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Language and Decision Making: Board Members and the Investment in the Future

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Abstract. Recent research has shown that the grammatical representation of the future in languages influences how future-oriented an individual behaves in her private life. In this paper, I examine whether this effect of language characteristics on a person's behaviour is also evident in the business world. I test the hypothesis that companies with board members whose native language grammatically separates the present from the future are less future-oriented. I find significant effects of the inflectional marking of the future in one language on the growth rate of a company's intangible assets, which I use as a benchmark for its future orientation.

Keywords: Language Structure, Future Tense, Research and Development Activities

JEL Codes: O10, O30, Z13

There are about 6500 languages worldwide. These languages differ in how they grammatically treat the future. In German it is perfectly fine to say "Es regnet morgen." (It rains tomorrow). In English on the other hand it sounds odd to talk in the present tense about future events. It is more natural to use "will" or "is going to" to mark the future (It will/is going to rain tomorrow.). In German, the present tense can thus be used to talk about the present and the future (weak future-time reference), while English speakers are required to make a distinction between the two (strong future-time reference). In this paper I find that such an difference in how languages grammatically handle the future has an effect on the behaviour of companies. Companies with a majority of board members who speak a language which has an obligatory grammatical distinction between future and present act less future-oriented. These results extend the existing literature

on factors that determine the level of R&D expenditure in companies and thus also help to explain the different long-term trends in productivity in countries.
Recent research by Chen (2013) and Roberts, Winters and Chen (2015) showed that this is not only of interest for linguists but also affects the decision making of individuals. Chen demonstrates in his paper that individuals with a native language with no required distinction between present and future act more future oriented: They save more, retire with more wealth, smoke less, practice safer sex, and are less obese. His findings hold up both across countries and within countries. In this article, I examine whether the native language of an individual and its grammatical identification of the future form also influence the business world and the decisions in it. More precisely, do companies with a management board that consists of members who speak a language related to more future orientation, also act more future-oriented?
A possible measurement for the future-orientation of a company is its investment into R&D. Does a company invest more into R&D when its board is composed of for example more German speakers than English speakers? This is not only an important question for companies and their owners, who look for long-term success but it is also of interest for the economy as a whole. Economic theory points to R&D as a main source of long term productivity growth (Solow, 1956; Romer, 1990). Therefore, the amount of R&D expenditures are important for the long term development of economies. But companies might not undertake research on their own but outsource it to suppliers. Other companies might not undertake research at all but buy market ready products or even whole companies to develop their business model for the future. To capture this kind of future-oriented behaviour of a company I also look at its intangible assets growth rate.
To address my hypothesis, I use data from BoardEx about board members of European companies from 2005 to 2017. The native language of the board members is approximated by their nationality. This information is then combined with data about R&D expenditures of the companies from the Amadeus database of the Bureau van Djik. The information about the future-time reference (FTR) of a language, which tells you how and when a language requires the speaker to mark the future, come from "The World Atlas of Language Structures" (Dahl and Velupillai, 2013) and Chen (2013). This provides me with a comprehensive panel data set containing observations from 1895 companies over a 13-year period to

examine the relationship between FTR characteristics of board members' native languages and companies' R&D expenditures.

I find a negative effect of inflectional marking on the growth rate of intangible assets, so companies with more board members who speak a language that grammatically distinguishes the future from the present by modifying the verb do act less future-oriented. When I use R&D expenditures as benchmark for the future-oriented behaviour of a company the effect turns positive. However, this change in direction of the effect most likely doesn't reflect the actual effect, but is due to the poor availability of data on R&D expenditure of enterprises in the EU in my data sources. The effect of the Strong- and Weak-FTR classification is positive throughout all of my regressions and therefore not in line with my hypothesis and the findings from the literature. But due to the criticism of various linguist (Section 5) I would argue that this classification is connected with many problems and is not suitable to differentiate languages. Therefore, I do not put much emphasis on these results and focus on the inflectional marking.

Closest to my own research is work done by Chi et al. (2020). They find in their work that countries with a weak FTR language and companies from such countries invest more into R&D. My research adds to the existing literature by not assigning companies the characteristic of the official language of the country they are based in but to focus directly on board members and their native language. Far-reaching decisions for the future of a company, like R&D investments, are made by its board. So to evaluated the a possible effect of a language characteristic on the future-orientation of a company, you have to look at the language of its board members, because they are the individuals who make these decisions and their thinking and ultimately their decision making is influence by their native language. A second important point is, that the current literature on the effect of FTR on economic decision making uses the classification in weak and strong FTR first introduced into economic research by Chen (2013). As mentioned before the linguists Pullum (2012) and Dahl (Chen 2012) criticise that an accurate classification of languages into strong or weak FTR is not so easily possible and that languages differ in their FTR marking on many parameters for which information is often lacking in grammar. In the WALS Dahl and Velupillai (2013) focus on inflectional marking as one characteristic in which languages differ in their marking of future events. I use this characteristic as a second variable to investigate the effect of FTR in languages on the economic behaviour and future-orientation.

In a follow up study, Roberts et al. investigate if the findings of Chen (2013) for savings and grammatical marking of the future are robust when controlled for geographic and historical relatedness of languages. In general, the statistical correlation between the two variables is weaker when controlled for relatedness but the correlation remained reasonably robust. Fuchs-Schündeln, Masella and Paule-Paludkiewics (2020) and Guin (2016) also find that a weak-FTR language leads to a higher savings of individuals. Chen et al. (2017) find a similar savings behaviour for companies. The relationship between FTR and earnings management is investigated by Fasan et al. (2016) and Kim, Kim and Zhou (2017). They both find that companies from weak-FTR countries are less likely to engage in earnings management. Pérez and Tavits (2017) find that weak-FTR languages are linked to a higher support for future-orientated policies. They randomly assign the language to bilingual persons in a survey and find that individuals are more likely to support such policies if the survey is conducted in the weak-FTR language. Galor, Özak and Sarid (2016) find that individuals speaking a language with an obligatory inflectional marking of the future are 4 percentage points less likely to attend college.

In addition to my primary research question, this research might also be able to expand the already existing literature about factors determining the level of R&D expenditures within a country. Some of these factors are tax incentives, location factors, democratic institutions and compensation schemes for board members. A large strand of literature finds a positive effect of tax incentives on R&D activities (Hall and Van Reenen, 2000; Bloom, Griffith and Van Reenen, 2002; Ernst and Spengel, 2011). However, tax incentives do not only affect the quantity of R&D but also the quality. Ernst, Richter and Riedel (2014) use patent applications to the European Patent Office (EPO) as a proxy for R&D activities of companies. They show that a low tax rate on patent earnings raises the average profitability and innovation level of projects. On the other hand, R&D tax credits and allowances exert a negative impact on project quality. Important location factors for R&D activities are high-quality infrastructure and the supply of R&D staff (Cantwell and Piscitello, 2005). For public R&D expenditures, democratic institutions play a role (Kim, 2011). On an individual level, Rapp, Schaller and

Wolff (2012) find that a share based compensation of board members yield higher investments into R&D.
The paper is structured as follows: First, I explain in more detail what FTR means and how it differs between languages. Section II talks about my hypothesis and how your native language might affect your decision making. Section III explains my variables in more detail of interest and which controls I will use for my analysis. Section IV presents my empirical model and the results of my regressions. Section V discusses issues surrounding the interpretation of my results and known criticism from the literature. In Section VI, I conclude my findings.

1 Future-time Reference in Languages

Languages differ widely in how and when they require their users to mark the future. As mentioned above, an English speaker mostly uses some form of ”will” or ”going to” when she is speaking about the future. For example, if I want to tell a friend what I’m going to do tomorrow, I can’t say ”I go to the theater”. In the English language it is obligatory to say ”I’m going to the theater tomorrow”. In German it is perfectly fine to use the present tense to talk about future plans.

(1)	Morgen	regnet	es
	Tomorrow	rains	it
	It	will rain	tomorrow

Only because there is no obligation to use the future tense in German doesn’t mean there is no possibility to grammatically mark the future. It would also be totally fine to say:

(2)	Morgen	wird	es	regnen
	Tomorrow	will	it	rain
	It	will rain	tomorrow	

which is not so commonly used but also correct.
Even within Europe, these differences are surprisingly widespread. It ranges from Finnish with almost no distinguishing between present and future time to French, which has separate and obligatory forms of verbs to use in the future tense.

(3)

Tänään	on	klymää	
Today	is	cold	
It	is	cold	today

Huomenna	on	klymää	
Tomorrow	is	cold	
It	will be	cold	tomorrow

It also equally correct to use the present tense for the present and the future in Finnish like it is in German as mentioned before. In English, it again requires this auxiliary construct with ”will” to grammatically mark the future. Another way to grammatically mark the future which is commonly used in languages is inflectional. Inflectional in general means the modification of a word to express different grammatical categories, i.e tense, case or gender. Thus in French present and future differ in the form of the verb.

