauren” are given one point and all other firms with names consisting of more than two words, i.e., “Bank of New York Melon” or “Fidelity National Information Services” receive zero out of two points in this category.

Next two dimensions of the fluency measure are linked to the ease of pronunciation. In this case, survey methods may lead to biased conclusions due to the fact that the names of the blue-chip companies, to which the investors are constantly exposed on a daily basis, may seem easier to pronounce, even though they may be in fact more difficult to mentally process. Therefore, in order to prevent this bias, I use the text-based scores to evaluate Englishness and dictionary measure.

The Englishness score is based on the linguistic algorithm developed by Travers and Olivier (1978). In order to determine the Englishness score, I check the frequency with which each 3-letter string (i.e., F (L_1, L_2, L_3)) constituting the company name appears in the English language. The frequency is checked using data available in The Corpus of Contemporary American English. This dataset is composed of more than one billion words from 485,202 texts from 1990 to 2019. Green and Jame (2013) use the dataset spanning from 1990 to 2010, therefore I update the sample against which the Englishness is evaluated. Due to the correlation between the Englishness of a word and its length, the score will be regressed on the length of the analyzed word. Moreover, due to the fact, that one highly non-English expression may significantly reduce the overall ease of pronunciation of the company name, I focus on the least fluent word in each name. After obtaining the scores, the companies are ranked based on their Englishness score. Those in the bottom quintile receive zero points and all the rest receive one point in this category.

The last of the classical measures of fluency is a dictionary score. According to Green and Jame (2013), if the word can be found in the English dictionary, it seems more familiar and is more easily recognizable than the words entirely created by the companies. Following this logic, "American Airlines" should be more fluent stimulus than a made-up name as for example "Amcor." Therefore, in order to assign the dictionary score to the company, I use the online spell check[3] on all the words constituting the listed firms' names. If all the words can be found in the dictionary, the company name is given one point as a dictionary score, zero otherwise. Therefore, the final fluency score for the company name ranges from 0 to 4.

Table 4 presents the summary statistics for the fluency measure and its components. The mean score is 1.06 for length, 0.34 for dictionary, 0.86 for Englishness, and 2.27 for the overall name fluency measure.

Variable	**Number of Observations**	**Mean**	**Standard Deviation**	**Min**	**Max**
Name Fluency	2,122,737	2.27	0.83	0	4
Length	2,122,737	1.06	0.61	0	2
Dictionary	2,122,737	0.34	0.47	0	1
Englishness	2,122,737	0.86	0.35	0	1

Table 4: Summary statistics of name fluency

Table 5 presents the distribution of the name fluency scores across companies.

[3] https://design215.com/toolbox/spellcheck.php

Variable	Scores	Frequency	Percent	Cumulative
Name Fluency	0	46,157	2.17	2.17
	1	311,156	14.66	16.83
	2	850,133	40.05	56.88
	3	849,510	40.02	96.90
	4	65,781	3.10	100.00
Length	0	331,944	15.64	15.64
	1	1,327,572	62.54	78.18
	2	463,221	21.82	100.00
Dictionary	0	1,396,195	65.77	65.77
	1	726,542	34.23	100.00
Englishness	0	299,003	14.09	14.09
	1	1,823,734	85.91	100.00

Table 5: Distribution of name fluency scores across companies

The categories that are the least frequently observed are those with extreme name fluency scores, i.e., zero (46,157) and four (65,781). The score that is the most frequently observed is two (850,133), followed by three (849,510) and one (311,156).

Moreover, as I expand on this measure, my fluency score takes into consideration not only the legal name of the company, but also its ticker. According to Xing et al. (2016) the pronounceability and likeability of the stock ticker symbol is highly and positively correlated with the high Tobin's Q of the company. Therefore, as these companies' valuations are high compared with their book value, a likeable ticker should also be negatively correlated with the stock returns. However, as it is shown by Head et al. (2009), the companies with "clever" tickers are constantly outperforming the market.[4] To measure the fluency of the ticker symbol, I propose including the length, dictionary, and alphabet score to the symbols. They are measured as follows.

Length score for the ticker follows exactly the same logic as the length score for the name, but in case of the ticker length, the symbols that consists of three or less letters (i.e., for example "FB" standing for Meta Platforms or "V" standing for Visa) are assigned one point in this category, and all other companies receive zero points.

[4] According to Head et al. (2009), "clever" tickers are related to company activity in an original and/or witty way. Among the examples of such clever tickers, there are: "GEEK" standing for Internet America, "BEER" standing for Big Rock Brewery or "GRRR" standing for Lion Country Safari.

I measure the ticker dictionary score using the same tool as in case of the company legal name dictionary score. Therefore, I once again use the online spell check tool in order to determine whether the ticker can be found as a word in the English Dictionary, or it cannot be found there. If the code exists in the dictionary, the company receives one point in this category, zero otherwise.

Since some tickers contain less than three characters, i.e., one or two letters, the Englishness score is not applicable in this case, because it is impossible to calculate. Therefore, the ticker Englishness score is not estimated for the companies in the sample.

Simon (1957) pointed out that a person confronted with a wide variety of options is not rational in terms of the decision-making process, therefore an investor confronted with thousands potential opportunities to invest does not choose the best opportunity, but rather the first bearable one. Moreover, according to Xing et al. (2016), 30% of the most likeable tickers start with "A", "B" or "C". Following that logic, I include the alphabet score for the ticker. The companies are sorted alphabetically by the name or the ticker, therefore those with the tickers starting with the first letters of the alphabet should be chosen more often by naive investors. If the ticker starts with "A", "B", "C" or "D", the company is assigned one point in the ticker alphabet score, zero otherwise. Therefore, the final range for fluency score for the ticker symbol is from 0 to 3.

Table 6 presents the summary statistics for the fluency measure and its components. The mean score is 0.4 for length, 0.05 for dictionary, 0.28 for alphabet, and 0.73 for the overall fluency measure. The scores are significantly lower than those observed with relation to company names. The first reason is that the maximum score itself is lower, and the second is that the variables that measure the fluency are different in both cases.

Variable	**Number of Observations**	**Mean**	**Standard Deviation**	**Min**	**Max**
Ticker Fluency	2,122,737	0.73	0.70	0	3
Length	2,122,737	0.40	0.49	0	1
Dictionary	2,122,737	0.05	0.23	0	1
Alphabet	2,122,737	0.28	0.45	0	1

Table 6: Summary statistics of ticker fluency

Table 7 presents the distribution of the ticker fluency scores across companies.

Variable	Scores	Frequency	Percent	Cumulative
Ticker Fluency	0	866,846	40.84	40.84
	1	968,685	45.63	86.47
	2	274,381	12.93	99.40
	3	12,825	0.60	100.00
Length	0	1,268,933	59.78	59.78
	1	853,804	40.22	100.00
Dictionary	0	2,008,019	94.60	94.60
	1	114,718	5.40	100.00
Alphabet	0	1,520,653	71.64	71.64
	1	602,084	28.36	100.00

Table 7: Distribution of ticker fluency scores across companies

The category with the fewest observations is the maximum score, i.e., score three (12,825). The category with the most observations is score one (968,685), followed by scores zero (866,846) and two (274,381).

Furthermore, Table 8 presents the matrix of name and ticker fluency scores in the sample.

