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Does company name matter?

Evidence from Finnish stock market

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Abstract

Multiple studies both from psychology and from finance suggest that investors in equity markets tend to favor fluent and familiar names when choosing companies to invest in. This study provides novel information on the role of company names in the Finnish stock market. Studying the data collected from the stocks listed in NASDAQ OMX Helsinki between 2010 and 2020, I find positive correlations between company name Finnishness, stock turnover and firm valuation. Cross-sectional panel regression shows that companies with more Finnish names have higher stock turnover and are traded at premiums in comparison to companies with not so Finnish names. The results show clear similarities to earlier research made elsewhere and further validates the results of previous studies. The results are significant and robust with alternative regressions too.

Keywords company name, domestic holding ratio, trading volume, firm value

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1. Introduction

1.1. Hypothesis

In this thesis I am going to study the relationship between company name fluency, investor recognition and stock characteristics in the Finnish stock market. My main hypothesis is that Finnish investors in Finland favour stocks with Finnish or Finnish-sounding names since they sound more familiar and fluent to Finnish-speaking investors. Thus, I assume that the stocks with more fluent names have a larger breadth of domestic ownership than the stocks with non-fluent names. I too presume that more fluent stocks have higher trading volumes and turnovers, and because of this they should have better market-to-book ratios and thus be more valuable (Fong et al., 2017).

My hypothesis is based on a wide selection of research conducted earlier, but for the most part it relies on a research conducted by T. Clifton Green and Russel Jame (2013). Motivated by their research and results, I will in my thesis find out whether their results and hypothesis hold in the Finnish stock market too. The methods I will use will for the most part be replicated from the original study, as well as the data features.

However, instead of rating company names based on their fluency like done in the original study, I rate them based on how Finnish they are. Since most of the investors operating in the Finnish equity market are from Finland (Euroclear, 2020), and most Finns speak Finnish as their native language (Statistics Finland, 2020), it can be concluded that most investors in the Finnish stock market are Finnish-speaking. Thus, for Finnish-speaking investors most familiar and relatable names are either completely Finnish – such as *Kone* – or at least Finnish-sounding. With this setting in mind, in my research I concentrate to find out whether Finnish investors native in Finnish favour stocks with Finnish or Finnish-sounding names and does this possible favouritism affect the market the same way Green and Jame (2013) find fluency affecting.

1.2. Literature review and motivation behind the thesis

We all know that name matters; we tend to predefine things based on their names. This is well acknowledged in societies, and research from psychology also supports the claim. For example, in their study Harari and McDavid (1973) suggest that teachers evaluate children's performances

based on stereotyped perceptions of their first names. The results were parallel in the research made by Rao and Monroe (1989) where they empirically prove, that consumers asses familiar names together with better quality. So, we evaluate people and decide which products to pay partly based on their names. However, research has shown that this name-bias also applies to the investment decisions we made. In the early 2000s, so called "dotcom" effect was discovered affecting stock returns; companies that changed their names to include ".com" experienced significant increases in stock prices and trading volumes (Lee, 2001). So, it seems fair to say that company name matters when choosing between stocks to invest in.

Several studies conducted in stock markets all over the world indicate too that investors are favouring familiar and relatable names in their investment decisions. According to the study conducted by French and Poterba (1991), investors favour domestic assets, and the same applies to mutual fund managers (Coval & Moskowitz, 2001). In addition, it is shown that investors overweight stocks that they are familiar with and are related to their nonfinancial income (Massa & Simonov, 2006). Since these kinds of results are discovered all over the globe, it seems highly unlikely that these biases in investment decisions are driven by local factors.

The relationship between the company name and stock details is also studied by Green and Jame (2013). In their research conducted in the American stock market they studied whether company name fluency can be linked to its breadth of ownership, trading volumes and firm value. The results of the research were significantly positive, so at least in English-speaking markets investors do make their decisions based in part on the company name fluency.

2. Data and formatting

2.1. Data sample

The main sample consists of all the stocks traded in the main list of the NASDAQ (OMX) Helsinki between January 1st 2010 and December 31st 2019. I choose not to include stocks listed in the First North Growth Market because they do not need to fulfil certain accounting standards and thus would compromise the comparability of the companies used in the research (Financial Supervisory Authority, 2020). However, those companies that were first listed in the First North and later made it to the main list are naturally included after their main listing. All the stocks with less than one year

of stock price data are not included in the data sample because of the lack of data and the risk of compromising comparability.