(4)

Il	fait	froid	aujourd'hui
It	do	cold	today
It	is	cold	today

Il	fera	froid	demain
It	do	cold	tomorrow
It	will be	cold	tomorrow

I will use both differences in marking the future I just described in my analysis. The first characteristic is the obligatory marking of future events, which is the central characteristic of the Weak- and Strong-FTR classification. This is the criteria that Chen uses in his analysis. The second characteristic I want to exploit is inflectional marking of the future like in French. This means not only an obligatory marking of the future but it is also done by the modification of the verb and not like in English with an auxiliary construction. This is the feature which is used in the World Atlas of Language Structures (WALS) in the Chapter about the future tense (Dahl and Velupillai, 2013) and also by Galor, Özak and Sarid (2016). I consider the inflecting marker to be the better distinction, as the distinction made by Chen is criticized by some linguists[1]. I have nevertheless included the Strong-FTR classification for completeness, as it is used in the literature.

[1]For more information see Section 5

2 Hypothesis

In this paper, I test the hypothesis that being required to speak in a certain form about the future affects the decision making of an individual, i.e. they act less future-oriented. If a language requires the speaker to distinguish between present and future grammatically, the future will be conceptual more distant. This distance leads to a less future-oriented behaviour. In the business environment, investments in the future lead to costs today, but the possible rewards from it are sometime in the future. For a speaker of a language with a certain grammatical marking of the future these possible rewards are even further in the future due to the grammatical distinction. Therefore, language speakers prefer to spend money on projects that yield a reward today. For speakers of Weak-FTR languages on the contrary, it might be easier to invest. By equating present and future grammatically, the future seems closer. Hence, the possible reward of an investment is mentally also closer, which makes it easier to bear the costs today. For the Strong- and Weak-FTR distinction Chen (2013) makes in his paper this hypothesis is very straight forward. A person whose native language has a Strong-FTR time reference acts less future-oriented than a speaker of a Weak-FTR language. Therefore, a company with board members who speak more Strong FTR languages should also act less future-oriented if this effect is transferred to the business world.
For the second characteristic the hypothesis changes a little bit and gets more specific. I will argue that it does not only matter if a language requires a speaker to distinguish between future and present but also how it requires her to differentiate. It might make a difference if a speaker is required to use an auxiliary term to talk about the future like in English or she has to use a ”special” form of the verb, like in French. To really alter the word of what you are doing, in this case spending money/bearing costs to get a reward in the future, might make mentally a huge difference. In doing so, it really shows that the earning is in the future because the verb ”earn” is in its future form. When an auxiliary construct is used the ”earning” remains in its present form and thereby might not be perceived to be in the future. At least not as distant in the future compared to a language in which the speaker is required to use a future form of the verb itself.

3 Data

3.1 Dependent Variable

As a measurement for the future orientation of a company, I use tow different variables. The market and the demand of customers change over time, new technologies emerge and old ones disappear. Companies must constantly adapt and evolve their business model to stay relevant and competitive in a changing world. One way to measure how future orientated a company thinks, is their expenditures into R&D to develop their business model and to be prepared for the market of the future. The data about R&D expenditures of companies come from the Amadeus database of the Bureau van Djik which has financial data for thousands of European firms. The data is per company per year and denominated in local currency. To make it comparable between companies, I relate R&D expenditures to the total assets. This results in a proportion, that shows how much of the company's current capital is invested into the future. Observations with negative R&D expenditures are excluded, because they can't be reasonably explained. Furthermore, observations with a proportion of R&D expenditures to total assets over 50% are excluded, because they seem unreliably high and are most likely reporting errors. Investment into R&D and development of new products for yourself is not the only way to prepare your company for the market of the future. Another possibility is to buy the research and developments of others. To capture this, I will also look at the growth rate of the intangible assets of the companies. As you can see in table 1, there are growth rates that seem to be unreliably high. Because of this observations above the 93th percentile are excluded from the regressions. The 93th percentile with a growth rate just over 100% is still pretty high, but the lowest value I can use without running into sample selection problems. I will talk more on sample selection problems in chapter IV.

For the R&D regressions I'm left with 4830 observations from 868 companies that range from 2005 to 2017. These companies are based in ten different European countries (Appendix: Table 12) and come from 34 different sectors (Appendix: Table 13). On average there are 5.57 observations per company.

The data set for regressions with the intangible assets growth rate as dependent variable has 9968 observations from 1895 companies that range from the years

Table 1: Distribution of dependent variables

R&D expenditures		Growth Rate of int. assets	
Minimum	-0.267	Minimum	-1
25th Percentile	0	25th Percentile	-0.068
50th Percentile	0.0142	50th Percentile	0.005
75th Percentile	0.063	75th Percentile	0.148
93th Percentile	0.245	81th Percentile	0.248
97th Percentile	0.496	87th Percentile	0.460
98th Percentile	0.687	93th Percentile	1.027
Maximum	140.080	Maximum	1.62×10^8
Mean	0.149	Mean	11631.830

2007 to 2017. These companies are based in 24 different European countries (Appendix: Table 14) and come from 37 different sectors (Appendix: Table 15). On average there are 5.26 observations per company.

Table 2: Company descriptives

	R&D Expenditures	Intangible Asset Growth Rate
Female Share	0.14	0.13
Avg. Age of Board Members	62.37	62.11
Country Share	0.85	0.83
Avg. R&D	0.05	
Avg. Growth Rate		0.01
Avg. Nb. Observation	5.56	5.26

3.2 Independent Variable

The data about Strong-FTR and Weak-FTR languages is adopted from Chen (2013). He bases his data mostly on the research of Dahl (2000) and Thieroff (2000) about the characteristics of European languages and extends it with other sources for non-European languages. The information about the board members of a company in a certain year come from BoardEx. The data also ranges from 2005 to 2018. Both databases are connected by the nationality of the board member. The board member gets assigned the language characteristics of the official language of her nationality. The variable is 0 if the language is a Weak-FTR language, like German, and 1 if it is a Strong-FTR language, like English. Afterwards, the data for all board members per company and year are collapsed to form a continuous variable that ranges from 0 to 1. The observation takes the average value of all the language variables of the board members. That means if a company has 10 board members in 1990, of whom 4 are German speakers and 6 are English speakers, the value of the language variable would be 0.4.

Table 3: Descriptive Statistics Mean Strong-FTR

R&D Expenditures

		Mean	Variance	Min	Max	Observations
SFTR	overall	0.797	0.356	0	1	N = 4830
	between		0.365	0	1	n = 868
	within		0.050	0.462	1.464	T-bar = 5.565

Intangible Asset Growth Rate

		Mean	Variance	Min	Max	Observations
SFTR	overall	0.759	0.389	0	1	N = 9968
	between		0.398	0	1	n = 1895
	within		0.048	0.230	1.359	T-bar = 5.260

Note: T-bar is the average number of years observed for all companies

Another way to condense the language variable of board members per company is to use the median instead of the mean. You can possibly argue that decisions in a board are not made by a compromise that represents the preferences of all board members according to their share, but by a majority winner takes it all kind of vote and therefore the median language characteristic is of more interest than the mean value. As one can see from the data, there is variance of the language characteristic between companies but unfortunately not much within companies. For the second approach, I will use data from ”The World Atlas of Language Structures” (Dahl and Velupillai, 2013) about whether a language has an inflectional marking of the future/non-future distinction. The data for the board members is the same as before and they are again linked by the nationality of the board members. The variable is 0 if the language has no inflectional marking and

Table 4: Descriptive Statistics Median Strong-FTR

R&D Expenditures

		Mean	Variance	Min	Max	Observations
SFTR	overall	0.808	0.390	0	1	N = 4830
	between		0.400	0	1	n = 868
	within		0.057	0.031	1.642	T-bar = 5.565

Intangible Asset Growth Rate

		Mean	Variance	Min	Max	Observations
SFTR	overall	0.764	0.421	0	1	N = 9968
	between		0.432	0	1	n = 1895
	within		0.057	-0.111	1.576	T-bar = 5.260

Note: T-bar is the average number of years observed for all companies

1 if there is an inflectional marking of the distinction between future and present. The observations are again collapsed to get one observation per company and year which is the mean of all board members and a continuous variable between 0 and 1.

Table 5: Descriptive Statistics Inflectional Marking Mean

R&D Expenditures

		Mean	Variance	Min	Max	Observations
Inflectionl	overall	0.403	0.447	0	1	N = 4830
Marking	between		0.442	0	1	n = 868
	within		0.049	-0.397	0.903	T-bar = 5.565

Intangible Asset Growth Rate

		Mean	Variance	Min	Max	Observations
Inflectionl	overall	0.275	0.411	0	1	N = 9968
Marking	between		0.407	0	1	n = 1895
	within		0.044	-0.141	0.859	T-bar = 5.260

Note: T-bar is the average number of years observed for all companies

Additionally, I will also use the median to condense the language variables of all board members to one value per company per year. There is again variance between the companies but very little within the companies over time.

Table 6: Descriptive Statistics Inflectional Marking Median

R&D Expenditures

		Mean	Variance	Min	Max	Observations
Inflectionl	overall	0.421	0.490	0	1	N = 4830
Marking	between		0.480	0	1	n = 868
	within		0.062	-0.436	1.310	T-bar = 5.565

Intangible Asset Growth Rate

		Mean	Variance	Min	Max	Observations
Inflectionl	overall	0.278	0.445	0	1	N = 9968
Marking	between		0.439	0	1	n = 1895
	within		0.057	-0.558	1.153	T-bar = 5.260

Note: T-bar is the average number of years observed for all companies

3.3 Controls

As mentioned before, the quantity and quality of R&D activities of companies greatly depends on country specific factors, like taxation, infrastructure and institution. To control for these factors I will use country fixed effects for the general situation in a country, like the underlying institutions, that don't usually change on a yearly basis. To capture possible tax incentives for R&D expenditures and the general economic state of a country, which can change more often, I will use an interaction term between the country and the year fixed effect. A second effect I want to control for is the fact that different amounts of R&D activities between companies from different countries can just be rooted in different cultural preferences of its board members. It might be that some cultures are just more future oriented than others and therefore board members from these cultures do invest more into R&D than board members with a different cultural background. To test for a possible cultural effect, I will use two cultural dimensions from the Global Preferences Survey (GPS) (Falk et al., 2016, 2018).