		Ticker Fluency				
		0	1	2	3	Total
	0	21,827	20,399	3,682	249	46,157
	1	130,290	142,485	36,906	1,475	311,156
Name Fluency	2	339,535	390,012	115,519	5,067	850,133
	3	356,209	379,539	107,769	5,993	849,510
	4	18,985	36,250	10,505	41	65,781
	Total	866,846	968,685	274,381	12,825	2,122,737

Table 8: Name and ticker fluency scores matrix

The categories that are the least frequently observed are those with extreme name fluency scores, i.e., maximum points in both name and ticker fluency (41) as well as the maximum score in ticker index and minimum score, i.e., zero in name fluency (249). The score that is the most frequently observed is two in name fluency and one in ticker fluency (390,012), followed by combination of three in name fluency and one in ticker fluency (379,539).

In order to determine whether the fluency effect has a significant influence on the stock returns, I perform three separate tests divided in two major groups. First, I build an econometric model for the universe of all the listed companies taken into consideration by Green and Jame (2013). Since the fluency measure may be correlated with several company characteristics, I estimate the Fama-MacBeth regressions from Edmans (2011). The final model which explains the excess stock returns of i-th company at time t ($R_{i,t}$) is presented in Equation 1.

$$R_{i,t} = \beta_1 FN_{i,t-1} + \beta_2 FT_{i,t-1} + \beta_3 X_{i,t} + \varepsilon_{i,t}, \tag{1}$$

where $R_{i,t}$ is the excess return of i-th company in month t; $FN_{i,t-1}$ is the company name fluency score at the beginning of the month; $FT_{i,t-1}$ is the company ticker fluency score at the beginning of the month; $X_{i,t}$ is a vector of firm characteristics from Edmans (2011), and $\varepsilon_{i,t}$ is the error term. The vector of characteristics includes firm size, defined as the log of i-th firm's market capitalization at the end of month t−2; the log of the book-to-market ratio, calculated each July and held constant through the following June; the ratio of dividends in the previous fiscal year to market value at calendar year-end, calculated each July and held constant through the following June; log of cumulative returns over months t−3 through t−2, log of cumulative returns over months t−6 through t−4, and log of cumulative returns over months t−12 through t−7; the log of the USD trading volume of the i-th stock in month t−2; the log of the i-th stock price at the end of month t−2. The summary statistics for the Edmans control variables are presented in detail in Table A in Appendix.

Thus, in order to measure the long run relationship between fluency and stock returns, I estimate Pooled OLS regressions of excess returns controlling for a vector of company characteristics following Edmans (2011). There is a threat of omitted variables, therefore, I also estimate the described model using Fama-MacBeth regressions with Newey-West standard errors, because the Pooled OLS standard errors may be downward-biased (Hoechle, 2007). Due to the fact that Fama-MacBeth standard errors may be also biased if there are firm effects present in the error term, or if there is any form of serial correlation in the sample (Petersen, 2009), I also estimate Two-Way Fixed Effects regressions to measure the tested relation.

Due to the fact that several studies find that the fluency effect may be more pronounced among companies of certain size (Green and Jame, 2013; Montone et al., 2021), and that the fluency biases are significantly larger for smaller and lesser-known firms (Parks and Toth, 2006), I divide my sample of stocks into five market value-based portfolios and run additional regressions separately for all the subsamples. Each period, I divide my sample of analysed companies into five quintiles of stocks, where the first quintile consists of the bottom 20% of firms with regard to market capitalization, and the last quintile (5) denotes the top 20% of the biggest companies. Once again, I estimate Pooled OLS, Fama-MacBeth with Newey-West standard errors and Two-Way Fixed Effects with cluster on company and year regressions.

The second part of the empirical research consists of two event studies, through which I determine whether changing the ticker of the company causes a change in the abnormal returns of the company in the short and the long run. It is crucial to perform two separate tests, because the change in the short run may be interpreted as the immediate market response to the increase of the fluency of a ticker. Then, in the short run, a given company should observe an increase in price depicted by abnormal returns of its stocks in the first few days after changing the firm's credentials. With the long-run test I seek to determine if the changing effect really pays off. In other words, I examine whether the ticker change permanently increases stock returns or whether it only causes price spike in the short run and consequently the abnormal stock return decrease in the long run. Both event studies are based on the Fama and French Three Factor Model extended with the momentum factor implemented by Carhart (1997), because in this case, the analysed companies are diverse in size and value, so there is necessity to adjust for these characteristics of the firms. Additionally, the momentum factor accounts for winners and losers in terms of stock returns. Moreover, this model should lead to more reliable conclusions than the event study based on the Capital Asset Pricing Model (CAPM).

Fama and French (1993) identify three market factors that determine the stock returns. These are: overall market factor and two other factors related to the company characteristics, which are company size and book-to-market ratio respectively. Carhart (1997) finds that the momentum factor is also a significant stock return determinant, and therefore, I include this factor in my final model that is presented in Equation 2.

$$E(R_{i,t}) - R_{f,t} = \alpha_i + \beta_{1i} MKT_t + \beta_{2i} SMB_t + \beta_{3i} HML_t + \beta_{4i} MOM_t + \varepsilon_{i,t}, \qquad (2)$$

where α_i is firm specific intercept; *MKT* is defined as the overall market factor, computed as a difference between the stock market return and risk free rate; *SMB* is Small Minus Big factor, which is defined as the size effect computed as the return spread between small and large stocks; *HML* is High Minus Low factor, which is defined as the value effect computed as the return spread between cheap and expensive stocks in terms of book-to-market ratio; *MOM* is the Momentum Factor from Carhart (1997), which is computed as the return spread between the stocks that increased in value in the previous twelve months to the analysed year and the stocks that decreased in value over the same period ; $\varepsilon_{i,t}$ is the error term.

The short run event study is a Cumulative Average Abnormal Return (CAAR) analysis. I begin with creating the estimation window of 252 trading days prior to all event windows for each stock in order to determine the intercept and factor loadings for all observations. The specific timeframe is used there due to the fact, that on average there are 252 trading days in a year. I continue with creating a 7-day long event window, i.e. I compare the actual stock returns with the expected returns for the days -3, -2, -1, 0, 1, 2, 3 where 0 denotes the day when the event takes time. NYSE and NASDAQ are relatively efficient stock exchanges, and the information is absorbed quickly there, however not as quickly as in case of the companies constituting S&P500 index. Therefore, there is no need to control for a wide date range (i.e., for example -10, +10 days) as in case of the emerging markets. On the other hand, I cannot use 1-day long event window, because not all the analysed companies are blue chips, and the information flow is not immediate there. With the gathered data, I calculate Expected Excess Return for each company ($E(R_i)$) using Carhart Four Factor Model that has been explained above in Equation 2. Afterwards, I compute Abnormal Returns (AR) for each company, using the Equation 3.

$$AR_{i,t} = R_{i,t} - E(R_{i,t}), \tag{3}$$

where $R_{i,t}$ is the actual excess return, and $E(R_{i,t})$ is the expected excess return for each stock computed using Carhart Four Factor Model. Afterwards, I sum up the returns for all the 7 days (full event window) for each stock to obtain the Cumulative Abnormal Returns (CARs) for every observation. To obtain CAR for each company, I use Equation 4.

$$CAR_i(T_1, T_2) = \sum_{t=T_1}^{T_2} AR_{i,t}, \tag{4}$$

Finally, I obtain the Cumulative Average Abnormal Return (CAAR) through summation of all the Cumulative Abnormal Returns (CARs) of all stocks and division of that sum by the number of companies. The process is presented in Equation 5.

$$CAAR = \frac{1}{n}\sum_{0}^{n} CAR_i\,(T_{1,}T_2), \tag{5}$$

Thereafter I check with the t-test presented in Equation 6 if the change of the returns is statistically significant.

$$t = \frac{CAAR}{\sigma_{CAR}/\sqrt{n}}, \tag{6}$$

where σ_{CAR} is standard deviation of Cumulative Abnormal Returns.

