The effect of alphabetic bias on turnover in the Finnish settings

Abstract

Alphabetical ordering has been proven to drive market outcomes without fundamental differences in firm characteristics (Jacobs and Hillert, 2013). This novel study measures the effect of alphabetic bias on turnover in NASDAQ OMX Helsinki during 2001-2012. The results, however, turn out to be inconsistent with the existing literature. The first 25% of shares at the top of the alphabetical list experience 25.8% to 38.7% lower turnover rates than shares in the middle. The findings might partly be explained by the omitted variable bias or the impact of outliers, but the statistical significance and the substantially high coefficients imply that some other bias is likely to be stronger than the alphabetic one.

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1 Introduction

1.1 Alphabetic bias

"A name doesn't make a man worse, if the man doesn't make his name worse."
-Finnish saying, author and date unknown.

Unlike this Finnish saying states, a name matters both in good and bad. For example, the study of Harari and McDavid (1973) revealed that teachers have lower expectations towards pupils with unattractive names. These lower expectations translate in the long-run to lower performance of those pupils. This is parallel to the observations by Kumar, Niessen-Ruenzi and Spalt (2012) in the field of finance, where mutual fund inflows are lower, when the fund manager has a female or foreign-sounding name. The name-related expectations do not then apply only to other people but also to potential investments. In the beginning of the 21th century during the technological boom, just changing to a dotcom ending name would lead to abnormal returns (Cooper, Dimitrov and Rau, 2001) and after the bubble burst, deleting the dotcom-suffix created abnormal returns again (Cooper et al., 2005). Also, the present success of Apple and Google might be partly explained through their catchy names (Green and Jame, 2013).

A deeper look into the literature reveals that the initials of a name alone may determine career success. Van Praag and van Praag (2006) claim that "being an A author and thereby often the first author is beneficial for someone's reputation and academic performance". The fact that A is preferred over B is typical affect heuristics (Ang, Chua and Jiang, 2010), which means a shortcut in individual's decision making processes. Thus, in political elections, candidates at the top of the alphabetically ordered ballot paper lists gain more votes (Wood et al., 2011). But even if the list is not alphabetically ordered, it pays off to be at the top (King and Leigh, 2009). There is an unconscious tendency to regard the first as being the best (Carney and Banaji, 2012). Moreover, these strands of literature come from different parts of the world, which suggests that the effects of alphabetical ordering are somewhat universal.

There has been a recent novel study by to examine this alphabetical ordering bias in the stock markets. It reveals that in stock exchanges, NASDAQ, NYSE and AMEX firms with their names and or tickers at the top of the alphabet have a relative advantage towards firms with initials situated at the end, when considering trading volume and costs of trading (Jacobs and

Hillert, 2013). The authors show this 5% to 15% statistically significant relation that is stronger for smaller firms and companies with broader shareholder base through various regression models and using up to 48 years of stock data. These are economically significant results, since higher visibility experienced at the top of the list translates into lower costs of trading. Especially, it is noteworthy that many companies are willing to pay for that extra visibility in form of advertising expenditures (Armstrong and Zhou, 2011), but the name's alphabetical position does this practically for free. However, if alphabetical ordering affects stock's attractiveness in the USA, it raises the question, whether this applies to other stock exchanges as well?

1.2 Research problem

This paper is known to be the first address this question of a stock's alphabetic position and its effect on turnover in the Finnish environment. The hypothesis is stated as follows: stocks with their name at the top of the alphabet have a relative advantage to stocks at the end, when considering share turnover in NASDAQ OMX Helsinki during the years 2001-2012. The issue is not only to look, whether the alphabetic bias exists, but to provide an estimate of its quantity. The question is economically of importance, since the existents of any bias threatens market efficiency.

For testing of the research problem, the study from Jacobs and Hillert (2013) is used as a basis to provide comparable results. The Finnish settings are notably different from the benchmark study's NASDAQ, NYSE and AMEX stock universe due to stock availability. The latter have over 6000 shares available compared to the roughly 130 firms in NASDAQ OMX Helsinki that it is later referred to as HEX. This small amount of companies requires extra care, when treating with outliers and drawing generalized conclusions.

To account for the evidently smaller share count to provide statistically significant results, a daily data of the shares' characteristics for 12 years is collected in 2001-2012 in Datastream. Since daily data tends to have some missing values especially for smaller firms, the data is treated as monthly averages to assure a more balanced panel data set.

The approach will follow model 1 in the study of Jacobs and Hillert (2013) due its feasibility and comparability to other settings. Thus, to provide a quantified estimate of the alphabetic bias the following models are used:

$$\log(TURN)_{it} = \beta_0 + \beta_1 PC_{it} + \beta_2 \log(MV)_{it} + \beta_3 \log(AGE)_{it} + \beta_4 \log(P)_{it} + \beta_5 EXCESS_{it} + \beta_6 BETA_{it} + \beta_7 LEVER_{it} + \beta_8 B2M_{it} + u_{it} \quad (1A)$$

$$\log(TURN) = \beta_0 + \beta_1 p25_{it} + \beta_2 \mathrm{p}50_{it} + \beta_3 p75_{it} + \beta_4 \log(MV)_{it} + \beta_5 \log(AGE)_{it} + \beta_6 \log(P)_{it} + \beta_7 EXCESS_{it} + \beta_8 BETA_{it} + \beta_9 LEVER_{it} + \beta_{10} B2M_{it} + u_{it}, \quad (1B)$$

where u is the error term, i denotes the different shares (i=1,2,…, 130) and t the consecutive months (t=1,2,…,144). The used variables are summarized in the table 1 below.