Investments into R&D are normally risky at least to some extent and have a potential return somewhere in the future. Therefore, I will include the GPS's measurements for *patience* and *risk preference*.
Different business sectors can greatly differ in their R&D activity. In pharmacy, R&D is a very important part of the business model. Companies have to constantly develop new drugs, which is a very costly process. In retail, on the other hand R&D plays nearly no significant role. I will use sector fixed effects to control for these fundamental differences between different sectors as I am not interested in the effect of the sector on the volume of the R&D expenditures.
To make investments a company first needs the financial capacities to make them, so the general financial situation could also play an important role for the R&D activities of a company. To address this issue I will also control for that by using the EBIT margin (ratio earnings before interest and taxes to operational revenue) and the EBITDA margin (ratio earnings before interest, taxes, depreciation and amortization to operational revenue) of the companies.
Languages can't be assumed to be independent from each other because they have common ancestors. As Roberts, Winters and Chen (2015) argue in their paper, this can lead to an overestimation of the correlation (Galton's problem). Therefore, I will add dummies for the language families and language genera to control for possible effects of historical relatedness between languages. These dummies are again specific to an individual and then collapsed on the company level to form a continuous variable between 0 and 1 as the other language characteristics. For a company with a board consisting of 5 members of whom 3 are English speaking (Germanic language) and 2 are French speaking (Romance language) for example the variable for Germanic languages would take the value 0.6.
Another effect that should be taken into account is the effect of someone entering or leaving the board. New board members try to implement their ideas for the future of the company and therefore the R&D expenditures rises or they invest in new intangible assets. A change of board members might also be a sign for an overall poor financial situation of the company which leads to cuts in the R&D budget or the sale of intangible assets. Board members usually knew beforehand when their tenure ends and it could be that they do not want to make big decisions about the future of the company in their last year and leave it to their successors instead. I will control both, for new member entering the board and an old

member leaving it because these two events do not have to occur at the same time. There might be some delays in finding a successor for a leaving member or there is always the possibility for an increase or decrease of the overall board size.

Country Share gives the share of board members with a nationality equal to the country the companies is based in. This share is 83% and 85% for the samples of companies used in the regressions of the intangible asset growth rate and the proportion of the R&D expenditures, respectively.

4 Results

4.1 Model

I will use the following equation for all my regressions:

$$y_{i,t} = \beta_0 + \beta_1 \ell_{i,t} + \beta_2 X_{i,t} + \beta_3 X_i + \varepsilon \quad (1)$$

The dependent variable $y_{i,t}$ is either the R&D expenditures in relation to the amount of total assets or the intangible assets growth rate of company i in year t. The variable $\ell_{i,t}$ is the language variable I am interested in. In the first approach, this is the share of Strong-FTR language speaking board members in company i in year t. In the second approach, it is the share of board members speaking a language with an inflectional distinction between future and present in company i in year t. $X_{i,t}$ is a vector of company and time variant control variables and X_i is a vector of only company variant control variables.

I will estimate a random effects model with standard errors clustered at the company level. As my dataset is unbalanced I will use the Swamy-Arora estimator of the variance components (Swamy and Arora, 1972; Baltagi, 2013).

4.2 Unbalanced Panel Data

Unfortunately I don't have observations for all companies for every year, so my dataset is unbalanced. This wouldn't be a problem if you could argue that the data is missing completely at random (MCAR), this means that the missing data are a totally random set of the data. If this were be the case, it would be possible to just use the same empirical methods as in the case of a balanced panel dataset. But in the case of company you can easily argue that the data of some companies is missing because they were founded later, went bankrupt, merged with another company or were just too small to report any data. They are not missing completely at random but their missing is conditional on other variables, i.e. the economic situation in the market they are operating in or their size. A sample selection problem arises if this selection is related to the idiosyncratic errors, even when controlled for the conditional explanatory variables. Wooldridge (2010) suggests a simple test to test if the selection is related to the idiosyncratic errors. A lead of the selection indicator, $s_{i,t+1}$ is added to the regression with all other explanatory variables. For observations that are in the sample every time period, $s_{i,t+1}$ is always zero. But for attriters, $s_{i,t+1}$ switches to one in the period just before attrition. Selection in the succeeding time period should not be significant in the equation at time t, when the idiosyncratic errors are uncorrelated to the selection.

Table 7: S-Test for Sample Selection Bias

	(1)	(2)	(3)	(4)	(5)	(6)
Strong-FTR	0.028		0.028	0.012		0.012
	(0.037)		(0.037)	(0.013)		(0.013)
Inflectional-FTR		−0.139	−0.139		0.298***	0.290***
		(0.156)	(0.157)		(0.106)	(0.105)
Attrition Control						
$s_{i,t+1}$	−0.025	−0.025	−0.025	0.000	−0.000	0.000
	(0.017)	(0.017)	(0.017)	(0.005)	(0.005)	(0.005)
Country	√	√	√	√	√	√
Country × Year	√	√	√	√	√	√
Language Family	√	√	√	√	√	√
Language Genus	√	√	√	√	√	√
Sector Fixed Effects	√	√	√	√	√	√
Sector × Year	√	√	√	√	√	√
Observations	9968	9968	9968	4830	4830	4830

Note: All All Regressions are random effect models with the Swamy-Arora estimator of the variance components. Standard errors clustered at company level are reported in parenthesis. Companies from the financial sector are excluded from all regressions. Growth rates in the regressions are restricted to be smaller than the 93th perenctil. Negative proportions and proportions over 0.5 are excluded from the regression for R&D Expenditures. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table 7 show the results for these tests. In all four regressions the selection indicator is statistically not significant and therefore there is no sample selection bias. Consequently, the same methods can be used as in the case of MCAR data.

4.3 Intangible Asset Growth Rate

Tables 8 and 9 show the results for the regressions with the intangible assets growth rate as dependent variable and Strong-FTR and Inflectional-FTR as variables of interest respectively. Table 8 uses the mean value for the language characteristics and table 9 the median. The control variables are introduced in the same order in both regressions. Regression 1 controls only for country fixed effects and the interaction term between country fixed effects and year fixed effects. In the second regression, I additionally add variables for language family and genus to control for possible effects of relatedness between languages. Regression 3 adds the GPS's values for *patience* and *risk preference*. In regressions 4 to 6, I add controls for the financial situation, sector fixed effects, interaction terms between sector fixed effects and year fixed effects, the share of board members being nationals of the country the company is located in, the average age of the board, the share of female board members, the share of new board members, the share of board members who left the board that year and the amount of total assets a company has. In regression 7 I add additionally the growth rate of the next period as additional control. I drop all observations above the 93th percentile of the growth rate. Therefore, my sample selection is conditional on the proportion of R&D expenditures to total assets. To prevent a possible sample selection bias this conditionality must be taken into account.
The coefficient of the Strong-FTR characteristic is not significant in any of the seven regressions, but it is also positive in all regressions in contrast to our predictions. Inflectional distinction between future and present as variable of interest is also not significant in any of the regressions. Its coefficient is negative in all regressions as expected. The coefficient for the share of members leaving the board is significant at 10% level and yields a negative effect of about 0.05. The size of the company is significant at the 1% level. But the coefficient is very small.
In table 9 I use the median value of the Strong-FTR and the Inflection-FTR characteristic as independent variable. The coefficient for Strong-FTR is significant

Table 8: Effect on Intangible Asset Growth Rate Mean

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Strong-FTR	-0.002	0.034	0.038	0.038	0.038	0.040	0.041	0.028
	(0.030)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.034)	(0.037)
Inflectional-FTR	-0.047	-0.058	-0.129	-0.133	-0.130	-0.127	-0.126	-0.143
	(0.032)	(0.165)	(0.154)	(0.155)	(0.154)	(0.153)	(0.154)	(0.155)
Financials								
EBIT Margin			0.000	0.000	0.000	0.000	0.000	0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
EBITDA Margin			-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Board Characteristics								
Country Share			-0.015	-0.015	-0.016	-0.014	-0.014	-0.012
			(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.019)
Mean Age				-0.000	-0.001	-0.001	-0.001	-0.001
				(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Female Share				0.023	0.025	0.021	0.021	0.021
				(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Enter					-0.030	-0.030	-0.030	-0.030
					(0.021)	(0.020)	(0.020)	(0.020)
Exit					-0.048*	-0.047*	-0.047*	-0.047*
					(0.025)	(0.025)	(0.025)	(0.025)
Size								
Total Assets						0.000***	0.000***	0.000***
						(0.000)	(0.000)	(0.000)
Culture								
Patience							0.002	-0.040
							(0.051)	(0.069)
Risk Taking								0.122
								(0.159)
Country	√	√	√	√	√	√	√	√
Country × Year	√	√	√	√	√	√	√	√
Language Family	×	√	√	√	√	√	√	√
Language Genus	×	√	√	√	√	√	√	√
Sector Fixed Effects	×	×	√	√	√	√	√	√
Sector × Year	×	×	√	√	√	√	√	√
Attrition Control	√	√	√	√	√	√	√	√
Observations	9968	9968	9968	9968	9968	9968	9968	9968
Clusters	1895	1895	1895	1895	1895	1895	1895	1895