For the long run analysis, I use the most popular estimator of the long-run abnormal performance, which is Average Buy and Hold Abnormal Return (ABHAR) event study. I construct the estimation window using the same logic as in case of CAAR event study, however in case of the event window I use a 252-day long period. The principal difference between using Cumulative Abnormal Return (CAR) approach and Buy and Hold Abnormal Return (BHAR) approach is that the first one uses the sum of the returns of the stock in the event window days, while the latter uses multiplication, which is more suitable in the long run event studies. Therefore, to compute BHAR for each company, I compare the actual stocks returns with the expected returns for the investigated period, i.e., 252 days following the ticker change. This process is presented in Equation 7.

$$BHAR_i = \left[\prod_{t=T_1}^{T_2}(1 + R_{i,t}) - 1\right] - \left[\prod_{t=T_1}^{T_2}(1 + E(R_{i,t})) - 1\right], \tag{7}$$

Afterwards I take sum of all the BHARs and divide it by the number of companies to obtain the ABHAR measure as in Equation 8.

$$ABHAR = \frac{1}{n}\sum_{0}^{n} BHAR_i, \tag{8}$$

As in the short run event study, I check if the effect of the ticker change is significantly different than zero in the long run using the t-test presented in Equation 9.

$$t = \frac{ABHAR}{\sigma_{BHAR}/\sqrt{n}}, \tag{9}$$

Using the explained above methodology regarding event studies techniques, I obtain both short run CARs and long run BHARs for all the analysed companies, no matter the changes in their ticker symbol fluency. Afterwards, I run OLS regressions separately on CARs and BHARs in order to determine if a change in the fluency measure affects the abnormal returns observed in both short and the long run. As an additional robustness check, besides the Carhart Four Factors used in the basic setting, I add several firm and event characteristics as control variables. Among the firm characteristics there are: the company industry that is known to affect the firm performance (Hull and Rothenberg, 2008; Adner and Kapoor, 2010), and the stock exchange where the company was listed during the event (i.e., Nasdaq, NYSE and AMEX) to control for the possible differences in returns between the stock exchanges (Loughran, 1993; Goyal et al., 2008). Additionally, to control for the overall market sentiment effect on the stock prices and subsequently on the returns (Baker and Wurgler, 2006), I include the Investor Sentiment Index score during the event date. Moreover, I assign all the events to a five-year timeframe in order to control for varying effects of fluency and control variables. The summary statistics of control variables are presented in detail in Table B in Appendix.

After determining the overall change in ticker fluency effect on abnormal stock returns in the short and the long run, I examine whether it is more pronounced among or confined to companies of particular size. Several researchers including Green and Jame (2013), and Montone et al. (2021) find that the fluency effect is more visible among small companies. Therefore, I divide my sample of 876 companies that changed their tickers into five equally sized market value-based portfolios to determine whether the change in the ticker fluency effect is more noticeable among companies of particular size.

5. Results

In this section, I present my empirical findings on name and ticker fluency effect on stock returns in the long run. Subsequently, I examine the influence of a change in ticker fluency on stock abnormal returns in both short and long run.

5.1. Fluency Effect regression models

In this section, I estimate various regression models of stock returns as a dependent variable. First, I estimate Pooled OLS model. Second, I run Fama-MacBeth model with Newey-West standard errors, and finally the Two-Way Fixed Effects (2FE) with cluster on company and year. In all settings, the models look as follows. In the first model (1), only the name fluency is taken into consideration, in the second model (2), only the ticker fluency is examined and in the last setting (3), both name and ticker fluency are inputs. Due to the fact that the excess stock returns may be correlated with several firm characteristics, a large vector of company characteristics from Edmans (2011) is controlled for. These characteristics are included in every estimated model, but I do not report them, because their influence is not subject to an analysis.

5.1.1. Pooled OLS regression model

The results of the estimated Pooled OLS regressions are presented in Table 9 below. The model accounts for 5.61% of the variance between separate panel units and 0.61% of the variance within the panel units. The overall R-squared measure suggests that the model does not explain a big part of the variability. The reason for the low goodness of fit measure lies in the difficulty of predicting the stock returns at this frequency comparable to quarterly, annual, and longer data horizons (Rossi, 2018). Moreover, it may be also caused by the omitted variables. Nevertheless, the effect within company shows that a change of the firm's return predictors in the sample is not as important as the between effect. The F-test results of 121.33, 121.95, and 110.08 respectively suggest that the explanatory variables in all the models are jointly significant.

Dependent Variable: Excess Return	(1)	(2)	(3)
Name Fluency	-0.0001		-0.0001
	(-0.94)		(-1.03)
Ticker Fluency		0.0001***	0.0001***
		(5.39)	(5.4)
Constant	0.0295***	0.0294***	0.0298***
	(32.62)	(34.98)	(32.69)
Firm Controls	YES	YES	YES
Observations	2,122,737	2,122,737	2,122,737
R-squared	0.001	0.001	0.001

*Table 9: Pooled OLS regression of companies' excess returns (*p<0.10, ** p<0.05, *** p<0.01). The vector of characteristics includes firm size, defined as the log of i-th firm's market capitalization at the end of month t−2; the log of the book-to-market ratio, calculated each July and held constant through the following June; the ratio of dividends in the previous fiscal year to market value at calendar year-end, calculated each July and held constant through the following June; log of cumulative returns over months t−3 through t−2, log of cumulative returns over months t−6 through t−4, and log of cumulative returns over months t−12 through t−7; the log of the USD trading volume of the i-th stock in month t−2; the log of the i-th stock price at the end of month t−2.*

The coefficients of this model indicate that the relation between excess returns and name fluency is not significant at any usual significance level. Therefore, I cannot reject the null hypothesis that the company name fluency does not influence the stock returns. Although, the relation between excess returns and the ticker symbol fluency is positive and significant at 99% confidence level. When the ticker fluency score increases by one, the monthly excess return of a stock increases by 0.01 percent ceteris paribus on the control variables. This result suggests that a stock with more fluent ticker performs better than a stock with a less fluent ticker symbol.

Moreover, the F-test for name and ticker fluency shows that these variables are jointly significant and they positively influence the stock returns. The results of the F-test are presented in the Table 10 below. Therefore, the joint effect of the name and ticker fluency of stock returns is positive. Thus, with this setting, I would be able to reject the null hypothesis that name and ticker fluency are zero at any level of significance commonly used in practice. When the name and ticker fluency both increase by one, the monthly excess return of the stock increases by 0.09 percent ceteris paribus on the control variables. However, due to a threat of omitted variables, the Pooled OLS model may not be trustworthy. Moreover, it should be used in situations when the sample is different in every analysed period (Wooldridge, 2010), while in case of my research, the sample is highly persistent.