Table 1. Variable descriptions. This table summarizes the variables used in the main two estimation models above. The abbreviation PC stands for position continuous and p25, p50 and p75 for the different position dummies 25, 50 and 75. The variables are defined more in depth in section 2.

log(TURN)	Logarithmized share turnover.
PC	Relative rank of the stock's name's position in the alphabet in the interval]0,1]
p25	= 1 if the name of the stock is below 25th percentile in the relative ranking
p50	= 1 if the name is between 25-50% in the ranking
p75	= 1 if the name is between 50-75% in the ranking
log(MV)	Logarithmized market value
log(AGE)	Logarithmized firm's age
log(P)	Logarithmized share price
EXCESS	Percentual excess return over the risk-free rate
BETA	Beta of the stock compared to equally weighted market index.
LEVER	Leverage is defined as book debt to market value ratio
B2M	Book to market is defined as book value to market value ratio

The estimation results in rejecting the original hypothesis. There is no evidence of the primacy bias. But the statistically significant results yield that being in the middle pays off as much as 25.8% to 38.7% higher turnover compared to the first fourth of stocks. Because, these findings are contradictory to the similar model 1 of Jacobs and Hillert (2013) and to the existing literature about ordering effects, the model might suffer from an omitted variable bias or the impact of outliers. However, as robust check on these findings shows, results regarding the mid-position stay parallel in the alternative approach as well. Thus, the familiarity bias and the name-letter effect are introduced as possible explanations for the non-existence of the conventional alphabetic ordering bias.

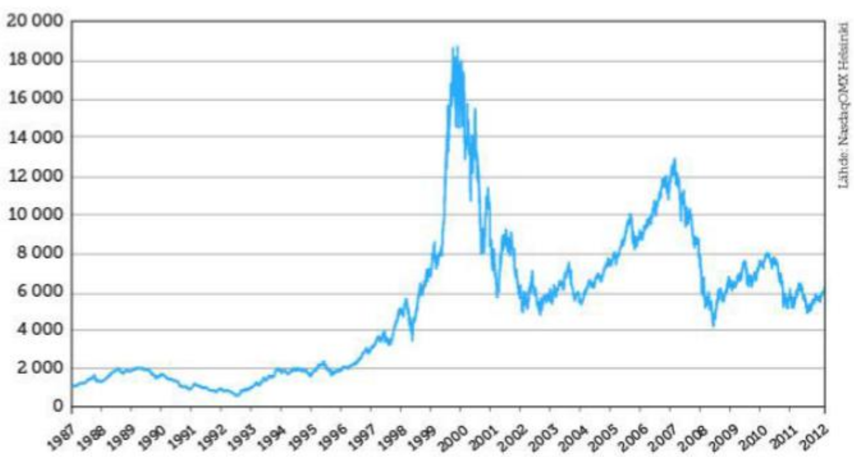
After this quick review to the whole study, the paper proceeds more in depth as follows: gathered information and regressions are covered in the following section, Data & Methods. Then in section 3, an alternative model is provided to check for robustness. After that, the main conclusions are summarized in section 4 with suggestions for further research. Finally, the 5th section, the appendix, is presented to help to redo this study.

2. Data and methods

2.1 Sample data

The data consists of publicly traded stocks listed in the HEX during the time period from the beginning of January 2001 to the end of December 2012. As figure 1 (NASDAQ, 2013a) depicts, the time period can be considered to be a conservative choice, since HEX had just survived the technology bubble and stayed on average at 8000 base points. Of course, the recession hit the stock markets hard in 2008, but the effect was still smaller and it affected the companies on a broader scale than the rise and fall of the technology firms in 1997-2001.

Figure 1: NASDAQ OMX Helsinki's development (NASDAQ, 2013a). Figure 1 illustrates the development of the stock exchange during the time period 1987-2012. The base points of the exchange are shown on the y-axis and the years on the x-axis. The base year is 1912.



Helsinki Stock Exchange has experienced 37 listings during 2001-2012. In this sample only 22 companies are regarded as listed, since firms with demergers are considered to be listed newly only once. For example 30.6.2006, when Orion demerged into two firms, Oriola KD and Orion, the old Orion is treated as existing for the whole time and not as relisted share. This approach is justified, because the variable market value will allow for the change in firm size. However, the name of the old company, Orion, has been around all the time in HEX and stuck in investors' minds'. Then, the four late listings in 2011 and 2012 are discarded due to lack of data. The youngest firm in the sample, Tikkurila, was listed in April of 2010 so that it contributes to the study only one and a half years. On average, the listings happened in the middle of the sample on 17. of September 2005. Limitations are further put on companies that went bankrupt or shares that were delisted before the end of the time period. Two stocks are discarded from the sample due to lack of trading data that was caused by a very low liquidity stock, and finally publicly traded mutual fund, OMX25, was omitted from the sample, since it is a combination of other firms, which makes it hard to define its characteristics and it attracts different investor clienteles than direct stock holdings. The sample firms are comprehensively listed in the appendix.

The key thing in this study was to acknowledge the name changes, where the initial of the firm changed, since the first initial mostly determines the share's alphabetical position. This choice reflects the tickers that often go hand in hand with the first letter of the name. However, one firm name doesn't match the ticker at all. That's why Ålandsbanken is considered as if it was called Alandsbanken so to capture roughly the alphabetic bias both in names and tickers at the same time. Another reason is that the letter å is not used that much in internet and it is often just replaced with an a. This issue arises only once, since Ålandsbanken didn't change name during the time period. In this sample there are then 36 name changes, of which seven firms account for two name changes each. The information about the name changes was collected in company news from NASDAQ's website (2013b). Table 2 summarizes the IPOs and name changes of the sample firms during the time period.