Note: All Regressions are random effect models with the Swamy-Arora estimator of the variance components. Standard errors clustered at company level are reported in parenthesis. Companies from the financial sector are excluded from all regressions. Growth rates in the regressions are restricted to be smaller than the 93th perenctil. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table 9: Effect on Intangible Asset Growth Rate Median

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Strong-FTR	0.028	0.058**	0.059**	0.059*	0.059**	0.061**	0.061**	0.055*
	(0.027)	(0.029)	(0.030)	(0.030)	(0.030)	(0.030)	(0.031)	(0.032)
Inflectional-FTR	-0.077**	-0.102**	-0.107**	-0.105**	-0.103**	-0.102**	-0.103**	-0.102**
	(0.030)	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)
Financials								
EBIT Margin			0.000	0.000	0.000	0.000	0.000	0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
EBITDA Margin			-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Board Characteristics								
Country Share			-0.012	-0.012	-0.012	-0.011	-0.010	-0.008
			(0.018)	(0.018)	(0.018)	(0.018)	(0.018)	(0.019)
Mean Age				-0.000	-0.001	-0.001	-0.001	-0.001
				(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Female Share				0.022	0.025	0.021	0.021	0.020
				(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Enter					-0.030	-0.030	-0.030	-0.030
					(0.020)	(0.020)	(0.020)	(0.020)
Exit					-0.048*	-0.047*	-0.047*	-0.047*
					(0.025)	(0.025)	(0.025)	(0.025)
Size								
Total Assets						0.000***	0.000***	0.000***
						(0.000)	(0.000)	(0.000)
Culture								
Patience							0.005	-0.029
							(0.050)	(0.063)
Risk Taking								0.108
								(0.149)
Country	√	√	√	√	√	√	√	√
Country × Year	√	√	√	√	√	√	√	√
Language Family	×	√	√	√	√	√	√	√
Language Genus	×	√	√	√	√	√	√	√
Sector Fixed Effects	×	×	√	√	√	√	√	√
Sector × Year	×	×	√	√	√	√	√	√
Attrition Control	√	√	√	√	√	√	√	√
Observations	9968	9968	9968	9968	9968	9968	9968	9968
Clusters	1895	1895	1895	1895	1895	1895	1895	1895

Note: All Regressions are random effect models with the Swamy-Arora estimator of the variance components. Standard errors clustered at company level are reported in parenthesis. Companies from the financial sector are excluded from all regressions. Growth rates in the regressions are restricted to be smaller than the 93th perenctil. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

and positive from regression 2 onwards. So a switch from a board with a majority of Weak-FTR language speaker to a Strong-FTR language speaking majority in regression 8 is accompanied by a 5.5 percentage points higher intangible asset growth rate. This is again in contrast to what I expected and to Chen's findings. In contrast the coefficient for the Inflection-FTR is significant in all regressions an is always negative. A change from a board with a majority of speakers of a language with no inflectional distinction to a board with a majority of speakers of a language with inflectional distinction yields 10 percentage points lower intangible asset growth rate. This is in line with my hypothesis. As in the regressions before the coefficient for the share of members leaving the board yield a significant negative effect and the coefficients for company's size is highly significant but very close zero.

Overall there are only significant results when I use the median of the language characteristic of the board members instead of the mean. Here the Strong-FTR characteristic has a positive effect, e.g. companies with a majority of board members speaking a Strong-FTR language act more future orientated. This effects contradicts my hypothesis and is also not in line with Chen's findings of the effect on an individuals behaviour. The effect for the Inflectional-FTR variable is as expected by my hypothesis. A company with a board with a majority of speakers of a language with inflectional distinction has a lower intangible asset growth rate, e.g. acts less future orientated.

4.4 R&D Expenditures

In my second approach, I use the proportion of R&D expenditures to total assets as dependent variable. The control variables are added in the same order to regressions 1 to 7 as before. I drop all observations with a negative proportion or a proportion higher than 0.5. Therefore, my sample selection is conditional on the proportion of R&D expenditures to total assets. To prevent a possible sample selection bias this conditionality must be taken into account. As in the regressions for the growth rate I add the proportion of the next period to control for this conditionality.

The effect of the Strong-FTR characteristic isn't significant in all regressions, but is positive throughout all of them. The coefficient for the Inflectional-FTR characteristic is significant in all regressions. Its effect is negative and turns positive from regression 2 onwards. In regression 8 it yields a positive effect of 0.288 that is significant at the 1% level. If a company's board switches from with only speakers of a language with no inflectional distinction to a board with only speaker of a language with an inflectional distinction this will result in a 28 percentage points higher proportion of R&D expenditures to total assets.

Table 10: Effect on R&D Expenditures Mean

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Strong-FTR	0.025**	0.028**	0.020*	0.019	0.019	0.018	0.024*	0.012
	(0.011)	(0.012)	(0.012)	(0.012)	(0.013)	(0.012)	(0.012)	(0.013)
Inflectional-FTR	−0.031***	0.134***	0.288***	0.292***	0.294***	0.301***	0.295***	0.288***
	(0.010)	(0.032)	(0.101)	(0.107)	(0.106)	(0.105)	(0.104)	(0.104)
Financials								
EBIT Margin			0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
EBITDA Margin			−0.000***	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Board Characteristics								
Country Share				−0.002	−0.002	−0.002	−0.000	0.002
				(0.008)	(0.008)	(0.008)	(0.008)	(0.007)
Mean Age				−0.000	−0.000	−0.000	−0.000	−0.000
				(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female Share				−0.011	−0.012	−0.011	−0.011	−0.011
				(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Enter					0.002	0.002	0.002	0.002
					(0.006)	(0.006)	(0.006)	(0.006)
Exit					−0.009	−0.009	−0.009	−0.009
					(0.008)	(0.008)	(0.008)	(0.008)
Size								
Total Assets						−0.000**	−0.000**	−0.000**
						(0.000)	(0.000)	(0.000)
Culture								
Patience							0.063**	0.024
							(0.030)	(0.045)
Risk Taking								0.138
								(0.098)
Country	√	√	√	√	√	√	√	√
Country × Year	√	√	√	√	√	√	√	√
Language Family	×	√	√	√	√	√	√	√
Language Genus	×	√	√	√	√	√	√	√
Sector Fixed Effects	×	×	√	√	√	√	√	√
Sector × Year	×	×	√	√	√	√	√	√
Attrition Control	√	√	√	√	√	√	√	√
Observations	4830	4830	4830	4830	4830	4830	4830	4830
Clusters	868	868	868	868	868	868	868	868

Note: All Regressions are random effect models with the Swamy-Arora estimator of the variance components. Standard errors clustered at company level are reported in parenthesis. Companies from the financial sector are excluded from all regressions. Negative proportions and proportions over 0.5 are excluded from the regression. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

In regression 8 only the controls for the financial situation of the company and the size of the company are significant. Both coefficients for the company's financials and the size are zero.

In table 11 I use again the median value of the language characteristic instead of its mean. The coefficient for the inflectional marking of the future is only significant in the first regression. In all other regressions neither of the both language characteristics yields a significant effect.

Table 11: Effect on R&D Expenditures Median

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Strong-FTR	0.017	0.018	0.013	0.012	0.012	0.012	0.014	0.004
	(0.011)	(0.011)	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)	(0.015)
Inflectional-FTR	−0.019**	−0.006	−0.005	−0.003	−0.003	−0.003	−0.003	0.000
	(0.009)	(0.011)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Financials								
EBIT Margin			0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
EBITDA Margin			−0.000***	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Board Characteristics								
Country Share				−0.001	−0.001	−0.002	0.000	0.002
				(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Mean Age				−0.000	−0.000	−0.000	−0.000	−0.000
				(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female Share				−0.012	−0.012	−0.011	−0.011	−0.012
				(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Enter					0.002	0.002	0.002	0.002
					(0.006)	(0.006)	(0.006)	(0.006)
Exit					−0.009	−0.009	−0.009	−0.009
					(0.008)	(0.008)	(0.008)	(0.008)
Size								
Total Assets						−0.000**	−0.000**	−0.000**
						(0.000)	(0.000)	(0.000)
Culture								
Patience							0.056*	0.012
							(0.030)	(0.042)
Risk Taking								0.171*
								(0.093)
Country	√	√	√	√	√	√	√	√
Country × Year	√	√	√	√	√	√	√	√
Language Family	×	√	√	√	√	√	√	√
Language Genus	×	√	√	√	√	√	√	√
Sector Fixed Effects	×	×	√	√	√	√	√	√
Sector × Year	×	×	√	√	√	√	√	√
Attrition Control	√	√	√	√	√	√	√	√
Observations	4830	4830	4830	4830	4830	4830	4830	4830
Clusters	868	868	868	868	868	868	868	868

Note: All Regressions are random effect models with the Swamy-Arora estimator of the variance components. Standard errors clustered at company level are reported in parenthesis. Companies from the financial sector are excluded from all regressions. Negative proportions and proportions over 0.5 are excluded from the regression. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

The cultural trait risk taking yields a positive effect of 0.17, which is significant at the 10% level. From the other controls again the company's financials and size are highly significant but their effect size is zero.