F (2; 14,887) = 14.89
Probability > F = 0.0000

Table 10: Joint significance test

5.1.2. Fama – MacBeth regression model

OLS requires independent and identically distributed (i.i.d.) standard errors. Due to the concern that the residuals may be correlated, because of set of omitted variables, I also estimate a model that does not need i.i.d. standard errors. Therefore, to provide pooled time-series coefficient averages from many cross-sections, I estimate Fama-MacBeth regressions. The results of the estimated Fama-MacBeth regressions with Newey-West standard errors are presented in Table 11 below. The Newey-West standard errors allow to avoid problems with spurious regression for non-stationary series, as well as the issues related to heteroscedasticity and residual-dependency. The goodness of fit measure is 0.0274, 0.0279, and 0.0282 respectively. The F-test results of 2.77, 2.72, and 2.52 respectively suggest that the explanatory variables in all the models are jointly significant.

Dependent Variable: Excess Return	**(1)**	**(2)**	**(3)**
Name Fluency	0.0000		0.0000
	(0.18)		(0.17)
Ticker Fluency		0.0000	0.0000
		(0.04)	(0.04)
Constant	0.0256***	0.0257***	0.0256***
	(5.65)	(5.53)	(5.67)
Firm Controls	YES	YES	YES
Observations	2,122,737	2,122,737	2,122,737
Adjusted R-squared	0.0274	0.0279	0.0282

*Table 11: Fama - MacBeth regressions of companies' excess returns (*p<0.10, ** p<0.05, *** p<0.01). The vector of characteristics includes firm size, defined as the log of i-th firm's market capitalization at the end of month t−2; the log of the book-to-market ratio, calculated each July and held constant through the following June; the ratio of dividends in the previous fiscal year to market value at calendar year-end, calculated each July and held constant through the following June; log of cumulative returns over months t−3 through t−2, log of cumulative returns over months t−6 through t−4, and log of cumulative returns over months t−12 through t−7; the log of the USD trading volume of the i-th stock in month t−2; the log of the i-th stock price at the end of month t−2.*

Both name and ticker fluency effects are insignificant at any usual significance level. Therefore, after running separate cross-sectional regressions each month, the ticker fluency effect disappears with regard to Pooled OLS regressions, where it is a significant stock returns predictor. I also run the joint significance test in order to examine the joint effect of name and ticker fluency on stock returns, and as it can be seen in Table 12, the joint effect is also insignificant. The results are in line with Green and Jame (2013), and Montone et al. (2021), who find that the fluency as a standalone variable is not a significant stock returns predictor.

F (2; 493) = 0.01
Probability > F = 0.9856

Table 12: Joint significance test

5.1.3. Fixed Effects regression model

Both name and ticker fluency are highly persistent variables. According to Petersen (2009), this kind of issue may lead to biased standard errors in Fama – MacBeth regressions. Therefore, to solve this potential problem, I also estimate panel regression with firm and year-fixed effects, while clustering for both company and year. The results of such regressions are shown in Table 13.

Dependent Variable: Excess Return	**(1)**	**(2)**	**(3)**
Name Fluency	-0.0001		-0.0001
	(-0.41)		(-0.44)
Ticker Fluency		0.0013	0.0015
		(1.16)	(1.16)
Constant	0.0295***	0.0295***	0.0298***
	(3.46)	(3.34)	(3.48)
Firm Controls	YES	YES	YES
Observations	2,122,737	2,122,737	2,122,737
Adjusted R-squared	0.0010	0.0010	0.0010

*Table 13: Two-Way Fixed Effects regressions of companies' excess returns (*p<0.10, ** p<0.05, *** p<0.01). The vector of characteristics includes firm size, defined as the log of i-th firm's market capitalization at the end of month t−2; the log of the book-to-market ratio, calculated each July and held constant through the following June; the ratio of dividends in the previous fiscal year to market value at calendar year-end, calculated each July and held constant through the following June; log of cumulative returns over months t−3 through t−2, log of cumulative returns over months t−6 through t−4, and log of cumulative returns over months t−12 through t−7; the log of the USD trading volume of the i-th stock in month t−2; the log of the i-th stock price at the end of month t−2.*

The results are quite similar to Fama – MacBeth regressions. Once again, name and ticker fluencies as standalone variables have no significant effect on stock returns. To determine if these are jointly significant, I run the joint significance test, the result of which is shown in Table 14 below.

F (2; 2,122,726) = 0.68
Probability > F = 0.5063

Table 14: Joint significance test

As it is presented in Table 14, the joint effect of name and ticker fluency on stock returns is not significant at any usual significance level. It means that I cannot reject the null hypothesis that says that the name and ticker fluency does not affect the stock returns positively in the long run.

5.2. Additional tests on market value-based portfolios

In order to examine whether the fluency effect is more pronounced among the companies of particular size, I estimate additional regressions on five market value-based portfolios. The numbers above the models indicate the quintile of companies that is analysed in particular setting. Number one (1) stands for the bottom 20% of companies in terms of market value, and number five (5) denotes the top quintile of analysed firms. As in the section 5.1., I estimate Pooled OLS model, then Fama-MacBeth model with Newey-West standard errors, and finally the Two-Way Fixed Effects with cluster on both company and year. The control variables from Edmans (2011) are also included in the models, however I do not report them, because they are not important for the analysis.

Dependent Variable: Excess Return		(1)	(2)	(3)	(4)	(5)
Pooled OLS	Name Fluency	0	0	-0.001**	0	0
		(-0.098)	(0.182)	(-2.047)	(-1.487)	(1.039)
	Ticker Fluency	0.001**	0	0.001	0.001***	0
		(2.198)	(-0.177)	(1.46)	(4.264)	(1.467)
	Constant	0.143***	0.035***	0.024***	0.025***	0.012***
		(24.297)	(3.923)	(2.74)	(3.592)	(5.406)
	R-squared	0.003	0	0.001	0.001	0
Fama-MacBeth	Name Fluency	0.003	0	0	0	0
		(1.135)	(1.038)	(-0.592)	(-1.144)	(0.159)
	Ticker Fluency	0	-0.001*	0	0	0
		(0.103)	(-1.705)	(0.245)	(-0.413)	(-0.665)
	Constant	0.255***	0.045***	0.025*	0.023**	0.013*
		(3.272)	(3.141)	(1.919)	(2.009)	(1.931)
	R-squared	0.062	0.052	0.057	0.054	0.077
Fixed Effects	Name Fluency	0	0	-0.001	0	0
		(-0.092)	(0.106)	(-1.271)	(-0.846)	(0.399)
	Ticker Fluency	0.001	0	0.001	0.001	0
		(1.256)	(-0.084)	(0.541)	(1.262)	(0.324)
	Constant	0.143***	0.035**	0.024*	0.025*	0.012*
		(6.101)	(1.968)	(1.648)	(1.884)	(1.744)
	R-squared	0.003	0	0.001	0.001	0
	Observations	424,555	424,540	424,548	424,547	424,547

Table 15: Regressions of companies' excess returns with size breakdown (p<0.10, ** p<0.05, *** p<0.01). The vector of characteristics includes firm size, defined as the log of i-th firm's market capitalization at the end of month t−2; the log of the book-to-market ratio, calculated each July and held constant through the following June; the ratio of dividends in the previous fiscal year to market value at calendar year-end, calculated each July and held constant through the following June; log of cumulative returns over months t−3 through t−2, log of cumulative returns over months t−6 through t−4, and log of cumulative returns over months t−12 through t−7; the log of the USD trading volume of the i-th stock in month t−2; the log of the i-th stock price at the end of month t−2.*

In the first setting, I analyse the basic Pooled OLS model, which surprisingly indicates that the fluency effect is not related to any specific size of the company. As it is shown in Table 15, the name fluency is a significant and negative stock returns predictor for the medium-sized firms at 95% confidence rate, while the ticker fluency is more visible among the micro-caps and companies that constitute the fourth quintile of the sample, i.e., firms with above-the-average market value. Although the ticker fluency effect is significantly positive at 95% and 99% confidence level respectively, it is not of great magnitude. In both cases, fluent companies' stocks generate 0.1 percent more profit than the nonfluent ones.