Table 2. Sample events.
Table 2 sums up the IPOs and name changes that happened during the sample's time period. The sample consists of 122 firms that combined trade with 130 stocks, since 9 firms have two stocks each.

	Stocks	Firms
Sample size	130	122
Went public	22	18
Changed name	36	29*
(*7 firms have changed name twice)		

To capture the essence of "alphabetic bias" the firms' (changing) names are used to create a position variable called position continuous that was introduced by Jacobs and Hillert (2013). Firstly, this variable is calculated correspondingly by giving all stocks a ranking from 1 to

130 based on their names' position in the alphabet. Number one is at the top of the list with names starting with the letter A. Secondly, this ranking is divided by the total number of firms to create a relative ranking that takes values between the interval]0,1]. In addition to this continuous variable position dummies are created. They are defined correspondingly to Jacobs and Hillert (2013) as well, but using only three categories: 25%, 50%, 75%. Stocks whose name is located at the first quarter of the alphabetical ranking, position dummy 25, take on the value of one. Accordingly, shares whose names' are between 25th and 50th (50th and 75th) percentile in the ranking give position dummy 50 (75) the value of 1. The last 25% of the ranks serve as a base group. Since these variables are used as monthly factor, the firm name changes during the month, for example on day 15th are considered as if they had happened on the 1st day of that month. This suits the one month lag of the explanatory variables, because the name change contributes always from behind the past.

Since the name is only a part of firm's visibility and potential trading activity, several descriptive variables are introduced. These variables follow the model 1 (Jacobs and Hillert, 2013) with a few modifications. First of all, the logarithmized age is an important factor to see, if new freshly listed companies experience abnormal increase in trading volume or do old firms benefit from their familiarity. It is calculated on monthly bases.

Next, book-to-market ratio and market value are defined likewise following the example of Chordia, Huh and Subrahmanyam (2007), but using logarithmized geometric monthly averages of them. Geometric means capture here, as with other variables, the dependence of the daily values of one another. Market value requires a special mention, since the 10 biggest firms account for 70% of total market capitalization in the sample, which exposes a potential problem with the outliers.

Chordia, Huh and Subrahmanyam (2007) use leverage ratio as the book debt to book assets - ratio as an account based method. To capture the dynamic market based leveraged ratio, it is calculated instead using book debt divided by market capitalization. This creates an imbalance between the yearly accounting data and monthly market value, which is why the previous year's annual book debt was used repeatedly for the following 12 months. For the first year, 2001, the accounting data of the end of fiscal year 2000 is used.

Also the following two return-based variables, beta and excess returns, are calculated with the help of monthly geometric means of returns. Monthly beta is estimated with the approach of Chordia, Huh and Subrahmanyam (2007), but with daily data and equally weighted market portfolio as the market index.

Then, signed stock returns in the model 1 from Jacobs and Hillert (2013) is replaced with alike variable, monthly excess returns over the risk-free rate that is the Finnish Government's five year bullet bond's yield obtained from the website of Suomen Pankki (2013). Firstly, this risk-free rate choice reflects the investment behavior of Finnish investors, since they have been proven to suffer from home bias (Grinblatt and Keloharju, 2001), which might affect not just direct stock holdings, but alternative investment choices as well. Secondly, Finland has rightly maintained the best AAA –credit rating during the 21th century according to Fitch Ratings (2013). Thirdly, the 5 year maturity expresses a moderate investment horizon.

In addition to signed stock returns, Jacobs and Hillert (2013) employ nominal share price as one of the explanatory variables. But as they themselves bring up, it tends to be highly correlated with the logarithmized market value and age. In this sample the price adjusted to company actions has a correlation factor of 0.61 (0.24) with market value (age) and it does not add much explanative power to the regression. Therefore price is omitted from the model 1 here.

These independent variables explain the variability in the dependent variable, share turnover. It is defined by share volume divided by total number of shares and preferred to other turnover measures since it yields the sharpest results (Lo and Wang, 2000). Daily turnovers are again used as monthly geometric averages. The summary of variables is provided in table 1 in the introduction section. All the market and accounting data of these stocks are gathered in Datastream.

2.2 Methods and results

To provide comparable results, the method of choice relies on Jacobs and Hillert (2013) model 1 -approach that consists of Fama and MacBeth (1973) typed predictive OLS estimation regression with Newey and West (1987), heteroskedasticity- and autocorrelation-consistent (HAC) standard errors. The approach is here called model 1 accordingly. This feasible approach is also in line with the trading activity measures suggested by Chordia, Huh and Subrahmanyam (2007).

In total of 17462 observations of firm months are included in this sample, which creates a large enough panel data set to carry out the regression. The model 1 is divided into two parts: A and B. In part A the variable of interest is position continuous, whereas in B the discontinuous position dummies are used in its place. The regression model 1A measures the magnitude between the dependent variable, logarithmized turnover, and position continuous variable, when controlling for logarithmized market value, logarithmized firm age, excess returns, beta, leverage ratio and book-to-market ratio. All the independent variables are lagged by one month. This same regression is repeated by replacing the position continuous with the position dummies to measure the model 1B. Later, some robust checks using alternatives 1A and 1B are provided.