The list of the companies is formed by following the closing prices of the companies in the NASDAQ Helsinki between 2010 and 2020 at intervals of six months. The closing prices are observed through the online service upheld by Kauppalehti, Finnish newspaper focused on economic phenomena. In their database, all the companies in the main list of the exchange are listed with their Finnish names. Based on these closing price listings I form the initial list of companies used in the research. Companies' current and previous names together with possible changing dates are obtained from the Finnish Trade Register uphold by the Finnish Patent and Registration Office. Company names are recorded precisely as they are registered in Finnish and possible parallel and auxiliary names are ignored.

I take all the financial data of the companies apart from their foreign ownership ratios from the database of Thomson Reuters Eikon. Like in the research made by Green and Jame (2013) daily stock-level data – for example stock prices – is stated at monthly intervals. Company level data – for example book value of equity – is stated at fiscal quarterly intervals since with accounting data it is the closest option available to monthly intervals. Foreign ownership ratios are recorded 2010 onwards by Euroclear Finland. The final sample with all the modifications consists of 149 companies, 188 unique company names and 14870 company-month observation points.

2.2. Data adaptation

Since company-level data and stock-level data are recorded at different intervals, I must extend the fundamental company-level data to match with the monthly stock-level data. In order to do so, I expand the quarterly reported fundamental data to cover every month of a fiscal year. Because every fiscal quarter at least in theory represents three months preceding it, I simply copy the fundamentals reported at the end of every quarter to act as fundamentals for preceding months too. For instance, every January and February has the same fundamentals as the following March.

Some Finnish firms are listed with two separate share series. Since the research uses accounting data from companies' balance sheets, and both these series use the same data, I decide to include only one stock series per company. Otherwise these two stocks of the same company with one name

would form double observations. This could possibly cause unwanted multiplier effects in the final modelling section of the research. Although leaving dual listings out of the regression may skew the final results of the study, I find the skewing effect less severe than possible multiplying effect of the dual listings. After all, only 7% of listings are left out, and most of the dual listings in the market are relatively short-lived.

For many companies, both company-level and stock-level data can be found well before their IPOs and long after their exits from the market. To avoid this extra data affecting the results, I eliminate all the data recorded outside the stocks' trading period. As a baseline I use the recorded price data. For example if a stock is traded and price data exists between January 1st 2010 and December 31st 2015 but the company has outstanding stock numbers recorded after this, I simply delete all the existing data recorded after the last observed price point.

3. Measuring name Finnishness and class division

3.1. Measuring the Finnishness of company names

To measure the Finnishness of company names, I use a model that divides company names into six classes based on how Finnish a name is. Classes are labelled with numbers from 1 to 6, first class being the least Finnish and sixth the most Finnish, respectively. The model consists of seven parts: First and second part test if a word in a name is Finnish and next four parts detect possible ungrammaticalities from a name. The seventh part's function is to evaluate abbreviations in names. The whole model with an example rating can be found in Appendix A.

Since there are no clear way to measure how Finnish a word is, I decide to develop a measurement model of my own. The model rests in its entirety on Finnish vocabulary, grammar and research conducted in the areas of lexicology, phonology and morphology. Before evaluating Finnishness of the company names, I remove all the parts of the names that exist only because of the legislation. In the sample this includes single letters mandatory in distinguishing different stock series, compulsory 'oyj' abbreviations standing for 'julkinen osakeyhtiö' – or 'public company limited' in English – and its Swedish counterpart 'abp'. However, I do not edit the spelling of the names in any other way.

I start my modelling by checking if a name can be found in the Dictionary of Contemporary Finnish (Kotus, 2020a). The dictionary is published by the Institute for the Languages of Finland[1], which is "a national expert institute specialised in languages" and functions under the auspices of the Finnish Ministry of Education and Culture (Kotus, 2020b). In this part, I give a name points from two to zero based on how many words of the name can be found in the dictionary. If all the names in a word can be found, the name gets two points. If some – but not all – words included in a name can be found, the name gets one point. If none of the words included can be found, the name gets zero points.

Because some of the names come from common Finnish names of people or places, my second criterion is to check similarly as in part one whether words included in the names are Finnish proper nouns. If a word can be found in the dictionaries of place names, forenames or surnames published by Kotus (Kotus, 2020c), the word is deemed to be a common Finnish name. The scoring system is arranged exactly like in part one. If a word is already given points in part one, it is not evaluated again in part two to avoid possible double points.