With Fama – MacBeth regressions, I estimate that the name fluency is not a significant stock returns predictor as a standalone variable at any usual confidence level. On the other hand, the ticker fluency affects the second quintile below-the-average sized companies' stock returns significantly. In case of this set of regressions, the effect is negative and significant only at 90% confidence interval. The magnitude of the effect is again small, as the analysed stocks with fluent tickers generate 0.1 percent smaller returns monthly in comparison to the nonfluent constituents of a sample.

Finally, I estimate Two-Way Fixed Effects (2FE) regressions with cluster on company and year. Therefore, when the unobserved company-specific and time-specific confounders are controlled for, neither the name, nor the ticker fluency effects are significant when it comes to predicting the stock returns. It means that there is no visible and significant difference in terms of stock returns between fluent and nonfluent companies, no matter the firm market value. Therefore, with this setting, I cannot reject the null hypothesis that the name and ticker fluency affect the companies' stock returns at any usual confidence level. These findings are in line with the existing literature on the fluency effect.

5.3. Results of the short run event study

In this section, I determine whether a company may affect their stock returns in the short run through changing the ticker symbol, and what is the effect that ticker fluency has during this event. Therefore, through a Cumulative Average Abnormal Return event study, I examine what is the effect of a ticker change in general on stock returns in days from -3 to +3 in relation to the event. Second, I use OLS regression model in order to determine whether the fluency effect influences the magnitude of a change while several additional firm and event characteristics are controlled for on top of the Carhart's four factors used in the basic model. Finally, I divide the sample into five market value-based portfolios and run the OLS regressions separately to establish whether the ticker fluency change effect in the short run is more pronounced among a particular group of companies.

5.3.1. Effects of a ticker change on stock returns in the short run

The analysis of the short run effects of the ticker changes shows that the highest observed CAR was 60.64%, while the lowest equalled -66.11%. In terms of the Cumulative Total Return, the highest observed one was 92.73%, while the lowest equalled -89.55%. Mean abnormal returns of the companies for days -3 to +3 are presented on Graph 1.

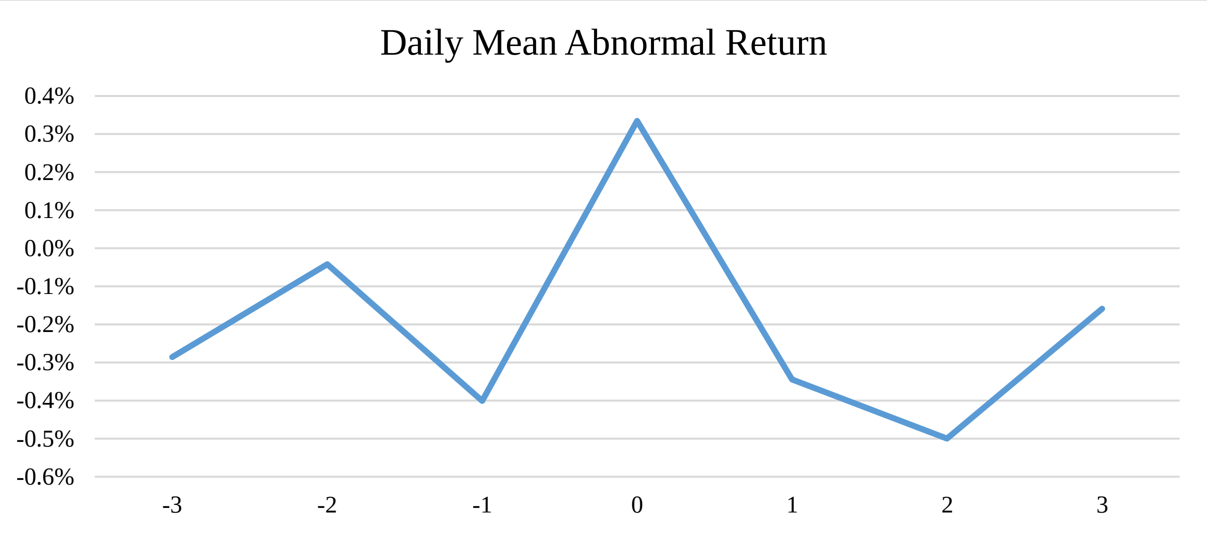

Figure 1: Mean Abnormal Returns on days from -3 to +3

The abnormal returns are positive on day zero, but negative on all the remaining days in the sample (-3, +3). The exact mean abnormal return measures, t-statistic scores and probability measures are presented in Table 16.

Day	Mean Cumulative Abnormal Return	Cross-sectional t-statistic for Abnormal Return	Probability, Cross-sectional t-statistic for Abnormal Return
-3	-0.29%	-1.5955	0.1109
-2	-0.33%	-0.2078	0.8354
-1	-0.73%	-2.0597	0.0397
0	-0.39%	0.8941	0.3715
1	-0.57%	-1.2478	0.2124
2	-1.07%	-2.1417	0.0325
3	-1.2%	-0.6938	0.4879

*Table 16: Statistics for daily Mean Abnormal Returns on days from -3 to +3 (*p<0.10, ** p<0.05, *** p<0.01).*

As it can be seen in the Table 15, the mean abnormal returns are significantly negative on days -1 and +2 at the 95% confidence level. On day -1 preceding the event, the ticker change is associated with 0.73 percent abnormal returns decrease, while on day +2 following the change, it is associated with a stock abnormal return decrease by 1.07 percent. The mean abnormal returns on other days are not significant at any usual confidence level. The final Cumulative Average Abnormal Return (CAAR) analysis results are presented in Table 17.

Cumulative Average Abnormal Return	-0.0131
Standard Deviation	0.1403
Standard Error	0.0047
Cross-sectional t-statistic for Abnormal Return	-2.7807
Probability, Cross-sectional t-statistic for Abnormal Return	0.0055

Table 17: Cumulative Average Abnormal Return (CAAR) analysis

The result of the CAAR analysis is significant at the 99% confidence level, as the t-statistic equals -2.7807 and the p-value is 0.0131. Therefore, I reject the null hypothesis that a change of a company ticker in general does not influence the stock abnormal returns at the 99% confidence level. Therefore, when a company changes its ticker, this action is associated with 1.31 percent decrease of abnormal returns in the short run.

Furthermore, the results of the research may suggest that the investors are sceptical about the company identity change through changing the ticker symbol. Thus, the executives of companies should not be encouraged to perform this manoeuvre, unless they want to decrease the abnormal returns of company’s stocks in the short run. Additionally, the investors should not incorporate the ticker changing instruments in their portfolios.