To sum up, the following model 1A depicts to what extend there is a relationship between the position continuous and the logarithmized turnover. The results of the control variables are not of interest, but their coefficients are in line of what one would expect. The correlations between the position variable PC and the control variables are between -0.02 and 0.08, with the largest correlations of 0.08 are found with the logarithmized age and book-to-market ratios. In other words, end-of-the-alphabet named firms tend to be older and have more book value than the ones in the beginning. The regression output of model 1A is shown below in table 3.

The positive coefficient of position continuous in table 3 implies that the alphabetic bias exists as an opposing trend than predicted. It would seem that a firm in the end of the alphabet has as much as 11.1% greater turnover than a firm situated right in the beginning. This result is statistically significant on 5% significance level with a t-value of 2.234. However, the spread on the confidence interval shows us that on the lower limit the position continuous has only a 1.4% effect on turnover. All the control variables provide meaningful coefficients on 1% level of significance, but the direction of logarithmized age is unexpected. One might think that newly listed companies would experience abnormally intense trading after the IPO, because the news focus is on them. This would be especially possible in Helsinki Stock Exchange, since it has not experienced that many IPO's in the 21th century. Now it seems that age has provided firms with long term visibility that can be seen in trading figures. For further discussion, we repeat this same regression model with dummy variables

Table 3. Regression output of model 1A. The output shows the observation count and adjusted r-squared of the regression and the coefficients, standard errors, t- and p-values with confidence intervals for the variables. In model 1A the logarithmized share turnover was regressed on position continuous, logarithmized market value, logarithmized age, excess returns, beta, leverage ratio and book-to-market ratio using the same method as Jacobs and Hillert (2013): predictive Fama and MacBeth (1973) OLS estimation method with heteroskedasticity and autocorrelation-consistent (HAC) Newey and West (1987) standard errors. Thus, turnover is measured on monthly bases, so that all the control variables are lagged by one month. The variable of interest is position continuous which takes values in the interval]0,1] based on the share's name's relative ranking in the alphabet.

Dependent variable:	logarithmized share turnover					
Observations in total:	17462					
Adjusted R-squared:	0.154					
					Confidence interval	
Explanatory variables:	Coefficient	Standard error	t	P>|t|	Lower limit	Upper limit
Position continuous	0.111	0.049	2.234	0.025	0.014	0.207
Logarithmized market value	0.260	0.009	30.268	0.000	0.243	0.276
Logarithmized age	-0.175	0.020	-8.776	0.000	-0.214	-0.136
Excess returns	0.008	0.001	5.842	0.000	0.006	0.011
Beta	0.141	0.014	10.449	0.000	0.115	0.168
Leverage ratio	-0.001	0.000	-3.037	0.002	-0.001	-0.000
Book-to-market ratio	-0.001	0.000	-6.689	0.000	-0.001	-0.001

Model 1B is carried out by replacing position continuous with 3 dummies as explained before. Here, the correlation between the position measures with any of the explanatory variables is between -0.13 and 0.13. The position dummy 25 yields the most extreme negative correlations of -0.13 with logarithmized market value and second biggest -0.13 with logarithmized firm age. The position dummy 50 is, on the contrary, positively as correlated, 0.13, to market value and age. This suggests that at least companies with their names right at the beginning of the alphabet are definitely smaller and younger than those between the 25th and 50th percentiles. The findings are shown in table 4.

Table 4: Main results of regression model 1B. The table summarizes the ranking, coefficients, observation count, standard errors and t- and p-values for the variables of interest, position dummies in the regression of logarithmized share turnover on the control variables: position dummies, logarithmized market value, logarithmized age, excess returns, beta, leverage ratio and book-to-market ratio. The regression follows the approach of Jacobs and Hillert (2013) using predictive Fama and MacBeth (1973) OLS estimation method with heteroskedasticity and autocorrelation-consistent (HAC) Newey and West (1987) standard errors. Thus, turnover is measured on monthly bases, so that all the control variables are lagged by one month. A position dummy takes on value one if the name of the stock belongs on that month to the according ranking group and zero otherwise. The ranking is calculated as the relative ranking of the firm from the beginning of the alphabets.

Dependent variable:	logarithmized share turnover					
Observations in total:	17462					
Adjusted R-squared:	0.168					
Position dummies:	Relative ranking	Observations	Coefficient	Standard error	t	P>|t|
p25	0-25%	4337	-0.076	0.040	-1.894	0.058
p50	25-50%	4366	0.311	0.043	7.209	0.000
p75	50-75%	4406	0.292	0.043	6.788	0.000
p100	75-100%	4353	Base group			

The findings of model 1B are in line with 1A; according to this approach it didn't pay off to be at the top of the alphabet in the Helsinki Stock Exchange during the years 2001 to 2012, since the coefficient of position dummy 25 is negative -0.076. The t-value of p25 is also statistically significant at the 10% level. The somewhat low t-value relates partly to the fact that the coefficient of p25 is not that far from zero. Besides, on this significance level there doesn't seem to be a big difference between the coefficient of the position dummy 25 and the base group, last ranked 25% of names. Therefore, last is not the best either. It seems that placing in the middle contributes best towards turnover, because firms with their names belonging to the position group 25-50% (50-75%) from the top have 31.1% (29.2%) higher turnover than the firms at the last quarter of the alphabet. In other words, compared to the position dummy 25, the position dummy 50 (75) stocks have as much as 38.7% (36.8%) turnover gain. All the other variables than p25, are statistically significant even at 1% level.