The third part evaluates whether a name is written according to Finnish grammar and advices of Kotus (Kotus, 2020d). If there are any violations, the name is given -1 point, and zero points if no violations are observed. For example, if a name is lacking hyphen or there are capital letters in the middle of a word, the name is given -1 point. Similar scoring system is applied in fourth part, where I evaluate whether a name complies with the vowel harmony of the Finnish language. In the Finnish language, a word cannot include vowels *a*, *o* and *u* simultaneously with vowels *ä*, *ö*, and *y* (Suomi et. al. 1997). If the rule is violated, the name is given -1 point.

Parts five and six measures the use of consonants in a name. Both parts follow the same scoring system as parts three and four. In part five I evaluate if a name or a word in it ends with a proper consonant. A Finnish word can only end with consonants *t, n, s, r* or *l* and no combinations of consonants are allowed (Hakulinen et al., 2004a). Likewise, part six evaluates whether a name contains impossible combinations of consonants for a Finnish words. Finnish words can only contain certain combinations and certain number of consecutive consonants (Hakulinen et al., 2004b).

[1] In Finnish: Kotimaisten kielten tutkimuskeskus. Later in the text stated and marked in references as 'Kotus'.

Part seven evaluates whether a possible abbreviation used in a name makes sense to a Finnish speaker or not. If an abbreviation is common and can be found either in the Dictionary of Contemporary Finnish or in the list of abbreviations published by Kotus (2020e), it gets zero points, otherwise it is given -1 point. The function of this part is to balance the measuring system so that these abbreviations do not appear as Finnish words in the model.

After every name is evaluated through all seven parts, the points the name has got are summed up. Every name gets a final score between -3 and 2 based on how Finnish a name is, -3 being the least and 2 being the most Finnish. This score I then turn into the final class score. Since the class scores must be positive for the final model to work properly, I add four to each score. Thus, every name gets a final class score between one and six. These class scores act simultaneously as class numbers.

Since a company may have changed its name during the observation period, a company may be included in several classes over time. In these cases, the changing dates for the class scores are the dates company has registered its name change in the Finnish Trade Register.

3.2. Classes and descriptive statistics

Table 1 presents the averages of daily variables reported once a month from the beginning of 2010 to the end of 2019. The data sample includes 149 companies in total. The average company has a stock price of 8.66 euros, market capitalization of 2 billion euros and a domestic holding ratio of 81%. The means of the most variables are significantly larger than their medians. Like Green and Jame, to reduce the effects of outliers on the analysis, I decide to use log-transformations of most of the variables in my upcoming regressions (Green & Jame, 2013).

Table 1. Descriptive Statistics.

The table reports the averages of daily variable statistics reported once a month. The data sample consists 149 stocks traded in the NASDAQ Helsinki between 2010 and 2020. Stocks are divided into six classes based on their Finnishness. *N* marks the number of companies in each class in total over the observation period. *Class 1* is the least Finnish class and *class 6* the most Finnish. Since a company may have changed its name during the observation period, one company may be included in different classes at different times. Therefore, the total number of class participants is larger than the total number of companies. All the

variables, except for domestic ownership ratio, are retrieved from the database of Thomson Reuters Eikon. *Size* is market capitalization and *shareholders* is the reported number of common shareholders. *Domestic ownership ratio* is calculated by subtracting foreign ownership ratio reported by Euroclear Finland from one. *Volatility-%* is the standard deviation of monthly stock returns over the past two 12 months. *Stock turnover-%* is the daily trading volume divided by the total number of shares outstanding. *Tobin's q* is the market value of assets divided by the book value of assets.

Table 1

	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	All
N=	6	17	48	48	12	42	149
Name example	*Kone*	*Stora Enso*	*Altia*	*Bittium*	*Cargotec*	*PKC Group*	
Share price							
Average	8.11	7.16	7.77	7.50	5.45	12.47	8.66
Median	4.93	4.47	5.45	5.82	4.79	8.92	6.20
Standard Deviation	6.58	9.29	7.71	7.30	3.63	10.93	8.76
Size (in millions of euros)							
Average	328	3358	2340	713	1403	3139	2035
Median	182	82	218	162	151	421	208
Standard Deviation	414	10001	6043	1843	2472	6217	5589
Revenue (in millions of euros)							
Average	954	1487	10289	1516	2464	2365	4166
Median	830	94	130	234	111	444	217
Standard Deviation	939	2889	39913	7927	4805	5177	21842
Shareholders (in thousands)							
Average	8.65	54.38	51.49	19.54	23.35	32.35	33.92
Median	9.04	10.41	7.90	8.90	8.63	12.97	9.10
Standard Deviation	3.45	127.81	128.30	52.71	30.89	50.84	86.33
Domestic ownership ratio							
Average	0.80	0.82	0.83	0.84	0.81	0.76	0.81
Median	0.83	0.89	0.92	0.93	0.98	0.86	0.92
Standard Deviation	0.18	0.22	0.20	0.18	0.30	0.24	0.22
Volatility-%							
Average	4.42	4.26	3.80	3.85	3.67	3.51	3.80
Median	3.97	3.62	3.19	3.12	3.11	3.03	3.18
Standard Deviation	2.40	2.86	2.56	3.17	2.27	2.40	2.74
Stock turnover-%							
Average	0.10	0.19	0.15	0.14	0.13	0.24	0.17
Median	0.05	0.04	0.04	0.06	0.04	0.09	0.06
Standard Deviation	0.15	1.94	1.58	0.23	0.19	1.61	1.30