The obtained results are different from the ones that have been expected. The negative coefficient of the ticker symbol change on the stock returns in the short run can be in fact caused by several factors that have not been taken into consideration in the basic setting. Among these factors there are: several company and event characteristics, as well as a change in the ticker fluency that may influence a change in abnormal returns. Thus, the expansion of the basic model is examined in Section 5.3.2.

5.3.2. Change in ticker fluency regression models

In this section, I examine whether a change in ticker fluency affects the Cumulative Abnormal Returns in the short run. As a robustness check, next to the change in ticker fluency, I include several company and event characteristics such as a stock exchange where particular company was listed, the timeframe when the analysed event occurred, the company's industry according to North American Industry Classification System (NAICS), and Investor Sentiment Data from Jeffrey Wurgler's website. Moreover, several researchers, including Montone et al. (2021) suggest that the fluency effect may be more pronounced among firms with low market capitalization. Therefore, I run an additional test on market value-based portfolios in order to determine, whether the ticker fluency change effect is confined to a certain group of companies. Following the methodology from Section 5.2., the numbers above the models indicate the quintile of companies that is analysed in particular setting. Name "Full" denotes the model where the whole portfolio is analysed, number one (1) stands for the bottom 20% of companies in terms of market value, and number five (5) denotes the model, which takes into consideration only the top quintile of companies. The final models can be seen in Table 18 below.

Dependent Variable: Cumulative Abnormal Return	**Full**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Fluency Increase	0.037**	-0.043	0.080	0.050	0.050**	0.072**
	(2.121)	(-0.904)	(1.352)	(1.155)	(2.393)	(2.074)
No Change in Fluency	0.016	-0.0390	-0.017	0.039	0.015	0.056**
	(1.218)	(-1.137)	(-0.400)	(1.216)	(0.815)	(2.107)
Sentiment	0.014	-0.015	-0.023	0.050	0.021	0.005
	(1.018)	(-0.446)	(-0.579)	(1.429)	(0.784)	(0.235)
Constant	-0.015	0.0720	-0.019	-0.050	-0.098	-0.055
	(-0.145)	(0.877)	(-0.162)	(-0.439)	(-0.783)	(-0.632)
Industry	YES	YES	YES	YES	YES	YES
Stock Exchange	YES	YES	YES	YES	YES	YES
Period	YES	YES	YES	YES	YES	YES
Observations	876	175	175	175	175	176
R-squared	0.048	0.147	0.157	0.134	0.159	0.195

*Table 18: Cumulative Abnormal Returns in the short run event study analysis regression model (*p<0.10, **p<0.05, ***p<0.01). Industry variable denotes the industry of a company according to North American Industry Classification System (NAICS), Stock Exchange denotes the market of listing (Nasdaq, NYSE, AMEX), Period denotes a 5-year period when a company changed its ticker. Fluency Decrease has been omitted, as it is a base scenario captured by a constant.*

As it is shown, a change in ticker fluency significantly affects the abnormal returns in the short run, therefore I can reject the null hypothesis that a change of a ticker to a more fluent one does not affect the stock CAR in the short run at 95% confidence level.

When a company changes its ticker to a more fluent one, this action generates 3.7 percent higher abnormal returns compared with the action of a change to a less fluent ticker symbol. The results are in line with my expectations.

Additionally, the difference between the returns of the companies that increased or at least maintained their ticker fluency level after the ticker change in comparison to the stocks that lowered their ticker fluency varies across the analyzed portfolios. The effect is particularly visible among the biggest companies, i.e., the ones from the fourth and the fifth quintile of the sample. The effect of a ticker fluency increase among the blue chips from the fifth quintile is strong as it is significant at the 95% confidence level. Moreover, the magnitude of the effect is large. A change of a ticker to a more fluent one by a big company is associated with 7.2 percent higher abnormal returns in the short run than changing it to a less fluent ticker symbol. When it comes to the effect of maintaining the ticker fluency level compared to lowering it, it is also significant at 95% confidence level. In this case, the magnitude is also lower, but still high. Keeping the fluency level constant is associated with abnormal returns higher by 5.6 percent compared to the companies that decrease their ticker fluency. Among the big companies excluding blue chips, the ticker fluency change effect is also visible. When a company from the fourth quintile of market value-based portfolios changes its ticker to a more fluent one, this action is associated with a 5.0 percent higher abnormal returns in the short run compared to a change to less fluent ticker symbol. The magnitude is, again, considerable on both statistical and economical level. The largest magnitude of the ticker fluency change effect among the biggest companies in the short run may be caused by the fact that these companies are to most popular, and therefore any change in their symbol is noticed automatically by the wide audience as it is covered by media. Thus, the media coverage and increased exposure may in fact bolster the fluency effect in the short run.

5.4. Results of the long run event study

In this section, I once again examine the effect of a ticker change on stock returns, but this time, I analyse the long run influence. Moreover, I also check the effect of ticker fluency change during this event. Therefore, through an Average Buy and Hold Abnormal Return event study, I examine what is the effect of a ticker change in general on stock returns in the year following the event. Then, I use OLS regression model to decide whether the fluency effect affects the direction and magnitude of a change while several firm and event characteristics are controlled for on top of the Carhart's four factors used in the basic model. Finally, as in the previous sections, I divide the sample into five market capitalization-based portfolios and run the OLS regressions separately for each portfolio to establish whether ticker fluency change effect in the long run is dependent on the size of analysed companies.

5.4.1. Effects of a ticker change on stock returns in the long run

The highest observed BHAR for 252 following the ticker change to a more fluent equalled 290.58% and the lowest is -820.06%. A statistic exceeding 100% decrease of the stock returns is possible to obtain, because the Buy and Hold Abnormal Return measure takes into consideration the abnormal returns and not the actual ones. In terms of the Cumulative Total Return, the highest observed one was 336.54%, while the lowest equalled -98.92%. Mean abnormal returns of the companies for days 0 to +251 are presented on Graph 2.

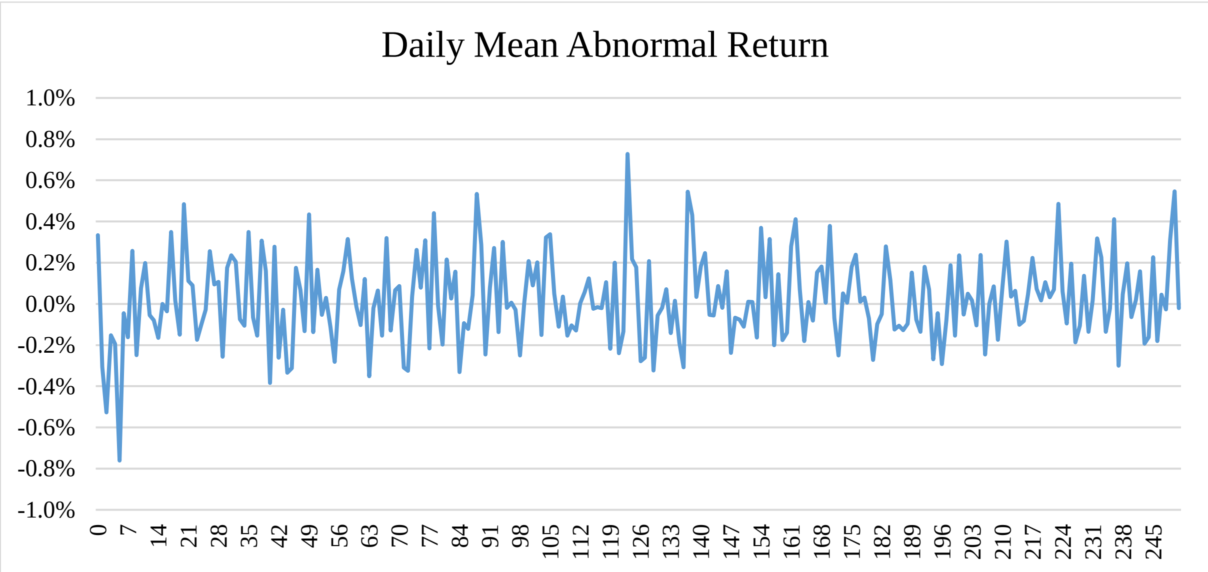

Figure 2: Mean Abnormal Returns on days from 0 to +251

Unlike in the short run event study analysis, in the long run, there is no observable abnormal stock returns pattern on the graph. The final Average Buy and Hold Abnormal Returns (ABHAR) analysis results are presented in Table 19.