There might be several reasons for these findings. First of all, it is to be noticed that the adjusted R-squared is around 0.168, so the model explains little of the total variation in the logarithmized turnover. If more explanatory variables would be included such as analysts and news coverage, as in model 2 and model 3 of Jacobs and Hillert (2013), the adjusted R-squared would probably increase markedly and the results might change. Also, the panel data setting is unbalanced opposite to the benchmark study from Jacobs and Hillert (2013), since some of the firms went public during the time period, which is, why they are lacking the data for the earlier years of the sample. As the newly listed firms are not evenly distributed across the names' position groups, the imbalance affects directly the coefficients of the position variables.

It is noteworthy, that the biggest firms by market value are clearly located in the middle of the alphabet. In addition to the correlation factors, this is proven by the market value means. The highest average of logarithmized market value is found among those firms whose name places to the position dummy 50 group, whereas the lowest with the first ranked 25% of companies. Of the biggest 10 firms in HEX, five (two and three) of them are included in pos50 (pos75 and base group) almost in every sample month. The logarithmized market value's coefficient in table 3 reveals that companies that are 1% larger have 26% higher trading volume, which highlights the importance of size on trading volume. Even though firm size is controlled for, there might still be some unobserved effects that are in non-linear relationship with the firm size. For example, in Nokia's days of glory, there used to be many analytics that were focusing only on its stock. Analysts' recommendations have then a direct influence on a broad scale of investors that ought to be controlled in the regression.

Second unexplained most likely crucial variable is media coverage. This intuitive explanation receives support from an experimental Google hits count. Typing in the names of the five biggest firms by size into web search of Google (2013) discovers that they receive over three times more hits than firms on the positions 11 to 15. Of course this simple search engine test does not reveal, how the hits have changed over time, but it provides some suggestive evidence that media coverage could be an essential omitted variable. Indeed, this could be the case, because investors are more likely to trade shares that have been in the news of late (Barber and Odean, 2008). As the model 3 in the study of Jacobs and Hillert (2013) controls for both analysts' expectations and press coverage, its R-squared is not surprisingly at 0.50 points significantly higher than the R-squared in model 1 presented here.

Yet, another size-related explanation is the search costs that investors encounter (Merton, 1987). Although this is highly more relevant in the U.S, where there are over 6000 stocks available in NASDAQ, NYSE and AMEX universe, the searching of potential shares costs something in Finland as well. Since, older and bigger companies tend to be more well-known, investors start the search by looking among known firms to avoid information costs, as Merton (1987) suggested. If these first options satisfy portfolio's needs, there is no reason for the investors to go through the list of stocks from top to bottom. The following intuitive evidence supports Merton's theory: 8 of the biggest 15 firms in HEX are on the list of most beloved shares among domestic investors (Pörssisäätiö, 2013). Moreover, it has even been proven empirically that familiarity breeds investment particularly in the Finnish environment (Grinblatt and Keloharju, 2001). It may well be that the familiarity bias overruns the alphabetic one considering the findings of this study.

Then again, bigger Finnish firms may be more potential investment opportunities to foreign investors than smaller ones. Foreign investors tend to pursue momentum strategies and trade more than Finnish investors in all horizons in HEX (Grinblatt and Keloharju 2000), which cannot be done with low liquidity stocks. These foreign individuals and institutions play an economically important role in HEX, since they account for 46% of the total share ownership. Thus, controlling for the analysts' forecasts, news reports, familiarity and shareholder base, are interesting topics for further research.

3. Robust checks

3.1 Limited sample data

As described before, model 1 contained all firms that met the data requirements, whereas in this section a more limited alternative model, referred later as alternative 1, is provided. Creating a balanced panel involves discarding all 22 companies that went public during the sample period, since they are lacking information for the earlier years. Furthermore, seven A-shares of companies that have also a B-share available are left out, since the trading of these two shares might be strongly correlated and overemphasize the effect of few firms in the sample. B-shares are here preferred to A-shares, because of their higher trading volume that reflects their characteristics as the speculative stock and not as the voting oriented one. Actually, excluding the double shares for those firms answers partly to the problem of size-related side-effects, since mainly larger firms have listed two stocks. Finally, to treat with the most substantial outlier, Nokia's share is eliminated from the sample. These adjustments in total create a balanced panel data set of 100 firms with 144 monthly observations each.

The variables are defined in alternative 1A and 1B as in models 1A and 1B, but one additional firm characteristic is controlled for: the share price adjusted to company actions. The adjusted price is used as a monthly geometric average. Thus, the alternative 1 is closely equivalent to the original model 1 by Jacobs and Hillert (2013), but applied in HEX and with evidently smaller amount of observations. Here, the relative ranking of position continuous and the position dummies are recalculated to match the smaller amount of firms. In alternative 1B the base group is now the first 25% of companies at the top of the alphabet and position dummy 100 is introduced. It takes the value of 1, when a company's name is placed between percentiles 75 and 100. In the alternative 1B approach, all the position dummies have equal amount of observations, 3600.

The correlations between the position variables and the other independent variables are this time smaller than in model 1, which indicates that the alternative has a less biased basis to explain the variability in turnover. In alternative 1A, position continuous' correlation factor with the other independent variables varies between -0.02 and 0.05. The latter being the correlation with logarithmized age. In the case of position dummies, the most extreme correlations resemble the ones in model 1B. This time the factor of p25 with logarithmized market value is -0.10 and with logarithmized age -0.10. In contrast, p50 is almost like a mirror image with corresponding correlations of 0.11 and 0.07.