Tobin's q							
Average	4.32	1.65	1.97	1.71	1.70	1.93	1.90
Median	1.75	1.18	1.27	1.51	1.16	1.64	1.42
Standard Deviation	5.03	1.40	2.83	3.72	1.23	1.27	2.80

In the table we can see that company name Finnishness seems to be correlated with certain firm characteristics. Companies with Finnish names tend to have higher stock prices and higher median market values. They also tend to have higher Tobin's q ratios and stock turnovers with smaller return volatilities. However, they seem to have lower domestic ownership ratios. Although nothing can be deduced from this yet, these results implicate that a relationship between a company name and characteristics exists.

4. Research and results of effects of the name Finnishness

4.1. Finnishness and breadth of domestic ownership

In order to investigate the relationship between company name Finnishness and the breadth of domestic ownership of a company stock, I utilize the model developed by Green and Jame in their paper (2013). Like them, I estimate a regression where the dependent variable is the natural log of breadth of the ownership. Since my study concentrates on the Finnish market, I use the number of domestic owners as a measure of breadth of domestic ownership.

The estimated regression is as follows:

$$\log\left(Domestic\ Owners_{i,t}\right) = a_0 + \beta_1 Finnishness_{it} + \beta_2 x_{it} + \varepsilon_{it},$$
$$i = 1, \dots, N; t = 1, \dots, T,$$

where *Finnishness* is a company's class score, x_{it} is a vector of stock and company characteristics and ε_{it} is an error term (Green & Jame, 2013). According to my hypothesis, β_1 should be greater than zero.

Stock and company characteristics included in the model help to explain variation in the breadth of domestic ownership. For example, it can be assumed that companies with larger market capitalization and more stocks available have a larger amount of individual stock owners. Thus, *log(Size)* is included as a variable. *Log(Turnover)* and *1/Price* are included, since a stock's liquidity and availability together with transaction costs affect the holdings of an investor (Falkenstein, 1996).

Variables *log(Book-to-Market Ratio)*, *Momentum*, *log(Volatility)* and *Profitability* are all included too, since it is possible that investors prefer value stocks, momentum stocks and stocks with a greater volatility or better profit (Gompers & Metrick, 2001). (Green & Jame, 2013).

At most parts I follow the model of Green and Jame (2013), but I do some adjustments to the independent control variables. Due to the data limitations caused by the Finnish setting, I must leave some variables out of the model or alter their definitions. For example, advertising costs cannot be observed. Some variables are even irrelevant in Finnish setting. For example, stock exchange dummy can be left out since all the stocks in Finland are traded in the same exchange. Every variable is defined in detail in Appendix B.

Table 2 presents the results of the panel regression, the T-statistics and the robust T-statistics in separate columns.

Table 2. Company name Finnishness and the number of domestic shareholders.

The table below reports the estimates from the time-series panel regression of the natural log of the number of domestic shareholders on company name class score and other company characteristics. The data sample consists of 149 stocks traded in the NASDAQ Helsinki between 2010 and 2020. The first column lists the independent variables used in the regression and the second column their β-coefficients. Third and fourth column report the T-statistics and the robust T-statistics of each variable, respectively. *Domestic owners* is the number of domestic – in this case, Finnish – shareholders. *Class* of a company is defined in section 2 and represents the Finnishness of a company name. *Size* is market capitalization. *Profitability* is EBITDA divided by the book value of assets both reported at the end of a fiscal year. *Turnover* is a stock's daily trading volume divided by the number of shares outstanding. *Momentum* is return on the stock over the past 12 months. *Volatility* is the standard deviation of monthly returns during past six months. R^2 of the regression is reported on the last row.