Average Buy and Hold Abnormal Return	-0.2641
Standard Deviation	1.0543
Standard Error	0.0352
Cross-sectional t-statistic for Abnormal Return	-7.5000
Probability, Cross-sectional t-statistic for Abnormal Return	0.0000

Table 19: Average Buy and Hold Abnormal Returns (ABHAR) analysis

The result of the ABHAR analysis is significant at the 99% confidence level, which means that a change of a company ticker in general affects the abnormal stock returns of a firm in the long run. Therefore, when a company changes its ticker, this action is associated with 26.41 percent decrease of abnormal returns in the long run. Like in the short run analysis, the effects are different than the ones expected. The reasons for that are exactly the same as the ones mentioned in case of the short run analysis, i.e., the unmeasured company and event characteristics, as well as the effect of the ticker fluency change. Thus, the expansion of the basic model is examined in Section 5.4.2.

5.4.2. Change in ticker fluency regression models

In this section, I examine whether a change in ticker fluency affects the Buy and Hold Abnormal Returns in the long run, i.e., in the year following the event. As a robustness check, exactly as in case of the short run event study that was analysed in Section 5.3., next to the change in ticker fluency, I include several company and event characteristics such as a stock exchange, the year when the analysed event occurred, the company's industry according to North American Industry Classification System, and Investor Sentiment Data from Jeffrey Wurgler's website. Due to the fact that the fluency effect may be more visible among firms with extremely low or high market capitalization, I run an additional test on market value-based portfolios to determine, whether the ticker fluency change effect is observable among certain group of companies. Therefore, as in case of the short run event study analysis, I divide my initial sample of 876 companies into five market value-based portfolios. Following the methodology from Section 5.3., the numbers above the models indicate the quintile of companies that is analysed in particular setting. Name "Full" denotes the model in which I take into consideration the whole sample of companies, number one (1) stands for the bottom 20% of the firms with regard to their market capitalization, and the last model (5) denotes the top quintile. The final model can be seen in Table 20 below.

Dependent Variable: Buy and Hold Abnormal Return	**Full**	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**
Fluency Increase	0.145	-0.368	0.266	0.714**	0.256	0.356*
	(1.165)	(-1.308)	(0.663)	(2.253)	(1.068)	(1.779)
No Change in Fluency	0.143	0.136	-0.209	0.432*	0.016	0.313*
	(1.508)	(0.671)	(-0.703)	(1.829)	(0.091)	(1.785)
Sentiment	0.016	0.113	-0.296	0.115	0.144	0.057
	(0.173)	(0.575)	(-1.094)	(0.451)	(0.785)	(0.292)
Constant	-0.519	0.444	-0.931	-0.211	-0.790	-1.257
	(-0.710)	(0.860)	(-1.134)	(-0.252)	(-0.927)	(-1.533)
Industry	YES	YES	YES	YES	YES	YES
Stock Exchange	YES	YES	YES	YES	YES	YES
Period	YES	YES	YES	YES	YES	YES
Observations	876	175	175	175	175	176
R-squared	0.031	0.193	0.178	0.125	0.234	0.214

*Table 20: Buy and Hold Abnormal Returns in the long run event study analysis regression model (*p<0.10, **p<0.05, ***p<0.01). Industry variable denotes the industry of a company according to North American Industry Classification System (NAICS), Stock Exchange denotes the market of listing (Nasdaq, NYSE, AMEX), Period denotes a 5-year period when a company changed its ticker. Fluency Decrease has been omitted, as it is a base scenario captured by a constant.*

As it can be seen, a positive change in ticker fluency does not significantly affect the abnormal returns in comparison with the stocks that lowered their ticker fluency in the long run when the whole sample is analysed, therefore I cannot reject the null hypothesis that a change of a ticker to a more fluent one does not affect the stock abnormal returns in the long run at any usual confidence level. Moreover, when the ticker fluency level is maintained, it also does not affect the stock abnormal returns in the long run in comparison with the case when the negative change in ticker fluency occurs. The results are different to the ones expected.

However, when I consider the market value-based portfolios, among some groups of companies, there is a significant difference between the abnormal returns generated in the year following the event by the stocks that changed their ticker symbols to more fluent ones or at least maintained their ticker fluency level, and the firms that changed their tickers to less fluent ones. This effect is driven by the biggest and the medium-sized companies in the sample. The effect of fluency is statistically significant at 90% confidence level for the blue chips and at 95% for the medium-sized companies. A change of a ticker to a more fluent one by a blue chip is associated with 35.6 percent higher abnormal returns in the short run than changing it to a less fluent ticker symbol. For the medium entities, the magnitude of the effect is even larger as it equals 71.4 percent. Keeping the fluency level constant is associated with abnormal returns higher by 31.3 percent compared to the stocks that decrease their ticker fluency when the biggest companies are analysed, and 43.2 percent when medium companies are considered. The magnitude of the effect is surprisingly high; however, the annual abnormal returns are analysed in this section. Thus, the obtained result is plausible.

6. Discussion and Conclusion

According to the recent literature, stocks with fluent names and ticker symbols have higher valuations than nonfluent stocks. The name fluency effect on stock returns is also deemed to be positive, which means that fluent stocks outperform those with less fluent names. When it comes to the relation between ticker fluency and stock returns, there is no scientific consensus. In my thesis, I examine whether name and ticker fluency scores are significant determinants of stock returns.

My empirical analysis does not lend support to hypothesis that both name and ticker fluency are significant variables that affect the monthly stock returns in any way. After controlling for a large vector of company characteristics, but also firm and year effects, I find that neither a fluent name nor a ticker symbol influences the companies' stock returns in the long run. Additionally, this result is consistent among the companies of all sizes, i.e., I observe the same effects among all the market value-based portfolios. The results of my research are different to those presented in current literature. However, I analyse the fluency as a standalone variable, and in this case, my findings seem to be in line with the current scientific consensus. The other reasons may lie in lack of persistence of the fluency effect in the previous years. Most of the papers on fluency measure analyse the data until 2008, while I update the sample up to 2021. The limitations of this part of paper lie in the number of control variables that are used. With that being said, the results of the research may differ if more firm characteristics are implemented. The inclusion of all Fama and French Factors is also a possible expansion of the model.