The predictive regression (Fama and MacBeth, 1973) of the alternative approach with Newey and West (1987) HAC standard errors equals the regression in model 1A and 1B, but with the slight adjustments to the variables as mentioned before. The dependent variable logarithmized share turnover is regressed on lagged control variables: the position variable(s) logarithmized market value, logarithmized firm age, logarithmized price, excess returns, beta, leverage ratio and book-to-market ratio. The regression output for the variables of interest of alternatives 1A and 1B is provided in table 5.

3.2 Findings and discussion

In table 5 the coefficient of position continuous in alternative 1A is higher than it was before in model 1. Besides, it is statistically more significant at 1% level. However, its directions still opposes the implications of the existing literature, since now it would seem that the lower in the alphabet a firm's name is placed, the more it yields investor recognition in the form of trading activity. All the control variables, in the contrary, had now predicted directions and they were statistically significant on 1% level as well. The adjusted r-squared of alternative 1A is 0.229 that is already close to the model 1 in Jacobs and Hillert (2013).

Table 5: Main results of alternative approaches 1A and 1B. The table shows the coefficients, standard errors, t- and p-values for the position variables in the two different regressions of alternative model 1A on the left side and 1B on the right. In both regressions the logarithmized share turnover was regressed on position variable(s), logarithmized market value, logarithmized age, logarithmized price, excess returns, beta, leverage ratio and book-to-market ratio using the same method as Jacobs and Hillert (2013): predictive Fama and MacBeth (1973) OLS estimation method with heteroskedasticity and autocorrelation-consistent (HAC) Newey and West (1987) standard errors. Thus, turnover is measured on monthly bases, so that all the control variables are lagged by one month. In alternative 1A position continuous takes values in the interval]0,1] according to a stock's name's relative ranking in the alphabet. In 1B the discontinuous position dummy p50 takes the value of one, if the stocks name is between the percentiles 25 and 50. Accordingly position dummy p75 (p100) is given the value of one, when the stocks name is between the percentiles 50 and 75 (75 and 100).

		Coefficient	Standard error	t	P>|t|
1 A	Position continuous	0.146	0.051	2.870	0.004
1 B	p25	Base Group			
1 B	p50	0.258	0.039	6.598	0.000
1 B	p75	0.158	0.039	4.034	0.000
1 B	p100	0.181	0.040	4.517	0.000

When looking at the coefficients of the position dummies in alternative 1B, they reveal enormous differences between the 25th and 100th percentiles against the benchmarked first 25% of names. In particular, the coefficient of p50 is more moderate 25.8% compared to the 38.7% in model 1. However, groups p75 and p100 differ notably from the approach before; the firms between percentiles 50-75 (75-100) have now approximately twice less (more) percentage points than in model 1. Moreover, their places have switched, since here p100's coefficient is at 18.1% higher than the value 15.8% of the coefficient for p75. Without going further into detail, why this switch of places happened, the focus will be on the remarkable difference between the dummy p25 and the rest, and why this difference might exist in spite of the existing literature. All the variables are in 1B statistically significant on 1% level as was in 1A and the adjusted r-squared is 0.242. Next, the implications of alternative 1 are introduced.

As suspected from the correlations, the market values across position dummy groups are still very centered in the middle in alternative 1B. Table 6 below summarizes the differences in means of logarithmized market value. The averages here no longer directly support the claim from model 1B that the alphabetic bias cannot be observed due to an omitted variable bias which is related to the firm size. This is because, the coefficient of p100 increased markedly, when at the same time the whole group average market value dropped by 2.8%, when adjusting for the total drop in the average market value across all groups. In other words, in alternative 1B the p100's coefficient in relation to p25 and the average of logarithmized market values moved into totally different directions, when comparing to model 1B. Still, the non-existence of the alphabetic bias could be explained with one new aspect.

Table 6. Arithmetical averages of logarithmized market value sorted by position dummy groups in alternative 1B compared to the model 1B. In 1B, position dummy p25 (p50) takes the value of one, if the stocks name is between the percentiles 0 and 25 (25 and 50). Accordingly, position dummy p75 (p100) is given the value of one, when the stocks name is between the percentiles 50 and 75 (75 and 100). The averages of market values and the percentual change compared to the corresponding averages in model 1A are shown for each group. In the rightmost column the percentual change is adjusted to the total decrease in average logarithmized market values for all groups. The observations are uniformly distributed across position groups.

	Average of logarithmized market value	Change in % compared to model 1A	Adjusted change in %
p25	4.702	0.452	2.579
p50	5.404	-3.240	-1.191
p75	5.155	-0.416	1.694
p100	4.893	-4.779	-2.762
All groups	5.039	-2.074	0.000

The outcomes of both regressions could be explained to some extent by the name-letter effect. The name-letter effect is known in psychology as people's tendency to like their own names and initials. This unconscious behavior leads to favoring names that resemble their own. For example Nuttin (1987) proved that people picked more likely letters of their own initials rather than other letters from a pool of options in 12 European countries, including Finland.