Table 2 – Log(Domestic owners)

Variable	β	T-Statistic	Robust T-Statistic
Class	-0.018	-3.246	-3.256
Log(Size)	0.457	85.929	96.179
Profitability	-0.104	-16.689	-7.707
Log(Turnover)	0.123	22.439	20.700

Log(Book-to-Market)	0.178	15.824	15.886
Momentum	-0.019	-5.444	-6.507
1/Price	0.106	12.233	14.282
Log(Volatility)	0.041	3.328	2.661
R^2	0.598		

From the table we can see that the coefficient on *Class* variable is negative and statistically significant with *p*-value being less than 0.01. The coefficients of all the other variables too are significant and robust, and the results are in line with the ones discovered by Green and Jame. For example, both *profitability* and *momentum* show negative correlation like in the research made by them. (Green & Jame, 2013).

Since the *Class* variable shows negative correlation with the breadth of domestic ownership, I can discard my original hypothesis of them being positively correlated. Thus, companies with Finnish names do not seem to have larger number of Finnish shareholders than the companies with not so Finnish names, which is consistent with the results found in section 3.2.

4.2. Finnishness and stock turnover

In the previous section, I show that companies with more Finnish names most likely do not attract domestic investors more than companies with not so Finnish names, quite likewise. However, motivated by section 3.2 and the results of Green and Jame (2013), I keep my original hypothesis that the stocks with more Finnish names have higher trading volumes. I test the hypothesis by following the methods of Green and Jame (2013) and estimate a panel regression of the natural log of total turnover on *Class* scores and other firm characteristics similarly as in section 4.1.

The estimated regression is as follows:

$$\log\left(Stock\ Turnover_{i,t}\right) = a_0 + \beta_1 Finnishness_{it} + \beta_2 x_{it} + \varepsilon_{it},$$
$$i = 1, \dots, N; t = 1, \dots, T,$$

where *Finnishness* is a company's class score, x_{it} is a vector of company characteristics and ε_{it} is an error term (Green & Jame, 2013). My hypothesis is that β_1 is greater than zero. Since the reasons to

hold and trade a stock are closely related, I use the same control variables as in section 4.1 (Green & Jame, 2013).

Table 3 presents the results of the panel regression, the T-statistics and the robust T-statistics in separate columns.

Table 3. Company name Finnishness and the stock turnover.

The table below reports the estimates from the time-series panel regression of the natural log of the total turnover of a company on its *Class* score and other characteristics. The data sample consists of 149 stocks traded in the NASDAQ Helsinki between 2010 and 2020. The first column lists the independent variables used in the regression and the second column their β-coefficients. Third and fourth column report the T-statistics and the robust T-statistics of each variable, respectively. *Turnover* is a stock's daily trading volume divided by the number of shares outstanding. *Class* of a company is defined in section 2 and represents the Finnishness of a company name. *Size* is market capitalization. *Profitability* is EBITDA divided by the book value of assets both reported at the end of every fiscal year. *Momentum* is return on the stock over the past 12 months. *Volatility* is the standard deviation of monthly returns during the past six months. R^2 of the regression is reported on the last row.

Table 3 – Log(Turnover)

Variable	β	T-Statistic	Robust T-Statistic
Class score	0.086	8.224	7.995
Log(Size)	0.334	43.192	33.286
Profitability	-0.050	-4.079	-3.971
Log(Book-to-Market)	-0.091	-5.406	-4.345
Momentum	-0.007	-1.125	-1.156
1/Price	0.074	6.934	4.720
Log(Volatility)	0.349	15.659	5.185
R^2	0.169		

From the table we can see that the coefficient on *Class* shows a positive and significant correlation with the stock turnover of a company. Thus, higher *class* score – and better name Finnishness –

seems to predict higher turnover. Based on the T-statistics, the results of most of the coefficients are highly significant and robust. Only the *Momentum* coefficient is neither significant nor robust.

The results of the regression are in line with my original hypothesis and with the statistics reported in section 3.2; companies with more Finnish names have higher trading volumes than companies with not so Finnish names. Thus, investors in Finland seem to prefer stocks with Finnish names in frequent day-to-day trading. This leads to a situation where the stocks of the companies with more Finnish names are more liquid than their not so Finnish counterparts.

4.3. Finnishness and firm value

In this section I investigate whether the positive correlation observed in section 4.2 and improved liquidity among other things have a positive impact on the value of a company. Like in previous sections, I follow the methods established by Green and Jame in their study (2013). I investigate the effects of a name Finnishness on a company value by estimating a panel regression of the natural log of company value on *class* scores and other firm characteristics similarly as in previous sections. The regression is much like the one used by Green and Jame, with some adjustments and simplifications made.