Contrary to my findings from the regressions with the intangible assets growth rate the effect of the Inflectional-FTR characteristic of a language has a positive effect if I use the proportion of R&D expenditures to total assets as indicator of the future orientation of a company. A possible explanation for this change in the direction of the effect may be the different sample I have for the regressions with the R&D expenditures. The sample is not only much smaller, but also less diverse when it comes to countries where companies are located with a majority of board members who speak a language with the Inflectional FTR. Almost every one of them (98%) is located in France. This is of interest to my findings because, according to the World Bank's World Development Indicators The World Bank (n.d.), France has much higher R&D spending than, for example, Spain or Italy, where a significant proportion of companies are located in the data set that I use in the regressions with the growth rate of intangible assets. I would argue that, on average, companies from Spain or Italy also have a lower proportion of R&D spending than companies from France and I'm only left with companies with a high proportion. It is this enormous over-representation of French companies in my data that most likely drives my results and makes the effect positive compared to the results of previous regressions

5 Discussion

In his comment to Chen (2013), the British linguist Prof. Geoffrey K. Pullum criticizes Chen's coding of Strong- vs. Weak-FTR. He gives some simple examples that it is very well possible to speak about the future in present tense in English in certain circumstances, i.e. "My flight takes off at 8:30". Therefore, he has no confidence in accurately describing English as Strong-FTR. Furthermore, he makes the point that if the facts are shaky for a so well studied language as English, how likely are they to be for less studied languages (Pullum, 2012)? A point that Dahl supports in his comment to Chen's answer to Pullum's critic (Chen, 2012). He says that in the EUROTYPE volumes (Dahl, 2000), one of the phenomena he is looking at, is the so-called "futureless area"' in Northern Europe in which languages lack inflectional futures and future-time reference

that is less systematically marked grammatically. He does therefore not introduce a binary coding like ”Strong- vs. Weak-FTR” and focuses more on predictive statements and not obligatory marking in general. The FTR marking differs across languages on many parameters for which information is often lacking in grammar. Because of this, the chapter on future tense in WALS (Dahl and Velupillai, 2013) focuses on inflectional marking, the second criteria I use in my analysis.
A second critic Pullum (2012) made, is the fact that a priori it is not clear if the correlation should be positive or negative, a point that Roberts, Winters and Chen (2015) also briefly address in their follow-up study. You can easily argue that the grammatical distinction between future and present does not lead to thinking less about the future but instead to think more about it. If an individual has to use a specific grammatical construct or a specific form of a word to speak about the future, the speaker has to pay more attention to the future and therefore might act more future orientated. This could be an explanation for my results on the inflectional distinction of future and present, which go against my hypothesis and are contrary to Chen's findings.[2]
With regard to the the interpretation of the results, it is important to mention that I can't completely rule out that language is reflecting deeper differences between individuals which drive the different behaviour instead of causing it. I try to rule out this possibility by including my control, especially the cultural dimensions, to find a causal relationship. The introduction of the cultural variables has almost no effect on especially the significant coefficients of the language characteristics. If they both were markers for the same causal factor you would expect these two to interact more.

6 Conclusion

Overall, my findings on the influence of inflectional marking on the growth rate of intangible assets are consistent with my hypothesis and the literature. I find a negative effect of considerable size for both the mean and median aggregation of the language characteristic. These results are tantamount to a less future-oriented behaviour of companies with more board members who speak a language that

[2]Similar criticism is brought forward by Dahl (2009)

grammatically distinguishes the future from the present by modifying the verb. The coefficient for the median regression is statistically significant at the 1% level.

When I use the proportion of R&D expenditures to total assets as a benchmark for the future-oriented behaviour of a company, the direction of the effect changes too positive. But this most likely does not reflect the actual effect but is due to the poor availability of data on R&D expenditure of enterprises in the EU in my data sources. Almost all companies with a majority of board members who speak a language that has an inflectional marking for the future are based in France. France spends more of its GDP on research and development than, for example, Spain or Italy, two other large European countries with a language that bears the inflection marking (The World Bank, n.d.). It is therefore highly likely that French companies also have higher R&D expenditure on average than Spanish or Italian companies. Therefore, I would argue that not only do I lose half of the observations by moving from the growth rate of intangible assets to R&D expenditure, but I also lose disproportionately many observations with low R&D expenditure, which fully drives the effect. The effect of the Strong- and Weak-FTR classification is positive throughout all my regressions and therefore not in line with my hypothesis and the findings from the literature. My findings thus support the critical view expressed by some linguists and discussed in the 5 section. As Pullum (2012) argues the direction of the language effect is a priori not that clear and the strong vs weak-FTR classification is in general not so clear cut. Therefore, I would not put too much emphasis on these results and concentrated more on the inflectional marking of future events.

In summary, the native language of person not only seems to play a role for decision making in her private life, but this effect also translate to the business world. The native language of its board members effects how future orientated a company acts.

7 Appendix

7.1 Company descriptives

Table 12: Observations per Country for R&D expenditures

	Overall		Between	
Country	Frequency	Percentage	Frequency	Percentage
Austria	10	0.21	2	0.23
Belgium	67	1.39	14	1.61
Denmark	40	0.83	12	1.38
France	2084	43.15	358	41.24
Germany	537	11.12	89	10.25
Ireland	31	0.64	7	0.81
Luxembourg	12	0.25	3	0.35
Netherlands	1	0.02	1	0.12
Sweden	270	5.59	61	7.03
United Kingdom	1778	36.81	321	36.98
Total	4830	100.00	868	100.00

Table 13: Observations per Sector (R&D Expenditures)

	Overall		Between	
Sector	Frequency	Percentage	Frequency	Percentage
Aerospace & Defence	108	2.24	16	1.84
Automobiles & Parts	151	3.13	22	2.53
Beverages	69	1.43	10	1.15
Business Services	202	4.18	39	4.49
Chemicals	215	4.45	33	3.80
Clothing & Personal Products	123	2.55	21	2.42
Construction & Building Materials	204	4.22	31	3.57
Consumer Services	11	0.23	3	0.35
Diversified Industrials	73	1.51	14	1.61
Electricity	42	0.87	5	0.58
Electronic & Electrical Equipment	271	5.61	49	5.65
Engineering & Machinery	311	6.44	54	6.22
Food & Drug Retailers	48	0.99	7	0.81
Food Producers & Processors	175	3.62	29	3.34
Forestry & Paper	15	0.31	2	0.23
Health	325	6.73	61	7.03
Household Products	83	1.72	16	1.84
Information Technology Hardware	217	4.49	43	4.95
Leisure Goods	39	0.81	8	0.92
Leisure & Hotels	100	2.07	16	1.84
Media & Entertainment	180	3.73	35	4.03
Steel & Other Metals	45	0.93	7	0.81
Mining	34	0.70	5	0.58
Oil & Gas	97	2.01	19	2.19
Containers & Packaging	64	1.33	9	1.04
Pharmaceuticals & Biotechnology	423	8.76	94	10.83
Real Estate	150	3.11	30	3.46
General Retailers	77	1.59	13	1.50
Renewable Energy	76	1.57	18	2.07
Software & Computer Services	645	13.35	120	13.82
Telecommunication Services	93	1.93	17	1.96
Tobacco	11	0.23	2	0.23
Transport	92	1.90	12	1.38
Utilities	61	1.26	8	0.92
Total	4830	100.00	868	100.00

Table 14: Observations per Country for Intangible Assets

	Overall		Between	
Country	Frequency	Percentage	Frequency	Percentage
Austria	75	0.75	16	0.84
Belgium	171	1.72	36	1.90
Croatia	12	0.12	2	0.11
Czech Republic	11	0.11	2	0.11
Denmark	56	0.56	24	1.27
Finland	198	1.99	36	1.90
France	1683	16.88	323	17.04
Germany	1142	11.46	233	12.30
Gibraltar	7	0.07	1	0.05
Greece	114	1.14	19	1.00
Hungary	11	0.11	4	0.21
Iceland	1	0.01	1	0.05
Ireland	105	1.05	23	1.21
Italy	437	4.38	86	4.54
Luxembourg	37	0.37	9	0.47
Monaco	2	0.02	1	0.05
Netherlands	99	0.99	31	1.64
Norway	115	1.15	30	1.58
Poland	9	0.09	2	0.11
Portugal	124	1.24	25	1.32
Russia	49	0.49	11	0.58
Spain	451	4.52	82	4.33
Sweden	533	5.35	94	4.96
United Kingdom	4526	45.41	804	42.43
Total	9968	100.00	1895	100.00

Table 15: Observations per Sector (Intangible Assets Growth Rate)