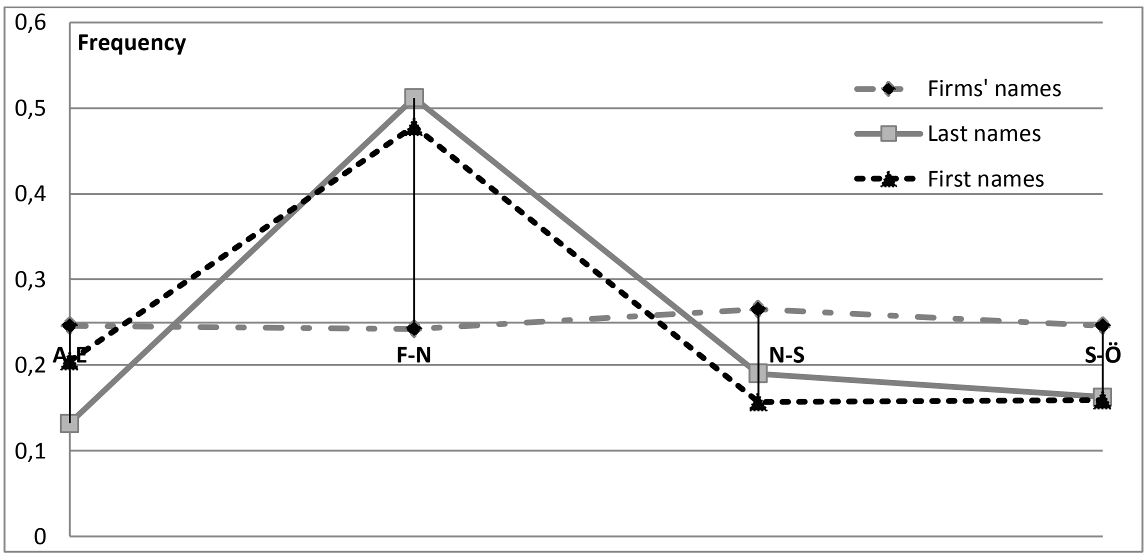
Furthermore, the name-letter has been proven to affect marriage choices (Jones et al., 2004) and choices where to live and work (Pelham, Mirenberg and Jones, 2002). This phenomenon is also relevant in the stock markets, since Knewtson and Sias (2010) found out a relationship with the breadth of ownership and the name-letter frequency in the United States. The findings show a positive correlation with securities that matched people's first or last name initials. Since broader breadth of ownerships means higher liquidity for stocks (Grullon, Kanatas and Weston, 2004), the share turnover could be biasedly affected by the name-letter effect experienced in HEX.

Some intuitive evidence of Finnish name statistics (Väestörekisterikeskus, 2012) supports this claim. They provide insight on, which 1000 most common first and last names center on which letters. Moreover, they account for 82.3% (53.1%) of all the first (last) names in Finland, assuming 2.5 (1) first (last) names per person. Looking at the big picture, there approximately 22% of market capitalization is held by individual Finnish households (Euroclear, 2013). Of these investors we can assume that their names follow on some level the overall name distribution in Finland, although these statistics are a static picture of 30. April 2012, so the possible time variation in the relationship between firms and the people's names is not captured by this graph.

Figure 2 illustrates the distribution of 130 sample stocks' names in model 1A with and people's names in Finland divided to specific name groups. The groups A-E, F-N, N-S and S-Ö roughly follow the name rankings of the position dummies so that each group account for 25% of the names. The name group A-E consists of names beginning with the letters "A,B,C,D and E". Then name group F-N begins with the letter "F" and ends to the last name "Nguyen". Then, group N-S goes on from there and ends with names starting "Sp", such as the firm, Sponda. Finally, the last group "S-Ö" covers the rest of the Finnish alphabet. From figure 2 it can be noted that share's names, the dash-dot line, frequency stays across the near the desired 25%, whereas people's names are distributed unevenly. To be more precise, the dotted line shows the distribution of the first names in Finland, whereas the solid line stands for the frequency of the last names.

This uneven distribution bears some resemblance with the coefficients in model 1B and alternative 1B; the according position dummy to the biggest first and last name group F-N would be p50, which has the highest coefficient of 31.1% (25.6%) in model 1B (alternative 1B). The high percentage of first names is economically meaningful, because the name-letter is found out to be stronger with first names than last names in Finland (Nuttin, 1987). Due to this same reason, not much can be said about the other name groups. Their frequencies stay between 13.2% and 20.5% depending, whether we look at first or last names, but there is no clear distinction how the coefficients of the regression models should be interpreted based on the name-letter effect.

Figure 2: Relative frequency of firms' and people's names illustrated in one chart. The figure illustrates the frequency of firm names and people's names across the following groups: A-E, F-N, N-S and S-Ö. The name group A-E consists of names beginning with the letters "A,B,C,D and E". Then name group F-N begins with the letter "F" and ends approximately to names starting "Ni". Then, group N-S goes on from there and ends with names starting "Sp" Finally, the last group "S-Ö" covers the rest of the Finnish alphabet. The firm names, the dash-dot line, are roughly distributed so that they account for 25% of each group. The dotted line shows the according distribution of the most popular 1000 first names (Väestörekisterikeskus, 2012) in Finland, whereas the solid line stands for the frequency of the most popular 1000 last names. The name statistics consist then of the 130 sample firms and the total of 2000 names in the end of April 2012. The frequencies within each group sum up to 1.



One might argue that the trading volumes and shareholder breadth of the Finnish investors do not always go hand in hand, since the Finns are more of contrarian traders than momentum traders (Grinblatt and Keloharju, 2000) and the individuals proportion is after all only 22% compared, for example, to the impact of the foreign traders 46%. So the name-letter effect maybe cannot be observed for other groups than the biggest F-N. However, further implications of the name-letter effect are beyond the scope of this study.

4. Conclusions

4.1 Recapitulation

Alphabetical ordering effects have been found out to affect people's decision making, when choosing which candidates to vote for in elections (Wood et al., 2011) or which academics to cite (van Praag and van Praag, 2006). Regarding options at the top of the list better than those at the bottom is an unconscious tendency towards primacy (Carney and Banaji, 2012).