The estimated regression is as follows:

$$\log(Value_{i,t}) = a_0 + \beta_1 Finnishness_{it} + \beta_2 x_{it} + \varepsilon_{it},$$
$$i = 1, \dots, N; t = 1, \dots, T,$$

where *Finnishness* is a company's class score, x_{it} is a vector of company characteristics and ε_{it} is an error term (Green & Jame, 2013). My hypothesis is that β_1 is greater than zero. The hypothesis is mainly motivated by the results shown in section 4.2: Finnishness is associated with higher trading volumes, which means better stock liquidity. In their original study, Green and Jame propose also that name fluency – or name Finnishness in my case – influences stock demand, and "demand curves for stocks are descending" (Green & Jame, 2013).

The company characteristics used in the regression help to explain variation in company values. To control for a company's economic situation and future prospects, I include variables *log(Revenue), Sales growth* and *Profitability*. Since companies with high asset turnovers may have large amounts of intangible assets and thus low book values and high Tobin's q ratios, I include *Asset Turnover* as

a variable. To control for possible agency problems, I include *Leverage* variable. (Green & Jame, 2013).

Table 4 below presents the results of the panel regression, the T-statistics and the robust T-statistics in separate columns.

Table 4. Company name Finnishness and a company value.

The table below reports the estimates from the time-series panel regression of the natural log of *Tobin's q* of a company on its *Class* score and other company characteristics. The data sample consists of 149 stocks traded in the NASDAQ Helsinki between 2010 and 2020. The first column lists the independent variables used in the regression and the second column their β-coefficients. Third and fourth columns report the T-statistics and robust T-statistics of each variable, respectively. *Tobin's q* is the market value of company's assets divided by their replacement cost – or in this case, by their book value. *Class* of a company is defined in section 2 and represents the Finnishness of a company name. *Revenue* is company's revenue reported at the end of every year. *Sales Growth* is the growth in revenue during past 12 months. *Asset Turnover* is a company's total revenue divided by its total assets and *Leverage* its total debt divided by its total assets. R^2 of the regression is reported on the last row.

Table 4 – Log(Tobin's q)

Variable	β	T-Statistic	Robust T-Statistic
Class score	0.040	9.938	9.337
Log(Revenue)	-0.031	-12.604	-8.756
Profitability	0.021	4.308	3.294
Sales Growth	0.000	-0.955	-1.468
Asset Turnover	0.009	2.882	3.359
Leverage	-0.027	-19.091	-29.398
R^2	0.041		

In the table 4 we can see that the correlation coefficient between the *Class* score and *Tobin's q* is positive. Although it is very close to zero, it still is positive, significant and robust. Based on the T-statistics, the results of most other coefficients too are highly significant and robust. Only the *Sales Growth* coefficient is neither significant nor robust.

The results are in line with both my hypothesis and the hypothesis and results from the original study by Green and Jame (2013). Companies with more Finnish names seem to have higher valuations in terms of Tobin's q ratios. Thus, it also seems highly likely that higher trading volumes are behind the difference. Like shown in part 4.2, companies with more Finnish names have better stock liquidity. Since investors prefer stocks with better liquidity, these companies also have higher valuations (Amihud & Mendelson, 1986).

5. Additional analyses and a brief discussion

5.1. Additional analyses with a different *class* variable

To check whether my results are robust, I decide to modify the regressions used in sections 4.1-4.3. I decide the alter my *class* variable, since I find it to be the largest possible flaw in the regressions. To make sure that the results hold with different *class* variables, I turn six name classes used in the regressions into three classes. These classes are labelled as '*Class 1*', *'Class 2*' and *'Class 3'* from least to most Finnish. *Class 1* is formed by combining the former classes 1 and 2, *class 2* by combining classes 3 and 4 and *class 3* by combining classes 5 and 6. Thus, these new classes are larger and contain more volatility in the name Finnishness still maintaining the same classification principles.

Table 5 presents the coefficients of the new *Class* variable. The regressions used are otherwise the same as in section 4, only modification is the *Class* variable. Since I am only interested to see how the coefficients of the *Class* variable are changed in the situation, it is the only variable I report. The whole tables can be found in Appendix C.

Table 5. Class coefficients with a different class division.