	Overall		Between	
Sector	Frequency	Percentage	Frequency	Percentage
Aerospace & Defence	116	1.16	17	0.90
Automobiles & Parts	235	2.36	38	2.01
Beverages	137	1.37	28	1.48
Business Services	724	7.26	127	6.70
Chemicals	253	2.54	47	2.48
Clothing & Personal Products	197	1.98	38	2.01
Construction & Building Materials	599	6.01	94	4.96
Consumer Services	32	0.32	8	0.42
Diversified Industrials	221	2.22	36	1.90
Education	1	0.01	1	0.05
Electricity	163	1.64	27	1.42
Electronic & Electrical Equipment	388	3.89	67	3.54
Engineering & Machinery	552	5.54	99	5.22
Food & Drug Retailers	134	1.34	24	1.27
Food Producers & Processors	273	2.74	51	2.69
Forestry & Paper	87	0.87	16	0.84
Health	377	3.78	83	4.38
Household Products	166	1.67	29	1.53
Information Technology Hardware	211	2.21	46	2.43
Leisure Goods	58	0.58	12	0.63
Leisure & Hotels	438	4.39	82	4.33
Media & Entertainment	641	6.43	114	6.02
Steel & Other Metals	131	1.31	26	1.37
Mining	185	1.86	47	2.48
Oil & Gas	500	5.02	99	5.22
Containers & Packaging	77	0.77	14	0.74
Pharmaceuticals & Biotechnology	510	5.12	115	6.07
Publishing	24	0.24	4	0.21
Real Estate	415	4.16	89	4.70
General Retailers	343	3.44	66	3.48
Renewable Energy	178	1.79	38	2.01
Software & Computer Services	882	8.85	175	9.23
Telecommunication Services	291	2.92	60	3.17
Tobacco	25	0.25	3	0.16
Transport	255	2.56	53	2.80
Utilities	148	1.48	21	1.11
Wholesale Trade	1	0.01	1	0.05
Total	9968	100.00	1895	100.00

7.2 Additional Regressions

Table 16: Effect on Intangible Asset Growth Rate Mean

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Strong-FTR	-0.002	0.029	0.039	0.036	0.037	0.038	0.029	0.029
	(0.034)	(0.037)	(0.036)	(0.036)	(0.036)	(0.036)	(0.038)	(0.042)
Inflectional-FTR	-0.032	-0.088	-0.142	-0.157	-0.151	-0.149	-0.159	-0.159
	(0.036)	(0.190)	(0.192)	(0.190)	(0.189)	(0.189)	(0.190)	(0.193)
Financials								
EBIT Margin			0.000	0.000	0.000	0.000	0.000	0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
EBITDA Margin			-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Board Characteristics								
Country Share			-0.010	-0.010	-0.011	-0.010	-0.014	-0.014
			(0.021)	(0.021)	(0.021)	(0.021)	(0.022)	(0.023)
Mean Age				-0.002*	-0.002**	-0.002**	-0.002**	-0.002**
				(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Female Share				0.012	0.015	0.013	0.013	0.013
				(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
Enter					-0.043*	-0.043*	-0.043*	-0.043*
					(0.025)	(0.026)	(0.025)	(0.025)
Exit					-0.067**	-0.066**	-0.067**	-0.067**
					(0.032)	(0.032)	(0.032)	(0.032)
Size								
Total Assets						0.000	0.000	0.000
						(0.000)	(0.000)	(0.000)
Cultur								
Patience							-0.058	-0.058
							(0.082)	(0.094)
Risk Taking								-0.000
								(0.199)
Country	√	√	√	√	√	√	√	√
Country × Year	√	√	√	√	√	√	√	√
Language Family	×	√	√	√	√	√	√	√
Language Genus	×	√	√	√	√	√	√	√
Sector Fixed Effects	×	×	√	√	√	√	√	√
Sector × Year	×	×	√	√	√	√	√	√
Attrition Control	√	√	√	√	√	√	√	√
Observations	10262	10262	10262	10262	10262	10262	10262	10262
Clusters	1911	1911	1911	1911	1911	1911	1911	1911

Note: All Regressions are random effect models with the Swamy-Arora estimator of the variance components. Standard errors clustered at company level are reported in parenthesis. Companies from the financial sector are excluded from all regressions. Growth rates in the regressions are restricted to be smaller than 200%. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table 17: Effect on Intangible Asset Growth Rate Mean

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Strong-FTR	-0.002	0.037	0.046	0.044	0.045	0.046	0.047	0.036
	(0.033)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.037)	(0.040)
Inflectional-FTR	-0.049	-0.055	-0.139	-0.148	-0.143	-0.141	-0.141	-0.156
	(0.034)	(0.196)	(0.211)	(0.211)	(0.209)	(0.209)	(0.210)	(0.216)
Financials								
EBIT Margin			0.000	0.000	0.000	0.000	0.000	0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
EBITDA Margin			-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Board Characteristics								
Country Share			-0.004	-0.004	-0.005	-0.004	-0.004	-0.002
			(0.019)	(0.019)	(0.019)	(0.019)	(0.020)	(0.020)
Mean Age				-0.001	-0.001*	-0.001*	-0.001*	-0.001*
				(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Female Share				0.016	0.019	0.016	0.016	0.016
				(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
Enter					-0.039*	-0.039*	-0.039*	-0.039*
					(0.023)	(0.023)	(0.023)	(0.023)
Exit					-0.056*	-0.055*	-0.055*	-0.055*
					(0.029)	(0.029)	(0.029)	(0.029)
Size								
Total Assets						0.000*	0.000*	0.000*
						(0.000)	(0.000)	(0.000)
Cultur								
Patience							0.003	-0.036
							(0.056)	(0.078)
Risk Taking								0.114
								(0.168)
Country	√	√	√	√	√	√	√	√
Country × Year	√	√	√	√	√	√	√	√
Language Family	×	√	√	√	√	√	√	√
Language Genus	×	√	√	√	√	√	√	√
Sector Fixed Effects	×	×	√	√	√	√	√	√
Sector × Year	×	×	√	√	√	√	√	√
Attrition Control	√	√	√	√	√	√	√	√
Observations	10163	10163	10163	10163	10163	10163	10163	10163
Clusters	1906	1906	1906	1906	1906	1906	1906	1906

Note: All Regressions are random effect models with the Swamy-Arora estimator of the variance components. Standard errors clustered at company level are reported in parenthesis. Companies from the financial sector are excluded from all regressions. Growth rates in the regressions are restricted to be smaller than 150%. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table 18: Effect on Intangible Asset Growth Rate Mean

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Strong-FTR	-0.011	0.014	0.020	0.020	0.021	0.023	0.025	0.014
	(0.029)	(0.030)	(0.031)	(0.031)	(0.031)	(0.031)	(0.033)	(0.035)
Inflectional-FTR	-0.028	0.017	-0.044	-0.046	-0.040	-0.038	-0.036	-0.050
	(0.029)	(0.163)	(0.155)	(0.156)	(0.156)	(0.155)	(0.155)	(0.157)
Financials								
EBIT Margin			0.000	0.000	0.000	0.000	0.000	0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
EBITDA Margin			-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Board Characteristics								
Country Share			-0.013	-0.012	-0.014	-0.012	-0.011	-0.009
			(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
Mean Age				-0.000	-0.001	-0.001	-0.001	-0.001
				(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Female Share				0.027	0.030	0.026	0.026	0.025
				(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Enter					-0.039**	-0.039**	-0.039**	-0.039**
					(0.018)	(0.018)	(0.018)	(0.018)
Exit					-0.037	-0.036	-0.036	-0.036
					(0.023)	(0.023)	(0.023)	(0.023)
Size								
Total Assets						0.000***	0.000***	0.000***
						(0.000)	(0.000)	(0.000)
Cultur								
Patience							0.009	-0.027
							(0.049)	(0.066)
Risk Taking								0.103
								(0.152)
Country	√	√	√	√	√	√	√	√
Country × Year	√	√	√	√	√	√	√	√
Language Family	×	√	√	√	√	√	√	√
Language Genus	×	√	√	√	√	√	√	√
Sector Fixed Effects	×	×	√	√	√	√	√	√
Sector × Year	×	×	√	√	√	√	√	√
Attrition Control	√	√	√	√	√	√	√	√
Observations	9774	9774	9774	9774	9774	9774	9774	9774
Clusters	1888	1888	1888	1888	1888	1888	1888	1888

Note: All Regressions are random effect models with the Swamy-Arora estimator of the variance components. Standard errors clustered at company level are reported in parenthesis. Companies from the financial sector are excluded from all regressions. Growth rates in the regressions are restricted to be smaller than 75%. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table 19: Effect on Intangible Asset Growth Rate Median

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Strong-FTR	0.038	0.064*	0.067**	0.066*	0.067**	0.068**	0.064*	0.065*
	(0.031)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.035)	(0.036)
Inflectional-FTR	-0.084***	-0.119***	-0.128***	-0.125***	-0.123***	-0.123***	-0.120***	-0.121***
	(0.032)	(0.045)	(0.045)	(0.045)	(0.045)	(0.045)	(0.046)	(0.045)
Financials								
EBIT Margin			0.000	0.000	0.000	0.000	0.000	0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
EBITDA Margin			-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Board Characteristics								
Country Share			-0.006	-0.006	-0.007	-0.006	-0.009	-0.010
			(0.021)	(0.021)	(0.021)	(0.021)	(0.022)	(0.023)
Mean Age				-0.002*	-0.002**	-0.002**	-0.002**	-0.002**
				(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Female Share				0.012	0.014	0.012	0.012	0.012
				(0.029)	(0.029)	(0.029)	(0.029)	(0.029)
Enter					-0.043*	-0.043*	-0.043*	-0.043*
					(0.025)	(0.025)	(0.025)	(0.025)
Exit					-0.067**	-0.066**	-0.067**	-0.067**
					(0.031)	(0.031)	(0.031)	(0.031)
Size								
Total Assets						0.000	0.000	0.000
						(0.000)	(0.000)	(0.000)
Cultur								
Patience							-0.049	-0.041
							(0.079)	(0.085)
Risk Taking								-0.025
								(0.187)
Country	√	√	√	√	√	√	√	√
Country × Year	√	√	√	√	√	√	√	√
Language Family	×	√	√	√	√	√	√	√
Language Genus	×	√	√	√	√	√	√	√
Sector Fixed Effects	×	×	√	√	√	√	√	√
Sector × Year	×	×	√	√	√	√	√	√
Attrition Control	√	√	√	√	√	√	√	√
Observations	10262	10262	10262	10262	10262	10262	10262	10262
Clusters	1911	1911	1911	1911	1911	1911	1911	1911