Recently, the power of primacy has been discovered to influence the stock markets so that shares at the top of the alphabetically ordered lists experience higher turnover rates than the rest (Jacobs and Hillert, 2013). This novel study tests the implications of model 1 from Jacobs and Hillert (2013) by focusing on the stock exchange, NASDAQ OMX Helsinki, to see, whether the impact of alphabetical ordering is a relevant factor in these totally different settings.

However, the findings of this study do not support the claim that the conventional alphabetic bias would affect stock markets worldwide. The results show a strong negative relation between a share's name positioning to the top of the alphabet and the turnover, when comparing to a position in the middle or even at the bottom of the list. For stocks whose names' relative position is between the 25th and 50th percentiles yield up to almost one third more share turnover than the first 25% at the top of the list. These findings are statistically significant over the 12 years' time period of this study.

The discovery of "middle is best" phenomenon may be impacted by outliers or the omitted variable bias, since the market capitalization is highly concentrated in a few firms and the approach here does not control for other kind of visibility, such as advertising or news coverage. Still, as the results hold in the balanced panel data setting of the robust check, one must consider the possibility that some other bias is stronger than the alphabetic one. Of course, it cannot be ruled out either that some exchange-specific factors in HEX impact the results.

4.2 Further research

The existing literature, combined to the results of this study, provide insight for interesting further research. In the Finnish settings the familiarity bias (Grinblatt and Keloharju, 2001), name-letter effect (Nuttin, 1987) and the shareholder base should be taken into consideration at the same time with the alphabetic bias. Thus, more in detail information could be obtained of the limited attention of individual investors and the proportions of these different effects on share liquidity and returns. It might be the case that so far some of these phenomena have been overlapping one another and affecting the findings. This concern was brought up by this study, as the most Finnish names are centered on those letters that match the most traded shares' names.

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6. Appendix

The appendix provides an alphabetically ordered list of shares in the sample by their name in 2013. Stocks that are underlined are omitted from the alternative 1 in section 3.

AFARAK GROUP
<u>AFFECTO</u>
<u>AHLSTROM</u>
<u>AKTIA 'A'</u>
<u>AKTIA 'R'</u>
<u>ALANDSBANKEN 'A'</u>
ALANDSBANKEN 'B'
<u>ALMA MEDIA</u>
AMER SPORTS 'A'
APETIT
ASPO
ASPOCOMP GROUP
ATRIA 'A'
BASWARE
BIOHIT 'B'
BIOTIE THERAPIES
<u>CAPMAN 'B'</u>
<u>CARGOTEC 'B'</u>
CENCORP
CITYCON
<u>COMPONENTA</u>
COMPTEL
CRAMO
DIGIA
DOVRE GROUP
EFORE
ELECSTER 'A'
ELEKTROBIT
ELISA
EQ
ETTEPLAN
EXEL COMPOSITES
FINNAIR
FINNLINES
FISKARS 'A'
FORTUM
F-SECURE
GLASTON
HKSCAN 'A'
HONKARAKENNE 'B'
HUHTAMAKI
<u>ILKKA 1</u>
ILKKA 2
INCAP
INNOFACTOR
IXONOS
KEMIRA
KESKISUOMALAINEN
<u>KESKO 'A'</u>
KESKO 'B'
KESLA 'A'
KONE 'B'
KONECRANES
LASSILA & TIKANOJA
LEMMINKAINEN
MARIMEKKO
MARTELA 'A'
<u>METSA BOARD 'A'</u>
METSA BOARD 'B'
METSO
NEO INDUSTRIAL 'B'
<u>NESTE OIL</u>
<u>NOKIA</u>
NOKIAN RENKAAT
NORDEA BANK FDR
NORVESTIA
NURMINEN LOGISTICS
OKMETIC
OLVI 'A'
ORAL HAMMASLAAKARIT
<u>ORIOLA-KD 'A'</u>
<u>ORIOLA-KD 'B'</u>
<u>ORION 'A'</u>
ORION 'B'
OUTOKUMPU 'A'
<u>OUTOTEC</u>
PANOSTAJA
PKC GROUP
POHJOIS-KARJALAN KRJ.
POHJOLA PANKKI A
PONSSE
POYRY
<u>QPR SOFTWARE</u>
RAISIO
RAISIO 'K'
RAMIRENT
RAPALA VMC
RAUTARUUKKI 'K'
RAUTE 'A'
REVENIO GROUP
SAGA FURS
SAMPO 'A'
SANOMA
<u>SAV RAHOITUS</u>
SIEVI CAPITAL
SOLTEQ
<u>SOPRANO</u>
SPONDA
<u>SRV YHTIOT</u>
SSH COMMUNICATIONS
<u>STOCKMANN 'A'</u>
STOCKMANN 'B'
STONESOFT
<u>STORA ENSO 'A'</u>
STORA ENSO 'R'
<u>SUOMINEN</u>
TAKOMA
TALENTUM
<u>TALVIVAARA</u>
TECHNOPOLIS
<u>TECNOTREE</u>
TELESTE
<u>TELIASONERA</u>
TIETO OYJ
TIIMARI
<u>TIKKURILA</u>
TRAINERS HOUSE
TULIKIVI 'A'
TURVATIIMI
UPM-KYMMENE
UPONOR
VAAHTO GROUP 'A'
VACON
VAISALA 'A'
WARTSILA
VIKING LINE
WULFF-GROUP
YIT
YLEISELEKTRONIIKKA
<u>ZEELAND</u>