The table below reports the *Class* coefficients, the T-statistics and the robust T-statistics calculated for each regression used in sections 4.1-4.3. The first column lists the dependent variables used and thus separates the regressions from each other. Column two reports the coefficients for *Class (new)* variables used to measure the Finnishness of company names in regressions. Original *Class* variable is replaced with a newly formed *Class (new)* variable. Column three and four report the T-statistics and their robust counterparts, respectively.

Table 5

Dependent variable	*Class (new)* β	T-Statistic	Robust T-Statistic
Log(Domestic owners)	-0.052	-4.067	-3.684
Log(Turnover)	0.121	5.194	5.068
Log(Tobin's q)	0.078	8.753	8.803

As we can see in the table 5, the results of the regressions run with newly formed *Class (new)* variables are similar to the original results in terms of the coefficients of the *Class* variable. These results further validate the robustness of the results of the original regressions.

5.2. Brief discussion of results

The results and conclusions stay consistent throughout the paper. The positive relationships between company name Finnishness, a stock turnover and a firm value can be observed already in the descriptive statistics in table 1, and regressions made in sections 4.2 and 4.3 and additional analyses in section 5.1 further reassert these results. Previous research also supports my findings. In my study, I suggest that Finnish investors favour companies with Finnish names in their day-to-day trading partly because they find Finnish names more familiar, relatable and fluent. This improves the liquidity and value of the stocks of these companies.

Although I do not find any positive correlation between company name Finnishness and the breadth of domestic ownership, my original hypothesis in section 4.1 may still not be completely wrong. In regression I measure the number of domestic shareholders by multiplying the total number of common shareholders by the portion of domestic holdings. This measure merely estimates the number of domestic shareholders, since it assumes that every shareholder holds the same number of a company's stocks. This is rarely the case, and thus if measured with the actual numbers of domestic shareholders, the results may be different and consistent with my original hypothesis. Unfortunately, there are no data available to prove this, and I must settle for the results.

I recognize that one possible flaw in my research is the fact that not all Finnish investors are native Finnish speakers. Especially the number of native Swedish speakers in Finland is substantial, over 5% of the total population (Statistics Finland, 2020). This Swedish-speaking minority is also known

to be over-represented in individuals' directly owned stock holdings (Keloharju & Lehtinen, 2015). However, since it is nearly impossible to conclude the true portion of Swedish-speaking Finnish owners of each company, I must settle for the fact that I cannot capture this minor, yet actual, phenomenon.

Another possible flaw of my research is the apparent lack of data. The results of the regressions could be a bit different if I could have used all the variables I wanted to use but was not able to do so. These variables are used in the original research, and I acknowledge that they would have been a significant addition to my research too. However, I do not think these variables would have changed the final conclusions of my thesis.

6. Conclusion

In this bachelor's thesis I researched whether companies with Finnish or Finnish-sounding names have wider breadth of domestic ownership, higher trading volumes and thus higher values. My hypothesis was, that like shown by Green and Jame in their study, companies with higher name fluency – or in my case, Finnishness – have higher levels of shareholders, greater turnovers and thus are traded with premiums compared to companies with less fluent names (Green & Jame, 2013). My findings are mainly consistent with the hypothesis and previous research conducted. I find a positive, significant and robust correlation between company name Finnishness and higher trading volumes. Possibly caused by better turnover and thus better stock liquidity, I also find that companies with higher name Finnishness have better firm values in terms of Tobin's q. The correlation between these two factors is positive, significant and robust.

All in all, I conclude that Finnish investors find Finnish names more familiar, fluent and relatable. Because of this, they trade stocks of the companies with Finnish names more often, which improves the liquidity and firm value of these companies. This conclusion has a practical implication: for companies in the Finnish stock market, Finnish or close-to-Finnish name is better if a company is chasing for higher daily trading volumes and thus better liquidity for their stock. This is an important fact to be aware of for a company that is considering changing its name; choosing a Finnish name may have positive effects in the domestic stock market. However, when assessing practical implications of my results, it is important to keep in mind that explaining factors behind the breadth

of a company's ownership, trading volumes and firm value are ambiguous. Company name seems to be only one of them.

7. Appendices

7.1. Appendix A

Table 6. Measuring system for name Finnishness.

The table illustrates the method I use to evaluate company names' Finnishness. In the first column are listed the criteria I use to measure the Finnishness. Next three columns report the points given with different outcomes of a criterion. For example, if the outcome in criterion no. 5 is 'No', the name gets zero points. In the column far right, we can see an example name, *Metsä Board,* evaluated through the seven criteria. *Total* row in the bottom tells the final score of the name, and *Class* row tells the final class of the name. The final class acts as *Class* variable in the regression models used in sections 4.1-4.3.