Note: All Regressions are random effect models with the Swamy-Arora estimator of the variance components. Standard errors clustered at company level are reported in parenthesis. Companies from the financial sector are excluded from all regressions. Growth rates in the regressions are restricted to be smaller than 200%. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table 20: Effect on Intangible Asset Growth Rate Median

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Strong-FTR	0.035	0.068**	0.072**	0.072**	0.072**	0.073**	0.074**	0.068**
	(0.030)	(0.032)	(0.032)	(0.032)	(0.033)	(0.033)	(0.033)	(0.034)
Inflectional-FTR	-0.095***	-0.135***	-0.143***	-0.141***	-0.139***	-0.138***	-0.139***	-0.138***
	(0.032)	(0.044)	(0.045)	(0.044)	(0.044)	(0.045)	(0.044)	(0.044)
Financials								
EBIT Margin			0.000	0.000	0.000	0.000	0.000	0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
EBITDA Margin			-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Board Characteristics								
Country Share			-0.000	-0.000	-0.001	0.000	0.000	0.002
			(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Mean Age				-0.001	-0.001*	-0.001*	-0.001*	-0.001*
				(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Female Share				0.015	0.018	0.015	0.015	0.015
				(0.027)	(0.027)	(0.027)	(0.027)	(0.027)
Enter					-0.039*	-0.039*	-0.039*	-0.039*
					(0.023)	(0.023)	(0.023)	(0.023)
Exit					-0.056*	-0.055*	-0.055*	-0.055*
					(0.029)	(0.029)	(0.029)	(0.029)
Size								
Total Assets						0.000*	0.000*	0.000*
						(0.000)	(0.000)	(0.000)
Cultur								
Patience							0.008	-0.023
							(0.054)	(0.070)
Risk Taking								0.098
								(0.155)
Country	√	√	√	√	√	√	√	√
Country × Year	√	√	√	√	√	√	√	√
Language Family	×	√	√	√	√	√	√	√
Language Genus	×	√	√	√	√	√	√	√
Sector Fixed Effects	×	×	√	√	√	√	√	√
Sector × Year	×	×	√	√	√	√	√	√
Attrition Control	√	√	√	√	√	√	√	√
Observations	10163	10163	10163	10163	10163	10163	10163	10163
Clusters	1906	1906	1906	1906	1906	1906	1906	1906

Note: All Regressions are random effect models with the Swamy-Arora estimator of the variance components. Standard errors clustered at company level are reported in parenthesis. Companies from the financial sector are excluded from all regressions. Growth rates in the regressions are restricted to be smaller than 150%. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table 21: Effect on Intangible Asset Growth Rate Median

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Strong-FTR	0.027	0.049*	0.052*	0.052*	0.052*	0.054*	0.055*	0.051*
	(0.027)	(0.028)	(0.029)	(0.029)	(0.029)	(0.029)	(0.030)	(0.031)
Inflectional-FTR	-0.069***	-0.103***	-0.108***	-0.107***	-0.105***	-0.104***	-0.105***	-0.104***
	(0.026)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)
Financials								
EBIT Margin			0.000	0.000	0.000	0.000	0.000	0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
EBITDA Margin			-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Board Characteristics								
Country Share			-0.009	-0.009	-0.010	-0.008	-0.007	-0.006
			(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.018)
Mean Age				-0.000	-0.001	-0.001	-0.001	-0.001
				(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Female Share				0.027	0.030	0.025	0.025	0.025
				(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Enter					-0.038**	-0.038**	-0.039**	-0.039**
					(0.018)	(0.018)	(0.018)	(0.018)
Exit					-0.037	-0.037	-0.036	-0.036
					(0.023)	(0.023)	(0.023)	(0.023)
Size								
Total Assets						0.000***	0.000***	0.000***
						(0.000)	(0.000)	(0.000)
Cultur								
Patience							0.015	-0.010
							(0.047)	(0.060)
Risk Taking								0.079
								(0.142)
Country	√	√	√	√	√	√	√	√
Country × Year	√	√	√	√	√	√	√	√
Language Family	×	√	√	√	√	√	√	√
Language Genus	×	√	√	√	√	√	√	√
Sector Fixed Effects	×	×	√	√	√	√	√	√
Sector × Year	×	×	√	√	√	√	√	√
Attrition Control	√	√	√	√	√	√	√	√
Observations	9774	9774	9774	9774	9774	9774	9774	9774
Clusters	1888	1888	1888	1888	1888	1888	1888	1888

Note: All Regressions are random effect models with the Swamy-Arora estimator of the variance components. Standard errors clustered at company level are reported in parenthesis. Companies from the financial sector are excluded from all regressions. Growth rates in the regressions are restricted to be smaller than 75%. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table 22: Effect on R&D Expenditures Mean

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Strong-FTR	0.015	0.021	0.012	0.009	0.009	0.008	0.014	–0.005
	(0.015)	(0.016)	(0.017)	(0.018)	(0.018)	(0.018)	(0.017)	(0.020)
Inflectional-FTR	–0.013	0.206***	0.189	0.219	0.229	0.237	0.246	0.233
	(0.015)	(0.041)	(0.152)	(0.162)	(0.164)	(0.164)	(0.164)	(0.165)
Financials								
EBIT Margin			0.000	0.000	0.000	0.000	0.000	0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
EBITDA Margin			–0.000	–0.000	–0.000	–0.000	–0.000	–0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Board Characteristics								
Country Share				–0.008	–0.007	–0.008	–0.006	–0.003
				(0.012)	(0.012)	(0.012)	(0.011)	(0.011)
Mean Age				–0.000	–0.000	–0.000	–0.000	–0.000
				(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female Share				–0.018	–0.018	–0.018	–0.017	–0.018
				(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Enter					0.005	0.005	0.005	0.005
					(0.010)	(0.010)	(0.010)	(0.010)
Exit					–0.019*	–0.019*	–0.019	–0.019*
					(0.011)	(0.011)	(0.011)	(0.011)
Size								
Total Assets						–0.000	–0.000	–0.000
						(0.000)	(0.000)	(0.000)
Cultur								
Patience							0.060*	–0.003
							(0.034)	(0.044)
Risk Taking								0.220**
								(0.107)
Country	√	√	√	√	√	√	√	√
Country × Year	√	√	√	√	√	√	√	√
Language Family	×	√	√	√	√	√	√	√
Language Genus	×	√	√	√	√	√	√	√
Sector Fixed Effects	×	×	√	√	√	√	√	√
Sector × Year	×	×	√	√	√	√	√	√
Attrition Control	√	√	√	√	√	√	√	√
Observations	4910	4910	4910	4910	4910	4910	4910	4910
Clusters	873	873	873	873	873	873	873	873

Note: All Regressions are random effect models with the Swamy-Arora estimator of the variance components. Standard errors clustered at company level are reported in parenthesis. Companies from the financial sector are excluded from all regressions. Negative proportions and proportions over 1 are excluded from the regression. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table 23: Effect on R&D Expenditures Mean

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Strong-FTR	0.021*	0.028**	0.020	0.018	0.018	0.017	0.022	0.007
	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.015)
Inflectional-FTR	−0.023**	0.163***	0.353***	0.365***	0.365***	0.373***	0.371***	0.363***
	(0.011)	(0.035)	(0.127)	(0.135)	(0.136)	(0.135)	(0.135)	(0.135)
Financials								
EBIT Margin			0.000	0.000	0.000	0.000	0.000	0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
EBITDA Margin			−0.000	−0.000	−0.000	−0.000	−0.000	−0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Board Characteristics								
Country Share				−0.001	−0.001	−0.002	−0.000	0.002
				(0.009)	(0.009)	(0.009)	(0.008)	(0.008)
Mean Age				−0.000	−0.000	−0.000	−0.000	−0.000
				(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female Share				−0.020*	−0.019*	−0.019*	−0.018*	−0.019*
				(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Enter					−0.002	−0.002	−0.003	−0.002
					(0.007)	(0.007)	(0.007)	(0.007)
Exit					−0.007	−0.007	−0.006	−0.007
					(0.008)	(0.008)	(0.008)	(0.008)
Size								
Total Assets						−0.000**	−0.000**	−0.000**
						(0.000)	(0.000)	(0.000)
Cultur								
Patience							0.048	−0.000
							(0.032)	(0.045)
Risk Taking								0.167
								(0.106)
Country	√	√	√	√	√	√	√	√
Country × Year	√	√	√	√	√	√	√	√
Language Family	×	√	√	√	√	√	√	√
Language Genus	×	√	√	√	√	√	√	√
Sector Fixed Effects	×	×	√	√	√	√	√	√
Sector × Year	×	×	√	√	√	√	√	√
Attrition Control	√	√	√	√	√	√	√	√
Observations	4885	4885	4885	4885	4885	4885	4885	4885
Clusters	872	872	872	872	872	872	872	872