However, even though results of my thesis do not support the idea of the positive effect of fluency, the previous papers and the effect in general may be noticed not only by researchers, but also by clever executives that may want to exploit it in order to increase their companies' stocks returns. Therefore, I determine whether a change of a company ticker symbol pays off in the short and the long run. Through the event study analysis of such a change, I show that a change of a ticker symbol is associated with negative abnormal returns in the short and the long run. In the short run, the stocks that change their tickers generate 1.31 percent lower abnormal returns than they are expected to generate and this effect is significant at 99% confidence level. In the long run, the influence is even more visible as the ticker changers abnormal returns are then 26.41 percent lower than they should be according to Fama and French Three Factors and Momentum measures.

Additionally, even though I find that the ticker fluency effect on stock returns is not significant, a change of a ticker to a more fluent one or at least maintaining the ticker fluency level after a change is associated with significantly different abnormal returns than changing it to a less fluent ticker symbol in the short run. The effect is the most visible among the biggest companies, however it is not confined to only blue chips. Among the biggest companies, a change of a ticker to a more fluent one is associated with 7.2 percent higher abnormal returns compared to a negative change in fluency, while maintaining the fluency level generates 5.6 percent higher abnormal profit compared to events when the ticker fluency is lowered. Among the fourth quintile of the biggest companies, the effect of increasing the ticker fluency is also positive compared with lowering the fluency level, however the magnitude in this case is lower than in case of the influence on the biggest companies' abnormal returns as it equals 5.0 percent in the short run. In the long run, there is also a significant difference in abnormal returns between companies that increased or maintained, and those that lowered their fluency levels. In general, increasing the fluency after a ticker change is associated with higher abnormal returns in the year following the event, when compared with lowering the fluency level. In this case, the effect is driven by the blue chips and medium-sized companies. The lack of a difference in abnormal returns in the long run between the companies that changed their ticker to more fluent ones and those which lowered their fluency levels among the small companies is unexpected in light of the previous findings about the ticker fluency effect in general, however one may find a possible explanation for that. A reason for a ticker change is not taken into consideration in my research. The analysed companies changed their symbols for various reasons including mergers and acquisitions, changing the company values, changing the company name, expanding the brand abroad, being forced to change by legal authorities or by the stock exchange. Unfortunately, measuring this variable is time and cost demanding, due to the fact of requiring a direct contact with several executives and former executives in order to determine a true cause of a ticker change in majority of the analysed cases. Therefore, this control may be used in the further research on the ticker fluency effect or on the ticker change effect in general.

The further research on the name and ticker fluency in general may be directed to expand the measure utility for non-English speaking countries. Such an improvement would allow to compare the fluency effect across different countries and stock exchanges. Moreover, the measure may be also applied in original or a modified version to determine its influence on other financial instruments including cryptocurrencies.

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8. Appendix

Monthly Excess Return				
Percentiles				
	25%	-0,07		
	50%	0,00	Mean	0,01
	75%	0,07	Std. Dev.	0,19
	90%	0,17	Variance	0,03
	95%	0,27	Skewness	7,11
	99%	0,59	Kurtosis	362,15
log of Company Market Value				
Percentiles				
	25%	4,49		
	50%	5,13	Mean	5,20
	75%	5,86	Std. Dev.	0,98
	90%	6,52	Variance	0,97
	95%	6,93	Skewness	0,31
	99%	7,66	Kurtosis	2,85
log of Book-to-Market Value (-2)				
Percentiles				
	25%	-0,49		
	50%	-0,23	Mean	-0,27
	75%	-0,02	Std. Dev.	0,40
	90%	0,17	Variance	0,16
	95%	0,29	Skewness	-0,82
	99%	0,56	Kurtosis	5,74
Dividend Yield (-1)				
Percentiles				
	25%	0,00		
	50%	0,00	Mean	0,03
	75%	0,02	Std. Dev.	1,07
	90%	0,04	Variance	1,14
	95%	0,06	Skewness	208,91
	99%	0,35	Kurtosis	50179,74

Cumulative Returns (-2,-3)

Percentiles			
25%	-0,03		
50%	0,00	Mean	0,00
75%	0,03	Std. Dev.	0,11
90%	0,07	Variance	0,01
95%	0,11	Skewness	4,70
99%	0,23	Kurtosis	127,86

Cumulative Returns (-4,-6)

Percentiles			
25%	-0,05		
50%	0,00	Mean	0,00
75%	0,05	Std. Dev.	0,15
90%	0,10	Variance	0,02
95%	0,15	Skewness	3,29
99%	0,36	Kurtosis	66,93

Cumulative Returns (-7,-12)

Percentiles			
25%	-0,08		
50%	0,00	Mean	0,00
75%	0,08	Std. Dev.	0,24
90%	0,17	Variance	0,06
95%	0,26	Skewness	1,84
99%	0,85	Kurtosis	28,10

log of Trading Volume (-2)

Percentiles			
25%	3,77		
50%	4,62	Mean	4,68
75%	5,53	Std. Dev.	1,30
90%	6,45	Variance	1,70
95%	6,96	Skewness	0,14
99%	7,72	Kurtosis	2,87

log of Stock Price (-2)				
Percentiles				
	25%	0,69		
	50%	1,11	Mean	1,02
	75%	1,43	Std. Dev.	0,58
	90%	1,66	Variance	0,34
	95%	1,80	Skewness	-0,62
	99%	2,13	Kurtosis	4,12

Table A: Edmans control variables summary statistics

Year	Number of Events	Share	Cumulative
2001-2005	188	21.46%	21.46%
2006-2010	407	46.46%	67.92%
2011-2015	194	22.15%	90.07%
2016-2020	87	9.93%	100.00%
Total	876	100.00%	

Type of Exchange	**Number of Events**	**Share**	**Cumulative**
NASDAQ	623	71.12%	71.12%
NYSE	177	20.20%	91.32%
AMEX	76	8.68%	100.00%
Total	876	100.00%	

Change in Fluency	**Number of Events**	**Share**	**Cumulative**
Fluency Increase	128	14.61%	14.61%
No Change	605	69.07%	83.68%
Fluency Decrease	143	16.32%	100.00%
Total	876	100.00%	

Industry	Number of Companies	Share	Cumulative
11- Agriculture, Forestry, Fishing and Hunting	2	0.23	0.23
21- Mining	32	3.65	3.88
22- Utilities	10	1.14	5.02
23- Contruction	9	1.03	6.05
31- Manufacturing	20	2.28	8.33
32- Manufacturing	129	14.73	23.06
33- Manufacturing	172	19.63	42.69
42- Wholesale Trade	24	2.74	45.43
44- Retail Trade	11	1.26	46.69
45- Retail Trade	16	1.83	48.52
48- Transportation and Warehousing	23	2.63	51.14
49- Transportation and Warehousing	2	0.23	51.37
51- Information	126	14.38	65.75
52- Finance and Insurance	157	17.92	83.68
53- Real Estate Rental and Leasing	29	3.31	86.99
54- Professional, Scientific and Technical Services	43	4.91	91.89
56- Administrative and Support and Waste Management and Remediation Services	14	1.60	93.49
61- Educational Services	4	0.46	93.95
62- Health Care and Social Assistance	13	1.48	95.43
71- Arts, Entertainment and Recreation	5	0.57	96.00
72- Accommodiation and Food Services	14	1.60	97.60
81- Other Services (except Public Administration)	4	0.46	98.06
99- Nonclassifiable Establishments	17	1.94	100.00
Total	876	100.00%	

Table B: Event study control variables summary statistics