Table 6

	Points			**Name example**
Criterium	**Yes**	**Partly**	**No**	*Metsä Board*
1. In the Dictionary of Contemporary Finnish	2	1	0	*1*
2. In some of the name dictionaries	2	1	0	*0*
	Yes		**No**	
3. Violations against writing rules	-1		0	*0*
4. Violations against vowel harmony	-1		0	*0*
5. Irregular consonant(s) in the end of a word	-1		0	*-1*
6. Irregular combination of consonants	-1		0	*-1*
7. Meaningless abbreviation	-1		0	*0*
			Total	**-1**
			Class	**3**

7.2. Appendix B

The appendix defines the independent and dependent variables used in the regression analyses in section 4.1, 4.2 and 4.3. All variables all calculated from January 1st 2010 to December 31st 2019 at monthly intervals. The data used is collected from the database of Thomson Reuters Eikon, except

for the foreign holding ratios, which are from the archives of Euroclear Finland. Most of the variables are defined as in the paper of Green and Jame (2013), but I have made some necessary adjustments.

Variables:

Domestic owners – number of domestic owners. Calculated by multiplying the number of common shareholders reported by the percentage of domestic ownership of shares issued. Domestic ownership of shares issued is calculated based on the statistics reported by Euroclear Finland.

Class – class score of a company name measured in section 2, see Appendix A for further details.

Size – market capitalization of a firm in euros.

Profitability – EBITDA divided by the book value of assets in total, both reported every fiscal quarter.

Turnover – daily traded number of shares divided by the total number of shares outstanding reported every fiscal quarter.

Book-to-Market – book value of assets in total divided by the market value of assets. Book value of debt is used as a market value of debt. Market value of equity is reported daily, book values every fiscal quarter.

Momentum – return on the stock over the past 12 months.

Volatility – standard deviation of monthly returns during past six months.

Revenue – total revenue of a company in euros reported at the end of every fiscal year.

Sales Growth – growth in revenue during past 12 months.

Asset Turnover – total revenue divided by total assets, both reported at the end of every fiscal year.

Leverage – total debt divided by total assets, both reported at the end of every fiscal quarter.

7.3. Appendix C

The tables in this appendix are the regression tables from the regressions used in section 5.1.

Tables 7, 8, 9. Regression tables with a different class division.

The tables below report the β-coefficients, the T-statistics and the robust T-statistics calculated for each regression used in section 5.1. Table headlines state dependent variables used in each regression and thus

separate the regressions from each other, whereas column one lists the independent variables used. Column two reports the β-coefficients for independent variables. Original *Class* variable is replaced with newly formed *Class(new)* variable. Otherwise the formulas used in the regressions are exactly the same as in sections 4.1-4.3. The independent variables and their definitions too are the same, and the descriptions for independent variables used in tables seven, eight and nine can be found attached to tables two, three and four, respectively. R^2 ratios of the regressions are reported on the last row of each table.

Table 7 - Log(Domestic owners)

Variable	β	T-Statistic	Robust T-Statistic
Class (new) score	-0.052	-4.067	-3.684
Log(Size)	0.459	85.831	96.032
Profitability	-0.104	-16.649	-7.777
Log(Turnover)	0.123	22.269	20.496
Log(Book-to-Market)	0.178	15.813	15.825
Momentum	-0.019	-5.461	-6.513
1/Price	0.106	12.269	14.329
Log(Volatility)	0.040	3.257	2.602
R^2	0.598		

Table 8 - Log(Turnover)

Variable	Log(Turnover)	T-Statistic	Robust T-Statistic
Class (new) score	0.121	5.194	5.068
Log(Size)	0.336	43.289	33.237
Profitability	-0.050	-4.112	-4.010
Log(Book-to-Market)	-0.095	-5.630	-4.466
Momentum	-0.007	-1.122	-1.150
1/Price	0.075	6.986	4.757
Log(Volatility)	0.345	15.442	5.199
R^2	0.166		

Table 9 - Log(Tobin's q)

Variable	Log(Tobin's q)	T-Statistic	Robust T-Statistic

Class score	0.078	8.753	8.803
Log(Revenue)	-0.031	-12.693	-8.776
Profitability	0.021	4.325	3.345
Sales Growth	0.000	-1.024	-1.595
Asset Turnover	0.010	2.950	3.437
Leverage	-0.028	-19.465	-29.868
R^2	0.039		

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