Note: All Regressions are random effect models with the Swamy-Arora estimator of the variance components. Standard errors clustered at company level are reported in parenthesis. Companies from the financial sector are excluded from all regressions. Negative proportions and proportions over 0.75 are excluded from the regression. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table 24: Effect on R&D Expenditures Mean

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Strong-FTR	0.007	0.007	0.002	0.002	0.002	0.001	0.004	–0.004
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.011)
Inflectional-FTR	–0.021**	0.048**	0.162**	0.161**	0.159**	0.159**	0.148**	0.145*
	(0.009)	(0.022)	(0.070)	(0.075)	(0.075)	(0.074)	(0.074)	(0.074)
Financials								
EBIT Margin			0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
EBITDA Margin			–0.000***	–0.000***	–0.000***	–0.000***	–0.000***	–0.000***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Board Characteristics								
Country Share				0.001	0.001	0.001	0.002	0.003
				(0.007)	(0.007)	(0.006)	(0.006)	(0.006)
Mean Age				–0.000	–0.000	–0.000	–0.000	–0.000
				(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female Share				–0.006	–0.005	–0.005	–0.005	–0.005
				(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
Enter					–0.004	–0.004	–0.004	–0.004
					(0.004)	(0.004)	(0.004)	(0.004)
Exit					–0.001	–0.001	–0.001	–0.001
					(0.004)	(0.004)	(0.004)	(0.004)
Size								
Total Assets						–0.000***	–0.000***	–0.000***
						(0.000)	(0.000)	(0.000)
Cultur								
Patience							0.036	0.009
							(0.026)	(0.037)
Risk Taking								0.095
								(0.084)
Country	√	√	√	√	√	√	√	√
Country × Year	√	√	√	√	√	√	√	√
Language Family	×	√	√	√	√	√	√	√
Language Genus	×	√	√	√	√	√	√	√
Sector Fixed Effects	×	×	√	√	√	√	√	√
Sector × Year	×	×	√	√	√	√	√	√
Attrition Control	√	√	√	√	√	√	√	√
Observations	4659	4659	4659	4659	4659	4659	4659	4659
Clusters	854	854	854	854	854	854	854	854

Note: All Regressions are random effect models with the Swamy-Arora estimator of the variance components. Standard errors clustered at company level are reported in parenthesis. Companies from the financial sector are excluded from all regressions. Negative proportions and proportions over 0.25 are excluded from the regression. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table 25: Effect on R&D Expenditures Median

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Strong-FTR	0.006	0.009	0.005	0.003	0.002	0.002	0.004	−0.010
	(0.012)	(0.012)	(0.015)	(0.016)	(0.016)	(0.016)	(0.016)	(0.018)
Inflectional-FTR	−0.001	0.005	0.007	0.011	0.011	0.011	0.010	0.016
	(0.011)	(0.012)	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)	(0.015)
Financials								
EBIT Margin			0.000	0.000	0.000	0.000	0.000	0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
EBITDA Margin			−0.000	−0.000	−0.000	−0.000	−0.000	−0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Board Characteristics								
Country Share				−0.008	−0.008	−0.008	−0.007	−0.004
				(0.012)	(0.012)	(0.012)	(0.011)	(0.011)
Mean Age				−0.000	−0.000	−0.000	−0.000	−0.000
				(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female Share				−0.018	−0.019	−0.018	−0.018	−0.019
				(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Enter					0.005	0.005	0.005	0.005
					(0.010)	(0.010)	(0.010)	(0.010)
Exit					−0.019*	−0.019*	−0.019	−0.019*
					(0.011)	(0.011)	(0.011)	(0.011)
Size								
Total Assets						−0.000	−0.000	−0.000
						(0.000)	(0.000)	(0.000)
Cultur								
Patience							0.056	−0.006
							(0.034)	(0.044)
Risk Taking								0.232**
								(0.100)
Country	√	√	√	√	√	√	√	√
Country × Year	√	√	√	√	√	√	√	√
Language Family	×	√	√	√	√	√	√	√
Language Genus	×	√	√	√	√	√	√	√
Sector Fixed Effects	×	×	√	√	√	√	√	√
Sector × Year	×	×	√	√	√	√	√	√
Attrition Control	√	√	√	√	√	√	√	√
Observations	4910	4910	4910	4910	4910	4910	4910	4910
Clusters	873	873	873	873	873	873	873	873

Note: All Regressions are random effect models with the Swamy-Arora estimator of the variance components. Standard errors clustered at company level are reported in parenthesis. Companies from the financial sector are excluded from all regressions. Negative proportions and proportions over 1 are excluded from the regression. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table 26: Effect on R&D Expenditures Median

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Strong-FTR	0.013	0.016	0.011	0.010	0.010	0.010	0.012	−0.000
	(0.011)	(0.012)	(0.014)	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)
Inflectional-FTR	−0.008	0.002	0.005	0.007	0.007	0.008	0.007	0.012
	(0.009)	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)	(0.014)
Financials								
EBIT Margin			0.000	0.000	0.000	0.000	0.000	0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
EBITDA Margin			−0.000	−0.000	−0.000	−0.000	−0.000	−0.000
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Board Characteristics								
Country Share				−0.001	−0.001	−0.001	−0.000	0.002
				(0.009)	(0.009)	(0.009)	(0.008)	(0.008)
Mean Age				−0.000	−0.000	−0.000	−0.000	−0.000
				(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female Share				−0.021*	−0.020*	−0.019*	−0.019*	−0.020*
				(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Enter					−0.002	−0.002	−0.002	−0.002
					(0.007)	(0.007)	(0.007)	(0.007)
Exit					−0.007	−0.007	−0.006	−0.007
					(0.008)	(0.008)	(0.008)	(0.008)
Size								
Total Assets						−0.000**	−0.000**	−0.000**
						(0.000)	(0.000)	(0.000)
Cultur								
Patience							0.042	−0.010
							(0.032)	(0.041)
Risk Taking								0.194*
								(0.100)
Country	√	√	√	√	√	√	√	√
Country × Year	√	√	√	√	√	√	√	√
Language Family	×	√	√	√	√	√	√	√
Language Genus	×	√	√	√	√	√	√	√
Sector Fixed Effects	×	×	√	√	√	√	√	√
Sector × Year	×	×	√	√	√	√	√	√
Attrition Control	√	√	√	√	√	√	√	√
Observations	4885	4885	4885	4885	4885	4885	4885	4885
Clusters	872	872	872	872	872	872	872	872

Note: All Regressions are random effect models with the Swamy-Arora estimator of the variance components. Standard errors clustered at company level are reported in parenthesis. Companies from the financial sector are excluded from all regressions. Negative proportions and proportions over 0.75 are excluded from the regression. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

Table 27: Effect on R&D Expenditures Median

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Strong-FTR	0.002	0.002	−0.003	−0.003	−0.002	−0.003	−0.002	−0.008
	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Inflectional-FTR	−0.015*	−0.009	−0.004	−0.004	−0.004	−0.004	−0.004	−0.002
	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.009)	(0.009)
Financials								
EBIT Margin			0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
EBITDA Margin			−0.000***	−0.000***	−0.000***	−0.000***	−0.000***	−0.000***
			(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Board Characteristics								
Country Share				0.001	0.001	0.001	0.002	0.003
				(0.007)	(0.007)	(0.007)	(0.006)	(0.006)
Mean Age				−0.000	−0.000	−0.000	−0.000	−0.000
				(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female Share				−0.006	−0.005	−0.005	−0.005	−0.005
				(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Enter					−0.004	−0.004	−0.004	−0.004
					(0.004)	(0.004)	(0.004)	(0.004)
Exit					−0.001	−0.001	−0.001	−0.001
					(0.004)	(0.004)	(0.004)	(0.004)
Size								
Total Assets						−0.000***	−0.000***	−0.000***
						(0.000)	(0.000)	(0.000)
Cultur								
Patience							0.035	0.007
							(0.025)	(0.034)
Risk Taking								0.104
								(0.075)
Country	√	√	√	√	√	√	√	√
Country × Year	√	√	√	√	√	√	√	√
Language Family	×	√	√	√	√	√	√	√
Language Genus	×	√	√	√	√	√	√	√
Sector Fixed Effects	×	×	√	√	√	√	√	√
Sector × Year	×	×	√	√	√	√	√	√
Attrition Control	√	√	√	√	√	√	√	√
Observations	4659	4659	4659	4659	4659	4659	4659	4659
Clusters	854	854	854	854	854	854	854	854

Note: All Regressions are random effect models with the Swamy-Arora estimator of the variance components. Standard errors clustered at company level are reported in parenthesis. Companies from the financial sector are excluded from all regressions. Negative proportions and proportions over 0.25 are excluded from the regression. *** Significant at the 1% level. ** Significant at the 5% level. * Significant at the 10% level.

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